Pakistan Journal of Engineering and Technology, PakJET
Multidisciplinary & Peer Reviewed
Volume: 4, Number: 3, Pages: 18- 26, Year: 2021

Analytical Solution of Stochastic Real-time Power Dispatch with Large Scale Wind Farms

Ali Sarfraz[2], Muhammad Shahzad Pansota[1], Nabeel Abdulhadi Mohammad Fahal[2], Ahsan Sarfaraz[1]
Haseeb Javed[1]

[1]Electrical Engineering Department, MNS University of Engineering & Technology, Multan, Pakistan
[2]School of Electrical and Electronics Engineering, North China Electric Power University, Beijing 102206, P.R. China
Corresponding author: Muhammad Shahzad (e-mail: shahzadpansota@hotmail.com)

ABSTRACT: The automated gain control (AGC) units as well as other the non AGC equipment may be utilized in real-time power transmitting (RTPD) to coordinate the operations (RTD). In order to guarantee high-probability system security and to save operating costs, it is essential to correctly define the probable Wind Energy Forecast (WPFE) mistakes in RTD. The Cauchy Distribution (CD) is the perfect match for the "leptokurtic" characteristic of WPFE small-scale distributions, following previous research and our onsite testing. In this study the CD represents WPFE, which is suggested to provide a chance-controlled real-time dispatch (CCRTD) paradigm (Chance-Constrained Randomization). The suggested CCRTD Model may be analytically converted to the "Convex Optimization Problem," which takes into consideration the dependency of the wind farm outputs because of the stability and attractive mathematical features of the CD. The inclusion of a refined control method that may also be used in combination with AGC systems is an additional aspect of the suggested model. This technique, when combined with the WPFE RTD Stage, allows the CCRTD to respond to the higher ramping power requirements as well as power variations on WPFE-generated transmittal lines. The proposed technique was shown to be trustworthy and efficient in numerical testing. It is nevertheless extremely effective as well as suitable of usage. Basically, I apply 20 winds farms data on different distribution and you see that in numerical portion and results shows that error in Cauchy distribution is less from other distribution which you can see in below plots and numerical tables.

INDEX: **"**Stochastic Optimization, Wind-power Forecast error, Real-time dispatch, Cauchy Distribution"

I. INTRODUCTION

In the past year electricity penetration has risen markedly. This technique enables the CCRTD to more effectively respond to WPFE's of the additional ramping power requirements as well as the power fluctuation on RTD-phase of the transmission lines. Based on numerical tests, the proposed approach has been found to be both confident and effective. In the Meanwhile, it may be used extremely efficiently and in real-time [1-4]. Traditional Stochastic ED-Models are employed to handle wind-energy production uncertainties; however, there are two key flaws that must be dealt with. The first is how prediction inaccuracies may be defined in a manner that is precise and model-friendly. Another difficulty is to find out how uncertainties are properly included into operational limitations and target functions to create the Stochastic ED Model. The detailed summary for these many difficulties is provided below:

a) First build a 'proper' WPFE model with a declining fitting error to reduce operating costs and enhance system reliability. Due to the similar and divergent conditions of wind, the wind power of different wind farm areas therefore it exhibits the correlation / complementary at different places which should be incorporated in proper. WPFE model. A model friendly WPFE model usually includes the following mathematical characteristics in a manner to ease operations of wind power systems:

(1) For the representation of a linear combination of associated random variables a similar type distribution may be employed

2) Inverse Cumulative Distribution's function has analytically to construct and transform the chance to constraints in the deterministic restrictions.

(3) Analytically, the cost anticipated may be computed as integration. In ED problems, it is helpful to use WPFE models with some of the above characteristics. Neither has the ability to simultaneously access all of these features.

b) CCED with changing degrees of trust provides a viable way of balancing safety and economic dispatch in the process of modeling uncertainty and resolving of problems. Wind power is unpredictable and imbalanced power transfer, with operating constraints, between the regulating generators, the branch flow and power breakage; make it more difficult to run the CCED [5-10]. Moreover, inefficiency is the most serious restriction to handle problems related to opportunity, making it difficult to dispatch in the time.

1) WIND POWER FORECAST MODEL:

WPFE have typically been thought of as random variables with a predetermined distribution. According to certain research, small timescale WPFE-Distributions are "leptokurtic," which implies they have both the high kurtosis as well as a fat tail. “Good kurtosis” denotes high prediction accuracy, but “fat tails” denotes frequency of the extreme occurrences & stores essential data reliably [11-15].

The author of the study examined the errors made by the Operational Wind-power Fore-casting Systems & determined that normal distribution failed to adequately reflect WPFE. Other current models, as the Weibull beta distributions, were unable to properly describe WPFE data's “heavy-tailed nature”. In dynamic ED, a detailed analysis of Output Correlation and dependency between varieties of wind-farms is required for power networks with numerous wind farms [16-20].

Neglecting the correlation might result in additional costs and an increased risk of transmission lines becoming overloaded. Xie developed a unique data-driven wind speed prediction framework in the literature by exploiting spatial-The transmission capacity limitations in their research were ignored because they were unable to construct a Random variable distribution described by the VD/TVD for Linear Combination. Recently the Gaussian Mixture Model (GMM) explained the related forecast error of the wind generation in CCED [21-28].

2) STOCHASTIC ED MODEL AND SOLUTIONS: Stochastic optimization (SO) modeling is often used by ED to decrease the uncertainty of wind turbines and the volatility. A stochastic optimization model with chance limits may be used to offset economic security with a changeable risk threshold in order to meet various criteria for reliability. Even if it is convex, the problem is difficult to solve. A scenario-based approach was created to replace this possibility.

Offline uncertainty limitations are provided to accelerate online strategy planning in real time. Bilinear and linear formulations were given for limited opportunity of mixed integer programming utilizing a "Monte Carlo Simulation" decomposition method. The study authors have improved their approach to "stochastic programming" on problems relating to unit engagement via a dynamic decision-making method for wind scenarios. To estimate the target function, scenario sampling was employed. In order to solve a two-stage stochastic program of opportunity in research, a combination average sample approximation (AAA) technology was utilized. All these methods are centered on the construction of scenarios. If the sample size is adequate [23-25], the trust may be secured in a limited sense. The scenario-based method, on the other hand, carries considerable cost for computation, limiting its applicability when making choices in real time. In articles [6] and [28-34], the suggestion to mimic WPFE has been made utilizing 'Versatile Distribution,' and 'Truncated Versatile Distribution,' as proposed. Deterministic restrictions may be changed by means of quintile, VD/TVD chances, and the VD or the TVD may much better correspond with WPFE than Gaussians and Beta distributional and analytic mathematical formulations of their Inverse-CDF. The limitations on transmission capacity were ignored in their research since they were unable to construct a distribution of random variables for the linear combination represented with the VD/TVD. Recently, the "Wind output in CCED" was explained using the Gaussian Mixture Model [7], or "ramping capacity assignment" [9] related prediction mistakes. In these studies, a 4th order polynomial was used to match approximately the CDF of the Gaussian distribution and the possibility restrictions became deterministic limit.

3) CONTRIBUTIONS:

We analyse in this study statistically the distributions of WPFE in 20 wind farms in southwestern China. On-site research showed that CDs outperform other distributions, such as Gauzanne, Beta and Weibull in particular, for curtosis and tail behavior, as shown in researches [1, 10]. Therefore, we use the Affine AGC Control technique to define WPFE uncertainty in the model CCRTD (A-CCRTD). Thanks to its possible CD features, the A-CCRTD is analytically transformed into a stochastic issue with Convex Optimization. Some of the publications below are more thorough [35-40]. The following are some more details.

1. Due to its attractive CD features that can effectively be handled with no approximation, the A-CCRTD will be analytically transformed into a stochastic problem for convex optimization. The matrix shows how many wind farms depend on their output.

2) CD has numerous mathematical advantages. It’s CDF and the Inverse CDF may be analytically defined as a cost component of the CD can be predicted. As a consequence, by utilizing the Copula function, we may convert any linear constraints into stochastic linear constraints. The selection of scenarios still needs a significant load of computation, solution and A-CCRTD can be addressed quickly.

This method makes the chance-complicated optimization issue for power stations with high wind penetration practically tractable in real-time applications. In addition, given that chance constraints are analytically transformed, sensitivity analysis is simple such as changing risk levels.

3) A refined control method for the AGC system comprises a chance limited dispatch mechanism. In the suggested model, both the APRR and the power fluctuations in the transmission system induced WPFE in RTD stage were considered.

In order to guarantee system reliability, enough control capacity of AGC units must be set aside in RTD phase to rectify real time power imbalance generated by wind power uncertainty. The remaining article is as follows structured. Section-II deals with both the Cauchy distribution and the WPFE model in the mathematical aspects. Section III contains the Cauchy distribution A-CCRTD model mathematical formula.

Section IV deals with case studies and Section V presents the conclusion.

II. WPFEMODELING WITH THE MULTIVARIATE CAUCHY DISTRIBUTION

If a "Multivariate Cauchy Distribution" with the location vector μ & the scaling matrix ∑ is applied to a p-dimensional Random vector X, then the PDF is [29]:

$$fx\,(x;\mu,\Sigma) = \frac{\Gamma\,(\frac{1+p}{2})}{\Gamma\left(\frac{1}{2}\right)\pi^{\frac{p}{2}}\Sigma^{\frac{1}{2}}[1+(x-\mu)^{T}\Sigma^{-1}(x-\mu)]^{\frac{1+p}{2}}} \qquad (1)$$

The x~ Cauchy, PDF of the one-dimensional CD when p = 1, is:

$$fx(x;\mu,\sigma^2) = \frac{1}{\pi}\left[\frac{\sigma}{(x-\mu)^2+\sigma^2}\right], x\epsilon R \qquad (2)$$

The following are some key qualities that can help you overcome A-CCRTD:

1) **Internal property**:

$$\int x.PDF(x)dx = \frac{\sigma}{2\pi}\ln(1+\left(\frac{x-\mu}{\sigma}\right)^2 + \arctan\left(\frac{x-\mu}{\sigma}\right) + c \quad (3)$$

$$\int x^2.PDF(x)dx = \frac{\sigma}{\pi}(x-\mu) + \frac{(\mu^2-\sigma^2)}{\pi}\arctan\left(\frac{x-\mu}{\sigma}\right) + \frac{\mu\sigma}{\pi}\ln(1+\left(\frac{x-\mu}{\sigma}\right)^2 + c \quad (4)$$

2) **Stable property:**

The term "stable" [5] refers to the fact that the “linear transformation of x in (1)” may be represented “one-dimensional CD”. Consider the case when an is a p-dimensional vector, and we have

$$a^T \sim Cauchy(a^T\mu, a^T\Sigma a) \quad (5)$$

CDF and inverse CDF analytical expressions

$$CDF(x) = \frac{1}{\pi}\arctan\left(\frac{x-\mu}{\sigma}\right) + \frac{1}{2} \quad (6)$$

$$CDF^{-1}(F) = \mu + \sigma\tan\left[\pi\left(F-\frac{1}{2}\right)\right] \quad (7)$$

4) “Fitting & sampling”

The Multive package [30]'s msc Fit function is used for data adapting multivariate CD-parameters using R Statistical Computing Environment [31]. Whereas rmvc may be utilized in sampling a multivariate Cauchy dispensing function of R's Laplaces Demon Package [32], operators can employ a multivariate CD that fits a WPFE to any wind farms.

III. MATHEMATICAL MODEL FORMULATION OF A- CCRTD

This section describes the A-CCRTD model formulation. In the nomenclature section, the declarations of the variables may be found. Since the results of the load prediction are sufficiently accurate using state-of-the-art prediction technologies [33], this research solely examines errors in the prediction of wind power. This model may be scaled to accommodate for uncertainties in demand for load.

$$F = min\sum_{t=1}^{T}\{\sum_{i=1}^{N} CF_{i,t}(P_{i,t}^{s}) + \sum_{j=1}^{J} CF_{j,t}(P_{j,t}^{a}) + \sum_{j=1}^{J} E[CR_{j,t}^{+}(w_t^{\sim})] + \sum_{j=1}^{J} E[CR_{j,t}^{-}(w_t^{\sim})]\} \quad (8)$$

The generating costs of the AGC & the non-AGC units, respectively, are CFit and CFjt. The upward as well as the downward directive or regulating costs (corrective control costs) of AGC units are represented by CRj and CRjt, respectively; these words may alternatively be thought of as penalty costs of the overestimation as well as underestimating of the wind power production. Below is a list of the detailed formulas.

(1) Generation cost: The expenses generated by the AGC & non-AGC unit are shown by the quadratic power output functions

$$CF_{i,t}(P_{i,t}^{s}) = a_{i,t}(P_{i,t}^{s})^2 + b_{i,t}P_{i,t}^{s} + c_{i,t} \quad (9)$$

$$CF_{j,t}(P_{j,t}^{a}) = a_{j,t}(P_{j,t}^{a})^2 + b_{j,t}P_{j,t}^{a} + c_{j,t} \quad (10)$$

2) Corrective control cost

The discrepancy between actual wind Power output wt. and planned output wt. causes corrective control expenses.

The AGC units should be able to balance the power imbalance at any time using specific principles. In practice, participation factor are generally allocated to the AGC units in proportion to their capacity, based on control principles. As a result, the affine control approach is established.

$$p_{j,t}^{\sim a} = p_{j,t}^{a} - \alpha_j.(w_t^{\sim} - w_t), \sum_{j=1}^{J}\alpha_j = 1(\alpha_j \geq 0) \quad (11)$$

The estimated corrective costs are proportionate to the AGC units expected positive and negative capacity deployed, i.e.

$$\{E = [CR_{j,t}^{+}(w_t^{\sim})] = \gamma_{j,t}^{+}\alpha_j\int_0^{w_t}(w_t - \theta_t^{\sim})\varphi_t(\theta_t^{\sim})d\theta_t^{\sim} \quad (12)$$

$$\{E = [CR_{j,t}^{-}(w_t^{\sim})] = \gamma_{j,t}^{-}\alpha_j\int_0^{w_t^{-}}(\theta_t^{\sim} - w_t)\varphi_t(\theta_t^{\sim})\,d\theta_t^{\sim} \quad (13)$$

where the PDF (probability density function) is in period t of the random variable. Assume that all wind farms have a probability density function output in the time period t. We finally get to Section II, utilizing the mathematical features of the CD and WPFE model.

$$\sum_{j=1}^{J} E[CR_{j,t}^{+}(w_t^{\sim})] + \sum_{j=1}^{J} E[CR_{j,t}^{-}(w_t^{\sim})] = \sum_{j=1}^{J}[A + B.w_t - \frac{C\sqrt{\sum w_t^{\sim}}}{2}.\ln(1+\left(\frac{w_t-\mu_{w_t^{\sim}}}{\sqrt{\sum w_t^{\sim}}}\right)^2) + C.(w_t - \mu_{w_t^{\sim}})arctan\frac{w_t-\mu_{w_t^{\sim}}}{\sqrt{\sum w_t^{\sim}}}] \quad (14)$$

Where A, B, and C are the constants of which Appendix A contains the formulae and k-dimensional vector of all 1 elements. The goal function description is convex in Appendix B. Deterministic limitations of system and possibility restrictions are set forth below.

$$\sum_{i=1}^{N} p_{i,t}^{s} + \sum_{j=1}^{J} p_{j,t}^{a} + \sum_{k=1}^{K} p_{k,t}^{W} = \sum_{d=1}^{D} p_{d,t}^{d} \quad (15)$$

$$\mathrm{P}_{-j,t}^{a} \leq \mathrm{p}_{j,t}^{a} \leq \mathrm{P}^{-a}{}_{-j,t}, \mathrm{P}_{-i,t}^{s} \leq \mathrm{p}_{i,t}^{i} \leq \mathrm{P}^{-s}{}_{i,t}, 0 \leq \mathrm{p}_{k,t}^{w} \leq \mathrm{p}_{k,t}^{-w} \quad (16)$$

$$\Pr\{\alpha_j.(w_t - w_t^{\sim}) + p_{j,t}^{a} \leq P_{j,t}^{-a}\} \geq 1-\delta \; \Pr\{P_{-j,t}^{a} \leq p_{j,t}^{a} + \alpha_j.(w_t^{\sim} - w_t)\} \geq 1-\delta \quad (17)$$

$$\Pr - RD_{j,t}^{s}.\Delta T \leq p_{i,t}^{s} - p_{i,t-1}^{s} \leq RU_{i,t}^{s}.\Delta T$$

$$\Pr\{-RD_{j,t}^{a}.\Delta T \leq p_{j,t}^{\sim a} - p_{j,t-1}^{\sim a}\} \geq 1-\beta \quad (18)$$

$$\Pr\{p_{j,t}^{\sim a} - p_{j,t-1}^{\sim a} - RU_{j,t}^{a}.\Delta T\} \geq 1 - \beta \tag{19}$$

$$\Pr\{R_t^{+} \leq \sum_{j=1}^{J}(P_{j,t}^{-a} - p_{j,t}^{\sim a})\} \geq 1 - \varepsilon \tag{20}$$

$$\Pr\{R_t^{+} \leq \sum_{j=1}^{J}(p_{j,t}^{\sim a} - P_{-j,t}^{-a})\} \geq 1 - \varepsilon \tag{21}$$

$$\Pr\left\{\left|\sum_{i=1}^{N} G_{l,i}\, p_{i,t}^{s} + \sum_{j=1}^{J} G_{l,j}\, p_{j,t}^{\sim a} + \sum_{k=1}^{K} G_{l,k}\, p_{k,t}^{\sim w} + \sum_{d=1}^{D} G_{l,d}\, p_{d,t}^{d}\right| \leq L_{l,t}\right\} \geq 1 - \eta \tag{22}$$

The limit of the power balance is equated (13). Equation (14)'s limit on power production means that the AGC unit's, the projected electricity production of non-AGC units and wind farms cannot go above the limitations. Equation is the opportunity constraint that says that a certain degree of trust is provided for the real regulatory capability of AGC units. The limitation of the ratio for the non-AGC units is equation (16). Equation (17), which constitutes an opportunity constraint, limits the actual incremental output of the AGC over the next several times. The extra "Electricity Ramping Requirement" is to be included in the shipping process, because the imbalanced wind farm power competes in real-time for ramp capacity.β is the tolerable probability of a pre-specified violation. In order to ensure system security for specific eventualities, reserve restrictions (equations 18) are used. Equation (19) is a limited transmission capacity, showing that there is a lower probability of overflowing a transmission line. The unbalanced power supplied in real time to each AGC unit helps to activate power on lines overlooked in traditional CCED models.

Form is compact, and there is a solution for the Chance Constraints. Equations (21) and (22) may be used to represent chance restrictions in A-CCRTD in the compact forms:

$$\Pr\left[\left(A^{(g)}\right)^{T}\boldsymbol{u} + \left(B^{(g)}\right)^{T}\boldsymbol{y}^{\sim} \leq D^{(g)}\right] \geq 1 - \zeta^{(g)} \tag{23}$$

$$\Pr\left[\left(A^{(g)}\right)^{T}\mathbf{u} + \left(B^{(g)}\right)^{T}\mathbf{y}^{\sim} \geq D^{(g)}\right] \geq 1 - \zeta^{(g)} \tag{24}$$

According to the CD's mathematical characteristics, which are stated in Equations (20) and (21) in section II are transformed to Constraints that are deterministic (22) and (23):

$$D^{(g)} - \left(A^{(g)}\right)^{T}\mathbf{u} \geq \left(B^{(g)}\right)^{T}\mathbf{u}_{y^{\sim}} + \sqrt{(B^{(g)})^{T}\sum y^{\sim}B^{(g)}}\tan[\pi(1 - \zeta^{(g)} - \tfrac{1}{2})] \tag{25}$$

$$D^{(g)} - \left(A^{(g)}\right)^{T} \leq \left(B^{(g)}\right)^{T}\mathbf{u}_{y^{\sim}} + \sqrt{(B^{(g)})^{T}\sum y^{\sim}B^{(g)}}\tan[\pi(1 - \zeta^{(g)} - \tfrac{1}{2})] \tag{26}$$

In A-CCRTD, any chance restrictions may be transformed in the same way. A-transformation CCRTD's of chance limitations. Chance constraint (15) is transformed into constraint using the WPFE model presented in section II (24),

$$\alpha_j w_t + p_{j,t}^{a} - P_{j,t}^{-a} \leq \alpha_j.CDF_{w_t^{\sim}}^{-1}(\delta) \tag{27}$$

$$\alpha_j.CDF_{w_t^{\sim}}^{-1}(1-\delta) \leq \alpha_j w_t + p_{j,t}^{a} - P_{-j,t}^{-a} \tag{28}$$

Constraint (25) is converted from Chance Constraint (17):

$$p_{j,t}^{a} - p_{j,t-1}^{a} + \alpha_j(w_t - w_{t-1}) - RU_{j,t}^{a}.\Delta T \leq \alpha_j.CDF_{w_{t,t-1}^{\sim}}^{-1}(\beta) \tag{29}$$

$$\alpha_j.CDF_{w_{t,t-1}^{\sim}}^{-1}(1-\beta) \leq p_{j,t}^{a} - p_{j,t-1}^{a} + \alpha_j(w_t - w_{t-1}) + RU_{j,t}^{a}.\Delta T \tag{30}$$

Constraint (26) is converted from chance constraint (18):

$$w_t + R_t^{+} + \sum_{j=1}^{J}\left(p_{j,t}^{a} - p_{j,t}^{-a}\right) \leq CDF_{w_t^{\sim}}^{-1}(\varepsilon) \tag{31}$$

$$CDF_{w_t^{\sim}}^{-1}(1-\varepsilon) \leq w_t - R_t^{-} + \sum_{j=1}^{J}(p_{j,t}^{a} - p_{-j,t}^{a} \tag{32}$$

And constraint (27) is transformed from chance constraint (19):

$$CDF_{a_l p_t^{\sim w}}^{-1}(1-\eta) \leq L_l\left[\sum_{i=1}^{N} G_{l,i}\, p_{i,t}^{s} + \sum_{j=1}^{J} G_{l,j}\, p_{j,t}^{a} + \left(\sum_{j=1}^{J} G_{l,j}\,\alpha_j\right)\sum_{k=1}^{K} p_{k,t}^{w} + \sum_{d=1}^{D} G_{l,d}\, p_{d,t}^{d}\right] - L_l\left[\sum_{i=1}^{N} G_{l,i}\, p_{i,t}^{s} + \sum_{j=1}^{J} G_{l,j}\, p_{j,t}^{a} + \left(\sum_{j=1}^{J} G_{l,j}\,\alpha_j\right)\sum_{k=1}^{K} p_{k,t}^{w} + \sum_{d=1}^{D} G_{l,d}\, p_{d,t}^{d}\right] \leq CDF_{a_l p_t^{\sim w}}^{-1}(\eta) \tag{33}$$

The A-CRTD model is finally converted analytically into a Convex Objective function, which is reported with Deterministic Linear Limits (9), (10) and (12). Note: Convex is the finished model and there are no vertices. In the process of transformation, approximation or iteration is used. Numerical experiments demonstrate the rapid calculation capacity of this model.

IV. NUMERICAL TESTS

Numerical experiments were carried out in this part to ensure that the suggested approach was effective. First, Current evidence of the accuracy of CD fitting in WPFE was taken from 20 wind farms in Southwest China. A modified IEEE 24 bus system showed the benefits of the proposed paradigm. Meanwhile, in RTD, the consequences of numerous wind farms' interdependence were explored.

The next item is the updated IEEE 24-bus system parameters. During load times in the valley and 15:3021:30, the loading profile of the system is depicted on the left hand side of Fig 1. Fig. 1. On the right side of Figure 1, the projected wind output profile is displayed and the power output follows the rule that wind production is higher at night.

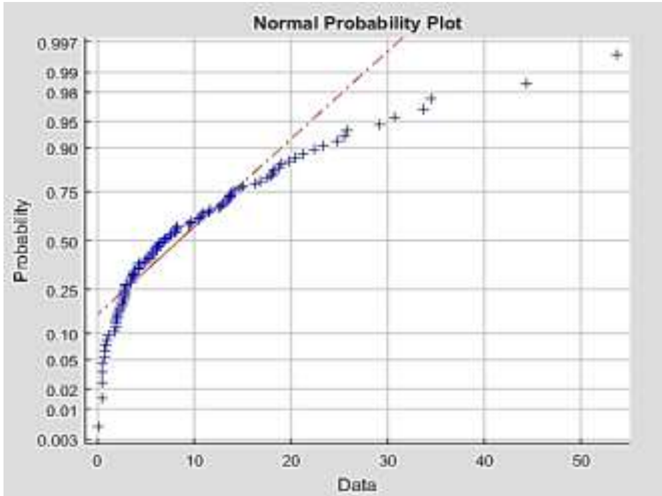

FIGURE 1: Normal probability

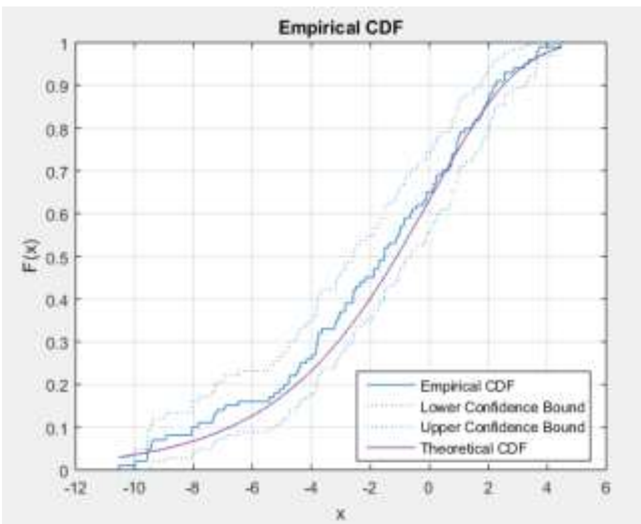

FIGURE 2: Empirical CDF

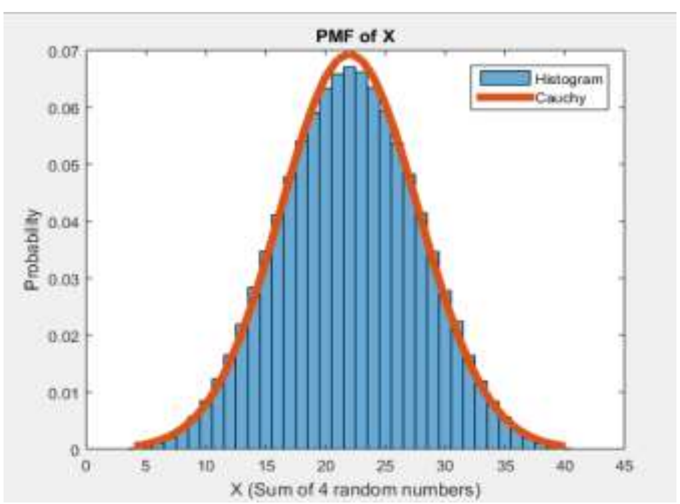

FIGURE 3: Cauchy distribution fitting on wind farm data

There are four wind farms connected to buses #1, #2, #3 and #4, 7, 14, 16 and 21. The The 4 wind farms have a capacity of 220, 280, 90 and 190 MW. The AGC connection units are proportionate to their capacity to participate on AGC units and to buses 5-8, 23 and 31-33. Furthermore, in this simulation all confidence levels are set at 0.98. [36] contains setup and settings adjusted for IEEE 24-bus and settings modify for IEEE 118-bus. A. Comparison of precision fitting WPFE in various distributions.A Statistical analysis of 20 wind farms with over 80,000 data in southwestern China has shown the excellent accuracy of the Cauchy distribution on the WPFE fitting. A. The electric power control centre provided all current and ultrashort forecast data used in this study. We normalised all expected and actual wind power in [1][26][29] and WPFE were then supplied with conditional distributions at various real values. The actual values range from 0.1 p.u. to 0.8 p.u.

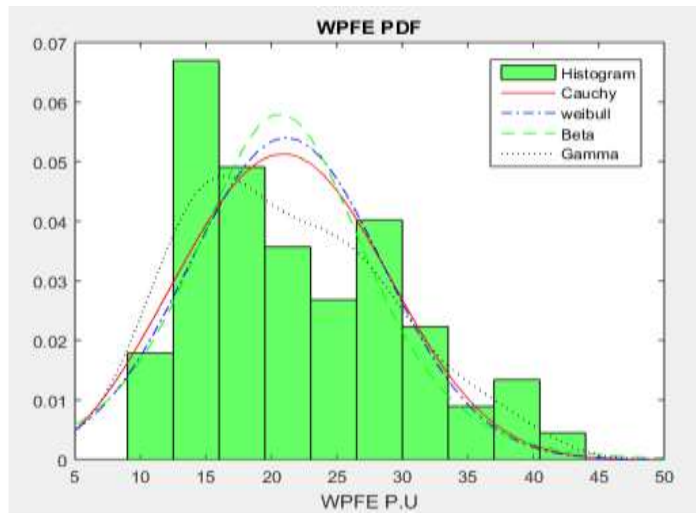

FIGURE 4: “PDF fitting results of different distributions using data 1”

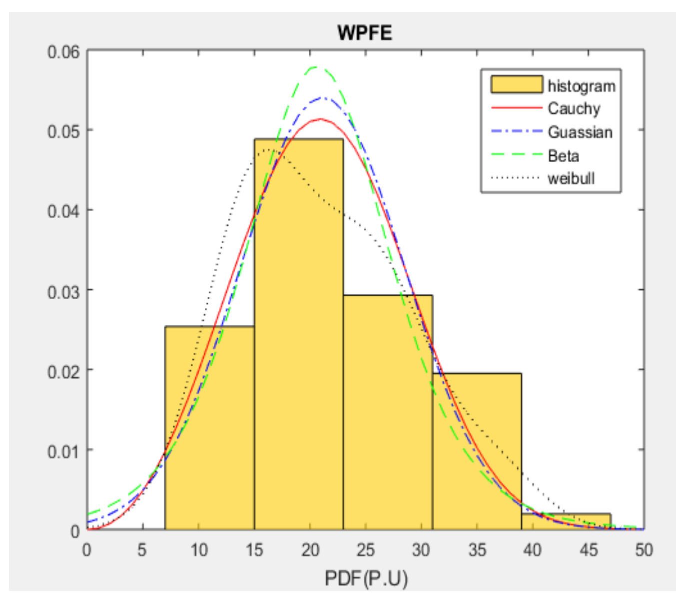

FIGURE 5: “PDF fitting results of different distributions using data 2”

We therefore choose two random data sets of about 7000 pairings each. We found that the CD provides different distributions, particularly in respect of curtosis and tail conduct, in Figs. 2 and 3. The likelihood in the centre is considerably underestimated by the gaussian, beta and females, while in the head and dress area the probability is dramatically overestimated.

TABLE I: “RMSEs of Different Distributions comparison ”

Data Set	**RMSE (p.u)**			
	Cauchy:	**Gaussain:**	**Beta:**	**Weibull:**
Data 1.	0.3221	2.1144	2.2739	2.5273
Data 2.	0.3220	0.6365	0.7021	0.8695

In this paragraph, the proposed A-CCRTD was compared with the CCED models and the AGC refined control technique was not covered by APRR. The cost was a total of 12 dispatch times between 21:00 and 22:00 in all the situations. "Monte Carlo simulations (MCS)," utilising the economic and safety performance of A-CCRTD has been compared with other systems using 10,000 scenarios.

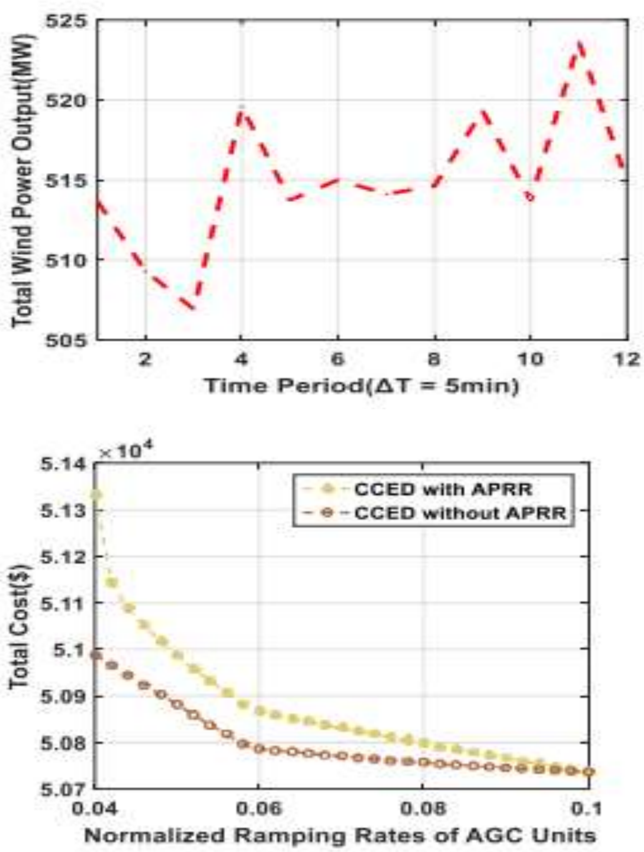

FIGURE 6: a) “Total wind power output curve predicted for 21:00-22:00.(b) Total cost for CCED with APRR and CCED without APRR in two scenarios”.

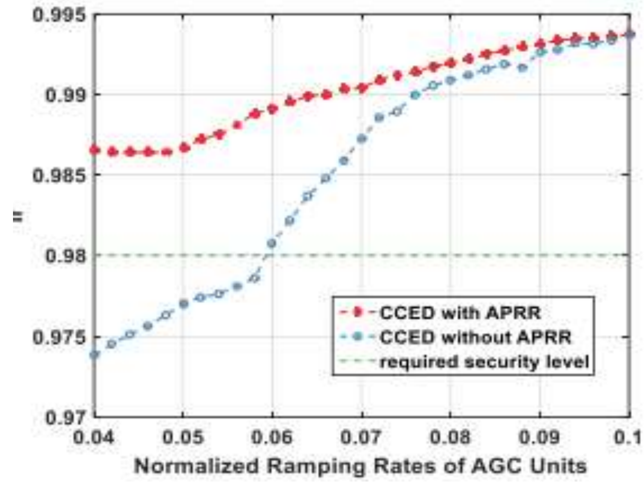

FIGURE 7: The unit's security level increasing from period 4 to period 5.

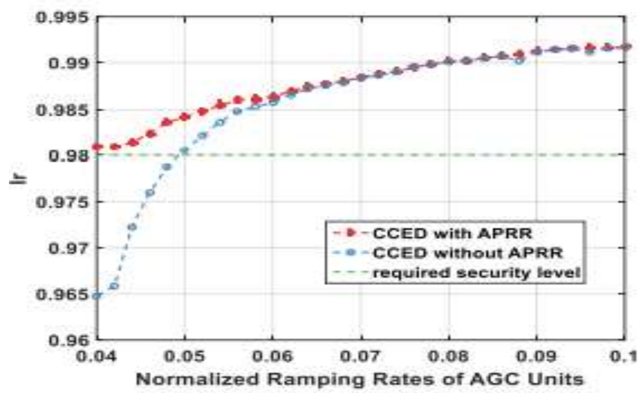

FIGURE 8: The device's security level increases from time period 11 to 12.

APRR'S IMPACT ON RAMPING LIMITATIONS**:** The normal ramp rates were evenly adjusted from 0,04 to 0,1 in this experiment for all AGC units. The security index for the increasing resources is provided for easy comparison:

$$Ir = \frac{N_r}{N_M} \tag{34}$$

The average number of adequately resourced scenarios is N, whereas the total number of scenarios for the MCS is NM. A greater value of Ir thus means a higher degree of safety. Fig.5. the anticipated profile of the overall wind production will be between 21:00 and 22:00 (a). Fig. 5b shows that, for low unit ramping rates, considering the effect of APRR, the total expenses for every simulation will increase the timetable cost. In severe circumstances, uneconomical scheduling outcomes offer a tempting decision to avoid a shortage of ramping resources.
Figure 7, providing findings for AGC units in two distinct instances respectively of the Monte Carlo Simulation:
1) period 4 to period 5 (2) period 10 to period 11. Due to the depleted resources in which the ramping rate for AGC units is low, the safety level of ramping without APRR is not able to achieve the required levels in Fig. 6 and Fig.7, as shown by the wind energy fluctuation in the two situations Fig. 5. Figures 6 and 7 also show that only if the system has a large ramping resource can the effect of APRR be ignored in the ED.

2) Limiting the transmission capabilities and effect of the affinity control approach

We increased Line 11's transmission capacity from 155 MW to 170MW in this simulation, in order to show the effect on the limits of transmission capacity of a revised control approach.

The transmission capacity security index may be defined as

$$It = \frac{N_t}{N_M} \qquad (35)$$

Nt is average number of the scenarios without the transmission congestions for the line #11 throughout all the 12 dispatching periods. It can be concluded from Fig.7 that, while using an affine control approach increases operating costs, it ensures adequate transmission capacity for the security. It is for the reason, if the AGC control method is not considered in advance, “the redistribution of real-time power mismatch may cause transmission line congestion”. To avoid network congestions, it is important to include AGC unit regulation technique in the scheduling stage.

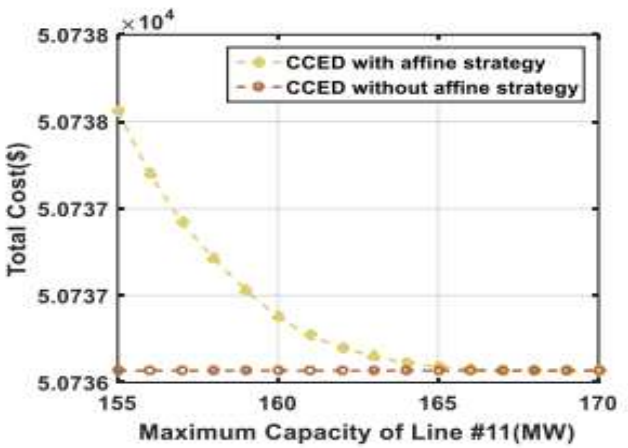

FIGURE 9: The cost is calculated as the average of 13 dispatching periods.

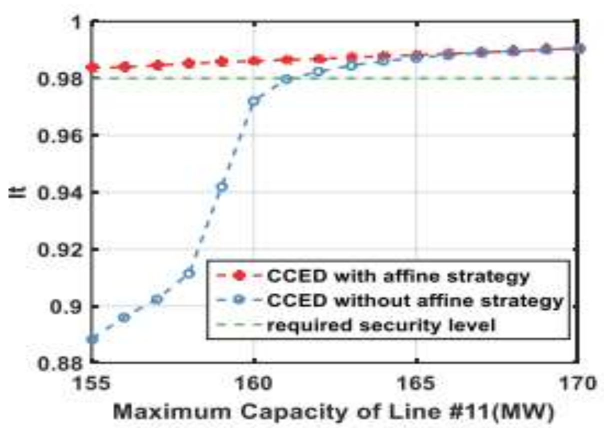

FIGURE 10: The average security level across 13 periods is the security level.

THE IMPACT OF MULTI-WIND FARM INTERDEPENDENCE: The aim of this experiment was to explore how the performance of the system affected the dependence of various wind farms. In comparison, we utilised two alternative scenarios: one with and one without taking the dependency of four wind farms into account: File I: the position of the vector and the scale of the matrix are consistent with previous parameters; case II: vector location and scale of matrix are incompatible. Field I: Field II: In contrast to Case I, the PDF for all wind farms is controlled exclusively by a marginal distribution, meaning that the random variables are the outputs of each wind farm. Each sample used an A-CCRTD 12-period. The distribution parameters in Case I used to demonstrate costs and risk impacts of dependency were used to generate 10000 random wind turbine scenarios. Table II shows the potential danger reduced at the disadvantage of greater costs by taking into consideration ED dependency. This is because WPFE is enhanced by the combining of several wind farms in our simulation. As a result, reliance on wind farms should be taken into account in real time power supply.

TABLE II: CORRELATION'S EFFECT ON THE ECONOMY AND OPERATIONAL RISK

Case	**CaseI dependent**	**Case II Independent**
Cost	50736	50387
Risk level of the reserve constraints	1.58%	2.39%
Risk level of the unit ramping constraints	0.82%	0.79%
Risk level on the transmission line constraints	0.74%	0.65%

A-EFFECTIVENESS CCRTD'S**:** For IEEE-24-bus and IEEE-118-bus systems, Table III illustrates the model size and the computation time of A-CCRTD. Note that because the reverse CDF on CD is analytical, it is possible to directly obtain the quantities of chance limits. Although A-CCRTD contains 1225 variables and 6275 limitations for the IEEE 118-bus system, it can be solved within 7.23 seconds. This technique is thus suited for application in real time in big power networks with substantial wind energy penetration.

TABLE III: THE ACC-RTD MODEL'S COMPUTATIONAL EFFICIENCY COMPARISION

System	**24 bus**	**118bus**
CPU time(s)	2.16511	7.2335
Bus No	24	118
Line No	38	181
Unit and wind farm No	35	78
Variables No	626	1235
Constraints No	2378	6285

V. CONCLUSION

This study offers a coordinated A-CCRTD method. There are three types of wind power stations, Non-AGC and AGC systems. There are two main factors to be considered. We differ with traditional CCED in several aspects of our approach. The A-CCRTD model based on precise description and mathematical features of the WPFE distribution, is equated to issue of convex optimization which is easily resolved without approximations. However, both the APRR and the voltage fluctuations of the transmission lines produced by the assignment in real time of retail power imbalances via AGC's affinity control methods. The suggested approach is better and more rational than the present CCED models, according to the numerical trials. Using Monte Carlo simulations the significance of reliance on multi-wind farms is further studied in real time constructs. The technique presented makes the RTD traceable even in real time applications of large power systems and significant wind energy penetration, via the use of generic optimizer solutions. Basically I apply 20 winds farms data on different distribution and you see that in numerical portion and results shows that error in Cauchy distribution is less from other distribution.

APPENDICES

A. Constants in the section-III

$$\frac{d^2}{ds^2}\left[\sum_{j=1}^{J}\left(k_{i,j}.\alpha_j\int_s^{s_m}(v-s)p(v)dv + k_{2,j}.\alpha_j\int_0^s(s-v)p(v)dv\right)\right] = \frac{d}{ds}\left[\sum_{j=1}^{J}\left(k_{2,j}.\alpha_j\int_0^s p(v)dv - k_{1,j}.\alpha_j\int_s^{s_m}p(v)dv\right)\right] = \sum_{j=1}^{J}\left[\alpha_j\left(k_{1,j}+k_{2,j}\right)p(v)\right] \quad (36)$$

B. The objective function's convexity, where k1 & k2 are cost coefficients for underestimation & overestimation, v is actual power production, and s is planned decision variable.

REFERENCES

[1] B. M. Hodge and M. Milligan, "Wind power forecasting error distributions over multiple timescales," in Proc. IEEE Power and Energy Society General Meeting, Detroit, MI, USA, 2011.

[2] Y. Wang, Q.H. Hu, D. Srinivasan, Z. Wang, "Wind Power Curve Modeling and Wind Power Forecasting with Inconsistent Data," IEEE Trans. Sustain. Energy, [Pre-print].

[3] C. Feng, M. Cui, B.-M. Hodge, J. Zhang, A data-driven multi-model methodology with deep feature selection for short-term wind forecastin, Appl Energy, vol. 190, pp. 1245-1257, 2017.

[4] Y. Zhang, X. Wang, X. Wu, P. Zeng and H. Shi, "Transmission planning considering spatial correlation of wind power," 2016 IEEE PES 13th International Conference on Transmission & Distribution Construction, Operation & Live-Line Maintenance (ESMO), Columbus, OH, 2016, pp. 1-5.

[5] Statisticat, LLC. (2018). LaplacesDemon: Complete Environment for Bayesian Inference. Bayesian-Inference.com. R package version 16.1.1.

[6] Z. S. Zhang, Y. Z. Sun, D. W. Gao, J. Lin, and L. Cheng, "A versatile probability distribution model for wind power forecast errors and its application in economic dispatch," IEEE Trans. Power Syst., vol. 28, no. 3, pp. 3114–3125, Aug. 2013.

[7] Z. Wang, C. Shen, F. Liu et al., "Chance-Constrained Economic Dispatch With Non-Gaussian Correlated Wind Power Uncertainty," IEEE Transactions on Power Systems, vol. 32, no. 6, pp. 4880-4893, 2017.

[8] Z.Wu, P. Zeng, X.-P. Zhang , et al., "A solution to the chance-constrained two-stage stochastic program for unit commitment with wind energy integration", IEEE Trans. Power Syst., vol. 31, no.6, pp. 4185–4196, 2016.

[9] Z. Wang, C. Shen, F. Liu, J. Wang and X. Wu, "An Adjustable Chance-Constrained Approach for Flexible Ramping Capacity Allocation," IEEE Trans. on Sustainable Energy, vol. 9, no. 4, pp. 1798-1811, Oct. 2018.

[10] B. M. S. Hodge, E. G. Ela, and M. Milligan, "Characterizing and modeling wind power forecast errors from operational systems for use in wind integration planning studies," Wind Eng., vol. 36, no. 5, pp. 509–524, 2011.

[11] W. Lin, J. Wen, S. Chen, and W.-J. Lee, "An investigation on the active-power variations of wind farms", IEEE Trans. Ind. Appl., vol.48, no.3, pp. 1087–1094, 2012.

[12] H. Bludzuweit, J. Dominguez-Navarro, A. Llombart, "Statistical Analysis of Wind Power Forecast Error," IEEE Transactions on Power Systems, vol. 23, pp. 983-991, August 2008.

[13] K. Bruninx and E. Delarue, "A Statistical Description of the Error on Wind Power Forecasts for Probabilistic Reserve Sizing," in IEEE Transactions on Sustainable Energy, vol. 5, no. 3, pp. 995-1002, July 2014.

[14] B.-M. Hodge, E. Ela, and M. Milligan, "The distribution of wind power forecast errors from operational systems," 10th International Workshop onLarge-Scale Integration of Wind Power Into Power Systems as well as on Transmission Networks for Offshore Wind Farms Proceedings, Aarhus, Denmark, October 25–26, 2011.

[15] V. Pappala, et al., "A Stochastic Model for the Optimal Operation of a Wind-Thermal Power System," IEEE Transactions on Power Systems, vol. 24, pp. 940 - 950, May 2009.

[16] K. Dietrich, et al., "Stochastic unit commitment considering uncertain wind production in an isolated system," in 4th Conference on Energy Economics and Technology, Dresden, Germany, 2009.

[17] H. Bludzuweit, et al., "Statistical Analysis of Wind Power Forecast Error," IEEE Transactions on Power Systems, vol. 23, pp. 983 - 991, August 2008.

[18] D. Liu, J. Guo, W. Wang, C. Liu, Y. Huang and M. O'Malley, "A dynamic economic dispatch method considering with the uncertainty and correlation of wind power," 2014 IEEE PES General Meeting | Conference & Exposition, National Harbor, MD, 2014, pp. 1-5.

[19] J. Liu et al., "The impacts of correlation of multi-wind farms in day-ahead economic dispatching," 2017 IEEE Power & Energy Society General Meeting, Chicago, IL, 2017, pp. 1-5.

[20] L. Xie, Y. Gu, X. Zhu and M. G. Genton, "Short-Term Spatio-Temporal Wind Power Forecast in Robust Look-ahead Power System Dispatch," in IEEE Transactions on Smart Grid, vol. 5, no. 1, pp. 511-520, Jan. 2014.

[21] L. Bin, M. Shahzad, Q. Bing, M. U. Shoukat, M. Shakeel and E. K. Mohammedsaeed, "Probabilistic Computational Model for Correlated Wind Farms Using Copula Theory," in IEEE Access, vol. 6, pp. 14179-14187, 2018.

[22] M. Xie, J. Xiong, S. Ke and M. Liu, "Two-Stage Compensation Algorithm for Dynamic Economic Dispatching Considering Copula Correlation of Multiwind Farms Generation," in IEEE Transactions on Sustainable Energy, vol. 8, no. 2, pp. 763-771, April 2017.

[23] S. Bolognani, E. Arcari, and F. Dorfler, "A fast method for real-time chance-constrained decision with application to power systems," IEEE Control Systems Letters, vol. 1, no. 1, pp. 152–157, July 2017.

[24] Y. Zhang, J. Wang, B. Zeng and Z. Hu, "Chance-Constrained Two-Stage Unit Commitment Under Uncertain Load and Wind Power Output Using Bilinear Benders Decomposition," in IEEE Transactions on Power Systems, vol. 32, no. 5, pp. 3637-3647, Sept. 2017.

[25] C. Uçkun, A. Botterud and J. R. Birge, "An Improved Stochastic Unit Commitment Formulation to Accommodate Wind Uncertainty," in IEEE Transactions on Power Systems, vol. 31, no. 4, pp. 2507-2517, July 2016

[26] Q.F. Wang, Y.P.Guan,and J.H.Wang,"A chance-constrained two stage stochastic program for unit commitment with uncertain wind power output," IEEE Trans. Power Syst., vol. 27, no. 1, pp. 206–215, Feb. 2012.

[27] C. Y. Zhao, Q. F. Wang, and J. H. Wanget al., "Expected value and chance constrained stochastic unit commitment ensuring wind power utilization," IEEE Trans. Power Syst., vol. 29, no. 6, pp. 2696–2705, Nov. 2014.

[28] C. Tang et al., "Look-Ahead Economic Dispatch With Adjustable Confidence Interval Based on a Truncated Versatile Distribution Model for Wind Power," in IEEE Transactions on Power Systems, vol. 33, no. 2, pp. 1755-1767, March 2018.

[29] H.Y. Lee, H.J. Park, and H.M. Kim, "A Clarification of the Cauchy Distribution," Communications for Statistical Applications and Methods, vol. 21, no.2, pp. 183-191, 2014.

[30] Diethelm Wuertz et al., fMultivar: Rmetrics - Analysing and Modeling Multivariate Financial Return Distributions, R package version 3042.80, 2017.

[31] M. Sedghi, A. Ahmadian and M. Aliakbar-Golkar, "Optimal storage planning in active distribution network considering uncertainty of wind power distributed generation", *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 304-316, Jan. 2016.

[32] K. Bruninx and E. Delarue, "A statistical description of the error on wind power forecasts for probabilistic reserve sizing", *IEEE Trans. Sustain. Energy*, vol. 5, no. 3, pp. 995-1002, Jul. 2014.

[33] Z. W. Wang, C. Shen and F. Liu, "Probabilistic analysis of small signal stability for power systems with high penetration of wind generation", *IEEE Trans. Sustain. Energy*, vol. 7, no. 3, pp. 1182-1193, Jul. 2016.
[34] D. Ke, C. Y. Chung and Y. Sun, "A novel probabilistic optimal power flow model with uncertain wind power generation described by customized gaussian mixture model", *IEEE Trans. Sustain. Energy*, vol. 7, no. 1, pp. 200-212, Jan. 2016.
[35] Z. Wang, C. Shen, F. Liu, X. Wu, C. C. Liu and F. Gao, "Chance-constrained economic dispatch with non-gaussian correlated wind power uncertainty", *IEEE Trans. Power Syst.*, vol. 32, no. 6, pp. 4880-4893, Nov. 2017.
[36] Z. Wang, C. Shen and F. Liu, "A conditional model of wind power forecast errors and its application in scenario generation", *Appl. Energy*, vol. 212, pp. 771-785, 2018.
[37] C. Draxl, B. M. Hodge, A. Clifton and J. McCaa, "Overview and meteorological validation of the wind integration national dataset toolkit", Apr. 2015.
[38] C. Draxl, A. Clifton, B. M. Hodge and J. Mccaa, "The wind integration national dataset (WIND) toolkit", *Appl. Energy*, vol. 151, pp. 355-366, 2015.
[39] J.M. Morales, P. Pinson, H. Madsen, A transmission-cost-based model to estimate the amount of market-integrable wind resources, IEEE Trans. Power Syst. vol.27, no.2, pp. 1060-1069, 2012.http://dx.doi.org/10.1109/TPWRS.2011.2177281.
[40] A. Naimo, A novel approach to generate synthetic wind data, Proc. Soc. Behav. Sci. vol.108, pp. 187-196, 2014.
[41] N. Nawri, G.N. Petersen, H. Bjornsson, A.N. Hahmann, K. Jonasson, C.B. Hasager, N.-E. Clausen, The wind energy potential of Iceland, Renew. Energy, vol.69, pp. 290-299, 2014. http://dx.doi.org/10.1016/j.renene.2014.03.04