# Classification of vibration and ionization signals in pulse ionization chambers based on a temporal convolutional network

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## Abstract

The pulsed ionization chamber method has been widely applied in the field of environmental radon monitoring owing to its advantages such as high sensitivity, rapid response, strong radiation resistance, and low susceptibility to temperature and humidity. However, in dynamic environments, mechanical vibrations slightly displace chamber electrodes and transient electric field rearrangements, which leads to nonphysical counts significantly compromising accurate radon measurements. Most existing methods address this issue by incorporating vibration sensors for excluding measurement data collected during periods of mechanical disturbance. Although this approach effectively reduces false positives, it can inadvertently discard genuine alpha- particle signals, which results in incomplete measurements or systematic bias. To address this issue, a signal classification method based on a temporal convolutional network (TCN) is proposed to accurately identify and distinguish ionization signals from vibration-induced interference in the output of pulse ionization chambers. The constructed model integrates multilayer causal dilation convolution and a residual connection structure, effectively extracting multiscale time-series features while ensuring computational efficiency and enhancing the nonlinear modeling capability and training stability of the network. To evaluate the performance and generalization capability of the model in actual scenarios, 100,000 labeled samples (with ionization and vibration signals each accounting for 50%) are collected. These samples are divided into training and validation sets in an 8:2 ratio, and another 20,000 new samples are constructed to form an independent test set. After 600 training epochs, the TCN model achieved an accuracy and F1 score of 0.9915 on the validation set and reached 0.9954 on the test set, demonstrating its effectiveness in complex temporal feature recognition tasks. This

study provides an efficient, intelligent, and practical solution for signal identification in pulse ionization chambers under complex working conditions, offering broad application prospects and significant potential for widespread adoption.

## Full Text

## Preamble

Classification of vibration and ionization signals in pulse ionization chambers based on a temporal convolutional network∗ Feng Xiao,1 Yu-Xi Xie,1 Zhong-Kai Fan,1 Ruo-Mei Xie,1 Hai-Bo Yi,1 Hong-Bo Xu,1 Chen-Xi Zu,1 Xian-Fa Mao,1 Shi-Cheng Luo,1 Xin-Yue Yang,1 Hong-Zhi Yuan,1 and Yan-Liang Tan1, † 1College of Physics and Electronic Engineering, Hengyang Normal University, Hunan Province 421008, China The pulsed ionization chamber method has been widely applied in the field of environmental radon monitoring owing to its advantages such as high sensitivity, rapid response, strong radiation resistance, and low suscepti- bility to temperature and humidity. However, in dynamic environments, mechanical vibrations slightly displace chamber electrodes and transient electric field rearrangements, which leads to nonphysical counts significantly compromising accurate radon measurements. Most existing methods address this issue by incorporating vibra- tion sensors for excluding measurement data collected during periods of mechanical disturbance. Although this approach effectively reduces false positives, it can inadvertently discard genuine alpha-particle signals, which results in incomplete measurements or systematic bias. To address this issue, a signal classification method based on a temporal convolutional network (TCN) is proposed to accurately identify and distinguish ionization signals from vibration-induced interference in the output of pulse ionization chambers. The constructed model integrates multilayer causal dilation convolution and a residual connection structure, effectively extracting mul- tiscale time-series features while ensuring computational efficiency and enhancing the nonlinear modeling ca- pability and training stability of the network. To evaluate the performance and generalization capability of the model in actual scenarios, 100,000 labeled samples (with ionization and vibration signals each accounting for 50%) are collected. These samples are divided into training and validation sets in an 8:2 ratio, and another 20,000 new samples are constructed to form an independent test set. After 600 training epochs, the TCN model achieved an accuracy and F1 score of 0.9915 on the validation set and reached 0.9954 on the test set, demonstrat- ing its effectiveness in complex temporal feature recognition tasks. This study provides an efficient, intelligent, and practical solution for signal identification in pulse ionization chambers under complex working conditions, offering broad application prospects and significant potential for widespread adoption.

Keywords: Radon, pulse ionization chamber, temporal convolutional network, electrical signal classification, vibration inter- ference

## INTRODUCTION

Radon is a naturally occurring radioactive noble gas gen- erated from decaying uranium- and thorium-series radionu- clides in the Earth' s crust [1, 2]. Radon is colorless, odor- less, and easily released from the soil, rocks, and groundwater into the atmosphere, and therefore, it has become the primary source of natural radiation exposure for humans [3–5]. Ac- cording to the World Health Organization, radon is the second leading cause of lung cancer after smoking, with its health risks particularly pronounced in poorly ventilated indoor en- vironments [6, 7]. Radon and its short-lived decay products such as Po-218 and Po-214 can enter the lungs through in- halation. During decay, they emit high-energy alpha particles that can cause significant internal radiation damage to the ep- ithelial cells of the respiratory tract, leading to genetic mu- tations and carcinogenesis, thereby posing a serious threat to human health [8, 9].

For the precise monitoring and risk assessment of radon concentration, various radon detection instruments based on different principles have been developed in recent years.

Among these, the pulsed ionization chamber (PIC) method has been widely applied in the field of environmental radon ∗ This work was supported by the Natural Science Foundation of Hunan Province (Grant No. 2023JJ50091) and the Project of Hunan Provincial Department of Education (Grant No. 23A0516) † Corresponding author, hytyl@163.com monitoring owing to its advantages such as high sensitivity, rapid response, strong radiation resistance, and low suscep- tibility to temperature and humidity [10–12]. This method estimates the radon concentration in the air by detecting ion- ization events caused by alpha particles released during radon decay within the PIC. It is characterized by a compact struc- ture, stable operation, and suitability for long-term continuous monitoring.

Based on this principle, researchers developed various PIC- based radon measurement systems tailored to different appli- cation scenarios, which significantly enhanced their practical- ity and adaptability to diverse environmental conditions. For example, Dong et al. proposed a compact PIC system based on natural airflow, featuring noise suppression and humidity compensation capabilities, which makes it suitable for long- term online monitoring in underground environments [13].

Qiu et al. designed a system employing a dual-layer shield- ing structure for suppressing electromagnetic interference and utilizing oscilloscope-based sampling to accurately extract ion signals, which enables precise radon measurements across multiple locations [14]. Within the field of radioactive tracer studies, Xu et al. utilized a PIC-based approach combined with Rn-220 activity measurements for determining Ra-224 levels in natural water bodies. This method offers high mea- surement efficiency and eliminates the need for a carrier gas and drying equipment, which makes it well-suited for long- term field observations [15]. Kuzminov et al. developed a large-volume PIC device that maintains excellent

energy resolution (3.9%) even at radon concentrations as low as

## 1 Bq/m3, thereby meeting the stringent sensitivity require-

ments of low-background experiments [16]. Although the PIC method demonstrates strong perfor- mance in most application environments, it continues to face significant challenges in settings with complex mechanical vibrations. For example, in environments with strong me- chanical disturbances such as subway lines and construction sites, external vibrations can cause slight electrode displace- ments and transient electric field reconstructions, which re- sults in interference pulses that closely resemble alpha parti- cle ionization events [13, 14, 17].

The current mainstream coping strategies rely on vibration sensors to assist in judgment and avoid interference signals by shielding the measurement data during vibration. However, these methods often mistakenly delete the real alpha signal, which results in incomplete measurements or the introduc- tion of systematic bias. Although a few high-end radon detec- tors represented by the German ALPHAGUARD exhibit out- standing performance in terms of antivibration interference, their core signal recognition algorithms remain confidential, resulting in a lack of engineering implementation paths for related technologies. This indirectly increases the difficulty of technical exploration for other radon detection equipment manufacturers aiming to achieve functional optimization and performance improvement.

In a dynamic and complex en- vironment, accurately distinguishing ionization signals from vibration interference signals has become a key technical bot- tleneck for the further promotion and application of the PIC method.

In recent years, deep learning has demonstrated remarkable potential in the field of time-series signal classification and anomaly detection. The data-driven nature provides a new path for intelligent modeling of complex physical signals. In radiation detection, deep learning methods have been widely introduced into signal recognition and noise suppression tasks and demonstrated capabilities surpassing traditional signal processing algorithms in aspects such as particle identifica- tion, energy spectrum recognition, and signal reconstruction.

For example, Dutta et al. [18] employed deep neural net- works (DNNs) and recurrent neural networks (RNNs) to dis- criminate pulse shapes from low-energy scintillation detec- tors, significantly enhancing the distinction between "electron scintillation" and "nuclear recoil scintillation" events in the 4–20 keV energy range. Compared to the traditional charge integration and mean-time methods, both the area under the ROC curve (AUC) and quality factor were improved substan- tially. Fan et al. [19] proposed an event recognition model for high-purity germanium detector systems based on convolu- tional neural networks (CNNs), which directly learn discrim- inative features from raw pulse waveforms and effectively reduces the minimum detectable activity of the system for both full-energy peaks and partial energy deposition events.

Kimura et al. [20] developed a DNN-based algorithm for ra- dioactive nuclide identification, achieving high-precision au- tomatic nuclide recognition in portable $\gamma$-ray detection de- vices, which demonstrates the potential of deep learning in nuclear security and emergency response applications. In ad- dition, Lin et al. [21] conducted a systematic review of neu- ral network applications in radiation detection and imaging.

This highlights that deep learning is gradually becoming a key approach to improve the efficiency of radiation data ac- quisition and imaging, noting an emerging trend toward real- time inference on edge computing and low-power hardware.

Ortiz et al. [22] implemented deep learning algorithms on field-programmable gate array (FPGA) platforms, achieving real-time signal reconstruction under high pile-up conditions and effectively overcoming the limitations of traditional digi- tal filters in scenarios with overlapping pulses.

These studies confirmed the broad application prospects of deep learning for processing the radiation detection signal.

This can not only break away from the reliance of traditional methods on prior physical assumptions and manual feature extraction but also achieve higher signal recovery accuracy in complex noise backgrounds. However, the existing models have problems such as complex structure, high training cost, and limited modeling capability for long time-series de- pendencies, which makes it difficult for them to be widely applied in real-time detection or resource-constrained scenarios [23–25]. Among the numerous time-series models, the Temporal Convolutional Network (TCN), a new type of se- quence modeling architecture proposed in recent years, com- bines the parallel computing advantages of the CNN with the time-dependent modeling capability of the RNN [26]. Un- like traditional one-dimensional CNN, which can only cap- ture local temporal dependencies, TCN can cover the global temporal context while maintaining temporal causality by in- troducing causal dilated convolution and residual connection and realizing multiscale feature extraction [27]. This struc- ture overcomes common problems in RNN and long short- term memory (LSTM), such as vanishing gradients and low modeling efficiency caused by long-term dependencies, and the training process is fully parallelized, significantly enhanc- ing model stability and computational efficiency [28]. Exist- ing studies showed that TCN demonstrates superior perfor- mance compared to LSTM and gated recurrent unit (GRU) in tasks such as speech recognition, action segmentation, seis- mic wave analysis, and traffic flow prediction [29, 30], illus- trating outstanding robustness and generalization capability.

In some highly complex time-series modeling tasks, the per- formance of TCN surpasses that of convolution–recurrent hy- brid architectures such as CNN-LSTM, highlighting its ad- vantages in sequence modeling [31]. In addition, recent re- search [32, 33] indicates that the application of TCN and au- toencoder structures in the field of industrial fault detection demonstrates excellent

anomaly identification accuracy and stability in the analysis of complex vibration signals.

Given this background, this paper proposes a classifica- tion method for the output signals of PICs based on TCN, aiming to precisely distinguish ionization signals from vibra- tion interference signals by adopting its multiscale convolution structure and deep residual mechanism. The model can automatically extract hierarchical time features directly from the original pulse waveform without relying on an empirical threshold setting or external vibration sensor input, signifi- cantly improving the accuracy of signal recognition and sta- bility of instrument measurements. The results confirm that Fig. 1 [Figure 1: see original paper]. (Color online) Flowchart of the TCN-based pulse ionization chamber signal classification method this method can effectively separate ionization and vibration signals without relying on external sensors, providing a fea- sible solution for the intelligent application of PICs in highly reliable radon monitoring scenarios.

II. MATERIALS AND METHODS Figure 1 presents the overall framework of the study to sys- tematically present the overall technical route of the PIC sig- nal classification method based on proposed TCN. The entire process includes the following stages: data collection, raw signal display, data preprocessing and normalization, model construction, model training, and result output.

First, raw signals obtained through the PIC detector form one-dimensional time-series data of varying lengths, which can be used to reflect the characteristic distribution of ion- ization signals and vibration interference.

In the data pre- processing stage, the signal is normalized, and its length is unified to meet the requirements of the deep learning model for the consistency of the input tensor size while retaining the key timing features of the signal. Subsequently, a TCN model is constructed based on processed data, and the structural parameters of the model, the depth of the convolutional layer, number of channels, and kernel size are optimized to improve the classification performance and generalization ca- pability. The AdamW optimizer combined with warm-up and cosine-annealing learning rate strategies is optimized during the model training phase. Meanwhile, data augmentation methods are introduced for ensuring the stable convergence of the training process and improving classification accuracy.

Finally, the model outputs the classification results and con- ducts performance evaluations, including indicators such as the accuracy rate, F1 score, cross-entropy loss, and inference efficiency, comprehensively verifying the effectiveness and engineering feasibility of the proposed method for PIC sig- nal classification.

A. Data collection and standardized preprocessing A high-quality raw dataset was constructed by collecting 60,000 ionization and 60,000 vibration interference signals under controlled experimental conditions to enhance the gen- eralization capability of the model and ensure the authenticity and representativeness of

the training data. Figure 2 [Figure 2: see original paper] illus- trates the overall process of data collection and standardized preprocessing, including unprocessed raw acquired signals and schematics of signals under different preprocessing scenarios (e.g., short time-series samples, medium-length time- series samples, and ultralong time-series samples).

A PIC without a vibration sensor operated in the flow mode was used for data acquisition. The structural configuration of the PIC is illustrated in Fig. 3 [Figure 3: see original paper]. acquisition was Ionization signal conducted under vibration-free conditions. During the experiment, a radon source was placed at the chamber inlet to enable radon gas to diffuse into the cavity. As radon decayed, it emitted alpha particles that ionized the air, generating weak pulse signals. These signals were pre-amplified and recorded using a high-sampling rate system to determine the response char- acteristics of the detector to radon. Vibration signals were Fig. 2. (Color online) Flowchart of data collection and standardized preprocessing using various tools to simulate various types of mechanical disturbances. These actions induced structural vibrations that generated interference signals resembling ionization events in the waveform. All vibration signals were sampled independently and stored to construct a comparative dataset.

## 1. Segmented temporal normalization strategy

After analog-to-digital conversion, the original signal forms one-dimensional time-series data of different lengths.

A segmented temporal normalization strategy was developed considering the physical characteristics of the signal sources, sampling differences between the ionization and vibration signals, and requirements of deep learning models for con- sistent input tensor dimensions. This strategy uniformly ad- justed all raw signals x to a predefined target length Ltarget =

## 512. The aim was to preserve key signal features to the great-

est extent possible while enhancing input compatibility and training stability for the model.

Short Time-Series Samples (L < 300) Raw signal samples with lengths shorter than 300 are prone to insuffi- cient feature representation and loss of temporal context when input directly into a DNN, which can degrade the discrim- inative performance of the model. To address this issue, a refined processing strategy is proposed based on the original signal length. Differentiated compensation mechanisms are designed for ultrashort and moderately short sequences, ensuring that all samples are uniformly normalized to the target length Ltarget = 512.

Ultrashort Sequences (L < Ltarget/4) Conventional in- terpolation or zero-fill

methods often have difficulty effec- tively preserving the original waveform characteristics when the original signal length is extremely short (i.e., less than a quarter of the target length). This study adopts a periodic repetitive expansion strategy to avoid diluting the signal in- Fig. 3. (Color online) Basic structure of the pulsed ionization cham- ber detector acquired in a natural environment without a radon source, wherein the ambient radon concentration was sufficiently low to be considered negligible. The PIC was placed on a tabletop and subjected to impacts of varying intensities formation. The excess part is truncated at the end to ensure the consistency of the signal dimensions by periodically repli- cating signal fragments and concatenating them to a specified length. This process can be expressed as fallback in such cases for enhancing the robustness of the overall algorithm, thereby performing proportional resam- pling to adjust the original signal to the target length. xtarget = tile(x, (cid:20) Ltarget (cid:21) ) : Ltarget, where xtarget, x, tile( $\cdot$ ), $\cdot$ , and : Ltargetrepresent the signal after length normalization, original signal, periodic repetition operation, downward rounding operation, and selection of the first Ltarget sample, respectively. This method effectively ex- tends the temporal length of the signal while preserving its original local structural features, thereby making it suitable for short sequences that exhibit periodic patterns.

Medium and short sequences (Ltarget/4 $\leq$ L $<$ 300) Although the information density of medium-length signals is relatively sufficient, their length remains insufficient to di- rectly satisfy the requirements of deep networks for fixed input dimensions. Thus, the reflected padding strategy is adopted for length expansion. The boundary waveforms at both ends of the signal are mirrored and copied to complete the length, obtaining a normalized input sample given by xtarget = reflect pad (x, Ltarget) , where reflect pad( $\cdot$ ) represents the reflection padding op- eration. This strategy preserves the boundary structure of the original signal while avoiding nonphysical distortions intro- duced by zero-padding or random padding. This enhances the fidelity of the edge information and is well suited for ex- tending most physically measured signals. b. Medium-Length Time-Series Samples (300 $\leq$ L $\leq$ 1000) For signal sequences with a medium-length range, the dynamic time warping (DTW) algorithm is preferred for temporal alignment to achieve nonlinear stretching or com- pression of the signal morphology in the time dimension, maintaining good consistency with the standard reference template [34]. The core operations of this step are expressed xtarget = DTW(x, tref), where, tref represents the constructed reference template with a length of 512, which is defined as a uniformly spaced normalized time sequence within the interval [0, 1]. This serves as a unified temporal anchor for aligning signals from multiple sources. This template represents the distribution of the ideal signal under a standard time domain, and it is used to eliminate time-scale discrepancies caused by varying sam- pling lengths.

The DTW alignment may fail or produce unstable align- ment paths when signals contain substantial noise, severe dis- tortions, or exhibit length differences too large compared to that of the template. Linear interpolation is employed as a xtarget = interp(x, Ltarget, L), where interp( $\cdot$ ) represents the length normal-

ization func- tion based on linear interpolation. This method rapidly achieves uniform length normalization without introducing nonlinear distortions, making it suitable for signal samples that cannot be aligned stably using DTW. c. Ultra-Long Time-Series Samples (L > 1000) For ul- tralong signals exceeding a length of 1000, directly rescal- ing them to a target length can compress or eliminate critical information. Alternatively, applying DTW to global alignment incurs high computational cost and results in unstable alignment paths in the presence of noise or minor pertur- bations; this introduce significant registration errors. Given that ionization and vibration signals exhibit localized energy concentrations in the time domain, this study avoids full- length alignment and proposes a key region extraction strat- egy based on a sliding energy spectrum. This method iden- tifies and extracts the most representative local segments as model inputs by analyzing the energy distribution of the sig- nal. This approach significantly reduces computational com- plexity while preserving essential dynamic features, enhanc- ing the efficiency and classification accuracy of the model for long-duration signals. the sampled long signal be represented as x = [x1, x2, . . . , xL]. This strategy computes the energy spectrum distribution of the entire signal using a sliding-window ap- proach to identify the region with the highest energy concen- tration. The sliding energy function E[i] is defined as E[i] = (cid:88) k=−w/2 |xi+k| · h[k], where xi+k represents the amplitude of the signal at the (i + k)th sampling point, and h[k] represents the Hamming window function with a width of w = 200, which is used to suppress edge effects and reduce spectral leakage. The sliding window moves over the signal with a step size of 1, symmetri- cally covering 100 samples before and after the current point, producing a smoothed estimate of the energy spectrum.

The global energy spectrum distribution of the signal is ob- tained by sliding the window across all positions. The time point corresponding to the highest energy concentration is identified using the maximum energy criterion. ipeak = arg max E[i], where arg max E[i] represents the index i at which the en- ergy function E[i] reaches its maximum value across all pos- sible positions. The resulting ipeak represents the core region of the signal with the highest energy concentration, which contains the most critical dynamic patterns.

To focus on this key region and reduce redundant inter- ference, a local segment of length 256 is extracted centered around ipeak, serving as the primary energy segment. The ex- traction is performed using centered signal $x'$ is obtained by subtracting m from each sample in xtarget and aligning the distribution around zero.

This transformation facilitates more stable model training and improves the effectiveness of feature extraction.

Interquartile Normalization To further enhance ro- bustness, the IQR is used to scale the amplitude of the cen- tered signal $x'$. It is computed as xcore = x[ipeak − 128 : ipeak + 128], where xcore represents the most discriminative local seg- ment extracted from the original signal x, which is centered around the region of peak energy concentration.

A constant-edge padding strategy is applied to satisfy the requirements of the model for a fixed input length of 512. The amplitude of the last sample in the extracted local segment is appended repeatedly until the target length is reached. This approach ensures that the primary dynamic features remain undistorted while standardizing signal dimensions, thereby avoiding the introduction of artificial features that can neg- atively affect model performance.

Using this adjustment strategy, the most representative por- tion of each ultralong signal can be extracted as the model input, thereby ensuring both feature preservation and dimen- sional consistency. This approach effectively enhances the ca- pability of the model to process long time-series signals and improves classification accuracy.

## 2. Adaptive Amplitude Normalization Based on Median and

Interquartile Range During signal acquisition, raw data exhibit anomalies such as asymmetric distributions, baseline drift, and abrupt pulse spikes. Traditional mean-variance normalization is suscepti- ble to extreme values, distorting signal features and impairing model training and classification performance. This study in- troduces an adaptive amplitude normalization strategy based on the median and interquartile range (IQR) to enhance ro- bustness against such outliers. The basic idea of this method is completing signal centralization processing with the me- dian and using the IQR to compress the signal scale, alleviat- ing the effect of outlier fluctuations on the overall distribution.

The detailed steps are listed below. a. Median centralization processing For each signal xtarget, the median m is calculated as m = median(xtarget).

Then, the signal is shifted to a zero-centered distribution, which results in a centered signal $x'$ given by $x' = \text{xtarget} - \text{m}$, where median( $\cdot$ ) represents the function used to compute the median value of all samples in the input sequence. The median m represents the central tendency of the signal. The Q1 = percentile25($x'$) Q3 = percentile75($x'$) IQR = Q3 − Q1 where percentile25( $\cdot$ ) and percentile75( $\cdot$ ) represent func- tions that compute the 25th and 75th percentiles of the input sequence, respectively, and Q1 and Q3 represent the first and third quartiles of $x'$ reflecting the primary range of variation in the signal. The IQR captures the spread of the middle 50% of the data and serves as a robust scale estimator highly resis- tant to outliers.

After median centralization is completed, if the IQR is greater than the set fault-tolerant threshold $\epsilon$ (in this study, $\epsilon = 1 \times 10{-}6$), the amplitude normalization processing of the signal is conducted to further standardize its numerical scale.

If the IQR is too small (i.e., IQR $\leq \epsilon$), only the centralized operation is retained to avoid the risk of numerical instabil- ity or noise amplification at too small a scale. The specific normalization process is xnorm = , IQR $\leq \epsilon$ , IQR $> \epsilon$, where xnorm represents the signal sequence after the final normalization.

## 3. Data Augmentation and Final Normalization

A probabilistic data augmentation strategy is employed during training to enhance the generalization and robustness of the model under complex real-world conditions. This strategy includes various perturbations such as amplitude variation, temporal distortion, additive Gaussian noise, ran- dom cropping, and padding. These augmentations simulate diverse environmental noise and mechanical disturbances, which help create more representative and diverse training samples, improving the adaptability of the model to nonideal inputs.

After completing all structured preprocessing and augmen- tation steps, Z-score normalization was applied to each sam- ple for eliminating amplitude scale differences and accelerat- ing the model training convergence. This normalization trans- forms the signals to have zero mean and unit variance, which enables signals of varying scales to be processed uniformly.

The normalization formula is given as Fig. 4 [Figure 4: see original paper]. (Color online) Overall network structure of the TCN model: (a) Overall architecture of the TCN model. (b) Detailed structure of each module: (1) Causal dilation convolutional layer, (2) residual block, and (3) adaptive pooling classifier xfinal = xnorm − μ $\rho$ + $\delta$ where xfinal, μ, and $\rho$ represent the signal after final normal- ization, mean of the signal, and standard deviation, respec- tively. A small constant $\delta = 1 \times 10{-}6$ is added to prevent di- vision by zero when the standard deviation is extremely small or zero. This normalization transforms each signal into a stan- dard normal distribution with zero mean and unit variance, improving the robustness and adaptability of the model when handling signals of varying scales.

## 4. Dataset Partitioning and Loading

We adopted a stratified sampling method to divide the original dataset to ensure the scientificity, representativeness, and repeatability of the model evaluation results. Under the premise of maintaining the consistency of the various signal types and their length distributions, 100,000 pieces of data were divided into training (80%) and validation sets (20%) for the fitting and parameter adjustment process of the model.

In addition, a test set containing 10,000 samples for each type of signal was constructed independently for the final evalu- ation of the model performance. This partitioning strategy helps ensure the consistency of data distribution during the model training and testing processes, improving the fairness and robustness of the evaluation results.

B. Model Construction This paper proposes a deep learning model based on TCN to efficiently extract the time-dependent features and multi- scale structural information in ionization and vibration sig- nals [26, 35]. This model integrates the efficiency of CNN in parallel computing and local feature extraction [36, 37], as well as the advantages of RNNs in modeling long-term de- pendencies

[38, 39]. It is suitable for the classification tasks of complex temporal signals.

The proposed model includes three components: (1) an ini- tial causal dilated convolution layer to expand the receptive field while preserving temporal order; (2) five custom residual blocks built with causal dilated convolutions for progressively extracting deep features across multiple temporal scales; and (3) a lightweight adaptive pooling and fully connected clas- sifier for the final signal classification. The model architec- ture and parameter configuration are optimized for the char- acteristics of PIC signals, which enables the high-precision binary classification of the ionization and vibration signals while maintaining computational efficiency. The overall ar- chitecture of the model and detailed design of each module are presented in Fig. 4.

## 1. Causal Dilated Convolution Layer

A causal dilated convolution layer is introduced for the initial feature extraction to effectively extract discriminative temporal features between ionization signals and vibration in- terference in PIC outputs while strictly preserving temporal causality. This layer has a kernel size of seven and a dila- tion rate of one, which effectively extracts short-term timing features related to the physical response in the local electri- cal signal while ensuring the causal structure. A causal di- lated convolution combines the strict control of the time di- rection by causal convolution with the expansion capability of the receptive field by dilated convolution. In addition, it not only avoids future information leakage but also provides fundamental support for the subsequent extraction of multi-scale electrical signal patterns. This layer can be expressed $z(t) = (cid:88)$ $w(k) \cdot x(t - d \cdot k)$, where $z(t)$, $x(t)$, $w(k)$, $k$, and $d$ represent the convolution output at time step $t$, input sequence, $k$th weight of the convo- lutional kernel, kernel size, and dilation factor, respectively.

In dilated convolution, the sampling interval between adja- cent kernel elements is determined by $d$, which enables the network to perceive a wider temporal context by introducing "gaps" in the convolution.

In this model, the initial causal dilated convolution layer is configured with a small dilation rate ($d = 1$), which ensures strict temporal causality while precisely capturing local vari- ations in the ionization and vibration signals. This shallow layer establishes a strong feature foundation for subsequent residual blocks, integrating multiscale features and perform- ing high-level semantic abstractions. In addition, the causal dilated structure supports efficient parallel computation, sig- nificantly improving the training and inference speeds.

## 2. Custom Residual Block

Five custom residual blocks are introduced following the initial causal dilated convolution layer to further enhance the capability of the model to extract ionization features and interference patterns across multiple temporal scales from

PIC outputs while mitigating common deep network issues such as vanishing gradients and performance degradation.

Each custom residual block includes two layers of causal di- lated convolution, each followed by batch normalization, a LeakyReLU activation function, and a dropout-based regu- larization module. This design improves the nonlinear rep- resentational capacity of the model and stabilizes the train- ing. Each residual block optionally incorporates a $1 \times 1$ con- volution in the residual path for channel mapping to ensure dimensional consistency between the inputs and outputs, en- abling additive residual skip connections. These connections effec- tively alleviate gradient flow obstruction and promote ef- ficient learning. This architecture strengthens the capability of the model to discriminate between ionization and vibra- tion signals across varying temporal scales, reduce the risk of overfitting, and significantly improve generalization under complex operating conditions. The core components of each residual block are explained below. a. Double-layer causal dilated convolution Each cus- tom residual block contains two 1D causal dilated convolu- tion layers with a fixed kernel size of $k = 5$, which is con- sistent with the structure of the initial convolutional layer.

Dilation factors across the five residual blocks are set to $d = 1$, 2, 4, 8, and 16 for the progressive modeling of mul- tiscale temporal features. This results in an exponentially ex- panding receptive field with network depth. In addition, the number of channels increases across layers ($64 \to 128 \to 256 \to 256 \to 512$), equipping the network with an en- hanced feature extraction capacity at varying temporal res- olutions. This design enables the model to simultaneously capture fine-grained local details and broader global dynam- ics, improving its capability to model complex signal patterns and boost classification performance. b. Batch normalization Batch normalization is applied after each convolutional layer to reduce the internal covari- ate shift and enhance the stability and convergence speed of model training [40]. The normalization process is mathematically defined as BatchN orm1d(z) $= z - \mu \cdot \gamma + \beta$, where BatchN orm1d(z), z, $\gamma$, and $\beta$ represent the output of the batch normalization layer, output feature vector from the convolutional layer, learned scale parameter used to scale the normalized result, and learned bias parameter used for the result after translation normalization, respectively. Further, $\mu$ and $\phi$ represent the mean and standard deviation of z, respec- tively. c. LeakyReLU activation function A LeakyReLU acti- vation function is applied after each batch normalization layer to introduce nonlinearity into the network. Unlike the stan- dard ReLU function, which outputs zero for all negative in- puts, LeakyReLU enables a small, nonzero gradient in the negative region by multiplying the input by a small positive constant. This design helps prevent the "dying neuron" problem commonly associated with traditional ReLU activa- tions [41]. This function is defined as f (x) = (cid:40) if $x \geq 0$ $\alpha x$ if $x < 0$, where $\alpha$ represents a small positive constant that controls the slope of the negative region. This function can maintain the gradient flow in the negative-value area, improving the training performance of the deep network. d. Dropout regularization mechanism A dropout reg- ularization mechanism was incorporated into each residual block to mitigate overfitting

and enhance the robustness of the model to noise and perturbations. During training, dropout randomly deactivated a proportion of neurons with a predefined probability set to 0.35 in this study, effectively forcing the model to learn more robust and sparse feature representa- tions. This strategy improved the generalization performance of the model under complex and noisy operational conditions. e. Residual Skip Connections A residual connection mechanism was introduced to enable effective cross-layer feature fusion and alleviate the vanishing gradient problem in deep networks. Identity mapping can be applied directly when the number of input and output channels is identical. If the channels differ, a $1 \times 1$ convolution is used for the lin- ear projection to ensure dimensional compatibility. Four of the five residual blocks constructed in this study incorporate residual skip connections. The output of each block with a residual connection can be expressed as y = z2 + Skip(x), where y and z2 represent the final output of the residual block and output value after two layers of convolution, re- spectively. Further, Skip(x) represents the residual path function defined as (cid:40) Skip(x) = Conv1$×$1(x) otherwise Cin = Cout.

Among them, Conv1$×$1(x) represent the $1 \times 1$ convolution operation performed on the input x, and Cin and Cout repre- sent the number of channels of the input and output features, respectively. This structure realizes the fusion of the output after nonlinear transformation with the original input features, enhancing the capability of the model to perceive details and change patterns.

## 3. Adaptive Pooling Classifier

After five custom residual blocks are stacked, the result- ing output tensor possesses strong capabilities for temporal context modeling and multiscale feature representation of the ionization and vibration signals. A lightweight classification head is constructed on top of the residual feature outputs to further reduce the temporal dimension and enable efficient bi- nary classification between the ionization and vibration inter- ference signals. This classifier comprises an adaptive average pooling layer, a flattening layer, two fully connected layers, and regularization modules, with LeakyReLU activations in- tegrated to enhance nonlinearity.

First, the adaptive average pooling layer performs a global average operation on each channel in the time dimension, compressing the time-series feature of length L into a single channel value, significantly reducing the sequence dimension and retaining the key global information. Subsequently, the flattening operation converts the pooling results of multiple channels into one-dimensional vectors, serving as inputs for the subsequent fully connected layer. Finally, the nonlinear mapping of the feature space and final binary classification output are completed through two layers of fully connected networks. The first fully connected layer is followed by the LeakyReLU activation function, which introduces nonlinear expression capabilities and alleviates the vanishing gradient problem through the negative half-axis leakage mechanism.

A dropout regularization operation is introduced after activa- tion to enhance the generalization capability of the model and prevent overfitting. The second fully connected layer outputs the final binary classification prediction result, achieving au- tomatic discrimination between the ionization and vibration signals. This classification process can be formally expressed Y = Classifier(y) where Y represents the binary classification result pro- duced by the second fully connected layer.

The func- tion Classifier( • ) represents the entire adaptive-pooling-based classification module, which encompasses adaptive average pooling, flattening, and fully connected operations. Input y corresponds to the high-dimensional temporal features ex- tracted by the five custom residual blocks.

C. Model Training and Evaluation A systematic training and evaluation strategy was devel- oped to ensure the accuracy and generalization capability of the model for classifying ionization and vibration signals.

This strategy included designing the loss function, selecting the optimizer, scheduling the learning rate, and implementing performance evaluation metrics.

The cross-entropy loss function was adopted as the primary optimization objective to quantify the discrepancy between the predicted output of the model and ground-truth labels, guiding the parameter updates during training. This loss func- tion is widely used in classification tasks and is particularly well-suited for both binary and multiclass scenarios. In binary classification, the cross-entropy loss effectively indicates the divergence between the predicted probability distribution and the actual label distribution. This is defined as LCE($\theta$) = − (cid:88) (cid:104) (cid:98)Y • log(Y ) + (1 − (cid:98)Y ) • log(1 − Y ) (cid:105) where LCE($\theta$) and $\theta$ represent the cross-entropy loss func- tion and set of model parameters such as neural network weights and biases, respectively. Further, N , ˆY [0, 1], and Y {0, 1} represent the number of samples, predicted probability output by the model, and ground-truth label for the i-th sample, respectively. The model continuously updates its parameters to improve classification accuracy and reduce the likelihood of incorrect predictions by minimizing the cross- entropy loss.

Second, the AdamW optimizer was adopted to fur- ther enhance training efficiency and improve generalization.

AdamW is an improved variant of the traditional Adam op- timizer that decouples weight decay from the gradient-based update process. By explicitly incorporating a regularization term during parameter updates, it effectively prevents exces- sive parameter growth and mitigates overfitting [42]. The up- date rules for AdamW can be expressed as $\theta$t+1 = $\theta$t − $\eta$ • (cid:18) ˆmt√ ˆvt + $\epsilon$ (cid:19) + $\lambda\theta$t where $\eta$, $\epsilon$, $\lambda$, and $\theta$t represent the learning rate, a small constant for numerical stability, weight decay coefficient, and model parameters at iteration t, respectively. Further, ˆmt and ˆvt represent the bias-corrected first- and second-order moment estimates, respectively. The training process bal- ances the classification accuracy with the generalization ca- pability by combining

the cross-entropy loss function with the AdamW optimizer, ensuring robust and effective perfor- mance in distinguishing between the ionization and vibration signals under complex conditions.

A cosine-annealing learning rate scheduler was adopted in conjunction with a warm-up strategy to further enhance the training stability and accelerate convergence. This combined approach enabled the dynamic and adaptive adjustment of the learning rate throughout different training phases, improving the efficiency of parameter updates and optimizing the overall model performance [43].

During the initial training phase, a warm-up strategy is em- ployed to gradually increase the learning rate from a small starting value to a predefined initial rate. This phase reduces the sensitivity of the model to early parameter updates and prevent instability caused by large-gradient steps. The linear increase in the learning rate during the warm-up phase can be expressed as $\eta$t = $\eta$min + Twarmup · ($ $0 − $\eta$min) where $\eta$t, $\eta$min, $ $0, and Twarmup represent the learning rate at the tth step, predefined minimum learning rate at the beginning, initial learning rate at the end of the warm-up phase, and total number of steps during the warm-up period.

After the warm-up phase, the model transitioned to the main training stage, during which the learning rate decayed periodically, following a cosine annealing schedule. Starting from $ $0, the learning rate decreased gradually toward a pre- defined minimum value. This approach reduced the step size in the later stages of training, facilitating fine-tuned parame- ter adjustments and improving convergence toward a global optimum. The learning rate update is defined as (cid:19)(cid:19) $\eta = \eta$min + (cid:18) ($ $0 − $\eta$min) 1 + cos (cid:18) t − Twarmup Tcosine where $\eta$ and Tcosine represent the learning rate of each pe- riod in the cosine-annealing stage and total number of steps in the cosine-annealing schedule, respectively.

The learning rate schedule ensures stable model training in the early stages by preventing abrupt parameter updates that may lead to poor convergence by integrating the warm-up and cosine annealing strategies. In the later stages, the gradual de- cay of the learning rate improves the optimization precision and reduces the risk of becoming trapped in the local minima.

This combined approach enhances overall training effective- ness and model performance.

During the model training and testing processes, multiple evaluation indicators were introduced to assist in monitor- ing the generalization capability and classification effect of the model to comprehensively evaluate its performance in the classification task in addition to using the cross-entropy loss function as the main optimization objective. The main evalua- tion metrics adopted in this study include accuracy, precision, recall, F1 score, and AUC. The comprehensive evaluation of the model classification capability for different dimensions.

## 1. Accuracy: This is used to measure the proportion of cor-

rect samples predicted by the model to the total number of samples and the most intuitive performance metric. It is de- fined as Accuracy = where T P (true positive), T N (true negative), F P (false positive), and F N (false negative) represent the number of true cases, number of true negative cases, number of false positive cases, and number of false negative cases, respec- tively.

## 2. Precision: This measures the proportion of samples that

are positive among all those predicted to be positive, thereby reflecting the ability of the model to avoid false positives. It is defined as Precision =

## 3. Recall: This is used to measure the proportion of mod-

els that are successfully identified among all actual positive class samples, reflecting the coverage ability of the model for positive class samples. It is defined as Recall = 4.F 1 Score: It is the harmonic mean of precision and re- call, and it is particularly suitable for scenarios in which the distribution of sample categories is unbalanced and can more Fig. 5 [Figure 5: see original paper]. (Color online) Convergence trends of loss functions and changes in performance metrics during model training for the training and validation sets: (a) Loss curves, (b) accuracy curves, (c) F1 score curves, (d) precision curves, (e) recall curves, and (f) AUC comprehensively reflect the actual capability of the model in minority class identification. It is defined as validation datasets. The corresponding classification perfor- mance results are presented in Table 1 .

F1 Score = 2 · Precision · Recall Precision + Recall TABLE 1. Performance metrics of the TCN model after 600 training epochs

## 5. AUC : It is used to measure the overall capability of the

model to distinguish between positive and negative classes at different thresholds. The closer the value is to 1, the stronger the discrimination ability of the model. The AUC does not rely on classification thresholds and is thus more stable than accuracy, effectively reflecting the overall discriminative abil- ity of the model.

The accuracy provides a macroscopic assessment of the prediction performance of the model, while precision and re- call characterize the behavior of the model from the perspec- tives of false-positive controls (false detections) and false- negative controls (missed detections), respectively. The F1 score, as the harmonic mean of precision and recall, offers a balanced evaluation of both metrics and becomes important under class-imbalanced conditions. The AUC further evaluates the overall discriminative capability of the model based on its probabilistic outputs. The combination of these met- rics enables a more comprehensive assessment of the practi- cal performance of the model in the binary classification

of ionization and vibration signals addressed in this study.

III. RESULTS AND DISCUSSION The TCN model developed in this study is trained over 600 iterations and systematically evaluated on both training and Parameter Cross-entropy loss Accuracy Precision Recall F1 score Training set Verification set Table 1 shows that the TCN model demonstrates excellent performance on the training set, achieving a cross-entropy loss of 0.0823 with an accuracy of 0.9682 and an F1 score of 0.9687, indicating that the model fully acquired discrim- inative features in the training data. Further, the precision (0.9566) and recall (0.9825) are both at a good level, and the AUC value is as high as 0.9949. This indicates that the model can maintain stable and strong separability under different discrimination thresholds. The performance of the model on the validation set is enhanced further: the cross-entropy loss has been reduced to 0.0387, and both the accuracy rate and F1 score reached 0.9915. The precision (0.9896) is close to the recall (0.9938), indicating that the model achieved a well- balanced trade-off between false positives (false detections) and false negatives (missed detections). The AUC value of the validation set is as high as 0.9984, which proves that the TCN model has an almost perfect capability to distinguish ionization signals from vibration interference signals.

In addition, Fig. 5 presents the evolution trends of vari- Fig. 6 [Figure 6: see original paper]. (Color online) Convergence trends of the loss function on the training and validation sets during training for each model TABLE 2 . Performance comparison of all models Accuracy F1 score Cross-entropy loss AvgT/epoch (s) Avg Inf (ms) Model 1D-CNN Transformer Dataset Training Validation 0.9915 Training Validation 0.9396 Training Validation 0.9897 Training Validation 0.9260 ous performance indicators during the model training process, which reflect the convergence process and performance im- provement of the model.

As shown in Fig. 5, the TCN model rapid converges dur- ing the initial training phase, with the training loss decreasing sharply within the first few epochs. This confirms that the model quickly captures core discriminative features distinguishing ionization signals from vibration signals. The loss curve enters a more gradual and stable decline as training pro- gresses, which suggests that the model performs fine-grained modeling of more complex temporal boundary features.

In the recent approximately 50 epochs, the standard devi- ation of the validation accuracy remained below 0.15%, and that of the validation loss was less than 0.001. These val- ues indicate minimal curve fluctuations and that the model reached a stable “plateau” phase. Trends across the six eval- uation metrics (loss, accuracy, F1 score, precision, recall, and AUC) were highly consistent between the training and vali- dation sets, indicating no significant deviation and confirm- ing that the model did not exhibit overfitting, demonstrating strong training stability. Further, the validation accuracy, F1 score, precision, and recall consistently remained high, and the AUC curve remained close to 1. This

confirms that the TCN model possesses excellent discriminative capability and robustness in distinguishing ionization signals from vibration signals, thereby maintaining stable and reliable classification performance across varying decision thresholds.

This paper systematically compares it with three represen- tative time-series modeling methods to build on the achieved high recognition accuracy and comprehensively evaluate the effectiveness of the proposed TCN model: (1) the LSTM net- work capable of capturing long-range temporal dependencies, (2) 1D CNN, which is widely used in engineering applica- tions because of its high computational efficiency, and (3) the Transformer model, which shows outstanding sequence modeling performance in recent years. This is based on the self-attention mechanism and can learn long-distance tempo- ral dependencies and establish global dynamic weights.

All models are trained using a unified data normalization and preprocessing procedure to ensure the relative fairness of the comparison. The number of training epochs fixed at 600 and hyperparameter scales were kept approximately consistent. The key structural parameters of each model, including the number of hidden units, convolutional kernel sizes, at- tention heads, and dropout rates, were tuned individually to ensure that each model achieved optimal performance.

The comparison results are presented in Table 2. The TCN model significantly outperformed the LSTM, 1D CNN, and Transformer models in terms of classification accuracy, F1 score, and cross-entropy loss, which confirms that it has a stronger expressive capability and stability in the task of boundary feature modeling and discrimination between ion- ization signals and vibration interference signals.

In terms of training time consumption, the average training time per epoch (AvgT/Epoch) of TCN was 284.4 s, which was slightly higher than those of LSTM (58.1 s) and 1D-CNN (71.0 s).

This difference can be considered a reasonable cost when achieving a higher recognition accuracy and more robust con- vergence.

In addition, the training time of TCN remained considerably lower than that of the Transformer model (334.8 s), whose more complex architecture and attention compu- tations introduced a substantially greater overhead. These results indicated that TCN achieved a favorable balance be- tween high performance and low computational redundancy.

The loss convergence trend in Fig. 6 shows that TCN not only indicates a faster convergence speed (with a greater loss decline slope) in the early stage of training but also maintains an extremely low fluctuation amplitude throughout the training process (the loss curves of the training and validation sets show almost no oscillation), further verifying the high stabil- ity and excellent generalization capability of its optimization process.

In the inference stage, the average inference time (Avg Inf) of the TCN model

is only 0.043 ms per sample, which is slightly slower than those of the 1D-CNN (0.015 ms) and LSTM (0.018 ms) models. However, the TCN model achieves the highest classification accuracy rate (0.9915) and the most stable overall performance among the four types of models. For application scenarios such as ionization signal recognition that are extremely sensitive to false and missed detections, the reliability improvement brought about by high accuracy is far more crucial than the difference in inference time below the millisecond level. Therefore, TCN achieves a better comprehensive tradeoff between accuracy and real- time performance.

The McNemar significance test was employed to conduct pairwise comparisons of the models (see Table 3 ) and evalu- ate the statistical significance of the performance differences.

The results show that the P-values of the TCN model com- pared to those of the other three models are considerably lower than 0.05. This indicates that its performance improve- ment is statistically significant instead of being attributed to random fluctuations, further verifying the robust performance advantages of the model proposed in this study.

The TCN model not only significantly outperforms LSTM, 1D-CNN, and Transformer model in key performance indi- TABLE 3. McNemar significance test p values for pairwise model comparisons (Note: $p < 0.05$ indicates statistically significant differences.) Comparison of model combinations TCN vs. 1D-CNN TCN vs. LSTM TCN vs. Transformer p value $1.18 \times 10{-}7$ $7.47 \times 10{-}243$ cators such as classification accuracy, F1 score, and cross- entropy loss, but also maintains sub-millisecond latency in the inference stage, demonstrating strong engineering usabil- ity. Compared to the other models, the TCN exhibits a superior balance in terms of expressive capability, convergence stability, and computational efficiency, thereby exhibiting ex- cellent comprehensive performance.

The model was tested on a large-scale test set completely independent of the training process to further verify its gen- eralizability in practical applications. This test set contained 20,000 unseen samples of the model (10,000 ionization sig- nals and 10,000 vibration signals), which were highly repre- sentative. The test results are listed in Table 4 . The over- all classification accuracy and F1 score of the model both reached 0.9954, indicating not only strong performance on known data but also excellent adaptability and robustness when handling unknown signals.

TABLE 4. Test results of the TCN model Parameter Signal Type Vibration signal Ionization signal Accuracy F1 score Recognition correct Recognition errors The model achieved over 99% accuracy in recognizing both signal types with very few misclassified samples. This validates its robust capability in modeling complex high- dimensional temporal features and underscores its potential for the intelligent classification of ionization and vibration signals.

Although the model demonstrated excellent performance on the standard test set, its training and validation were based on individual waveform samples ac-

quired from a high- frequency sampling circuit. As illustrated in Figs. 7(a) and Fig. 7 Figure 7: see original paper, the ionization and vibration signals occur indepen- dently. However, in practical applications, there remains a low-probability risk of encountering complex edge cases that can pose challenges to the classification robustness of the model. As shown in Fig. 7(c), when two physical events such as ionization and vibration occur in close temporal proximity or almost simultaneously, they can be captured within the same sampling window, thereby forming a composite wave- form with mixed characteristics. Such waveforms exhibit peak stacking or localized overlap in the time domain, inte- grating the sharp spike patterns of ionization signals with the noisy components of vibration interference. These mixed fea- tures can confuse the feature extraction process of the model, potentially leading to misclassification.

For such occasional aliasing issues, a pulse pile-up rejec- tion circuit can be integrated via hardware design to iden- tify and shield these superimposed samples in real time at the signal acquisition stage, thereby avoiding incorrect entry into the model discrimination pipeline. A statistical correc- tion coefficient mechanism can also be introduced in the post- processing stage to systematically compensate for the over- all measurement results. Although the probability of such phenomena is relatively low, their potential impact cannot be ignored. The overall stability of the system and robustness of the model under real operating conditions can be effec- tively enhanced through the collaborative optimization design of software and hardware.

While ensuring recognition accuracy, the deployment ef- ficiency of the model is an important factor determining its practicality, considering that the final application scenario of the model constructed in this study is an online real-time in- ference in embedded measuring instruments rather than rely- ing on high-performance computing platforms for offline pro- cessing. This application places higher demands on the com- putational complexity and memory footprint of the model.

Therefore, a systematic deployment adaptability analysis of the proposed TCN model is conducted in this study to evalu- ate its feasibility for resource-constrained devices.

Compared with general DNN models that require a large amount of memory and computational resources for support, the TCN model considers the trade-off between accuracy and deployability at the beginning of its design. The model ef- fectively avoids redundant computations and structural bloats by adopting 1D convolutional structures instead of complex attention mechanisms and limiting the network depth to a reasonable scale; however, it significantly reduces computa- tional complexity. While maintaining high classification ac- curacy, the original model comprises 5.82 million parame- ters, demonstrating strong learning capacity and convergence characteristics and showing preliminary feasibility for em- bedded deployment [44, 45]. This parameter scale imposes a burden on resource-constrained platforms, particularly in cost-sensitive scenarios where large-scale deployment and broad applicability remain challenging.

A lightweight version of the TCN model was developed by compressing the number of channels while preserving the original network structure to further improve the deployment versatility of the TCN model. This compressed model re- duced the total number of parameters to 0.37 million, (only 6.4% of the original model), and yet, it still achieved an ac- curacy of 99.41% for the test set. The detailed performance metrics are listed in Table 5 . Despite the significant reduc- tion in model size, the performance dropped by only approximately 0.1 percentage point, indicating an excellent balance between accuracy and computational efficiency.

In terms of resource deployment, the memory usage of the lightweight TCN model in the 32-bit floating-point rep- resentation is 1.50 MB. If INT8 quantization compression is adopted, the model volume can be reduced to within 400 KB and directly deployed to typical edge hardware platforms TABLE 5. Test results of the lightweight version of the TCN model Parameter Signal type Vibration signal Ionization signal Accuracy F1 score Recognition correct Recognition errors (such as the ARM Cortex-M series, etc.) [46, 47]. In addi- tion, the current mainstream toolchains (such as TensorFlow Lite Micro, CMSIS-NN, and ONNX Runtime for MCUs) widely support the conversion and deployment of lightweight neural networks in bare-metal or RTOS systems, which fur- ther reduces the engineering threshold for model implemen- tation [48].

The proposed TCN model achieves substantial structural compression and computational optimization while maintain- ing high classification accuracy. The model exhibits a strong generalization performance and excellent deployment adapt- ability, providing a practical and intelligent solution for the recognition of vibration and ionization signals in embedded measurement systems. Future work can focus on integrating the model with specific hardware platforms, such as ARM- based processors or FPGA acceleration modules, to imple- ment model pruning, weight quantization, and inference en- gine optimization. These efforts aim to further accelerate inference speed and reduce power consumption, enabling a "model-as-a-service" edge intelligence loop and advanc- ing the practical application of intelligent sensing systems in fields such as nuclear radiation detection and structural health monitoring.

IV. CONCLUSION This study proposed an intelligent signal recognition method based on a TCN to address the issue of nonphys- ical counts in PICs caused by mechanical vibrations under dynamic conditions. The proposed approach overcomes the limitations of conventional vibration sensor-based shielding strategies, which risk discarding genuine signals and intro- ducing systematic biases. The proposed model integrated a causal dilation convolution and multilayer residual connec- tion structure. While ensuring the temporal causality con- straint, the TCN effectively enhanced its modeling capability for the characteristics of the ionization and vibration signals across different time scales. This not only significantly im- proved the discrimination accuracy between the two signal types but also fundamentally mitigated signal omission and systematic

deviations that can arise from the shielding strate- gies of traditional vibration sensors.

At the system-design level, a lightweight version of the TCN model was further developed in this study. Through structural compression and INT8 quantization, the parameter size was reduced substantially, enabling the overall storage footprint to be constrained to within 400 KB. This lightweight Fig. 7. (Color online) Typical and composite waveform characteristics of ionization and vibration pulse signals: (a) Ionization signal, (b) vibration signal, and (c) mixed signal architecture was well suited for resource-limited environ- ments, offering low-power, low-latency online inference ca- pability, and strong practical deployability. Further, it can form a stable synergy with a pulse pile-up rejection circuit and a post-processing correction mechanism, providing an in- telligent recognition solution that can be directly deployed for actual instruments.

The proposed TCN model achieves significant improve- ments in both the accuracy and stability of PIC signal classifi- cation, while also demonstrating strong adaptability in terms of structural compactness and suitability for edge deploy- ment. This approach offers an effective solution for achiev- ing high-precision, low-interference intelligent monitoring in radon measurement systems operating under complex and dy- namic conditions. The proposed TCN model presents promis- ing prospects for practical engineering implementations and has broad applicability in real-world scenarios. [1] Z.K. Fan, J.L. Sun, H.X. Li et al., A novel method for simul- taneous measurement of 222Rn and 220Rn progeny concentra- tions measured by an alpha spectrometer. Nucl. Sci. Tech. 36, 8 (2025). https://doi.org/10.1007/s41365-024-01570-7 [2] M. Xia, Y.J. Ye, S.Y. Liu, Numerical simulations for radon mi- gration and exhalation behavior during measuring radon exha- lation rate with closed-loop method. Nucl. Sci. Tech. 35(1), 9 (2024). https://doi.org/10.1007/s41365-024-01362-z [3] C. He, Z. Zeng, L. Zhang et al., A new-designed system for water. Appl. Radiat. https://doi.org/10.1016/j.apradiso.2022.110320 continuous measurement Isot. radon (2022). [4] F. Xiao, S. Liu, R. Xie et al., A simple improvement on the Al- phaGUARD PQ2000PRO to accurately measure the radon exhalation rate from soil. J. Radioanal. Nucl. Chem. 334, 2839–2849 (2025). https://doi.org/10.1007/s10967-025-10018-0 [5] W.C. Ding, Y.J. Wang, F. Fang et al., A practical soil radon (222Rn) measurement method. Nucl. Sci. Tech. 21(3), 182–186 (2010). https://doi.org/10.13538/j.1001-8042/nst.21.182-186 [6] V.J. Cogliano, R. Baan, K. Straif et al., Preventable exposures associated with human cancers. J. Natl. Cancer Inst. 103(24), 1827–1839 (2011). https://doi.org/10.1093/jnci/djr483 [7] J.Y. Yoon, J.D. Lee, S.W. Joo et al., Indoor radon exposure and lung cancer: a review of ecological studies. Ann. Occup.

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*Note: Figure translations are in progress. See original paper for figures.*