Gated Recurrent Units Based Abnormal Detection Method for Imbalanced Electricity Consumption Data

Songping Meng, Chengdong Li, Wei Peng, and Chenlu Tian

***Abstract*—Timely detection of abnormal electricity consumption behaviors plays a key role in saving energy. However, the detection of abnormal electricity consumption faces many problems. Imbalanced data are important challenges in this field. When the normal data are much more than the abnormal data, the network can hardly recognize the features of the minority class data, which generates low detection efficiency. Therefore, in this paper, we employ adaptive synthetic sampling (ADASYN) to achieve effective expansion of the minority class data. In addition, we adopt gated recurrent units to complete the classification of electricity consumption data. We conduct detailed experiments to verify this proposed method. Experimental results show that this method is more effective than other methods.**

***Index Terms*—Anomaly detection, gated recurrent units, imbalanced data, abnormal electricity consumption detection**

I. Introduction

With the increasing demand for electric energy, it is more and more important to find abnormal electricity consumption behaviors in time, and abnormal electricity consumption detection has become an important topic. Efficient abnormal electricity detection can not only help users reduce unnecessary economic expenditure, but also save limited resources.

A. Related Work

Abnormal electrical detection methods are divided into classical machine learning methods and deep learning methods.

Machine learning method plays a key role in anomaly detection. The authors in Refs. [1, 2] proposed a K-nearest neighbor (KNN) based algorithm to detect anomalies. In Refs. [3], authors used support vector machine (SVM) to diagnose abnormalities caused by electricity theft. In Ref. [4], authors improved the decision tree model and used the density of abnormal and normal classes to detect anomalies in consumption data. Ensemble learning methods also contribute to abnormal electricity consumption detection. In Ref. [5], the gradient tree boosting (GTB) based method was proposed to detect anomalies. In Ref. [6], a random forest model as a classifier was proposed to detect anomalies.

With deep learning coming into the public eye, deep learning methods have also been successfully applied to abnormal electricity consumption detection. In Ref. [7], a recurrent neural network (RNN) based anomaly detection system was designed, which could remove seasonal factors from the data, so as to better capture the real distribution of data. In Ref. [8], the mixed model of RNN and K-means was used to identify abnormal consumption. In Refs. [9, 10], an autoencoder with the long short-term memory (LSTM) method was proposed to identify anomalies in electricity data. In Ref. [11], a variational recurrent autoencoder was proposed to detect anomalies. In Ref. [12], authors combined random forest with convolutional neural network (CNN) to detect electric theft. In Refs. [13, 14], authors proposed CNN models and converted the electricity data into two-dimensional data to learn the data characteristics.

B. Motivation of Our Work

Although abnormal electricity detection has made many achievements, there are still many problems. One of the most important problems is that there is a serious imbalance in electricity consumption data. Because electricity consumption data are related to the privacy of users, users generally do not disclose their electricity consumption data. Even if they are public, we can get normal electricity consumption data, almost cannot get abnormal data. If the number of normal data in the dataset is much larger than the abnormal data, the detection model is more inclined to learn the normal data and cannot learn the data characteristics of abnormal data when training the detection model, resulting in poor detection effect.

The synthetic minority oversampling technique (SMOTE) provides us with a solution. In Ref. [15], the authors used SMOTE to generate data for rock groutability classification. In Ref. [16], the authors used SMOTE and SVM to implement intrusion detection. Therefore, in this paper, with the help of above ideas, we can use the adaptive synthetic sampling (ADASYN), which is a modified method of SMOTE, to expand the abnormal data and then use the balanced dataset to train the abnormal electricity consumption detection model.

In addition, since the electricity consumption data are typical time series data, how to select the classifier is also an important problem. In Ref. [17], the authors used gated

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Songping Meng, Chengdong Li, Wei Peng, and Chenlu Tian are with School of Information and Electrical Engineering, Shandong Jianzhu University, Jinan 250101, China (e-mail: mengsongping@foxmail.com; lichengdong@sdjzu.edu.cn; pengwei19@sdjzu.edu.cn; chenlutian2017@sdjzu.edu.cn).

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recurrent unit (GRU) to work out the long-term dependence problem in time series data for gesture recognition. In Ref. [18], authors transformed the GRU into a neural network performing computed tomography (CT) image reconstruction. Inspired by the above works, we employ GRU as the classifier of electricity consumption data to realize the detection of abnormal electricity consumption.

C. Main Content and Contribution

In this paper, the gated recurrent unit and adaptive synthetic sampling (GRU-ADASYN) based abnormal electricity consumption detection model is given. The novelties and contributions of this paper are as follows:

(1) We adopt ADASYN to work out the problem of imbalanced data. ADASYN is used to expand abnormal data to make its quantity consistent with normal data and alleviate the problem of poor detection effect caused by insufficient abnormal data.

(2) We employ GRU to classify electricity consumption data. GRU can effectively learn data features and solve the long-term dependence and gradient disappearance problems.

(3) Detailed experiments and comparisons are made. Experimental results verify the effectiveness of our proposed method.

II. Proposed GRU-adasyn Model

In this section, we first give the framework of GRU-ADASYN and then detailedly describe each module in the model.

A. GRU-ADASYN Model Framework

ADASYN is adopted to expand minority class data to get a balanced dataset, and GRU is employed to recognize the electricity consumption data in this paper. Detailed steps are as follows and also plotted in Fig. 1.

Step 1 Data are cleaned to remove outliers and replace missing values with an average value.

Step 2 Due to the serious imbalance problem of electricity consumption data, that is, the number of normal electricity consumption data is much larger than that of abnormal data, ADASYN is adopted to expand minority class data and get a balanced dataset.

Step 3 The expanded balanced dataset is applied to train the GRU classification model, and the results of abnormal electricity detection are obtained.

B. ADASYN for Data Expansion

ADASYN has the following advantages over oversampling methods like SMOTE: (1) reducing the bias caused by class imbalance, (2) adaptively moving the classification boundary to the difficult data. Therefore, we use ADASYN to implement the extension of minority class data. The detailed steps are as follows and plotted in Fig. 2.

First, the generated number of samples G is calculated as

$$G = (m_l - m_s) \times \beta \quad (1)$$

where m_l is the number of data of the majority class, m_s is the number of data of the minority class, and β is a random value of 0–1.

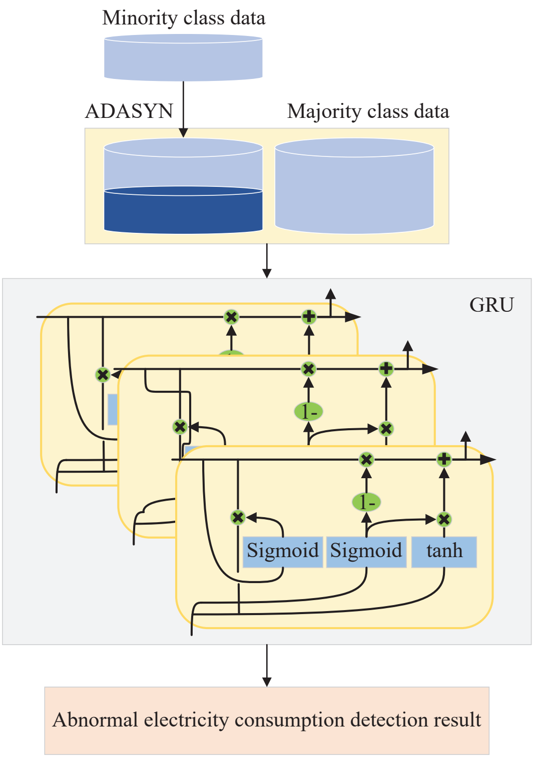

Figure 1 Framework of GRU-ADASYN.

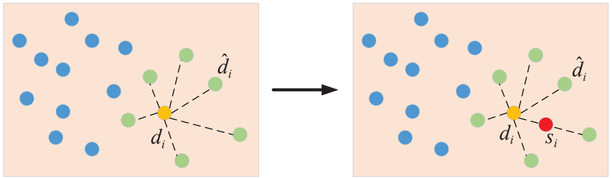

Figure 2 Schematic diagram of ADASYN.

Then, the majority class proportion in K-nearest neighbor r_i is calculated as

$$r_i = \frac{\Delta_i}{K} \quad (2)$$

where Δ_i is the number of data of the majority class in K-nearest neighbor, $i = 1, 2, ..., m_s$.

The r_i is normalized as

$$\hat{r}_i = \frac{r_i}{\sum_{i=1}^{m_s} r_i} \quad (3)$$

Based on the sample weight, the number of new samples generated for each minority sample g is expressed as

$$g = \hat{r}_i \times G \quad (4)$$

Finally, the SMOTE algorithm is used to generate samples, which can be calculated as

$$s_i = d_i + \left(\hat{d}_i - d_i\right) \times \lambda \quad (5)$$

where s_i is the generated sample, d_i is the i-th sample in minority class samples, $\hat{d}_i$ is a random sample of minority class in the K-nearest neighbor of d_i, and $\lambda \in [0, 1]$, respectively.

C. Gated Recurrent Unit for Classifying

Recurrent neural network is effective for time series data, but it cannot solve the long-term dependence in time series, and there is a problem of gradient disappearance. Therefore, LSTM and GRU are proposed. LSTM and GRU both have gate structures. Different from LSTM, GRU has only two gate structures, which can decrease the training time on the basis of ensuring the learning effect. We use GRU as a classifier to classify the electricity consumption data. The principle of GRU is described and also plotted in Fig. 3.

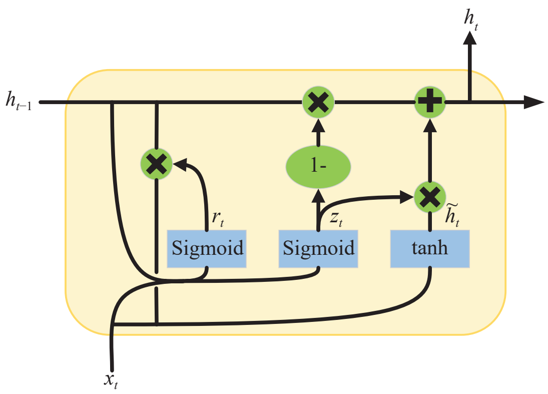

Figure 3 Schematic diagram of GRU [19].

The gate structure in GRU is composed of dot product and sigmoid, through which information can be discarded and retained. GRU has two gate structures, called reset gate and update gate.

First, at time step t, reset gate r_t can be regarded as

$$r_t = \mathrm{Sigmoid}(x_t W_{xr} + h_{t-1} W_{hr} + b_r) \tag{6}$$

where x_t is the input variable, W_{xr} is the weight parameter corresponding to the input variable, h_{t-1} represents the hidden state of the previous time step, W_{hr} is the weight parameter corresponding to the hidden unit, and b_r is bias, respectively. The sigmoid takes the value of 0–1, so it can act as a gating signal to decide how much information to discard and how much to retain.

Then, update gate z_t can be obtained as

$$z_t = \mathrm{Sigmoid}(x_t W_{xz} + h_{t-1} W_{hz} + b_z) \tag{7}$$

where W_{xz} is the weight parameter corresponding to the input variable, W_{hz} is the weight parameter corresponding to the hidden unit, and b_z is bias, respectively.

After the above r_t and z_t are obtained, the candidate hidden state $\tilde{h}_t$ can be calculated as

$$\tilde{h}_t = \tanh(x_t W_{hx} + r_t \odot h_{t-1} W_{hh} + b_h) \tag{8}$$

where W_{hx} and W_{hh} are the weight parameters, h_{t-1} contains information from the past, b_h is the bias, and $\odot$ is multiplied by elements.

Finally, the final hidden state h_t is written as

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{9}$$

where z_t is 0–1. When z_t tends to 1, it means that the long-term dependence has been present. When z_t tends to 0, it means that the unimportant information in the hidden information is forgotten.

In summary, the reset gate in GRU determines how current input is combined with previous memory information, and the update gate determines how much of the previous memory is reserved to the current time. Through the above operations, the problem of long-term dependence in time series data can be solved, and the gradient disappearance can be alleviated.

III. Experiment

A. Applied Dataset

We use a dataset from Ref. [20], which is from a provincial power utility, BC Hydro, and includes normal and five types of abnormal electricity usage data. Abnormal electricity consumption behaviors include abnormal decrease of electricity consumption, fault of main line, fault of branch, abnormal augment of electricity, and abnormal augment of the electricity consumption at random time. The randomly selected six types of data are shown in Fig. 4.

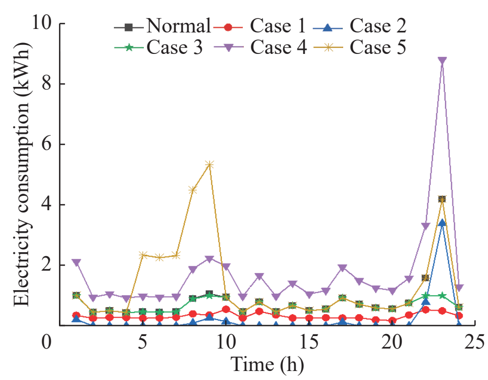

Figure 4 Example of six cases data.

B. Evaluation Index

To measure the ability of model to deal with unbalanced data, we use four indices: accuracy, precision, recall, and F1-score. Before introducing the four indices, we first introduce four concepts, true positive (TP), true negative (TN), false positive (FP), and false negative (FN), which are plotted in Fig. 5.

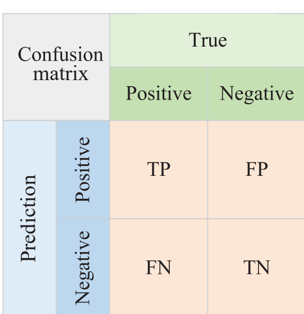

Figure 5 Description of the four concepts.

With the above four concepts, we can define evaluation indices. Accuracy (Acc) can be expressed as

$$\text{Acc} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{FN}+\text{TN}+\text{FP}} \tag{10}$$

Precision (P) can be calculated as

$$P = \frac{\text{TP}}{\text{TP}+\text{FP}} \tag{11}$$

Recall (R) can be denoted as

$$R = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{12}$$

F1-score (F1) can be written as

$$\text{F1} = \frac{2P\times R}{P+R} \tag{13}$$

C. Comparative Method

In this section, we compare GRU with the classical classification model SVM and the time series model LSTM.

As a typical classification model, SVM has been successfully used in remote sensing [21], precision agriculture [22], and other areas. SVM can not only classify linear data, but also process nonlinear data by mapping nonlinear data to high-dimensional space with the help of kernel technique. A nonlinear multidimensional support vector classifier is employed in this paper. The penalty coefficient is 1, the kernel function is Gaussian radial basis function (RBF), and the gamma is "auto".

To solve the problem that RNN cannot recognize the long-term dependence and gradient disappearance, LSTM is proposed. The key of LSTM is the three gate structures, which are called forget gate, input gate, and output gate. Each gate structure consists of a sigmoid and a dot product operation. We construct a bidirectional LSTM model as comparative method, whose number of hidden layer nodes is 72.

In addition, to verify the effect of ADASYN, we compare it with the generative adversarial network (GAN), which is composed of a generator and a discriminator. The generator is responsible for generating data that are close to the original data, and the discriminator is responsible for determining whether the data are generated or real. Through the game between generator and discriminator, the generated data similar to the original data can be obtained.

D. Experimental Result and Analysis

a. Verifying the Balanced Dataset Generated by ADASYN

To verify the validity of the data generated by ADASYN, we use the generated data as training set and the real data as test set to perform experiments. In addition, to verify that the balanced dataset is conducive to training the model, we compare the expanded balanced dataset with the imbalanced dataset. We also compare the performance of expanded balanced dataset with different amounts of real data. The experimental results are shown in Fig. 6.

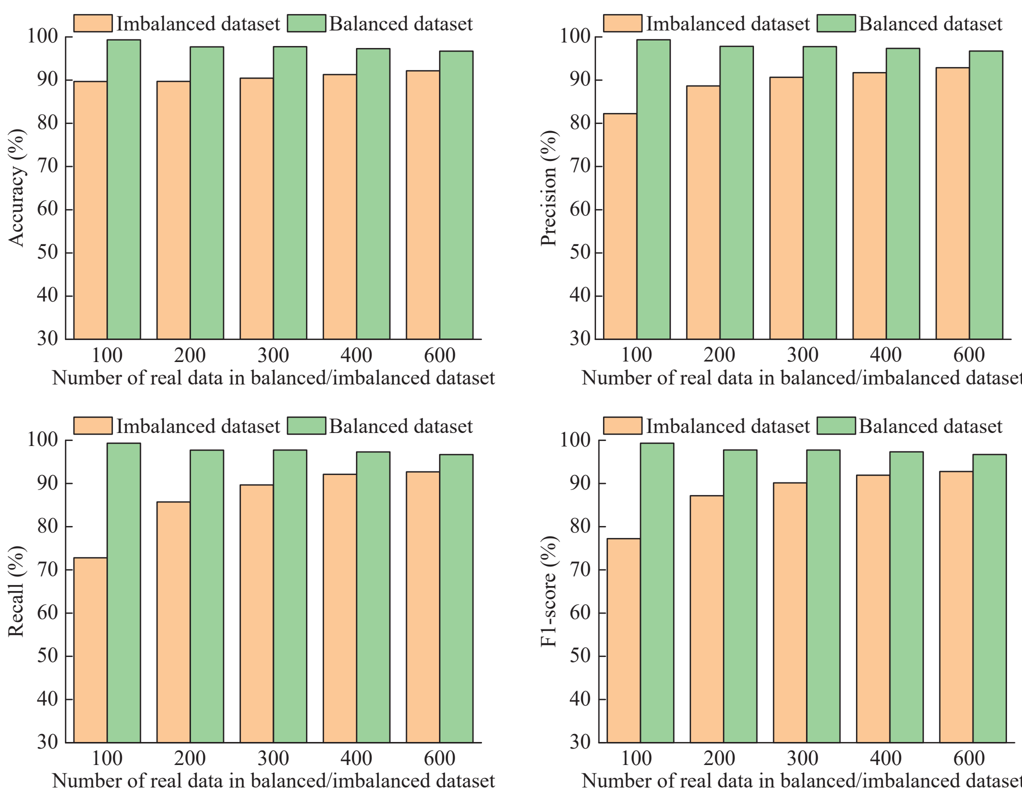

Figure 6 Comparison result on balanced and imbalanced datasets.

As can be seen from the green square in Fig. 6, when test data are real data, the detection results of abnormal electricity consumption are also very good, with all the four evaluation indices being higher than 96.00%. It means that the data generated by ADASYN are very similar to real data, and ADASYN is successful in the expansion of abnormal electricity consumption data. In addition, we can also see that the balanced dataset is better than the imbalanced dataset. It means that the balanced data are more conducive to training the model, so that the model can easily recognize the characteristics of different classes of data.

b. Verifying the Classification Ability of GRU

To verify the effectiveness of GRU classification, we compare it with SVM and LSTM. In this experiment, the three models use the balanced dataset expand by ADASYN. In these experiments, we also consider the classification effect when the ratio of real data to generat data is different, and the results are displayed in Table 1.

From Table 1, the results of our proposed method are superior to those of other methods. When generated data:real data = 11:1, the four evaluation indices of GRU are improved by 4.53%–4.90% compared with LSTM and 2.96%–5.69% compared with SVM, respectively. When generated data:real data = 5:1, the four evaluation indices of GRU are improved by 5.91%–6.33% compared with LSTM and 3.40%–7.66% compared with SVM. When generated data:real data = 3:1, the four evaluation indices of GRU are improved by 5.13%–5.33% compared with LSTM and 3.54%–7.86% compared with SVM. When generated data:real data = 2:1, the four evaluation indices of GRU are improved by 6.11%–6.28% compared with LSTM and 3.48%–8.10% compared with SVM. When generated data:real data = 1:1, the four evaluation indices of GRU are improved by 4.74%–4.95% compared with LSTM and 3.57%–8.62% compared with SVM.

Table 1 Comparison result of SVM, LSTM, and GRU. Bold indicates the optimal result in experiment.

Ratio of generated data to real data	Method	Acc (%)	*P* (%)	*R* (%)	F1 (%)
	SVM	96.37	93.65	96.37	94.99
11:1	LSTM	94.43	94.81	94.43	94.62
	GRU	**99.33**	**99.34**	**99.33**	**99.33**
	SVM	94.29	90.16	94.33	92.19
5:1	LSTM	91.38	91.91	91.42	91.66
	GRU	**97.71**	**97.82**	**97.73**	**97.77**
	SVM	94.21	89.91	94.16	91.99
3:1	LSTM	92.43	92.64	92.41	92.52
	GRU	**97.75**	**97.77**	**97.74**	**97.75**
	SVM	93.81	89.25	93.81	91.47
2:1	LSTM	91.01	91.24	91.03	91.13
	GRU	**97.29**	**97.35**	**97.31**	**97.33**
	SVM	93.13	88.11	93.12	90.55
1:1	LSTM	91.76	91.99	91.74	91.86
	GRU	**96.71**	**96.73**	**96.69**	**96.71**

c. Verifying the Generation Ability of ADASYN

To prove the effectiveness of ADASYN method, we compare it with GAN. In these experiments, the balanced datasets are expanded by ADASYN and GAN, and the classification effect of different expansion ratios is considered, the results are listed in Table 2.

It can be seen from Table 2 that the model detection effect of data generated by ADASYN is better than that of GAN. When generated data:real data = 11:1, the four indices of ADASYN and GAN increase by 6.53% on average. When generated data:real data = 5:1, the four indices of ADASYN increase by 5.34% on average compared with GAN. When generated data:real data = 3:1, the four indices of ADASYN increase by 4.09% on average compared with GAN. When generated data:real data = 2:1, the four indices of ADASYN increase by 4.39% on average compared with GAN. When generated data:real data = 1:1, the four indices of ADASYN increase by 4.40% on average compared with GAN.

IV. Conclusion

To solve the problem of imbalanced data, we present ADASYN and GRU based abnormal electricity consumption detection method. ADASYN can effectively augment the minority class data. GRU can efficiently detect abnormal electricity consumption. Detailed experiments and comparison are made to verify our method. Experimental results show that the proposed method is optimal compared with other methods.

Although the above method solves the problem of imbalanced data and achieves good abnormal electricity consumption detection results, it fails to consider its own time series characteristics during data expansion. Therefore, in the

Table 2 Comparison result of GAN and ADASYN. Bold indicates the optimal result in experiment.

Ratio of generated data to real data	Method	Acc (%)	*P* (%)	*R* (%)	F1 (%)
11:1	GAN	92.82	92.76	92.83	92.79
	ADASYN	**99.33**	**99.34**	**99.33**	**99.33**
5:1	GAN	92.36	92.51	92.36	92.43
	ADASYN	**97.71**	**97.82**	**97.73**	**97.77**
3:1	GAN	93.57	93.81	93.57	93.69
	ADASYN	**97.75**	**97.77**	**97.74**	**97.75**
2:1	GAN	92.89	93.01	92.89	92.92
	ADASYN	**97.29**	**97.35**	**97.31**	**97.33**
1:1	GAN	92.24	92.44	92.24	92.34
	ADASYN	**96.71**	**96.73**	**96.69**	**96.71**

future work, we will study data generation methods that can consider the characteristics of time series to solve the problem of imbalanced data.

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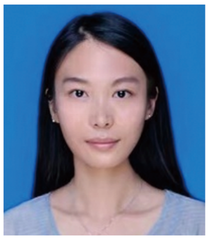
Songping Meng received the BS degree from Shandong Jianzhu University, China, in 2020. She is currently pursuing the MS degree in control science and engineering at School of Information and Electrical Engineering, Shandong Jianzhu University, China. Her research interests include data-driven modeling, time series forecasting, and intelligent buildings.

Chengdong Li received the PhD degree from Institute of Automation, Chinese Academy of Sciences, Beijing, China, in 2010. He is currently a professor at School of Information and Electrical Engineering, Shandong Jianzhu University, China. He has authored and co-authored over 100 papers in international journals and conferences. He has been an associate editor of *IEEE/CAA Journal of Automatica Sinica*, the program committee member of several international conferences, and the reviewer for several international conferences and journals. His research interests include data-driven modeling and control, fuzzy logic theory and applications, fuzzy neural networks, and other computational intelligence methods. His research interests also include the intelligent control methods with applications to intelligent buildings and smart homes.

Wei Peng received the PhD degree from School of Control Science and Engineering, Shandong University, Jinan, China, in 2018. He is currently a lecturer at School of Information and Electrical Engineering, Shandong Jianzhu University, China. His research interests include fuzzy logic theory and applications, data-driven modeling and control, and fuzzy neural networks.



Chenlu Tian received the PhD degree from Shandong Jianzhu University, Jinan, China, in 2020. She is currently a lecturer at Shandong Jianzhu University, China. Her research interests include the theory and application of big data, deep learning, and other artificial intelligence in buildings and cities.