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Collaboration Platform for Sustainable Wind Energy Distribution Network

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Abstract: Rapidly rising needs for generating electricity with little or no pollution make wind energy imperative. Fluctuations in output of wind turbines and their frequent stoppages for maintenance or breakdowns, however, limit their penetration into power grids. In this research, pattern recognition models are applied to enhance output estimation by improved failure prediction. In addition, a collaboration platform is developed with demand and capacity sharing and best Matching Protocols that facilitate rationalized collaboration between energy providers to create sustainable distribution networks. A simulation of two communities with two farms and 100 members is conducted to measure the impact of the collaboration platform.

Keywords: Best matching protocol, collaborative control theory, demand and capacity sharing protocol, pattern recognition, sustainable network, wind energy, wind farms.

1. INTRODUCTION

Wind energy has been gaining more attention recently as an environmentally-friendly alternative to traditional fossil fuel or nuclear energy. Wind power generates electricity in a clean, sustainable, and affordable manner without leaving any environmental pollution or wastes. Therefore it will play an important role in protecting the environment while keeping up with the increasing electricity demands. The performance of wind turbines in terms of electricity generation, however, depends on numerous environmental, mechanical, and electrical parameters, e.g. operational status of wind turbines, wind direction, wind speed, weather conditions, etc. As a result, wind power output is highly variable and only partially controllable (Coughlin and Eto, 2010).

In spite of the high uncertainties in energy generation and distribution, wind resources have been integrated gradually into the electric grid as one of the major players. Various programs and studies have been established to increase the share of renewable resources into the electric grid (Enslin, 2009; Lund, 2005; Lund and Kempton, 2008). The U.S. Department of Energy's report "20% Wind Energy by 2030" envisioned that wind power could supply 20% of all electricity nationwide (U.S. DoE, 2008). The UK Government expects offshore wind energy to be a major contributor to its target to generate 15% of UK electricity from renewable sources by 2020 (Miguelanez and Lane, 2010). The high uncertainty in wind power generation, however, is the major obstacle in achieving these goals. The penetration and integration level of wind energy into the electric grid is relatively low due to the uncertainty, and thus the majority of the electricity demand is still fulfilled by traditional energy sources with well-established infrastructure and stable supplies. Part of the fluctuations in daily energy output of a wind turbine depends on environmental changes such as wind speed and direction. The fluctuating characteristic of wind power is often referred to as intermittency. It is important to note that intermittency is not the same as unpredictability. To the extent that intermittency in wind power is driven directly by weather, it is somewhat predictable, and could be managed in part through the use of near-term wind power forecasts (Matevosyan and Söder, 2006).

In addition to wind power's dependency on weather conditions, turbine failures influence the electricity generation. The performance and failure rates of wind turbines affect the energy output from a wind power system. The wind turbines are often inaccessible because they are situated on extremely high towers or offshore. A large wind turbine outputting, for example 2,400 kW, has a maximum height over 100m (Minowa et al., 2012). Therefore predicting imminent or potential failures in remote wind turbines before they cause severe damages is critical to assure their continuous operation and more accurate output estimation. Since multiple wind turbines in a wind farm working under similar conditions, the correlation between their performances could enhance detecting small changes in the turbine performance before they cause severe damages (Uluyol and Parthasarathy, 2012). Machine learning techniques are widely used to detect faults in several areas including vibrational signals, control systems, sensor validations, etc. (Fernandes et al., 2007; Hush et al., 1997; Xu et al., 1999). In this research, wired and wireless sensor networks are deployed to collect data from a wind farm, which are classified through machine learning methods to improve fault detection and diagnosis in the wind farm.

There have been a number of studies concerning variability reduction in wind farm outputs through prediction of failures for wind turbines, yet the uncertainty in energy output from wind farms is still challenging. This uncertainty could be partly handled by enhanced statistical and machine learning methods; however, the uncertainty in a wind farm output is also condition-based, which cannot be entirely eliminated in spite of being predictable. Moreover, advanced control schemes have been developed to increase the efficiency and reliability of wind turbines. For instance Song et al. (2000) developed a nonlinear and adaptive algorithm to control wind turbine speed. Modern collaborative control theory algorithms (Nof, 2007) are applied in this research to accelerate wind energy penetration in power grids.

Wind farms are naturally subject to fluctuations in their power generation rates that vary with seasonal, environmental, and operational factors. Besides, breakdown of wind turbines are inevitable and could affect the performance of the wind farm in terms of power generation. Thus, a wind farm may encounter two situations regarding its promised amount of supply: 1) capacity shortage, 2) excess capacity (here capacity refers to the amount of power generated over time). The ongoing technological innovations and research works being conducted on smart grid areas, such as supplier and consumer behaviours in automated fashion, are discussed by Gensollen et al. (2013). This paper facilitates the use of collaborative control theory (CCT) to handle these uncertainties in demand and supply of the wind energy. Assuming the participants in the network are willing to share their demand and capacity, this article proposes a CCT-based collaboration platform, which supports communities to fulfil their electricity demand within the network by the collaboration in an effort to create a sustainable energy network. In order to facilitate collaboration between participants for dynamic demand and capacity sharing and matching, the collaboration platform is developed based on two CCT-based protocols: 1) Demand and Capacity Sharing Protocol (DCSP) and 2) Best Matching Protocol (BMP) (Ko and Nof, 2012; Nof, 2007; Velasquez and Nof, 2008, 2009; Yoon and Nof, 2010, 2011a, b).

To summarize, this research aims at 1) reducing uncertainty in output estimation by accurate failure prediction; and 2) designing collaboration protocols to create and control a sustainable wind energy distribution network. This paper is organized as follows. Section 2 describes a pattern recognition model for failure prediction. Section 3 explains the two CCT-based protocols under the collaboration platform. A simulation study with two communities is illustrated in Section 4. Finally, Section 5 concludes this article.

2. MULTIVARIATE FAILURE PREDICTION MODEL

Wind turbine failure is one of the major sources of output variability in a wind farm. Environmental conditions as well as turbines' mechanical and operational attributes impact the performance and reliability of wind turbines. For instance, lightning strike to wind turbines is a critical factor for wind turbine operation since it can damage blades, which leads to lowered capacity and increased cost for repairs. Tavner et al. (2010) analysed the data from three different wind farms to study environmental conditions' impacts on wind turbines. They applied a cross-correlation technique to study the dependency between environmental conditions and power outputs. According to their study, the true correlation is between failure rate and changes in weather rather than just wind speed.

To attain a more comprehensive model, we have developed a pattern recognition model to classify the existence of a failure based on multiple variables. The theoretical developments of pattern recognition and newer algorithms are collected by Theodoridis et al. (2010)

The variables used in the model are actual rotation speed of the blade, actual torque, DC bus power, and wind speed. Different failure prediction models can be developed based on the size and/or type of renewable energy sources (e.g. solar panels) or the failure type desired to be controlled, i.e., the input variables of the pattern recognition model might be different to predict the failures of a solar panel. The objective is to determine whether a wind turbine has a general electrical error based on the input variables. The major failures we consider in this initial analysis include Gio Expansion Module-1 short circuited, Gio Expansion Module-2 short circuited, and battery failures, which are recorded by the controller in the wind turbine installed at Environmental Resource Training Center of Southern Illinois University Edwardsville. To collect the required data, a wireless sensor network has been added to the wind turbine equipped with accessible wired sensors. Total 360 observations associated with the major electrical failures have been obtained during July and August 2013. The collected data are partitioned into train/validation/test sets (70%/15%/15%), which are used to create and train an artificial neural network (ANN) model for pattern recognition for failure detection in the wind turbine. The ANN is composed of three layers with 4 input variables, 10 hidden layers and one binary output, and trained by scaled conjugate gradient back-propagation algorithm.

The performance plot of the pattern recognition model is depicted in Fig. 1. According to the results, the mean squared error for the validation data is 0.12962. Thus, the probability of false electrical alarm or missed true failures based on the selected multiple input variables is 12.96% which is considered to be acceptable for the wind turbine data. The plot also shows no sign of over-fitting.

The confusion matrix in Fig. 2 shows how well the model clusters the data based on their input variables. Outputs are classified as class 1 if they are electrically failed and classified as class 2 if they are in normal working status. The error for the test data set is 11.1% which is acceptable. Therefore it is concluded that the ANN model is effective in predicting the failure, but there is still some room to improve. The error in prediction and the subsequent uncertainty can be handled by 1) improving the prediction model that considers additional input factors and different classes of failures; and 2) reducing the negative impact of uncertainty by collaboration, which is described in Section 3.

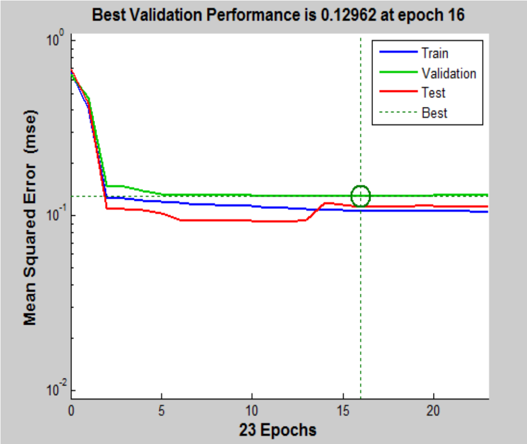

Fig. 1. Performance plot of the pattern recognition model

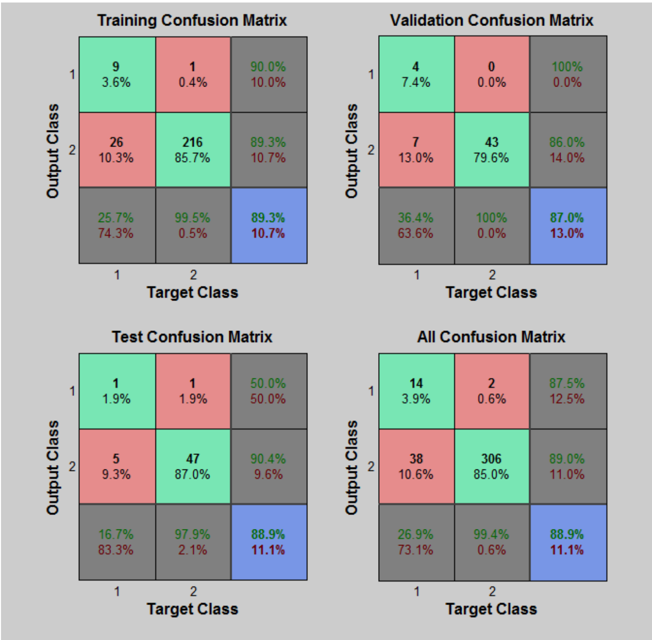

Fig. 2. Confusion matrix of the pattern recognition model

3. COLLABORATIVE WIND ENERGY DISTRIBUTION NETWORK

This research is motivated by the stochastic nature of the electricity demands, the dynamic changes in power generation over time, and the ability to overcome such uncertainty through collaboration between energy providers to build a sustainable energy distribution network. In this network, each energy provider is deemed to be a self-operative organization who is willing to collaborate with one another to achieve higher benefits. For example, when a wind farm cannot fulfil a customer order, the demand will be shared with other collaborating providers who have excess capacity. As a result, the possibly unfulfilled demand can be delivered by other farms and the remaining capacity of collaborating farms can be utilized, such that mutual benefits can be achieved. This collaboration, controlled by a well-defined Demand and Capacity Sharing Protocol (DCSP; Yoon and Nof, 2010, 2011a, 2011b), can encourage the energy providers to improve their benefits by selling their excessive power outputs and motivate the customers to join the sustainable network for getting the renewable energy with more economical prices.

This sustainable energy network is characterized by a heterarchical framework, such that a farm does not have total control over the other collaborating farms. The collaborating farms achieve their goals only through collaborative decision making processes that involve information exchange, negotiation, and coordination.

Consider a set of collaborative wind farms $F = \{f_1, f_2, ..., f_n\}$, where each farm serves its own community $C = \{c_1, c_2, …, c_n\}$. Each farm will try to serve its community in the first place based on its forecasted electricity demand. A forecasting model can be developed based on complex regression methods coupled with classical time series techniques such as the seasonal ARIMA (Cho et al., 2013). Suppose that the electricity demand of k-th community on day t is forecasted to be d_k^t. The corresponding wind farm needs to evaluate whether it can serve the whole or a part of the community demands on the given day based on the farm's capacity constraints and environmental/operational conditions. If the capacity constraint is violated, a portion of d_k^t cannot be accepted by the farm. By sharing the demands and capacities among collaborative wind farms dynamically, it would be possible for that portion of the demand to be fulfilled by a set of collaborating energy providers, such that the mutual benefits can be achieved, i.e., the demand sharing farm fulfils its own community demand, and the capacity sharing farm receives the additional demand. This collaboration will be controlled by the DCSP, which will increase the reliability of demand fulfilment in the network and motivate communities to participate in the network.

Let CA_k^t be the capacity of the wind farm that belongs to community k on day t, and d_k^t be the forecasted demand of the same community. The shared capacity (SC_k^t) and shared demand (SD_k^t) of community k on day t can be calculated as:

$$SC_k^t = \begin{cases} CA_k^t - d_k^t & \text{if } CA_k^t > d_k^t \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$SD_k^t = \begin{cases} d_k^t - CA_k^t & \text{if } CA_k^t < d_k^t \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

The DCSP can be defined as follows:

1) Start at period T. Periods can be daily or weekly, depending on the possibility in terms of available resources (for forecasting, for example) and the anticipated precision in decisions.
2) At the beginning of each period, define sets A and B based on 1) output forecasts, 2) turbine breakdown forecasts, and 3) demand rates associated with each wind farm.
3) The information on Sets A and B are shared with all wind farms in the corresponding coalition.
4) Wind farms in Set A receive orders, evaluate, and based on their available capacity either 1) accept the order, or

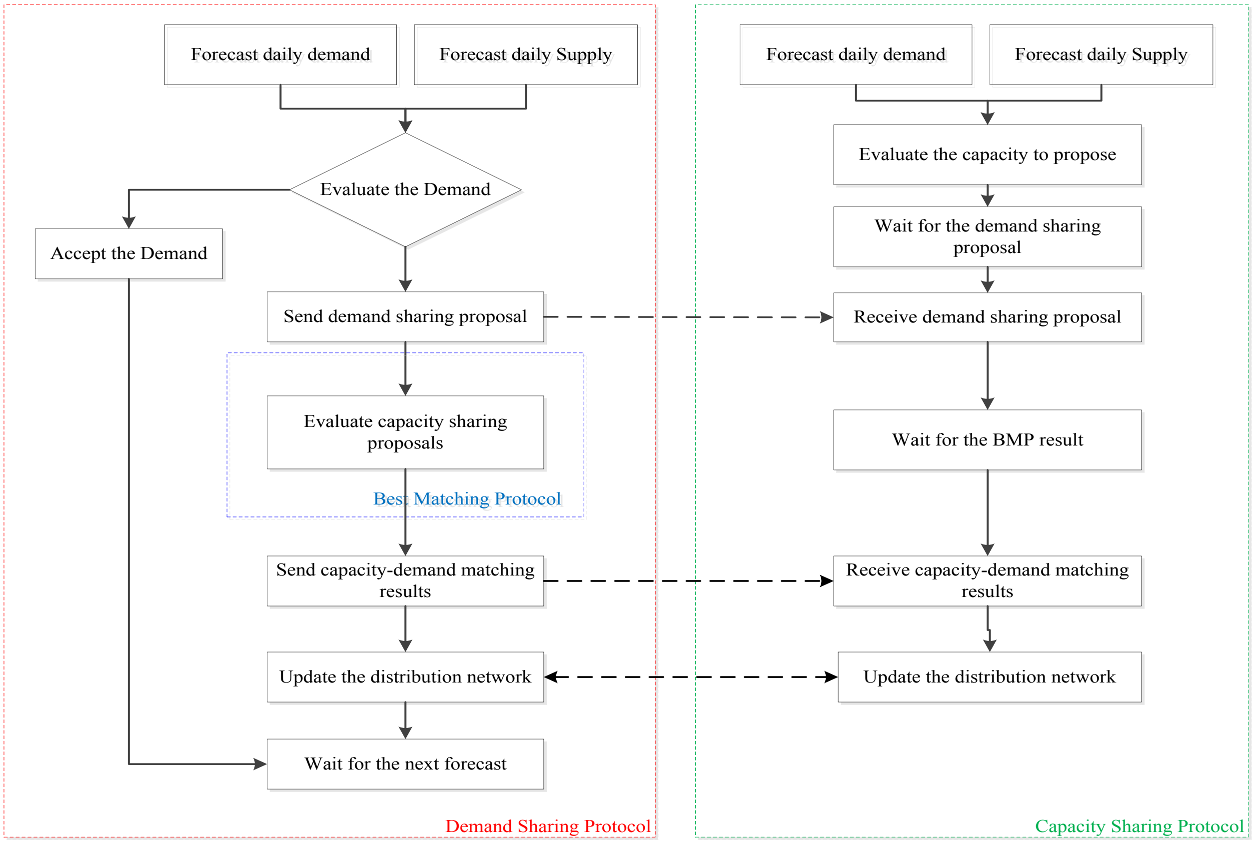

Fig. 3. DCSP and BMP for the collaboration platform (Yoon and Nof, 2010, 2011a, 2011b

2) generate and send a demand sharing proposal to the Set B wind farms in their coalition and wait for their capacity sharing proposals.

5) Wind farms in Set B receive different proposals (if any) from Set A, evaluate the capacities that they can promise to each proposal, prepare their capacity sharing proposals and send them back to the wind farms in Set A.
6) Wind farms in Set A receive the capacity sharing proposals and accordingly either 1) reject the order, or 2) accept the order and send the allocation results to corresponding wind farms in Set B.
7) Wind farms in Set B receive the allocation results and accept the shared demand.

Fig. 3 illustrates the overall collaboration process based on DCSP and BMP. Due to technical limitations, a portion of the generated electricity will be wasted during the transmission. This waste of energy is an increasing function of the length of transmission line, from the source to the sink nodes. This phenomenon could have an effect on the efficiency of DCSP. In other words, having an order, related to a specific wind farm, satisfied by some wind turbines in another wind farm may be inefficient in practice due to the pair wise distances. A Best Matching Protocol (BMP) is proposed to bridge the aforementioned gap through dynamic matching of the source and sink nodes, in the 4th step in the DCSP (Velasquez and Nof, 2008, 2009). Having the waste of energy as another decision criterion, there may exist some cases in reality in which some wind farms in Set B (i.e., with excess capacity) prefer to leave a part of their corresponding orders to be satisfied by some other wind farms in Set B or even Set A. In other words, it may be worthwhile (in terms of the waste rate/pair wise distance) that a given farm, despite having enough capacity to fulfil its own orders, would be better off leaving a part of those orders to be satisfied by a second wind farm, thus having enough capacity to fulfil an order related to a third wind farm. In this setting, all wind farms may belong to both Sets A and B, and the BMP will match the best ($a \in A$, $b \in B$) based on certain criteria, e.g., distance. The BMP, which is indeed an optimization problem dealing with the overall waste in the network of wind farms, must be implemented in conjunction with the DCSP. More details are provided in Jahanpour and Ko (2013).

4. SIMULATION

A simulation study including two wind farms and 100 residential members (shown in Fig. 4) is developed to evaluate the effect of the proposed DCSP. Both energy outputs and community demands are stochastic. The same data set mentioned in Section 2 is used to develop a statistical model for outputs required for this study. According to goodness-of-fit results, the following Weibull distribution best describes the energy output:

$$f(x)=\frac{\kappa}{\lambda}\left(\frac{\kappa}{\lambda}\right)^{\kappa-1}e^{-\left(\frac{x}{\lambda}\right)^{\kappa}} \qquad \lambda=1.0132, \kappa=17.719 \tag{6}$$

The energy demand for a residential area depends on many factors, such as household income, weather condition, temperature, family size, etc. Average summer residential

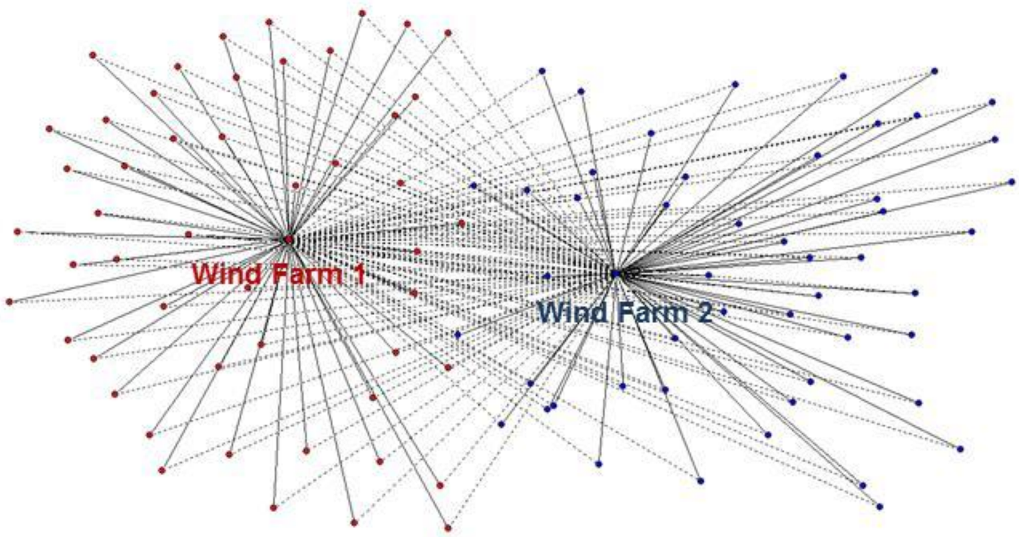

Fig. 4. A sustainable energy distribution network with two wind farms, two communities, and 100 members

electricity usage, however, tends not to vary significantly. According to the 5-year power usage in the U.S. during 2008 to 2012 (U.S. Energy Information Administration, 2013), the average electricity usage follows a normal distribution with mean of 3323.6 and standard deviation of 148.34. These models are used to simulate the energy network.

Both wind farms are assumed to own 60 wind turbines. Since there are only two wind farms operating in this study, BMP is not required to pair communities with farms. If a wind farm cannot fulfil all its community's demand on a given day, the other farm will share its surplus electricity, if any exists, to fulfil the demand. A Monte-Carlo simulation is conducted for 90 days with Matlab. It is assumed that failure of wind turbines in a farm is already reflected in the model and there is a strong correlation between them; however, the correlation across the farms is assumed to be zero. The simulation runs 100 times and the average electricity output before and after DCSP is illustrated in**Error! Reference source not found.** Fig. 5. The solid lines in Fig. 5 illustrate the percentage of fulfilled demand before applying DCSP and dashed line indicate after DCSP. According to the results, DCSP significantly improves the demand fulfilment rates and also decreases the variability. Table 1 contains descriptive statistics of the experimental results. According to the results, each wind farm would be able to fulfil approximately 85% of its corresponding community's energy demands without collaboration. Applying DCSP not only increases the demands fulfilled by the farms, but also decreases the level of uncertainty by reducing the variability in demand fulfilment as indicated by standard deviation.

Table 1. Demand fulfilment rates with and without DCSP

	Before DCSP		After DCSP	
	Comm. 1	Comm. 2	Comm. 1	Comm. 2
Mean	84.03	83.47	93.64	93.55
StDev.	2.78	3.41	2.06	2.24

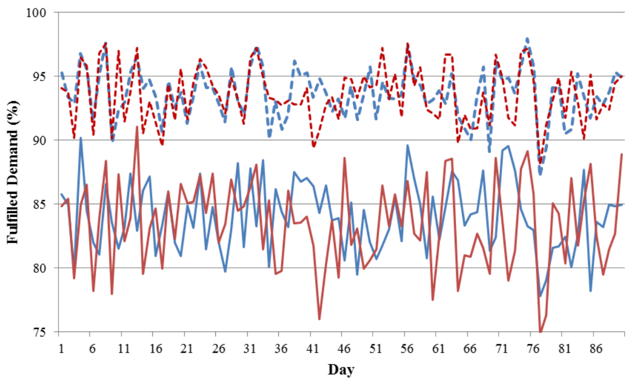

Fig. 5. Demand fulfilment rates with and without DCSP

5. CONCLUSIONS

This article addresses a major challenge in creating a sustainable and reliable wind energy distribution network without substantial dependence on traditional resources. The uncertainty in power generation has been a huge obstacle in introducing the cost-effective renewable energy. The major sources of variability in output forecasting include uncertainty in the environmental conditions and predicting turbine failures. In this article, a pattern recognition method is applied to diagnose and predict the turbine failures based on multiple factors. The results have shown that the pattern recognition model is helpful in diagnosing the major electrical failures of the wind turbine. In the future, the model will be enhanced by exploring a broader range of factors and including more classes of electrical and mechanical failure. In addition, the correlation between wind turbines located in the same farm will be studied to improve the accuracy of prediction.

Although fluctuations in the energy output of a wind farm could be reduced, it is impossible to completely remove them. Two CCT-based protocols are developed in this research to reduce the negative impact of the uncertainty by collaboration and to create a sustainable distribution network. The simulation results of a network with two communities and 100 members show that collaboration protocols improves the efficiency of the network through increasing the probability of demand fulfilment and decreasing the variability of the number of fulfilled demands. By reducing the uncertainty and enhancing collaboration, it is expected wind energy will be more cost-effective and the distribution network will be more sustainable, which will increase the level of integration of renewable energy into the electricity grid. In the future, CCT-based protocols, including BMP, will be studied more in depth for dynamic coalition formation in the sustainable network.

In the future, this study will extend the scope to failure prediction models for other types of failure modes and renewable energy sources such as solar panels. A community-based network of hybrid renewable energy can enhance smart grid development and improve the sustainability of power generation processes while reducing dependence on fossil fuel and nuclear energy.

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