Reliability Assessment of Wind Farm Active Power Based on Sequential Monte-Carlo Method

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***Abstract*- The conventional deterministic methods have been unable to accurately assess the active power of wind farm being the random and intermittent of wind power, and the probabilistic methods have been commonly used to solve this problem. In this paper the multi-state fault model is built considering running, outage and derating state of wind turbine, and then the reliability model of wind farm is established considering the randomness of the wind speed, the wind farm wake effects and turbine failure. The probability assessment methods and processes of wind farm active power based on the Sequential Monte Carlo (SMC) method are given. The related programs are written in MATLAB, and the probability assessment for wind farm active power is carried out, the effectiveness and adaptability of the proposed reliability models and assessment methods are illustrated by analysis of the effects of reliability parameters and model parameters on assessment results.**

Keywords- Wind Farms; Multi-state Fault Model; Probability Assessment; Sequential Monte Carlo Method

I. INTRODUCTION

Wind power is recognized as one of an ideal renewable energy power generation and large-scale development of wind power is beneficial for energy development and environmental protection. However, due to the randomness, intermittent and volatility of wind power, large-scale wind power integration will seriously affect the grid voltage stability, system stability, and dispatch scheduling [1]. So there is an urgent need to carry out in-depth research on the reliability of the wind farm active power. A large number of studies have shown that the reliability of wind farm active power is mainly affected by wind speed and wind turbines operating status.

In terms of wind speed model, the literature [2-4] show that the wind speed variation approximately obeys Weibull distribution, and each wind turbine is at a same wind speed which equals to the wind speed of the wind farm, but this approach ignores the mutual influence between the wind turbines, and the wind speed correlation between the adjacent sampling points is not taken into account. Literature [5-6] introduced ARMA (Auto-Regressive Moving the Average) model to solve the correlation of adjacent sampling point issues, but it did not consider the impact of wake effects in wind farm.

In terms of wind turbine operation status, the literature [6-8] establish the two-state fault model considering the outage and run state, but the derating state is not taken into account. This modeling method for the traditional reliability model of other power system components is feasible, but it will bring large errors for modeling wind farm because the duration time of derating state is relatively longer [9].

In response to these above problems, firstly, the wind speed in a wind farm is simulated utilizing ARMA model, and the Jensen model is employed to simulate the wake effects in a wind farm; secondly, the three-state fault model of a wind turbine is built considering running, failure and derating status; finally, the probability assessment methods and processes for wind farm active power based on the Monte Carlo method are given. The related programs are written in MATLAB and the probability assessment for active power of a wind farm is carried out. The effectiveness and adaptability of built reliability models and assessment methods are illustrated by analysis of the effects of reliability parameters and model parameters on assessment results.

II. RELIABILITY MODEL OF WIND FARM

The wind farm active power is mainly affected by wind speed and wind turbine operation status, which are uncertain.

A. Wind Speed Model

ARMA model is an important method to study the time sequence issues. For a particular wind farm, the wind speed time series can be represented by the ARMA model [10], shown as formula (1).

$$y_t = \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_{\mathrm{n}} y_{t-n} + \alpha_t + \theta_1 \alpha_{t-1} - \theta_2 \alpha_{t-2} - \cdots - \theta_{\mathrm{m}} \alpha_{t-m} \tag{1}$$

Where y_t is the time-series values of the time *t*; φ_i (i = 1,2,3 ... n) and θ_j (j = 1,2,3 ..., m) stand for autoregressive moving and average parameter, respectively; α_t is the white noise which obeys (0, σ^2) normal distribution. These parameters can be estimated through analysis of historical data.

Formula (1) represents the smooth wind speed sequence with a mean of 0, and then the wind speed of the time *t* can be expressed as:

$$v(t) = \mu + \sigma y_t \tag{2}$$

where, μ and σ are historical average wind speed and standard deviation, respectively.

Due to the impact of the wake effects in large wind farms, the wind speed located downwind will be lower than on the wind direction, in this paper the Jensen model is employed to simulate the wake effects of the flat terrain, shown in Figure 1.

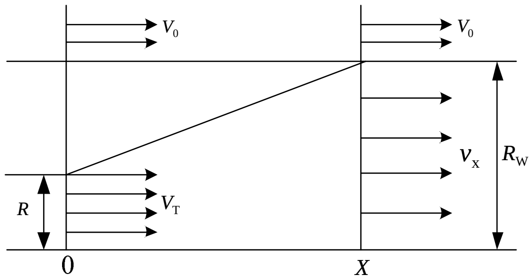

Fig. 1 Jensen wake effect model

where, R is the radius of turbine impeller, R_W is the radius of the wake, V_0 represents average wind speed, V_T is wind speed of the blade, v_x is wind speed affected by the wake, X is the distance between the two turbines.

According to Figure 1，the wind speed affected by wake effects can be calculated as [11]:

$$v_x(t) = V_0(t)\left(1 - \left(1 - (1 - C_T)^{1/2}\right)\left(\frac{R}{R + kX}\right)^2\right) \tag{3}$$

where, *k* and C_T stand for flow declined coefficient of wake and thrust coefficient of wind turbine, respectively.

B. Wind Energy Conversion Model

After a large number of studies [11], there is a specific relationship between the output power of the wind turbine and wind speed curve, called a wind turbine power curve.

A typical wind turbine power curve is shown as:

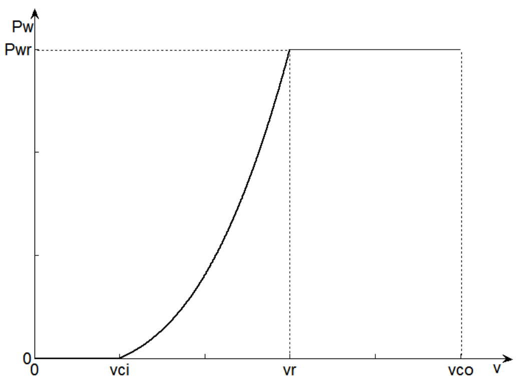

Fig. 2 Wind turbine power curve

Where, v_{ci} is cut-in wind speed, v_{co} is cut-out wind speed，v_r is rated wind speed，P_{WR} is the active power under the rated wind speed，v is the wind speed value of the wind farm.

According to the aerodynamics, the wind turbine electric power is proportional to the third power of wind speed. Its output power can be expressed as:

$$P_W\left(v_x\right)=\begin{cases}0 & \left(v_x<v_{\text{ci}}\right)\cup\left(v_x>v_{\text{co}}\right)\\ \dfrac{P_{\text{WR}}}{v_{\text{r}}^3-v_{\text{ci}}^3}\left(v_x^3-v_{\text{ci}}^3\right) & \left(v_{\text{ci}}\le v_x\le v_{\text{r}}\right)\\ P_{\text{WR}} & \left(v_{\text{r}}<v_x\le v_{\text{co}}\right)\end{cases} \tag{4}$$

where， $P_W\left(v_x\right)$ $P_W(V)$ is the active power under wind speed v_x .

C. Wind Turbine Fault Model

Wind turbine three-state fault model including operation, derating and outage status is shown as:

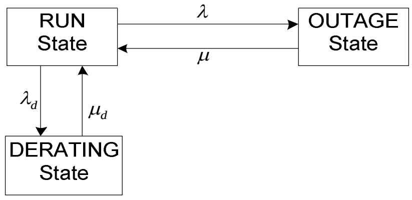

Fig. 3 Wind turbine multi-state fault model

where λ and λ_d are outage and derating rate, respectively; μ 和 μ_d are repair rate.

Generally, wind turbine outages and derating status are random event, the Markov method is used to solve this problem, according to the state space diagram shown in Figure 3, and the results are shown as:

$$P_{\text{fo}}=\frac{\mu_d\lambda}{\lambda_d\mu+\lambda\mu_d+\mu_d\mu} \tag{5}$$

$$P_{\text{do}}=\frac{\lambda_d\mu}{\lambda_d\mu+\lambda\mu_d+\mu_d\mu} \tag{6}$$

According to the law of large numbers, wind turbine operation status can be expressed as:

$$\text{S}=\begin{cases}0\ (\text{RUN}) & P_{\text{do}}+P_{\text{fo}}<U\le 1\\ 1\ (\text{OUTAGE}) & P_{\text{do}}<U\le P_{\text{do}}+P_{\text{fo}}\\ 2\ (\text{DERATING}) & 0\le U\le P_{\text{do}}\end{cases} \tag{7}$$

where S represents the operational status of the wind turbine， P_{fo} is the probability of occurrence of the outage state; P_{do} is the probability of occurrence of the derating state； U is uniformly distributed random number in [0，1].

D. Wind Farm Output Model

According to equation (5), (6), (7), the active power of the wind turbine is shown as:

$$P_{\text{G}i}=\begin{cases}P_W\left(v_x\right) & P_{\text{do}}+P_{\text{fo}}<U\le 1\\ 0 & P_{\text{do}}<U\le P_{\text{do}}+P_{\text{fo}}\\ \alpha\cdot P_W\left(v_x\right) & 0\le U\le P_{\text{do}}\end{cases} \tag{8}$$

where $P_{\text{G}i}$ is the active power of ***i***-th wind turbine， $P_W\left(v_x\right)$ is absorbed energy of the wind turbine under wind speed v_x , α is derating factor.

The active power of the wind farm can be expressed as:

$$P_{\text{F}}=\sum_{i=1}^{m}P_{\text{G}i} \tag{9}$$

Where, *m* represents the number of the WTG.

III. PROBABILISTIC ASSESSMENT OF WIND FARM ACTIVE POWER

A. Sequential Monte Carlo Method [12]

Sequential Monte Carlo method is simulation tool which is used to solve time-series problems, in which establishing cycle process of system state transition is very important. Generally, the state duration-time sampling method is used to solve the problem whose basic principle is that the system state transition cycle process can be obtained by combining all the elements' state transition process cycle which could be obtained by probability sampling. And then, some relevant indexes can be obtained through the analysis and calculation of different system status.

B. State Transition Process of Wind Farm Active Power

According to Markov theory, wind turbine's state transfer process is composed of run, outage and derating, as shown in Figure 4.

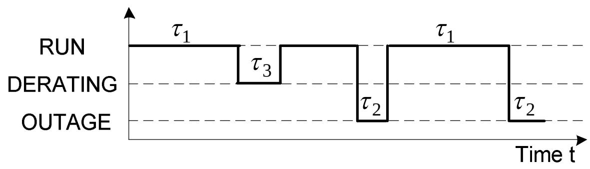

Fig. 4 Transfer process of wind turbine operation status

where, τ_1 、 τ_2 and τ_3 are the duration time of run, outage and derating status, respectively.

Usually, the duration time of run, outage and derating state is treated as random variables which obey exponentially distribution. The duration time of each status for a sample period can be obtained utilizing inverse function method, are shown as (10), (11), (12).

$$\tau_1 = -\left(\frac{1}{\lambda} + \frac{1}{\lambda_d}\right)\ln U_1 \tag{10}$$

$$\tau_2 = -\frac{1}{\mu}\ln U_2 \tag{11}$$

$$\tau_3 = -\frac{1}{\mu_d}\ln U_3 \tag{12}$$

Where, U_1, U_2 and U_3 are uniformly distributed random numbers between [0, 1].

C. Reliability Assessment Process of Wind Farm Active Power

Assuming that the active power output of the wind farm is divided into N states, and then the *n*-th status of the active power can be expressed as:

$$P_{\mathrm{F}n} = (n-1)P_{\mathrm{Fint}} / N \quad n = 1, 2\cdots N-1, N, N+1 \tag{13}$$

The range of each state can be expressed as:

$$P_{\mathrm{F}n} = \begin{cases} P_{\mathrm{sF}} < \dfrac{P_{\mathrm{Fint}}}{2N} & n = 1 \\ \dfrac{(2n-3)P_{\mathrm{Fint}}}{2N} \le P_{\mathrm{sF}} < \dfrac{(2n-1)P_{\mathrm{Fint}}}{2N} & n = 2\cdots N \\ P_{\mathrm{sF}} \ge \dfrac{(2N-1)P_{\mathrm{Fint}}}{2N} & n = N+1 \end{cases} \tag{14}$$

where， $P_{\mathrm{F}n}$ is *n*-th state output， P_{sF} is sampled wind farm active power， P_{Fint} is the installed capacity of the wind farm.

In order to quantitatively analyze the wind farm active power, defining the assessment index as AAUH （Annual Average Utilization Hours), the *n*-th status formula can be expressed as:

$$\mathrm{AAUH}_n = \frac{\text{Total occurrences of state } n}{\text{Total evaluation time(}yeras\text{)}} \tag{15}$$

The flow diagram of the reliability assessment for wind farm active power is shown in Figure 5.

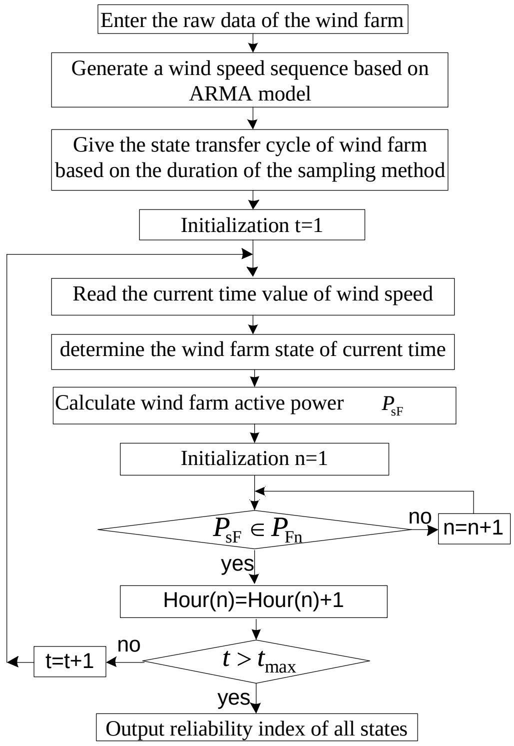

Fig. 5 Reliability assessment flowchart of wind farm active power

According to Figure 5, the basic steps of the probabilistic assessment of the wind farm active power are shown as:

1) Enter the raw data of the wind turbine: wind turbine outage and derating rate; wind speed distribution parameters; maximum simulation time;

2) Before the simulation, generate a wind speed sequence based on ARMA model; Give the state transfer cycle of wind farm based on the duration of the sampling method;

3) Read the wind speed value and determine the wind farm status at current time, calculate the wind farm active power according to the formula (4), (8), (9);

4) According to formula (13) and formula (14) determine which status the wind farm active power belongs to and accumulate the time of related status;

5) Calculate the simulation time, if it achieves the maximum values, the sampling ends, otherwise t = t +1, go to step 3.

IV. SIMULATION RESULTS

Simulation analysis of a wind farm with installed capacity of 100MW is carried out in MATLAB, the wind farm contains 67 units of 1.5MW double-fed wind turbines whose cut-in wind speed, rated wind speed and cut-out wind speed are 3 m/s, 11 m/s, 25 m/s, respectively, impeller diameter and hub height are 77 m and 80 m, respectively. Assuming that all the wind turbines are arranged regularly, and the distance between each two wind turbines is 750 m. Wind turbine reliability parameters are shown in Table I.

TABLE I WIND TURBINE RELIABILITY PARAMETERS

Capacity /(MW)	Outage rate / (Occ/ye)	Repair rate / (Occ/ye)	Derating rate / (Occ/ye)	Repair rate / (Occ/ye)	Derating factor
1.5	7.96	58.4	5.84	43.8	0.6

Historical hourly wind speed data collected over 15 years by Environment Canada for Swift Current (SC) in the Province of Saskatchewan Canada are used to obtain the respective ARMA models. The data were recorded at a height of 10 m. SC has an average wind speed of 5.41 m/s and standard deviation wind speed of 2.69 m/s. The time series wind speed ARMA models [13, 14] for the SC locations are shown in (16).

$$y_t = 1.1772 y_{t-1} + 0.1001 y_{t-2} - 0.3572 y_{t-3} + 0.0379 y_{t-4} + \alpha_t - 0.5030\alpha_{t-1} - 0.2924\alpha_{t-2} + 0.1317\alpha_{t-3}, \alpha_t \in N\left(0, 0.524760^2\right) \quad (16)$$

A. Wind Farm Probability Assessment Results

The wind farm's output is divided into 11 statuses, to run this simulation the outage rate and derating rate of each wind turbine in the wind farm are set to 3.96 and 3.84, respectively. The assessment results are shown in Figure 6.

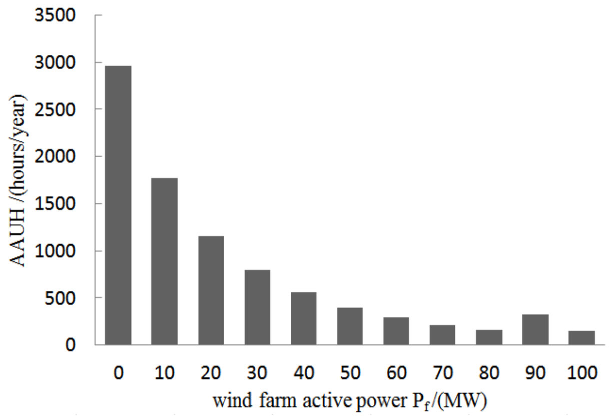

Fig. 6 Variations of AAUH against P_f

Figure 6 shows the reliability index AAUH against P_f histogram. It is observed that the active wind farm active power P_f of 0 in a year is longer, nearly 3000 hours, the AAUH becomes lower as the P_f is increased. In addition, the AAUH of full-fat status, which is 100MW, is shortest.

B. Reliability Parameter Sensitivity Analysis

In order to analyze the effects of reliability parameters for diffident values on the AAUH against P_f histograms, the force outage rate (FOR) and force derating rate (FDR) have been set to 0, 10, 20 and 0, 9, 18, respectively.

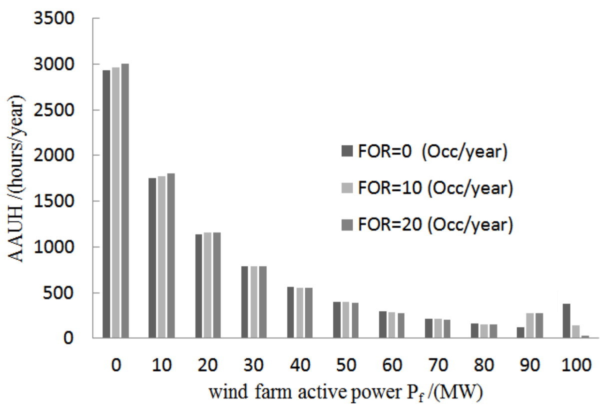

Fig. 7 Variations of AAUH against Pf for diffident FORs

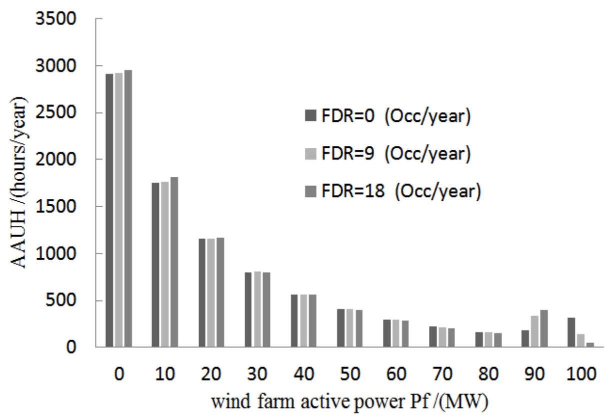

Fig. 8 Variations of AAUH against Pf for diffident FDRs

Figure 7 shows the impact of wind farm active power P_f on the AAUH, for diffident FORs, in which the 'FOR = 0' represents that the fault status is not taken into account. It is observed, as expected, for the P_f of 100MW, the AAUH decreases as outage rate is increased, but for the P_f of 90MW, the AAUH increases as outage rate is increased, furthermore, for other P_f, diffident FORs have almost no effect on the AAUH.

Figure 8 shows the impact of wind farm active power P_f on the AAUH, for diffident FDRs, in which the 'FDR = 0' represents that the derating state is not taken into account. Similarly, it indicates that, for the P_f of 100MW, the AAUH decreases as FDR is increased, but for the P_f of 90MW, the AAUH increases as FDR is increased. Moreover, the impact of diffident FDRs on AAUH becomes negligible at other P_f.

Figure 9 demonstrates the effect of the derating factor (DF) on the AAUH against P_f histograms. To run this simulation, the DF has been set to 0, 0.5 and 1, respectively. Figure 9 shows that for the P_f of 100MW, the AAUH increases as DF is increased, but for the P_f of 90MW, the AAUH decreases as DF is increased, besides, for the rest of P_f, diffident DFs have almost no effect on the AAUH.

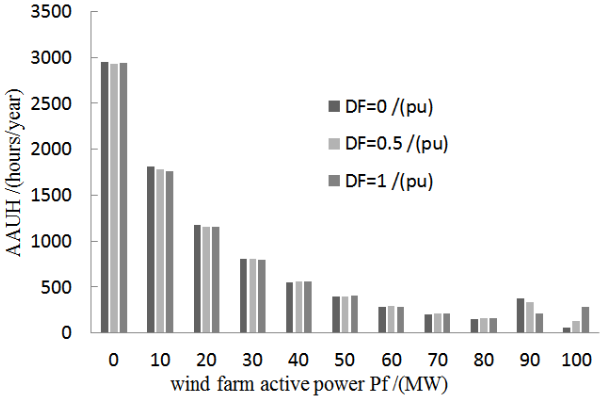

Fig. 9 Variations of AAUH against Pf for diffident DFs

C. Model Parameter Sensitivity Analysis

In order to analyze the effects of the number of status on the AAUH, the number of status has been set to 5 and 10, respectively. Figure 10 indicates that for a given P_f the AAUH is more accurate as the number of status is increased.

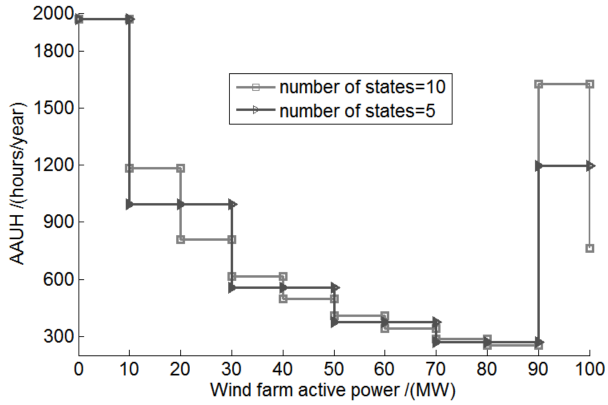

Fig. 10 Variations of AAUH against Pf for diffident number of states

Figure 11 and Figure 12 demonstrate the impact of the wind speed average value (WSAV) and wind speed standard deviation value (WSSDV) on the AAUH against Pf histograms. It is observed that, as expected, for a given Pf the wind speed parameters, such as WSAV and WSSDV, have a greater impact on the AAUH compared to wind turbine reliability parameters, besides, the scope of its influence is related to all of Pf.

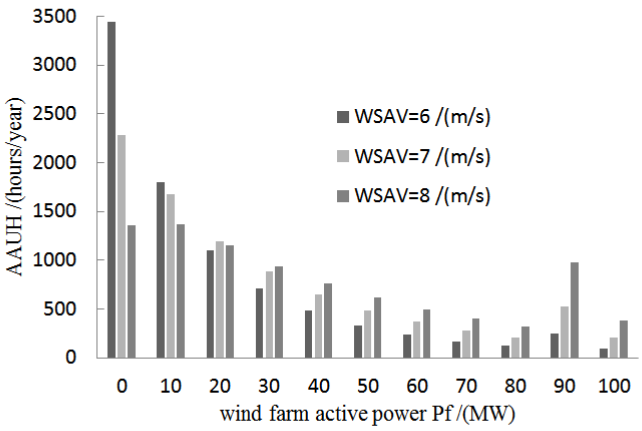

Fig. 11 Variations of AAUH against Pf for diffident WSAVs

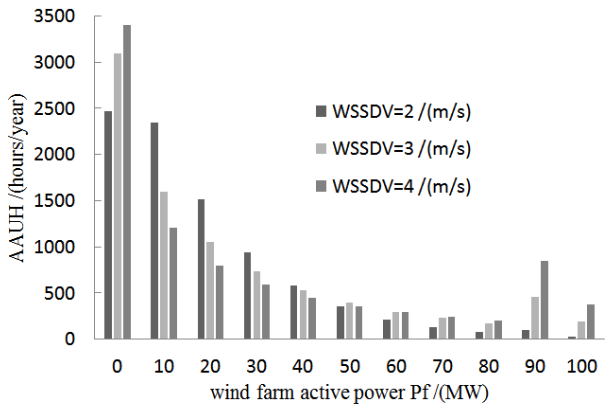

Fig. 12 Variations of AAUH against Pf for diffident WSSDVs

Figure 11 and Figure 12 demonstrate the impact of the wind speed average value (WSAV) and wind speed standard deviation value (WSSDV) on the AAUH against P_f histograms. It is observed that, as expected, for a given P_f the wind speed parameters, such as WSAV and WSSDV, have a greater impact on the AAUH compared to wind turbine reliability parameters, besides, the scope of its influence is related to all of P_f.

V. CONCLUSIONS

From simulation and analysis of a typical wind farm, the following conclusions can be obtained:

Active power issued by a wind farm is generally smaller than their installed capacity, in this case, the AAUH of Pf=0 is almost 3000 hours, and the AAUH of Pf=100 MW is less than 100 hours.

The wind turbine reliability parameters have some impact on the AAUH for some larger status of P_f; however the wind speed parameters have a greater impact on the AAUH for all status of Pf.

The accuracy of the assessment model could be improved by increasing the number of states, but the computation time required is increased, so there is a need to coordinate the relationship between accuracy and speed.

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