Time-Varying Stochastic Assessment of Conservation Voltage Reduction Based on Load Modeling

Zhaoyu Wang, *Student Member, IEEE*, and Jianhui Wang, *Senior Member, IEEE*

***Abstract*—This paper presents a time-varying stochastic technique to assess conservation voltage reduction (CVR) effects based on load modeling. A time-varying exponential load model is developed to represent voltage dependences of loads. The recursive least square (RLS) method is applied to identify model parameters in a recursive way. CVR factors can be calculated using the identified model parameters. The time-varying stochastic model for CVR effects can then be constructed by the Kolmogorov-Smirnov (K-S) test. The proposed CVR assessment method is applied to one-year measurement data from a utility company. The calculated CVR factors are verified by a Euclidian distance-based comparison method. Stochastic models of CVR effects in each time window are constructed. Compared with previous efforts on assessing CVR effects, the proposed method does not require control groups or assumptions of linear relationships between the load and its impact factors. The probabilistic nature of CVR effects is also fully considered.**

***Index Terms*—Conservation voltage reduction, Kolmogorov-Smirnov (K-S) test, load model identification, recursive least square, stochastic modeling.**

NOMENCLATURE

P_{cvron}, P_{cvroff}	Active load consumption with and without CVR.
V_{cvron}, V_{cvroff}	Reduced/normal voltage level.
P_d	Active load power demand.
P_0	Nominal active power.
V_0	Nominal voltage.
k_p	Active load-voltage dependences of exponential load model.
$P_0(t)$	Time-varying active load components.
$k_p(t)$	Time-varying active load-to-voltage dependences.
$P(t), \hat{P}(t)$	Measured active load and identified model output at time t.
P_{pre}	Active load consumption before CVR test.
P_{red}	Active load consumption during CVR period.
P_{post}	Active load consumption after CVR test.
P_{est}	Estimated active load at normal voltage during CVR period.
T_1, T_2, T_3	Pre-CVR, CVR, and Post-CVR period.
ε_{pk}	Euclidian distance-based load index for kth non-test day.
P_j	Active load at time j on the test day.
P_{jk}	Active load at time j on the kth non-test day.
N'	Number of data points during T_1 (pre-CVR) and T_3 (post-CVR) periods.
ε_{vk}	Euclidian distance-based voltage index for kth non-test day.
V_j	Voltage at time j on the test day.
V_{jk}	Voltage at time j on the kth non-test day.

Manuscript received July 15, 2013; revised October 29, 2013 and January 02, 2014; accepted January 29, 2014. Date of publication February 12, 2014; date of current version August 15, 2014. The submitted manuscript has been created by UChicago Argonne, LLC, Operator of Argonne National Laboratory ("Argonne"). Argonne, a U.S. Department of Energy Office of Science laboratory, is operated under Contract No. DE AC02-06CH11357. The U.S. Government retains for itself, and others acting on its behalf, a paid-up non-exclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the Government. This work was supported by the U.S. Department of Energy Office of Electricity Delivery –and Energy Reliability. Paper no. TPWRS-00919-2013.

Z. Wang is with the School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332 USA (e-mail: zhaoyuwang@gatech.edu).

J. Wang is with Argonne National Laboratory, Lemont, IL 60439 USA (e-mail: jianhui.wang@anl.gov).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TPWRS.2014.2304641

I. INTRODUCTION

CONSERVATION voltage reduction (CVR) controls distribution voltage levels in the lower range of ANSI standards in order to reduce peak demand and energy consumption [1]. CVR works on the principle that many loads are voltage dependent and consume less power when the supplied voltage is reduced [2]. As a popular and economical energy-saving measure, CVR has attracted many utilities for implementation in their distribution systems.

Reference [3] introduced CVR studies of the Northwest Energy Efficiency Alliance (NEEA) and found a summer CVR factor of 0.67 compared to the CVR factor of 0.20 in winter. Hydro Quebec implemented a CVR pilot project in 2005, and found the overall CVR factor of 0.4 [4]. The study in [5] used an equivalent ZIP model to calculate the energy conservation gains due to CVR in New York City networks. It was found that CVR factors for the test networks were between 0.5 and 1. The study in [6] analyzed the CVR data of Dominion Virginia Power. Results show 1% reduction in voltage produced approximately 0.92% reduction in energy consumption for tested substations. The study in [7] proposed a real-time adaptive CVR system using intelligent agents. The study in [8] introduced CVR tests conducted on a typical distribution feeder of Avista Unitlity. The results of the study confirm significant energy conservation on those feeders: 2%–3% reduction of voltage yielded 3%–4% reduction in electricity consumption. The study in [9] investigated implementing CVR through the use of line drop compensation (LDC) in Oneida-Madison Electric Cooperative (OMEC). It was found the annual energy consumption could be reduced by 0.9–1.1% and the system losses could be reduced by 0.07–0.13% in OMEC feeders. Reference [10] reviews the implementation and assessment methodologies of CVR. A recent report shows that deployment of CVR on all distribution feeders of the United States could provide a 3.04% reduction in the annual national energy consumption [11]. CVR can benefit both consumers and distribution network operators (DNOs). For consumers, the CVR benefits come from reduced energy consumptions. For DNOs, the CVR benefits come from both operational and economic aspects such as peak load relief, net loss reduction [12], emission reduction as well as potential incentives and requirements from regulatory agencies. Moreover, the optimal voltage/var control can be achieved by combing CVR with system improvements such as adding capacitors, load and phase balancing.

There are two ways to perform CVR: short-term demand reduction [13], [14] and long-term energy reduction [12]. In short-term CVR, voltage reduction is applied during peak hours to reduce peak demand. In long-term CVR, the voltage is reduced permanently to save energy. Utilities choose the type of CVR to be implemented in their systems based on operational, economic and security considerations. One of the critical problems about CVR is how to assess its energy-saving effect, which is useful for utilities in selecting candidate feeders to implement voltage reduction and conduct cost/benefit analysis. CVR effects are evaluated by a conservation voltage reduction factor (CVRf), which is defined as the percentage of load consumption reduction resulting from 1 percent reduction in voltage. Previous assessment methodologies can be mainly classified into three categories: comparison-based methods [1], [15], [16], regression-based methods [12], [13] and synthesis-based methods [17], [18]. Comparison-based methods compare load consumptions of the voltage-reduction group (test group) and normal-voltage group (control group). The control group can be a different feeder than the test group with a similar load composition or the same feeder but on a different day with similar operation conditions (e.g., similar weather). The load consumptions between the two groups are compared and the difference shows the effect of CVR. However, a good control group may not exist since there are no two feeders or two days whose operation conditions are exactly the same. Regression-based methods assume a linear model for the load with a linear dependence on voltage and other factors. Multivariate regression is often used to detect sensitivities of load to its impact factors. The problems with this method are that the regression errors may bias the CVR factor which is usually small itself (only a few percent), and the linear model is not accurate enough to capture nonlinear load behaviors. Reference [19] improved the linear regression method by applying a support vector regression (SVR) technique to assess CVR effects. The synthesis-based methods aggregate CVR effects of different customer types based on load composition information. However, this method assumes the CVR effects on each customer type are deterministic. Moreover, it is difficult to collect accurate load composition information for a feeder.

Measuring load-to-voltage (LTV) sensitivities is crucial for assessing CVR effects. CVR effects will decrease when the LTV changes from a constant impedance type to a constant power type. Many efforts have been done in the broader area of load modeling, which can be classified into two groups: component-based modeling [20]–[22] and measurement-based modeling [23]–[25]. The component-based approach is an aggregate method, which requires prior knowledge on load models and corresponding load model parameters of individual load components. The measurement-based approach estimates load model parameters by collecting field measurements and solving an optimization problem.

This paper proposes a time-varying stochastic method for assessing CVR effects. In comparison with the previous efforts (comparison, regression or synthesis-based), the proposed method calculates the CVR factors by identifying LTV sensitivities based on load modeling. The proposed stochastic method considers the complexity, stochasticity and time variability of load, which were widely recognized (e.g., in [25] and [26] for voltage stability analysis) but not captured in previous studies for CVR effect analysis. A time-varying exponential load model (TELM) is used to represent load's dependence on voltage and other impact factors. A recursive least square (RLS) algorithm is then employed to identify load models, and the CVR factor can be calculated using the identified model parameters. Since CVR effects are subject to different types of uncertainties (load composition, season, time of the day, weather conditions, human behaviors, etc.), different CVR effects may occur at different times for a certain substation. Accordingly, the time-adaptive probabilistic analysis framework proposed in this paper analyzes the statistics and uncertainties of CVR effects so that the interested utilities can be better informed in selecting target feeders and suitable times to launch voltage reduction as well as perform cost/benefit analysis. The Kolmogorov-Smirnov (K-S) goodness-of-fit test [27] is implemented to identify the most suitable probability distribution representing CVR factors for each time window. Finally, the proposed method is applied to field measurements from a utility company.

The major contributions of this paper can be summarized as

1) assessment of CVR effects by load modeling;
2) time-adaptive stochastic framework to capture the time-varying and probabilistic nature of CVR effects.

The organization of the paper is as follows. Section II discusses CVR factors, the time-adaptive exponential load model and the RLS filter. In Section III, field measurements from a utility company are introduced, the identified load model and calculated CVR factors are validated. In Section IV, a time-adaptive stochastic model of CVR effects is constructed. Section V concludes the paper with the major findings.

II. Conservation Voltage Reduction and Load Modeling

The CVR factor (CVR_f) can be defined as the relating change in active load consumption to the change in voltage. The CVR factor can be calculated by comparing load consumptions with and without voltage reduction as [10], [19]

$$CVR_f = \frac{\%\ Active\ Load\ Change}{\%\ Voltage\ Reduction} = \frac{\frac{(P_{cvroff} - P_{cvron})}{P_{cvroff}}}{\frac{(V_{cvroff} - V_{cvron})}{V_{cvroff}}}. \tag{1}$$

TABLE I
CVR FACTORS OF DIFFERENT SEASONS

References	Spring	Summer	Fall	Winter
AEP [13]	0.79-0.89	0.78-1.01	0.33-0.64	0.53-0.87
NEEA [12]	0.57	0.78	0.60	0.51
HQ [4]	N/A	0.10-0.97	N/A	0.60-0.80
BC Hydro [28]	0.60	0.77	N/A	N/A

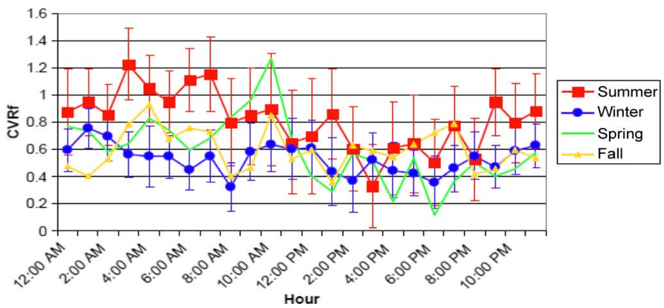


Fig. 1. CVR factors of different times in four seasons [12].

Since active load consumption has a direct economic impact on DNOs and customers, this paper focuses on active CVR effects. A similar ratio can be defined for reactive CVR effects. The CVR factor and CVR effects discussed in the following contents specifically refer to the active CVR factor and active CVR effects.

Previous test results show that CVR factors may change with time of the day and seasons [4], [12], [13], [28]. Table I summarizes seasonal CVR factors of several utilities. It can be seen CVR factors are different from season to season, which might be due to the various load compositions in different seasons (e.g., air conditioning loads dominate the summer and heating loads dominate the winter).

Fig. 1 further shows the detailed CVR factor profile during a day in four seasons [12]. The changes of CVR factors in Table I and Fig. 1 necessitate the need to assess CVR effects by time and season.

Accordingly, CVR factors are calculated in this paper by identifying the time-varying LTV sensitivities. The first step is to model the load as a function of voltage. A substation is composed of thousands of load components, such as lights, motors and so on [20]. As it is impossible to model every load component, the load model for a substation is usually an aggregate model to represent the overall load behaviors of all downstream load components and associated equipments.

One of the most widely used load models to express the input-output relationship between power and voltage and capture the load restoration characteristics is the exponential load model whose active part is in the following form [29]:

$$P_d = P_0\left(\frac{V}{V_0}\right)^{k_p}. \tag{2}$$

Since the purpose of this paper is to analyze energy-saving effects, the steady-state model defined in (2) can be used. As it is obvious that the load consumption is always changing with time due to factors such as human behaviors, weather conditions and continuous on/off switches of different kinds of loads, parameters of the load model are not constants. Even for the same circuit, different load models may be found at different times. Hence, a time-varying exponential load model (TELM) is proposed as

$$P = P_0(t)\left(\frac{V(t)}{V_0}\right)^{k_p(t)} \tag{3}$$

where $P_0(t)$ and $k_p(t)$ are time-varying model parameters that need to be identified.

Let us focus on the TELM defined in (3). V_0 is set to be 1.0 p.u. and (3) can be linearized as follows:

$$\ln P(t_k) = \ln P_0(t_k) + k_p(t_k)\ln V(t_k). \tag{4}$$

Equation (4) can be written as

$$P(k) = \varphi(k)^T\theta(k) \tag{5}$$

where $P(k) = \ln P(t_k)$, $\varphi(k) = \left[\begin{smallmatrix}1\\ \ln V(t_k)\end{smallmatrix}\right]$ and $\theta(k) = \left[\begin{smallmatrix}\ln P_0(t_k)\\ k_p(t_k)\end{smallmatrix}\right]$. $\theta(k)$ represents the kth parameters needed to be identified. Assume that the errors between measured system outputs and estimated model outputs to be $\boldsymbol{\varepsilon} = [\varepsilon_0, \varepsilon_1, \ldots, \varepsilon_N]^T$, N is the number of measurement points, then the kth error function $\varepsilon_k(\theta)$ can be defined as

$$\varepsilon_k(\theta) = \left(P(k) - \hat{P}(k|\theta)\right)^2 \tag{6}$$

where $\hat{P}(k) = \varphi(k)^T\hat{\theta}(k)$ and $\hat{\theta}(k)$ is the identified $\theta(k)$.

In order to take advantage of the updated information to perform the identification, an RLS method is used. RLS is a widely used adaptive filtering algorithm and proven to be suitable for parameter identification and fast in convergence [29]. The identification procedure tries to tune model parameters by solving the following problem:

$$\hat{\theta} = \arg\min_{\theta}\sum_{k=1}^{N}\lambda^{N-k}\varepsilon_k^2(\theta) \tag{7}$$

where λ is the forgetting factor of the RLS algorithm. The proposed identification algorithm requires only load consumption data and voltage, which can be easily obtained from utilities.

Fig. 2 shows a schematic of the time-varying framework for CVR assessment. Measurement devices are installed at substations to continuously monitor system operations. The measurement devices provide the basic operation data, such as real and reactive power and voltage. To identify load models in (3), the identification algorithm, which is RLS in this paper, tunes the parameter set $\theta(k)$ so as to minimize the difference between model output $\hat{P}(k)$ and measured system output $P(k)$. The time step for the time-varying load modeling is set to be 1 min in this paper. For the identified load parameters, the corresponding CVR factors can be calculated as

$$P_{cvroff} = P_0\left(\frac{V_{cvroff}}{V_0}\right)^{k_p(t)},\ P_{cvron} = P_0\left(\frac{V_{cvron}}{V_0}\right)^{k_p(t)} \tag{8a}$$

$$CVR_f = \frac{\left(1-\left(\frac{V_{cvron}}{V_{cvroff}}\right)^{k_p(t)}\right)}{\left(1-\left(\frac{V_{cvron}}{V_{cvroff}}\right)\right)}. \tag{8b}$$

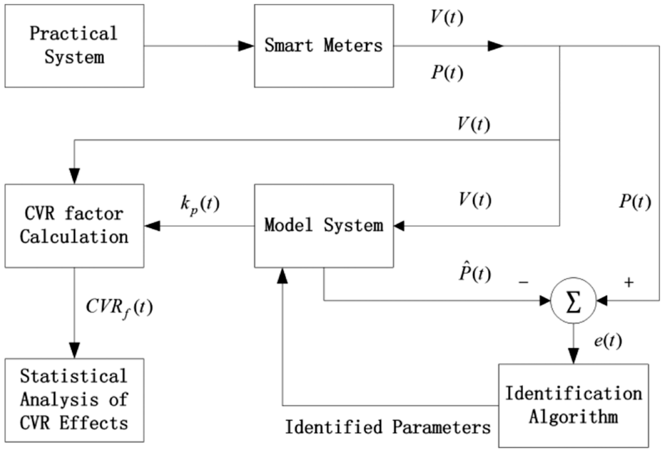


Fig. 2. Time-varying load modeling framework for assessing CVR effects.

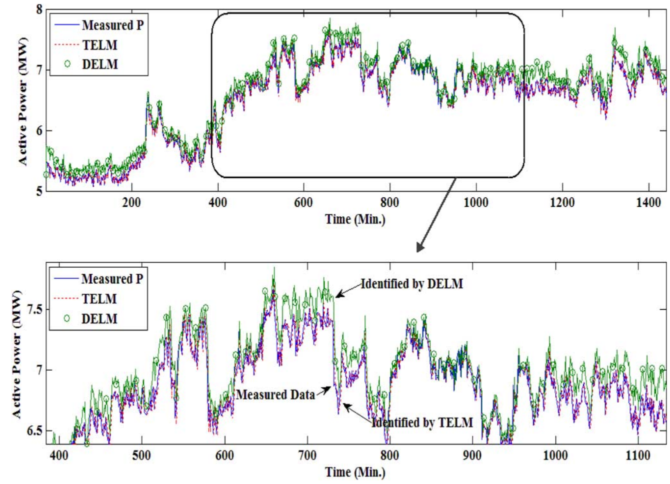


Fig. 3. Measured active power and model outputs on September 28, 2012.

The calculated CVR factors will be stored in a database and utilized to find the statistical law behind CVR effects, which will be discussed in the following sections.

III. Field Test Results and Methodology Validation

In this section, field measurements from a substation of a utility company are introduced, and the CVR factors of the substation are calculated using the proposed approach in Section III. The studied utility conducted CVR tests on one substation from January 2012 to December 2012. During this period, 210 days are reduced-voltage days, 155 days are normal-voltage days. Measurement devices are installed at the substation. The meters can trend kW, kVAR, voltage and current of the test circuits at 1-min intervals. One-year data $(365 * 24 * 60 = 525\,600 \text{ data points})$ are stored and available for analysis. Before constructing the time-varying stochastic model for CVR effects, we first validate the performance of the proposed method: 1) whether the identified TELM can represent load behaviors sufficiently; 2) whether the calculated CVR factors can accurately reflect CVR effects.

A. Validation of Identified Load Model

The identified load models should be validated for their expected performance. The easiest way for model verification is to compare the identified load model outputs with measured system outputs. Fig. 3 shows the measured data, the identification results of the active load based on TELM and the traditional deterministic exponential load model (DELM) on September 28, 2012. In the DELM, the LTV sensitivity is a time-invariant constant. The active LTV of DELM is set to be 0.7 in this comparison, which is the typical value used by utilities for simulation [30]. It can be seen that the identified load by TELM can fit the measured load curve better than DELM.

Performances of the proposed TELM and traditional DELM are compared in Table II. In this comparison, the active sensitivity is set to be 0.7. The performance of the identified load model is quantified with the relative error percentage (REP), mean absolute percentage error (MAPE) and normalized mean square error (NMSE). The definitions of these indexes can be found in [31].

Table II shows the comparison results of the three indexes. One-year average REP, NMSE, and MAPE as well as maximum and minimum daily MAPE of the two models are compared. These results indicate that the TELM provides significantly better approximation to the actual load than DELM. For example, it improves the average REP over the DELM by 55.34% for active power.

TABLE II
One-Year Average Model Errors

	Avg. REP	Avg. NMSE	Avg. MAPE	Max. MAPE	Min. MAPE
TELMP	1.5676%	1.1210	1.2253%	2.7883%	0.1171%
DELMP	3.5104%	3.2213	3.3111%	6.7343%	0.5312%

TELMP: active power of TELM, DELMP: active power of DELM, Avg.: average, REP: relative error percentage, NMSE: normalized mean square error, MAPE: mean absolute percentage error.

B. Validation of Calculated CVR factors

In order to validate the CVR factors calculated by the proposed method, peak-hour voltage reduction tests and a Euclidian distance-based comparison method are developed. The Euclidian distance has been applied to solve clustering problem in power systems [32]. Since one of the challenges in calculating CVR factors is that the load without voltage reduction during the CVR period cannot be measured, the Euclidian distance based-comparison method can select a load profile (control group) from all non-test days so that the profile can approximate what the load on the test day would be if there is no CVR. As shown in Fig. 4, load and voltage profiles of a test day can be divided into three parts: $\text{pre} - \text{CVR}\ (T_1)$, $\text{CVR}\ (T_2)$, and $\text{post} - \text{CVR}\ (T_3)$.

The Euclidian distance based-indexes for a non-test day k are defined as

$$\varepsilon_{pk} = \sum_{j=1, j\in T_1, T_3}^{N'} \frac{\sqrt{(P_j - P_{jk})^2}}{\max(P_{jk}) \cdot N'} \times 100\%$$
$$\varepsilon_{vk} = \sum_{j=1, j\in T_1, T_3}^{N'} \frac{\sqrt{(V_j - V_{jk})^2}}{\max(V_{jk}) \cdot N'} \times 100\% \quad (9)$$

where ε_{pk} and ε_{vk} can be used to select a non-test day whose load and voltage profiles are the most similar to the current ones under estimation. Denote the selected day as k^*, then we can use

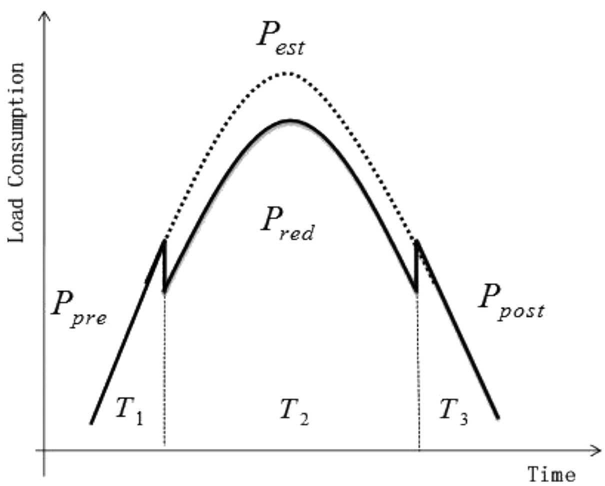


Fig. 4. Typical peak-hour CVR test.

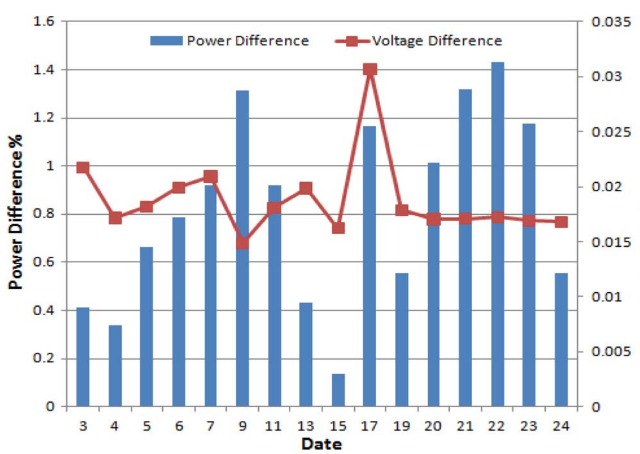


Fig. 5. Calculated Euclidian distance indexes.

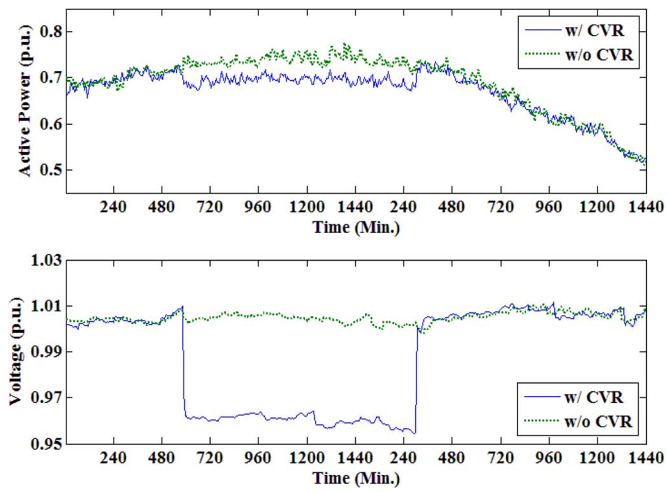


Fig. 6. Voltage and load profiles with and without CVR.

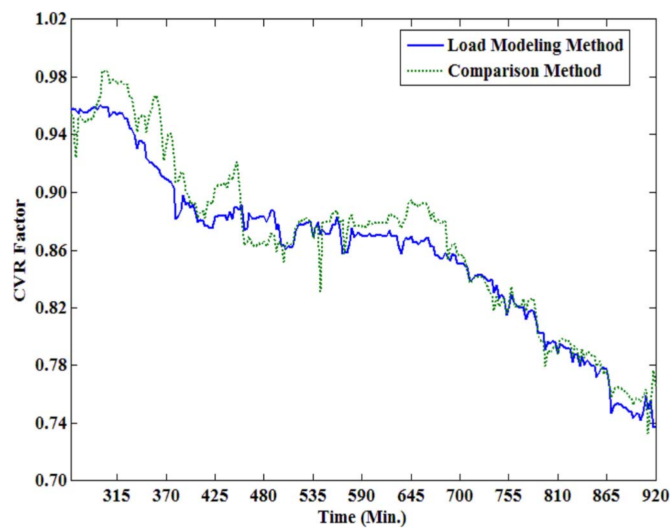


Fig. 7. CVR factors calculated by load modeling and comparison methods.

$\{P_{jk^*}\}_{j\in T_2}$ as P_{est} and calculate the CVR factor. The calculated CVR factor based on this Euclidian distance-based comparison method is compared with the one estimated by the proposed load modeling method for validation.

Take October 14, 2012 as an example and the peak-hour CVR is applied on this day. CVR starts at 4:20 AM (260 min) and ends at 3:20 PM (920 min). Therefore, T_1 represents 0:00–4:19 and T_2 represents 3:21–23:59. Power differences ε_p and voltage differences ε_v of all non-test days in the same month are calculated and the results are shown in Fig. 5. It is clear that date 15 should be selected as the control group since the power and voltage differences are the smallest.

Fig. 6 shows the 24-h (1440-min) active power and voltage profiles. The solid lines represent the measured load and voltage profiles of the test day. The dotted lines show the load and voltage profiles of the selected control group.

The RLS algorithm is then applied to estimate LTV sensitivities and the CVR factor is calculated from $k_p(t)$. The solid line in Fig. 7 shows the CVR factors during the test period. The dotted line in Fig. 7 shows the CVR factors calculated by the Euclidian distance-based comparison method. It can be seen that the two CVR factors are similar, which can validate the accuracy of the proposed method.

IV. Time-Varying Stochastic Model of CVR Effects

The one-year time-varying identification results make it possible to reveal the statistical law behind the seemingly irrelevant CVR factors. In this section, the one-year identification results are summarized and used to construct a time-adaptive stochastic model for CVR factors, so as to quantitatively analyze the uncertainties of CVR effects.

A. Analysis of One-Year Identification Results

In order to better represent the time-varying nature of CVR effects, one year is firstly divided into four seasons: spring (March, April, and May), summer (June, July, and August), fall (September, October, and November) and winter (December, January, and February). Then, every day of each season is divided into 24 1-h intervals.

Fig. 8 shows the color mapping plots of identified CVR factors of four seasons. Take spring as an example, there are 20, 17, and 21 randomly selected CVR test days in January, February, and March, respectively. Thus, there are k $(\mathrm{k} = (20 + 17 + 21) * 24 * 60 = 83520)$ test data points in spring. The k data points are classified into M $(\mathrm{M} = 24)$ groups $(\mathrm{X}_1, \ldots, \mathrm{X}_M)$ according to their time tags. Each group has n $(\mathrm{n} = (20 + 17 +$

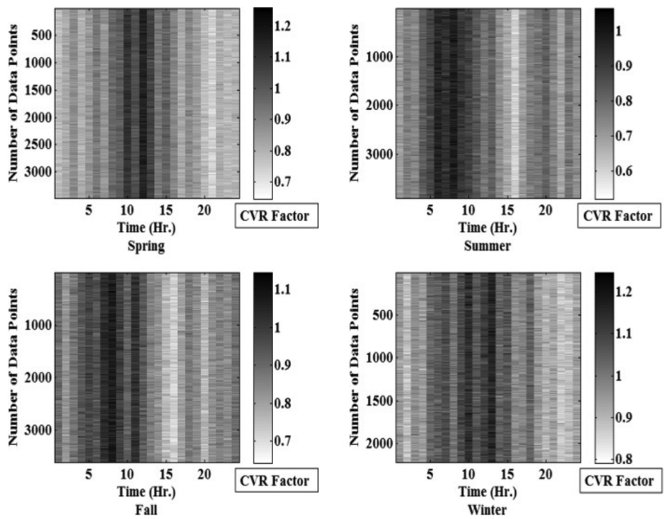


Fig. 8. 24-h color mapping plots of CVR factors in four seasons.

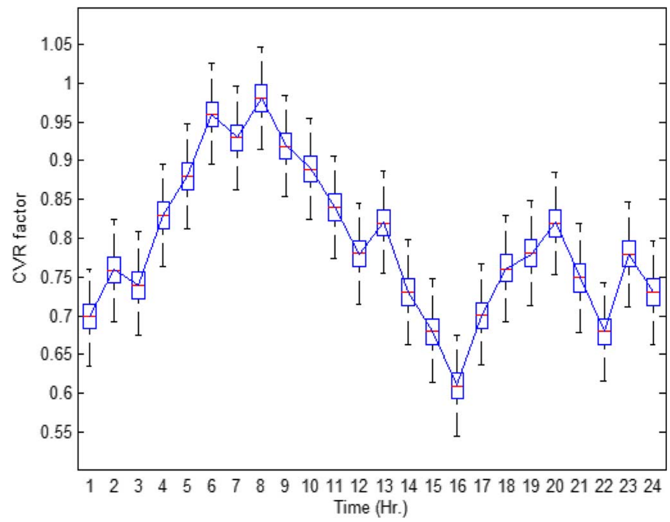


Fig. 10. 24-h box plot of CVR factors in summer.

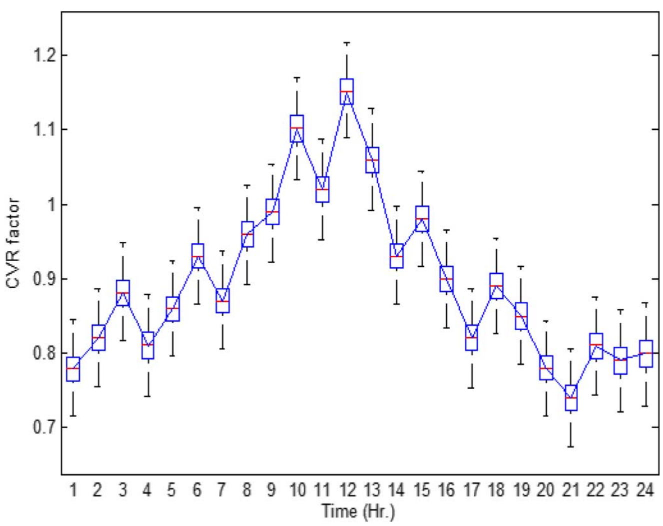


Fig. 9. 24-h box plot of CVR factors in spring.

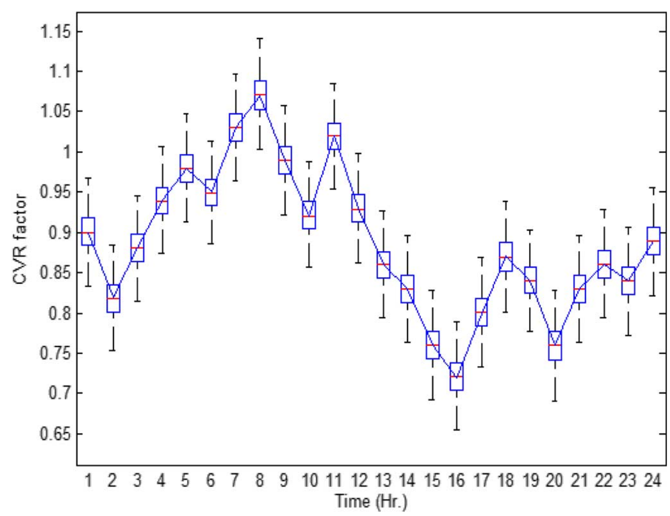


Fig. 11. 24-h box plot of CVR factors in fall.

$21) * 60 = 3480)$ data points. The CVR factors of each X_i are calculated and subplotted for spring. It is clear that CVR factors are changing with time. The peak values of CVR factors usually appear around noon in spring. The basic trends of each X_i can be seen from the figure. However, more quantitative analysis is still necessary to determine which probability density function can best fit the data.

Figs. 9–12 show the boxplots of X_i for four seasons. For example, the boxplot in Fig. 9 shows the mean, lower quartile and upper quartile of CVR factors during every hour in spring. For 0:00 to 1:00, the mean value is 0.786, the lower quartile is 0.764, which means 25 percent of data are lower than this value during the first hour; the upper quartile is 0.791, which means 25 percent of data are higher than this value. Thus, there is a certain level of variation. However, due to the small time interval, CVR factors do not vary a lot.

Figs. 9–12 also show the tendency of CVR factors. It can be seen that CVR factors of spring and winter are higher, and those of summer are lower. Throughout the year, CVR factors are relatively high in the morning, noon and early evening. Take Fig. 10 as an example. There are two peaks in the figure: one is in the morning, the other is in the evening. This phenomenon may be ascribed to the increase of electric cooking appliances, while the lower values in the afternoon may be due to the increase of working air-conditioners and refrigerators. It should be noted that more load information is needed to identify the actual reasons.

B. Construction of Time-Varying Stochastic Model of CVR Factors

In order to identify the most suitable probability distributions for CVR factors of each time interval, the Kolmogorov-Smirnov (K-S) goodness-of-fit test [27] is carried out. The K-S test computes the test error ψ, which is the maximum vertical distance between a sample cumulative distribution function (CDF) and a fitted CDF. This error is compared to a critical value ψ_{crit}, and any distribution probability fit satisfying $\psi \leq \psi_{crit}$ could be accepted. ψ_{crit} can be calculated based on the sample size and the selected level of significance [33]. The K-S test can be repeated for each data group to construct a time-varying probability distribution. In fact, the calculated CVR factors are at 1-min interval, since the measured data are at 1-min resolution. However, the time window of the created time-varying stochastic model is set to be one-hour so as to collect more data in a time

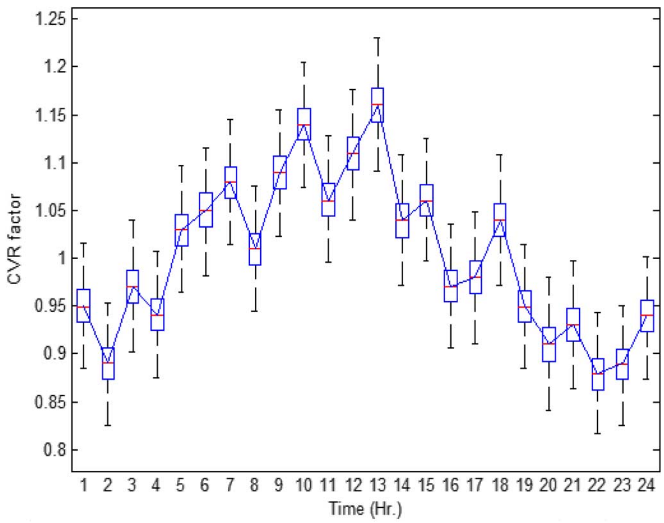


Fig. 12. 24-h box plot of CVR factors in winter.

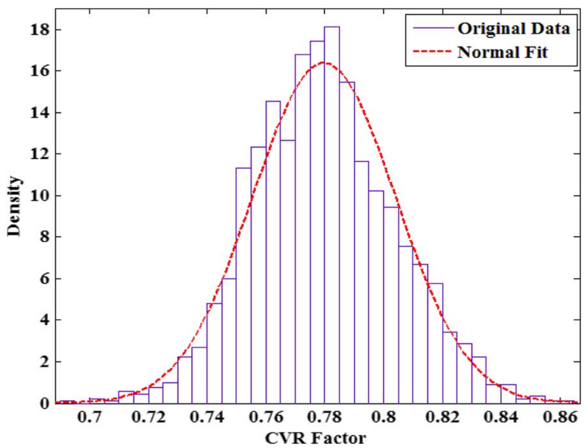


Fig. 13. Histogram of CVR factors during 0:00–1:00 in spring.

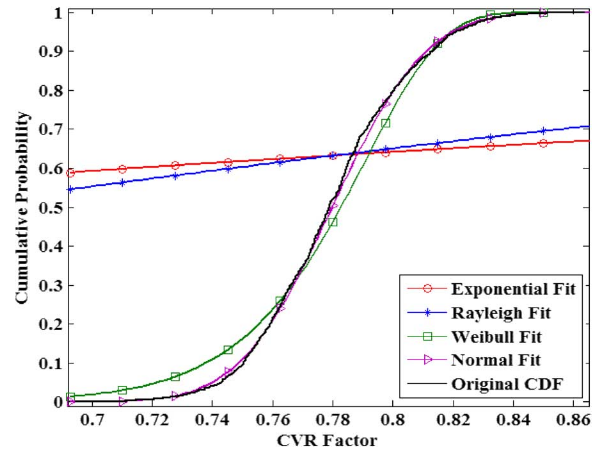


Fig. 14. CDF of CVR factors during 0:00–1:00 in spring and various probability distributions.

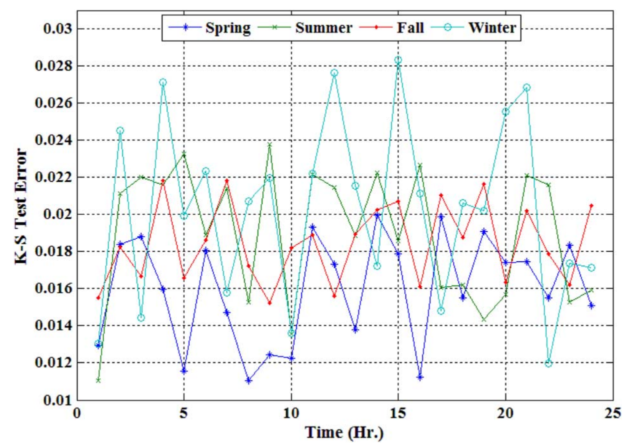


Fig. 15. K-S test errors for CVR factors.

window for K-S tests and to better capture the statistical characteristics of CVR effects. It should be noted the time window can be smaller as long as there are enough data to perform the K-S test.

Fig. 13 shows the histogram of CVR factors during 0:00–1:00 in spring. After running the K-S test, it is found that the normal distribution exhibits the most promising goodness-of-fit for each time interval.

Fig. 14 shows the differences between the CDF of CVR factors during 0:00–1:00 in spring and various other CDFs (Normal, Weibull, Rayleigh, and Exponential). It is clear that Normal distribution can fit the original CDF better.

Fig. 15 shows the K-S test errors with normal distribution, with $\psi_{crit} = 0.0319$ for the normal distribution fit with a level of significance 5%. It can be seen that the test error of each time interval in every season is under the critical value.

Detailed quantitative analysis of CVR effects is highly desirable by utilities. The above time-varying stochastic model for CVR effects can assist utilities to select suitable substations and times to implement voltage reduction. Moreover, since the electricity prices and load consumptions are time-variant and stochastic, the constructed model of CVR effects can be used for more detailed cost/benefit analysis. The benefits of CVR can be analyzed more realistically by using the proposed model.

V. Conclusion

A time-varying stochastic model is developed in this paper to represent the time-dependent nature and uncertainties of CVR effects. The first step of the proposed method is to calculate the load model parameters, which is completed by using TELM to represent loads and RLS to recursively identify model parameters. Comparison results show that the proposed TELM is better than traditional exponential load models. The second step is to calculate CVR factors using the identified model parameters. The results confirm that CVR factors change with season and time of the day. A Euclidian distance-based comparison method is developed to validate the calculated CVR factors. The third step is to split the CVR factors into each time window and perform K-S tests to find the most suitable probability distribution representing CVR factors in each time window. We find normal distribution is shown to be the best choice.

Compared with previous efforts to assess CVR effects, the proposed method has several advantages: 1) it does not depend on the selection of control groups or assumption of a simple linear relationship between load and its impact factors; 2) it captures the nature of CVR by modeling LTV sensitivities; 3) it considers the time-varying and uncertain nature of CVR effects. The proposed assessment method can potentially be used to guide the selection of suitable substations and appropriate time to implement voltage reduction. It can also be used to assist utilities to perform cost/benefit analysis.

REFERENCES

[1] T. L. Wilson, "Measurement and verification of distribution voltage optimization results," in *Proc. 2010 IEEE Power and Energy Society General Meeting*, 2010, pp. 1–9.

[2] M. Chen, R. Shoults, J. Fitzer, and H. Songster, "The effects of reduced voltages on the efficiency of electric loads," *IEEE Trans. Power App. Syst.*, vol. PAS-101, pp. 2158–2166, 1982.

[3] T. A. Short and R. W. Mee, "Voltage reduction field trials on distributions circuits," in *Proc. 2012 IEEE PES Transmission and Distribution Conf. Expo. (T&D)*, 2012, pp. 1–6.

[4] S. Lefebvre, G. Gaba, A.-O. Ba, and D. Asber, "Measuring the efficiency of voltage reduction at Hydro-Québec distribution," in *Proc. 2008 IEEE Power and Energy Society General Meeting—Conversion and Delivery of Electrical Energy in the 21st Century*, 2008, pp. 1–7.

[5] M. Diaz-Aguilo, J. Sandraz, R. Macwan, F. de Leon, D. Czarkowski, and C. Comack *et al.*, "Field-validated load model for the analysis of CVR in distribution secondary networks: Energy conservation," *IEEE Trans. Power Del.*, vol. 28, pp. 2428–2436, 2013.

[6] M. A. Peskin, P. W. Powell, and E. J. Hall, "Conservation voltage reduction with feedback from advanced metering infrastructure," in *Proc. 2012 IEEE PES Transmission and Distribution Conf. Expo. (T&D)*, 2012, pp. 1–8.

[7] M. Manbachi, M. Nasri, B. Shahabi, H. Farhangi, A. Palizban, and S. Arzanpour *et al.*, "Real-time adaptive VVO/CVR topology using multi-agent system and IEC 61850-based communication protocol," *IEEE Trans. Sustain. Energy*, to be published.

[8] B. Shah, A. Bose, and A. Srivastava, "Load modeling and voltage optimization using smart meter infrastructure," in *Proc. 2013 IEEE PES Innovative Smart Grid Technologies (ISGT)*, 2013, pp. 1–6.

[9] J. Triplett and S. Kufel, "Implementing CVR through voltage regulator LDC settings," in *Proc. 2012 IEEE Rural Electric Power Conf. (REPC)*, 2012, pp. B2-1–B2-5.

[10] Z. Wang and J. Wang, "Review on implementation and assessment of conservation voltage reduction," *IEEE Trans. Power Syst.*, to be published.

[11] J. F. K. Schneider, F. Tuffner, and R. Singh, 2010, Evaluation of Conservation Voltage Reduction (CVR) on a National Level [Online]. Available: http://www.pnl.gov/main/publications/external/technical_reports/PNNL-19596.pdf (Access Date: Jul. 2010)

[12] R. W. Beck, 2007, Distribution Efficiency Initiative Final Report [Online]. Available: http://neea.org/docs/default-source/rfp's/long-term-monitoring-and-tracking-distribution-efficiency.pdf?sfvrsn=4 (Access Date: Dec. 2007)

[13] V. Warnock and T. Kirkpatrick, "Impact of voltage reduction on energy and demand: Phase II," *IEEE Trans. Power Syst.*, vol. 1, pp. 92–95, 1986.

[14] V. Dabic, C. Siew, J. Peralta, and D. Acebedo, "BC Hydro's experience on voltage VAR optimization in distribution system," in *Proc. 2010 IEEE PES Transmission and Distribution Conf. Expo.*, 2010, pp. 1–7.

[15] T. J. Krupa and H. Asgeirsson, "The effects of reduced voltage on distribution circuit loads," *IEEE Trans. Power Syst.*, vol. 2, pp. 1013–1018, 1987.

[16] B. Kennedy and R. Fletcher, "Conservation voltage reduction (CVR) at Snohomish County PUD," *IEEE Trans. Power Syst.*, vol. 6, pp. 986–998, 1991.

[17] D. Kirshner, "Implementation of conservation voltage reduction at Commonwealth Edison," *IEEE Trans. Power Syst.*, vol. 5, pp. 1178–1182, 1990.

[18] J. De Steese, S. Merrick, and B. Kennedy, "Estimating methodology for a large regional application of conservation voltage reduction," *IEEE Trans. Power Syst.*, vol. 5, pp. 862–870, 1990.

[19] Z. Wang, M. Begovic, and J. Wang, "Analysis of conservation voltage reduction effects based on multistage SVR and stochastic process," *IEEE Trans. Smart Grid*, vol. 5, pp. 431–439, 2014.

[20] J. Ribeiro and F. Lange, "A new aggregation method for determining composite load characteristics," *IEEE Trans. Power App. Syst.*, vol. PAS-101, pp. 2869–2875, 1982.

[21] W. W. Price, K. A. Wirgau, A. Murdoch, J. V. Mitsche, E. Vaahedi, and M. El-Kady, "Load modeling for power flow and transient stability computer studies," *IEEE Trans. Power Syst.*, vol. 3, pp. 180–187, 1988.

[22] C. Chong and A. Debs, "Statistical synthesis of power system functional load models," in *Proc. 1979 18th IEEE Conf. Decision and Control Including Symp. Adaptive Processes*, 1979, pp. 264–269.

[23] H. Renmu, M. Jin, and D. J. Hill, "Composite load modeling via measurement approach," *IEEE Trans. Power Syst.*, vol. 21, pp. 663–672, 2006.

[24] C.-J. Lin, A.-T. Chen, C.-Y. Chiou, C.-H. Huang, H.-D. Chiang, and J.-C. Wang *et al.*, "Dynamic load models in power systems using the measurement approach," *IEEE Trans. Power Syst.*, vol. 8, pp. 309–315, 1993.

[25] I. R. Navarro, Dynamic Load Models for Power Systems: Estimation of Time-Varying Parameters During Normal Operation, Department of Industrial Electrical Engineering and Automation [Institutionen för industriell elektroteknik och automation], Univ., 2002.

[26] K. Srinivasan, C. Nguyen, Y. Robichaud, A. S. Jacques, and G. Rogers, "Load response coefficients monitoring system: Theory and field experience," *IEEE Trans. Power App. Syst.*, vol. PAS-100, pp. 3818–3827, 1981.

[27] R. B. D'Agostino and M. A. Stephens*, Goodness of Fit Techniques*. Boca Raton, FL, USA: CRC, 1986, vol. 68.

[28] A. Dwyer, R. E. Nielsen, J. Stangl, and N. S. Markushevich, "Load to voltage dependency tests at BC Hydro," *IEEE Trans. Power Syst.*, vol. 10, pp. 709–715, 1995.

[29] M. Begovic and R. Mills, "Load identification and voltage stability monitoring," *IEEE Trans. Power Syst.*, vol. 10, pp. 109–116, 1995.

[30] J. V. Milanovic, K. Yamashita, S. Martinez Villanueva, S. Z. Djokic, and L. M. Korunovic, "International industry practice on power system load modeling," *IEEE Trans. Power Syst.*, vol. 28, pp. 3038–3046, 2013.

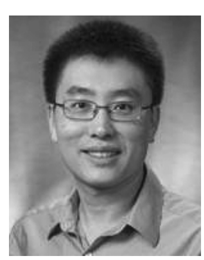
[31] E. E. Elattar, J. Y. Goulermas, and Q. Wu, "Generalized locally weighted GMDH for short term load forecasting," *IEEE Trans. Syst., Man, Cybern. C: Applicat. Rev.*, vol. 42, pp. 345–356, 2012.

[32] G. Nourbakhsh, G. Eden, D. McVeigh, and A. Ghosh, "Chronological categorization and decomposition of customer loads," *IEEE Trans. Power Del.*, vol. 27, pp. 2270–2277, 2012.

[33] D. Kececioglu*, Reliability and Life Testing Handbook*. Lancaster, PA, USA: DEStech, 2002, vol. 2.

Zhaoyu Wang (S'13) received the B.S. degree in electrical engineering from Shanghai Jiaotong University, Shanghai, China, in 2009, the M.S. degree in electrical engineering from Shanghai Jiaotong University in 2012, and the M.S. degree in electrical and computer engineering from the Georgia Institute of Technology, Atlanta, GA, USA, in 2012. He is now pursuing the Ph.D. degree in the School of Electrical and Computer Engineering, Georgia Institute of Technology.

His current research interests include volt/var control in power systems, conservation voltage reduction, load modeling and identification, stochastic optimization and its applications in power systems.



Jianhui Wang (M'07–SM'12) received the Ph.D. degree in electrical engineering from Illinois Institute of Technology, Chicago, IL, USA, in 2007.

Presently, he is a Computational Engineer with the Decision and Information Sciences Division at Argonne National Laboratory, Argonne, IL, USA.

Dr. Wang is the chair of the IEEE Power & Energy Society (PES) power system operation methods subcommittee. He is an editor of the IEEE TRANSACTIONS ON POWER SYSTEMS, the IEEE TRANSACTIONS ON SMART GRID, an associate editor of Journal of Energy Engineering, an editor of the IEEE PES Letters, and an associate editor of Applied Energy. He is an Affiliate Professor at Auburn University and the University of Notre Dame.