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Dynamic Thermal Rating Forecasting Methods: A Systematic Survey

OLATUNJI AHMED LAWAL^{ID} AND JIASHEN TEH^{ID}, (Senior Member, IEEE)

School of Electrical and Electronic Engineering, Universiti Sains Malaysia (USM), Nibong Tebal, Penang 14300, Malaysia

Corresponding author: Jiashen Teh (jiashenteh@usm.my)

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ABSTRACT Dynamic Thermal Rating (DTR) allows optimum electric power line rating use. It is an intelligent grid technology predicting changes in line rating due to changing physical and environmental conditions. This study performed a meta-analysis of DTR forecasting methods by classifying the methods, implementing them, and comparing their outputs for a 24hr forecast lead time. It implemented deep learning methods of Recurrent Neural Network (RNN), Ensemble Means forecasting and Convolution Neural Network (CNN). RNN uses the initial outcome of a specific neural network layer as feedback to the network to predict the layer's outcome. Ensemble Means forecasting is a Monte-Carlo simulation process producing random, equally viable forecasting solutions. On the other hand, CNN uses unsupervised learning to predict features with minimal errors. This survey systematically implements Quantile Regression (QR), RNN, CNN and Ensemble means forecasting. Point error metrics and probabilistic error metrics of sharpness, skill, and bias were used in the methods' evaluation. All methods tested prove to be efficient, but 50th percentile QR appears more conservative, secure and less error-prone. It achieved between 35% - 45% line capacity utilization over the Static Thermal Rating (STR). On average, judging by the error metrics of all methods, 50th percentile quantile regression proves highly reliable and provides a better conviction in our choice of DTR forecasting.

INDEX TERMS Dynamic thermal rating, smart grids, stochastic forecasts, deep learning forecasts, point forecast errors, probabilistic forecast errors.

I. INTRODUCTION

Electric power transmission lines are rated using limited assumptions of environmental conditions known as Static Thermal Rating (STR) [1]. STR provides a pre-set maximum allowable current-carrying capacity on the lines. On the contrary, Dynamic Thermal Rating (DTR) uses real-time weather monitoring and communication devices and the deployment of algorithms to forecast transmission line current capacity, known as ampacity. DTR is a means of improving the line capacity and comes into play in the planning and controlling operations of the power system. Weather stations along the transmission lines can measure and model the atmospheric parameters to be used in the forecast. A study on the significance of weather monitoring in energy-related systems was done in [2]. The study was relevant to meteorological

measurements, modelling, and forecasting. Another disadvantage of the STR is that it allows the emergence of new transmission lines because the lines often reach their limits due to increasing loads. To solve this problem, studies in [3], [4] have proposed the DTR system to expand the capacity of transmission lines. The actual line ratings due to DTR are higher than the STR most of the time [5]. In [5], DTR was presented to also benefit the lines by reducing wind energy curtailment. Studies in [6]–[8] showed that DTR allowed an increase in line ampacity than the traditional STR. It reduces carbonisation and allows decentralisation of the power grid. In [9], it was shown that DTR could achieve savings on constructing new lines by benefitting the existing lines with decongestion. DTR integration with smart grid technologies was also studied [10], [11]. The studies showed how beneficial DTR could be to the transmission line capacities when integrated with other smart grid technologies.

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Challenges foreseen in DTR implementation can be in line monitoring, communication, and forecasting. Some recent studies have proffered solutions to these challenges. The reliability of the communication devices and control operations was studied in [11], [12]. The studies highlighted the importance of the reliability of the wireless communication links between the monitoring devices and the control stations. In [13], the authors stated cyber security issues of smart grid power system components. They surveyed the impact of integrating ICT components in enhancing intelligent grid operations. A study examined the reliability of the Operational Tripping Schemes (OTS) and System Integrity Protection Scheme (SIPS) on a system with STR and DTR [14]. The study analysed the relief of congestion created with DTR when increasing the penetration of Renewable Energy Sources (RES). The fuzzy-based OTS introduced showed how network operators could prevent generators from tripping due to the

fixed STR. Critical span identification studied in [15] availed us with information that using a single span with the worst thermal capability can provide the line rating. Changing initial weather conditions and error level reduction were considered in [16] to better the line rating. The study employed the stochastic method to calculate a day-ahead rating for system planning. Other DTR studies considered the risks involved in DTR forecasts [17] and the prospects and safety assessments of the thermal loading of lines with DTR [18]–[20]. These studies clarified that the major environmental factors which need accurate data monitoring for better forecasting are the wind and temperature parameters. These parameters need to be adequately monitored by sensors or forecasted to determine line ampacity values. However, these solutions have not addressed the need for an efficient, reliable forecasting method mostly devoid of significant errors.

Reliable DTR forecasting is crucial for efficient power delivery using DTR systems, as depicted in a comprehensive DTR review [21]. Ambitious forecasting rates the line more than its actual ampacity; this results in thermal overload and may be catastrophic to the power system component and personnel. However, forecast values below the actual DTR ampacity underutilise the line and will not allow demands for power to be met [22]. This will lead to financial losses by the electric utility companies and the consumers.

A meta-analysis of DTR forecasting methods is needed to assess the performance of the DTR forecasting methods and ascertain the most reliable, least error-prone method. This study aims to attain this systematic survey with the following structure: Section II will review DTR forecasting methods, state the findings and limitations of past studies on DTR forecasting, and end with a classification of the reviewed methods. Section III will emphasize the importance of forecasting in DTR implementation and explain the point and probabilistic error metrics to evaluate the methods. Section IV will deploy probabilistic and point forecast error metrics to assess the forecasting methods and determine the most reliable

method devoid of errors. The concluding observations and recommendations for further works will come in section V.

II. DTR FORECASTING METHODS

DTR forecasting methods obtained from several studies are described in this section and presented in Table 1. The table described the forecasting methods, presented the findings of the studies, and offered their limitations and/or recommendations to improve them. DTR forecasting studies in Table 1 use estimation [1], [23], [24], Affine Arithmetic [6], [18], Regression [19], [20], [25], [26], Ensemble Learning [27], ANN [28], Enhanced learning [29] and Dynamic Stochastic General Equilibrium [30] to calculate, estimate and forecast DTR. These are good algorithms, but the studies have limitations in their data collection, algorithm training leading to over-fitting, algorithm testing, computational cost, and proliferation of errors in short forecast lead time. In addition, none of the DTR studies presented has implemented stochastic and deep learning methods on the same network for the same forecast lead time and data to perform a comparison using point and probabilistic error metrics. All forecasting methods reviewed will be classified, and a few promising ones will be implemented, evaluated, and compared in subsequent sections.

A. DLR FORECASTING METHODS CLASSIFICATION

DTR forecasting methods use stochastic (analytical statistics) or deep learning to filter randomness from past data to attain systematic patterns. The selection of any forecasting method depends on the quantity and nature of available data, how far ahead one is forecasting (the lead time), computational burden, forecasters' technical knowledge, and the acceptability of the method to forecast users [28]. Figure 1 shows the classification of DTR forecasting methods.

1) STOCHASTIC FORECASTING METHOD

Stochastic forecasting methods include regression, moving averages and exponential smoothing. A further division of stochastic forecasting includes Linear and QR. Linear regression estimates the mean of data and determines the relationship between variables. Linear regression's linearity, normality and independence assumptions do not make it suitable to forecast DTR [32]. The KDE of the DTR calculated values is shown in figure 2. The pattern and skewness displayed, as shown, are of utmost importance in describing the actual ampacity of the line. The KDE showed a positive skewness in its distribution, with its mean greater than the median. The KDE shows that linear regression assumptions do not hold for this data and will not be explored in the forecasting.

Forecasting DTR is more complicated than assessing line conditions. Simple conditional means analysis does not detect all relationships between variables. QR methods provide a means to study the relationship between random variables [30]. QR describes estimates conditional percentiles and expands modelling options for forecasting analysis.

TABLE 1. DTR forecasting methods studies.

Citation	Method Description	Findings	Limitations / Recommendations
[1]	Weather data statistical analysis was used to form a data set to estimate typical line ratings and risk associated. Standard ratings and associated risk levels were compared with the nominal and actual line ratings.	The method used increased the energy throughput when compared with the STR.	Environmental parameters used do not include extreme values. Data may have been fitted to arrive at the results. The study recommended precautions should be taken to avoid thermal overload and line ageing.
[4]	This paper depicted the dependence of transmission lines on wind power. The time-series data were modelled with the auto-regressive moving-average (ARMA) model. This paved the way for a Sequential Monte Carlo (SMC) simulation.	DTR system reduced the load shedding required in a balanced system at high loading levels, thereby improving line capacity	ARMA assumes no differencing is involved in the dependent variable. To be fair, the authors recommended integrating other intelligent power grid technologies.
[6]	This study compared Affine Arithmetic Approximation with the Monte-Carlo simulation method for a specific ambient temperature, heat flux, wind speed and wind direction.	The Affine Arithmetic approximation technique appeared to be more conservative than the Monte-Carlo simulation.	Approximations do not accurately represent data but may only reflect the pattern. The demerits are the scarcity of experimental data and theoretical studies for the analysis and computation requirements in the presence of uncertainties.
[18]	Affine Arithmetic was used to forecast meteorological conditions in a robust corrective control mechanism for dispatch, procurement, and operational cost reduction.	The study gave control actions calculated centrally and deployed affine arithmetic with procedures to ensure a reduction in total cost.	Only point forecast was considered. Forecast uncertainties for intermittent energy sources were not considered. High computational cost and approximations are inherent.
[20]	Linear Models and Multivariate Adaptive Regressions with Numerical Weather Prediction models forecast the DTR. A probabilistic forecast was developed from a point forecast afterwards.	The feasibility of using computed line rating forecasts in power system planning and operation was established. The method may be used to calculate the actual values of DTRs.	As much as the forest forecasting method deployed does not overfit, it has a constraint of slow training and is unsuitable for linear methods with many sparse features. Two conductor lines were used, and a static set of independent variables were the model's inputs. The choice of the independent variables not being dynamic tends to affect the accuracy of forecasts.
[27]	Ensemble Learning Algorithms were used in the DTR forecasting models concerning historical meteorological data as a viable alternative. Cases designed to explore the strength and precision of the technique were made. Simple boost, bagging and gradient boost models were compared with STR.	Ensemble learning algorithms simulations could be successfully used in forecasting DTR. The simulation yielded a 30% increase in line capacities.	Error metrics for the models are point forecast errors and do not specify the reliability and confidence levels of all outcomes to make the forecasts probabilistic
[25]	Quantile regression (QR) methods were proposed to predict line ampacity. The proposed methods considered the conductor thermal inertia in its modelling	When the model was reformulated with risk-based constraints, results confirmed their efficiency and better utilisation of conductor capacity. Energy transfer was also increased at reduced risk levels	Parameters are more complicated to estimate than in Gaussian or generalised regression. Weather data from weather stations were used to implement and validate each tested model's efficacy.
[31]	The novel methodology in this research focused on the safest reliability levels, and this was benchmarked on the maximum permissible conductor temperature on a distribution network traversing different terrain.	Line capacity utilisation is related to weather forecasts' error level and the probabilistic forecasts' sharpness. A technique that reduces the error level can improve the line ampacity.	The proliferation of errors for short horizons was the demerit of the algorithm used in this study.
[24]	This study compared the implementation of SLR with Real-time Monitoring (DLR-RTM) and Ambient Adjusted Dynamic Line Ratings (DLR-AA)	Real-time weather, clearance, tension, and sag can be monitored to gain line thermal capacity to calculate DLR. The measurement interval can be days or hours for DLR-AA and 5 to 15 minutes for DLR-RTM methods.	The temperature difference between worst spans and maximum permissible temperature should not exceed ten degrees Celsius. Hours or days temperature measuring interval may be too long where the surface temperature rise against ambient temperature is low.
[19]	A multivariate regression between the DTR and weather conditions was proposed to reduce the significant change in the DTR.	The method results in an efficient model to reduce the significant change in DTR, not undermining the improvement of capacity done by DTR.	An outlier in the data plot can seriously disrupt polynomial regression results. Its models are prone to overfitting, and the model proposed may not perform well in other cases if direct monitoring of the line parameters is done.

TABLE 1. (Continued.) DTR forecasting methods studies.

[26]	Weather factors were selected for a regression model. Random variables were used to model the line ratings of chosen spans, and the minimum was selected	Corresponding percentiles and distribution of the DTR were obtained. Line segment ratings, when tested, showed that the technique provides a secure and high rating.	A strong correlation in regression analysis does not depict a cause-effect relationship, and a single span chosen is usually not a true reflection of the whole transmission line. The current work showed a promising probabilistic grid network approach with a low computational requirement in the future.
[23]	The study here considered conductor temperature and weather models to estimate line ampacity. The study divided line ratings into typical, short-term emergency and long-term emergency periods allocating conductor temperatures and allowable duration to each of the ratings.	An algorithm proposed for calculating DTR produced 4-hr output 12% lower on average than DTR. Ampacity increment from 20 to 70% on average over existing STR was noticed	The uncertainties that may have occurred in measuring parameters in the two models called for the weighted average, which may be another source of error in the ampacity estimation
[30]	Dynamic stochastic general equilibrium (DSGE) was deployed as a probabilistic forecasting method.	DSGE, the proposed density forecast method, outperformed reference models of regression and machine learning.	DSGE is costly in computational terms. A Pareto-efficient solution deployment to balance the trade-off between a conservative solution and optimising the objective function to increase accuracy against confidence level is not easy
[28]	An ANN-based method was used to evaluate the conductor temperature and DTR of a transmission line and was compared with a physical temperature estimation method using the Council of Large Electric Systems (CIGRE)	The ANN deployed performed better in terms of the absolute error than the physical method compared	Hourly samples with a wind speed lower than two m/s were used to compare the two estimation methods. Performance beyond this limit was, however, not tested.
[29]	Enhanced Learning Method (ELM) was deployed to calculate DTR, which was compared with the actual ampacity of the line and the STR.	The predicted DTR performed better than the STR, closely to the actual ampacity of the line.	Over 90% of the data collected were used for training, while the remaining were used for validation. This account for the over-fitting of the output.

QR usually seeks the median known as the 50th percentile instead of the variable's mean to be predicted. It can also seek any other percentile below or above it. The 75th percentile, for instance, is the value below which 75% of all observations may be found. The application of QR to computer performance experiments was studied in [33]. The study allowed for the understanding that variables usually have relationships outside of the mean of the data. Moving averages have a characteristic of not responding to slight, transient changes in data; this makes them slow to react to rapid changes. ARMA and Autoregressive Integrated Moving Average (ARIMA) are instances of moving averages. ARIMA is an improvement over ARMA.

A comparison of neural network and ARIMA models has been studied in [34]–[38]. The studies compared the performance of ANN models and ARIMA. Results obtained from analyses revealed the superiority of the neural network models. Exponential smoothing considers weighted averages of observations. The weights of these observations decay exponentially over time.

The constraints of the stochastic methods above affect forecasts with moving averages and exponential smoothing. Examples of exponential smoothing are Single Exponential Smoothing (SES), which uses a smoothing parameter known as weight, and Double Exponential Smoothing (DES), which

uses two weights. Holt-Winters method combines weighted average, trend, and seasonality in its forecasts. Studies in [39]–[41] compared exponential smoothing with neural networks for forecasting and found out neural networks outperformed exponential methods. However, forecast data possess non-linear forms often not modelled effectively with other stochastic methods.

2) DEEP LEARNING FORECASTING METHOD

Deep learning in [42] presents an approach combining simple but non-linear modules in a multi-level input representation. The transformation of one level of representation to an abstract level allows deep learning to understand the features of the input [43]. Unlike traditional statistical forecasting models, deep learning methods can approximate non-linearity; examples include Neural Networks such as the Convolution Neural Network (CNN), Recurrent Neural Network (RNN) and Ensemble forecasting. The non-linearity often results in inaccurate forecasting accuracy, as shown in [44]. The study presented a novel time-series model designed to learn the features of time-series data thoroughly, but the outcomes were inaccurate. Ensemble means forecasting, CNN, and RNN forecasting will be explored because they have been proposed to be efficient methods of forecasting in [16], [42]–[45].

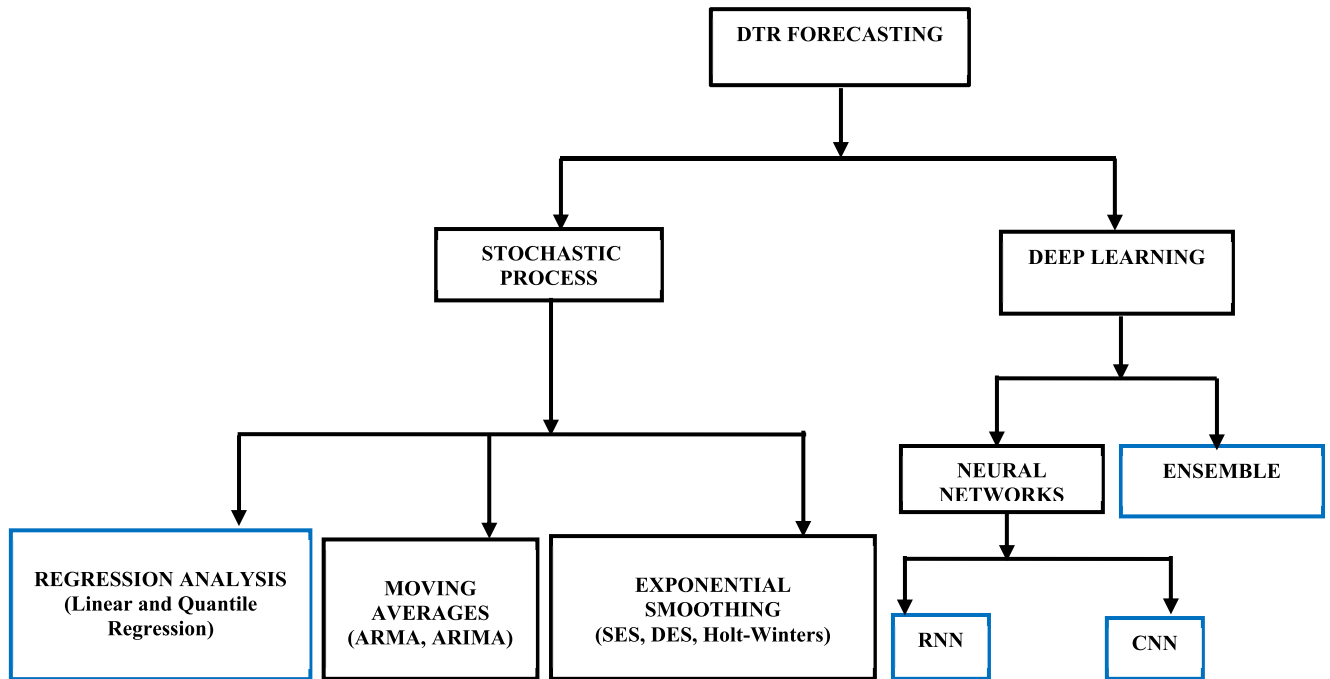


FIGURE 1. Forecasting classification.¹

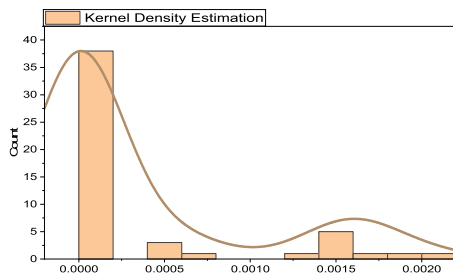


FIGURE 2. Kernel density estimation of line ampacity.

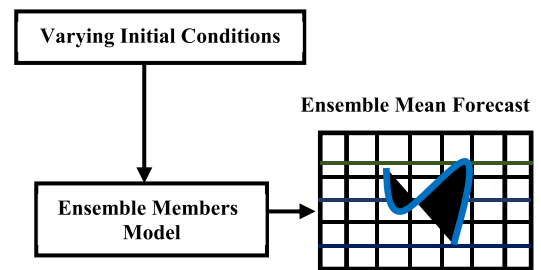


FIGURE 3. Schematic diagram of Ensemble Forecasting.

a: ENSEMBLE FORECASTING METHOD

Ensemble forecasting foresees forecast errors during each Numerical Weather Prediction system. Studies in [46], [47] suggested that errors could independently proliferate, but ensemble forecasting is an efficient solution to reduce the proliferation of errors. An ensemble forecast outputs a set of randomly equally viable solutions instead of a single definite forecast outcome. It is a form of Monte-Carlo simulation [48], [49]; it produces a set of solutions for the future and finds the average of these solutions. DTR was forecasted for a transmission line in Alberta, Canada [16]. The study recommended ensemble forecasting for better results. The expected value of a forecast using ensemble means is given by equation (1). As shown in figure 3, an ensemble forecast is produced from Ensemble mean considering varying initial conditions. It is likely to have more skill than a single

definite solution.

$$E(X) = \frac{1}{N} \left(\sum_{n=1}^N (x_n) \right) \tag{1}$$

- $E(X)$: Expected value of the simulation
- N : Sample size
- x_n : nth random variable.

b: NEURAL NETWORKS

CNN and RNN have been successfully deployed in forecasting complex spatial-temporal dynamics [50]–[53]. RNN is a neural network used when data is treated as a sequence, considering the order of the data points. It learns functions that can be one-to-many, many-to-one, and many-to-many [54]. As shown in figure 4(a), it takes input sequences from a stored initial state of $h(t - 1)$, present state $h(t)$ to run the model and gives an output $h(t + 1)$. This sequence continues in that manner to better the subsequent output. So, when much

¹Boxes highlighted in blue are the forecasting methods to be implemented and evaluated

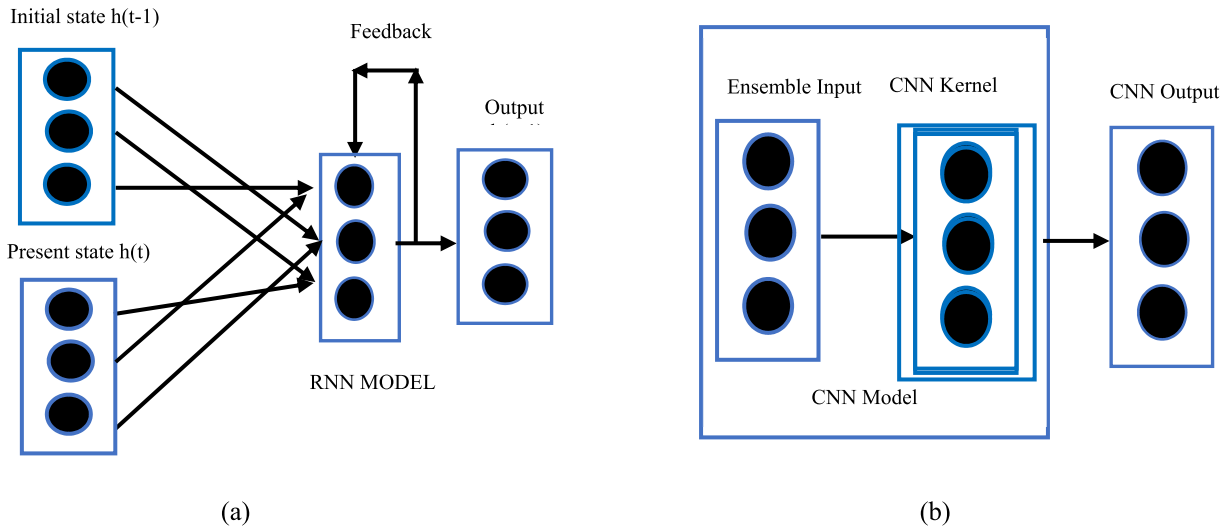


FIGURE 4. (a) Schematic diagram of RNN forecasting. (b) Schematic diagram of CNN forecasting.

information is conveyed sequentially, the recurrent neural network thrives in the temporal change of the data.

- $h(t)$: present cell state,
- $h(t - 1)$: initial cell state
- W : state weight parameter

An updated RNN hidden state is given by equation (2),

$$h(t) = \tanh(W_{hh}^T h_{t-1} + W_{xh}^T x_t) \quad (2)$$

$$h(t + 1) = \tanh(W_{hh}^T h_t + W_{xh}^T x_t) \quad (3)$$

CNN allows learning in a computationally efficient way, just like RNN. It is, however, composed of a feed-forward network, unlike RNN. It involves the formation of a feature map to indicate the positions and intensity of identified features of an input. CNNs are primarily used with images with local spatial patterns, but it works well when other forms of data have closer related values than those far away. It is applicable here because weather conditions within a few hours are closely related. A typical convolutional layer takes a three-dimensional data block as input (X), i.e., the input depth, d is 3. These layers have trainable kernel (k) parameters that extend to the input depth. The depth of the output Y is always the same as the number of kernels we have.

The output (Y) of a CNN is given by equation (4)

$$Y = B_i \sum_{j=1}^n X_j * K_{ij}, \quad \text{for } i = 1 \dots d \quad (4)$$

As shown in figure 4(b), the ensemble means of forecasting serve as input to the CNN model; the kernels are the layers of Neural Network (NN) Multilayer Perceptron architecture and have their biases (B) for parameter training and testing. These are used to produce the output of the CNN model. Combining forecasts from different methods leads to greater accuracy than any individual method. A consistent finding in empirical studies [55], [56] showed that combined forecasting methods

have higher accuracy than single methods. Selecting an excellent model for each series is a difficult task due to filtering noise from a pattern, which may lead to over-fitting. Combining several techniques allows the cancellation of random errors [57]; this is the rationale behind CNN forecasting. It is to be deployed here as a convolution of Ensemble forecasting with a kernel of CNN.

B. CHOSEN METHODS' RATIONALE

Linearity, homoscedasticity, normality, and independence assumptions of linear regression do not hold in forecasting the DTR of transmission lines. A regression method that will put this consideration in place is reasonable. Percentiles of the dependent variables can be forecasted to describe the dependence of DTR on environmental covariates. 25th, 50th and 75th percentile of the dependent variable will be predicted and evaluated using the point and probabilistic forecast error metrics.

Ensemble means forecast tends to provide seemingly accurate forecasts. On the other hand, varying weather conditions are catered for in ensemble forecasting. A set of random equally viable expected outputs are averaged over time to determine the ensemble forecast. Patterns can be learnt by Neural Networks in feedback or feed-forward loop. The location and strength of these patterns can be learnt and used in their reproduction. Pattern learning informs the use of RNN and CNN to forecast the DTR of transmission lines.

III. DTR IMPLEMENTATION

The stated benefits of DTR cannot be harnessed without an excellent DTR forecasting method. Forecasting is pivotal to DTR deployment, as shown in stage 3 of figure 5. As pertinent as DTR forecasting is to DTR deployment in intelligent grids, input parameters to the forecasting algorithms are very important. Environmental and physical parameters must be

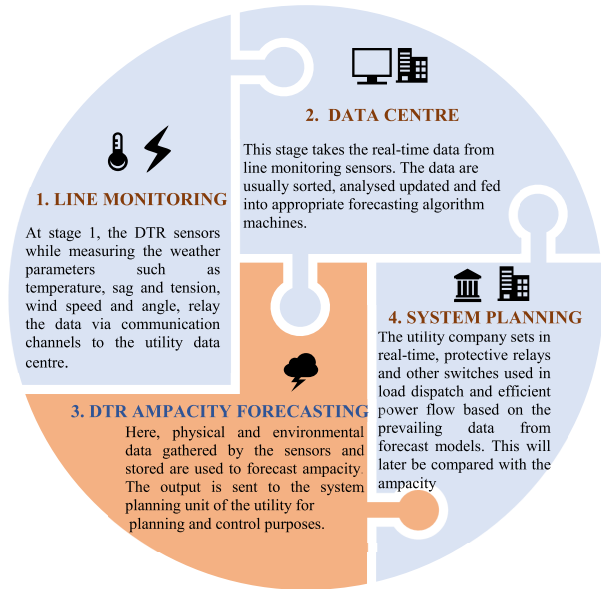


FIGURE 5. DTR implementation.

monitored in real-time in the first stage by sensors or weather stations along the transmission lines, as shown in figure 5 [4]. These monitored data are sent to the forecasting algorithms for weather inputs and DTR calculations. The algorithms and calculations are used in utility companies’ data centres and system planning units to set protective relays and DTR of the lines [58].

A. LINE MONITORING

Methods of monitoring the physical and environmental parameters of the line may be direct or indirect. DTR is calculated using weather data used for model prediction. This method is known as weather dependent line rating [59]. Direct and indirect means of monitoring to validate probabilistic forecasts were presented in [60]–[64]. The studies laid bare how best data for forecasting can be obtained from the lines. Indirect monitoring uses weather stations along a transmission line to record weather data used in forecasting ampacity [65]. This study will employ this type of monitoring for the data collection, and it will be used for DTR calculation and forecasting.

B. DTR AMPACITY FORECASTING

The weather parameters used in the IEEE 738 DTR model for calculating relationships between conductor temperature and its current capacity were stated in [67]. Weather stations were used to obtain the same weather parameters hourly for 30 days along a transmission line in the United Kingdom. The parameters were used to obtain the line ampacity every 1hr for 30days. The calculated current capacity alongside the multi-variate of ambient temperature, wind angle and wind speed forming convective cooling, radiative cooling and solar heating will forecast the ampacity for the next 24hrs. The forecast values for the next 24hrs will then be compared with the

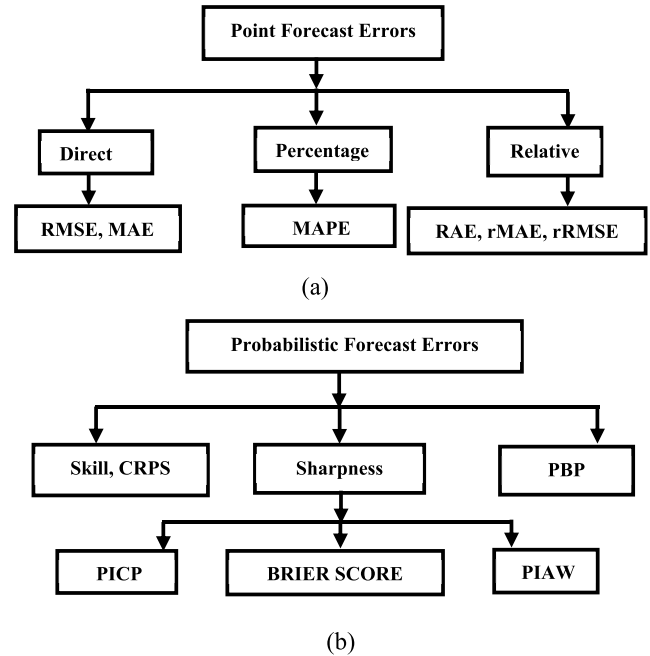


FIGURE 6. (a) Error metrics of point forecasting. (b) Error metrics of probabilistic forecasting.

calculated values for the same period, and the errors will be deduced. Methods to be evaluated are QR from the stochastic process because of the non-normality of the ampacity data as estimated by the KDE. Ensemble means on account of the intermittency of the environmental parameters used in the forecasting and RNN and CNN from the deep learning techniques. Three deep learning methods will be evaluated here because they have been proposed in studies [44], [66] to be more accurate than most stochastic methods. This assertion must be validated, considering the error metrics described in figures 6(a) and 6(b). DTR forecasting algorithm with the least values of these errors will be determined.

Ampacity forecasts using Stochastic and Deep learning algorithms will be evaluated. Inputs to these algorithms are weather and environmental parameters monitored along the 100km transmission line having weather stations at 50km intervals. These monitored data were used to calculate the DTR of the line every top of the hour for 30 days using the IEEE 738 model. The STR of the line was estimated to be 3305A, and other DTR ampacities for a 720hr period were also calculated. These calculated values of DTR, alongside the independent weather variables of wind speed, wind angle, ambient temperature, convective cooling, radiative cooling, and solar radiation, will be used to forecast the DTR of the line for the next 24 hrs. The forecast ampacity values for each method at 1hr interval will be compared with the calculated values for the same period using the variables measured for the period, and the errors will be determined. The method with the least values of errors would have performed better than the method with higher values of the point forecast errors. Line graphs of methods compared will also be displayed to appreciate how dynamic the line ratings could be.

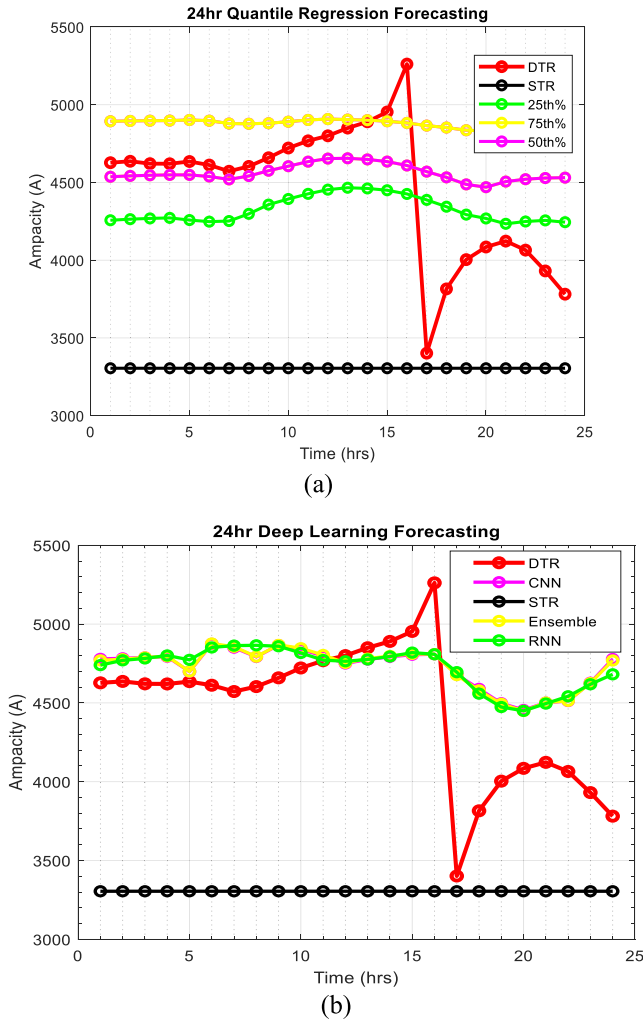


FIGURE 7. (a) QR forecasting plots. (b) Deep learning forecasting plot.

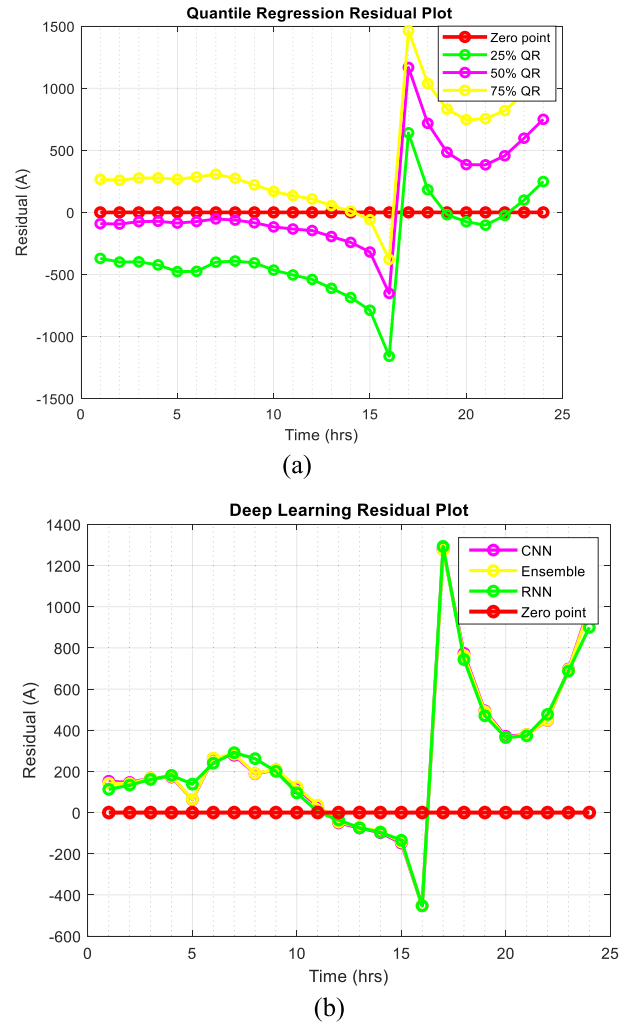


FIGURE 8. (a) QR residual plot. (b) Deep learning residual plot.

C. ERRORS IN FORECASTS

Forecast simulations performed are error-prone due to incomplete and inaccurate line monitoring, poor data communication, significant variations in data, and poor forecast algorithms and methods. As shown in figure 6(a), errors in point forecasts may be direct, percentage errors or relative measures of error [67].

Direct error metrics are the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) while MAPE is an example of a percentage error. Figure 6(b) shows that Skill, Sharpness, and Positive Bias Probability (PBP) are error metrics that describe probabilistic forecasting. In contrast, relative Mean Absolute Error (rMAE), Relative Absolute Error (RAE), and relative Root Mean Square Error (rRMSE) are relative error metrics [68]. They are benchmarked against a typical reference. Forecast skills can be gauged with a reference [69]; in some other form, the Continuous Ranked Probability Score (CRPS) compares a forecast with an observed outcome, thereby depicting how good forecast values are in matching observed outcomes [70]. The lower the CRPS, the

better the forecast. Three sharpness metrics, Prediction Interval Coverage Probability (PICP), Brier score and Prediction Interval Average Width (PIAW) and Positive Bias Probability, are novel metrics to be used to assess DTR forecasts as they have been used in [71], [72].

Point forecasting and probabilistic forecasting techniques try to predict the outcome of events. Information on the uncertainty of each expected outcome is only present in the probabilistic forecast [67]. All forecast error metrics have their prospects and constraints in evaluating the error in any forecasting method. It means a forecasting method performing skilfully well may have a minor error in RMSE and perform woefully in other point forecast error metrics.

PBP is important in DTR forecasting to determine the probability that the forecast value will always be less than the actual DTR value. The higher the PBP, the better the forecasting method. The Brier score is a vital probabilistic forecast error metric in that it measures calibration, purity, and noise. The calibration, purity and noise are determined by the forecast reliability, resolution, and uncertainty, respectively.

TABLE 2. Forecasting error metrics formulae and characteristics.²

Citation	Error Metrics	Formulae	Characteristics
POINT FORECAST ERRORS			
[67]	RMSE	$\sqrt{\frac{\sum C_i - F_i ^2}{N}}$	RMSE measures the spread of data and its biases along the line of best fit. It gives a high weight to significant errors. It is an absolute measure of fit
[73]	MAE	$\frac{1}{N} \sum_{i=1}^N C_i - F_i $	MAE as a direct method has the advantage of being easily interpreted. Considerable MAE value, however, does not depict a bad method.
[73]	MAPE	$\frac{\sum C_i - F_i }{\sum C_i}$	When minor outcomes, percentage errors like APE and MAPE exaggerate errors and accuracies, but they are reasonable measures with large values.
[67]	RAE	$\frac{\sum C_i - F_i }{\sum C_i - rF_i }$	RAE greater than 1 indicates that the method is less accurate than a reference, e.g. (naïve) method.
[68]	rMAE	$\frac{1}{N} \sum_{i=1}^N \frac{ C_i - F_i }{C_i}$	rMAE is a reasonable error metric, and values less than 1 are good.
[68]	rRMSE	$\sqrt{\frac{1}{N} \sum_{i=1}^N \frac{ C_i - F_i ^2}{C_i}}$	rRMSE covers up the inadequacies of some methods, but the less they are than 1, the better the method.
PROBABILISTIC FORECAST ERRORS			
[73], [74] [75]	SKILL, CRPS	$1 - \frac{MSE_{forecast}}{MSE_{reference}}$ $CRPS = \int_{-\infty}^x (F(y))^2 dy + \int_x^{\infty} (F(y) - 1)^2 dy$	CRPS compares the forecasts' Cumulative Distribution Function (CDF) with the observed values. The closer the CRPS is to zero, the better the forecast accuracy. A skill value less than 1 indicates the forecast method is more skilful than a reference method.
[71], [76]	SHARPNESS (PICP)	$F_i \pm c\sigma$	Prediction Interval Coverage Probability (PICP) clarifies the confidence in the accurate prediction of each data. It predicts the next forecast value using the standard deviation of errors biases and multipliers of confidence intervals
[72]	SHARPNESS (BRIER SCORE)	$B.S = (x - p)^2$ $p = \left[\frac{COUNT\ IF\ F_i > C(STR)_t}{N} \right]$	This error metric depends on three factors: reliability, which depicts the forecast calibration; resolution, which measures purity; and uncertainty, which measures noise. Lower values of the brier score represent accurate forecast measures.
[71]	SHARPNESS (PIAW)	$\frac{1}{N} \sum_{t=1}^N [U_t - L_t]$	PIAW is a measure of sharpness through calibration. The narrower this prediction width, the better.
[77]	PBP	$\frac{COUNT\ IF\ (C_i - F_i) > 0}{N}$	The Positive Bias Probability is useful to determine the probability that the forecast value will always be less than the calculated value. A value close to 1 shows the method is suitable.

The Brier score is 0 if the probability of an event is one and the event occurs. The Brier score is one if the event's probability is 0 and occurred [67]. The smaller the Brier score, the better the forecast.

rRMSE and rMAE assess the gain in performance of forecasting methods [68]. They penalize significant forecast errors, while MAE does not. RMSE measures how

²Where F_i and C_i are forecasted, and calculated values of ampacity and N is the time lead, i.e. the maximum number of hours we are forecasting; this is 24hrs in the case of this study. P = probability that the forecast will be greater than STR. U_t and L_t are Upper bound and Lower bound, respectively. c = confidence interval multiplier, σ = standard deviation of biases, r = forecast reference such as naïve.

spread-out biases are and is commonly used in forecasting analysis [68]. The performance of forecasting methods may be assessed with many metrics [73]. In this study, which aims to review different forecast methods, error metrics shown in figures 6(a) and 6(b) will evaluate stochastic and deep learning methods. Table 2 shows the formulae and characteristics of point and probabilistic forecast error metrics used to evaluate the tested methods. The evaluation results will be presented and discussed in the next section.

IV. RESULTS AND DISCUSSION

The discussion of the forecasting evaluation and forecast plots will be done here. This is to appreciate the similarities

TABLE 3. Methods' error metrics.

Forecasting models	25% QR	50% QR	75% QR	Ensemble Means	RNN	CNN
POINT FORECAST ERROR METRICS						
MAE (A)	412.0	309.7	461.5	333.5	330.0	335.3
MAPE(%)	9.240	6.950	10.35	7.52	7.40	7.51
RMSE	486.0	421.6	603.4	455.3	448.9	456.3
RAE	1.186	0.891	1.328	0.960	0.950	0.964
rMAE	0.090	0.076	0.114	0.082	0.134	0.083
rRMSE	0.104	0.110	0.157	0.121	0.081	0.121
PROBABILISTIC FORECAST ERROR METRICS						
SKILL(%)	77.54	83.10	65.39	80.29	80.84	80.08
CRPS	0.057	0.052	0.088	0.059	0.058	0.059
PICP (90%) (A)	4244±432	4531±479	4893±651	4769±519	4681±510	4779±522
BRIER SCORE	0.000	0.000	0.000	0.000	0.000	0.000
PIAW (%)	11.61	7.75	3.21	17.84	17.33	17.723
PBP (%)	16.67	33.33	91.70	79.17	79.17	79.17
EXTREME VALUES OF AMPACITY FORECAST (A)						
UPPER LIMIT	4264	4656	4908	4877	4865	4881
LOWER LIMIT	3985	4470	4831	4449	4449	4455
RANGE	279	186	77	428	416	436

and differences between tested methods and allow conclusions to be drawn quickly.

A. METHODS' ERROR METRICS COMPARISON

A comparison of all methods using the point and probabilistic error metrics is presented in Table 3. The deep learning methods performed averagely well with a high PBP, excellent brier score and a wide range of PICP. The 50th percentile quantile regression was the best among the deep learning and the stochastic methods tested, judging by the point and probabilistic forecast errors. It had the best forecast skill of 83% followed by RNN with 80.84%, it performed better than all the tested methods with lowest MAE (415A), MAPE(6.95%), RMSE (421.6), RAE (0.891), rMAE (0.076) and CRPS (0.052). RNN on the other hand had the lowest rRMSE of 0.081. The range of ampacity specifies how wide the ampacities can vary. However, the DTR forecast value should not exceed the maximum line ampacity. This is achievable if the maximum allowable conductor temperature has been exceeded. The QR forecasts appeared more conservative, with a good range and lower ampacity values than the calculated DTR. Any of them can be picked where conservativeness to achieve transmission line security and avoidance of the likelihood of failure is of utmost importance.

The line plot shows that the outcomes of QR in figure 7(a) are below the calculated ampacities. On the contrary, in figure 7(b), deep learning methods have most of their values above the calculated ampacities. The methods have modelled the relationship between independent variables, i.e., wind and solar and dependent variable (the line ampacity).

Quantile Regression, and the deep learning techniques deployed, showed values higher than the nominal STR of

3305A throughout the forecast lead time. This shows the line rating can be increased with the forecasted values. All the deep learning regression models possess about 80% PBP and a wider ampacity range; this makes them a better choice where high transmission capability is a top priority.

B. FORECASTING METHODS PLOTS

Quantile regressions plots in figure 7(a) represent the 25th, 50th and 75th percentile regressions, respectively. They are the 24hrs forecast of ampacity from QR. The ensemble means, RNN and CNN plots are shown in figure 7(b).

The figure showed that current-carrying capacity values were slightly lower than the actual ampacity values. In Figures 7(a) and 7(b), a sudden change in ampacity was noticed between 16:00 and 17:00 hrs due to a sharp variation in wind direction from the perpendicular axis to the parallel axis. The 75th percentile QR depicts the narrowest PIAW and a PICP within the upper and lower limit values. Assuming a 90% prediction confidence interval, the PICP shows that the next predicted value is within the maximum and minimum forecast values. It also showed that the higher the forecasting percentile, the more ambitious the QR forecast is and the more the likelihood to have outliers in the forecast. Similarly, the ensemble means forecasting has a conservative range among the deep learning methods. The point and probabilistic error metrics for all methods are close in value; this makes all methods evaluated reliable.

A setback to most of the methods used was depicted in the RAE. RAE values more than 1 prove that the method used is not better than the reference (naïve) method.

The residuals depicted in figure 8(a) show that most of the QR forecasted ampacities are not smooth. They are below

the actual ampacity of the line, while figure 8(b) has most values above the zero mark to depict that the deep learning forecasts are ambitious. Nonetheless, the residuals of deep learning methods have a lower dispersion around the zero-point mark.

Throughout the forecast lead time, the QR method increased the ampacities of the line over the STR between 20% and 48%, while the deep learning methods had between 35% and 48% increase over the STR.

V. CONCLUSION

DTR is a smart grid technology that has forecasting critical to its deployment. Forecasting methods presented in this study were classified broadly into stochastic and deep learning techniques. These allowed the implementation of viable DTR forecasting methods such as ensemble forecasting, RNN, CNN, and QR. Point and probabilistic error metrics were used to evaluate the forecasting methods. The methods deployed were compared based on the point and probabilistic error metrics described. As they all gave an efficient method for assessing DTR forecasts, the 50th percentile QR performed best with most of the error metrics. All QR and neural network methods tested have the probability of being higher than the STR at all times of the forecast lead time.

In future works, an improved DTR forecasting will be achieved with classification algorithms developed considering the close relationship of weather data of immediate past and subsequent hours. This algorithm should also be able to respond quickly to sharp variations in environmental parameters and reduce the point and probabilistic error more. Accuracy may also be improved with a lower forecast lead time.

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OLATUNJI AHMED LAWAL was born in Kwara, Nigeria. He received the B.Eng. degree in electrical engineering from the University of Ilorin, Ilorin, Nigeria, in 2009, and the M.Sc. degree in power system engineering from the University of Ibadan, Ibadan, Nigeria, in 2017. He has been a Lecturer with the Department of Electrical and Electronics Engineering, Institute of Technology, Kwara State Polytechnic, Ilorin, since 2011. He registered as an Engineer with the Council for the Regulation of Engineering in Nigeria. He is currently a Postdoctoral Researcher with the School of Electrical and Electronics Engineering, University Sains Malaysia. His research interests include power system stability and reliability, smart grid technologies, renewable energy, and climate change.



JIASHEN TEH (Senior Member, IEEE) received the B.Eng. degree (Hons.) in electrical and electronic engineering from Universiti Tenaga Nasional (UNITEN), Malaysia, in 2010, and the Ph.D. degree in electrical and electronic engineering from The University of Manchester, Manchester, U.K., in 2016.

Since 2016, he has been a Senior Lecturer/an Assistant Professor with Universiti Sains Malaysia (USM), Malaysia. In 2018, he was an Adjunct Professor with the Green Energy Electronic Center, National Taipei University of Technology (Taipei Tech), Taipei, Taiwan. Since 2019, he has been an Adjunct Professor with the Intelligent Electric Vehicle and Green Energy Center, National Chung Hsing University (NCHU), Taichung, Taiwan. His research interests include probabilistic modeling of power systems, grid integration of renewable energy sources, and reliability modeling of smart grid networks. He is a member of the IEEE Power and Energy Society, the Institution of Engineers Malaysia (IEM), and the Institution of Engineering and Technology (IET). He is also a Chartered Engineer (C.Eng.) with the Engineering Council, U.K., and a Registered Professional Engineer (P.Eng.) with the Board of Engineers Malaysia (BEM). He received outstanding publication awards from USM, in 2017 and 2018. He serves as a Regular Invited Reviewer for the *International Journal of Electrical Power and Energy Systems*, *IEEE Access*, *IEEE Transactions on Industry Applications*, *IEEE Transactions on Vehicular Technology*, *IEEE Transactions on Reliability*, the *IEEE Transactions on Industrial Electronics*, and *IET Generation, Transmission and Distribution*.

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