Sanjay R. Arwade[1]
Assistant Professor
Department of Civil
and Environmental Engineering,
University of Massachusetts Amherst,
Amherst, MA 01003
e-mail: arwade@ecs.umass.edu

Matthew A. Lackner
Assistant Professor
Department of Mechanical and
Industrial Engineering,
University of Massachusetts Amherst,
Amherst, MA 01003
e-mail: lackner@ecs.umass.edu

Mircea D. Grigoriu
School of Civil and Environmental Engineering,
Cornell University,
Ithaca, NY 14853
e-mail: mdg12@cornell.edu

Probabilistic Models for Wind Turbine and Wind Farm Performance

A Markov model for the performance of wind turbines is developed that accounts for component reliability and the effect of wind speed and turbine capacity on component reliability. The model is calibrated to the observed performance of offshore turbines in the north of Europe, and uses wind records obtained from the coast of the state of Maine in the northeast United States in simulation. Simulation results indicate availability of 0.91, with mean residence time in the operating state that is nearly exponential and has a mean of 42 days. Using a power curve typical for a 2.5 MW turbine, the capacity factor is found to be beta distributed and highly non-Gaussian. Noticeable seasonal variation in turbine and farm performance metrics are observed and result from seasonal fluctuations in the characteristics of the wind record. The input parameters to the Markov model, as defined in this paper, are limited to those for which field data are available for calibration. Nevertheless, the framework of the model is readily adaptable to include, for example: site specific conditions; turbine details; wake induced loading effects; component redundancies; and dependencies. An on-off model is introduced as an approximation to the stochastic process describing the operating state of a wind turbine, and from this on-off process an Ornstein–Uhlenbeck (O–U) process is developed as a model for the availability of a wind farm. The O–U model agrees well with Monte Carlo (MC) simulation of the Markov model and is accepted as a valid approximation. Using the O–U model in design and management of large wind farms will be advantageous because it can provide statistics of wind farm performance without resort to intensive large scale MC simulation.
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Keywords: wind energy, reliability, Markov chain, availability, wind farm

1 Introduction

Rapidly increasing emphasis on wind as an energy source is being accompanied by growth in the size of individual turbines and the number of turbines included in industrial scale farms. The development of offshore wind energy resources is also being emphasized both to exploit the tremendous potential of the offshore wind resource and mitigate the impact of large scale wind farm development on human populations [1]. Growth in turbine and wind farm size and the possibility of offshore installations substantially increase the capital investment required to develop wind generating stations, and in the case of offshore wind farms, the operating costs. The offshore environment also introduces many more sources of uncertainty to the performance of a wind farm such as the loads generated by the sea and the difficulty of access for repair and maintenance. These factors motivate the need for probabilistically based assessments of the performance of large scale wind farms.

This paper describes an approach that can deliver assessments of the probability distribution of wind turbine and wind farm performance metrics such as availability, the length of operating and down periods, and power generation. The model, as described, accepts many different kinds of input parameters, yet the set of input parameters has been limited to those which can be calibrated to available field observations. Without any theoretical adjustments, however, the model could be adapted to include site specific conditions, turbine specifics, wake induced structural loading, and component redundancy and dependency. Two approaches are described, one based on the direct Monte Carlo simulation of a Markov model for wind turbine and farm performance, and one based on analytical treatment of a stochastic process describing performance that can be derived if certain simplifying assumptions are made. The accuracy of the more efficient simplified model, which is based on an Ornstein–Uhlenbeck process, is evaluated with respect to the Monte Carlo simulations. The MC simulation model begins with performance models for the mechanical components of a turbine, and, assuming series linking of the components, develops models for turbine performance. The component performance models are calibrated to data that describes the actual, in-service, performance of an ensemble of wind turbines off the northern coast of Europe [2], and the input wind speed model, which partially defines the component performance and the power generation process, is calibrated to observed wind speeds off the coast of Maine over a 20 yr period [3]. Although there is a geographic mismatch between the calibration of the component performance models and the wind speed model, the component performance models are assumed to be typical for industrial scale turbines, and the offshore Maine site is a likely location for future consideration of offshore wind generating installations. The approximate model directly models the operating state of a large scale wind farm without the need to simulate the performance of each individual turbine.

Previous efforts at probabilistic evaluation of wind turbine and farm performance have focused either on collection of performance data from the field or performance modeling and simulation. Although most performance data are considered proprietary, the German "250 MW Wind" test program has made a database of observed turbine reliabilities publicly available [2]. Data mining of this database has revealed a strong negative correlation between turbine reliability and turbine size [4], and between reliability and wind speed [5]. Field observations have also been used to develop predictive models for turbine reliability [6]. One critical evaluation of reliability models has shown that average

[1]Corresponding author.
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in-service turbine availability is 0.93 [7], somewhat lower than projections made from models [8].

Much of the probability-based modeling of turbine performance accomplished thus far has focused on the effect of turbine design, for example, direct drive versus geared drive, on reliability [9], or the probabilistic determination of design loads based on the stochastic wind and sea models [10–13]. A small number of studies have applied the methods of system reliability to the modeling of wind farm performance, incorporating wake effects on the fatigue life [14] or using the direct Monte Carlo simulation of Markov models to evaluate availability and power generation [8,15]. One study has explicitly addressed the role of reliability analysis in scheduling inspection of offshore turbines [16].

This study builds directly upon previous simulation-based [8] and analytical [17] approaches to evaluating the reliability of wind turbines or similar systems, and makes the following novel contributions:

1. The component reliabilities depend on wind speed in a way supported by field observations,
2. The turbine reliabilities are derived directly from component reliabilities that are calibrated to observations,
3. A stochastic process model for the availability of wind farms is found to agree well with simulation results.

The paper also contains the description of the wind turbine and wind farm models along with a description of the MC simulation procedure, the simplified analytical model for turbine performance, and a numerical example in which the performance of a realistic model wind farm is evaluated by MC simulation and the simplified method and the accuracy of the simplified method is evaluated.

2 Markov Model for Turbine and Farm Performance

The Markov wind farm performance model described here integrates performance at the component, turbine, and farm scales. Beginning at the component scale, it is assumed that each component of the wind turbine can be in one of two states, the on state or the off state, represented by 1 and 0, respectively. The state of component i in turbine j can be represented as a continuous time stochastic process $C_{i,j}(t)$, or as a series of time-indexed random variables $C_{i,j,k}$ representing the state of component i during time interval $[t_{k-1},t_k)$. The component state processes are at this point assumed to be stochastically independent.

The time intervals are defined as a partitioning $0 = t_0 < t_1 < \cdots < t_{k-1} < t_k < \cdots < t_{\bar{k}}$ of the reference time interval $[0,\tau)$ where $t_k - t_{k-1} = \Delta t = \tau/\bar{k}$ for $k = 1, 2, \ldots, \bar{k}$. The state of turbine j in time interval $[t_{k-1},t_k)$ is denoted by $M_{j,k}$, can take the values 0 and 1 if the turbine is off or on, and depends on the component states according to

$$M_{j,k} = \prod_{i=1}^{n_c} C_{i,j,k} \tag{1}$$

where n_c is the number of components considered in the wind turbine model and the components are in series, so that the turbine is in an off state in a given time interval if a single component is in an off state during that time interval. The model can be modified to incorporate either interdependency of the component reliabilities or redundancy of the components. If interdependence of the component reliabilities were to be included, motivated either by data indicating such interdependence or a plausible physical mechanism for such interdependence, the turbine state would be defined by a series of n_c dimensional random vectors. Appropriate definition of the transition probabilities could account for the fact that failure of one component may influence the likelihood of other components to fail. The drawback of this approach is that the resulting matrix of transition probabilities becomes very large (at least $n_c \times n_c$) making calibration potentially unwieldy. To introduce component redundancy would require modifying Eq. (1) such that each $C_{i,j,k}$ would represent a group of redundant components. This random variable would indicate failure only when all of the redundant components failed. The turbine model would essentially become a series of parallel subsystems, where the parallel subsystems include the component redundancy.

In modeling the state of a wind farm composed of n_m turbines, the state of each turbine can be tracked in the series of n_m -dimensional random vectors $\mathbf{F}_k$, which have components $[\mathbf{F}_k]_j = M_{j,k}$ such that each component of $\mathbf{F}_k$ tracks the state of an individual turbine. If only the fraction of turbines in the on state is desired, the availability, then the wind farm state can be represented by the fraction of turbines in the on state

$$F_k = \frac{1}{n_m}\sum_{j=1}^{n_m} M_{j,k} \tag{2}$$

Our model for wind turbine and farm performance depends on the wind speed process in two ways. First, the component reliabilities depend on wind speed, capturing the effect that component and turbine failures occur more frequently when the wind speed is high, and second, power generation depends directly on the wind speed through the turbine's characteristic power curve. We neglect explicit treatment of wake effects, directionality, and spatial variability of the wind speed at this point, so that the stochastic process $V(t)$ defines the wind speed at all turbines in the farm. In the numerical example presented later in the paper wake losses will be approximated by a wake loss factor of 0.9 [18]. The effect of wakes on the structural loads acting on turbines, and therefore on the reliabilities, is not explicitly included in the model, yet such wake effects are present implicitly in the turbine reliability data used to calibrate the model since such turbines were themselves installed in wind farms. Referring to the partitioned time index, $V_k = \langle V(t)\rangle$, $t_{k-1} \leq t \leq t_k$ is the average wind speed in the interval $[t_{k-1}, t_k)$, $k = 1, 2, \ldots, \bar{k}$. We further divide the range of observed wind speeds into m intervals $[\nu_{q-1},\ \nu_q), q = 1, 2, \ldots, \bar{q}$, where $0 = \nu_0 < \nu_1 < \cdots < \nu_{m-1} < \nu_m = \infty$.

We assume that at $t = t_0$, the beginning of the reference time interval, all components are in the on state, that is, $C_{i,j,1} = 1$ for all $i = 1,2,\ldots,n_c$ and $j = 1,2,\ldots,n_m$. Residence times in the on state are assumed to be exponential so that $P(C_{i,j,k-1} = 1 \cap C_{i,j,k} = 1) = p_{11,i,q} = exp(-\lambda_{1,i,q}\Delta t)$ and $P(C_{i,j,k\text{-}1} = 0 \cap C_{i,j,k} = 0) = p_{10,i,q} = 1 - p_{11,i,q}$, where $p_{11,i,q}$ and $p_{10,i,q}$ are transition probabilities and $\lambda_{1,i,q}$ is the expected residence time in the on state of component i of turbine j when $V_k \in (\nu_q - 1,\ \nu_q)$. Residence times in the off state, which represent the time required for repair, are assumed to be deterministic and independent of wind speed in our model, and are denoted by $r_{0,i} = \lambda_{0,i}^{-1}$. We note that if the wind speed remains steady within a specified interval $[\nu_{q-1},\nu_q)$ then the residence times in the on state are exponential with average $\lambda_{1,i,q}^{-1}$, but that the residence times in the on state are not in general exponential because of the dependence of failure rate on wind speed. We note that, although preventive maintenance is not explicitly included in the model, it is included implicitly through the calibration data on component reliabilities, which reflect whatever preventive maintenance was performed on the monitored turbines. The operation and maintenance model assumed here is one in which turbine repair begins immediately following a component failure and in which the repair period is deterministic. In the absence of suitable calibration data, we have not treated more complicated and realistic O&M strategies in which, for example, preventive maintenance occurs, repair of multiple turbines is schedule simultaneously, repair times are stochastic, or turbine access is limited by weather conditions.

The model for wind turbine and wind farm state provides the foundation for the modeling of wind farm performance in terms of power generation. For a turbine, the power curve $P(v)$ gives the electrical power generated as a function of the wind speed. The power curve is characteristic of a particular turbine design and features lower and upper cutoff wind speeds ν_{lower} and ν_{upper} such

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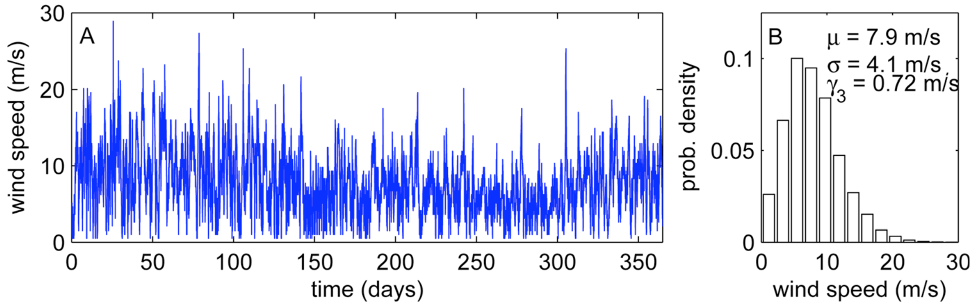

Fig. 1 (*a*) Wind speed time history for one typical year. (*b*) Histogram of wind speeds with statistics.

that $P(v)=0$ if $v < \nu_{\text{lower}}$ or $\nu > \nu_{\text{upper}}$. Below the lower cutoff the wind speed is insufficient to efficiently generate electricity and above the upper cutoff the turbine is shut down to avoid damage. We assume that the wind farm comprises turbines with identical power curves, so that the power generated by each turbine can be expressed as the random sequence $P_{j,k}=M_{j,k}\times P(V_k)$ and the total power generated by the wind farm is $P_k = w\sum_{j=1}^{n_m} P_{j,k}$ where $w \leq 1.0$ is a wake loss factor meant to approximate the effect of wake losses on overall wind farm energy production.

A Monte Carlo approach, in which ω_r indicates an element of the sample space, to evaluating wind turbine and wind farm performance based on this Markov model is:

1. Calculate, either from an observed or simulated wind speed record, the average wind speed sequence $\{V_k, k=1,2,\ldots,\bar{k}\}$, and assign numerical values to the mean failure rates $\lambda_{1,i,q}, i=1,2,\ldots,n_c, q=1,2,\ldots,\bar{q}$.
2. Generate samples $\{C_{i,j,k}(\omega_r), r=1,2,\ldots,\bar{r}\}$ of state sequence for each component $i=1,2,\ldots,n_c$ of each turbine $j=1,2,\ldots,n_m$ during each time interval $[t_{k-1},t_k)$, $k=1,2,\ldots,\bar{k}$.
3. Calculate the turbine state sequences $\{M_{j,k}(\omega_r)=\prod_{i=1}^{n_c} C_{i,jk}(\omega_r)\}$, $j=1,2,\ldots n_m$ and $k=1,2,\ldots,\bar{k}$ from the component state sequences.
4. Calculate the corresponding power output sequences for each turbine $\{P_{j,k}(\omega_r)\}$ and $\{P_k(\omega_r)\}$, $k=1,2,\ldots,\bar{k}$ including, if desired, the wake loss factor to reduce overall power production.

The resulting samples of $\{M_k\}$, $\{F_k\}$, $\{P_{j,k}\}$, and $\{P_k\}$ can be used to estimate various statistics describing the turbine and farm state and power generation process. For example, we may estimate the distribution of the residence time in the on and off states for a turbine and compare them with the exponential distribution. We emphasize here that the main purpose of this paper is to describe a probabilistic modeling framework that spans from the component scale to the wind farm scale. Our implementation has necessarily been limited by the data available for calibration, and the model can be extended in straightforward ways to include many of the complexities of real win turbines and farms.

2.1 Numerical Example. In this section we present a numerical example to illustrate the application of the models described in the previous sections, to give an indication of realistic statistics of wind turbine and farm performance, and to provide data for the quantitative comparison of the Markov and simplified models.

2.1.1 Wind Speed Characteristics. The wind speed process that partially drives wind farm performance is modeled on a record captured at station MISM1 of the US National Oceanic and Atmospheric Administration located on Matinicus Rock, 10 miles off the coast of the State of Maine in the Northeast United States [19]. The record consists of 20 consecutive years of wind speed data, with day 1 being January 1, 1985, measured 32.7 m above mean sea level. The record contains hourly average wind speeds. Figure 1 shows a typical year of the wind speed record from which the non-Gaussianity, positive skewness, and non-stationarity of the process can be observed. Specifically, wind speeds are generally higher in the winter and spring (days 325–140) than in the summer and fall (days 140–325).

2.1.2 Wind Farm Characteristics. The example wind farm we consider consists of 2.5 MW wind turbines that are assumed to be placed in the near offshore environment off the coast of the State of Maine in the far northeastern part of the United States. We assume that 100 of these turbines are arranged on a regular grid with spacing of 500 m, and that the deterministic wake loss factor is $w=0.9$. We calibrate the failure rates $\lambda_{1,i,q}$ to data provided by the German 250 MW monitoring campaign [2], which tracked reliability of the components listed in Table 1. We note that the number of components tracked is relatively small, and that the total number of components in a turbine can be much larger. Because of the structure of our model an arbitrary number of components can be included without theoretical changes to the model. Simulation times should not increase substantially, since simulation amounts to little more than the generation of calibrated random variables.

The data from the German 250 MW monitoring campaign has been reduced to the component reliabilities summarized in Table 2 in terms of the failure frequency and the mean time between failure (MTBF). It is interesting to note that most components have MTBF of greater than 1 year, but none, with the possible exception of the drive train (12), are greater than the expected service lifetime of a wind turbine. The reliabilities summarized in Table 2 represent statistics aggregated over approximately 1200 turbines with generating capacities ranging from below 500 KW to greater than 1 MW. Since it has been shown that reliability depends on both wind turbine generating capacity [4] and wind speed [5], we adjust the reliabilities to account for these dependencies.

The published data on the dependency of component reliability on turbine size groups turbines into three size categories, those

Table 1 Wind turbine components included in reliability model

Component number	Component
1	Electrical system
2	Electronic control
3	Sensors
4	Hydraulic system
5	Yaw system
6	Rotor blades
7	Mechanical brake
8	Rotor hub
9	Gearbox
10	Generator
11	Supporting structure/housing
12	Drive train

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Table 2 Wind turbine component reliabilities

Component	1	2	3	4	5	6	7	8	9	10	11	12
MTBF (years)	1.9	2.5	4.2	4.4	5.6	5.9	7.8	9.4	10.3	11.2	11.5	19.5
Failure freq. (1/years)	0.53	0.40	0.24	0.23	0.18	0.17	0.13	0.11	0.097	0.090	0.087	0.051

Table 3 Wind turbine component reliabilities for turbines with greater than 1 MW capacity

Component	1	2	3	4	5	6	7	8	9	10	11	12
MTBF (years)	0.59	0.80	1.3	1.4	1.7	1.8	2.4	2.9	3.3	3.5	3.6	6.2
Failure freq. (1/years)	1.7	1.2	0.75	0.71	0.56	0.53	0.40	0.33	0.30	0.28	0.27	0.16

with generating capacities less than 500 KW, between 500 and 1000 KW, and greater than 1000 KW. Let $n_{m,r}$, $r=1,2,3$ denote the number of turbines in the monitoring group with capacity in the intervals [0, 500), [500, 1000), and [1000, ∞), respectively, with all capacities expressed in kilowatts, and let $\lambda_{1,i,\cdot,r}$ denote the failure rate of component i for turbines in capacity class r , and irrespective of wind speed as indicated by the $\cdot$ in place of the wind speed index q. The failure rate of components in capacity class 3 is given by

$$\lambda_{1,i,\cdot,3} = \frac{\lambda_{1,i,\cdot,\cdot} n_{m,\cdot}}{c_1 n_{m,1} + c_2 n_{m,2} + n_{m,3}} \tag{3}$$

where $\lambda_{1,i,\cdot,\cdot}$ represents the aggregate failure rate for all wind turbines in the monitoring group, $n_{m,\cdot}$ is the total number of turbines in the monitoring group, and c_1 and c_2 are constants. By interpreting the published data [4], the values of the parameters in the above expression are, approximately, $n_{m,1}=1000$, $n_{m,2}=180$, $n_{m,3}=20$, $c_1=0.275$, and $c_2=0.475$. Note that the monitoring group is dominated by small capacity turbines, so these estimates of capacity dependent reliabilities have high uncertainty associated with them. Nevertheless, these represent the only measurements of capacity dependent reliability of which we are aware, and so we use the adjustment for large turbines to calibrate our reliability model. The capacity adjusted reliabilities are given in Table 3 and show that increasing turbine generating capacity can substantially lower reliability.

Our model for wind farm performance includes dependency of the component reliabilities on wind speed. The German 250 MW program [2] reports the frequency of failures conditional upon the daily average wind speed, and the distribution of daily average wind speeds over the same reference time period. We divide the domain of possible wind speeds into three intervals by $\nu_0=0$, $\nu_1=3$, $\nu_2=11$, and $\nu_4=\infty$, all in meters per second, and note that the peak daily average wind speed in the reference time period is 17 m/s. From the previous paragraphs, $\lambda_{1,i,q,3}$ is the failure frequency for component i of a wind turbine with generating capacity greater than 1 MW when the wind speed is in the interval (ν_{q-1},ν_q). Let $p_{w,q}$ denote the probability that the average daily wind speed falls in the interval (ν_{q-1},ν_q) and $p_{c,i,q,}$ is the probability that a failure of component i occurred when the wind speed was in interval $[\nu_{q-1},\nu_q)$. The wind speed adjusted failure frequencies are then $\lambda_{1,i,q,3}=\lambda_{1,i,\cdot,3}p_{c,i,q,}/p_{w,q}$. The failure frequencies $\lambda_{1,i,q,3}$ therefore represent the rate of failure of component i when the wind speed is in interval $[\nu_{q-1},\nu_q)$, and for turbines with generating capacity greater than 1 MW. Since this example only considers turbines with capacity greater than 1 MW, we drop the final index from the reliabilities, adopting the notation $\lambda_{1,i,q}=\lambda_{1,i,q,3}$. These reliabilities are given in Table 4. Note that there is a significant sensitivity to wind speed, with failure frequency increasing by more than a factor of three. In general, structural loads on variable pitch and speed wind turbines are known not to scale monotonically with wind speed, but rather to peak at or near the rated wind speed of 10–15 m/s. In our windspeed dependent model for wind turbine reliability, the high windspeed category includes the rated speed of the turbine, which is why the reliabilities decrease with increasing windspeed. Our choice of the windspeed categories was limited by the form of the calibration data available.

The repair times $r_{0,i}$ are assumed to be deterministic and independent of wind speed and are given in Table 5.

In addition to availability, our model is intended to characterize the random sequences $\{P_{j,k}\}$ and $\{P_k\}$ representing the power generation from each turbine and the wind farm, respectively. In this example we use a power curve $P(v)$ representative of a 2.5 MW turbine suitable for offshore deployment. The power curve is obtained by linear scaling of the power curve for a General Electric 1.5 MW pitch controlled turbine (Fig. 2), which has lower cutoff of 3 m/s, reaches peak production at 14 m/s, and has an upper cutoff of 25 m/s.

Table 4 Wind turbine component reliabilities for turbines with greater than 1 MW capacity at low, medium, and high windspeed

Component	1	2	3	4	5	6	7	8	9	10	11	12
$\lambda_{1,i,1}$ Failure frequency (low wind)	0.83	0.62	0.37	0.35	0.27	0.26	0.20	0.16	0.15	0.14	0.13	0.08
$\lambda_{1,i,2}$ Failure frequency (med wind)	2.00	1.49	0.89	0.85	0.66	0.63	0.48	0.40	0.36	0.33	0.32	0.19
$\lambda_{1,i,3}$ Failure frequency (high wind)	3.00	2.23	1.34	1.28	1.00	0.94	0.72	0.60	0.54	0.50	0.49	0.28

Table 5 Wind turbine component repair times

Component	1	2	3	4	5	6	7	8	9	10	11	12
Repair time (days)	1.8	2.3	1.8	1.4	3.3	5.1	3.3	4.4	7.9	9.3	4.1	7.1

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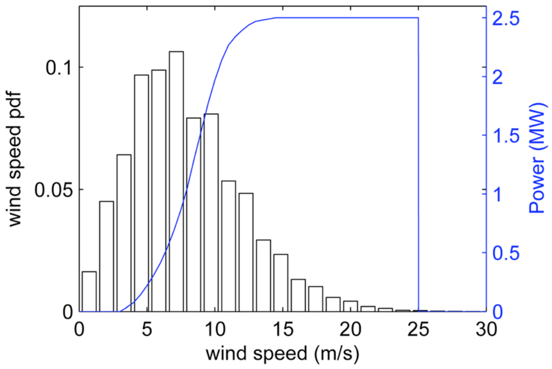

Fig. 2 GE 2.5 MW turbine power curve and histogram of wind speeds

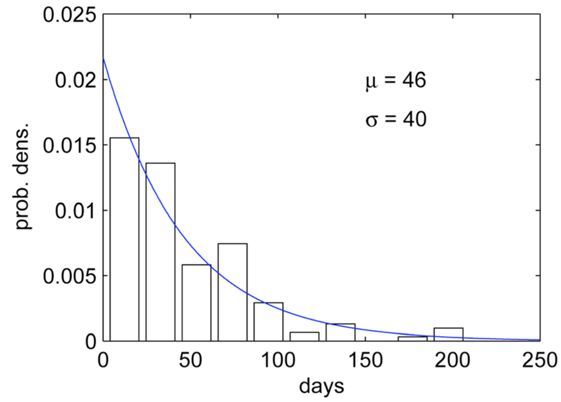

Fig. 4 Interarrival times for turbine failures. Each interarrival time consists of a residence period in the on state followed by a repair time. The line is the best fit exponential pdf.

2.1.3 MC Simulation Results. This section contains the results of Monte Carlo simulation of the Markov model for wind turbine and farm performance and contains comments on the results of the simulations including distributions of performance metrics such as availability and power generation. We simulate the performance of 100 turbines subject to the same 19 yr wind record, but with different turbine state series $\{M_{j,k}\}$ generated by independent simulation of turbine component failures. The simulation, therefore, provides a 19 yr record of the performance of a single, 100 turbine wind farm. Assuming that each year of the wind record is statistically representative of conditions at the observation site, that each year of wind data is independent of the others, and that the wind and turbine/farm performance processes are ergodic, this simulation is equivalent to 19 independent trials of a single year of wind turbine and farm performance.

2.1.3.1 Single turbine performance. Figure 3 shows the capacity factor for a single turbine in a typical year in the reference time interval with the turbine state shown below along a horizontal line where the heavier weighting indicates a period in the off state. We focus first on the characteristics of the turbine state $\{M_{j,k}\}$, then on the characteristics of the power output $\{P_{j,k}\}$, and finally on the performance characteristics of the wind farm. Although most of the periods of zero power production are associated with component failures, some short periods of zero power production result simply from low daily wind speed, such as a short period around day 190 (See Fig. 3). For this particular year of wind data, sustained maximum power generation is not achieved, and a seasonal variation in power is observed. The dependence of component reliability results in a higher likelihood of sustained residence in the off state during seasons in which average wind speed is higher. This appears as the long periods of residence in the off state between days 0 and 50 and around day 325.

The availability of a turbine $\{A_{j,k}=Pr(M_{j,k}=1)\}$ is the likelihood that turbine j will be in the on state during the time interval $[t_{k-1},t_k)$. The estimate of availability based on the entire 19 yr wind record is $A_{j,\cdot}=0.91$. By calculating availability for each year of the reference time we can estimate higher order statistics of the yearly availability. The estimate of the variance of the yearly availability is 0.056, the skewness -1.2, and the kurtosis 3.5, indicating that the availability is non-Gaussian, and any management plan based on the assumption of Gaussianity will be in error. The variance of the yearly availability is substantial, corresponding to a coefficient of variation of approximately 20%, and would propagate into the power production from a turbine. In the wind farm simulations presented later it is shown that wind farms consisting of many turbines, as expected, show much less variability in overall availability.

During the 19 yr reference time, there are 150 periods during which the turbine is in the on state, interrupted by 150 periods in the off state. In a classical Poisson model of mechanical failure, the failures are treated as arrivals of a Poisson process, with the resulting exponential distribution. A histogram of the time between the beginning of periods in the off state is superimposed with the best fit exponential distribution (Fig. 4), showing that, although these times cannot be exactly exponential due to the dependence of component reliability on wind speed and the deterministic nature of the repair times, an exponential fit to the failure interarrival times is reasonable. This conclusion is supported by the near equivalence of the mean and standard deviation of the interarrival times. For an exponential variable these statistics should be equal, and in the case of the simulated interarrival times the difference is largely attributable to the addition of the repair time, which averages 4 days.

The input wind record includes seasonal variation in the average wind speed, which induces seasonality in the availability of the wind turbine. The availability for each day of the year can be estimated as $\frac{1}{19}\sum_{i=1}^{19} M_{j,365(i-1)+1}$, and this availability is shown in Fig. 5 along with the similarly estimated seasonally varying power generated. The seasonal variability of the availability is much lower than that of the power generation, although the days with

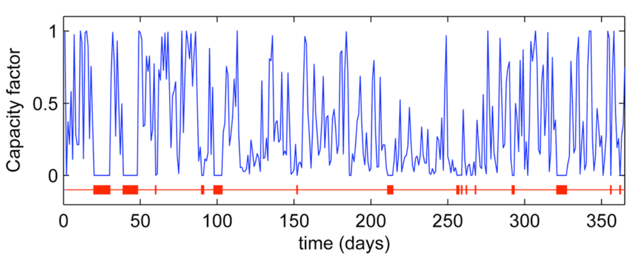

Fig. 3 Typical year of simulated power generation for a single turbine. The turbine state is shown on the horizontal line below the power with the heavier weighted line indicating an off period resulting from component failure.

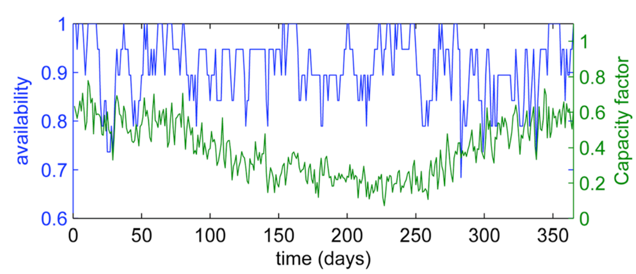

Fig. 5 Seasonal variation of availability and power generation based on estimation for the 19 yrs included in the reference time period

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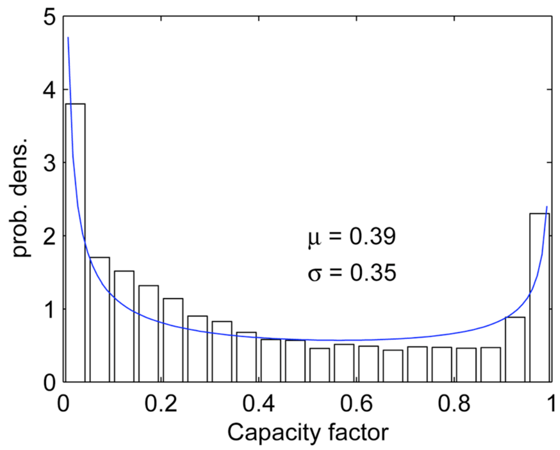

Fig. 6 Histogram and best fit beta pdf for daily capacity factor for 19 yrs of simulation

the lowest average availability do occur during the winter and fall, times of high wind speed.

The statistics and distribution shape for power generation, presented in the form of the capacity factor, based on the entire 19 yr record shown in Fig. 6 illustrate the nearly beta shaped distribution of power production generated by the convolution of the wind speed and turbine power curve. Yearly average capacity factor is 0.39 with standard deviation, skewness, and kurtosis of 0.033, −0.93, and 2.6, respectively, indicating that the power generation, as the availability, is non-Gaussian.

2.1.3.2 Wind farm performance. We assume that the example wind farm is composed of 100 nominally identical turbines, incorporate wake effects through a wake loss factor $w = 0.9$ and neglect other sources of spatial variation of the wind speed. The only source of variation of performance among the constituent turbines is therefore the uncertainty associated with component failure. Simulation of the performance of 100 nominally identical turbines subject to the same wind record shows that the expected number of turbines operating at any given time instant is 91. This is equivalent to the product of the number of turbines in the farm and the average availability since we assume independence of the turbine reliabilities and neglect spatial variation of the wind speed. The standard deviation, skewness, and kurtosis of the number of available turbines are 3.0, −0.27, and 2.98, indicating mild non-Gaussianity as expected since the number of turbines available is bounded from above by the number of turbines in the wind farm. The coefficient of variation of the wind farm availability, about 3%, is of course much less than the coefficient of variation of the availability of an individual wind turbine. There is a measurable seasonal affect in the wind farm availability, with peak availability occurring in the summer months (Fig. 7). The seasonal availability is negatively correlated, however, with seasonal power production because the seasonal fluctuations in wind speed overwhelm the seasonal fluctuations in availability. Finally, yearly average capacity factor is an important design parameter for large scale wind farms. For our example wind farm, the average yearly capacity factor is 0.35 with standard deviation, skewness, and kurtosis of 0.017, −0.59, and 2.4, respectively. Even for a 100 turbine farm the performance metrics are substantially non-Gaussian.

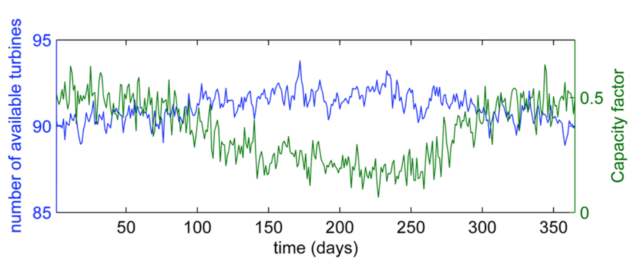

Fig. 7 Seasonal variation of the number of available turbines and the power generated by a 100 turbine wind farm averaged over a 19 yr period

3 Approximate Model

The Markov model described in the preceding sections allows relatively efficient simulation of turbine and farm state provided sufficient data are available to calibrate the model. In practice it is useful to have a model from which exact expressions for the statistics of the turbine and farm state can be developed, even if the model contains approximations. This section describes such an approximate, but analytical, model for turbine and farm performance that is based on treatment of the turbine state as a binary stochastic process and the farm state as an Ornstein–Uhlenbeck process. In the following section the results of the approximate model are compared to those obtained by direct Monte Carlo simulation. The approximate models are developed under the simplifying assumption of stationarity of the turbine state process and also only for the turbine and farm availability. Approximations to the turbine and farm power production process or capacity factor process are beyond the scope of the analytical work in this paper, but are the subject of current study by the authors.

3.1 Turbine State. Let $M(t)$, $t \geq 0$ be an on/off stochastic process that is on at $t = 0$ and remains in this state for a random time Y_1, such that, $M(t) = 1$ for $t \in [0, Y_1)$. The process switches to the off state at time Y_1 and remains in the off state for a random time Z_1 such that $M(t) = 0$ for $t \in [Y_1, Y_1 + Z_1)$. Here $M(t)$ represents the state of the turbine, Y_1 represents the residence time in the on state and Z_1 represents the repair time, denoted earlier as $r_{0,i}$ for component i. In the approximate model the individual components are not treated separately and so the notations Y_1 and Z_1 are adopted for the residence times in the on and off states. The on-off cycling is repeated indefinitely, that is, $M(t) = 1$ for $t \in \left[\sum_{i=1}^{k}(Y_i + Z_i), \sum_{i=1}^{k}(Y_i + Z_i) + Y_{k+1}\right)$ and $M(t) = 0$ for $t \in \left[\sum_{i=1}^{k}(Y_i + Z_i) + Y_{k+1}, \sum_{i=1}^{k+1}(Y_i + Z_i)\right)$. It is assumed that the random variables $\{Y_1, Y_2, \ldots\}$ are independent and identically distributed (iid), the random variables $\{Z_1, Z_2, \ldots\}$ are iid, and that the families $\{Y_i\}$ and $\{Z_i\}$ are mutually independent.

Properties of interest for the turbine state process $M(t)$ include the probability $P(t) = Pr\{M(t) = 1\} = E[M(t)]$ that the turbine is in the on state at any specified time t, and the second moment properties of $M(t)$. Exact expressions for $P(t)$ and var$[m(t)]$ can be obtained under certain conditions on Y_1 and Z_1, and an approximation to the covariance function of $M(t)$ can be obtained.

If $E[Y_1 + Z_1] < \infty$ and the distribution of $Y_1 + Z_1$ is not a lattice distribution, then ([20], Theorem 3.4.4)

$$p = \lim_{t \to \infty} P(t) = E[M(t)] = \frac{E[Y_1]}{E[Y_1 + Z_1]} \tag{4}$$

meaning that the availability is simply the ratio of the mean residence time in the on state to the sum of the mean residence times in the on and off states. The variance of $M(t)$ is readily calculated as

$$\sigma_M^2 = \lim_{t \to \infty} \mathrm{var}[M(t)] = p(1 - p) \tag{5}$$

The second moment properties of $M(t)$ are further characterized by the covariance function $c_M(\tau) = E[M(t)M(t+\tau)] - E[M(t)]\,E[M(t+\tau)]$. Depending on the distributions of Y_1 and Z_1 it may be difficult or impossible to calculate $c_M(\tau)$ exactly, but an approximation can be developed as follows. Introduce the notation $\tilde{M}(t) = M(t) - p$ so that the covariance is $c_M(\tau) = E[\tilde{M}(t)\tilde{M}$

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$(t+\tau)]$ and denote $\tilde{M}_1 = 1-p$ and $\tilde{M}_0 = -p$. For $\tau > 0$, and invoking the law of total probability,

$$E[\tilde{M}(t)\tilde{M}(t+\tau)] = E[\tilde{M}(t)\tilde{M}(t+\tau)|\tilde{M}(t) = \tilde{M}_1]\,P(\tilde{M}(t) = \tilde{M}_1) + E[\tilde{M}(t)\tilde{M}(t+\tau)|\tilde{M}(t) = \tilde{M}_0]\,P(\tilde{M}(t) = \tilde{M}_0) \quad (6)$$

Replacing $P(\tilde{M}(t) = \tilde{M}_1)$ and $P(\tilde{M}(t) = \tilde{M}_0)$ by their asymptotic values p and $1-p$ respectively, and under the assumptions $Y_1 \sim \exp(\lambda_{\rm on})$, $\lambda_{\rm on} > 0$ and $Z_1 \sim \exp(\lambda_{\rm off})$, $\lambda_{\rm off} > 0$,

$$\begin{aligned} E[\tilde{M}(t)\tilde{M}(t+\tau)] &= \tilde{M}_1^2 \exp(-\lambda_{\rm on}\tau)p \\ &\quad + \cdots + \tilde{M}_0^2 \exp(-\lambda_{\rm off}\tau)(1-p) + \cdots \\ &\approx \tilde{M}_0^2 \exp(-\lambda_{\rm off}\tau)(1-p) \end{aligned} \quad (7)$$

Noting that $\tilde{M}_1 \propto E[Z_1], \tilde{M}_0 \propto E[Y_1], p \propto E[Y_1]$ and $1-p \propto E[Z_1]$, the approximation is good when $E[Y_1] \gg E[Z_1]$ and implies that $c_M(\tau)$ is approximately exponential with parameter $\lambda_{\rm off}$. Note that this approximation assumes stationarity of the turbine state $M(t)$, and therefore neglects the seasonality in wind turbine availability induced by seasonal fluctuations in wind speed characteristics. Der Kiureghian, Ditlevsen and Song [17] have developed exact expressions for on-off processes that are quite suitable for modeling the state of mechanical systems with alternation operating and repair times, and their approach should be used when neither condition $E[Y_1] \gg E[Z_1]$ or $E[Z_1] \gg E[Y_1]$ is valid since the approximation of Eq. (7), or an alternate one when $E[Z_1] \gg E[Y_1]$, will be poor.

3.2 Wind Farm State. Consider the definition of wind farm availability

$$F(t) = \frac{1}{n_m}\sum_{j=1}^{n_m} M_j(t), \quad t \geq 0 \quad (8)$$

which is a continuous time version of Eq. (2) defining the fraction of turbines in a wind farm consisting of n_m turbines that are on at time $t \geq 0$. In Sec. 3.1, M(t) is defined as the state of a wind turbine at time t. Here, the subscript j is added to denote by M_j(t) the state of turbine j at time t.

At any arbitrary but fixed time $t, S_{n_m}(t) = \sum_{j=1}^{n_m} M_j(t)$ is a Binomial random variable with (asymptotic) probability of success $P(t)$ so that $E[S_{nm}(t)] = n_m P(t)$ and $\mathrm{Var}[S_{nm}(t)] = n_m P(t)(1-P(t))$ implying ([21], p. 253)

$$P\left(\frac{S_{n_m}(t) - n_m P(t)}{\sqrt{n_m P(t)\,(1-P(t))}} \leq x\right) \to \Phi(x), \quad n \to \infty \quad (8)$$

and $F(t) \sim N(P(t),\ P(t)(1-P(t))/n_m)$ for relatively large values of n_m. Asymptotically as $t \to \infty$ these properties become $F(t) \sim N(p, p(1-p)/n_m)$.

The second moment properties of $F(t)$ are defined by

$$\begin{aligned} r_F(\tau) = E[F(t)F(t+\tau)] &= \frac{1}{n_m^2}[n_m r_M(\tau) + (n_m^2 - n_m)E[M(t)^2]] \\ &= (1/n_m)r_M(\tau) + (1-1/n_m)P(t)^2 \end{aligned} \quad (9)$$

so that the covariance function of $F(t)$ as $t \to \infty$ is

$$\begin{aligned} c_F(\tau) &= E[(F(t) - E[F(t)])\,(F(t+\tau) - E[F(t+\tau)])] \\ &= (r_M(\tau) - p^2)/n_m \\ &= E[(M(t) - E[M(t)])\,(M(t+\tau) - E[M(t+\tau)])]/n_m \end{aligned} \quad (10)$$

This shows that the covariance functions of $M(t)$ and $F(t)$ have the same functional form. For example, the covariance function of $F(t)$ is exponential if that of $M(t)$ is exponential.

If the correlation function of $M(t)$ can be approximated as exponential and n_m is sufficiently large, then $F(t)$ can be modeled by

$$\begin{aligned} F(t) &= p + \sqrt{p\,(1-p)/n_m}\,V(t) \\ dV(t) &= -\rho\,V(t)\,dt + \sqrt{2\,\rho}\,dB(t), \quad \text{with} \\ V(0) &\overset{\rm d}{=} N(0,1) \end{aligned} \quad (11)$$

that is, $V(t)$ is a stationary Ornstein–Uhlenbeck process with mean 0 and covariance function $E[V(s)V(t)] = \exp(-\rho|s-t|)$. The parameter $\rho \approx \lambda_{\rm off}$ is directly obtained from the performance of a single turbine provided the approximation of Eq. (3) is good. The model of $F(t)$ can be used to find whatever statistics are needed for this process. Monte Carlo simulation or the associated Fokker–Planck equation can be used for this purpose.

3.3 Model Validation. In this section the approximate model is validated against results of direct MC simulation of wind turbine and farm performance. The features that are validated are: (1) the assumption of exponential distribution of Y_1; (2) the form of the correlation function $r_M(\tau)$; (3) the distribution of $F(t)$; (4) the form of the correlation function $r_F(\tau)$; and (5) the mean down-crossing rate of a threshold farm availability based on the Ornstein–Uhlenbeck approximation.

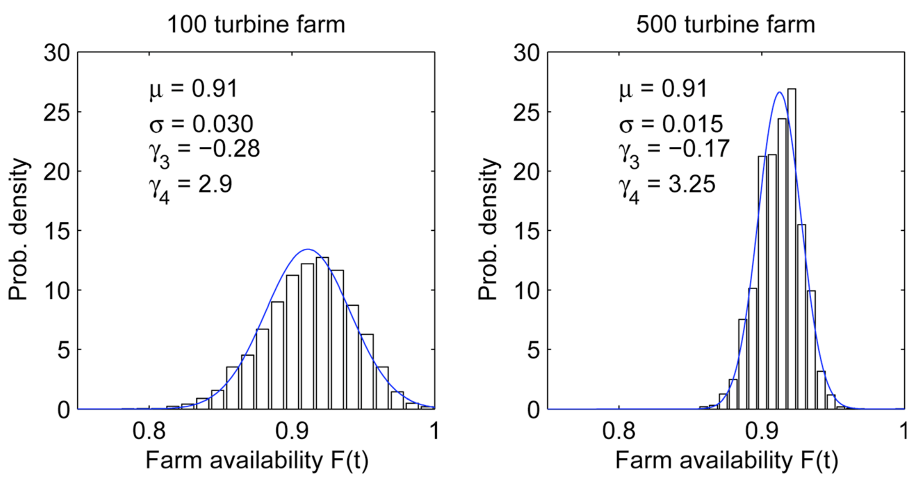

Fig. 8 Histograms and best fit Gaussian pdfs for the wind farm state $F(t)$ for 100 and 500 turbine wind farms

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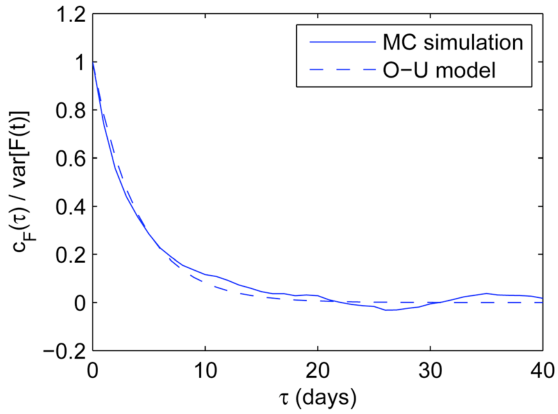

Fig. 9 Covariance function of *F*(*t*) for a farm with 500 turbines based on MC simulation and the Ornstein–Uhlenbeck model. The MC simulation results show a very nearly exponential covariance. The covariance is scaled by the process variance to be unit at $\tau = 0$.

Figure 4 shows the histogram and best fit exponential probability density function (pdf) for the failure interarrival times $Y_1 + Z + 1$, and the exponential appears to be a reasonable fit to the data. Histograms of Y_1 and Z_1 are not shown here in the interest of brevity, but both random variables have distributions that are reasonably well approximated as exponential with parameters $\lambda_{\rm on} = 1/E[Y_1] = 0.024$ and $\lambda_{\rm off} = 1/E[Z_1] = 0.24$. The approximation to $c_M(\tau)$ introduced in Eq. 7 underpredicts the actual covariance by about 10%, and is deemed suitable for use in these calculations.

Figure 8 shows histograms and best fit Gaussian pdfs for $F(t)$ with $n_m = 100$ and $n_m = 500$ based on direct MC simulation using the 19 yr wind record introduced previously. In both cases the agreement with the Gaussian pdf is reasonably good, though it appears that the fit is better when $n_m = 500$ as expected since the distribution of $F(t)$ is asymptotically Gaussian only as $n_m \rightarrow \infty$. Skewness and kurtosis values agree reasonably well with the expected Gaussian values of 0 and 3, respectively, although there is a persistent negative skewness that results from the proximity of $E[F(t)]$ to the upper bound $F(t) \leq 1$. The standard deviations also agree well with the predictions of the properties of $F(t)$ given immediately following Eq. (8), which predict $\sigma = 0.028$ and $\sigma = 0.013$ for $n_m = 100$ and $n_m = 500$, respectively.

The covariance function $c_F(\tau)$ of $F(t)$ is shown in Fig. 9 and has the exponential form predicted by the approximate model.

One major convenience of the Ornstein–Uhlenbeck (O–U) model for wind farm state is that samples can be simulated very efficiently using Eqs. 11, and statistics of the wind farm state can be estimated without the more intensive process of simulating the performance of individual turbines. For example, a statistic of interest is the frequency ν_{F0} of the event $\{F(t) = F_0 \cap dF(t)/dt < 0\}$, the mean downcrossing rate of $F(t)$ at threshold F_0. Simulation of the O–U model for 100,000 days with $F_0 = 0.88$ predicts this rate to be $\nu_{F_0} = 0.0090$ day^{-1}, whereas direct simulation of the wind farm state gives $\nu_{F_0} = 0.0080$ day^{-1}. The O–U models overestimates ν_{F_0}, which is a conservative result in the context of wind farm planning and operation. Overall, the approximate models agree well with all features of the MC simulation results, and it would be justified to use the model in performance evaluation of large wind farms with $n_m \geq 100$. Extension of the approximate model to capacity factor is straightforward in principle, requiring the introduction of a model for the wind speed and a subsequent mapping through the turbine power curve. As shown in the earlier MC simulation results, the capacity factor is highly non-Gaussian, and therefore could not be directly modeled by an Ornstein–Uhlenbeck type process. Translations of Gaussian processes may provide a suitable model for capacity factor, and can also provide direct evaluation of performance metrics such as downcrossing rates [22].

4 Conclusions

A Markov model for wind turbine and farm performance has been developed that: (1) is based on turbine component reliabilities that are calibrated to observations of field performance of turbines; (2) accounts for sensitivity of turbine reliability to wind speed; (3) accounts for variable repair times for different turbine components; (4) uses a power curve representative of turbines currently being considered for offshore deployment. By direct MC simulation of the Markov model, one can obtain samples of turbine and farm performance characteristics such as turbine and farm availability and capacity factor. Statistics such as the distribution, seasonal variation, and correlation functions of the performance metrics can be readily estimated from the simulated samples and used in design or management of offshore wind farms.

For a numerical example of 100 offshore wind turbines hypothetically located off the coast of Maine in the northeastern United States, the average availability is estimated to be 0.91, which is agreement with reported wind farm performance. The capacity factor is highly non-Gaussian, with a mean of 0.39, but the availability is found to be nearly Gaussian. Seasonal effects appear in the capacity factor but not in the availability. For an individual turbine the residence time in the on state is found to be nearly exponential, with a mean of 42 days.

These results demonstrate the practical applicability of a Markov model for wind turbine and farm performance. The details of the model have largely been tailored to the available calibration data. Throughout the paper instances where the model could be enriched to consider complications such as site specific conditions and component dependencies and redundancies have been identified, and the minimal changes to the theoretical framework that would be required are described. Incorporating these features of wind turbine and farm performance will be important to improving the practical implications of the model, and such improvement essentially awaits the collection of suitable calibration data.

The properties of the samples of the capacity factor, and the nearly exponential distribution of time periods of turbine operation suggest approximate analytical models for turbine and farm availability. The turbine model is based on binary stochastic process with exponential waiting times that represents the on or off state of the turbine, and, when the farm consists of a sufficiently large number of turbines an Ornstein–Uhlenbeck model for availability is proposed. Comparison of the approximate models against MC simulation of the Markov model indicate that the model gives accuracy of 10% or better when the number of turbines is greater than approximately 100. The advantage of the approximate model for wind farm availability is that its properties can be calculated directly without the need to simulate the performance of a wind farm with many turbines over many years, thereby delivering a dramatic increase in efficiency.

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