Bayesian Networks for Wind Turbine Fault Diagnosis

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Abstract

Wind turbine reliability studies have become more important because good wind turbine reliability with predictable turbine maintenance schedule will reduce the cost of energy and determine the success of a wind farm project. Previous research on wind turbine SCADA system has made progress in this respect. However, SCADA data volume is usually too huge and alarm information is too unclear to indicate failure root causes. In addition, SCADA signals and alarms are not currently interpreted as a whole. This highlights the need for more intelligent methods which can use existing SCADA data to automatically provide accurate WT failure diagnosis. This paper presents a new approach, based on Bayesian Network, to describe the relationship between wind turbine failure root causes and symptoms. The Bayesian Network model was derived from an existing probability-based analysis method – the Venn diagram, and based upon 26 months of historical SCADA data. The Bayesian Network reasoning results have shown that the Bayesian Network is a valuable tool for WT fault diagnosis and has great potential to rationalise failure root causes.

Keywords: Wind Turbine, Bayesian Network, SCADA, Fault Diagnosis.

1 Introduction

Wind turbine (WT) downtime and Operation & Maintenance (O&M) costs constitute a sizable share of the annual cost of a wind farm (WF) [1]. With the increase of wind energy development, especially the rapidly growing number of offshore WFs, research regarding WT reliability is becoming significant and critical [2].

The essence of improving the reliability of WT is to reduce the downtime and increase its availability by optimizing both the WT design and the maintenance schedule. Both of these strategies require a full understanding of the WT system and a detailed analysis of it failure mechanisms. WT monitoring systems provide a rich resource of data to achieve this as they archive comprehensive historical signal & alarm information, with detailed fault logs and environmental & operational conditions [3, 4, 5]. A WT's systematic performance can be monitored through a proper analysis of the information collected by those monitoring systems which cover all the major WT sub-assemblies. Initial attempts to use WT monitoring data, including Supervisory Control and Data Acquisition (SCADA) and Condition Monitoring systems (CMS) to detect WT failure have been made [6, 7]. This paper is a further study of Venn diagram analysis from [8], which focuses on using Bayesian Networks (BN) to analyse SCADA data and proves its feasibility on WT fault diagnosis.

2 SCADA System

WTs are monitored for a variety of reasons with different systems offering different analysis methods and possibilities for fault detection. Among them, SCADA system is a standard installation on large WTs and wind farms, their data being collected from individual WT controllers. According to [3] the SCADA system assesses the status of the WT and its sub-assemblies using sensors fitted to the WT, such as anemometers, thermocouples and switches. The signals from these instruments are monitored and recorded at a low data rate, usually at 5 or 10 minute intervals.

SCADA system contains signals and alarms and has been widely researched over the last decade [3, 6]. Some recent studies include signal-based analysis approaches for WT gearbox and generator [9], a system called SIMAP based on artificial neural network aimed to detect and diagnose gearbox failures [10], a probability analysis of pitch performance curves for identifying faults in pitch system [11], an automated analysis system also based on artificial neural network [3], time-sequence and probability based analysis method to rationalise and reduce SCADA alarm data [8], and a pattern recognition approach for identifying faults in WT pitch system [12].

From above literature, it can be seen that the SCADA data volume is usually too huge and alarm information is too unclear to indicate failure root cause. In addition, SCADA signals and alarms are not interpreted as a whole. This highlights the need for more intelligent methods that can use existing SCADA data to automatically provide accurate WT failure diagnosis.

This paper presents a new approach, based on BN, to describe the relationship between WT failure root causes and symptoms. The BN model was derived from the Venn diagram of [8]. Both SCADA signals and alarms are used to prove the great potential to rationalise failure root causes.

3 Bayesian Networks

BN are directed acyclic graph models for describing the relationships between causes and effects [13]. The model consists of nodes and arcs as shown in Figure 1. The nodes represent variables and the arcs express the probability dependences between the linked variables. In addition, each node in BN has an associated priori probability table - Node Probability Table (NPT) [13].

3.1 Constructing Bayesian Network

The structure or topology of the BN should capture qualitative relationships between variables. In particular, two nodes should be connected directly if one affects or causes the other, with the arc indicating the direction of the effect. So, in our WT example, we might ask what factors affect a turbine’s chance of stop? If the answer is “Low Wind” and “Maintenance” then we should add arcs from “Low Wind” and “Maintenance” to “Turbine Stop”. Similarly, having turbine stop will affect the power output and the changes of nacelle temperature. So we add arcs from “Turbine Stop” to “Power Output” and “Nacelle Temperature”. The resultant is shown in Figure 1(a). It is important to note that this is just one possible structure for the problem; the alternative network structure is shown in Figure 1(b) [13].

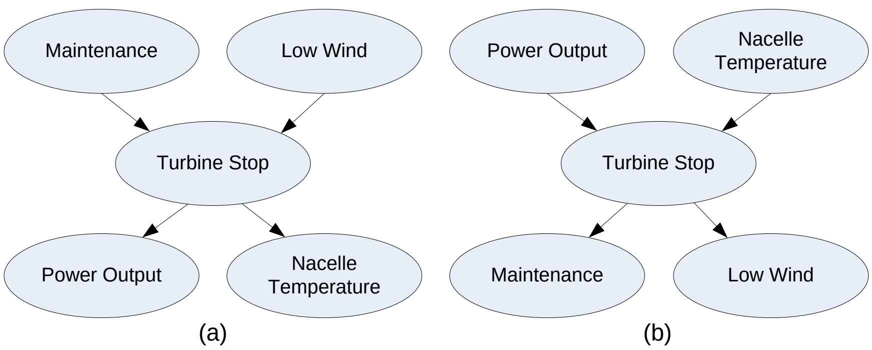

Figure 1: Two different BN models for WT case study

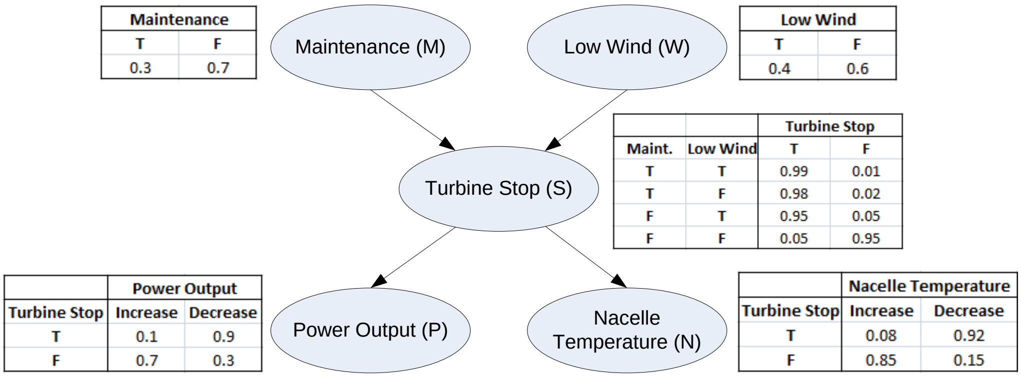

Figure 2: BN with node probability table

3.2 Bayesian Network Learning

The BN learning is done by specifying connectional probability distribution for each node, the NPT [13].

For each node, we need to look at all the possible combination of values of those parent nodes. Each such combination is called an instantiation of the parent set. For each distinct instantiation of parent node values, we need to specify the probability that the child will take each of its values.

For example, consider the "Turbine Stop" node of Figure 1 (a). Its parents are "Maintenance" and "Low Wind" and take the possible joint value $\{<T,\ T>, <T,\ F>, <F,\ T>, <F,\ F>\}$. The conditional probability table specifies in order the probability of Turbine stop for each of these cases are: $\{0.99,\ 0.98,\ 0.95,\ 0.05\}$. Since these are probabilities, and must sum to one over all possible states of the "Turbine Stop" variable, the probability of turbine running is already implicitly given as one minus the above probabilities in each case; therefore, the probability of turbine running in the four possible parent instantiations are $\{0.01,\ 0.02,\ 0.05,\ 0.95\}$, as shown in Figure 2.

Root nodes also have an associated NPT, although it contains only one value representing its prior probabilities. In our example, the prior for a turbine under maintenance is given as 0.3, indicating that 30% of population that the turbine sees are under maintenance.

Clearly, if a node has many parents or if the parents can take a large number of values, the NPT can get very large. In fact, the size of the NPT is exponential growth with the increase of parent node numbers [13].

3.2 Maths behind Bayesian Networks

BN are considered to be representations of joint probability distribution with the introduction of the independence assumption [13].

Consider a BN containing n nodes, X_1 to X_n. A particular value in the joint distribution is represented by $P(X_1 = x_1,\ X_2 = x_2, \dots,\ X_n = x_n)$, or more compactly, $P(x_1,\ x_2, \dots,\ x_n)$. The chain rule of probability theory allows us to factorise joint probabilities so:

$$\begin{aligned} P(x_1, x_2, \dots, x_n) &= P(x_1) \times P(x_2|x_1) \dots, \\ &\times P(x_n|x_1, \dots, x_{n-1}) \\ &= \prod_i P(x_i|x_1, \dots, x_{i-1}) \quad (1) \end{aligned}$$

The structure of a BN implies that the value of a particular node is conditional only on the values of its parent nodes, thus the equation (1) is reduced to:

$$P(x_1, x_2, \dots, x_n) = \prod_i P(x_i|Parents(X_i)) \quad (2)$$

where $Parents(X_i) \subseteq \{x_1, \dots, x_{i-1}\}$ denotes the set of parent of x_i. For example, by exampling Figure 2, we can simplify its joint probability expressions like below:

$$\begin{aligned} &P(P = Inc, N = Inc, S = T, M = T, W = T) \\ &= P(P = Inc|N = Inc, S = T, M = T, W = T) \\ &\quad \times P(N = Inc|N = Inc, S = T, M = T, W = T) \\ &\quad \times P(S = T|M = T, W = T) \\ &\quad \times P(M = T|W = T) \\ &\quad \times P(W = T) \end{aligned}$$

$$= P(P = Inc|S = T) \times P(N = Inc|S = T) \times P(S = T|M = T, W = T) \times P(M = T) \times P(W = T)$$

3.3 Reasoning with Bayesian Network

The key feature of BN is that they enable us to model and reason about uncertainty. The BN forces the assessor to expose all assumptions about the impact of different forms of evidence and hence provides a visible auditable dependability.

The BN reasoning is a simple step of calculating new belief when new information, which is called evidence, is available. Suppose we want to know the probability of Turbine is stop, given evidences $Power\ Output = Inc$, $Nacelle\ Temp = Inc$, $Maintenance = T$ and $Low\ Wind = T$. Then, according to Bayes Theorem, the question can be expressed as:

$$P(S = T|P = Inc, N = Inc, M = T, W = T)$$

$$= \frac{P(S = T, P = Inc, N = Inc, M = T, W = T)}{P(P = Inc, N = Inc, M = T, W = T)}$$

$$= \frac{P(S = T, P = Inc, N = Inc, M = T, W = T)}{\sum_{S\in\{T,F\}} P(P = Inc, N = Inc, M = T, W = T)}$$

After that, by using equation (2) and entering value from BN NPT, we can easily get the result.

The uses of BN have been increasing in many domain problems and in many kinds of application, including but not limited to diagnosis problem and fault detection [14].

4 Implementation of Bayesian Network

4.1 Bayesian Network Model

A study using SCADA data to detect and locate faults in a 2MW variable speed WT's electrical pitch system is presented. The BN model was derived from results of a Venn diagram probability-based analysis [8] and based upon 26 months of historical SCADA data. 3 SCADA signals and 5 SCADA alarms were used in this study as shown in Table 1.

Name	Type	Sampling Rate	Description
Power Output (Avg)	Signal	10 minutes	Average power output in the past 10 minutes.
Blade 1 Motor Torque (Max)			Maximum blade 1 motor torque in the past 10 minutes.
Blade 1 Angle (Avg)			Average blade 1 angle in the past 10 minutes.
Blade 1 Emergency	Alarm	1 second	Due to a fault, blade 1 feathers its angle of attack to 86º for a stop.
PCP EFC			PCP has initiated emergency feather control.
SPA Fault in Blade 1			This alarm occurs due to a blade specific servo power amplifier fault.
Short Circuit Blade 1			This alarm occurs due to power interruption caused to the blade 1's inverter.
Motor 1 Saturation Limit			This alarm occurs due to motor over-current.

Table 1: SCADA data used in this study

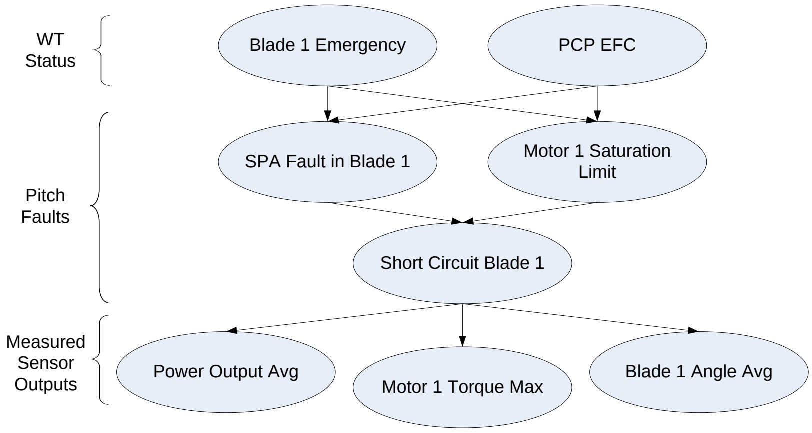

Figure 2: BN model for WT pitch system

Figure 2 shows the derived BN model for a WT pitch system representing a knowledge structure that models the relationship between WT Status, Pitch Faults and Measured Sensor Outputs.

4.2 Data Preparation

The original SCADA data in Table 1 is required to be processed to resolve the following problems:

- **Representation:** Signals are continuous data and are difficult to represent WT running status;
- **Inconsistency:** Signals and alarms have different sampling rate;

Therefore, Signal Variance (v_t) and Alarm Presence Length (a_t) are introduced. The v_t is defined as:

$$v_t = s_t - s_{t-1} \quad (3)$$

where v_t denotes the Signal Variance at time t. s_t and s_{t-1} represent the original SCADA signal data at time t and $t-1$ respectively. Where a_t denotes the Alarm Presence Length in seconds from time $t-1$ to t, defined as:

$$a_t = f(t-1, t) \quad (4)$$

f is a function used to calculate the amount of time in seconds. Equation (4) will update Alarm sampling rate from 1 second to 10 minutes to make it consistent with the SCADA signal.

After that, indicator functions are introduced to represent SCADA data in different data range, defined as:

$$Signal = \begin{cases} Rapidly\ Increasing, & v_t > 100 \\ Almost\ Constant, & -100 \le v_t \le 100 \\ Rapidly\ Decreasing, & v_t < -100 \end{cases} \quad (5)$$

$$Signal = \begin{cases} Rapidly\ Increasing, & v_t > 10 \\ Almost\ Constant, & -10 \le v_t \le 10 \\ Rapidly\ Decreasing, & v_t < -10 \end{cases} \quad (6)$$

$$Alarm = \begin{cases} Serious, & a_t > 200 \\ Warning, & 20 < a_t \le 200 \\ OK, & a_t \le 20 \end{cases} \quad (7)$$

where equation (5) is for *Power Output* and equation (6) is for *Blade 1 Motor Torque* and *Blade 1 Angle*. Equation (7) is applied on all alarms.

4.3 Training Bayesian Network

A WT's 26 months SCADA data was used to train the BN and obtain corresponding probabilistic dependencies. The trained result is shown in Figure 3, named the BN with the given priori probability.

Figure 3: Trained BN with the given priori probability (Note: Data from healthy condition has been filtered as they occupied most of the training data)

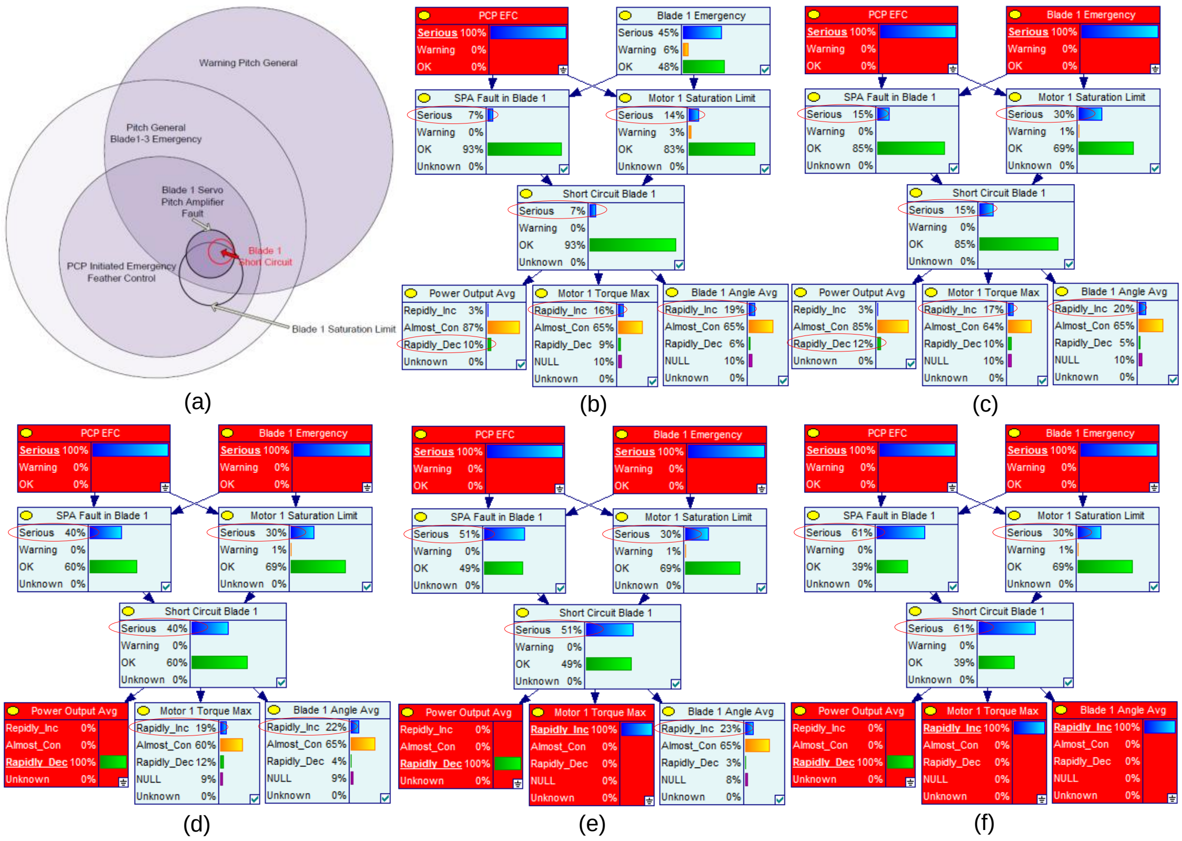

Figure 4: (a) The Venn diagram result from [8], (b)-(f) the BN reasoning with different given evidence(s) (The given evidences are highlighted by filling red colour).

4.4 BN Reasoning

BN are a way of describing complex probabilistic reasoning. By giving user knows posterior probabilities (also known as evidences), the network is able to infer the probabilities of other events, which haven't as yet been observed. Some BN reasoning tests, with the given evidences, are shown in Figure 4 and Figure 5; the corresponding inference results are highlighted in red circle.

The probability-based analysis result from [9] is shown in Figure 4 (a). This result indicated *Blade Short Circuit* was the root cause of the pitch system failure on this occasion. Figure 4 (b)-(f) show the derived BN model used for reasoning with the given evidence(s). Figure 4 (b) shows the BN reasoning with the given evidence of serious *PCP EFC*. By comparing this inference results with the initial trained BN in Figure 3, we could find that the probability of *SPA Fault*, *Motor Saturation Limit* and *Blade Short Circuit* have been increased. Also, in this situation, in order to initialise the blade emergency feather control, *Blade Motor Torque* is required to increase *Blade Angle* and result in decreasing *Power Output*, as shown in Figure 4 (b) and highlighted in red circle.

Figure 4 (c) shows the evidence of serious *Blade Emergency* was added into the BN model. By comparing this result with previous one, we found the new result has got the increased probabilities (As highlighted in red circle). This could be explained as the PCP has initialised the emergency control and the blade had also feathered its angle of attack for a stop, consequently, the probability of pitch fault is increased and corresponding measured outputs are changed to indicate the WT running status.

The evidence of decreasing *Power Output* was added in Figure 4 (d) and the result shows a greater fault probability. This is quite easy to understand as blade feathers its angle of attack for a stop will definitely result in decreasing *Power Output*. On the contrary, the added evidence of decreasing *Power Output* will lead to a corresponding increase in event probability. Figure 4 (e) and (f) show the BN reasoning with adding the evidence of increasing *Motor Torque* and *Blade Angle* respectively. Their inference results show the gradual increase in the change of the events' probabilities.

Through analysing the results from Figure 4 (b) to (f), we found the BN reasoning exactly infer the probabilities of the other events. By simply inputting the current WT's running status as evidence, this model can be applied online to diagnose WT faults.

Another three BN reasoning tests are shown in Figure 5 to represent a WT with and without pitch faults.

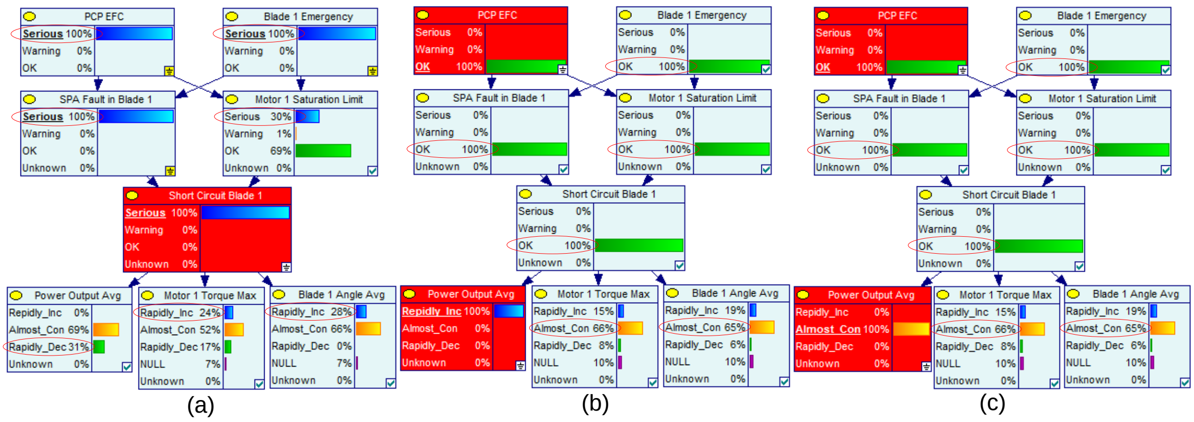

Figure 5: (a) A WT with pitch fault, (b) and (c) A WT without pitch fault.

Figure 5 (a) shows the BN reasoning with the given evidence of serious *Blade Short Circuit*. According to this result, we found that a WT with *Blade Short Circuit* will certainly have the occurrence of *PCP EFC*, *SPA Fault* and *Blade Emergency*. It will also have a large probability of *Motor Saturation Limit*. And in this situation, the WT will require big *Blade Motor Torque* to increase the *Blade Angle* and result in decreasing *Power Output*. Above BN inferences clearly reflects the preventive actions when a pitch fault occurred and it also proved the result of the probability-based analysis [8], as shown in Figure 4 (a).

Figure 5 (b) shows the BN reasoning with the given evidence of no *PCP EFC* and increasing *Power Output*. The BN reasoning results show no fault and the WT is running under good condition. Figure 5 (c) shows the similar results when BN is given the evidence of no *PCP EFC* and constant *Power Output*.

5 Discussion

In this work, the BN model was derived from results of a Venn diagram probability-based analysis [8] and based upon 26 months of historical SCADA data. The trained BN has shown its feasibility to reason root causes in the presence of uncertainty. Comparing to the Venn diagram approach, the BN has the following advantages:

- **Better rationalisation of the data:** This is because in BN models, there is a relationship between cause and effect;
- **More feasible for online fault diagnosis:** By inputting the current WT running status as evidence(s), the BN will be able to infer the probability of other events, E.g. a fault probability;

A drawback of using BN found from this work was that the BN complexity grows exponentially with the increase of parent node numbers. In addition, the size of training data is critical to the success of BN reasoning. So for better performance, large numbers of training data covering a wider range of representative symptoms are needed to assure BN performance.

6 Conclusion

In conclusion, this study of the suitability of BN for the diagnosis of WT pitch system faults has demonstrated that it is a valid technique for automatic WT fault root cause detection.

The results show that the BN approach has the potential to reduce WT O&M cost by making accurate detection, diagnosis and prognosis.

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