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APPLIED RESEARCH

High-Precision Intelligent Identification of Complex Power Quality Disturbances Based on Improved KST and CNNs

WENYUAN BAI [1], GUOFENG ZHUANG [1], XIUZHEN ZHAO [2], AND ZHANHONG WEI [3]

[1]Gansu Electric Power Corporation, Gansu 730030, China
[2]Gansu Electric Power Corporation Ultra High Voltage Company, Gansu 730030, China
[3]Department of Electrical Engineering, Lanzhou University of Technology, Gansu 730030, China

Corresponding author: Zhanhong Wei (zhanghw8109@163.com)

ABSTRACT With the widespread usage of power electronics and other non-linear loads, the power quality (PQ) issue in the power grid is becoming increasingly prominent, threatening the power system's stability. As a result, accurate identification and categorization of complicated power quality disturbances (PQD) is a necessity and critical to mitigating grid pollution. In this paper, a new approach for high-precision intelligent recognition of complex PQDs based on improved Kaiser window s-transform (IKST) and convolutional neural network (CNN) (KSTCNN) is proposed. Firstly, KST is applied for PQD time-frequency (TF) signal detection, and then the control function is modified to adjust the shape of the KS-window, and its parameters can be automatically optimized according to the maximum energy concentration to satisfy the various TF signal detection requirements. Then, the CNN architecture is improved using a SimAM attention mechanism that assigns higher weights to the neurons conveying useful PQD feature information and suppresses the surrounding neurons with irrelevant information. Then, an improved hierarchical 2D dense network structure is proposed to achieve the feature extraction and high-precision recognition of PQDs. Then, the results of simulation experiments demonstrate that the classification accuracy of the proposed KSTCNN is better than other compared methods under different noise levels. Finally, in the practical hardware platform, the recognition accuracy of PQDs reaches 97.93, and the real-time detection time is 0.11s, which further verifies the practicality of the KSTCNN and meets the requirement of real-time recognition of complex PQDs.

INDEX TERMS Power quality (PQ), power quality disturbances (PQD), improved Kaiser window S-transformation (IKST), CNN, SimAM attention mechanism, Lion.

I. INTRODUCTION

As the utilization of power electronics and other nonlinear loads becomes more prevalent, PQ challenges within the electrical grid are gaining prominence, posing a threat to the overall stability of the power system [1], [2], [3]. These concerns manifest primarily through a blend of diverse PQDs, including voltage transient, interruption, harmonics, notch, etc. [4]. The complexity of PQDs places more demands on the models' detection and identification skills, posing a severe challenge to the applicability of traditional PQD identification techniques [2], [3], [4]. The accurate and efficient detection and classification of complex PQDs is crucial for solving the PQ problem, which has significant research significance for effectively analyzing and managing, and governing the PQ interference problem [3], [4], [5].

As we all know, the two processes that lead to PQD identification are feature extraction and PQD categorization [2], [5]. During the feature extraction phase, TF analysis is commonly employed to conduct PQDs feature signal extraction from both time and frequency domains. The common TF analysis methods used for PQD feature extraction are Fourier transform (FT), wavelet transform (WT), S-transform (ST), etc [6], [7], [8], [9]. Satpathi et al. utilized the TF window function to obtain the TF information of transient signals based on FT. However, the window width, which affects the

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TF resolution, is fixed, resulting in the approach's detection precision for transient signals in PQD [6]. In response, the WT based on tunable TF resolution was utilized to obtain the abrupt signal in the PQDs, but it suffers from the disadvantage of being sensitive to the noise [7]. ST combines FT and WT with powerful TF analysis, and thus is widely used for feature recognition of complex PQDs [8], [10]. Ma et al. improved ST using sigmoid to control the window width, which significantly improved the TF resolution of the model, but the parameters of the window still depended on empirical values [5]. Aiming at the limited energy concentration of Gaussian windows in ST and the difficulty in determining the time-rate resolution in extracting the TF information of the pqd, Liang et al. proposed a KST method that employs a Kaiser window with the optimal energy concentration performance instead of a Gaussian window, which significantly improves the performance of PQD recognition [8]. However, the parameters of its windows still need to be determined manually. For this, Ma et al. proposed an improved KST method to adjust the Kaiser window by automatically optimizing the control function of the parameters according to the maximum energy concentration, which significantly improves the TF resolution [9].

During the classification stage, the traditional approaches to classify the features of PQD signals mainly include support vector machine (SVM) [11], k-Nearest Neighbor (KNN) [12], and extreme gradient boosting (XGBoost) [13] and artificial neural network. As the complex PQD types considered increase, the classifier will face dimensionality catastrophe, while the accuracy of such classifiers depends on manual selection of characteristic information, thus greatly reducing the accuracy and categorization efficiency of the classifiers. Recently, with the rapid development of deep learning in machine vision, image processing and other fields, deep learning (DL) approaches have been widely used in PQD categorization and have attracted more and more attention from scholars [2]. In the DL-based approach, PQD feature extraction and categorization are performed automatically based on the CNN network structure, eliminating the need for manual feature design. Wang and Chen [14] et al. proposed an improved deep convolutional neural network approach for automatic PQD feature extraction and optimization by utilizing six stacked units. Deng et al. [15] extracted deep PQD features from the input sequences by constructing a dual GRU recurrent neural network (RNN) and achieved better categorization performance. Zhu et al. [3] proposed a lightweight classification approach for global deep shuffle CNN to improve the performance of automatic recognition of complex PQD characteristics by utilizing global deep convolutional layers and parameter-corrected linear units. In addition, since the attention mechanism can effectively boost the network's PQD feature representation by emphasizing PQD-relevant information and thus suppressing irrelevant characteristic information, it has aroused great interest among scholars [16], [17], [18], [19]. Gu et al. [16] combined the label-directed attention mechanism with a recurrent neural network (RNN) to enhance the feature representation of the network by assigning higher weights to features of important PQD categories. Cai et al. [18] proposed an approach for PQD classification based on the combination of CNN and gated recurrent unit (GRU). Meanwhile, squeezeand-excitation attention (SE) was utilized to enhance the PQD feature extraction capability of the network. Qiu et al. [20] developed a 1D CNN-based automatic extraction framework to extract and categorize multiple features of PQDs. Wang et al. [21] proposed a composite convolutional network combining standard convolution and depth-separable convolution for feature extraction and automatic recognition of complex PQDs.

Inspired by the above, this study provides a novel classification framework an intelligent classification framework for high-precision intelligent recognition of complex PQDs based on improved Kaiser window s-transform (IKST) and convolutional neural networks, so as to improve the TF resolution and the performance of accurate recognition of PQDs. Our major contributions are highlighted below.

1) KST is applied to complex PQD time-frequency signal analysis during the TF feature analysis and TF feature matrix acquisition stage. The control function is modified to adjust the shape of the KS-window, and its parameters can be automatically optimized according to the maximum energy concentration to meet various TF signal detection requirements.

2) In order to reduce information loss of PQD, the CNN architecture is improved using a SimAM attention mechanism that assigns higher weights to the neurons conveying useful PQD feature information and suppresses the surrounding neurons with irrelevant information. Then, an improved hierarchical 2D dense network structure is proposed to achieve the feature extraction and high-precision recognition of PQDs. Meanwhile, a new Lion optimizer is used to improve the performance of the model.

3) The experimental results show that the proposed KSTCNN not only outperforms the existing common TF analysis methods in simulation experiments on the dataset containing 28 complex PQD signals, but also the KSTCNN has the excellent practicality and real-time performance in complex PQDs recognition on the practical hardware platform.

The remainder of this work is structured as follows. The related work is described in Section II. Section III introduces the KSTCNN. The intelligent categorization framework for complex PQD is introduced in Section IV. Then, in Section V, experiments are carried out. Finally, Section VI brings this paper to a conclusion.

II. RELATED WORKS

A. KAISER WINDOW S-TRANSFORMATION (KST)

Accurate identification of complex PQDs relies heavily on feature information extracted from both the time domain and frequency domain. Therefore, achieving high TF resolution and energy concentration is essential to minimize information loss [9]. The KST was introduced as a method for conducting

TF analysis. This can be characterized as [8]:

$$KST(\tau,f) = \int_{+\infty}^{-\infty} x(t)w_k(\tau - t,f)e^{-i2\pi ft}dt, \quad (1)$$

where τ and f represent the time-shift factor parameter and signal frequency. $x(t)$ represents PQD siganal and i represents the imaginary unit. $w_k(t,f)$ corresponds to a Kaiser window function, characterized as:

$$w_k(\tau,f) = I_0[\gamma(f)\sqrt{1 - t^2/T^2}]/I_0[\gamma(f)], t \leq T, \quad (2)$$

where the function $\gamma(f)$ is associated with frequency f and acts as a control function, allowing the adjustment of the Kaiser window's shape to achieve a better TF resolution. $I_0(.)$ corresponds to the zeroth-order Bessel function of the first kind. Therein, $\gamma(f)$ can be expressed as:

$$\gamma(f) = \frac{\zeta_1}{f + \zeta_2}, \quad (3)$$

where ζ_1 and ζ_2 denote the parameters used to control the change in the shape of the Kaiser window. However, fixed ζ_1 and ζ_2 cannot adapt to the demands of complex PQD TF analysis, which may lead to a decrease in resolution.

B. SIMAM ATTENTION MECHANISM

Attention mechanisms are designed to augment the network's expressive capacity by highlighting relevant information while suppressing irrelevant information. As a result, they have found extensive application in the domain of computer vision and PQD classification [16], [18], [19], [22]. Xia et al. [17] increased PQD classification performance by employing the attention method to apply higher weight values to critical network features that hide state features. Liu et al. [19] suggested a new dual-attention optimization model for PQD classification. A SE network-based channel attention mechanism is inserted into each convolutional layer of the CNN to learn the important aspects of each feature channel automatically. It's worth highlighting that the attention module utilized in the aforementioned PQD classification approach often incorporates additional sub-network modules to produce attention weights, thereby enhancing the network's feature extraction capabilities. Recently, a parameter-free, three-dimensional attention mechanism called SimAM, was introduced in [23], drawing inspiration from well-established neuroscientific theories. SimAM surpasses existing channel and spatial attention mechanisms by integrating both mechanisms into a comprehensive 3D weighted attention module. This integrated approach facilitates efficient information selection during visual processing, resulting in remarkable speed and accuracy. Moreover, compared to the traditional attention mechanism, the CNN architecture is improved using the SimAM attention mechanism, which can allocate higher weights to neurons conveying useful feature information and suppress irrelevant feature information in the surrounding information to strengthen the feature extraction capability of the model.

Specifically, spatial suppression is a phenomenon observed in visual neuroscience that refers to the informative neurons exhibiting diverse firing patterns in the surrounding neurons while still maintaining the activity of those neighbors [24]. Neurons with substantial spatial suppressive effects typically have a more significant impact on the outcome of visual processing tasks. Such neurons can be identified by assessing the linear separability of a target neuron from others. Additionally, the image's edge characteristics closely resemble those of the spatially suppressed neurons, often showing extremely high contrast with respect to the surrounding texture features. By utilizing an energy function to allocate 3D weights for various visual tasks without the need for additional parameters, the SimAM attention mechanism efficiently enhances the characteristic extraction capability of CNNs, as depicted in Fig. 1. In this context, each pixel of the PQD feature map is treated as a neuron, and the minimum energy of the neuron can be represented as:

$$e_t = \frac{4(\sigma^2 + \alpha)}{(t - \beta)^2 + 2(\sigma^2) + 2\alpha}, \quad (4)$$

where t and i denote the target neuron and the spatial dimension index, respectively. The number of neurons on the channel is represented by M, where M = H × W, with α being a typical parameter value of 1e - 4. x_i denotes other neurons within the same channel, excluding the target neuron t. α and β represent the standard deviation and average value calculated for all neurons in the channel except for the target neuron t, respectively, which can be expressed as

$$\beta = \frac{1}{M}\sum_{i=1}^{M} x_i,$$
$$\sigma = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(x_i - \beta)^2} \quad (5)$$

The spatially suppressed neurons exhibit distinctive deviations both in β and t due to their high linear separability, which leads to a lower e_t value. Additionally, equation (4) illustrates that the lower the neuron's energy, the more distinguishable the neuron t is from its neighboring neurons. Thus, we can determine the weight parameter for each neuron by calculating $1/e_t$. The feature matrix is then augmented according to the attention mechanism's definition, and the formula is computed as follows:

$$\bar{\boldsymbol{X}} = \phi(\frac{1}{\boldsymbol{E}}) \odot \boldsymbol{X}, \quad (6)$$

where E represents the collective $1/e_t$ organized according to channel and spatial dimensions. ϕ represents sigmoid activation function (AF). The input and output feature maps are denoted by $\boldsymbol{X}$ and $\bar{\boldsymbol{X}}$, respectively. To determine the weight parameters of each neuron at each location, the sigmoid AF is employed.

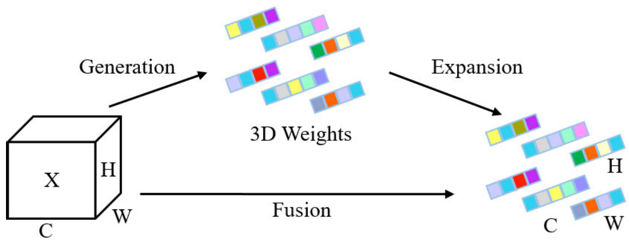


FIGURE 1. Schematic of SimAM.

III. PROPOSED METHOD

The schematic of the proposed KSTCNN framework is presented in Fig. 2. The proposed KSTCNN method consists of two main components: the IKST for TF analysis of complex PQD signals and the improved SimAM-based hierarchical DenseNet (SimDense) for feature extraction. Specifically, IKST is utilized to calculate the amplitude matrix IKST(m, n) for the complex PQD. The parameters in IKST are automatically modified based on the maximum energy density function. IKST(m, n) is then employed for obtaining the PQD's TF feature matrix. And then, the obtained PQD TF feature matrix is fed into the SimAM-based improved hierarchical dense network for PQD feature extraction and classification. In SimDense, the traditional CNN is first improved using the SimAM attention mechanism, which assigns higher weights to neurons conveying useful PQD feature information and suppresses surrounding neurons with irrelevant information. Based on this, a new improved 2D hierarchical Dense Network structure is proposed for PQD feature extraction. Then, the fully connected (FC) layer and softmax layer are utilized to categorize and identification of PQ. Next, we will provide a detailed description of the KSTCNN method.

A. IMPROVED KAISER WINDOW S-TRANSFORMATION (IKST)

In the proposed KSTCNN model, the IKST based on a maximum energy concentration is adopted to accommodate the TF analysis of complex PQDs signals. Firstly, in order to effectively improve its adaptability to the PQD signal, we propose a new control function. By setting the adjustment factor ρ (for dynamically adjusting the rate of change of the window shape) of the adjustment control function, the new control function was set:

$$\gamma(f) = \frac{\zeta_1}{(1-\rho)f + \zeta_2}, \tag{7}$$

where the value of ρ ranges from [0, 1). ζ_1 and ζ_2 denote the parameters used to control the change in the shape of the Kaiser window. However, fixed ζ_1 and ζ_2 cannot adapt to the demands of complex PQD TF analysis, which may lead to a decrease in resolution.

However, in practical signal processing, PQD signals are usually discretely sampled signals. Assuming that the actual sampling point and sampling period are N and T_s, respectively, and the sampling frequency is f_s. Combining Eqs. (1),(2) and (3), it is easy to obtain the improved KST (IKST). Subsequently, the PQDs signal $x(t)$ is transformed into a discrete signal $x(n)$ after the sampling process. Therefore, the discrete IKST of $x(n)$ can be expressed as:

$$\begin{aligned} IKST(m,n) &= \sum_{p=0}^{N-1} X_(n+p) W_k(n) e^{i\frac{2\pi mp}{N}} \\ &= |IKST(m,n)| e^{i\psi(m,n)} \end{aligned} \tag{8}$$

where m, n and p denote integers with values ranging from 0 to N-1. m is applied to change the time shift and p m is employed to regulate the translation length of the spectrum $X(n)$. $W_k(n)$ and $X_(n+p)$ represent the discrete Fourier transform outcomes of Eqs.(2) and $x(n)$. $|IKST(m,n)|$ and $\psi(m,n)$ denote the magnitude and phase of $IKST(m,n)$, separately. $IKST(m,n)$ is a $L \times W$ sized matrix. Furthermore, in order to dynamically alter the parameters of the control function $\gamma(f)$, inspired by the energy function [25], the energy density, $D_[KST](\rho, \zeta_1, \zeta_2)$, can be represented as:

$$D_{IKST}(\rho, \zeta_1, \zeta_2) = \sum\nolimits_{m=1}^{L} \sum\nolimits_{n=1}^{W} \left| \frac{IKST(m,n)}{\sqrt{\sum\sum |IKST(m,n)|^2}} \right| \tag{9}$$

In order to gain the maximum energy concentration by adjusting the parameters ρ,ζ_1 and ζ_2 to finally get the optimal resolution, then the optimization problem of solving to get the maximum energy concentration can be transformed into the minimum solution of solving the inverse of $D_{IKST}(\rho, \zeta_1, \zeta_2)$, which can be expressed as:

$$\underset{\rho,\zeta_1,\zeta_2}{\arg\min} \{1/D_{IKST}(\rho, \zeta_1, \zeta_2)\} \tag{10}$$

The objective function optimization problem in Eq. (10) is essentially a nonlinear optimization problem, which can be solved by the improved particle swarm optimization proposed in [26]. In this work, f_s takes the value of $6.4kHz$ and the benchmark frequency f_0 is $50Hz$.

B. SIMAM-BASED IMPROVED HIERARCHICAL DENSE NETWORK FOR FEATURE EXTRACTION

As we all know, CNN consists of multiple layers including convolutional, pooling, batch normalization (BN) and AF layers. CNN based models are made up of multiple convolutional layers stacked on top of each other [14], [19]. Each layer of the model extracts shallow feature information from the previous layer and transmits it to the subsequent convolutional layers, which facilitates accurate and efficient extraction of deep semantic feature information in the data stream [9].

In addition, different convolutional layers in CNNs extract distinct types of characteristic information. In shallow convolutional networks, the model extracts specific shallow characteristics. With the increase in the number of convolutional layers, the perceptual field increases, allowing the model to extract deeper semantic feature information [10], [27]. Hence, fully exploiting the hierarchical feature information

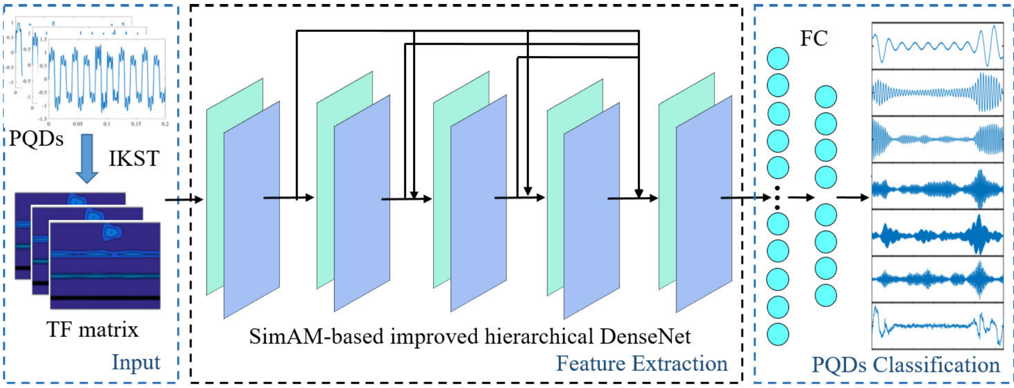


FIGURE 2. The schematic of the proposed KSTCNN framework.

of various convolutional layers can effectively boost the multi-scale feature representation ability of the DL-based PQD classification approach. Dense network (DenseNet) is one of the most often used approaches for CNNs to use hierarchical convolutional features, with the goal of improving the model's feature representation through dense connections across successive convolutional layers while minimizing gradient vanishing [10], [28]. Since SimAM can provide appropriate weight parameters to spatially informative neurons in the CNN while suppressing the information coming from surrounding neurons with irrelevant information, we employ SimAM to improve the DenseNet architecture in this paper.

Specifically, we build a hierarchical dense network structure using a SimAM-based 2D-CNN to retrieve complex PQ feature information. The schematic of the SimAM-based improved hierarchical DenseNet is illustrated in Fig. 3, where 2D-Conv stands for 2D convolution. Mish stands for mish AF.

In Fig. 3, k_s and m_i denote the dimensions of the convolutional kernel and the number of feature channels obtained from each convolutional layer within the SimAM-based dense network, respectively. The variable i takes integer values ranging from 0 to 4. The ability of extracting convolution kernels varies with different convolution kernel sizes when extracting PQD features in SimAM-based improved hierarchical DenseNet, and when the convolution kernel size is inappropriate, the network may lose some important perturbation feature information, which can lead to reducing the perturbation classification effect of the model, especially for lightweight models. As a result, choosing a suitable convolution kernel size is advantageous in order to fully use the model's feature extraction capability.

C. OPTIMIZATION OF POWER QUALITY CLASSIFICATION

In the PQDs classification optimization module, it is composed of 2 FC-layers, whose primary role is to optimize the pre-classification results, as well as to enhance the model's generalization ability and robustness. The optimized categorization outcomes are output through the softmax AF the model predicts the probability of each category softmax computation can be expressed as:

$$P_i = e^{x_i} / \sum_{j=1}^{c} e^{x_j} \tag{11}$$

where x_i represents the predicted value of the category before inputting softmax, and P_i represents the output probability after using softmax AF. The softmax works by converting the predictions of the network into the ratio of the exponent of the predicted value of the category to the sum of the exponents of the predicted values of all the categories to get the probability of each category being taken. It ensures that the predicted probability of each category is between 0 and 1, and that the sum of the predicted probabilities of all categories is 1. Moreover, the cross-entropy allows measuring the degree of difference between two different probability distributions of the same random variable, which can be expressed as the difference between the true probability distribution and the predicted probability distribution in DL. The smaller the value of cross-entropy, the better the model prediction. It has the advantage of faster derivation and accelerated network convergence. Therefore, the cross-entropy function is adopted as the training loss function of the proposed KSTCNN, which can be represented as:

$$Loss = -\frac{1}{r}\sum_{i=1}^{r}\sum_{j=1}^{c} p(x_{ij}) log(q(x_{ij})) \tag{12}$$

where r and c represent the number of samples and categories, respectively. $p(x_{ij})$ represents the true classification label of category c for the r-th sample and $q(x_{ij})$ represents the predicted classification result of category c for the r-th sample. After training the KSTCNN by employing the cross-entropy loss function, the test datas is input and the probability of each category is obtained by softmax, and the maximum value of the probability is considered as the final categorization result.

IV. EXPERIMENTS AND EVALUATIONS

In order to assess the categorization efficacy of the introduced KSTCNN model, a series of extensive experiments are conducted across varying levels of noise interference.

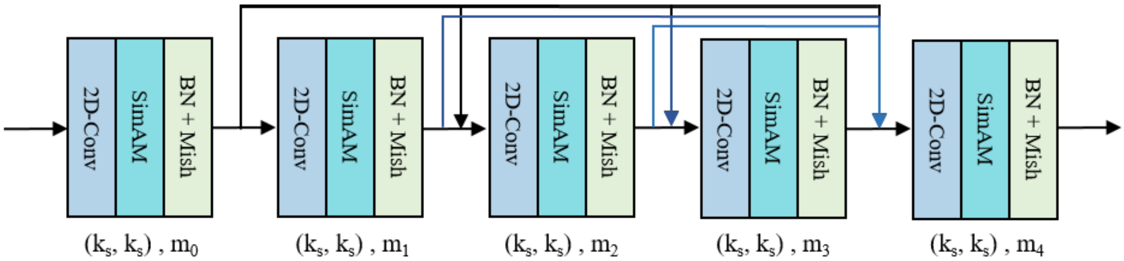


FIGURE 3. Schematic of the SimAM-based improved hierarchical DenseNet.

A. PQD SINGAL DATESET

In compliance with the stipulations outlined in IEEE-1159 regulations [29] and citation [9], [14], a comprehensive scrutiny is conducted on a total of 28 types of PQDs, encompassing 9 distinct single PQDs and 19 intricate PQDs signals. There are 28 distinct kinds of PQD signals as listed in Table 1. In the experiments, 28 PQD signals are simulated generated in MATLAB. The base frequency is 50 Hz, the signal sampling period is 200 ms, the sampling frequency is 6.4 KHz, and each PQD has 1280 sample points.The overall number of PQD labels is 28, and the total number of sample labels for each type of PQD is 2800, with three-fifths sample labels chosen at random for training and the rest utilized as validation and test sets, respectively. The suggested model's hyperparameters are tweaked using the grid search cross-validation method. The hardware platform configuration for the simulation experiment is i7-11800H CPU, 32G RAM and 1070Ti GPU. The software environment is Win10 and Keras framework.

B. MODEL PARAMETER SETTING AND OPTIMIZATION

In terms of parameter settings, since in DL-based feature classifiers, the model's convolutional layers are too deep or the size of the convolutional kernel is too large can affect the model's classification performance [27]. Thus, in the proposed KSTCNN model, the number of convolutional layers of the SimDense structure is set to 5 layers. The convolutional kernel size K_s of each layer is 5 and the number of feature channels of each layer is 16 (except for the first layer m_1 is taken to be 32). The detailed parameter settings for various layers of the network are listed in Table 2.

In order to evaluate the performance of KSTCNN on the problem of classifying power quality disturbance signals, we trained the network based on the PQD data in Table 1, and Fig. 4 shows the change curves of accuracy and loss during the network training. According to Fig. 4, the proposed KSTCNN model almost achieves convergence when the number of training iterations is up to 55, and the training loss is about 0.09, while the corresponding accuracy achieves more than 99.1%. Meanwhile, the accuracy curves of the training set and the validation set almost coincide with each other, indicating that the model does not have overfitting phenomenon, and further proving that the proposed KSTCNN has strong generalization capability.

Moreover, in order to enhance the classification performance of the proposed model, an alternative optimizer called Lion is employed, replacing the conventional Adam optimizer. Unlike typical manual optimizers like Adam, Lion operates as a programmatic auto-discovery optimization algorithm [30]. Unlike manual optimizers that store first- and second-order moments, Lion solely maintains momentum and calculates parameter updates using sign function operations. In comparison to Adam and conventional manual optimizers, the uniform update derived through the sign function often yields a larger norm, enabling Lion to necessitate a smaller learning rate during network training. Empirically, the learning rate of Lion optimizer in the proposed KSTCNN method is set to 0.00001.

In terms of batch size selection, a batch size that is too small tends to result in greater randomness in the updating of gradient values, making it difficult for the model to converge and increasing the training time. However, appropriately increasing the batch size can accelerate the training speed of the model and improve the memory utilization of the computer. The classification accuracy of PQDs with varying batch sizes under various noise conditions is presented in Fig. 5. Thus, the batch size in the KSTCNN model is set to 128.

C. VERIFICATION EXPERIMENTS UNDER VARIOUS TYPES OF NOISE CONDITIONS

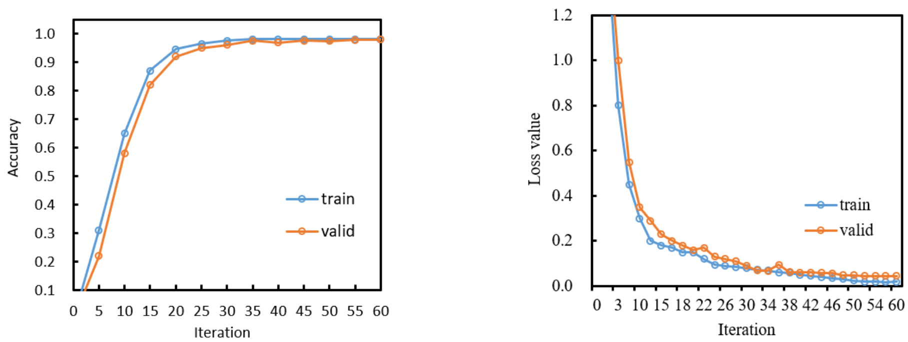
In order to verify the effectiveness of the KSTCN method under different PQD signals, extensive experiments were conducted under various noise conditions. The categorization accuracies of KSTCNN for different PQD singals under various noise conditions are presented in Table 3. It is clear from Table 3 that when there is no noise interference (i.e., clear), the classification performance of the KSTCNN is significantly better overall than in the case of interference with noise. In addition, the model's classification accuracy on a single PQD signal is significantly higher than the combined PQD signal, which indicates that the features of a single PQD signal are relatively simple, while the features of the combined PQD signal interact with each other and are more complex. Furthermore, the proposed KSTCNN has a minimum accuracy of 98.23% on N26 with a noise of 20 dB. The main reason for this is that when the transient signals are superimposed at the same time, the flickering is more insidious and the features are more difficult to recognize.

TABLE 1. 28 distinct kinds of PQD signals.

Categories	PQDs	Categories	PQDs
N1	Normal	N15	Swell + Transient
N2	Swell	N16	Sag + Transient
N3	Sag	N17	Notch + Transient
N4	Interrupt	N18	Spike + Transient
N5	Transient	N19	Sag + Flicker
N6	Flicker	N20	Sag + Flicker + Harmonic
N7	Harmonics	N21	Swell + Flicker + Harmonic
N8	Spike	N22	Interrupt+Flicker+Harmonic
N9	Notch	N23	Sag + Transient + Harmonic
N10	Swell + Harmonics	N24	Swell + Transient + Harmonic
N11	Sag + Harmonics	N25	Interrupt+Transient+Harmonic
N12	Flicker + Harmonics	N26	Flicker+Transient+Harmonic
N13	Interrupt + Harmonics	N27	Swell + Transient + Spike
N14	Transient + Harmonics	N28	Swell + Transient + Notch

TABLE 2. The detailed parameter settings for various layers of the SimAM-based improved hierarchical DenseNet.

Layers	Operation	Setup
2D-Conv0	(k_s, k_s), 32	padding=2, stride=1, SimAM, BN+Mish
2D-Conv1	(k_s, k_s), 16	
Concat0	concat(2D-Conv0, 2D-Conv1), 48	BN + Mish
2D-Conv2	(k_s, k_s), 16	padding=2, stride=1, SimAM, BN+Mish
Concat1	concat(2D-Conv0, 2D-Conv1, 2D-Conv2), 64	BN + Mish
2D-Conv3	(k_s, k_s), 16	padding=2, stride=1, SimAM, BN+Mish
Concat2	concat(2D-Conv0, 2D-Conv1, 2D-Conv2, 2D-Conv3), 80	BN + Mish
2D-Conv4	(k_s, k_s), 80	padding=2, stride=1, SimAM, BN+Mish



(a)Training and valid accuracy variation curve (b)Training and valid loss variation curve

FIGURE 4. Variation curves of accuracy and loss values on the training and validation sets during model training.

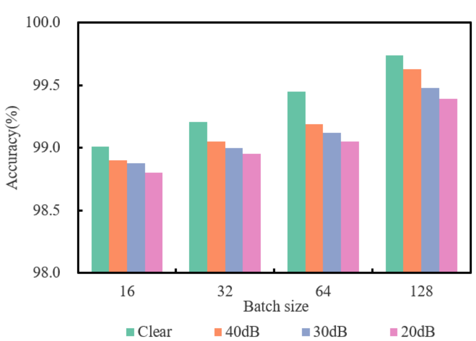


FIGURE 5. The classification accuracy of PQDs with varying batch sizes under various noise conditions.

Nevertheless, the accuracy of our proposed KSTCNN method is still higher than 98.2%, which demonstrates the excellent performance of KSTCNN in complex PQD detection.

In addition,in order to assess the efficacy of IKST within the proposed KSTCNN, various other TF methods, namely Octave S-Transform (OST) [1], Modified S-Transform (MST) [31], and the KST [8], are selected for comparison. To ensure a fair evaluation, all of these TF methods are integrated with the proposed MFCNN. The assessment criterion revolves around the classification performance under diverse levels of noise. Given the intricate grid conditions in modern power systems due to factors like power electronic devices and transient loads, and with reference to prior studies [3], [9], extreme noise scenarios including 40 dB, 30 dB and 20 dB are also taken into account to evaluate the model's resistance to noise. The comparative outcomes for various combinations of TF analysis approaches are tabulated in Table 4, where all outcomes are the average accuracy (AA) of the PQD classification accuracies, where the optimal value is marked in bold, and the SimDense

TABLE 3. The categorization results of the KSTCNN approach on different PQD signals.

Categories	Accuracy / %			
	Clear	40dB	30dB	20dB
N1	100	100	99.86	99.63
N2	100	100	99.81	99.60
N3	100	99.92	99.90	99.63
N4	100	100	100	100
N5	99.93	99.95	99.70	99.61
N6	99.65	99.65	99.61	99.60
N7	100	99.85	99.83	99.83
N8	100	99.76	99.76	99.71
N9	100	99.98	100	99.98
N10	100	100	99.82	99.85
N11	99.85	99.83	99.77	99.60
N12	99.51	99.49	99.45	99.36
N13	99.99	99.85	99.79	99.65
N14	99.51	99.51	99.45	99.43
N15	100	99.70	99.65	99.53
N16	100	99.99	99.90	99.63
N17	99.49	99.42	99.31	99.15
N18	99.70	99.61	99.55	99.29
N19	99.35	99.32	99.28	99.19
N20	99.68	99.32	99.05	98.63
N21	99.90	99.69	99.65	99.59
N22	99.52	99.23	99.08	98.85
N23	99.50	99.31	99.30	99.27
N24	99.19	99.15	99.15	99.13
N25	99.53	99.21	99.18	98.90
N26	99.01	98.95	98.77	98.23
N27	99.61	99.25	99.16	98.97
N28	100	100	99.91	99.25

TABLE 4. The comparative outcomes for various combinations of TF analysis approaches.

Categories	Classifier	Accuracy / %			
		Clear	40dB	30dB	20dB
OST	SimDense	99.10	99.02	98.89	98.31
MST	SimDense	99.13	98.92	98.15	97.86
KST	SimDense	99.34	99.28	99.06	98.89
IKST	SimDense	**99.74**	**99.63**	**99.48**	**99.39**

denote the SimAM-based improved hierarchical Dense network.

D. COMPARISON OF CLASSIFICATION PERFORMANCE OF VARIOUS APPROACHES

For further validation of the effectiveness and superiority of KSTCNN, we conducted comparison experiments between KSTCNN and state-of-the-art methods, which include traditional PQD classification techniques (based on manual crafted features) and deep-learning based PQD classification techniques (automated feature extraction). The results of PQD classification of various comparison methods under various noise conditions are shown in Table 5, where Manu. and Auto. indicate that the feature extraction and classification in the PQD classification process are manual and automatic, respectively.

According to Table 5, the AA of manual crafting-based feature extraction methods (ACMP+SVM [11], ICEEMDAN+KNN [12] and TQWT [13]) is lower than that of deep learning-based PQD automatic classification methods (CNN+GRU [18], CNN-LSTM [15], DCNN [14], 1D-ICNN [1], EITD+GSCN [3] and KSTCNN), indicating that manual feature extraction methods may result in the loss of certain feature information, whereas automatic classification techniques can effectively avoid this and make full use of the deep semantic feature information of the PQD signals. Notably, among all the experimental datasets, the proposed KSTCNN method in this paper has the most categories of PQDs (up to 28). Moreover, compared with the experimental datasets of the other compared methods, the categories of PQDs in the datasets of the other methods are fewer than and included in the experimental data categories of this paper. For example, the experimental PQD dataset in this paper considers one more PQD signal (class "N26") than the experimental data in the EITD+GSCN method, and than the experimental data of the TQWT method's experimental data considers two more PQD signals (category "N21" and category "N28"). Moreover, while DCNN's PQD classification accuracy is 0.17% greater than that of FITD+GSCN, the former examines just 24 PQD signal types, while the latter considers 27. Furthermore, despite the fact that 1D-ICNN, DCNN, and EITD+GSCN achieve classification accuracies of 99.26%, 98.83%, and 98.56%, respectively, they consider less PQD categories. Our proposed KSTCNN considers up to 28 different types of PQD signals and achieves a classification accuracy of 99.39%with an SNR of 20 dB. It also shows that the proposed KSTCNN approach in this study has improved accuracy and noise resistance, making it more suited for the deployment of complex PQD signal detection. In addition, compared with traditional CNNs-based methods (DCNN, 1D-ICNN CNN+GRU and CNN-LSTM), the proposed KSTCNN method designs an improved SimAM-based hierarchical 2D DenseNet structure for automatic feature extraction and high-precision intelligent recognition of PQDs. It not only can fully utilize the PQD feature information from different convolutional levels, but also the improved CNN architecture through the SimAM attention mechanism can assign higher weights to neurons conveying useful PQD feature information and suppress feature information from surrounding irrelevant information, to enhance the model's ability to acquire PQD features.

E. PRACTICAL EXPERIMENTAL VALIDATION ANALYSIS

In contrast to simulated signals, practical PQDs obtained from experiments exhibit greater authenticity and significant diversity. Hence, in order to validate the practical applicability of KSTCNN, an experimental hardware platform for PQD analysis is established, with its configuration depicted in Fig. 6. The setup comprises a conventional power source (Fluke 6105 A), a digital oscilloscope deployed for monitoring, and a customized PQ analyzer developed by our team. From Fig. 6, it can be observed that the initial step involves the generation of PQD signals from the signal source FLUKE 6105A. Subsequently, these signals are transformed through a signal conditioning circuit to meet the voltage input range (±2.5V) of ADS1278, resulting in low-level signals. Following this, the ADS1278 performs analog-to-digital

TABLE 5. The categorization results of the KSTCNN approach on different PQD signals.

Model	PQDs	Types of features	SNR / %	Accuracy / %
ACMP+SVM [11]	16	Manu.	20	97.13
ICEEMDAN+KNN [12]	21	Manu.	30	96.10
TQWT [13]	26	Manu.	20	97.63
CNN+GRU [18]	12	Auto.	20	98.30
CNN-LSTM [15]	12	Auto.	20	97.72
DCNN [14]	24	Auto.	20	98.83
1D-ICNN [1]	24	Auto.	20	99.26
EITD+GSCN [3]	27	Auto.	20	98.56
KSTCNN	**28**	**Auto.**	**20**	**99.39**

TABLE 6. Classification performance of different PQD signals under practical experimental platform.

Categories	Accuracy / %	Categories	Accuracy / %	AA / %	Test time / s
N1	100	N5	96.55	97.93	0.11
N2	97.63	N6	98.83		
N3	97.71	N7	98.75		
N4	98.90	N8	95.13		

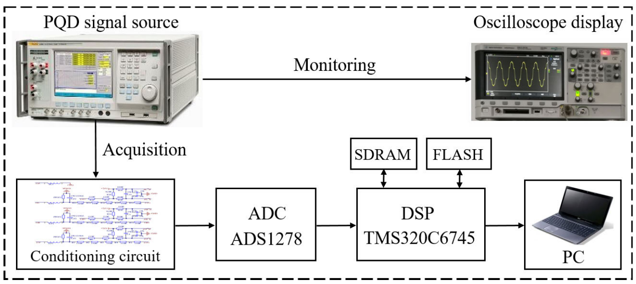


FIGURE 6. Hardware platform for PQD analysis.

conversion on the signals. Data processing is then carried out using the DSP (TMS3206735), and the processed data is communicated to the PC via SPI, facilitating the acquisition and measurement of real PQD signals. Specifically speaking in this hardware platform, the ADS1278 is a 24-bit ADC, which can sample at a rate of up to 128K in high-speed mode. The main frequency of the TMS320C6745 is 375MHz, and the SDRAM and Flash are the system's externally-expanded data and program storage modules. Finally, the PQD signals acquired and transmitted to the PC are then detected and recognized by the proposed KSTCNN.

Due to the limitations of Fluke's standard signal source performance, we created 8 types of pqd (N1-N8, N10). Each type of PQD signal was tested 90 times and the outcomes are shown in Table 6. As shown in Table 6, the suggested KSTCNN approach achieves satisfactory classification performance on real measurement data, with an AA of 97.93%. Furthermore, the average test time for each interference is 0.11s, which is less than the 0.2s sampling time and meets the real-time criterion. The results demonstrate the effectiveness of the proposed KSTCNN approach on practical experimental platforms and suit the requirements of real-time data processing.

V. CONCLUSION

In this study, we propose a new approach for high-precision intelligent recognition of complex PQDs based on improved IKST and SimAM-based CNN hierarchical network, which effectively enhances the TF resolution and PQD categorization performance. To meet the various TF signal detection requirements in PQD, IKST is utilized for TF signal detection in PQD at the feature extraction stage. The control function is modified to adjust the shape of the KS-window, and its parameters can be automatically optimized according to the maximum energy concentration. The SimAM-based improved hierarchical 2D DenseNet structure is then proposed to achieve automatic feature extraction and high-precision intelligent recognition of PQDs. Experimental outcomes demonstrate that the proposed KSTCNN categorization performance outperforms other popular methods and meets the real-time requirements for applications on practical hardware platforms.

In addition, feature selection prior to PQD classification may generate additional computational cost. Therefore, how to perform feature extraction and classification of PQDs only using deep networks is a problem that we will further explore in depth in the future.

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WENYUAN BAI received the M.S. degree in electrical engineering from North China Electric Power University, Beijing, China, in 2013.

He is currently a Senior Engineer with Gansu Electric Power Corporation, Gansu, China. His research interests include power quality analysis and processing, smart grids, machine learning applications in power grids, and signal processing.

GUOFENG ZHUANG received the B.S. degree from the College of Optoelectronic Engineering, Chongqing University, Chongqing, China, in 2008.

He is currently a Senior Engineer with Gansu Electric Power Corporation, Gansu, China. His research interests include power quality analysis and processing, smart grids, machine learning applications in power grids, and the governance of voltage problems caused by distributed photovoltaics.

XIUZHEN ZHAO received the B.S. degree from the College of Optoelectronic Engineering, Chongqing University, Chongqing, China, in 2008.

She is currently an Engineer with Gansu Electric Power Corporation Ultra High Voltage Company, Gansu, China. Her research interests include power quality analysis and processing, machine learning applications in power grids, and analysis of anomalous data variations in electrical equipment.

ZHANHONG WEI received the Ph.D. degree in electrical engineering from Xi'an Jiaotong University, Xi'an, China, in 2020.

He is currently a Lecturer with the Department of Electrical Engineering, Lanzhou University of Technology. His research interests include power quality analysis and processing, smart grids, power system operation and control, HVdc transmission, and renewable energy integration.