Applying Swarm Intelligence and Bayesian Inference for Wind Turbine SCADA-Based Condition Monitoring and Prognostics

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ABSTRACT

Diagnosis and prognosis of potential faults is crucial to maintain and improve the efficiency of the wind energy system. In this paper, we propose a SCADA-based condition monitoring and prognostics system. We apply particle swarm optimization to recognize different patterns of turbine health condition by fusing performance test results. As monitoring daily turbine health condition, we design a data-driven Bayesian inference approach to predict turbine potential failures by tracking the abnormal variations.

1. INTRODUCTION

Wind is an important renewable energy source. The energy and economic return from building wind farms justify the expensive investments in doing so. However, without an effective monitoring system, under-performing or faulty turbines will cause a huge loss in revenue (Chen and Blaabjerg, 2006). Therefore, to make wind energy more competitive in the future, efforts are required to enhance the availability, reliability and lifetime of the wind turbines.

Early detection and prediction of such failures helps prevent these undesired working conditions and allows the operators to develop maintenance plans with prioritized tasks (Yang and Tavner, 2010). If failures are detected and predicted at an early stage, the consequent damage is minimized or mitigated, and also repairs are better scheduled. This leads to shorter down-times and lesser revenue losses. Therefore, diagnosis and prognosis of under-performing and potential faults are crucial to maintain and improve the efficiency of the wind energy generation system.

Traditionally, condition monitoring systems for wind turbines have focused on the detection of failures in the main bearing, generator, and gearbox, some of the highest cost components on a wind turbine (Crabtree, 2010). Two widely-used methods are vibration analysis and oil monitoring (Sheng et al, 2009). These are standalone systems that require installation of sensors and hardware. A Supervisory Control and Data Acquisition (SCADA) based condition monitoring system uses data already being collected at the wind turbine controller and is a cost-effective way to monitor for early warning of failures and performance issues (Zaher, 2009).

This paper proposes an intelligent data-driven approach to monitor the turbine performance at real-time by fusing multiple test results and to predict the turbine abnormalities by tracking the turbine status variations. We develop three tests on power curve, rotor speed curve, and pitch angle curve of individual turbine. In each test, multiple states are defined to distinguish different health condition, including complete shutdown, under-performing, abnormally frequent default, as well as normal working. These tests are combined to reach a final conclusion, which cannot be made by a single test. To monitor the turbine performance on daily base and understand turbine daily health condition better, particle swarm optimization (PSO) algorithm is applied to determine the fusion rules more objectively and optimally.

Then, a Bayesian inference is implemented to predict turbine potential failures with a percentage certainty by tracking the abnormal variations. We assume that the faulty turbine follows specific degradation patterns due to differential failure before and after it happens. Based on turbine degradation, the Bayesian network is able to tell the wind farm operators what type of failures is happening to this turbine, and tell the time when it is probably going to shut down. Also, the test results have verified the effectiveness of our approach. This procedure is adaptable to each turbine using SCADA data, automatically. Our approach is advantageous in its applicability and data-driven nature, to monitor a large wind farm.

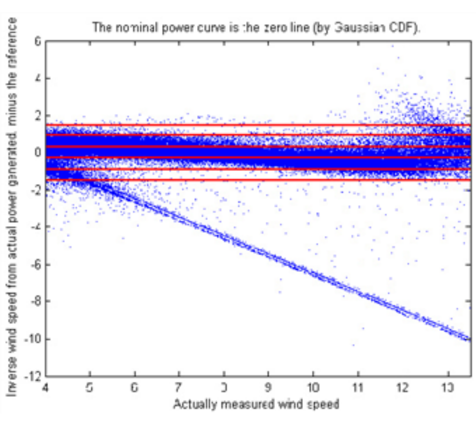
The rest of the paper is organized as follows. Section II presents the methodology of designing three tests on power curve, rotor speed curve and pitch angle curve of individual turbine for its fault detection. In Section III, we evaluate the fusion of multiple tests through PSO to monitor turbine health condition and detect its failures on daily basis. Section IV introduces the Bayesian inference approach for turbine failure prediction. Finally, conclusions are provided in Section V.

2. MULTIPLE TESTS DESIGNED FOR WIND TURBINE FAULT DETECTION

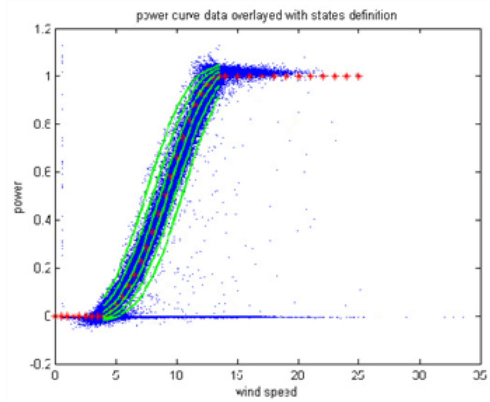
We choose three variables, power production, rotor rotating speed and blade pitch angle, significant to adjudicate on whether the turbine working properly. First of all, power production is one of the main yardsticks to measure turbine performance. Once there is a failure occurring to a turbine, the power it producing will be affected badly (Lu and Chu, 2009). Secondly, the rotor component converts wind energy to low speed rotational energy. Faster it rotates the more energy the turbine produces. Moreover, the blade pitch gives the turbine blades the optimum angle of attack. Allowing the angle of attack to be remotely adjusted gives greater control, so that the turbine collects the maximum amount of wind energy for the time of day and season (Zaher and McArthur, 2007). We measure these variables against wind speed, since the turbine performance is also determined according to how fast the wind blows.

2.1. Power vs. Wind Speed

The power curve, a plot of the generated power of the wind turbine averaged over unit time interval against the wind speed, is a key test for turbine health, since power production is the ultimate goal of the wind turbine (Osadciw et al, 2010).



(a)



(b)

Figure 1. Linearize the power curve when the wind speed is between cut-in 4 m/s and cut-off 25 m/s, by using Gaussian inverse cumulative distribution function: (a) in linearized domain, (b) in power curve domain.

The nominal power curve is a discrete set of power versus wind speed $\{(w_1, p_1), (w_2, p_2), ..., (w_m, p_m)\}$ .We first fit the nominal power curve using a Gaussian cumulative distribution function (CDF), where the parameters of the Gaussian CDF are optimized by particle swarm optimization (PSO) algorithm. A Gaussian CDF fitting function is defined by

$$\hat{P}(w \mid c, a, s, m) = -m + s \cdot \int_{-\infty}^{w} \frac{1}{\sqrt{2\pi a}} e^{-\frac{(x-c)^2}{2a^2}} dx \quad (1)$$

,

where w is the wind speed, $\hat{P}$ is the estimated power at specific w. In the Gaussian CDF fitting, c is its mean, a is the standard deviation, s is the scaling factor, and m is an extra shift. Then we construct the inverse function of the Gaussian CDF, $\hat{w} = f^{-1}(\hat{P})$, to linearize the nominal power curve, as shown in Figure 1. This linearization method simplifies the state definition, because the nominal power curve needs to be fitted only once; meanwhile, the states, in the linearized domain, are defined by thresholds, rather than the complicated boundary curves, in the power curve domain, where those boundary curves require multiple fittings.

Table I. State Definition of Linearized Power Values ($\hat{P}$) vs. Wind Speed (Vw, m/s)

State	Definition	Working Condition
1	$\hat{P}>1.5$	Under-performing with soft failures
2	$0.5<\hat{P}\leq 1.5$	Normal working
3	$-0.5<\hat{P}\leq 0.5$	Normal working
4	$-1.5<\hat{P}\leq -0.5$	Normal working
5	$\hat{P}\leq -1.5$	Under-performing with soft failures
6	Horizontal Power	Shut down with hard failures
7	$Vw<4$ and $\hat{P}>0$	Shut down with hard failures
8	$Vw<4$ and $\hat{P}\leq 0$	Abnormal defaults

The definition of the multiple states relative to the linearized power curve is shown in Table I. The colored sections in Figure 2 identify different regions in the power curve that represent potential problems in the wind turbine if the measurements change between regions. For example, the power measurements should reside in the yellow, blue and pink regions. However, the scattered red points in the upper left are typical of a faulty anemometer in the turbine. So, if the measurements move to this upper left region, there are some soft failures, which are insufficient to stop operations yet still cause power production losses, such as faulty anemometer or gearbox. Without timely maintenance, the turbine is continually breaking up until completely shut down. Some hard failures, like spindle failure and lightning strike, also cause turbine completely shut down. When it happens, the measurements move to the red or black horizontal region.

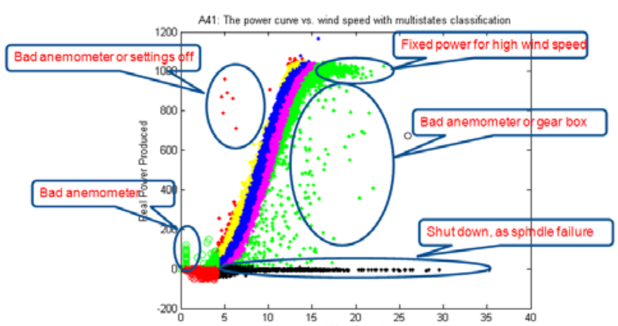


Figure 2. State diagram for power curve vs. wind speed

2.2. Rotor Speed vs. Wind Speed

The next variable analyzed is rotor speed as a function of measured wind speed. The turbine generally operates at a constant rotor speed if there is adequate wind. More power is produced as the wind force increase but the rotor speed remains constant. The cycle for a productive wind turbine is to begin with a rotor speed increasing linearly for wind speed between 0 m/s and 3 m/s, then reaches a speed of 20 cycles/s from 3 m/s to 6 m/s, and finally stays at 20 cycles/s. Based on this working cycle of wind turbines, we classify 7 states of the rotor speed curve, as shown in Table II. If the turbine is down or off due to some hard failures, the rotor speed is 0 cycles/s for all wind speeds, corresponding to the red horizontal region in Figure 3. Some of the measurements in the black region are caused by various types of failures, such as bad anemometer or rough blade.

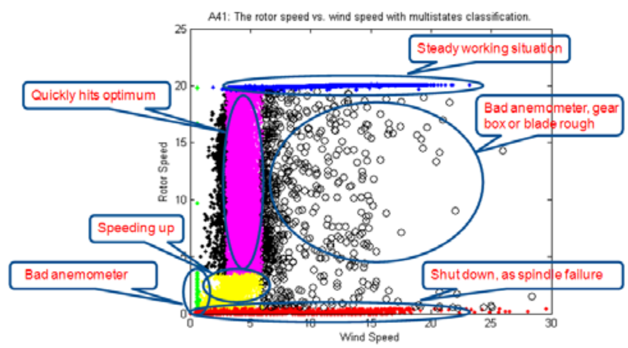


Figure 3. State diagram for rotor speed vs. wind speed

Table II. State Definition of Rotor Speed (Vr, rpm) vs. Wind Speed (Vw, m/s)

State	Definition	Working Condition
1	$Vr\leq 0.5$ (Horizontal state)	Shut down with hard failures
2	$Vw\leq 0.8$ (Vertical State)	Anemometer failures
3	$0.8<Vw\leq 6$ and $0.5<Vr\leq 3.5$	Ramping up/down
4	$3\leq Vw\leq 6$ and $3.5<Vr\leq 19.5$	Normal working
5	$Vr>19.5$	Normal working in high wind speed
6	Abnormal Vr when $Vw<3$	Under-performing, Low wind speed but relatively high rotor speed
7	Abnormal Vr when $Vw>6$	Under-performing, High wind speed but relatively low rotor speed

2.3. Pitch Angle vs. Wind Speed

The last test analyzes the pitch angle against the measured wind speed. Similar as the previous test, pitch angle keeps around -20 degree when the turbine is steadily working, as shown in the blue region in Figure 4. If the wind speed is really high, the pitch turns away the coming wind direction to avoid the damage. This condition is given in the upper right black region. Some of the measurements are in the pink line corresponding to -50 degree pitch angle. Since the pitch is set to -50 degree as preventative angle before the turbine is going down, this state is used to do prognostics of turbine failures. The state two, the lower vertical green line, is a critical indicator of the lightning event happening to the turbine.

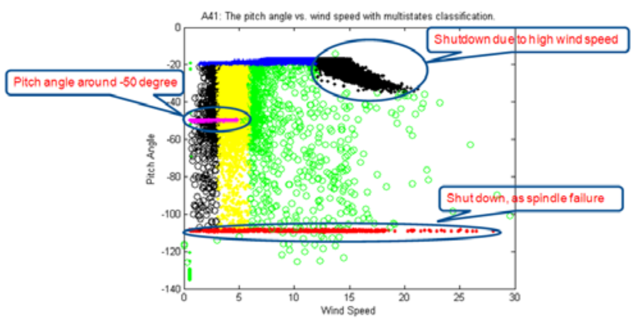


Figure 4. State diagram for pitch angle vs. wind speed

Table III. State Definition of Pitch Angle (Dp , °) vs. Wind Speed (Vw , m/s)

State	Definition	Working Condition
1	$-110< Dp \le -108$ (Horizontal state)	Shut down with hard failures
2	$0.5< Vw \le 0.7$ (Vertical State)	Anemometer failures
3	$Dp = -50$	Default setup
4	$3\le Vw \le 6$ and $-108< Dp \le -20$	Normal working or ramping up/down
5	$Vw \le 12$ and $Dp >-20$	Normal working
6	$12< Vw \le 22$ and $-35 \le Dp \le -15$	Switch pitch angle to avoid damage caused by high wind speed
7	Abnormal Dp when $Vw <3$	Under-performing in low wind speed
8	Abnormal Dp when $Vw >6$	Under-performing in high wind speed

These three tests are combined to reach a final conclusion, which cannot be made by a single test. For each test, our processing tracks changes in the number of measurements reported in the various colored regions over time, mathematically presented by the percentage distribution of multiple states. This provides us with a clearer picture of what is happening automatically. Through extensive data mining of historical data and verification form farm operators, some state combinations are discovered to be strong indicators of spindle failures, lighting strikes, anemometer anomalies, etc. To detect these failures, it is necessary to understand the turbine health condition fused from multiple performance tests.

3. PATTERN RECOGNITION BY FUSING MULTIPLE TEST RESULTS WITH PSO

After extracting turbine working features from the multiple performance tests, it is critical to recognize different patterns of turbine health condition at current time by fusing all the test results. To monitor the turbine performance on daily base and understand turbine daily health condition better, we apply particle swarm optimization (PSO) algorithm to determine the fusion rules more objectively and optimally.

3.1. Turbine Health Condition Analysis and Classification

The data for each day is analyzed as a unit to detect on which days the turbine behaves abnormally. Assuming that there are n observations per day, we run the multiple tests, designed for describing turbine performance, on each observation point. In each test, multiple features are extracted to indicate different health conditions (Osadciw et al, 2010), such as complete shut-downs, under-performing, abnormally frequent default, as well as, normal working.

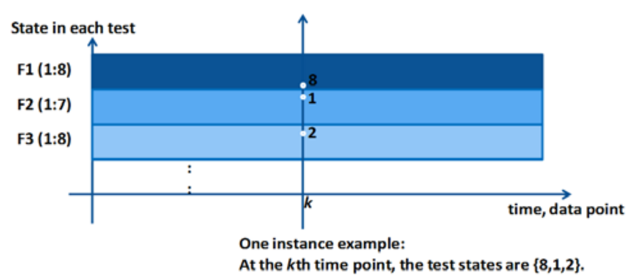


Figure 5. Turbine health condition analysis procedure

Through extensive data mining of historical data and verification from farm operators, every state combination corresponds to one type of turbine health condition. Some state combinations are also discovered to be strong indicators of turbine abnormalities. Figure 5 demonstrates the procedure of testing turbine performance at the *kth* time point. Functions *F1*, *F2*, *F3* are defined for the power curve test, the rotor speed test, and the pitch angle test, respectively. Each test result is one feature of turbine health condition at the *kth* time point. So, more tests extended, more specifically the turbine performance can be described.

At the *kth* time point, the corresponding state combination is {8, 1, 2}, in which the three numbers orderly represent the result states of the power curve test, the rotor speed test, and the pitch angle test. The result of the rotor speed test belongs to the horizontal state 1, which means that the rotor speed is relatively low while the wind speed is quite high; meanwhile, the power produced is negative at this time point, which is assigned as the abnormal working state 8. These two features indicate that this turbine is barely rotating due to failures. Moreover, the pitch angle also stays in the vertical state 2. This is because the turbine makes its blades get the least wind area to avoid a destructive break. All of the multiple tests tell that the turbine is in an abnormal condition due to a bad windy weather. The detection results have been verified as a lighting strike to this turbine.

Based on the knowledge from both wind energy experts and observation data, we classify the turbine health condition into 5 different categories:

1. Normal Operation
2. Ramping Up or Down
3. Under-performing and Degradation
4. Safe Shutdown
5. Abnormal Shutdown

Category 2 is defined as a working status when the turbine is ramping up or down caused by its normal reaction to wind speed varying, different control settings, etc. Category 3 describes the situation that even the turbine still keeps running but its performance has already been degrading. It is a warning sign to the later complete shut-down. The safe shutdown is due to some allowable reasons, such as annual maintenance; on the contrary, the abnormal shutdown happens unexpectedly because of several harmful faults, such as the spindle failure. Each state combination that has ever occurred to turbines is assigned to its relative health condition category, as shown in Table IV.

Table IV. Turbine Health Condition Category Assignment

Category	Relative State Combinations
1. Normal Operation	254, 255, 256, 354, 355, 356, 444, 455, 456, 556
2. Ramping Up/Down	813, 833
3. Degradation	378, 558, 578, 754, 755, 834, 837, 854, 855
4. Safe Shutdown	811, 812, 818, 911
5. Abnormal Shutdown	611, 633, 644, 618, 671

3.2. Applying PSO to Determine the Fusion Rules of Turbine Daily Health Condition

The whole data set of one turbine is divided into daily data, with *n* observations per day. As mentioned above, fault detection through data fusion is more robust than using individual tests. So, after running multiple tests as time goes by, each observation point is assigned one particular state combination. To monitor the turbine performance on daily base and understand turbine daily health condition better, the main problem is to fuse the *n-point* state combinations into one category for each day, which requires the construction of a weight matrix as the fusion rules. We utilize PSO to determine the weight matrix learning from historical working days objectively and optimally. Then, the fusion rules are tested on the future data.

Based on the previous analysis, the particle in this application is defined as a weight matrix,

$$Particle_l = \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} & w_{15} \\ w_{21} & w_{22} & w_{23} & w_{24} & w_{25} \\ w_{31} & w_{32} & w_{33} & w_{34} & w_{35} \\ w_{41} & w_{42} & w_{43} & w_{44} & w_{45} \\ w_{51} & w_{52} & w_{53} & w_{54} & w_{55} \end{bmatrix}_l, \qquad (2)$$

where the particle index is l going from 1 to L which is the total number of particles, and the weight w_{ij} means how determinant it is to daily category i when there are state combinations belonging to category j happened. Usually, the weights in the diagonal line are much higher than the others on the same row, since they are in a dominant role for defining the significance of the row-corresponding category.

The total daily percentage P_i of category i is defined in equation (3),

$$P_i = \sum_{j=1}^{5} (w_{ij} \times \sum_{k=1}^{K} p_{jk}), \qquad (3)$$

where p_{jk} is the daily percentage of *kth* state combination which is classified into category *j*. Then set the category with the maximum percentage to turbine health condition for this day by following equation (7),

$$category \equiv \arg\max(P_i), \qquad (4)$$

After the health condition category of each day is assigned, any weight matrix may incur inconsistency with identified daily category in the training set. The fitness function is the total amount of these un-matching days,

$$Fitness_l = \sum_n I(category_n \neq true\ category_n) \qquad (5)$$

where, for each particle solution, n is the set of day indices in the training set, I is a counting function, with value 1 when the argument is true, or else 0. The optimal solution minimizes the fitness function.

3.3. Simulation and Results

We have 900 days' worth of data, and we split them into training and testing sets. The training set includes the first 500 days. We use 200 particles and let them search in 100 iterations. Note that the number of particles could be reduced to maintain a similar performance, and our analysis indicates that more particles do not necessary improve performance, and hence we use 200 particles. We have tried different total number of iterations. PSO often converges in less than 40 iterations, and we choose 100 iterations to allow some tolerance.

In each iteration, the fitness of each particle is evaluated by equation (5). The best solution seen by each particle is used to update p_{best_i}, and the best solution seen by the whole population is used to update g_{best}. Through iterations, all particles move towards to the optimal locations driven by their own cognitive awareness and social influence.

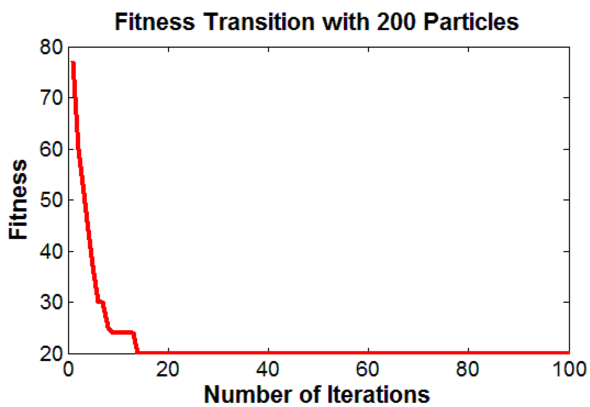


Figure 6. Fitness of PSO over 100 iterations

Figure 6 shows the progression of g_{best} versus iterations of PSO algorithm. As shown in Figure 6, the fitness value by PSO converges below 20 around the *15th* iteration.

After fusing the daily state combinations, with the learned weight matrix, each day will have one category to describe its turbine health condition. This novel approach gains a qualitative understanding of turbine performance to detect faults, and it also provides explanations on what has happened for detailed diagnostics.

4. DATA-DRIVEN BAYESIAN INFERENCE FOR TURBINE FAILURE PREDICTION

The main purpose of applying Bayesian inference is to identify and predict particular failures with statistical certainty by online monitoring turbine health condition. Assuming that the faulty turbine follows specific degradation patterns due to one differential failure before and after it happens, the Bayesian network is able to tell the wind farm operators what type of failures is happening to this turbine, and tell the time when it is probably going to shut down.

For the purpose of prognostics, we model the degradation pattern by analyzing the turbine health condition among 25 days backwards from the day when the interesting event starts. The network is given as a fully connected structure, in which each level of variables represents the all health condition ever occurred on this day, and each variable is binary, with value 1 when this health condition happens; otherwise, it is 0. The problem focuses on learning the joint probability distribution of each two health conditions between two adjacent days.

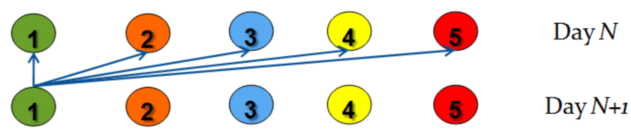


Figure 7. Bayesian inference structure of turbine health condition variation between two adjacent days

Let θ_{ijk} to denote $p(x_i = j \,|\, \Pi_i = k)$, where x_i is one of the 5 turbine health condition categories in day *N*. If *j* is 1, this health condition appears, or else does not. And, *k* is a combination of the health conditions happened in the next day *N+1*. The parameter vector Θ is estimated from a collection ***D*** of independent data cases $D_1, D_2, ..., D_m$ when the interesting event arises. The joint probability table is shown as

$$\Theta = [\ p_{ij}(x_i = 1,\ y_j = 1)\ ], \qquad (6)$$

where $i,\ j \in 1, 2, 3, 4, 5$. In this joint probability table, the row and column represent the category indices of turbine health condition in the current day *N* and its next day *N+1*, respectively. The value of p_{ij} is the joint probability that both health conditions x_i in day *N* and y_j in day *N+1* happen. If p_{ij} is equal to 0, there is no link between the nodes x_i and y_j.

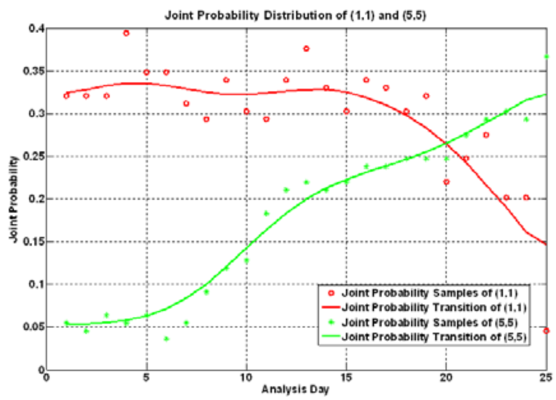


Figure 8. Joint probability transition of turbine health condition among 25 days before spindle failure happens

Considering spindle failure as an example, Figure 8 shows the joint probability transition of turbine health condition among a total of 25 analysis days before it happens. The red points are joint probability samples of variable (1, 1), meaning that the turbine keeps working properly in two adjacent days; whereas, the samples of variable (5, 5), represented by the green points, indicate that the turbine is shutting down completely in two adjacent days. As shown in this figure, the abnormal shut-down is gradually increasing, since 20 days before the spindle failure happens. Meanwhile, the turbine barely operates normally during the same time, especially around 10 days before this failure is verified. In other words, the good condition is decreasing and the bad one is increasing since 20 days before the spindle failure really happens.

To sum up, the Bayesian inference automatically monitors turbine health condition and predicts any particular failure before it happens. As a result, failures can be detected at an early stage, so that the potential damage could be minimized or mitigated through early repairs, avoiding drastic breakdowns of the wind turbine. Also, maintenance can be optimally scheduled, which leads to less down-times and more revenue.

5. CONCLUSION

In this paper, we propose a SCADA-based condition monitoring and prognostics system for early detection and warning of wind turbine failures and performance issues. We develop three tests on generated power, rotor speed and pitch angle against wind speed separately. In each test, multiple states are defined to distinguish different health condition, including complete shutdown, under-performing, abnormally frequent default, as well as normal working. These tests are combined to reach a final conclusion, which cannot be made by a single test.

To monitor the turbine performance better on daily base, it is critical to recognize different patterns of turbine health condition by fusing all the test results. We apply particle swarm optimization (PSO) algorithm to determine the fusion rules more objectively and optimally.

Then, assuming that the faulty turbine follows specific degradation patterns due to differential failure before and after it happens, we design a Bayesian inference approach to predict turbine potential failures with a percentage certainty by tracking the abnormal variations. The Bayesian network is able to tell what type of failures is happening to this turbine, and when it is probably going to shut down.

Our approach automatically monitors the dynamic health condition of a wind turbine. By doing so, we can detect and predict early or prevent the secondary defects and major break-downs, which minimizes the damage that the failures imposed on the turbine performance. Also, this procedure is advantageous in its adaptability to each turbine using SCADA data, to monitor a large wind farm.

REFERENCES

Z. Chen and F. Blaabjerg, *Wind energy: the world's fastest growing energy source*, IEEE Transactions on Power Electron Soc Newsletter, vol. 18, no. 3, 2006.

W. Yang, P. Tavner, C. Crabtree, and M. Wilkinson, *Cost-effective condition monitoring for wind turbines*, IEEE Transactions on Industrial Electronics, vol. 57, pp. 263-271, Jan. 2010.

C. Crabtree, *Survey of commercially available condition monitoring systems for wind turbines*, SuperGen Wind, November 2010.

S. Sheng, F. Oyague and S. Butterfield, *Investigation of various wind turbine condition monitoring techniques*, 7th International Workshop on Structural Health Monitoring, Stanford University, Stanford, Sept. 2009.

A. Zaher, S. McArthur, D. Infield, and Y. Patel, *Online wind turbine fault detection through automated SCADA data analysis*, Wind Energy, vol. 12, no. 6, pp. 574-593, Sept. 2009.

A. Kusiak and A. Verma, *Monitoring wind farms with performance curves*, IEEE Transactions on Sustainable Energy, vol. 4, no. 1, January 2013.

J. Kennedy and R. Eberhart, *Particle swarm optimization*, in Proceedings of IEEE International Conference on Neural Networks, vol. IV, pp. 1942-1948, 1995.

W. Lu and F. Chu, *Condition monitoring and fault diagnostics of wind turbines*, in Proceedings of IEEE Prognostics and System Health Management Conference, 2010.

Z. Chen, X. Lian, H. Yu and Z. Bao, *Algorithm of data mining and its application in fault diagnosis for wind turbine*, 2nd International Symposium on Knowledge Acquisition and Modeling, vol. 2, pp. 240-243, Nov. 2009.

A. Zaher and S. McArthur, *A multi-agent fault detection system for wind turbine defect recognition and* *diagnosis*, IEEE Lausanne of Power Tech., vol. 57, pp. 22-27, July. 2007.

X. Ye, K. Veeramachaneni, Y. Yan and L. A. Osadciw, *Unsupervised learning and fusion for failure detection in wind turbines*, in Proceedings of 12th International Conference on Information Fusion, July 2009.

Lisa. A. Osadciw, Y. Yan, X. Ye, G. Benson and E. White, *Wind turbine diagnostics based on power curve using particle swarm optimization*, in Book Wind Power Systems: Applications of Computational Intelligence, Springer, 2010.

B. D. Chen, *Survey of commercially available SCADA data analysis tools for wind turbine health monitoring*, Technical Report of SuperGen Wind EPSRC Project, Nov. 2010.

W. G. Garlick, R. Dixon and S. J. Watson, *A model-based approach to wind turbine condition monitoring using SCADA data*, in Proceedings of 20th International Conference on Systems Engineering, 2009.

Z. Hameed, Y. S. Hong, Y. M. Cho, S. H. Ahn, and C. K .Song, *Condition monitoring and fault detection of wind turbines and related algorithms: a review,* Renewable and Sustainable Energy Reviews, vol. 13, pp. 1-39, 2009.

S. F. Cheng and M. G. Pecht, *Multivariate state estimation technique for remaining useful life prediction of electronic products*, in Proceedings of AAAI Artificial Intelligent Prognostics, 2007.

Schwabacher, M., & Goebel, K. F. (2007). *A survey of artificial intelligence for prognostics,* in Proceedings of AAAI Fall Symposium, November 9–11, Arlington, VA.

T. Wang, J. Yu, D. Siegel, J. Lee, A similarity-based prognostics approach for remaining useful life estimation of engineered systems, in Proceedings of International Conference on Prognostics and Health Management, 2008.