Echo State Network based Noise Detection in Energy Internet Orienting Justice Blockchain Data

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***Abstract*—Energy Internet (EI) is a hot research topic which smartly combines the energy system and information and communication technologies to promote the efficiency and reduce the cost of energy generation, transmitting and utilizing, its related data need to be stored in justice blockchain for possible lawsuit. To ensure the integrate of EI data stored in justice blockchain, noise detection is a necessary function which can detect the amplitude of noise and further discover the cyber attacking. To solve this problem, many noise detecting algorithms are available, and the authors have firstly used three layers artificial neural network (ANN) to estimate the noise level quickly and efficiently. In this paper, based on previous research, the authors manage to use Echo State Network (ESN) to solve this problem, and get better simulation results in most scenes. As the simulation results show, the noise interference or cyber attacking behavior can be detected with probability 99% within 4 continuous samples. Applying this algorithm in justice blockchain will make the system more robust and secure, and its data handling cost can be largely reduced.**

Keywords—Energy Internet, justice blockchain, noise detection, Echo State Network, noise interference, cyber-attack

I. Background Introduction

Through many years' developing, Energy Internet is becoming gradually mature, and the scope of research view is largely extended [1-3]. Through data analysis and utilizing, the EI can be running effectively and efficiently, but in justice blockchain, the EI stored data may contain not to be ignored noise, which will impact the performance of EI and the running of possible lawsuit. To ensure the performance of EI, the noise data handling becomes a potential research topic.

Noise handling, especially noise estimation, has been used in many research areas, including wireless parameter estimation [4-12], AI processing in speech area [13-16] and image area [17-20], multi-forms of signal noise estimation [21-32] (like sinusoid signal, exponential signal, addition noise, multiplicative noise, impulsive noise and colored noise, etc.) and other related areas [33-40] (like seismic data processing), etc.

In these estimation proceedings, some algorithms mainly adopt mathematical processing methods (such as eigen decomposition [5], front-end estimator [10], parameter smoothing [14,15], Cramer-Rao lower bounds [24], high order moment [25,28], Newton iterative algorithm [26], function diagram [31], direct detection (DD) technique [37], and so on), and simulation modeling methods (such as enhanced MCRA algorithm [13], Bayer pattern of noise variance maps [17], Kalman filter [21,32], and so on), and probability and statistic methods (such as maximum likelihood [4,7,8,30], weighted least-squares [6], minimum mean square [9], probability density function handling [23,33], Parzen Window [34], and so on), and deep learning methods (such as hybrid deep learning [19], deep convolutional neural network [20], Multiscale Convolution and Densely Connected Network [39], and so on), and transform domain related methods (such as orthogonal decomposition [16,27], Cross-Channel [18], DFT [22], DCT [35], FFT [36], wavelet [40], frequency domain solutions [11,12,29,38], and so on), etc.

From above algorithms we can see, there is a contradiction between the complexity and estimation precision of noise estimation algorithm. In order to achieve high estimation precision, authors usually adopt high complex deducing models and data processing means, which heavily depends on application scenes. On the other side, in order to ensure real-time property, the calculating model is simplified, which may lower the running performance. Through finding gambling balance point of the two factors, these authors try to find the optimal means and efficient algorithms, where innovation techniques may make large breakthrough. Now, the emergence of neural network largely reduces the deduce complexity, with limited complexity adding, which can easily realize fast and precise data estimation automatically, and be applied across the application domain easily. So, this technique becomes one of the most potential application tools for noise detection.

With the emergence of justice blockchain, the usage of noise detection finds a new application scene. When utilizing noise detection means in justice blockchain, its data quality and security can be effectively ensured, so more efficient and precise evident samples will be obtained, which will further promote the performance of justice blockchain in the EI domain.

This paper is subsequently organized as follows: section II proposes the proceeding of the algorithm; section III detailed introduces the ESN programming; section IV analyzes the simulation result; section V discusses it using in justice blockchain, following section VI makes the conclusion.

II. ALGORITHM PROCEEDING

Based on previous study [41], the noise detection can be designed with following steps, as shown in Fig. 1.

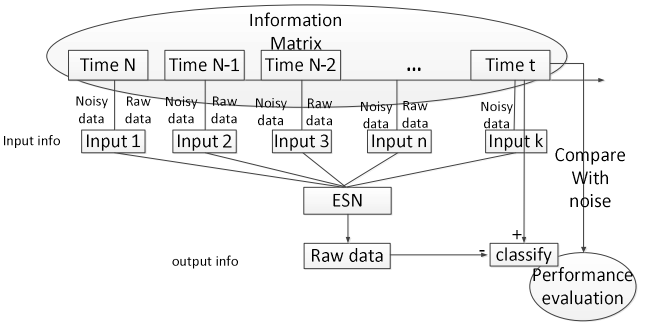

Fig. 1. Algorithm proceeding

1. We randomly generate the noise amplitude with the uniform probability distribution and normal distribution, and add it on the raw load data used for two types of simulations. Then we use the load data and corresponding noisy data to classify the noise levels, and obtain the noise range for each level.

2. We form the input matrix by noisy data sequence, and the target output matrix by raw data sequence. We train the ESN model with different parameter settings.

5. When we need to detect the noise level of new noisy data, we fetch the corresponding noisy data sequence belonging to the same time window of this new data, and use the ESN model to predict its corresponding raw value. We subtract the raw value with the noisy data, and classify the noise level using the range obtained in step1.

6. We calculate the average noise level index for some turns of new noisy data iterations, and choose proper parameter setting combinations of ESN.

7. We compare the performance of ESN based algorithm with ANN based algorithm, which embodies the advantage of ESN, and calculate the number of samples which can detect the noise attacking or apparent noise with probability larger than 99%.

III. ESN PROGRAMMING

A. ESN introduction

ESN is a high effective neural network especially suited for time sequence prediction, which uses the calculating model of reserve pool to replace the hidden layer and shows high predict precision.

As shown in Fig. 2, the basic idea of ESN is to generate a complex dynamic space by the reserve pool, which continually changes according to the input value. When the complexity of the state space is high enough, we can utilize the combination of internal states to estimate the corresponding output through linear optimization （such as least square）.

The ESN code is based on the download from https://github.com/search?q=echo+state+network, based on which some key parameters are modified, and data preprocessing function is added.

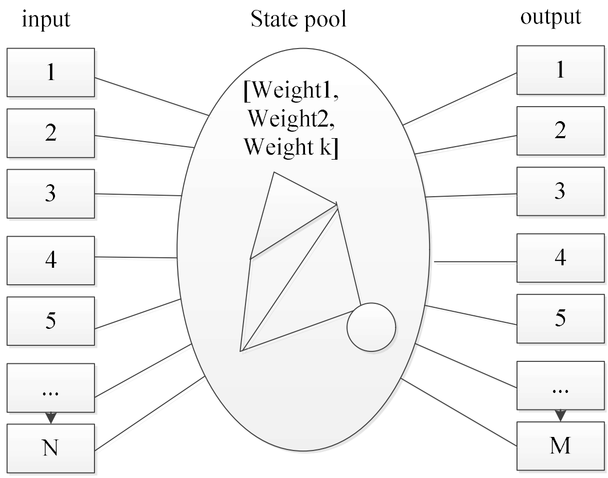

Fig. 2. ESN structure.

The structure of ESN includes following properties as shown in Fig. 3, where the related parameter value can be changed in real simulation:

```
esn.Nr = Nr;%50
esn.alpha = 1;%0.003
esn.rho = 0.9;%0.5
esn.inputScaling = 1;
esn.biasScaling = 1;
esn.lambda = 1;%1e-1
esn.connectivity = 1;
esn.readout_training = 'ridgeregression';
```

Fig. 3 parameter setting

B. A ESN programming

The simulating is running on MatLab 2014a.

1) Data preprocessing

In later simulation we found that ESN works well in the range [-1,1] with symmetry distribution, which is based on precise output weights calculation in that scene. So, we first get the max data and min data from the data sequence, and scale the data sample to be in the range [0,1] through linear transform using the max data value and min data value, then we change the range from [0,1] to [-1,1], which can be expressed as:

noise_data1=2(noise_data1-min1)/(max1-min1)-1;*

2) ESN training

When training the ESN, we use the sequence of noisy data as input data *P*, and the corresponding raw data as training target *T*.

P{1}=noise_data(1,1:end)';%14

T=raw_data(1,1+washout:end)';%15

esn = ESN(50, 'leakRate', 0.003, 'spectralRadius', 0.05, 'regularization', 1e-1);

esn.train(P, T, washout);

3) Internal state calculating

In the ESN, the dimension of the input weight *Win* is set as 50*1, that of *Wb* is set as 50*1, that of *Wr* is set as 50*50, and that of *Wout* is set as 1*52. And the idle round(*washout*) is set as 100, the *internal state* is iterated as follows, where *U* is the input data matrix, *x* is the internal state, and *Wb* is the bias value, when iteration number is larger than *washout*, the state information is recorded:

```
for i = 1:size(U,2)
  u = U(:,i);
  x_ = tanh(esn.Win*u + esn.Wr*x + esn.Wb);
  x = (1-esn.alpha)*x + esn.alpha*x_;
  if i > washout
     X(:,idx) = [1;u;x];
    idx = idx+1;
  end
end
```

4) ESN output parameter estimating

The output weight calculation in ESN is the key factor of ensuring prediction precise, which can be calculated as (using least square method):

```
W = Y'*X'*inv(X*X'+esn.lambda*eye(size(X,1)));
```

When running this simulation, we find that *esn.lambda* is the key factor influencing precise prediction which is hard to decide in theory, which is set as 0.1 in this simulation.

5) ESN output predicting

When predicting the raw data, we using the sequence of noisy data to be tested as input, and get corresponding raw value. Here the parameter of *washout* represents the number of idle turns.

```
ann_input{1}=noise_data2(1,(60000+1-washout):(60000+100))';
ref_test=esn.predict(ann_input, washout)';
```

6) Performance evaluating

The estimating error rate is calculated as follows, which can be seen as the probability of one step estimating error. And the noise level is set as 5.

```
for t=1:g
  assert(grade_test(t)<6);
  assert(grade_test(t)>0);
  total=total+abs(grade_test(t)-raw_grade(t));
  count_2=count_2+1;
end
index=total/count_2/5
```

This result can be seen as the average error probability for every noise level.

IV. Simulation Result

A. Simulated data

We used a load data set monitored for a single family from 2016-1-1 to 2016-12-31 with all day time and interval of 1 minute. The whole data sample number is 527401, and we fetched the front part from 1 to about 60000 for simulating.

Here we added the noise following the uniform distribution (rand function) and normal distribution (randn function), with amplitude 0.1, 0.2, 0.3, 0.5, 0.75and 1. For example

```
noise_array=rand(1,100000)*0.2*max(max(raw_data));
```

B. Simulation results analysis

We trained the ESN network and compared the results with the ANN method in [41]. In this simulation, we trained the ESN model using front 50000 data samples, and used the model to estimate 100 data points (the data from 60000 to 60100) for every round of estimation. Then we got every averaged result of 10 turns. We set the noise amplitude's coefficients as [0.1, 0.2, 0.3, 0.5, 0.75, 0.1], and plotted the results separately in Fig. 4 (uniform distribution) and Fig. 5 (normal distribution).

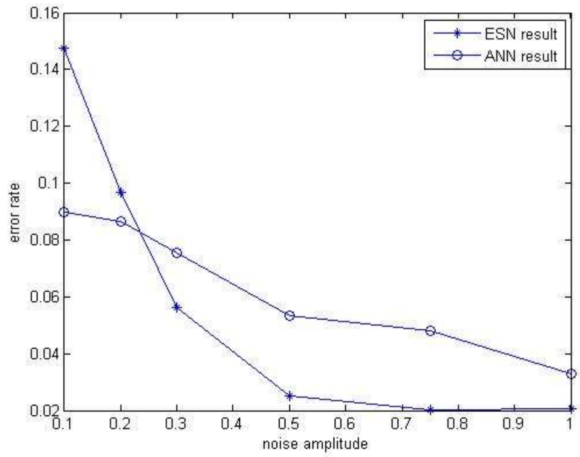

Fig. 4. Results comparison for uniform distribution

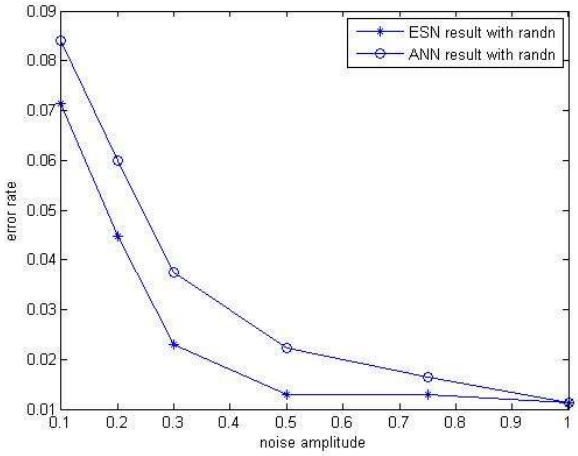

Fig .5. Results comparison for normal distribution

Form Fig. 4 we can see, for the uniform distribution, except two low noise amplitude points, the performance of ESN based algorithm is better than that of the ANN based algorithm, which shows the superior of ESN in medium and high noise amplitude for uniform distribution. And as the noise amplitude increases, the error rate always decreased, which may due to the more robust noise level classification for large amplitude. Considering the two exception points of the results, we have an intuition that the combination of different neural network may further promote the performance of this algorithm especially in low noise amplitude.

From Fig. 5 we can see, for normal distribution, the performance of ESN is always better than that of the ANN model, this shows the advantage of ESN algorithm for more precise in raw data estimating with normal distribution. And also, the two trend curves decline as the noise amplitude increases. When the coefficient of amplitude reaches 1, the performance of two algorithms converges, which may reach the ceil performance of the two algorithms.

Comparing Fig. 4 and Fig. 5, we can see that the performance of normal distribution is always better than that of the uniform distribution under the same parameter setting. Which may due to that the normal distribution is more condensed than uniform distribution, which can be rightly classified more easily, and the capability of ESN and ANN is more suited for normal distribution.

C. Needed sample umber for attack test

The error rate in the y axis shows the probability of estimating error for one level (noted as P_A), then the probability of no noise data sample ($level = 1$) being wrongly classified as noisy data sample ($level = 2,3,4,5$) can be roughly calculated as $P_1 = P_A + P_A * P_A + P_A * P_A * P_A + P_A * P_A * P_A * P_A$, the largest estimating error in the above simulating is $P_A = 0.178$, so the corresponding $P_1 = 0.2163$.

Under above scenes, if we can continuously classify N data samples as noisy data with probability large than 99%, then we can decide that there is data noise interference or data attacking with this probability. This can be presented as $1 - P_1^N > 0.99$. When $P_1 = 0.2163$, we can get $N \geq 4$, which means if more than 4 data sample are classified as noisy data continuously, there will be data noise interference (mainly due to device malfunction) or noise attack with probability more than 99%.

V. APPLICATION SCENE IN JUSTICE BLOCKCHAIN

This proposed algorithm can be effectively applied in justice blockchain for EI domain. When we collect the EI related sensor data, before analyzed and stored in blockchain, we should first check its data quality, prevent it from being distorted and malicious tampered. With this algorithm, we can detect cyber-attack and/or data distortion in this scene more quickly and efficiently, and make coping strategy as early as possible, then the effect of bad data quality can be largely limited. When the customer of justice blockchain needs to use the related data, its high quality can be assured by this algorithm, which enhances its performance and credibility, so the satisfaction can be kept high.

VI. CONCLUSION

The noise detection can be a hard work of EI data management. In this paper, we use ESN to fulfill the task of noise level estimation, which can be further used in justice blockchain. Through simulation we can see that the performance of ESN based algorithm is superior than that of ANN based algorithm in most scenes. But in the small noise amplitude scenes, the performance of ESN based algorithm is lower than that of ANN based algorithm, which derives that there may be some inefficiencies in ESN calculation of output weights for the two data points, so we will further test the structure of heterogenous cascading neural networks in this scene, which may promote related performance further. And at the same time, we will seek more probable data preprocessing techniques and broader parameter settings to further promote its computing performance. Finally, we emphasize the related application scene in justice blockchain.

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