# Noise Level Estimation in Energy Internet Based on Artificial Neural Network

Yangyang Ming, Junwei Cao
*Beijing National Research Center for Information Science and Technology*
*Tsinghua University*
Beijing, P. R. China

Haochen Hua
*College of Energy and Electrical Engineering*
*Hohai University*
Nanjing, P. R. China

***Abstract*—The massive data produced in energy Internet (EI) faces the challenge involved by disturbance of noise, especially the measurement noise and noise attacks by hackers. Traditional noise estimation mainly focuses on the non-white additional or multiplicative noise estimation with definite wave types, and others, e.g., the phase noise in direction-of-arrival of antenna array, or the frequency bias in orthogonal frequency division multiplexing, etc., which usually use traditional estimation technologies. In this paper, a novel noise level estimation algorithm is proposed based on artificial neural network prediction. In an EI scenario, the proposed algorithm only needs to know the noise amplitude of historical data when training the model. At the time of execution, the algorithm estimates the noise level of existing data based on the latest noisy historical data, and the algorithm can be used for most noise types. Through numerical simulations, we found that its performance is apparently improved compared to the low passband filter method.**

***Keywords—Artificial neural network, energy Internet, noise level estimation.***

## NOMENCLATURE

| | |
|---|---|
| ANN | Artificial neural network. |
| DFT | Discrete Fourier transform. |
| DOA | Direction-of-arrival. |
| EI | Energy Internet. |
| EMD | Empirical mode decomposition. |
| GAN | Generative adversarial networks. |
| KNN | K-nearest neighbour classification. |
| MCRA | Minima controlled recursive averaging. |
| OFDM | Orthogonal frequency division multiplexing. |
| SNR | Signal noise ratio. |
| SVAR | Structural vector autoregressive. |

## I. INTRODUCTION

EI is a new type of information-energy fused wide-area network based on the principle of Internet [1-3]. It treats the utility grid as the backbone network, and the microgrid or distributed energy network as local area network. By adopting the information-energy integration framework with open and peer-to-peer characters, bi-directional energy transmission and dynamic energy balance can be realized. Based on the advanced information and communication technologies, EI can effectively access the renewable energy such as wind power and solar power, which is continuously fluctuating. Thus, it is difficult to distinguish the quality level of measuring data. Besides, due to the characters of openness and sharing of EI, the widely adopted cyber-physic systems would be easily attacked in the information domain, such as data attacks in the process of data gathering and transmission. In this sense, noise level estimation is of great importance in ensuring the security of EI.

There exist many research outputs in the field of noise estimation, which are as follows: noise in DOA estimation [4]-[8], noise in OFDM frequency estimation [9]-[11], noise in speech enhancement [12]-[15], image noise estimation [16], [17], different types of noise in sinusoid signal estimation [18]-[21], multiplicative noise estimation [22], exponential signals estimation in noise [23], impulsive noise estimation [24], colored noise estimation [25], and other related noise estimation algorithms, e.g., [26]-[31]. In recent years, parameters estimation for subsampling and mixed frequency data with non-Gaussian noise interfering has been realized in [32]. The authors in [33] built tests for the market microstructure noise and judged the existence of signal with known parametric function. References [34] and [35] focused on noisy image. The aforementioned research outputs are detailly analyzed and reviewed as follows.

*DOA Estimation.* Reference [4] presented a maximum likelihood DOA estimation algorithm, but such algorithm worked well only when the DOA to be detected was at the negative of the direct path. References [5]-[8] can be viewed as the improvement of [4]. However, perfect modeling of the noise spectral matrix is required in [5]. The method in [6] was only applicable under some special non-Gaussian conditions. The models used in [7] and [8] should be satisfied with some pre-conditions.

*OFDM Estimation*. Considering the variation of the noise statistics, the authors in [9] proposed a minimum mean square error filtering technique to estimate the noise power, but the noise process is required to be time stationary. In [10] a front-end noise power is proposed with SNR estimation method based on one OFDM preamble, which might be the main limitation. The work [11] investigated a frequency domain channel estimator for OFDM with the presence of phase noise, which requires a large number of noise spectral components.

*Speech Enhancement*. The article [12] presented an enhanced MCRA algorithm to realize accurate noise power spectrum estimation in a noisy speech signal, but in some relatively stable noise environment its performance could be decreased. Reference [13] was the improvement of [12], which realized the trade-off between speed and accuracy. Reference [14] presented a low-complexity algorithm for tracking the noise spectral variance of speech contaminated by non-stationary noise sources, which was based upon a recursive refinement process, but it could not work well when the noise level fluctuated significantly. A noise estimation algorithm based on series expansion of orthogonal functions was proposed in [15], but the performance was still not satisfactory under some low SNR condition.

*Image Noise Estimation*. A novel noise estimation and removal method based on the Bayer pattern of noise variance maps was proposed in [16], but the Bayer pattern needed further validation. Reference [17] proposed a multivariate Gaussian approach to model the noise in color images, which

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explicitly considered the inter-dependence among color channels, but the unknown noise covariance could bring more complexity. The authors in [34] devised a noise level estimation method based on the statistics of orientational differences between image pixel values and those of their neighbors. However, it failed to perform well when the noise level was small. Reference [35] jointly utilized automatic feature extraction and mapping model. It first utilized convolutional neural network-based model to automatically extract the noise level-aware features. Then, the derived vector was directly mapped to its corresponding noise level via pretrained mapping model, but its high complexity might not be suitable for low-delay applications.

*Sinusoid Signal Estimation*. Reference [18] estimated the frequency of a single sinusoid in white Gaussian noise using Kalman filter, which needed the prior statistic knowledge. The marginal-median DFT was used to estimate complex sinusoidal signals embedded in an impulse noise environment [19], whose performance was based on the specific ratio of the transform magnitudes for current location with samples in the neighborhood. Reference [20] derived statistical models for the measurement phase noise in estimating the frequency and phase of a single sinusoid over the additive white Gaussian noise channel, which was highly complex and lacked detailed experimental results. Reference [21] estimated signal-to-noise ratio with a real deterministic sinusoid and unknown frequency, phase and amplitude. The derived estimator was based on high-order moments in blind estimator means. For high SNR, the number of observations required to obtain acceptable accuracy might be too large.

*Other Types of Noise Estimation*. Reference [22] developed an algorithm based on higher-order moments and cumulants to estimate the parameters of a linear or harmonic process which was corrupted by multiplicative noise or further corrupted by additive colored Gaussian noise. It is notable that the multiplicative noise should be independent identically distributed (i.i.d.) and have zero mean. Newton algorithm is used to solve the maximum likelihood estimation of the related parameters of multiple exponential signals with additive white Gaussian noise [23], which only suited for narrow band source and exponential damped sine waves in noise. The problem of estimating the amplitude and arriving time of composite signals in non-Gaussian noise was solved in [24], whose complexity may be increased due to iterations. The authors in [25] considered the estimation of the directions and frequencies of multiple signal sources arriving in an antenna array simultaneously, which could transfer the parameters estimated into system state-space model and constitute cross third-order cumulant to restrain Gaussian colored noise through auxiliary matrix. Notably, its performance did not improve much in case of white noise. Reference [26] investigated the phenomenon of noise enhanced systems to estimate a general parameter, whose complexity was relatively high. A novel method of amplitude estimation of signal white noise based on EMD algorithm and Parzen window according to the finite-duration signals was proposed in [27], which was not suited for low SNR. Reference [28] estimated and compensated phase noise in single-carrier digital communications, using an iterative feedforward decision-directed phase noise estimation algorithm. Nevertheless, obtaining the phase noise statistics at the receiver was not an easy job. In [29] the authors compared and discussed different estimation techniques from different groups with error introduced when extracting from the noise spectral density measurement in the speicfic frequency level, white noise level and lorentzian parameters, while it only shew the spectrum results with different noise. Reference [30] proposed a method to estimate the laser phase noise using the conversion of phase noise to intensity noise based on the direct detection (DD) technique. Its performance deteriorated when the bandwidth is larger than 1MHz. Reference [31] introduced a general nonparametric intensity and frequency-dependent noise model to handle remnant noise in image, and the estimation of more than 1000 parameters might be its bottleneck.

*Novel Estimation Techniques*. The paper [32] took a model-based approach using SVAR models to determine instantaneous and lagged effects between time series at the true causal scale, but its performance was limited by the local optimal result. The article [33] built tests for the presence of residual noise in a model where the market microstructure noise is a known parametric function of some variables from the limit order book, and this limitation would influence its application.

To summary, the aforementioned algorithms mainly focus on only one special noise scene with various types of limitation or preconditions, and the statistical characters of the targeted noise are required to be extracted by complex algorithms. In many EI related services, it is assumed that there are continuous noise interferences with a variety of reasons, and the noise level of the current data is required to be further estimated for running related service, which is the subsequent work when the estimated noise amplitude is obtained. In this paper, such problem is solved using our proposed ANN algorithm which only needs the noise amplitude and the level of historical data and can be applied in most of the big data applications, especially in EI scenarios. Although GAN can be used for solving similar problems, its complexity is relatively high. Within the author's knowledge, this is the very first time that neural network is used in the special scene of noise level estimation for one dimensional EI data sequence. It is notable that other neural network algorithms are mainly used in image or voice denoise, which has different characters compared with EI data. The image and voice noise has more spatial and temporal (frequency) relationship in raw image and noise data, but the raw data in EI has more periodical relationships with mixed scales (the day, the hour, or, the minute). As this algorithm is focused on one dimensional data using ANN, the designed algorithm runs much faster than that of image and voice noise estimation.

The structure of this paper is organized as follows: after introducing the background, the proceeding details of this algorithm is described in Section II, and simulation design is presented in Section III. Section IV analyzes the simulation results. Section V concludes the whole work.

## II. The Algorithm Proceeding

### A. Problem ModellingThreshold Parameter Setting

Before training the ANN model, we should define the noise level and corresponding threshold at first. If we have raw data and corresponding noisy data before time $t1$ (which is a prerequisite), we can calculate the noise data between them. Then, we sort the derived noise data in ascending order and divide the sorted data with equal length of data in each segment. Next, we set the mean value of each segment as the center value of corresponding noise level, the noise level can be decided through comparing the distance of the noise amplitude to all levels' center values, and we choose the nearest one as the corresponding level. If we don't have enough noisy data or raw data in EI, then the GAN method can be used.

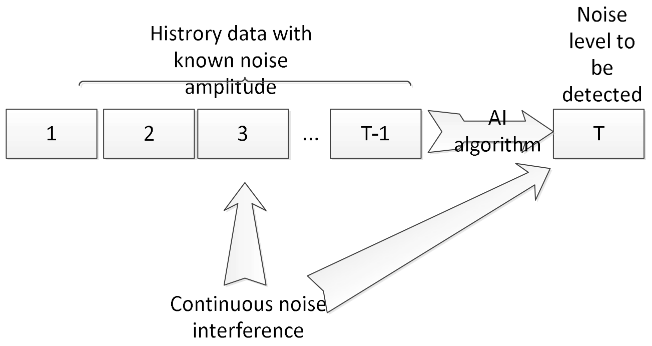


Fig. 1. Problem modelling

### B. Model Set Up and Training

We assume that there are lasting noises interfere with definite noise data type. Before time $t1$, we can simultaneously obtain the raw data and noisy data. It is easy to see that there are certain relationships between neighboring raw data, as the data produced in EI has certain time cyclic relationships. Meanwhile, we assume noise injection follows some definite probability distribution function, so we can set an ANN model to simulate and explore such potential relations, using the noisy data taken through the time segment from $t - N$ to $t$ as the input data to input layer, and taken the raw data to be predicted at time $t$ as expected output data to output layer. We train the ANN model using back-propagating means. After the ANN model is well trained, it can be used to estimate the new raw data without noise and further calculate the noise level.

In addition to the input layer and output layer, the ANN model has a hidden layer with different node numbers compared to input nodes. The 'logsig' function is used in the activation functions of input layer node to hidden layer node and the hidden layer node to output layer node. The training means 'traingdx' is used in ANN model's back-propagate training. The ANN model is shown in Fig. 2 and Fig. 3.

When testing new data in (with noise) in time $t$, we fetch this data and $N$ historical data whose time position is just before time $t$, which is from time $t - 1$ to time $t - N$, so the input data length is $N + 1$, and the output data dimension is one. Then, such buck of fetched data is input into the trained ANN model, and the corresponding output data is the estimated raw data without noise.

### C. Noise Level Estimation Accuracy Calculating

We subtract the tested data with the estimated raw data to get the noise value which are compared with the center value of each noise level. Let us choose the noise level corresponding to the amplitude center of the noise level nearest to the noise amplitude as the estimated noise level. Then, we compare the estimated noise level to calculate the error rate as:

$$ER = \sum\left|l - \bar{l}\right| / (c * N) \quad (1)$$

Here, $ER$ represents for the calculated error rate, $l$ means the real noise level of current data, $\bar{l}$ means the estimated noise level of current data, $c$ is the counted number of the data to be estimated, $N$ is the counted number of noise levels. If the noise density is not considered, the error rate roughly equals to the average difference of noise, e.g., error rate with 0.2 refers to approximately 20% in estimation error.

Table. 1 Algorithm Proceeding Steps

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|---|
| Step 1. Set the threshold parameter using classified historical data. |
| Step 2. Set ANN model structure parameter, and repeat step3-step7. |
| Step 3. Train ANN model using historical data with known noise amplitude. The training input is the noisy historical data, the estimated output is the raw amplitude of subsequent historical data. |
| Step 4. Predict the amplitude of current data using ANN with data of time $t - N$ to $t - 1$. |
| Step 5. Calculate the difference between the current value and the predicted amplitude. |
| Step 6. Estimate the noise level of current data. |
| Step 7. Evaluate the estimation accuracy. |
| Step 8. Choose the best result. |
| Step 9. Use the estimated noise level to improve the data quality for EI services. |

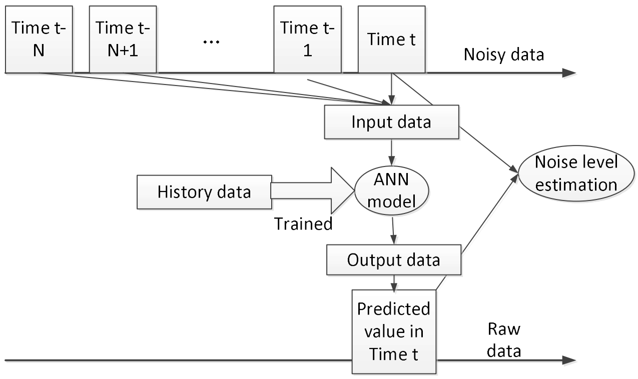


Fig. 2. ANN estimation model

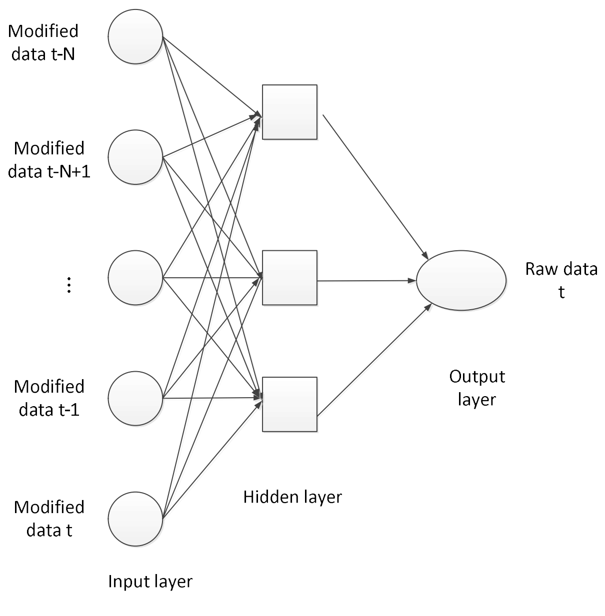


Fig. 3. ANN structure

### D. *The Advantages of the Proposed Algorithm*

To solve the above problem, the proposed ANN-based algorithm in EI scene has several advantages:

1. Few algorithm uses ANN in noise level estimation, and our proposed method has broad application scenes and huge application potentials.
2. It can be used to different forms of probability distributions, such as Gaussian, non-Gaussian, additive and multiplicative, only if there exist relationships between input data and expected output (explicitly or implicitly) and the relationship remains unchanging in long time series or data bulks.
3. As the algorithm is mainly based on three-layer ANN, its time and computing complexity is relatively low, both in training and testing, which satisfying the demand of most of noise level estimation services.
4. The ANN based algorithm is easy to be modified by changing the structure of ANN and updating the related parameters. This proceeding can be effectively solved using genetic algorithm.
5. The algorithm is easy to be combined with other artificial intelligence algorithms, e.g., GAN, particle swarm filtering, enhanced learning, etc., in EI scenes.

### E. *KNN Reference Algorithm*

Before this experiment, we propose another reference algorithm to estimate the previous noisy data sequence. We first find similar data sequence in historical data. The similar data sequence can be found by high correlation value between tested sequences (after low pass band filtering) as in (2), or almost the same sequence between the two as in (3) where $X$ and $Y$ are tested sequences and $M1$is the data length, or the sequence's variance itself is very low, as is presented in (4).

$$co = \left|\frac{\sum(X-EX)(Y-EY)}{\sqrt{\sum(X-EX)^2 * \sum(Y-EY)^2}}\right| \geq 0.95 \qquad (2)$$

$$\sum|X(1{:}M1) - Y(1{:}M1)| \leq 0.1 \qquad (3)$$

$$var(X) < 0.01 \qquad (4)$$

In (2), $co$ represents the absolute value of correlation factor. If the correlation factor is more than the threshold, we calculate the estimated value using the linear fitting. Here, we assume the two sequences are linearly correlated, and the factors can be calculated by solving equations using least square method based on (5). Then the estimated value can be obtained using these factors and the noisy data at the corresponding position (immediately after the noisy data sequence) based on (6). After we have the estimated value, the noise level is set as that of noisy data, and the distance is set as the distance of noisy data and the estimated value.

$$x_i = ay_i + b; x_j = ay_j + \text{b}. \qquad (5)$$

$$x_{i+1} = ay_{i+1} + b \qquad (6)$$

When the total distance of the two sequences is below the threshold, the estimated value equals to the noisy data at the same position, and the level is equal to that of the noisy data. The distance is set as zero. If the sequence's variance is lower than the threshold, then the estimated value is set as the average of the sequences. The level is classified using classifying threshold, and the distance is set as the difference of the corresponding noisy data with the mean value of the classified noise level. With the above data, the noise level can be obtained using the KNN algorithm. The two factors in KNN are the distance associated with the estimated value and the estimated noise level. In KNN, among $k$ nearest samples, the level with them that has the largest number of noise level is selected as the final noise level. The subsequent performance evaluating is the same with that using ANN method.

This algorithm works well in some scenes, but it works less satisfactory in other scenes. At the same time, its complexity far surpasses the ANN algorithm. The detailed processing introduction is omitted here, but its corresponding simulation result is shown in Fig. 4 and Fig. 5. Inspired by KNN reference algorithm, when we get the estimated raw value, we can use KNN to further finely classify the noise level, which can be a future work within this direction.

## III. Simulation Design

### A. *Simulation Environment Design*

We set up the numerical simulations by using MATLAB software, which are run on Windows 10 with Core i5, 8GB memory and 1.8GHz CPU. In this simulation, we use a section of previous noisy data to predict the noise level of current noisy data in an EI scene, such as load or power generation data. As this algorithm is only for noise level estimation, no definite EI parameters should be known in advance, so the parameter list is omitted. This special precondition makes it hard to set up or form traditional mathematical models, and this problem has not been deeply explored in previous literatures.

The simulation data source is from a domestic record of energy using in an EI scenario with measured interval of 1 minute. We take the 20000 to 50000 (i.e., 20000, 30000, 40000, 50000) samples prior to the data as historical data. Let us denote $m_v$ as the maximized data value. We import noise which is uniformly distributed in the range of $-0.05m_v$ to $0.05m_v$ and use these data to train the ANN model.

$$noise = (rand(1,N) - 0.5) * 0.1 * \text{m}_v \qquad (7)$$

Here, $rand(1,N)$ will produce a vector whose elements are uniformly distributed between 0 and 1 with a $N$-dimensional vector. In (7) $m_v$means the maximized absolute value of raw data's amplitude.

### B. *Proposed Algorithm Design*

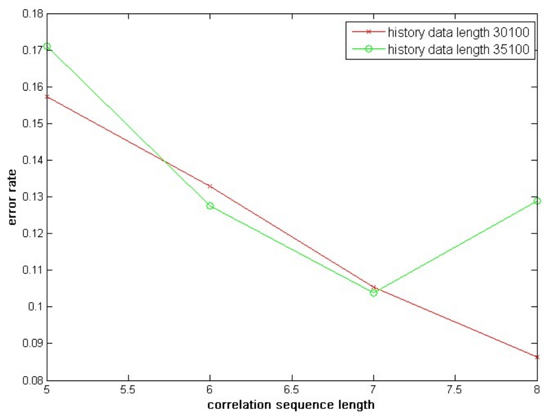


Fig. 4. Reference algorithm result with different correlation sequence length

Based on historical noises, we set up the corresponding noise level parameters. Then, we select samples in the location of 50001 to 50100, or 60001 to 60100, as the test data to be checked. Then we add a random noise on the test data, which is i.i.d. with the noise of historical data. After that, the noise level of noisy data is estimated and compared with the true noise level. In the estimating processions, every result is averaged for 5 simulation rounds to partially overcome the stochastic property.

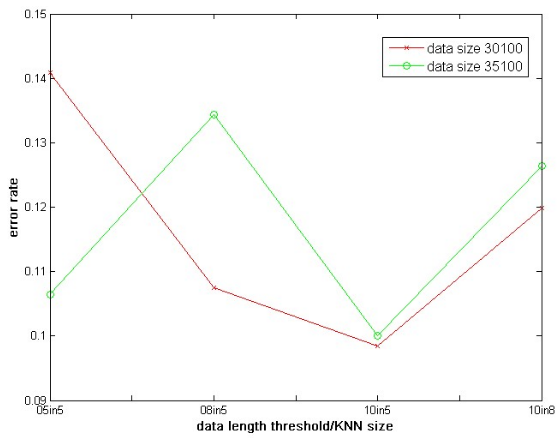


Fig. 5. Reference algorithm result with different data threshold and KNN size

When the data length equals to 7, the node number of the hidden layer is set as 8. When the data length equals to 10, the node number of the hidden layer is set as 11 or 7. When the data length equals to 15, the node number of the hidden layer is set as 13.

In Fig. 6 and Fig. 7, this algorithm is compared with the low-pass band filter based noise level estimation algorithm. This low-pass band filter method calculates the difference between the raw data (with noise) and the low-pass band filtered raw data, and it treats these values as the estimated noise and estimates the noise level as that of the nearest level center to the estimated noise. Again, we calculate the estimate accuracy using (1).

## IV. SIMULATION RESULT AND ANALYSIS

By comparing Fig. 4 and Fig. 5 with Fig. 6, we can see that the performance of reference algorithm based on KNN is not steady, and the whole performance of KNN is apparently worse than that of the ANN method. The execution time via KNN method is far more than that of ANN in MatLab software. So, this algorithm is treated as reference algorithm unless large novel improvement can be realized.

Fig. 6 is used to show the estimate accuracy of data items from 50001 to 50100; while Fig. 7 shows the result from 60001 to 60100. The horizontal axis refers to the training number used to train ANN model, while the vertical axis represents the estimate accuracy of the algorithm. From Fig. 6, we can see the estimate accuracy is varying for different parameters, which may largely due to the randomness of noise adding on the tested data, and the input of ANN is composed of random noisy and fluctuating data which may limit the estimation accuracy. Nevertheless, we can see from the simulation that the performance of our proposed algorithm apparently surpasses the low-pass band filter algorithm.

Form Fig. 7 we can see as the length increases, most of the results are improved, which satisfies our intuition. The result of length 15 apparently surpasses other cases, and the low-pass band filter algorithm has the worst performance, which may due to that the characters of this part of raw data is well coincided with the ANN model. Compared with the above figures, we can also see the reference algorithm using low-pass band filter has apparently better estimate accuracy in range from 60001 to 60100 than that of from 50001 to 50100, this may due to the former has relative flat shapes than the latter. So, the amplitude of high frequency is lower, and the valuable part of this data is less reduced. Thereby, better noise level estimation can be achieved.

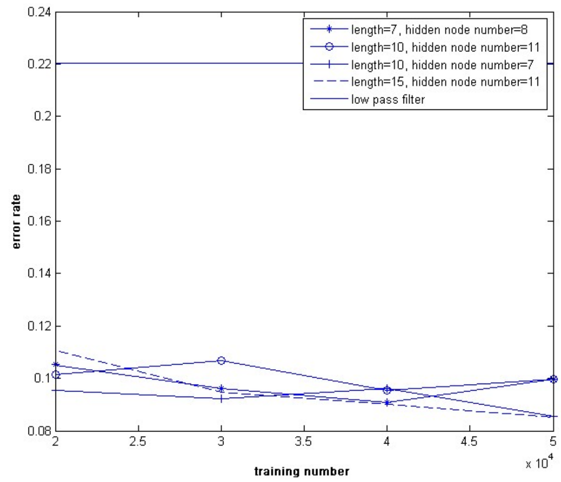


Fig. 6. Data source from 50001 to 50100

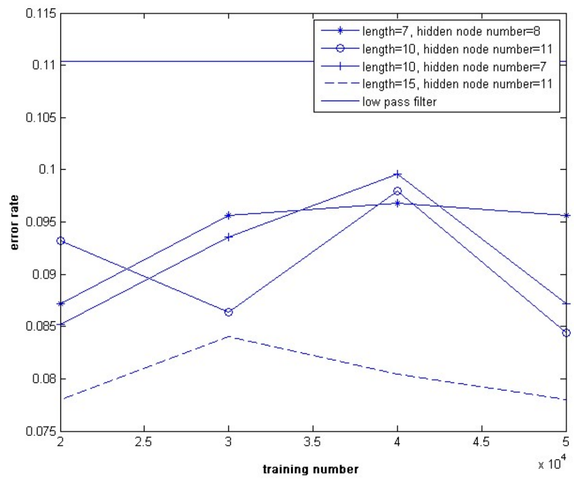


Fig. 7. Data source from 60001 to 60100

## V. CONCLUSION

Focusing on the noise level estimation in EI, we propose a novel algorithm based on ANN prediction. Relying analysis on the noise level of the historical data, we can see that there exist some relationships between the input data and output data of ANN, and we can compute the expectation value from noisy data samples using ANN. Through comparing the difference between the real noisy level and the estimated level, we finally obtain the noise level with high accuracy. This algorithm avoids the complex feature estimation and extraction, and it can be easily fulfilled in parallel computing as well as applied in the big data scene. Based on more subtle proceeding (e.g., time averaging in reference value, etc.), it can be easily extended into noise amplitude estimation with mixed distributed noise, which is our future research direction.

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