

Adaptive Ultra-short-term Wind Power Prediction Based on Risk Assessment

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Abstract—A risk assessment based adaptive ultra-short-term wind power prediction (USTWPP) method is proposed in this paper. In this method, features are first extracted from the historical data, and then each wind power time series (WPTS) is split into several subsets defined by their stationary patterns. A WPTS that does not match any of the stationary patterns is then included in a subset of non-stationary patterns. Each WPTS subset is then related to a USTWPP model that is specially selected and optimized offline based on the proposed risk assessment index. For online applications, the pattern of the last short WPTS is first recognized, and the relevant prediction model is then applied for USTWPP. Experimental results confirm the efficacy of the proposed method.

Index Terms—Error evaluation, offline optimization, online matching, positive error vs negative error, risk index, time series features, wind power prediction.

I. INTRODUCTION

IMPROVING the accuracy of wind power prediction (WPP) is an effective means to improve the wind power (WP) accommodation capability and enhance the reliability and efficiency of modern power systems [1]. Ultra-short-term wind power prediction (USTWPP), which runs on a 10 or 15 minute cycle [2], is vital for frequency modulation and spinning reserve optimization.

For USTWPP, the most popular statistical models include continuous linear [3], moving average [4], auto-regressive and moving average (ARMA), support vector machine (SVM) [5], Kalman filter [6], grey prediction [7], and artificial neural network (ANN) [8]. Each of these methods has its distinct features and different application situations [9]. To improve the prediction performance in USTWPP, it would be advantageous

if applicable prediction models and specific parameters can be adopted based on the different dynamic features of the WP generation laws. To achieve this, an adaptive USTWPP method [10] has been proposed for improving the robustness of the prediction performance when WP generation has particular dynamic features. The main procedures are as follows: distinctive features from historical data of wind power time series (WPTS) are analyzed and extracted; each short WPTS is classified into one of several different subsets defined according to the stationary patterns; prediction models and optimizing parameters are established offline for each of the above subsets using historical data; and finally the pattern of the last short WPTS is recognized and associated with the most relevant prediction model to complete the USTWPP for online applications.

It should be noted that both assessment and improvement of a prediction technique are based on a statistical performance indicator using prediction errors. However, most current error evaluation indices, such as mean absolute error (MAE) [11], mean absolute percentage error (MAPE) [12], and root mean square error (RMSE) [13] are based on average and absolute values of forecast errors. As a result, these indices can neither reflect the impacts of the error direction (sign) nor the events with large prediction errors but low probability. To overcome this shortcoming, a risk assessment index for WPP errors has been proposed in [14] based on distinguishing the impacts of a positive error from those of a negative error on electric power reliability. By adding a financial cost dimension, the risk assessment index can be directly accumulated as risk cost of WPP error on safety, adequacy, and economy.

This paper extends the application of the risk assessment index [14] from “post-evaluation” of WPP to prediction model selection in the adaptive USTWPP method [10] so that different preferences on WPP models of a practical system can be considered by integrating relevant prediction models for each subset. The efficacy of the proposed method is verified by simulations.

This paper is organized as follows. Section II describes the USTWPP method using offline classification and online model matching. The risk assessment of WPP error is discussed in Section III. The combination of the USTWPP method described in Section II and the risk assessment index discussed in Section III is presented in Section IV. Case studies for adaptive USTWPP based on risk assessment are presented and discussed in Section V. The conclusion is drawn in Section VI.

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II. USTWPP USING OFFLINE CLASSIFICATION AND OPTIMIZATION AND ONLINE MODEL MATCHING

A. Features Extraction and Dynamic Mode Classification

The suggested strategies for features extraction and dynamic mode classification are: 1) recognizing stationary periods of WPTS rather than non-stationary ones to improve WPP accuracy and reliability; and 2) other uncertain periods of WPTS are classified into a subset of “unknown (or non-stationary) form,” which can be associated with some universally acknowledged models. Because of the different training and optimizing samples adopted respectively in accordance with the two situations mentioned above, prediction quality will be improved consequentially.

1) Features of WPTS

Two types of features are considered in this paper. One is interval feature which reflects the global dynamic features of WPTS in a time window (L_1), including θ_m referring to the mean value of WP and θ_b (boundary feature) referring to the difference between first sampling point and last sampling point in the time window; the other is the sectional feature which reflects the change rate of WPTS dynamic in the time window, mainly relating to θ_v referring to the change rate between neighboring sampling points.

2) Threshold of Features

Both accuracy of classification and adequacy of samples are influenced by the threshold of features. Among them, the thresholds of θ_m have influence on the division of WP level; the thresholds of θ_b affect the division of smooth levels of average WP (ARIMA model applies to high smooth level while ARMA applies to low level); and the thresholds of θ_v impact the division of model complexity degrees. Methods of continuous linear, moving average, and ARMA, complexity of the order from low to high correspond to WPTS, relate to dynamic variations of the order from slow to fast dynamics.

3) Subsets Classification

The subsets are defined by combining features with different value range. Only when all features of WPTS in the time window meet one of the subset definitions, it can be classified into the subsets defined by the stationary patterns.

Assuming that P_{\max} is wind farm capacity, $x\%P_{\max}$, α , and β are the threshold of θ_m , θ_b , and θ_v respectively, m is the numbers of sample points in the time window before targeted time, then $\theta_{v1}, \dots, \theta_{v(m-1)}$ express all neighboring sampling points. Identification rules of each subset are given below.

- 1) Identification rules of subset of stationary pattern (S_1) related to WPTS with stable mean value and slow variation that are suitable for continuous linear or moving average method are given as

$$\begin{aligned} |\theta_b| &\leq \alpha_1 \cap |\theta_{v1}| \leq \beta_1 \cap |\theta_{v2}| \\ &\leq \beta_1 \cap \dots \cap |\theta_{v(m-1)}| \leq \beta_1. \end{aligned} \quad (1)$$

- 2) Identification rules of subset of stationary pattern (S_2) related to WPTS with stable mean value but quick variation that are suitable for ARMA method are given

as

$$\begin{aligned} |\theta_b| &\leq \alpha_2 \cap |\theta_{v1}| > \beta_2 \cap |\theta_{v2}| \\ &> \beta_2 \cap \dots \cap |\theta_{v(m-1)}| > \beta_2. \end{aligned} \quad (2)$$

- 3) Identification rules of subset of stationary pattern (S_3) related to WPTS with unstable mean value but slow variation that are suitable for ARIMA method are given as

$$\begin{aligned} |\theta_b| &> \alpha_3 \cap |\theta_{v1}| \leq \beta_3 \cap |\theta_{v2}| \\ &\leq \beta_3 \cap \dots \cap |\theta_{v(m-1)}| \leq \beta_3. \end{aligned} \quad (3)$$

The remaining subset (S_r), which is also called subset of non-stationary pattern, refers to the samples that filter the ones classified as one of the subset of stationary patterns from historical data of WPTS. If new subsets of stationary patterns can be defined reliably later, no matter stable or unstable, prediction quality will be improved without any influence on the availability of the above USTWPP framework.

B. Offline Model Construction for Each Subset

Both prediction models for subsets of stationary pattern and that of non-stationary pattern are built offline. Model M_1 , M_2 and M_3 are relevant to subset S_1 , S_2 and S_3 , respectively, while M_r is relevant to S_r . The above models can be optimized as the sample size increases.

C. How to Create a PostScript File

The steps of online model matching are as follows:

- 1) Select the length of observing window L , which is the number of sample points in the window. Due to the more stringent demands of subsets classification, the larger L may improve prediction accuracy, but also increase the proportion of samples divided into S_r . Similar to the length of observing window L , the threshold of features also affects the coordination of WPP accuracy and algorithm efficiency. According to practical engineering requirements for prediction accuracy and algorithm efficiency, the value of those parameters can be determined by repeated testing. The impacts of parameter settings on prediction results are analyzed in [10].
- 2) Calculate the features of WPTS in the observing window θ_m , θ_b and θ_v , and classify WPTS into one of the subsets by identification rules.
- 3) Call the relevant prediction model of the subset for USTWPP.

III. RISK ASSESSMENT OF WPP ERROR

A. Different Interpretations of Positive Error and Negative Error

Assume that t_0 is the present time and t_i is a future time instant to be predicted. With the measured value of WP y_i as the benchmark for comparison, the error e_i of the prediction value \hat{y}_i is defined as

$$e_i = \hat{y}_i - y_i \quad (4)$$

WP is overrated when $e_i > 0$ while it is underestimated when $e_i < 0$. The positive or negative error has different influence on power system reliability and economy.

B. Different Interpretations of Positive Error and Negative Error

Set n as the number of WPP within the range of investigation, then the error series (E) that consist of every relevant error (e_i) is given as

$$E = \{e_i \mid i = 1, 2, \dots, n\}. \quad (5)$$

Due to the WPP error (e_i), the reliability control costs of power system increase by $c_i(e_i)$. Thus, the global control costs increment (C) relevant to the whole error series (E) can be written as

$$C = \sum_{i=1}^n c_i(e_i) \quad (6)$$

which well reflects the predictive quality.

The above concept can be extended to extensive statistical results. The probability ($p_k(e_k)$) of forecast error (e_k) whose probability distribution function is $P(e)$ can be obtained from statistics. An important sample probabilistic method is proposed to coordinate the contradiction between sample size and high risk events with low probability [15]. When samples are not enough, statistical histograms can be used to replace distribution function $P(e)$.

Set $c_k(e_k)$ as the increased control costs caused by e_k with the distribution function $C(e)$. Neither $P(e)$ nor $C(e)$ is a symmetric function. Having a financial-cost dimension, the

risk assessment index (R) is defined as an integration of the probability of a power disturbance event caused by WPP error and the financial losses caused by the event:

$$R = \int_{-\infty}^{+\infty} P(\tau) C(\tau) d\tau. \quad (7)$$

IV. COMBINATION OF USTWPP USING OFFLINE CLASSIFICATION AND OPTIMIZATION, ONLINE MODEL MATCHING AND RISK ASSESSMENT INDEX

The application of the risk assessment index can be expanded from post-evaluation of WPP to prediction models selection in the adaptive USTWPP method using the method of offline classification and optimization, as well as online model matching. The risk assessment index is adopted as the evaluation standard of WPP models selection during offline modeling.

The framework of the proposed risk based USTWPP method is shown in Fig. 1. The left part shows the process of offline classification and optimization including extracting features from WPTS, setting thresholds of all features, classifying every short WPTS into one of several different subsets defined well by stationary patterns or non-stationary pattern, establishing prediction models for each subset and optimizing model parameters and thresholds if necessary. The right part gives the process of online model matching, which means recognizing the pattern of the last short WPTS and applying the relevant prediction model for USTWPP.

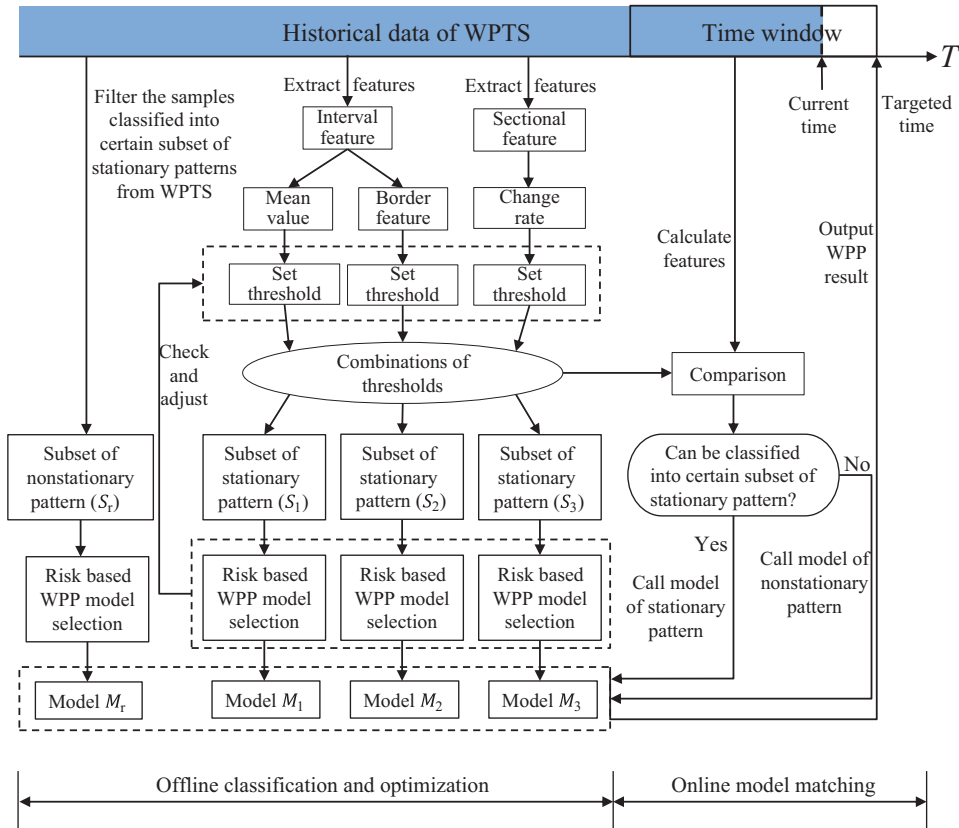


Fig. 1. The framework of the proposed risk based USTWPP method.

V. CASE STUDY

WP measured data (from April 1, 2007 to April 30, 2008) of a wind farm in Ningxia province in China is used in this study. The first 52,704 samples of the total 57,024 samples are used to establish the prediction models by offline classification and optimization, while the last 4320 samples are used to evaluate WPP performance. The sampling interval, mean value, minimum value and maximum value of the whole sample space are 10 min, 136.7 MW, 0.0 MW and 745.3 MW, respectively.

A. Implementation of the Proposed Method

1) Threshold of Dynamic Features and Subsets Classifying

Set L_1 (the length of time window during offline classification) to 6. Set $x\%P_{\max}$ (the threshold of θ_m) to 400.0 MW ($x = 53.7$), so that WPTS can be divided into two types – low output ($\theta_m \leq 400.0$) or high output ($\theta_m > 400.0$). Other features can be classified for each type and calculated in different ways: for low output type, features are calculated in absolute terms to avoid calculation difficulties; for high output type, features are calculated in relative terms to enhance the comparability. The threshold setting is shown in Table I where S_1 , S_2 , and S_3 refer to subset of a stationary pattern with stable mean value and slow variation, stable mean value but quick variety, unstable mean value but slow variety respectively. The measuring unit of WP in absolute terms is MW.

TABLE I
THE THRESHOLD SETTING

Subset	Features	Thresholds	Low Output	High Output
S_1	θ_b	α_1	20.0%	5.0%
	θ_v	β_1	15.0%	3.0%
S_2	θ_b	α_2	20.0%	5.0%
	θ_v	β_2	15.0%	3.0%
S_3	θ_b	α_3	20.0%	5.0%
	θ_v	β_3	50.0%	10.0%

Due to the availability of large samples, S_2 , which adopts the ARMA based prediction model, can be further divided into four subclass by output level: $S_{2.1}$ ($\theta_m \leq 200.0$ MW), $S_{2.2}$ (200.0 MW $< \theta_m \leq 400.0$ MW), $S_{2.3}$ (400.0 MW $< \theta_m \leq 600.0$ MW) and $S_{2.4}$ ($\theta_m > 600.0$ MW). Their relevant prediction models refer to $M_{2.1}$, $M_{2.1}$, $M_{2.3}$ and $M_{2.4}$, respectively.

The constant term of the ARIMA model, which is based on WPTS of first-order difference, is independent of WPTS's mean value in time window, so there is no need to divide S_3 further.

2) Offline Classification and Optimization Based on Risk Assessment

Taking $M_{2.4}$ which is relevant to $S_{2.4}$ as an example, four prediction models that have all already passed stationary test – ARMA(1,1), ARMA(2,1), ARIMA(1,2) and ARIMA(2,2), are chosen to be alternative models, and referred to as Model 1, 2, 3 and 4 for short.

1) Prediction model assessment using traditional index

The comparative results for each prediction model using traditional assessment indexes are shown in Table II where r means “rank.”

TABLE II
EVALUATE OUTCOME FOR VARIOUS MODELS BY USING DIFFERENT TRADITIONAL INDEXES

Indexes	Model 1		Model 2		Model 3		Model 4	
	Index Value	r	Index Value	r	Index Value	r	Index Value	r
RMSE (%)	2.20	1	2.27	4	2.22	3	2.21	2
MAE (%)	2.45	1	3.69	4	2.48	2	2.53	3
MAPE (%)	7.07	2	7.08	3	7.05	1	7.09	4
Correlation coefficient	0.42	4	0.45	1	0.43	3	0.44	2
Mean value	-14.52	3	-10.49	1	-14.41	2	-14.61	4
Standard deviation	1.18	1	1.65	4	1.24	2	1.27	3
Kurtosis	10.94	2	37.31	1	10.81	3	10.52	4
Skewness	-1.52	1	4.46	4	-1.64	3	-1.61	2
Negative maximum	-132.89	3	-48.66	1	-131.07	2	-133.12	4
Positive maximum	43.14	1	236.55	4	45.19	3	43.70	2

Among the results based on the four most commonly used traditional indexes, Model 1 is the best according to RMSE and MAE, while Model 3 is the best according to MAPE, and Model 2 outperforms others under the correlation coefficient. Other traditional indexes also give mutually exclusive conclusions. Every model except Model 4 is ranked as the first by at least one traditional index, while Model 4 takes the second place four times. Conversely, every model has the chance to be the worst or the second worst. Obviously, every traditional index produces its own preference different from others, thus the results are likely to be biased.

2) Prediction model assessment by proposed risk index

Making for convenience of computation, a simplified computation method of WPP error costs increment function $C(e)$ is given below: for positive error, spare spin reserve capability costs scheduled to counteract WP fluctuations is considered; for negative error, only the costs of wind curtailment is considered. Generally, assuming that the arranged reserve volume to compensate the WP fluctuations is according to $x\%$ predicted WP and the cost is represented as A , and wind curtailment is B . Thus, the increased costs caused by positive errors is $A \cdot e_i \cdot x$; and the one costs caused by negative errors is $e_i \cdot B$. The risk assessment index (R) is given as

$$R = R_+ + R_- = \sum_{j=1}^l e_j \cdot A \cdot x\% + \sum_{k=1}^m e_k \cdot B \quad (8)$$

where R_+ and R_- refer to the increased control risk costs of the power system to maintain the reliability for WPP positive errors and negative errors, respectively, and l and m refer to the number of samples of positive errors and negative errors, respectively.

Assuming x is 30%, then comparative results evaluated by proposed risk index are shown in Table III where r means “rank”.

From Table III, when reserve cost is much higher than wind curtailment cost ($A = 10B$), Model 1 is the best and Model 2 is the worst; when reserve cost is slightly higher than wind curtailment cost ($A = 2B$), Model 3 becomes the best; when reserve capacity and wind curtailment cost the same ($A = B$), Model 3 keeps the first place and Model 1 falls to the last

TABLE III
RESULTS OF RISK ASSESSMENT INDEX OF WPP ERRORS

Relation of A and B	Model 1		Model 2		Model 3		Model 4	
	Value of R	r	Value of R	r	Value of R	r	Value of R	r
$A = 10B$	7030 B	1	10715 B	4	7256 B	2	7492 B	3
$A = 2B$	3102 B	3	3483 B	4	3072 B	1	3100 B	2
$A = B$	2611 B	4	2579 B	3	2549 B	1	2551 B	2
$A = 0.1B$	2169 B	4	1765 B	1	2078 B	3	2057 B	2

place; when it is affected by policy or public opinion, reserve cost is much lower than wind curtailment cost ($A = 0.1B$), Model 2 becomes the best. This shows that due to the different generalized economic cost caused by WPP positive error or negative error, the power system has distinct preferences for prediction models. Therefore, different preferences on WPP models of practical systems can be considered when the proposed risk based index is adopted to select a prediction model for each subset. Also, the prediction models can be adjusted timely when the system situation changes.

For the sake of discussion, the case picks $A = B$ as the assumed condition, then Model 3 becomes the best option for $M_{2.4}$. Based on the same assumed condition and proposed risk index, the adopted prediction models and their parameters are shown in Table IV.

TABLE IV
THE USTWPP MODELS AND THEIR PARAMETERS

Model Code	Model	Parameters	$\mu\%$
M_1	Moving average	$k = 3$	66.4
$M_{2.1}$	ARMA(2,1)	$c = 58.70$; $AR(1) = 0.54$; $AR(2) = 0.14$; $MA(1) = -0.06$	3.1
$M_{2.2}$	ARMA(1,1)	$c = 345.32$; $AR(1) = 0.85$; $MA(1) = -0.37$	0.6
$M_{2.3}$	ARMA(1,1)	$c = 463.46$; $AR(1) = 0.87$; $MA(1) = -0.20$	0.4
$M_{2.4}$	ARMA(1,2)	$c = 691.22$; $AR(1) = 0.32$; $MA(1) = -0.08$; $MA(2) = -0.16$	0.4
M_3	ARIMA(2,1,1)	$c = 0.03$; $AR(1) = 0.89$; $AR(2) = 0.09$; $MA(1) = -1.00$	2.3
M_r	ARIMA(1,1,3)	$c = -0.01$; $AR(1) = 0.82$; $MA(1) = -0.76$; $MA(2) = 0.11$; $MA(3) = 0.06$	31.1

In Table IV, k is the number of the recent historical data for moving average method; c , $AR(1)$, $AR(2)$, $MA(1)$, $MA(2)$ and $MA(3)$ are the parameters of ARMA(p, q) or ARIMA(p, d, q) model; $\mu\%$ is the proportion of sample size for establishing each model.

3) Online Model Matching and Prediction

Also setting the length of online observing window as 6 ($L = L_1 = 6$), recognizing the pattern of the last short WPTS and calling the relevant prediction model for USTWPP.

B. Prediction Effect Assessment

1) Conventional Method for Assessment Reference

Using the whole historical data without classification as the modeling sample, the obtained conventional model (M_t) based on the same above assumed condition and proposed risk index is shown in Table V.

TABLE V
THE CONVENTIONAL MODEL AND ITS PARAMETERS

Model Code	Model	Parameters	$\mu\%$
M_t	ARIMA(2,1,1)	$c = 0.13$; $AR(1) = 0.95$; $AR(2) = 0.03$; $MA(1) = -1.00$	100.0

2) Comparison of WPP Error

Table VI gives the quality comparisons between the proposed method (I) and the conventional method (II), and the relevant data of S_2 has accumulated all the errors of the four subclasses. Error assessment indexes include commonly used root mean square error ($E_{RMSE}\%$), mean absolute error ($E_{MAE}\%$), the proportion of errors with a margin of ± 20 MW ($\alpha_{\leq 20}\%$) and the proposed risk based index (R).

TABLE VI
QUALITY COMPARISONS BETWEEN THE PROPOSED METHOD (I) AND THE CONVENTIONAL METHOD (II)

Number of Prediction Points	Method	S_1	S_2	S_3	S_r	Entirety
$E_{RMSE}\%$	I	11.51	31.71	16.85	46.77	14.68
	II	20.26	39.20	19.24	49.33	15.50
$E_{MAE}\%$	I	5.02	22.69	10.77	30.70	9.63
	II	14.14	27.33	12.51	32.63	10.25
$\alpha_{\leq 20}\%$	I	92.12	39.88	45.43	35.48	67.02
	II	67.24	32.02	43.64	33.53	51.19
$R(A = B)$: (thousand Yuan)	I	8.14 B	1.87 B	6.55 B	23.75 B	39.37 B
	II	14.98 B	2.15 B	7.61 B	24.55 B	49.29 B

Whether from the commonly used traditional indexes or the proposed more scientific risk based assessment index, the proposed new method is better than the conventional method. Specifically, for periods with high smoothness and obvious regularity, the accuracy of the prediction is improved significantly.

VI. CONCLUSION

A risk assessment based adaptive USTWPP framework is proposed in this paper to refine prediction models and reflect different preferences on WPP models of a practical system. The efficacy of the proposed method is verified by simulations.

It should be noted that the proposed Offline Classification and Optimization and Online Model Matching framework can be expanded to wind speed prediction based on spatial correlations. Introducing NWP information might further enhance the pertinence of the samples for each subset's model optimization. Based on the analysis of both the time series correlation based prediction results and spatial correlation based prediction results, to jointly coordinate these two kinds of results can further improve the reliability of final WPP results.

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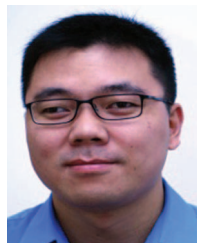
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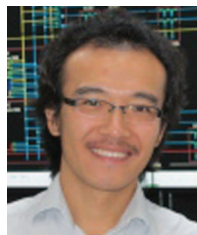
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