Short and Long-Term Reliability Assessment of Wind Farms

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***Abstract*—wind energy has been considered to be one of the main participants in supplying global energy needs. Meanwhile reliability and availability are critical issues to be studied with high wind penetration. While previous studies have focused on steady state behavior of wind turbines, this paper presents a Markovian method to study time-based reliability of wind farms. This method considers wind speed, failure and repair rates of wind turbines as well as load demands for short-term and long-term reliability calculation and comparison. Effect of change in initial number of working wind turbines and repair crew will also be investigated.**

***Index Terms*—wind farm, reliability, availability, short-term, long-term.**

I. Introduction

Wind energy as a renewable energy is continuing to be one of the fastest growing energy sources in the world [1]. Several countries have developed time-based renewable energy targets such as United States whose energy portfolio indicates 20% wind energy penetration in electricity production by 2030[2]. Many states in the U.S. have also adopted additional wind energy production [3]. On the other hand, as the number of wind farms is rising new challenges are introduced to the power grid [4].

One of the main issues of large wind turbines contribution to the system is the reliability and availability of the output energy of the wind farms [5]. In general, Reliability is defined as the probability that a component or system will perform a required function, for a given period of time, when used under stated operating conditions [6]. In power industry, there are various indices used to measure the reliability of systems. As an important index of reliability, Availability is the probability that a system or component is performing its required function at a given point in time, or over a stated period of time when operated and maintained in a prescribed manner [6].

In evaluating the reliability of wind farms, the first concern is about wind turbines themselves which consist of many moving and rotating subassemblies installed at a high elevation. These equipments include blades, rotor, gears and generator which bear more tension and wear during operation compared with conventional generation. In addition, wind turbines are exposed to the weather changes. So, variability of wind speed and direction not only increases the chance of failure due to additional imposing stress on wind turbines' parts but also affects the availability of their output power generation. These effects necessitate probabilistic modeling of wind turbines' operation to include both the turbines and wind speed states.

By increasing wind energy share of total electricity production in power system, like any other generation system, wind farm's output power should meet load demand changes with time. Long/short term changes in load introduce another stochastic variable which should be considered in order to study the reliability of a stand-alone wind farm. There are many methods developed by researchers to predict and model the load behavior with respect to time [7-9] which are not investigated in this paper.

Many studies have been conducted for reliability and availability assessment of wind turbines and some of them use Markovian processes [10]. These studies have mainly discussed steady state estimation of system availability and reliability indices but there has been no attempt to describe wind farm's reliability in different time domains.

In this paper, a Markovian model has been introduced to study wind farm availability and reliability due to wind variability and load changes for short-term and long-term periods. Reliability indices calculated in each case are Loss of Load Expectation (LOLE) and Loss of Energy Expectation (LOEE) which evaluate the expected generation capacity to satisfy the system load demand, and Expected Surplus Wind Energy (ESWE) which presents the average available wind energy that cannot be used by the load, and can therefore be stored or exported to the grid [11]. Other than its application in site selection and long term production estimation, calculation of time-based reliability of a wind farm is beneficial especially in deregulated energy market where the owner of a wind farm needs to evaluate cost-benefit of alternative decisions at different times while providing an acceptable level of reliability. The model has been applied to a study case and effects of different conditions such as number of repair crew, load changes and initial number of working wind turbines have been investigated.

II. Modeling

This section describes the models used for wind farm operation, wind speed and load. Although studies show a correlation between wind turbine failures and weather condition (humidity, temperature, and wind speed) at the installation site, it is difficult to find its effect explicitly specially in a short term because failures may often occur sometime after their causing event [12]. Here, wind turbine failures and wind speed changes are assumed to be independent for simplicity so that we can model them separately. However the effect of weather can still be taken into account by defining non-stationary failure rates for different periods, say each season.

A. Model of wind farm

In general in order to evaluate the reliability of wind farms, a two state Markov model ("working" or "failure") is used to present equipment such as wind turbine. In this case, the number of states for a wind farm will be 2^N for N wind turbines. Since there are tens of wind turbines installed in today's wind farms, this model increases the number of states dramatically.

However in most cases, the wind turbines of a wind farm are identical. In this paper the wind farm is modeled with (N+1) number of states by defining the states as number of working wind turbines at a time. Kendall-Lee notation can represent this birth and death process by M/M/S/GD/N/N where "M"s stand for Markovian assumptions for failure and repair times; "S" denotes the number of parallel repair crew (servers); failed turbines waiting times are based on general queue discipline "GD"; the first "N" shows the system capacity assuming that repair process has enough capacity for all wind turbines if they fail and the second "N" is the number of similar wind turbines installed in the wind farm. Figure 1 shows the diagram of this modelling where λ and μ are failure and repair rates respectively. To explain the repair transition rates, assume that there was r number of failed wind turbines being repaired simultaneously. In that case the repair rate would be r×μ according to markovian property. Because in our model number of repair crew is limited to S, at each time the coefficient of μ will be the minimum of S and number of failed wind turbines.

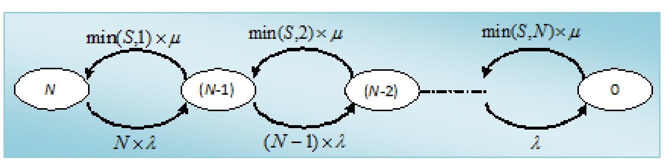

Fig.1. Rate diagram for wind turbine states

This model assumes wind turbines of the same make and model are identical. In a case that a wind farm consists of turbines from more than one manufacturer, each group of similar turbines must be modelled separately.

B. Model of wind speed

Wind speed variability can also be represented by various wind states at different times. To do so, wind speed changes is binned based on the corresponding output power changes of the installed wind turbine. For example, the power curve of a wind turbine is shown in Figure 2, where the cut-in and cut-out wind speeds are 4m/s and 25m/s; beyond those, the output power of the wind turbine will be zero. There is also a rated wind speed (12m/s in Fig.2) for which the turbine produces its rated output power and this rated power remains approximately constant within this rated and cut-out wind speed due to turbine's power control system. Wind changes between cut-in and rated wind speeds result different output power so they can be binned with 1m/s intervals.

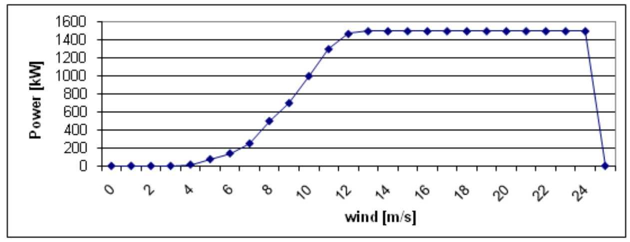

Fig.2.Power curve of a 1500kW wind turbine

This way, probabilistic changes of wind speed may be translated into relevant output power of the specific turbine installed at that location and represented by output power states. Each output power state, q_i, corresponds to a fraction of turbine's rated output power in which the output power of wind turbine is q_i times its rated power due to the wind speed. K is the total number of states assuming:

$$q_1 = 0\ ,\ q_K = 1\ and\ 0 < q_i < 1 \qquad (1)$$

Here, rather than looking for transition rates between the states, frequency of occurrence of different wind speeds (or equivalently histogram of corresponding power production) in a specific period is of interest which is more convenient and accurate to be analyzed, because it follows the format in which the data are provided by measurement or forecasted by weather stations.

C. Model of the Load

In order to determine the reliability of wind farms in supplying the load, its time-based behavior must be considered. Here for short-term studies, hourly load changes are used based on previously introduced load forecasting methods [7-8] and for long-term studies probability distribution of peak load will be considered to model the load [13].

III. Method of Study

A simple power system structure is used for this study and is depicted in Fig.3.

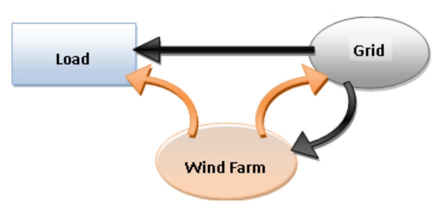

Fig.3. Power system model

The system consists of a regional load supplied by the conventional grid and an installed wind farm in that area. Arrows show the possible directions of power flow. Depending on the amount of power production and load demand, wind farm may send its excess production to the grid or even receive some power from the grid when there is no wind to supply its local loads. In this structure, the equivalent regional load can change with time and the grid has no limits on the amount of energy to provide or sink and so is seen as a slack bus.

The reliability is calculated from the wind farm's point of view to see how it can contribute to supply the changing demand in a certain period of time. This time duration may vary from hourly to yearly basis and so failure and repair rates can change accordingly.Fig.4 shows the steps toward reliability and availability calculation.

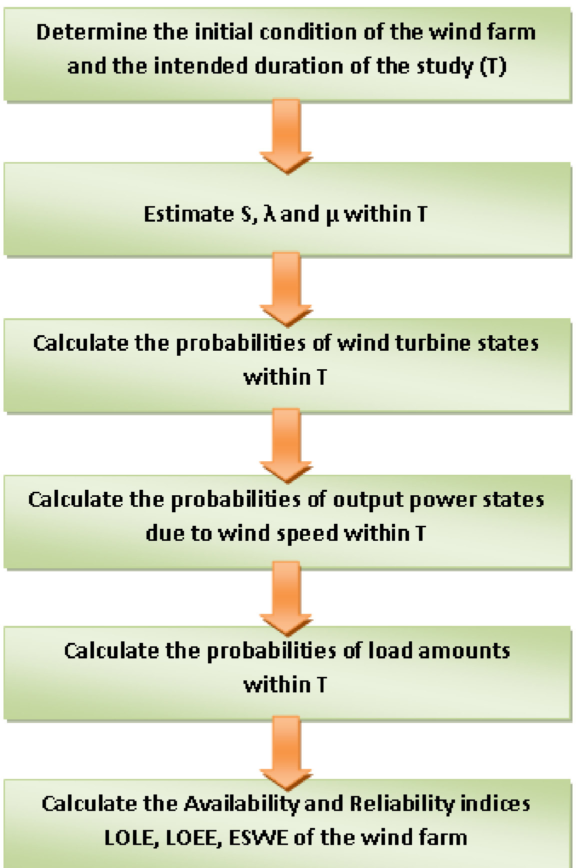

Fig.4. Procedure of wind farm reliability calculation

According to the formulation of continuous-time Markov processes [14], state probabilities of wind farm model in Fig.1 can be expressed by a row vector, $\boldsymbol{P}$, which should satisfy the following differential equation:

$$\frac{d\boldsymbol{P}}{dt} = \boldsymbol{P} \times \boldsymbol{A} \tag{2}$$

Where, $\boldsymbol{A}$ is the matrix of transition intensities. The solution to (2) as a function of time is given by:

$$\boldsymbol{P}(t) = \boldsymbol{P}(0) \times \exp(\boldsymbol{A}t) \tag{3}$$

Having the initial condition of working wind turbines, $\boldsymbol{P}(0)$, equation (2) can be solved by mathematical methods in software like MATLAB which gives the probabilities for working of any number of wind turbines at any time.

If intended study time, T, becomes long enough, the results will converge to steady state probabilities. Analytically, by definition, traffic intensity is the ratio of failure rate to the repair rate:

$$\rho = \frac{\lambda}{\mu} \tag{4}$$

Steady state probability of having j out of N number of turbines working together, π_j, can be written as [15]:

$$\pi_j = \begin{cases} \binom{N}{N-j} \rho^{(N-j)} \pi_N \text{ and } j = N-S, N-(S-1), \dots, N-1, N \\ \frac{\binom{N}{N-j} \rho^{(N-j)} j! \pi_N}{S! S^{(N-j-S)}} \text{ and } j = 0,1,\dots,N-(S+1) \end{cases} \tag{5}$$

Where π_N can be derived using the fact that:

$$\sum_{j=0}^{N} \pi_j = 1 \tag{6}$$

As mentioned before, probability of output power of each wind turbine is dependent on the wind speed. Based on the study, one can use weather forecasts for short term study or statistical wind speed distribution of the past years for long term seasonal or yearly studies. Similarly, load behavior may come from load forecasts or statistical load curves for duration of T.

IV. CASE STUDY

The procedure given in Figure 4 was applied to a wind farm in western Nebraska located at Kimball and is owned by Municipal Energy Agency of Nebraska (MEAN). This 10.5 megawatt wind farm consists of 7 turbines whose power curve provided by the manufacturer for each turbine was shown in Fig.2.

A. Short- term study

Suppose that availability and reliability of this wind farm for duration of one week is of interest. The data used for this site are the average failure and repair rates of turbines [5] as:

$$\lambda = 1.94 \times 10^{-4} \textit{per hour per turbine}$$
$$\mu = 2.94 \times 10^{-3} \textit{per hour per turbine} \tag{7}$$

As it can be perceived intuitively, initial number of working turbines at the beginning of the week can have a considerable effect on the study. So, from (2), (3) and (7), wind turbine states probabilities were calculated for each hour of the week while changing the initial conditions. Given these probabilities, equation (8) is used to calculate the total availability of the wind farm.

$$A(t) = \frac{\sum_{j=0}^{j=N} (\mathrm{P(j,t)} \times j)}{N} \tag{8}$$

where, $A(t)$ is the availability of wind farm at time t, $\mathrm{P(j,t)}$ is the probability of j turbines working at time t and total number of turbines, N, is seven in our study. For the calculation of $A(t)$, it is assumed that all wind turbines in the farm should be working.

As an example, Fig.5 depicts the Availability of the wind farm for a week assuming that all 7 turbines are available at the beginning. It can be seen that at the end of the week the availability become 0.975 and the average availability is 0.986.

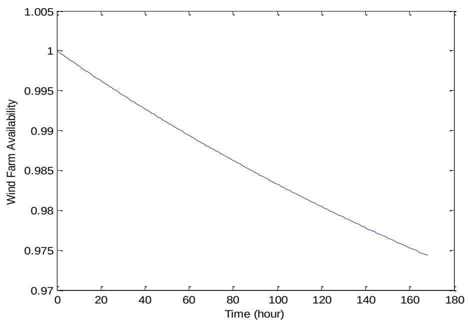

Fig.5. Wind farm availability during a week with all turbines working initially

Table I provides results obtained from calculation of the wind farm availability, based on initial number of working wind turbines at different times.

TABLE I
COMPARISON OF WIND FARM AVAILABILITY WITH RESPECT TO INITIAL CONDITIONS AND TIME

Time / Initial Number of working turbines	Beginning of the week	Middle of the week	End of the week
0	0	0.0333	0.0662
1	0.1429	0.1740	0.2047
2	0.2857	0.3147	0.3431
3	0.4286	0.4553	0.4816
4	0.5714	0.5960	0.6199
5	0.7143	0.7364	0.7569
6	0.8571	0.8739	0.8852
7	1	0.9862	0.9753

Wind speed data of Kimball within the first week of April 2009 were used to incorporate output power variations to this model (Fig.6).

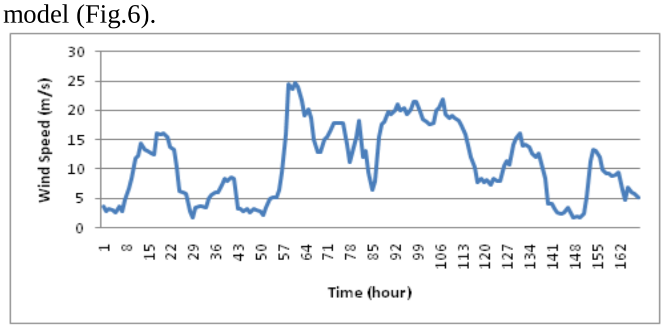

Fig. 6.Kimball wind farm's wind speed for one week in 2009

By observing this wind speed data and the turbine's power curve (Fig.2) output power of wind turbine at each hour can be calculated.

At each time instant, total output power of the wind farm results from the output power due to wind speed at that time multiplied by the availability of the wind farm. Next two figures compare total output power of the wind farm with typical hourly load demand for a week. Here again the effect of initial conditions on short term reliability of wind farm can be observed where Fig.7 and 8 illustrate the difference between having 7 and 3 initial available turbines respectively.

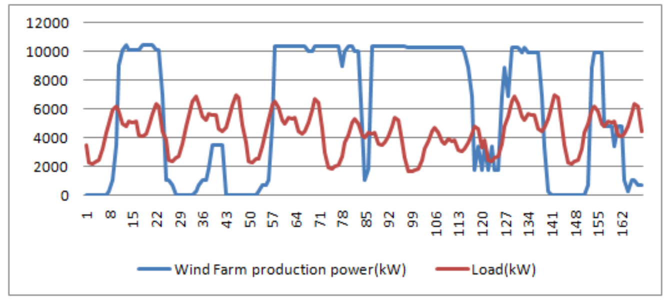

Fig.7. comparison of wind farm power production with load demand when all 7 wind turbines are working initially

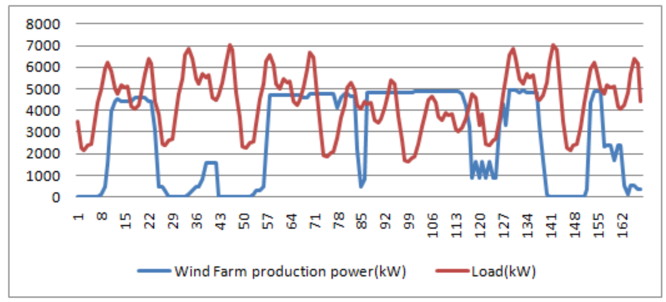

Fig.8. comparison of wind farm power production with load demand when 3 wind turbines are working initially

It is observed that for some hours during the week, production of the wind farm exceeds the load demand and so the excessive power can be transferred to the grid; other times, grid needs to compensate for the lack of wind farm power production. Occurrence of Loss Of Load at each hour t_k can be defined as:

$$LOL(t_n) = \begin{cases} 1\,, if\ (A(t_n) \times Power_{WT}(t_n) \times N) < Power_{load}(t_n) \\ 0\,, Otherwise \end{cases} \quad (9)$$

Where, $Power_{WT}(t_n)$ and $Power_{load}(t_n)$ are power production of a wind turbine and power demanded by the load at hour t_n, respectively. n is an integer denoting the number of hours passed. Consequently, LOLE from the wind farm's point of view for a period of T hours can be derived using equation (10).

$$LOLE(T) = \sum_{n=1}^{T} LOL(t_n) \quad (10)$$

As a result, table II gives wind farm's LOLE, LOEE and ESWE for a week starting at different number of working wind turbines.

TABLE II
LOLP, LOEE AND ESWE FROM WIND FARM'S POINT OF VIEW WITHIN A WEEK

Initial Number of working turbines	LOLE (hours/week)	ESWE (MWh/week)	LOEE (MWh/week)
0	168	0	705.8
1	164	0.7	567.3
2	152	14.9	442.3
3	124	57.2	345.4
4	93	145.4	294.4
5	80	265.7	276
6	76	388.3	263.4
7	75	489.5	254.7

Obviously, this wind farm without any connection to an external grid or energy storage system cannot be operated stand alone to supply the load.

B. Long-term study

In this section, it is assumed that the duration of study is long enough so that the effect of wind farm's initial condition is negligible and steady state probabilities are used accordingly.

Taking the same approach as the short-term study, wind turbine states probabilities were calculated first. This time, equations (5) and (6) were used to derive the steady state probabilities as follows:

$$\pi_7 = 0.5798, \pi_6 = 0.2678, \pi_5 = 0.106, \pi_4 = 0.035,$$
$$\pi_3 = 0.0092,\ \pi_2 = 0.0019, \pi_1 = 0.0003, \pi_0 = 0, \qquad (11)$$

Alternatively, equation (3) could be used to calculate wind farm steady state probabilities by setting the time to a large value. Fig.9 shows an example in which steady state probability of working 7 wind turbines is depicted in a long run where starting from different initial conditions leads to the same answer (π_7).

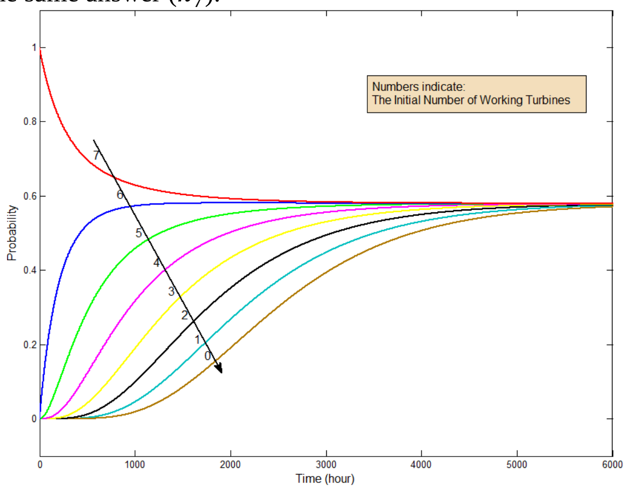

Fig.9. Long-run calculation of 7 working wind turbines' state probability starting at different initial conditions

Similar to (8), equation (12) calculates the estimated availability of the wind farm.

$$A = \frac{\sum_{j=0}^{j=N} (\pi_j \times j)}{N} \qquad (12)$$

Plugging the probabilities from (11) into (12), the long-term availability of our wind farm was calculated to be 0.9096.

To consider long-term wind speed variations, statistical data of wind speed for the last year were gathered whose probability distribution is shown in Fig.10.

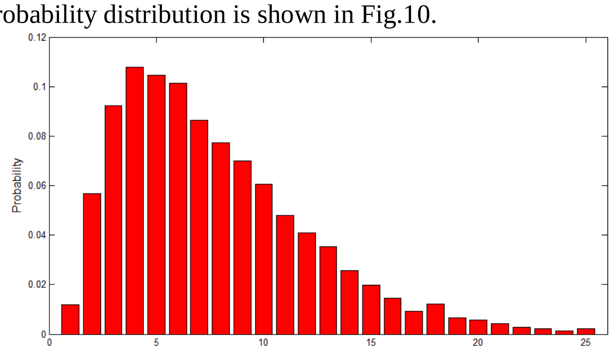

Fig.10. Probability distribution of wind speed within a year

Analysis shows that this distribution can be best fitted to Erlang distribution with exponential mean of 2.56 and shape parameter of 3. Wind speed changes can be translated to wind turbine output power changes by the described method in section II. So, using probability distribution of Fig.10, probabilities of output power states can be calculated. In our case, figure 11 shows the probability distribution of output power states (P_{q_i}).

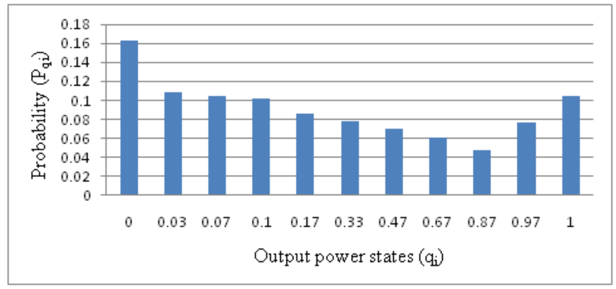

Fig.11. Probability distribution of the wind turbine output power states

Considering wind farm availability and turbines output power due to wind speed distribution, power production of the wind farm for each state (q_i) is:

$$Power_{WF,q_i} = q_i \times Power_{rated} \times A \times N \qquad (13)$$

Where, $Power_{rated}$ is the rated power of one turbine, which is 1500kW for our wind farm, and the other parameters have been previously defined. Eestimated energy production of wind farm for duration of T can be derived from (14).

$$E_{WF} = \sum_{i=1}^{K} (P_{q_i} \times Power_{WF,q_i}) \times T \qquad (14)$$

Depending on availability of wind speed data, equation (14) can be used to estimate long-term energy production of the wind farm. Since in our case wind speed data of one year were available, wind farm energy production within that year was calculated to be 29.26GWh. This turned out to be a good estimation because comparing with last year's actual energy production of the wind farm [16], there was just a 3%.error.

Additional repair crew could improve the availability due to increase in the number of parallel repair crew (S) and/or decrease in average repair time ($1/\mu$). So the revenue from wind farm power production increases, but at the same time additional costs are imposed. Therefore, studies should be conducted to determine the optimal repair crew.

Figure 12 shows that in our case, doubling the repair crew if they work in parallel, would increase the wind farm's availability by 0.025; but thereafter, it was not increased considerably. This improvement in availability is equivalent to production of 815MWh more energy during previous year whose revenues and costs are mainly dependent on energy price and technicians wages respectively.

Finally, long-term load demand was added to the system and as mentioned in section II, it can be expressed in terms of its probability distribution.

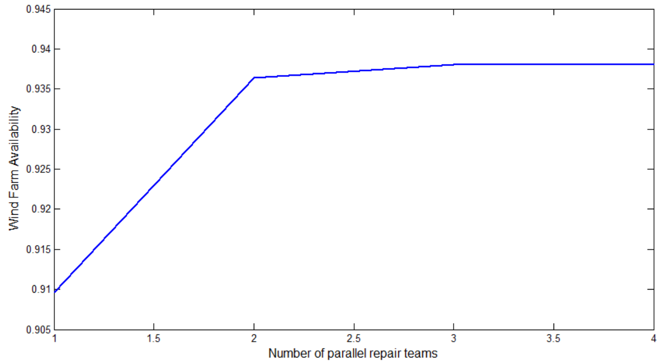

Fig.12. Wind farm availability with respect to number of parallel repair crew

Equation (15) calculates the LOLE of the wind farm for long time operation of T by total probability theorem.

$$LOLE = \sum_{i=1}^{K} P(\, Power_{load} > Power_{WF,q_i}) \times P_{q_i} \times T \quad (15)$$

Using probability distributions for wind farm power production of Fig.11 and the annual load demand, reliability indices of our wind farm were calculated and is given in table III.

TABLE III
LOLP, LOEE AND ESWE FROM WIND FARM'S POINT OF VIEW FOR A YEAR

study Period	LOLE (hours/year)	ESWE (GWh/year)	LOEE (GWh/year)
one year	5860	9.9	20.5

From long-term planning point of view, it means the grid needs to supply an estimated annual energy of 20.5GWh to compensate the lack of wind and turbines availability. On the other hand, the wind farm can export an estimated annual energy of 9.9GWh to the grid when its power production exceeds load demand.

V. Conclusion

This paper presented a method for time-based calculation of reliability and availability of a wind farm which can be used for short/long term planning and operation.

First, a Markovian model for the whole wind farm was introduced which considers the number of working wind turbines based on failure and repair rates, repair crew and wind speed changes. This model was applied to a power system whose load was also modeled according to the duration of the study.

The effect of initial number of working turbines in short-term and repair crew in long-term were investigated for a case study. The introduced method can adopt the maintenance model and be used to optimize the number of repair crew and maintenance strategy in future.

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VII. Biographies

Salman Kahrobaee is a PhD student at University of Nebraska Lincoln. His previous experiences are in power system simulations, specially power quality and reliability studies. He is currently working on reliability and maintenance modeling of wind turbines.

Sohrab Asgarpoor (S'80, M'86, SM' 91) received his B.S. (1978), M.S. (1981), and Ph.D. (1986) all in Electrical Engineering from Texas A&M University. From 1986 to 1989, he was with ABB Network Management Inc. (formerly Ferranti International Controls Corp.) as a Lead Engineer where he designed and developed advanced power system applications software for energy management systems. Since September 1989 he has been with the University of Nebraska-Lincoln, where he is an Associate Professor in the Department of Electrical Engineering. His areas of interest include reliability evaluation, maintenance optimization, and advanced computer applications in security and optimization of electric power systems.