A Stochastic DEVS Wind Turbine Component Model for Wind Farm Simulation

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Abstract

Wind farms use several wind turbines to generate electricity and provide a renewable source of energy. However, due to large forces as a result of hourly and seasonal variations in wind speed and direction, wind turbines experience stochastic loading that often lead to failures of wind turbine components such as the gearbox and generator. Wind turbine failures result in costly repairs and loss in revenue, while stochastic loading makes it difficult to predict the actual condition of a wind turbine. Consequently, it is challenging to schedule maintenance actions to avoid wind turbine component failures. In this paper, we present a stochastic discrete event system specification (STDEVS) model of a wind turbine component. In particular, we consider the wind turbine gearbox, which is one of the components that is often prone to failure, and model its stochastic degradation process. We implement a wind farm simulation with the STDEVS gearbox model and report on the impact of gearbox failures and maintenance scheduling on the performance of a wind farm over a 20-year period.

1 INTRODUCTION

Wind farms use a collection of wind turbines to generate renewable electricity using wind. Therefore, wind farms are usually located in parts of the world with high speed winds throughout the year. Due to harsh weather conditions and hourly and seasonal variations in wind speed and direction, wind turbines experience large stochastic forces that often lead to component failures. Wind turbine components include blades, gearbox, generator, electrical system and control system. Component failures result in costly component repairs and losses in revenue due to unavailability of the wind turbine to generate electricity. Many wind farms are located in remote areas or offshore and are therefore, less accessible. Furthermore, the stochastic nature of the forces experienced by the wind turbine makes it difficult to predict the actual condition of the turbine components. Consequently, scheduling maintenance to avoid wind turbine component failures is critical.

In this paper, we consider a stochastic discrete event system specification (STDEVS) [1] model of a wind turbine component. In particular, we model the stochastic degradation process of a wind turbine gearbox, which is one of the components that is often prone to failure. The STDEVS model we devise is an extension of the Parallel DEVS [2] wind turbine gearbox component model in [3]. We adopt the simulation model in [3] and incorporate the STDEVS wind turbine component model to simulate the stochastic degradation of the gearbox and its impact on wind farm performance. We consider two types of maintenance actions: scheduled maintenance (SM) and condition-based monitoring maintenance (CBM). Under SM, repair crews are dispatched to the wind farm to perform maintenance based on a fixed schedule as recommended by the turbine manufacturer, while under CBM maintenance is done as needed based on sensor information.

STDEVS is a formal framework for modeling and simulation of generalized non-deterministic discrete event systems. A formal specification of STDEVS is given in [1]. The authors use the system theoretic ba-

sis of DEVS and probability spaces to the devise the STDEVS formalism. STDEVS provides a suitable framework for modeling and simulating the stochastic degradation process of a wind turbine component. Mathematically, an STDEVS model has the following structure [1]:

$$MST = (X, Y, S, \mathcal{G}_{int}, \mathcal{G}_{ext}, \mathcal{P}_{int}, \mathcal{P}_{ext}, \lambda, ta)$$

where X is the set of input event values; Y is the set of output event values; S is the set of state values; λ is the output function; and ta is the time advance function. These functions define the system dynamics.

$\mathcal{G}_{int} : S \rightarrow 2^S$ is a function that assigns a collection of sets $\mathcal{G}_{int}(S) \subseteq 2^S$ to every state s. Given a state $s, \mathcal{G}_{int}(s)$ contains all the subsets of S that the next state might belong to with a known probability, calculated by a function $\mathcal{P}_{int} : S \times 2^S \rightarrow [0, 1]$. When the system is in state s the probability that the internal transition takes it to a set $s' \in \mathcal{G}_{int}(s)$ is calculated by $\mathcal{P}_{int}(s, s')$.

$\mathcal{G}_{ext} : S \times \Re_0^+ \times X \rightarrow 2^S$, is a function that assigns a collection of sets $\mathcal{G}_{ext}(s, e, x) \subseteq 2^S$ to each triplet (s, e, x). Given a state s and an elapsed time e, if an event with value x arrives, the next state belongs to $\mathcal{G}_{ext}(s, e, x)$ with a known probability calculated by $\mathcal{P}_{ext} : S \times 2^S \rightarrow [0, 1]$.

We refer the reader to [4] for a study of CBM and the physics of failure of wind turbine components. Work on fault diagnosis for wind turbine based on CBM is given in [5]. Other related work include TurbSim, a reliability-based wind turbine simulator [6]. The work in [6] investigates the impact of reliability in a life-cycle analysis simulation of a theoretical wind farm based on information from the literature. The study by [7] considers Monte Carlo simulation for wind farm maintenance operations based on both SM and CBM maintenance. Other work on wind farm operations and maintenance include [8, 9, 10].

The rest of the paper is organized as follows. In Section 2 we describe the overall wind farm simulation model and present a formal description of the STDEVS wind turbine gearbox degradation model in Section 3. We report preliminary simulation results based on an implementation of the simulation model in DEVSJAVA [11] in Section 4. The simulation results are for a realistic wind farm located in Texas. We end the paper with some concluding remarks in Section 5.

2 THE WIND FARM SIMULATION MODEL

A wind turbine at an abstract level produces a given amount of power based on given wind speed. An empirically verified power curve provided by the wind turbine manufacturer relates wind speed to power generated. The DEVS wind farm simulation we consider comprises several basic components as shown in Figure 1.

The wind turbine (WTURBINE) model is composed of a component degradation (CMPDEG) model and a power generation (PWRGEN) model. CMPDEG models the degradation of a wind turbine component of interest while PWRGEN models electrical power generation based on wind speed. The PWRGEN atomic model uses a power curve to calculate the amount of power generated at any given time based on the wind speed. WTURBINE is coupled to an evaluation (EVAL) model for evaluating the state/condition of WTURBINE based on sensor (SENSR) and smart sensor (SMSENR) output. Also coupled to WTURBINE is an operations and maintenance (OPMNT) coupled model, which is comprised of a maintenance scheduler (MSCHEDR) and a maintenance generator (MGENR).

External to the wind turbine model is the experimental frame (EF), which is composed of a transducer (TRANSD) and a wind generator (WGENR). TRANSD computes wind farm system performance measures such as total power generated, turbine availability, number of failures per turbine, maintenance cost per turbine, and capacity factor. Capacity factor is the ratio of the actual amount of power produced over time to the power that would have been produced at full capacity. WGENR generates sequences of wind speeds at turbine locations using a spatio-temporal wind model.

3 THE WIND TURBINE COMPONENT STDEVS ATOMIC MODEL

We consider a coupled wind turbine (WTURBINE) model consisting of two atomic models, power generator (PWRGEN) and component degradation (CMPDEG). We devise an STDEVS atomic model for CMPDEG to model wind turbine gearbox degradation over time as a stochastic process. We consider CMPDEG with ten probabilistic states; *off_normal*, *off_normal_waiting*,
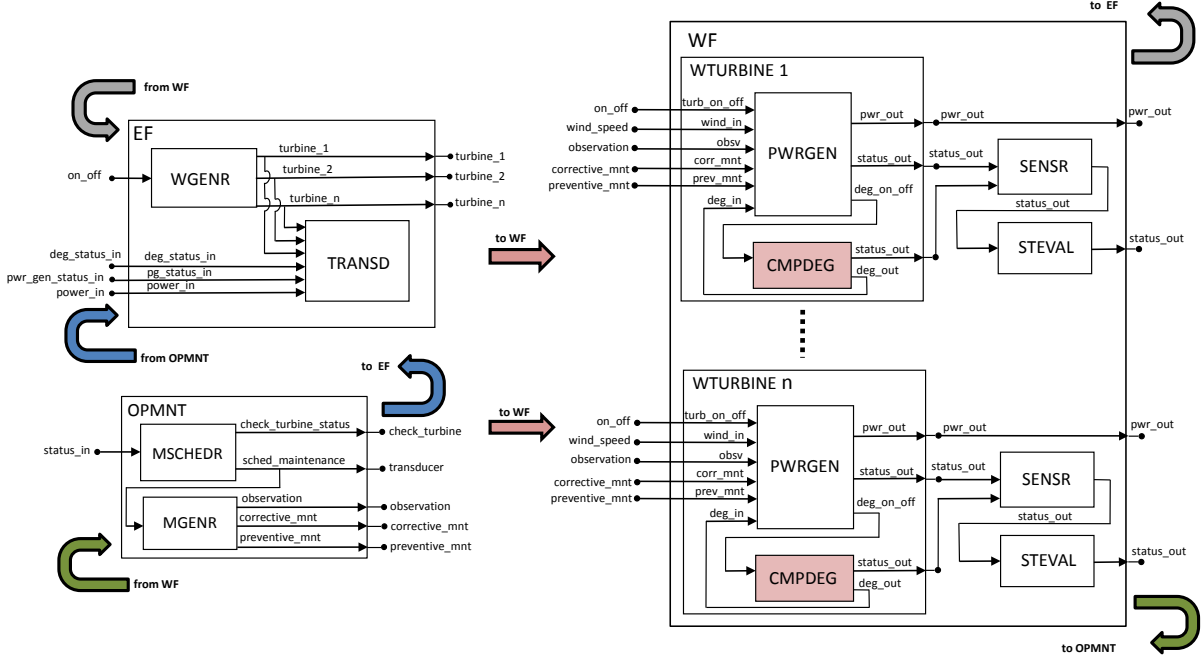
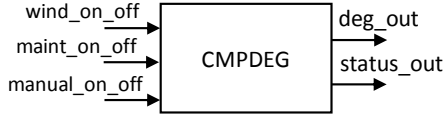Figure 1: The wind farm simulation model components

Figure 2: CMPDEG atomic model

on_normal, *off_alert*, *off_alert_waiting*, *on_alert*, *off_alarm*, *off_alarm_waiting*, *on_alarm*, and *failed*. Figure 2 depicts a block diagram of the CMPDEG atomic model.

CMPDEG has three input ports, namely; "wind_on_off", "maint_on_off", and "manual_on_off". The first input port is for receiving a message of whether or not the wind speed is within turbine operable range. The second input port is for receiving a turbine on or off maintenance signal, while the third input port is for switching on and off the turbine. CMPDEG has two output ports, "deg_out" and "status_out". The first output port is for notifying the PWRGEN atomic model that a change in the state of the turbine component has occurred. The second output port is for reporting the current state of the component (gearbox) to the system sensors.

The operation of CMPDEG is depicted in the state transition diagram in Figure 3. CMPDEG is initialized in the *off_normal* state. If an input is received

on the "manual_on_off" input port, the model transitions to the *on_normal* state. Once in the *on_normal* state six different things can happen. If a message is received on the "manual_on_off" the model transitions back to its initial state. However, if a message is received on the "wind_on_off" input port, the model transitions to the *off_normal_waiting* state. This happens when the wind turbine is turned off due to high wind speeds that may cause damage to the turbine. If no input is received, the model transitions from the *on_normal* to one of the following four states: *on_normal*, *on_alert*, *on_alarm*, and *failed*. This transition is probabilistic and depends on the stochastic deterioration model used for the gearbox. In this work we use a partially observed Markov deterioration model as in [3]. In general, we define a marginal probability distribution $P(s, s')$ for computing the probability of transition from state s to state s'. The model is scheduled to stay in any of the four states s a stochastic amount of time $ta(s)$.

Figure 3 shows an example of the state transition diagram where an empirical probability distribution is used. The model transitions from the *on_normal* state to *on_alert* with 0.05 probability, *on_alarm* with 0.03, and *failed* with 0.02. The model remains in the *on_normal* state with probability 0.95. When the model is in the *on_alert* state, there are five pos-

sible transitions. If a message is received on the "manual_on_off" input port, the model transitions to the *off_alert* state. If a message is received on the "wind_on_off" input port, the model transitions to the *off_alert_waiting* state. If no input is received and the delay in *on_alert* elapses, the model transitions to the *on_alarm* state with probability 0.10; transitions to the *failed* state with probability 0.05; or remains in the *off_alert* state with probability 0.85. If in the alarm state, the model transitions to the *off_alarm* state if an input is received on the "manual_on_off" input port, or transitions to the *"off_alarm_waiting* state if an input is received on the "wind_on_off" input port. If no input is received, there is 0.92 probability that the model will remain in the *on_alarm* state and a 0.08 probability that the model will transition to the *failed* state. If maintenance is performed to the component when it is in the *off_alert* state, *off_alert* state or the *failed* state, the model transitions to the *off_normal* state.

Next we provide a formal mathematical expression of the CMPDEG atomic model in STDEVS. In what follows, $\wedge$ denotes the logic AND operation and p is the name of the port receiving the input. A boolean variable named cut_off is used to define whether the wind is within specified thresholds ($true$) or not ($false$). The time remaining in the current state (σ) follows a uniform distribution. Specifically, σ_n, σ_t and σ_m follow a uniform distribution on the time intervals (ℓ_n, u_n), (ℓ_t, u_t) and (ℓ_m, u_m), respectively. To describe $\mathcal{P}_{int}$ we used three marginal distributions ($\mathcal{P}_{normal}, \mathcal{P}_{alert}$, and $\mathcal{P}_{alarm}$) for state transitions. For instance, $\mathcal{P}_{normal}(s, s')$ is the probability distribution for transitioning from the "on_normal": ("on_normal", "on_normal"), ("on_normal", "on_alert"), ("on_normal", "on_alarm"), and ("on_normal", "failed"). To allow for probabilistic state transitions, we need to invert $\mathcal{P}_{normal}$ and then use a pseudo random number generator to get a value u to determine the next state s'. Therefore, we define the following intervals within $(0,1)$: $(0, I_{N1})$, $[I_{N1}, I_{N2})$, $[I_{N2}, I_{N3})$, and $[I_{N3}, 1)$ that correspond to the above four state transitions. $\mathcal{P}_{alert}$ and $\mathcal{P}_{alarm}$ are defined in a similar way. $\mathcal{P}_{alert}$ involves the state transitions ("on_alert", "on_alert"), ("on_alert", "on_alarm") and ("on_alert", "fail"), with the following corresponding intervals on $(0,1)$: $(0, I_{T1})$, $[I_{T1}, I_{T2})$ and $[I_{T2}, 1)$. Similarly, $\mathcal{P}_{alarm}$ involves the state transitions ("on_alarm", "on_alarm") and ("on_alarm", "fail") with the following corresponding intervals on $(0,1)$: $(0, I_{M1})$ and $[I_{M1}, 1)$.

$$M_{CMPDEG} = (X, Y, S, \delta_{ext}, \mathcal{G}_{int}, \mathcal{P}_{int}, \lambda, ta)$$

$X = \{$ (on, "manual_on_off"), (off, "manual_on_off"), (out_cut_off, "win_on_off"), (in_cut_off, "win_on_off"), (maintenance, "maint_on_off")$\}$

$Y = \{$(stats, "status_out"), (msg, "deg_out")$\}$

$S = \{$ "off_normal", "off_normal_waiting", "on_normal", "off_alert", "off_alert_waiting", "on_alert", "off_alarm", "off_alarm_waiting", "on_alarm", "failed"$\}$

$\delta_{ext}(phase, \sigma)$

$$= (\text{``off\_normal''}, \infty), \quad \text{if}$$
$$\begin{cases} phase = \text{``off\_alert''} \\ \qquad \wedge\ p = \text{``maint\_on\_off''}; \\ phase = \text{``off\_alarm''} \\ \qquad \wedge\ p = \text{``maint\_on\_off''}; \\ phase = \text{``failed''} \\ \qquad \wedge\ p = \text{``maint\_on\_off''}; \\ phase = \text{``on\_normal''} \\ \qquad \wedge\ p = \text{``manual\_on\_off''}. \end{cases}$$

$$= (\text{``off\_normal\_waiting''}, \infty), \quad \text{if}$$
$$\begin{cases} phase = \text{``on\_normal''} \\ \wedge\ p = \text{``wind\_on\_off''} \wedge cut\_off = false. \end{cases}$$

$$= (\text{``on\_normal''}, \sigma_n), \quad \text{if}$$
$$\begin{cases} phase = \text{``off\_normal''} \\ \qquad \wedge\ p = \text{``manual\_on\_off''} \\ \qquad \wedge\ cut\_off = true; \\ \qquad \text{with}\ \sigma_n = \text{unif}(\ell_n, u_n); \\ phase = \text{``off\_normal\_waiting''} \\ \qquad \wedge\ p = \text{``wind\_on\_off''} \\ \qquad \wedge\ cut\_off = true; \\ \qquad \text{with}\ \sigma_n = \text{unif}(\ell_n, u_n). \end{cases}$$

$$= (\text{``off\_alert''}, \infty), \quad \text{if}$$
$$\begin{cases} phase = \text{``on\_alert''} \\ \qquad \wedge\ p = \text{``manual\_on\_off''}. \end{cases}$$

$$= (\text{``off\_alert\_waiting''}, \infty), \quad \text{if}$$
$$\begin{cases} phase = \text{``on\_alert''} \\ \qquad \wedge\ p = \text{``wind\_on\_off''} \\ \qquad \wedge\ cut\_off = false. \end{cases}$$

$$= (\text{``on\_alert''}, \sigma_t), \quad \text{if}$$

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Figure 3: State transition diagram for CMPDEG

$$\mathcal{G}_{int}$$

$$\left\{\begin{array}{l} phase = \text{``off\_alert''} \\ \qquad \wedge\, p = \text{``manual\_on\_off''} \\ \qquad \wedge\, cut\_off = true; \\ \qquad \text{with } \sigma_t = \text{unif}(\ell_t, u_t); \\ phase = \text{``off\_alert\_waiting''} \\ \qquad \wedge\, p = \text{``wind\_on\_off''} \\ \qquad \wedge\, cut\_off = true; \\ \qquad \text{with } \sigma_t = \text{unif}(\ell_t, u_t). \end{array}\right.$$

$$= \quad (\text{``off\_alarm''}, \quad \infty), \qquad \text{if}$$

$$\left\{\begin{array}{l} phase = \text{``on\_alarm''} \\ \qquad \wedge\, p = \text{``manual\_on\_off''}. \end{array}\right.$$

$$= \quad (\text{``off\_alarm\_waiting''}, \quad \infty), \qquad \text{if}$$

$$\left\{\begin{array}{l} phase = \text{``on\_alarm''} \\ \qquad \wedge\, p = \text{``wind\_on\_off''} \\ \qquad \wedge\, cut\_off = false. \end{array}\right.$$

$$= \quad (\text{``on\_alarm''}, \quad \sigma_m), \qquad \text{if}$$

$$\left\{\begin{array}{l} phase = \text{``off\_alarm''} \\ \qquad \wedge\, p = \text{``manual\_on\_off''} \\ \qquad \wedge\, cut\_off = true; \\ \qquad \text{with } \sigma_m = \text{unif}(\ell_m, u_m); \\ phase = \text{``off\_alarm\_waiting''} \\ \qquad \wedge\, p = \text{``wind\_on\_off''} \\ \qquad \wedge\, cut\_off = true; \\ \qquad \text{with } \sigma_m = \text{unif}(\ell_m, u_m). \end{array}\right.$$

$$\mathcal{G}_{int}$$

$$= \quad (\text{``on\_normal''}, \quad \sigma_n), \qquad \text{if}$$

$$\left\{\begin{array}{l} phase = \text{``on\_normal''} \\ \qquad \wedge \text{ if } (0 \le u < I_{N1}), \\ \qquad \text{with } u = \text{unif }(0,1); \\ \qquad \text{and } \sigma_n = \text{unif}(\ell_n, u_n) \end{array}\right.$$

$$= \quad (\text{``on\_alert''}, \quad \sigma_t), \qquad \text{if}$$

$$\left\{\begin{array}{l} phase = \text{``on\_alert''} \\ \qquad \wedge \text{ if } (0 \le u < I_{T1}), \\ \qquad \text{with } u = \text{unif }(0,1); \\ \qquad \text{and } \sigma_t = \text{unif}(\ell_t, u_t) \\ phase = \text{``on\_normal''} \\ \qquad \wedge \text{ if } (I_{N1} \le u < I_{N2}), \\ \qquad \text{with } u = \text{unif }(0,1); \\ \qquad \text{and } \sigma_t = \text{unif}(\ell_t, u_t) \end{array}\right.$$

$$= \quad (\text{``on\_alarm''}, \sigma_m), \qquad \text{if}$$

$$\left\{\begin{array}{l} phase = \text{``on\_alarm''} \\ \qquad \wedge \text{ if } (0 \le u \le I_{M1}), \\ \qquad \text{with } u = \text{unif }(0,1); \\ \qquad \text{and } \sigma_m = \text{unif}(\ell_m, u_m); \\ phase = \text{``on\_normal''} \\ \qquad \wedge \text{ if } (I_{N2} \le u < I_{N3}), \\ \qquad \text{with } u = \text{unif }(0,1); \\ \qquad \text{and } \sigma_m = \text{unif}(\ell_m, u_m); \\ phase = \text{``on\_alert''} \\ \qquad \wedge \text{ if } (I_{T1} \le u < I_{T2}), \\ \qquad \text{with } u = \text{unif }(0,1); \\ \qquad \text{and } \sigma_m = \text{unif}(\ell_m, u_m) \end{array}\right.$$

$$= \quad (\text{``failed''}, \infty), \qquad \text{if}$$

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$$\begin{cases} phase = \text{``on\_normal''} \\ \qquad \wedge \text{ if } (I_{N3} \le u \le 1), \\ \qquad \text{with } u = \text{unif } (0,1); \\ phase = \text{``on\_alert''} \\ \qquad \wedge \text{ if } (I_{T2} \le u \le 1), \\ \qquad \text{with } u = \text{unif } (0,1); \\ phase = \text{``on\_alarm''} \\ \qquad \wedge \text{ if } (I_{M1} \le u \le 1), \\ \qquad \text{with } u = \text{unif } (0,1). \end{cases}$$

$\mathcal{P}_{int}$: Joint distribution of $P(s, s')$.

$\lambda_S = \{(\text{stats, ``status\_out''}), (\text{msg, ``deg\_out''})\}$.

$ta(s) = \{\sigma\}$.

4 APPLICATION

We implemented the simulation model in DEVS-JAVA and simulated a 100-unit wind farm located in West Texas. We assumed the wind farm operates 24 hours 7 days a week. The parameters used to model the wind behavior were obtained from the West Texas Mesonet [12].

The wind farm operations were simulated using two strategies: scheduled maintenance (SM) and conditioned-based monitoring (CBM). Under SM, maintenance actions are performed twice a year regardless the deterioration status of the turbine. The CBM strategy consist in performing preventive maintenance actions only when sensors in condition monitoring equipment produce alarm signals.

Computational experiments were performed to gain management insights from the operational strategies. For each operational strategy twenty replications were run using a time horizon of twenty years. Twenty years is the average lifespan of a wind turbine.

Table 1 reports the simulation results for the average total power generation and the capacity factor under SM and CBM, respectively. For each performance measure we provide the mean, standard deviation (Std. Dev.), and the lower (L) and upper (U) bound for a 95% confidence interval (CI). The results show that CBM provides on average 10.76% higher power generation and 10.75% capacity factor for the 20-year period compared to SM. The simulation runs for both strategies lasted about 1.7 hours due to the length of the planning horizon (20 hours) and the large number of turbines in the system.

The average power generated per year for each operational policy are report in Figure 4. The figure shows that under CBM, the wind farm generates 12.05% more power for all the years on average. Figure 5 shows the average number of failures for the 20-year period. The number of failures for CBM is on average 14.13% lower than for SM over the 20-year period. We compared our results to those reported in the literature in Table 2. All the results are within the industry figures except for capacity factor. Our average values of 0.45 and 0.51 are well above the industry range of 0.25-0.4. We believe this is due to the fact that we only consider one component (the gearbox).

5 CONCLUSION

Wind farms use several wind turbines to generate electricity and provide a renewable source of clean energy. However, wind turbines experience large forces as a result of hourly and seasonal variations in wind speed and direction. This results in stochastic loading that often lead to failures of wind turbine components such as the gearbox. Wind turbine failures costly due to repairs and loss in revenue during turbine down time. Stochastic loading makes it difficult to predict the actual condition of a wind turbine. Consequently, scheduling maintenance actions to avoid wind turbine component failures is critical, especially if the wind farm is not easily accessible.

In this paper, we present a stochastic discrete event system specification (STDEVS) model of a wind turbine component. In particular, we consider the wind turbine gearbox, which is one of the components that is often prone to failure, and model its stochastic degradation process. We implement a wind farm simulation with the STDEVS gearbox model and report on the impact of gearbox failures and repairs on the performance of a wind farm over time. We consider scheduled maintenance (SM) and condition-based monitoring maintenance (CBM). The results show that CBM provides on average 10.76% higher power generation and 10.75% capacity factor over a 20-year period compared to SM. Furthermore, CBM provides 14.13% less number of failures on average than SM. Overall, the simulation results suggest that CBM has potential to provide significant benefits for wind power generation. Future work include devising and implementing degradation component models for all critical components of a wind turbine.

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Table 1: Simulation time, power generated and capacity factor for wind farm (20 years)

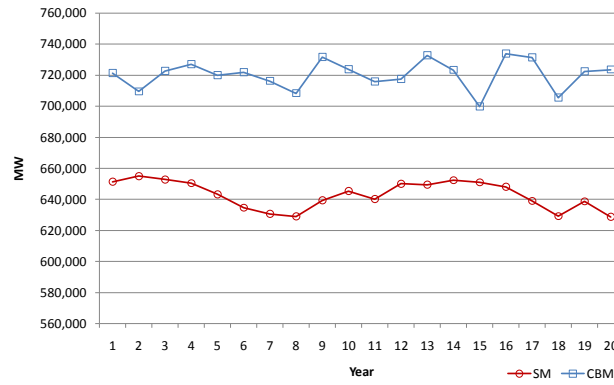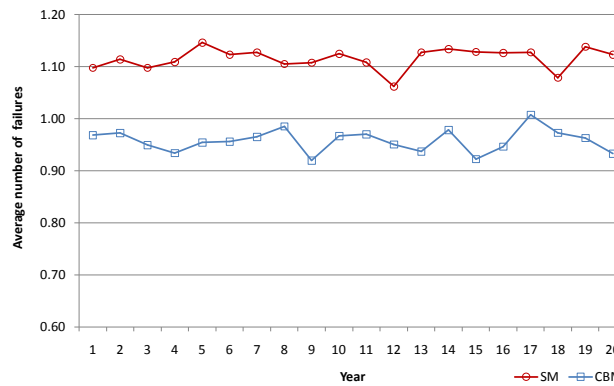|	Statistic	Power (MW)	Capacity Factor	CPU Time (secs)
SM	Mean	12,856,466.74	0.4516	6142.07
	Std. Dev.	8,931.50	0.0003	225.53
	CI L	12,852,286.67	0.4514	6036.52
	CI U	12,860,646.81	0.4517	6247.62
CBM	Mean	14,406,757.14	0.5060	6251.143
	Std. Dev.	9,264.47	0.0003	177.760
	CI L	14,402,421.23	0.5059	6167.949
	CI U	14,411,093.05	0.5062	6334.337

Figure 4: Average power generated by the wind farm annually

Figure 5: Average number of failures per turbine in each year

Table 2: Figures in industry

Criteria	Figures in industry	SM				SM			
		Mean	Std. Dev.	CI L	CI U	Mean	Std. Dev.	CI L	CI U
Capacity Factor	0.25-0.4	0.4516	0.0003	0.4514	0.4517	0.5060	0.0003	0.5059	0.5062
Availability	0.98	0.927	0.004	0.925	0.929	0.944	0.002	0.943	0.946
Number of failures per year	0.05-2.29	1.267	0.010	1.262	1.272	1.092	0.010	1.087	1.097

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