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A Markov chain-based model for wind power prediction in congested electrical grids

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Abstract: The large penetration of wind generators in existing electrical grids induces critical issues that are pushing the system operators to improve several critical operation functions, such as the security analysis and the spinning reserve assessment, with the purpose of mitigating the effects induced by the injected power profiles, which are ruled by the intermittent and not-programmable wind dynamics. Although numerous forecasting tools have been proposed in the literature to predict the generated power profiles in function of the estimated wind speed, further and more complex phenomena need to be investigated in order to take into account the effects of the forecasting uncertainty on power system operation. In order to deal with this issue, this paper proposes a probabilistic model based on Markov chains, which predicts the wind power profiles injected into the grid, considering the real generator model and the effects of the power curtailments imposed by the grid operator. Experimental results obtained on a real case study are presented and discussed in order to prove the effectiveness of the proposed method.

1 Introduction

The deployment of renewable energies has undergone a dramatic growth in the past 25 years, mainly induced by the need to implement the decarbonisation process of power systems. In this context, wind energy has been established as one of the most promising zero-carbon emissions technologies. Regrettably, the massive proliferation of this technology has also caused several critical issues in existing electrical grids, which have pushed power system operators to improve grid protection and control functions in order to mitigate the effects induced by the intermittent and not programmable nature of the wind [1].

Hence, with the purpose of promoting an effective integration of wind generators in the current electric grids, several wind power forecasting methods have been developed, outlining their role in supporting wind power producers in mitigating the effects induced by the wind uncertainty, reducing the imbalance charges, and obtaining strategic information in day ahead and real time markets trading [2–4].

Among the wind forecasting methods proposed in the literature, which are based on both physics and statistical models, many of them show adaptive features, in order to accurately describe the time varying phenomena characterising the wind dynamics, and require low computational resources, in order to satisfy the technical constraints of the available energy management systems [3].

Unfortunately, these forecasting methods do not allow modelling complex phenomena, such as the effects of the power curtailments imposed by the power system operator for mitigating the effects of network congestion, and the impacts of generator faults, which can influence the wind power production to a considerable extent [2, 5].

To address these complex issues, the modern research trends are oriented toward the conceptualisation of more sophisticated forecasting methods aimed at modelling the wind generators by probabilistic multi-state systems, where the state probabilities correspond to the expected levels of produced energy [6–8]. In this domain, the adoption of Markov chains-based models has been revealed as one of the most promising research direction to estimate the availability and reliability indexes characterising the wind generators in function of the forecasting wind profiles [9, 10].

The main limitations of these approaches derive by the need of discretising both the wind speed and the wind generator states in a proper number of classes. Since this process strongly influences both the accuracy and the complexity of the model, the selection of the optimal discretisation level that solves this dichotomy is still an open problem.

In order to deal with this issue, this paper proposes a probabilistic model based on Markov chains, which predicts the wind power profiles injected into the grid, considering the derating generator states and the effects of the power curtailments imposed by the grid operator. The insight principle is to estimate the derating probability profiles in function of each wind speed span by solving a multistate system, which describes the influence on the grid of the wind power production over time. Furthermore, the influence on the estimation of derating probabilities in function of the wind forecasting error has been taken into account by considering its real distribution. Experimental results obtained on a real case study are presented and discussed in order to prove the effectiveness of the proposed method.

2 Mathematical formalisation

This paper proposes a probabilistic model based on Markov Chains to predict, one-day ahead, the value of the power curtailments in derating conditions for each wind generator. To this aim, the developed algorithm fuses the outputs provided by a hybrid forecasting algorithm with an adaptive wind generator model, which considers the derating operation states, and it is continuously adjourned by real operation data.

The main idea is to estimate the probability density function of the wind forecasting error, analysing its influence on the probability to find a wind generator in a certain curtailed power state for each computed wind speed tolerance bounds. To solve this problem, the main steps described in the next Subsections have been applied.

2.1 Wind forecasting model

The predicted power profiles for each wind generator have been obtained by employing the adaptive algorithm proposed by the Authors in [11], which amalgamates the forecasted wind profiles supplied by a synoptic and local forecasting model by adopting a supervised learning system, where the primitive equation atmospheric general circulation model of the European Center for

Table 1 Wind speed states that are defined by classifying each hth element of $\mathbf{w}_z$ $\forall h \in [1,H]$ and $\forall z \in [1,N_{wg}]$

class	bounds
w1	$\mathbf{w}_z(h) < w_1$
w2	$w_1 \geq \mathbf{w}_z(h) < w_2$
w3	$w_2 \geq \mathbf{w}_z(h) < w_3$
w4	$\mathbf{w}_z(h) \geq w_3$

Table 2 Derated power states that are defined by classifying each hth element of $\mathbf{\Delta P}_z$ $\forall h \in [1,H]$ and $\forall z \in [1,N_{wg}]$

class	bounds
d1	$\mathbf{\Delta P}_z(h) < 0$
d2	$0 \leq \mathbf{\Delta P}_z(h) < \Delta P_1$
d3	$\Delta P_2 \leq \mathbf{\Delta P}_z(h) < \Delta P_3$
d4	$\Delta P_3 \leq \mathbf{\Delta P}_z(h) < \Delta P_4$
d5	$\Delta P_4 \leq \mathbf{\Delta P}_z(h) < P_R$

Table 3 Defined wind generator operator states

class	label
g1	Derated
g2	Not Derated

Medium-range Weather Forecast (ECMWF) [12] is the considered synoptic model.

This allows to consider the physical interactions between different several physical systems such as atmosphere, soil wetness, ocean and snow covering, and its predictions are successively corrected by adopting an adaptive learning algorithm that uses experimental data for improving the wind forecasting accuracy of the model. Hence, the effects of new operating conditions have been considered by updating the model in light of its adaptive features.

Hence, the authors have applied the described method in this work by considering its effectiveness proved in several previous works.

2.2 Generator reliability model

In order to be as more exhaustive as possible the generator operation states that can be defined are:

1. Alarm: operation in the presence of anomalous working conditions.
2. Derated: operation in the presence of an external reduction of generated power.
3. Faulted: operation inhibited due to a failure condition.
4. Run: normal operation.

Nonetheless, in light of the described scenario, the aim of this paper is to develop the model for describing the wind generator behaviour in derating conditions, keeping low the required computational burdens. Therefore, the wind generator has been reduced to a binary model, while the wind speed, which is one of the most influential variable ruling the generation state transitions, is classified in the classes shown in Table 1, where w_1, w_2, w_3 are the cut-in, rated and cut-off speeds, respectively.

2.3 Process of information fusion

To estimate the levels of power curtailments in derating conditions for the wind generators over the time a probabilistic model based on the Markov Chains has been adopted. The main idea is to start from data-driven power curves for each wind generator, and once knowing $\mathbf{w}_z$, which is the vector of the measured wind speed over the time for the zth wind generator, the corresponding theoretical power output $\mathbf{P}_{th_z} = f(\mathbf{w}_z)$ is calculated for each generator over the time. The experimental power curves have been calculated on the base of the available SCADA data.

This vector has been used to compute $\mathbf{\Delta P}_z = \mathbf{P}_{th_z} - \mathbf{P}_z$, which is the vector of the difference between the maximum power available and the measured one $\mathbf{P}_z$ over the time and where the ΔP_j are fractions of the rated Power value P_R, $\forall j \in [1, 5]$ and that are summarised in Table 2.

Hence, the operation data stored in the SCADA event register plays a strategic role in the development of this probabilistic model because their adoption has allowed to determine the transition probabilities by extracting the most relevant data and successively organising them in a double column matrix $\mathbf{C}_z$, which dimensions are [M(z),2], with $z \in [1,N_{wg}]$, where $m \in [1,M(z)]$ and where the second column contains the wind generator operation state for each time sample as shown in Table 3. Furthermore, the matrix of measurements set $\mathbf{D}_z$ has been introduced, which dimensions are $[H, V]$ and where it contains the averaged measured data on ten minutes, such as $\mathbf{w}_z$, $\mathbf{P}_z$, $\mathbf{P}_{\text{th}_z}$ and $\mathbf{\Delta P}_z$, and the codes for wind speed and derated power and the corresponding measurement time.

Hence, the measurement set of $\mathbf{D}_z$ have been uniquely labelled by following the code's list in Table 4, which has been developed by taking into account alg. 1, by fusing the deriving information from $\mathbf{C}_z$, which assigns the g codes for each generator state transition $g1-g2$ and vice versa, and from the couple of codes w and d, which are stored for each element in $\mathbf{D}_z$, allowing to uniquely assign codes to each hth element of $\mathbf{D}_z$.

In according with the described assignment for each row of this matrix will correspond an mth transition to a new state, the two columns describe the transition between two different states recorded time and the corresponding arrival state code, respectively.

Hence, by using the described labelling tool the following algorithm allows obtaining $\mathbf{O}_z$, which contains for each element the number of transitions from the state i-th to j-th one.

Where the number of total states is N, which is equal to 9 in the above case. Then, the obtained Matrix $\mathbf{O}_z$ allows to compute the transition probabilities as follows:

$$P(j \searrow i) = \frac{\mathbf{O}_z(i, j)}{\sum_{j=1}^{N} \mathbf{O}_z(i, j)} \tag{1}$$

Then, by iterating the following set of linear equations the generation state probabilities can be computed at each time class t (Figs. 1 and 2):

$$\mathbf{p}^t = \mathbf{p}^{t-1}\mathbf{P} \tag{2}$$

Hence, by solving the following equation system, the steady state probabilities $\boldsymbol{x}$ can be computed as follows:

$$\begin{cases} x_1(P_{11} - 1) + x_2 P_{12} + \ldots + x_N P_{1N} & = 0 \\ x_1 P_{21} + x_2(P_{21} - 1) + \ldots + x_N P_{2N} & = 0 \\ \ldots & = 0 \\ x_1 \quad + x_2 \quad + \ldots \quad + x_N & = 1 \end{cases} \tag{3}$$

where the above relation can be written by using a matrix-based formalism, as:

$$x^{\mathbf{P}*} = \gamma \tag{4}$$

where $\mathbf{P}*$ is the modified transition matrices. Hence, the previous equations show the ability to forecast on the behaviour of a certain system by only starting from an initial conditions set and the knowledge of the probabilities to change state over the time. Therefore, the authors aims to predict the evolution of a wind energy system by supplying the following reliability indexes in terms of probabilities as it will be shown in the next subsection.

Table 4 Obtained states for the final model

		w1	w2	w3	w4
	g2	9	9	9	9
g1	d1	9	9	9	9
	d2	9	1	5	9
	d3	9	2	6	9
	d4	9	3	7	9
	d5	9	4	8	9

for $m \leftarrow 1, (M(z) - 1)$ **do**
  for $h \leftarrow 1, H$ **do**
    if $\mathbf{D}_z(h,1) \geq \mathbf{C}_z(m,1)$ **and** $\mathbf{D}_z(h,1) < \mathbf{C}_z(m+1,1)$ **then**
      $\mathbf{D}_z(h, V+1) \leftarrow \mathbf{C}_z(m,2)$
if $\mathbf{D}_z(h, V+1) = g2$ **or** $\mathbf{D}_z(h, V) = d1$ **or** $\mathbf{D}_z(h, V-1) = w1$ **or** $\mathbf{D}_z(h, V-2) = w4$ **then**
  $\mathbf{D}_z(h, V+2) \leftarrow 9$
else
  if $\mathbf{D}_z(h, V-1) = w2$ *and* $\mathbf{D}_z(h, V) = d2$ **then**
    $\mathbf{D}_z(h, V+2) \leftarrow 1$
  ...
  if $\mathbf{D}_z(h, V-1) = w3$ *and* $\mathbf{D}_z(h, V) = d5$ **then**
    $\mathbf{D}_z(h, V+2) \leftarrow 8$

Fig. 1 *Algorithm 1 labelling: $\forall z \in [1, N_{wg}]$*

for $h \leftarrow 1, (H-1)$ **do**
  from $\leftarrow \mathbf{D}_z(h, V+1)$
  to $\leftarrow \mathbf{D}_z(h+1, V+1)$
  $\mathbf{O}_z(\text{from,to}) \leftarrow \mathbf{O}_z(\text{from,to}) + 1$

Fig. 2 *Algorithm 2 transitions counting: $\forall z \in [1, N_{wg}]$*

2.4 Evaluation of the effects related to the wind forecasting error

The described process for the information fusion allows to relate the wind speed with both the generator operation state and the quantity of power derating induced by the transmission system operator in order to mitigate the power lines congestion. Then, this can be strategic in the research of the most critical wind farms for a certain area going to evaluate the effects of the wind forecasting error. Hence, in order to quantify the effects on the estimation of the derating probabilities for each wind generator the total probability law has been applied as follows:

$$P(\Delta x_z(t)) = \sum_{k=1}^{N} P(x_{k_z}(t) | w_k(t) \leq w_z(t) + e(w_z(t)) < w_{k+1}) \cdot P(w_k(t) \leq w_z(t) + e(w_z(t)) < w_{k+1}) \tag{5}$$

where $P(\Delta x_z(t))$ is the total derating probabilities of the zth wind generator at time t when the probability of being in a certain wind generator derated state is $P(x(t)_{k_z})$ and the forecasted wind speed $w_z(t) + e(w_z(t))$ is included in kth wind speed class where $e(w_z(t))$ is the wind forecasting error that is has been computed by knowing its probability distribution on a real case study.

3 Case study

The proposed methodology has been applied to a real case study based on a wind farm located in the south of Italy, which is characterised by a rated power of 36 MVA shared among 18 wind generators. In order to accurately describe the effect of wind behaviour on the power curtailments, in this study the number of wind speed classes has been increased compared with the system shown in Fig. 3.

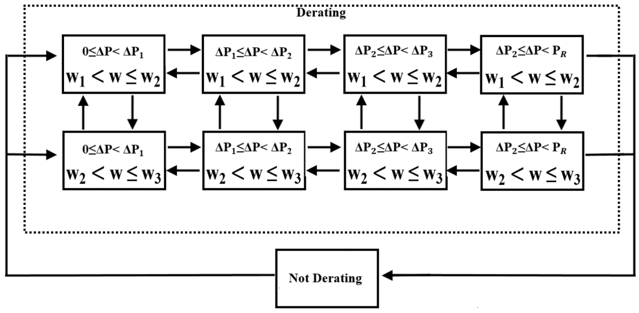

Fig. 3 *Graph of the Markov Chain model proposed in this study*

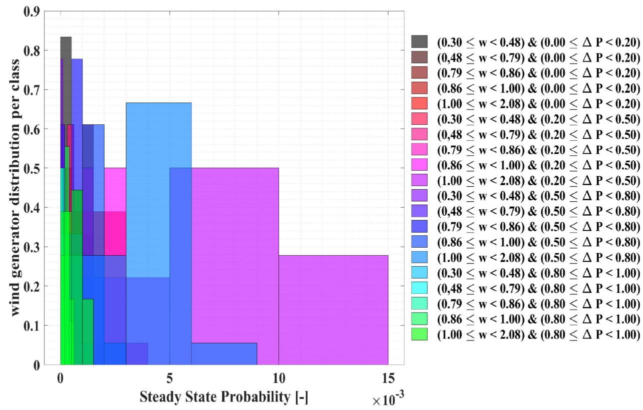

Fig. 4 *Wind generators distribution for each defined operation state. The quantities are expressed in p.u. where the rated wind speed and power values are 11 m/s and 2000 kW, respectively*

The steady state probabilities for each derated power and wind speed bins have been computed by solving the equation system shown in 4, where the results have been summarised in Fig. 4 for each machine of the wind farm object of study. These data represent the probability distribution of the actual derating probabilities over the defined wind speed bins, and allow to highlight the most critical conditions for which the highest power curtailments are caused.

In particular the described frequency distributions highlight the different behaviour of the wind turbines in function of both the wind and network conditions, because the frequency distribution has proved to be not homogeneous for all system states. Then, in light of this, the next objective will be the identification of the causes that have provoked this different spreads (Fig. 5).

Starting from these results, the derating probabilities shown in Fig. 4 have been processed in order to estimate the derating operation for each wind generator by considering also the effects of the wind forecasting error. This process has been implemented by estimating the probability distribution function of the wind forecasting error, and by performing a sensitive analysis aimed at changing the amplitudes of the wind forecasting error, which are shown in Table 5. The obtained profiles have been benchmarked with the corresponding theoretical power profiles (blue), which have been obtained by setting to zero the wind forecasting error. The wind forecasting problem has been computed for a time horizon of 24 h by setting an initial state the real generator operation condition at time $h - 1$, (Table 5)

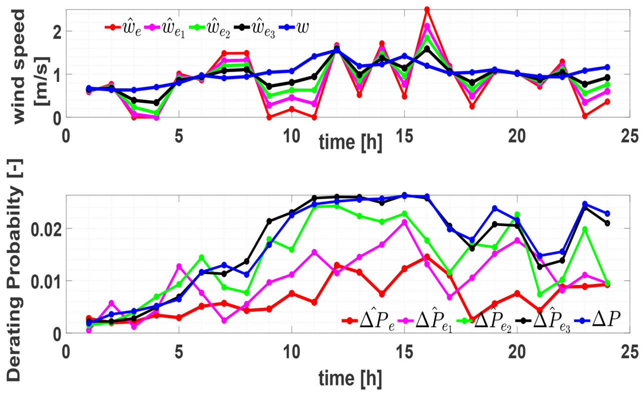

Fig. 5 *Lower figure shows the curtailed power probability profiles, which are obtained by changing the maximum amplitude of the wind forecasting error as shown in the upper figure. The blue profiles in the both figures are the wind speed and derated power benchmark profiles, respectively*

Table 5 Maximum amplitude of the wind forecasting error compared with the measured value

	–	e_3	e_2	e_1	e
percentage [%]	0	10	30	50	100
colour	blue	black	green	pink	red

Hence, by observing the following figures, it is possible to note the great influence of the wind forecasting error on the estimation of the wind power curtailment, which demonstrates the importance of quantifying the impacts of the occurrence probabilities on the generator operation state.

In particular, it is worth noting that the employed wind forecasting error algorithm tends to underestimate the real power profile, hence underestimating the derating probabilities profiles. Obliviously, this behaviour influences the dynamic of the proposed model, which has not been able to predict the true derating probability profiles.

Consequently, the obtained low probabilities values have been induced by the limited operation of the analysed wind generators in derating condition compared with the overall observed time period, which has been based on a 1 year time window. Therefore, the reduction of the wind forecasting error allows to reduce the certain wrong evaluation of wind generator operation states as it has proved in this figure other than increase the reactivity of the model.

Analysing this figure, it is also very clear how a large error could determine large deflections, which do not allow taking into the account the changing of the wind condition and its influence on the power grid. These issues could induce notable effects on the power system operation policies.

4 Conclusions

The effective integration of wind power generators in the existing electric networks requires adequate procedures aimed at reliable estimating the energy profiles available over the time, by taking into account the actual power system state, and managing the effects related to not programmable and stochastic generation profiles. In the light of this need, this paper proposed a probabilistic model based on Markov chains, which allows system operators to reliably predict the available generated profiles by taking in account the uncertainty of the wind forecasting methods, the derating operation states, and the probability of power curtailments imposed by the power system operator. The experimental results obtained on a real case study confirmed the effectiveness of the proposed method in describing the multiple effects of the wind power uncertainty on both the generation operation and real power production.

5 References

[1] Lerner, J., Grundmeyer, M., Garvert, M.: 'The role of wind forecasting in the successful integration and management of an intermittent energy source', *Energ. Cent. Wind Power*, 2009, **3**, (8), pp. 1–6

[2] González-Aparicio, I., Zucker, A.: 'Impact of wind power uncertainty forecasting on the market integration of wind energy in Spain', *Appl. Energy*, 2015, **159**, pp. 334–349

[3] Makarov, Y.V., Etingov, P.V., Ma, J., *et al.*: 'Incorporating uncertainty of wind power generation forecast into power system operation, dispatch, and unit commitment procedures', *IEEE Trans. Sustain. Energ.*, 2011, **2**, (4), pp. 433–442

[4] Zhang, Z.-S., Sun, Y.-Z., Cheng, L.: 'Potential of trading wind power as regulation services in the California short-term electricity market', *Energy Policy*, 2013, **59**, pp. 885–897

[5] Philbrick, C.: 'Wind integration and the need for advanced decision support tools'. 2011 IEEE Power and Energy Society General Meeting, Detroit, USA, 2011, pp. 1–7

[6] Chen, F., Li, F., Wei, Z., *et al.*: 'Reliability models of wind farms considering wind speed correlation and wtg outage', *Electr. Power Syst. Res.*, 2015, **119**, pp. 385–392

[7] Billinton, R., Karki, R., Gao, Y., *et al.*: 'Adequacy assessment considerations in wind integrated power systems', *IEEE Trans. Power Syst.*, 2012, **27**, (4), pp. 2297–2305

[8] Ghaedi, A., Abbaspour, A., Fotuhi-Firuzabad, M., *et al.*: 'Toward a comprehensive model of largescale dfig-based wind farms in adequacy assessment of power systems', *IEEE Trans. Sustain. Energ.*, 2014, **5**, (1), pp. 55–63

[9] Sulaeman, S., Benidris, M., Mitra, J., *et al.*: 'A wind farm reliability model considering both wind variability and turbine forced outages', *IEEE Trans. Sustain. Energ.*, 2017, **8**, (2), pp. 629–637

[10] Leite, A.P., Borges, C.L., Falcao, D.M.: 'Probabilistic wind farms generation model for reliability studies applied to Brazilian sites', *IEEE Trans. Power Syst.*, 2006, **21**, (4), pp. 1493–1501

[11] Vaccaro, A., Bontempi, G., Taieb, S.B., *et al.*: 'Adaptive local learning techniques for multiple-step-ahead wind speed forecasting', *Electr. Power Syst. Res.*, 2012, **83**, (1), pp. 129–135

[12] 'ECMWF description': Available at http://www.ecmwf.int/en/research/modelling -and -prediction/atmospheric-dynamics, accessed 13 February 2013.