

Hard Sample Mining Enabled Contrastive Feature Learning for Wind Turbine Pitch System Fault Diagnosis

Zixuan Wang, Bo Qin, Mengxuan Li, Mark D. Butala, Haibo Wang, Peng Peng, *Member, IEEE*, and Hongwei Wang, *Member, IEEE*

Abstract—The efficient utilization of wind power by wind turbines relies on the ability of their pitch systems to adjust blade pitch angles in response to varying wind speeds. However, the presence of multiple fault types in the pitch system poses challenges in accurately classifying these faults. This paper proposes a novel method based on hard sample mining-enabled contrastive feature learning (HSMCFL) to address this problem. The proposed method employs cosine similarity to identify hard samples and subsequently leverages contrastive feature learning to enhance representation learning through the construction of hard sample pairs. Furthermore, a multilayer perceptron is trained using the learned discriminative representations to serve as an efficient classifier.

To evaluate the effectiveness of the proposed method, two real datasets comprising wind turbine pitch system cog belt fracture data are utilized. The fault diagnosis performance of the proposed method is compared against existing methods, and the results demonstrate its superior performance. The proposed approach exhibits significant improvements in fault diagnosis accuracy, providing promising prospects for enhancing the reliability and efficiency of wind turbine pitch system fault diagnosis.

Index Terms—Wind turbine, Pitch system, Fault diagnosis, Hard sample mining, Class imbalance

I. INTRODUCTION

WIND energy has been widely used for decades. According to the statistic of the Global Wind Energy Council (GWEC) in 2022, nearly 94 GW of new wind turbine capacity was installed in 2021, bringing the global wind power capacity to 837 GW[1]. The maintenance cost is also increasing with the increasing number of wind turbines. Therefore, condition monitoring and fault diagnosis for wind turbines is crucial to control the operating costs of wind turbines.

A wind turbine is a complex electromechanical system consisting of blades, rotors, pitch system, yaw system, gearbox, generator, and other components[2]. According to a survey conducted by the China Wind Energy Association (CWEA)

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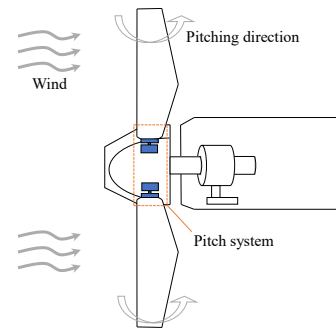


Fig. 1. The general structure of the wind turbine pitch system

between 2010 and 2012 among 47 wind turbine manufacturers, component suppliers and developers, damage to these components is the main cause of wind turbine failures. Among them, the frequency of failure of the pitch system ranked high[3].

The general structure of the wind turbine pitch system is shown in Fig.1. The Pitch system can adjust the blade pitch angle in real time according to the change of wind speed, so as to make full use of wind energy for power generation and reduce the impact of wind on the blade[4]. In addition, the pitch system can feather the blade to achieve a safe shutdown when the wind speed is too high or during an emergency shutdown[5]. There are two types of pitch systems for wind turbines: electric motor drive and hydraulic drive. Due to the oil leakage and maintenance problems of hydraulic drive, the pitch systems of wind turbines in China are mainly driven by electric motor[3]. The main failures of electric motor-driven pitch systems include electric motor failure, transmission component failure, and control system failure. Therefore, the timely diagnosis of wind turbine pitch system faults can effectively reduce downtime and losses.

The methods of wind turbine fault diagnosis are mainly divided into signal analysis methods, model-based methods, and data-driven methods[6–8]. Signal analysis methods acquire data through sensors installed in various components of the wind turbine and extract fault-related features for fault diagnosis[9–11]. For example, An et al. [12] put forward a fault diagnosis method of wind turbine bearing based on intrinsic time-scale decomposition. Zhang and Lang [13] proposed a wavelet energy transmissibility function that is robust to noise and sensitive to system property changes to diagnose the fault

in wind turbine bearings. Model-based methods require prior knowledge of the system operation mode, which is complete enough to be formalized into a quantitative or qualitative model for fault diagnosis[14]. For example, Chaaban et al. [15] modeled a utility-scale turbine using an aero-hydro-servo-elastic simulation tool to simulate the faults inside the pitch system and to study their effects as a function of the fault magnitude and wind speed. Odgaard and Stoustrup [16] proposed a fault-tolerant observer scheme to provide estimates of various components for a wind turbine. Lan et al. [17] proposed an adaptive sliding observer to estimate wind turbine parametric pitch actuator faults. Data-driven methods use a large amount of historical data which can be obtained through the supervisory control and data acquisition (SCADA) system installed in the wind turbine to train the fault diagnosis model. For example, Gao et al. [18] proposed a wind turbine fault diagnosis method based on integral extension load mean decomposition multiscale entropy and least squares support vector machine. Lei et al. [19] proposed an end-to-end Long Short-term Memory (LSTM) model for fault diagnosis of wind turbine. Pashazadeh et al. [20] proposed a data-driven approach based on the fusion of several classifiers for fault detection and isolation in wind turbines.

This paper proposes a novel fault diagnosis method for wind turbine pitch systems that combines supervised contrastive learning and hard sample mining. The purpose of the proposed method is to better distinguish the faults in the wind turbine pitch system whose severity varies with time. In order to achieve this purpose, we face two challenges. First, the amount of SCADA data on wind turbines is extremely large, so how to extract discriminative features from SCADA data is the problem we face. Second, the wind turbine pitch system may have multiple faults that evolve over time, and it is difficult to classify the overlap between different fault types. These two challenges are the key issues in building a fault diagnosis model for wind turbine pitch systems based on SCADA data.

The main contributions of this paper can be summarized as follows.

- A two-step approach consisting of supervised contrastive learning and a multi-layer perceptron is used to diagnose faults in wind turbine pitch systems. Supervised contrastive learning is used to extract discriminative features from SCADA data. The learned features are then used to classify the data and discriminate faults by the multi-layer perceptron.
- A hard sample mining method based on cosine similarity is used to distinguish hard-to-classify faults with temporal overlap. To the best of our knowledge, this paper is the first to introduce a hard sample mining method in the wind turbine pitch system fault diagnosis field.
- The proposed hard sample mining method is a unified framework acting on both supervised contrastive learning and multi-layer perceptron.

The rest of this paper is organized as follows. First, the background theory is discussed in Section II. Then, the proposed HSMCFL is described in detail in Section III. The data used for the experiments and the analysis of the experimental

results are presented in Section IV. Finally, the conclusions of this paper are given in Section V.

II. BACKGROUND THEORY

A. Related works

In practice, the wind turbine pitch system operates in a healthy state most of the time, resulting in a small number of faults collected by the SCADA system. To cope with this problem, researchers often perform data resampling or construct normal behavior models (NBM). Methods of data resampling include oversampling of the minor class[21], undersampling of the major class[22], and synthetic minority oversampling technique (SMOTE)[23]. For example, Karadayi et al. [24] used SMOTE to balance SCADA data and decision trees to predict wind turbine alarm conditions. However, data resampling methods may introduce undesirable noise or delete important information from the data, thus affecting the accuracy of fault diagnosis. NBM methods train the model using only normal data and use the residuals between the measured and model signals as indicators of a possible fault[25]. For example, Lu et al. [26] predicted failures for wind turbine electric pitch systems by an optimized relevance vector machine-based NBM method. A limitation of the NBM methods is that it is difficult to distinguish multiple faults.

In this paper, we propose, for the first time, a contrastive feature learning method enabled by hard sample mining that can well diagnose time-overlapping hard samples in wind turbine pitch systems.

B. Motivation

The components in the pitch system of a wind turbine gradually wear out during an increasing number of operations, making it challenging to accurately diagnose the health of the pitch system components. To demonstrate the existence of this phenomenon, we selected a real SCADA dataset of a wind turbine pitch system (This dataset is described in detail in Section IV-A1.) to diagnose its five health conditions by CFL-MLP, the result of which is shown in Fig. 2. From the figure, it can be seen that there is a serious misclassification problem between the normal class and the four fault classes. This problem may lead to higher maintenance costs or even damage to the whole wind turbine. This problem may occur because the health conditions of the pitch system components change gradually over time, and in addition, there is a class imbalance as the different health conditions last for different periods of time.

Although data-driven fault diagnosis techniques are widely used for wind turbine pitch systems, to the best of our knowledge, no work has explored the phenomenon of temporal overlap between pitch system health conditions, which is a typical hard sample problem. In this paper, we propose a hard sample mining method based on cosine similarity, which can construct hard sample pairs in mini-batch to make the training stage more challenging and make the distribution of samples in the feature space more compact and discriminative. Combining the proposed hard sample mining method with CFL-MLP can well solve the hard sample problem in wind turbine pitch

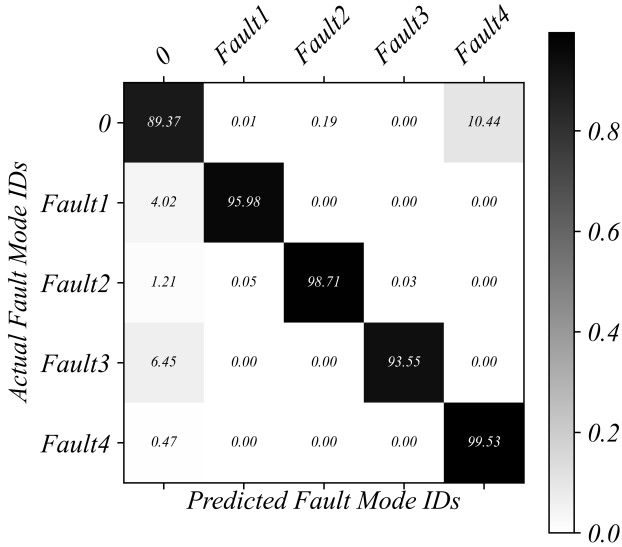


Fig. 2. Fault diagnosis result of wind turbine pitch system by CFL-MLP

system. The details of the proposed method will be described in Section III.

C. Contrastive Feature Learning

With its powerful feature extraction capability, contrast learning has been widely used as an efficient feature learning method in natural language processing[27, 28], computer vision[29, 30] and other fields. Supervised contrastive learning selects an anchor and chooses samples with the same label as the anchor as positives and samples with different labels as negatives. For each anchor, more discriminative representations are learned by pushing the anchor closer to the positives and farther away from the negatives in the embedding space[31]. The supervised contrastive loss is defined as follows:

$$\mathcal{L}^{\text{sup}} = \sum_{i \in I} \frac{-1}{|P(i)|} \sum_{p \in P(i)} \log \frac{e^{\text{sim}(z_i, z_p)/\tau}}{\sum_{a \in A(i)} e^{\text{sim}(z_i, z_a)/\tau}} \quad (1)$$

where $I \in D^l$ is a mini-batch of the labeled data, and $\tau \in \mathcal{R}^+$ is a scalar temperature parameter. $P(i) \equiv \{p \in A(i) : \tilde{\mathbf{y}}_p = \tilde{\mathbf{y}}_i\}$ is the set of indices of all positives of the anchor and $|P(i)|$ is its cardinality. Supervised contrastive learning leverages label information effectively, enabling models trained with supervised contrastive loss to acquire compact representations. Consequently, these models can capture more discriminative features.

D. Hard Sample Mining

The boundaries of samples of different classes in the feature space may be close to each other, so samples near the boundaries will be difficult to classify, and such samples are hard samples. If a sample is selected as an anchor, the hard samples of the anchor include hard positive samples with the same label but far away from it and hard negative samples

with different labels but close to it[32, 33]. Making full use of hard samples in the training phase of the model not only improves the learning efficiency but also enables the model to have better classification performance.

Hard sample mining has been widely used in computer vision and other fields. Suh et al. [34] proposed a stochastic hard negative mining method that adopts class signatures to keep track of feature embedding online. The method improves image retrieval accuracy substantially. In [35], a weighted complete bipartite graph-based maximum-value perfect matching for mining the hard samples was proposed to relieve adverse optimization and sample imbalance problems. Xue et al. [36] applied a hard samples mining method based on an enhanced deep multiple instance learning to find the hard samples from unlabeled training data.

III. PROPOSED METHOD

A. Overview

The structure of the proposed method is shown in Fig.3. The proposed method consists of five parts: data preprocessing, data augmentation, hard sample mining, supervised contrastive learning, and multi-layer perception.

- 1) Data preprocessing
- 2) Hard sample mining(HSM)

In this paper, the proposed HSM method based on cosine similarity is used to determine the hard samples. Specifically, when constructing a mini-batch, the proposed HSM method first randomly selects a sample from each class as initialization. Subsequently, either a random sample from the dataset is selected or a random anchor is chosen from the current mini-batch and its hard samples are determined to extend this mini-batch. In the latter case, the sample of a different class with the highest cosine similarity to the selected anchor is selected as its hard negative sample, while the sample of the same class with the lowest cosine similarity to the anchor is selected as a hard positive sample. We keep repeating the above process until the size of the mini-batch reaches the batch size. It is worth noting that the proposed HSM method is applied to construct the mini-batches of both CFL and MLP stages. In the MLP stage, specifically, the misclassified samples for the current stage are used to initialize the mini-batches in the next stage. In this case, each time at initialization, a sample is randomly taken from misclassified samples if it is not empty, or from the dataset otherwise.

- 3) Contrastive Feature Learning

The proposed method learns the rich representations in the dataset with the help of CFL. Moreover, constructing more challenging mini-batches by HSM allows CFL to learn better representations.

- 4) Multi-layer perception(MLP)

The representations learned by CFL will be constructed by HSM into a more challenging mini-batch for training MLP to classify the input data.

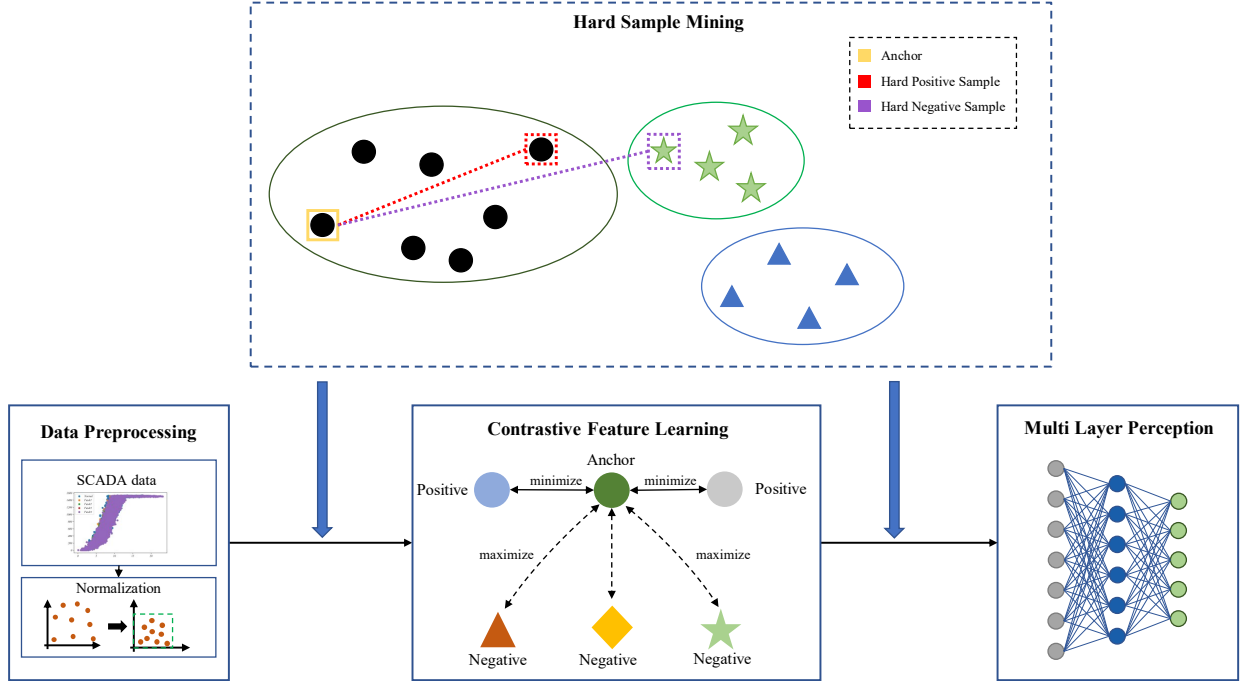


Fig. 3. Overview of proposed method

B. Hard sample mining enabled contrastive feature learning(HSMCFL)

The key to the proposed method is to combine HSM as a unified framework with CFL and MLP, allowing CFL to learn more compact representations and train better MLP classifiers for more accurate diagnosis of hard-to-classify faults in wind turbine pitch systems. As shown in detail in Algorithm1, the two stages, CFL and MLP, each invoke HSM as a framework to construct more challenging mini-batches.

IV. EXPERIMENT

A. Experimental Setup

1) *Data Description*: To validate the effectiveness of the proposed method, two pitch system cog belt fracture datasets collected from two real-world wind turbines numbered 23 and 29 are used[37] (in the remainder of this paper, they are referred to as WT 23 and WT 29). A cog belt is a transmission device with a toothed structure on the working surface and is a key component in the electric pitch system of a wind turbine. During wind turbine operation, the cog belt may gradually break due to stress fatigue, leading to the failure of the wind turbine pitch system. There are five health conditions in the datasets: normal, slightly worn, low risk of fracture, high risk of fracture, and complete fracture. If the cog belt completely fractures, it can significantly affect the wind turbine's power production and increase maintenance costs. Therefore, it is crucial to accurately diagnose the health condition of the cog belt and replace it before it fractures completely to ensure the normal operation of the wind turbine.

The original sensor data contains hundreds of variables recorded by a large number of sensors of the SCADA system

inside the wind turbine. After selection by experts in the field, the remaining irrelevant parameters were removed and 26 parameters related to the cog belt fracture of the wind turbine were retained. The details of the parameters are shown in Table I. The total number of data for WT 23 and WT 29 is 13,6709 and 215,012, respectively. Fig.4 shows the extreme imbalance in the duration of the different health conditions in the datasets. Fig.5 shows the output power VS wind speed for WT 23 and WT 29. It can be seen that the cog belt has different effects on the power generation efficiency of wind turbine when it is in different health conditions. During the experiment, we divided 70% of the data into the training set and 30% into the test set, where 20% of the training set is further divided as the validation set.

2) *Evaluation Metrics*: In this paper, In this paper, Accuracy and macro G-mean[38, 39] are used as evaluation metrics. G-mean is a good indicator of the classifier's performance in imbalanced classification problems[40]. Due to the extreme class imbalance in the dataset used in this paper, the macro average of G-mean was used in order to fully represent the effectiveness of different methods in classifying each health condition. The evaluation metrics are defined as follows.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (2)$$

$$\text{G-mean} = \sqrt{\frac{TP}{TP + FN} \times \frac{TN}{TN + FP}} \quad (3)$$

$$\text{macro G-mean} = \frac{1}{n} \sum_{i=1}^n \text{G-mean}_i \quad (4)$$



Fig. 4. The data distribution of the two datasets. (a) WT 23 (b) WT 29

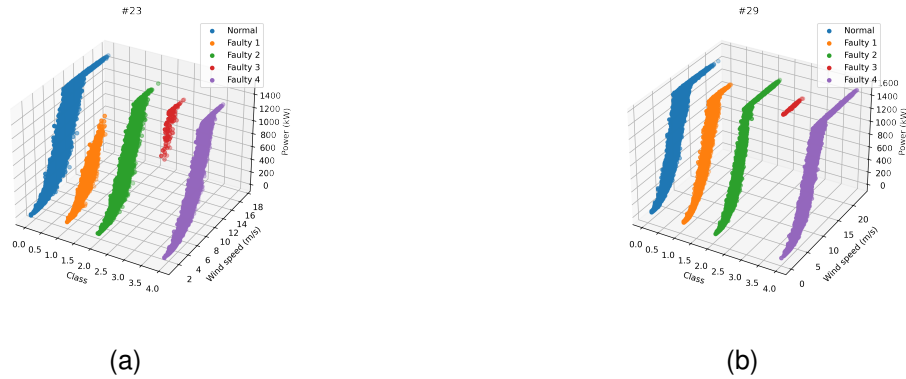


Fig. 5. The output power VS wind speed for WT 23 and WT 29. (a) WT 23 (b) WT 29

where TP, TN, FP, and FN refer to true positives, true negatives, false positives, and false negatives, respectively.

3) *Baseline*: To verify the effectiveness of the proposed method, we selected 5 baselines, namely CFL-MLP (with the HSM framework removed from the proposed method), ResNet101, BiLSTM, and CNN. In order to solve the problem of extreme class imbalance in the datasets, Focal Loss(FL)[41] was used in ResNet101, BiLSTM, and CNN. A brief description of the baselines is given below.

- 1) CFL-MLP is the method after removing the HSM framework from the proposed method.
- 2) ResNet101 is a residual network with a depth of 101 layers.
- 3) BiLSTM is a recurrent neural network consisting of a forward LSTM and a backward LSTM.
- 4) CNN used in this paper is a deep neural network consisting of 4 convolutional layers and 3 fully connected layers.
- 5) MLP used in this paper consists of three fully connected layers.

B. HSMCFL

1) *Experiment for WT 23*: We compared the proposed HSMCFL and the selected 5 baselines on the dataset of WT 23. We repeated the experiment ten times with different random seeds and the reported results are based on the average.

The results are shown in Table II. The corresponding t-SNE embeddings and confusion matrix are shown in Fig.6 and Fig.7. Compared with the baselines, the *Accuracy* of the proposed method is increased by 5.41%, 0.30%, 0.03%, 1.17%, 0.15% and 0.42%, and the macro G-mean of the proposed method is increased by 3.07%, 7.02%, 3.29%, 6.70%, 9.43% and 2.27%. The results in Table II show that the proposed HSMCFL performs significantly better than baselines, especially in the value of macro G-mean. Fig.6 indicates that the proposed method is able to diagnose the fault of the pitch system of WT 23 excellently. The confusion matrix shown in Fig.7 indicates that the proposed method can effectively solve the problem of difficulty in distinguishing multiple faults in the pitch system of WT 23.

2) *Experiment for WT 29*: To verify the generalization performance of the proposed method, we also compared it with baselines on WT 29. We repeated the experiment ten times with different random seeds and the reported results are based on the average. The results are shown in Table III. The corresponding t-SNE embeddings and confusion matrix are shown in Fig.8 and Fig.9. Compared with the baselines, the *Accuracy* of the proposed method is increased by 9.46%, 0.45%, 4.97%, 2.07%, 1.68% and 1.09%, and the macro G-mean of the proposed method is increased by 4.39%, 7.85%, 3.01%, 14.02%, 2.31% and 6.02%. The results in Table III, Fig. 8 and Fig. 9 once again verify that the proposed method has excellent hard-sample classification capability, which means that the proposed

Algorithm 1: Hard sample mining enabled contrastive feature learning for wind turbine pitch system fault diagnosis

Input: labeled train set $(x, y) \in D$, learning rate η , batch_size bs , epochs n , temperature τ , model f and g with parameters θ and θ_g , number of HSM stages num_stages , HSM threshold p_1 and p_2

Output: trained model with parameters θ^*

- 1 Net, $\theta \leftarrow \text{initialize}(Net)$;
- 2 $x \leftarrow \text{Normalize}(x)$;
- 3 **Function HSM**
- 4 | $bs, D, mis_samples$
- 5 | $hard_batches \leftarrow []$;
- 6 **For** $b = 1$ **to** $length(D) \div bs$:
- 7 | | $batch \leftarrow []$;
- 8 | | $batch \leftarrow \text{Initialization}(batch, D_i, mis_samples)$;
- 9 | | $left \leftarrow bs - length(batch)$;
- 10 | **While** $left > 0$:
- 11 | | | $append(batch, \text{random_sample}(D))$;
- 12 | | | $s \leftarrow \text{random_sample}(batch)$;
- 13 | | | $append(batch, \text{hard_positive}(s))$;
- 14 | | | $append(batch, \text{hard_negative}(s))$;
- 15 | | | $left \leftarrow left - 3$;
- 16 | | $append(hard_batches, batch)$;
- 17 **return** $hard_batches$;
- 18 **Stage 1: CFL**
- 19 **For** $stage = 1$ **to** num_stages :
- 20 | $hard_batches \leftarrow \text{HSM}(bs, D, [])$;
- 21 | **For** $epoch = 1$ **to** n :
- 22 | | **For** $(x_b, y_b) \in hard_batches$:
- 23 | | | $out_b \leftarrow f(\theta, x_b)$;
- 24 | | | $\mathcal{L} \leftarrow \text{loss_SCL}(y_b, out_b, \tau)$;
- 25 | | | $\theta \leftarrow \text{back_propagation}(\mathcal{L}, \theta, \eta)$;
- 26 **Stage 2: MLP**
- 27 $mis_samples \leftarrow []$;
- 28 **For** $stage = 1$ **to** num_stages :
- 29 | $hard_batches \leftarrow \text{HSM}(bs, D, mis_samples)$;
- 30 | **For** $epoch = 1$ **to** n :
- 31 | | **For** $(x_b, y_b) \in hard_batches$:
- 32 | | | $out_b \leftarrow g(\theta_g, x_b)$;
- 33 | | | $\mathcal{L} \leftarrow \text{loss_MLP}(y_b, out_b, \tau)$;
- 34 | | | $\theta_g \leftarrow \text{back_propagation}(\mathcal{L}, \theta_g, \eta)$;
- 35 | $mis_samples \leftarrow \text{misclassification}(g, D)$;

method is applicable to the hard-to-classify problem present in the wind turbine pitch system.

C. Ablation analysis of HSM

To verify the effectiveness of HSM framework for the two stages (CFL and MLP) in the proposed method, we compare the proposed method with the following two methods and evaluate their performance by macro G-mean.

HSM+CFL-MLP: The HSM framework is removed from MLP in the proposed method.

TABLE I
26 PARAMETERS OF SCADA DATA.

No.	Parameter
1	Wind speed
2	Generator speed
3	Active power
4	Wind direction
5	Average wind direction within 25s
6	Yaw position
7	Yaw speed
8	Angle of pitch 1
9	Angle of pitch 2
10	Angle of pitch 3
11	Speed of pitch 1
12	Speed of pitch 2
13	Speed of pitch 3
14	Temperature of pitch motor 1
15	Temperature of pitch motor 2
16	Temperature of pitch motor 3
17	Horizontal acceleration
18	Vertical acceleration
19	Environment temperature
20	Internal temperature of nacelle
21	Switching temperature of pitch 1
22	Switching temperature of pitch 2
23	Switching temperature of pitch 3
24	DC current of pitch 1 switch charger
25	DC current of pitch 2 switch charger
26	DC current of pitch 3 switch charger

TABLE II
COMPARISON OF FAULT DIAGNOSIS METHODS PERFORMANCE FOR WT 23

Algorithms	Accuracy	macro G-mean
HSMCFL	0.9979	0.9991
CFL-MLP	0.9467	0.9693
MLP	0.9949	0.9336
MLP+FL	0.9976	0.9673
ResNet101+FL	0.9864	0.9364
BiLSTM+FL	0.9964	0.9130
CNN+FL	0.9937	0.9769

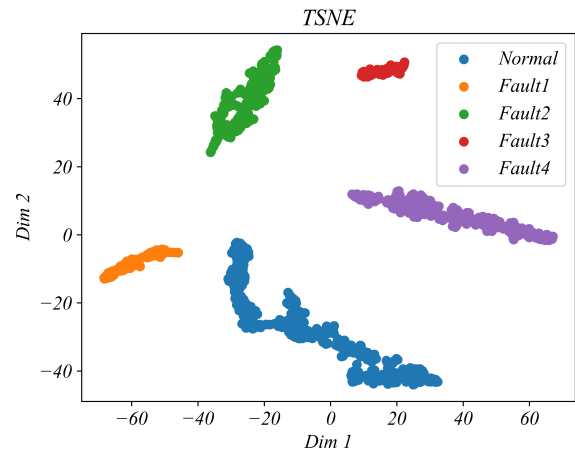


Fig. 6. t-SNE embedding for WT 23

CFL-HSM+MLP: The HSM framework is removed from CFL in the proposed method.

The results of the ablation analysis are shown in Table IV and Table V. From these two tables, it can be seen

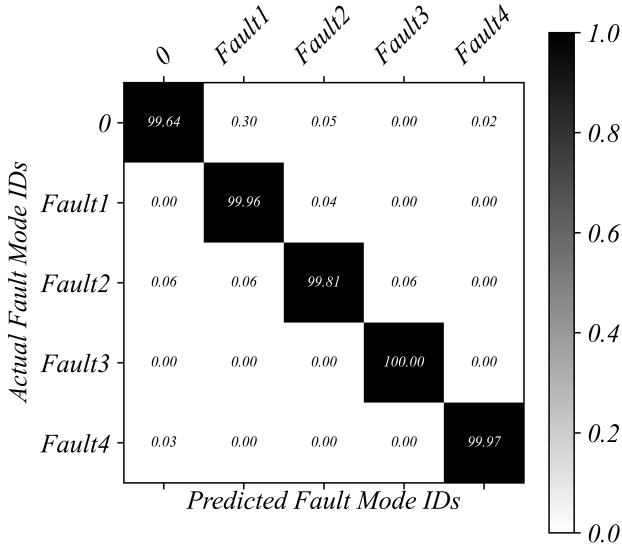


Fig. 7. Confusion matrix for WT 23

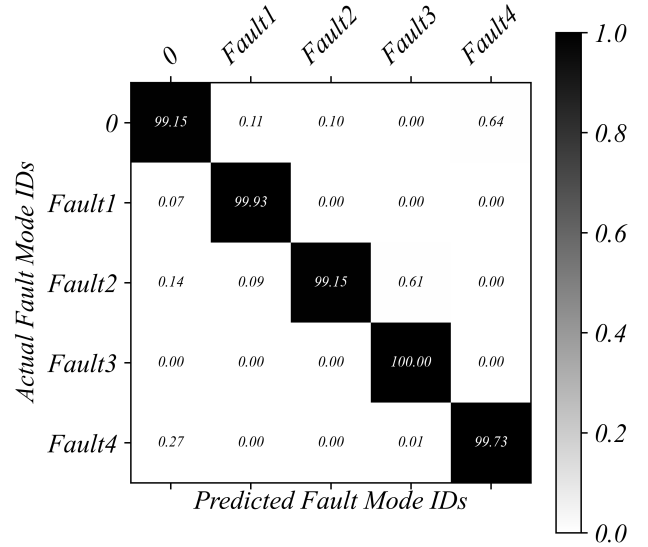


Fig. 9. Confusion matrix for WT 29

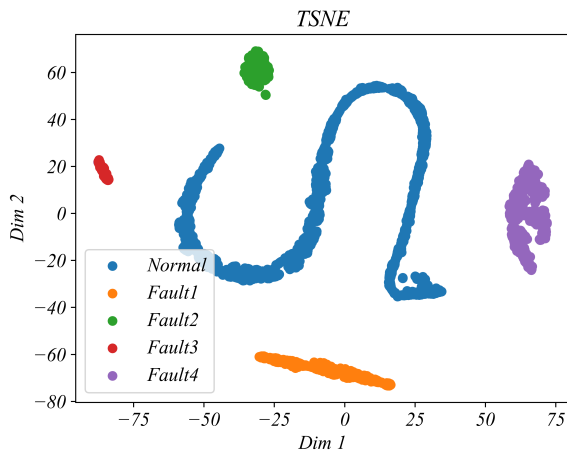


Fig. 8. t-SNE embedding for WT 29

that macro G-mean of the proposed method is significantly higher than that of the two compared methods. Taking the experimental results on WT 23 shown in Table IV as an example, the macro G-mean of the proposed method is 1.05% and 1.87% higher than that of HSM+CFL-MLP and CFL-HSM+MLP, respectively. The above results demonstrate the necessity of the HSM framework for the proposed method.

TABLE III
COMPARISON OF FAULT DIAGNOSIS METHODS PERFORMANCE FOR WT 29

Algorithms	Accuracy	macro G-mean
HSMCFL	0.9940	0.9971
CFL-MLP	0.9081	0.9552
MLP	0.9895	0.9245
MLP+FL	0.9469	0.9680
ResNet101+FL	0.9738	0.8745
BiLSTM+FL	0.9776	0.9746
CNN+FL	0.9833	0.9405

TABLE IV
ABLATION ANALYSIS OF HSM FOR WT 23

Algorithms	macro G-mean
HSMCFL	0.9991
HSM+CFL-MLP	0.9887
CFL-HSM+MLP	0.9808

TABLE V
ABLATION ANALYSIS OF HSM FOR WT 29

Algorithms	macro G-mean
HSM+CFL-HSM+MLP	0.9971
HSM+CFL-MLP	0.9682
CFL-HSM+MLP	0.9595

V. CONCLUSION

In this paper, hard sample mining enabled unified contrastive feature learning is proposed to diagnose the cog belt fracture fault in wind turbine pitch systems. The existence of temporal overlap between different health conditions is a practical problem in wind turbine pitch systems. The proposed method solves this problem by combining a hard sample mining framework with a two-step approach consisting of contrastive feature learning and multi-layer perceptron. Notably, this is the first time that a hard sample mining-based method is used for fault diagnosis of a wind turbine pitch system. The effectiveness of the proposed method is validated on two real wind turbine pitch system failure datasets. As demonstrated in the experiments, the proposed HSMCFL outperforms the baselines. This means that the proposed method introduces a new and effective solution for wind turbine pitch system fault diagnosis.

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