**1. Introduction**

Wind power, a renewable green energy, has been increasingly used in the world for the recent years. However, the tremendous maintenance expenditure, which can reach 20% of the total energy production cost, is the great obstacle to the widespread usage of this renewable and clean energy. [1] The wind turbine blades are the key part of the of the turbines and are susceptible to the corrosion and the destroy of the wind gusts[2]. The undetected defects of the wind turbine blades may cause devastating damage to the entire wind power generation system[31]. Therefore, the wind turbine blades defect detection plays an important role in the safe and stable operation of the wind power generation system. According to the survey results, the diagnosis of this field still uses the method of manual auscultation. This method is only suitable for experienced workers and has been unable to meet the needs of modern equipment troubleshooting. To improve the reliability of the wind turbine, it is urgent to develop the intelligent fault diagnosis method of wind turbine blades.

There have been several physics-based different methods, such as ﬁber-optic sensing method[3], impedance technique [4], ultrasonic waves[5], vibration and thermal imaging[7] , acoustic emission[6]. A.G. Dutton, M. J. Blanch et al[8] used acoustic emission technology to evaluate the blade state and detect damage, and concluded that the acoustic emission technology can reflect the conclusion of the blade damage process.AE-based detection methods are widely researched, but the AE signal is usually seriously disturbed by background noise, causing small fault difficult to be detected. Infrared detection is a temperature based nondestructive fault diagnosis method, which can be adopted to detect the hot spots due to component contact problems[a]. However, it requires an additional heat source to heat the components, and the sensitivity to the detection of deeper damage locations is not high. Cao Jinxiang analyzed the blade crack pattern by ultrasonic flaw detection. This method requires a higher crack shape. Pore-type spherical failure is difficult to obtain enough echo. UAV aerial camera technology can detect the size and specific location of cracks in the blade, but UAV have shortcomings in flight that are subject to environmental constraints. Short battery life is also an important factor restricting it. Although a variety of diagnostic methods have been developed, they are still immature and do not form a truly usable product. An automatically crack detection method with high accuracy and low false-alarm rate plays a vital role in improving the market competitiveness and production safety.

Recently, a significant part of literature concerns SVDD(Support Vector Data Description) and its applications [11-13]. In the process of classification model training, it is found that the acquisition of faulty samples is often difficult, resulting in a serious imbalance between the number of normal and faulty samples in the training set, thereby causing poor reliability and inaccuracy. The support vector data description method can only use the normal class sample set to train and establish the recognition model, which is an effective method to solve the single-value classification problem, Due to these preeminent advantages, SVDD has been applied in the field of fault diagnosis. For example, Feng et al. proposed an online recognition method of HRRP for radar systems based on ISVDD. However, to the best of our knowledge, SVDD is still rarely applied in current fault diagnosis of wind turbine blade.

This paper presents an fault diagnosis method of the wind turbine blade using improved SVDD.

The remaining part of the paper is organized as follows. Section 2 brieﬂy reviews the formulation of SVDD; Finally, conclusions are summarized in Section 4.

**2. The basic theory of SVDD**

SVDD was proposed by Tax and Duin (2004) to solve the original one-class classiﬁcation problem. The basic idea is to construct a spherically shaped decision boundary that envelops most of the data of interest, with a smaller set of support vectors describing the boundary. Given a set of data pointsin the d-dimensional real (or input) space , the objective is to minimize an objective function that depends on the radius R of a sphere and its center a.

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Here the parameter C controls the trade-off between the volume and the errors while  are slack variables which make the classiﬁer ‘soft-margin’, i.e. allow some possibility of outliers in the training set.