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Signal Restoration using Bayesian Neural Network

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ABSTRACT

Signal restoration can be defined as predicting original input signal which being affected by the noise using some prior information from the process or the desired output signal. This paper deals with signal restoration using estimation by applying a Bayesian Neural Network (BNN). Signal recovery emphasizes the challenge of predicting the original input signal from the distorted or noisy version of the original signal. Data that was lost or went missing during transmission or storage must be recovered and added back to the original signal. The objective of this project is to restore the lost signal with a high degree of precision. Three datasets, notably those related to Energy, Air Quality, and Combined Cycle Power Plants, were predicted for this study. These datasets will be trained utilising the Bayesian Regularized (BR), Levenberg-Marquardt (LM), and Gradient Descent (GD) training algorithms. The Coefficient of Determination (R^2) and Mean Square Error are used to gauge the effectiveness of signal restoration (MSE). In comparison to LM and GD, the results demonstrate that BR is the most effective training algorithm for signal restoration. In comparison to the LM and GD training algorithms, the majority of R^2 values for BR are close to 1 (0.7 to 0.99) and the MSE value is the lowest (-32.9387 dB). This proposed BNN model can be apply in the signal restoration and prediction for practical wireless communication system such as speech and audio processing, multimedia processing, underwater acoustic, biological signal and others.

1. Introduction

A signal is an electrical or electromagnetic current that transports data from one device or network to another. It serves as a medium for carrying or transferring information about the behaviours or state of a phenomenon. The IEEE Transactions on Signal Processing states that the term "signal" includes audio, video, speech, image, communication, geophysical, sonar, radar, medical and musical signals [1,12,14]. In a real situation, a signal which carries information usually has a noise [2,14]. Noise is an unwanted signal that accompanies an information signal. It also can affect some of information being transfer is missing. The missing of data will become a major problem for sensitive and highly precise devices such as medical, chemical and safety equipment. The solution

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that can be taken is to reduce the effect of noise on data and estimate the data that is acceptable. Several studies have been conducted in order to achieve or restore the best data from multi-state variables and uncertain data relationships using Bayesian estimation. Talmor *et al.,* [3] proposed a Bayesian Approach for Detecting System Reliability Using Failure Modes Analysis. It was demonstrated that the proposed approach not only provides system reliability estimation but also improves design quality. Ma *et al.,* [4] recommended a Bayesian learning method for detecting faults in broken rotor bars. Both experiments and simulations endorse the proposed Bayesian learning method, particularly for short measurement and/or high-noise data. Wu *et al.,* [5] improved the Bayesian Network in the dynamic model for unmanned ground vehicles (UGV) by using time-varying parameters. A simulation experiment based on battlefield background operations with UGV was carried out to validate the method's effectiveness when compared to traditional Bayesian networks. For simple reasoning, Wu *et al.,* [6] proposed a Bayesian network and learning algorithm. The experimental results show that the proposed Bayesian network and learning algorithm can successfully decrease the reasoning complexity of the Bayesian network, consequently enhancing the Bayesian network's reasoning efficiency in practical application. Yang *et al.,* [7] improved an Artificial Neural Network (ANN) for positron emission tomography (PET) image reconstruction using a Bayesian learning algorithm. According to the findings of this study, the proposed ANN enhancement using the Bayesian method has the potential to quantitatively improve clinical PET imaging. Sparse Bayesian Learning for the off-grid direction of arrival (DOA) valuation for the Collocated MIMO Radar was introduced by Mao *et al.,* [8]. The proposed valuation method outperforms the conventional peak searching algorithm in terms of DOA estimation accuracy. Yang *et al.,* [9] proposed a hierarchical synthesis of lasso (HLS) priors for off-grid signals using an estimator from the Bayesian algorithm. Numerical simulations also verify the superiority of the proposed Bayesian algorithm using HSL in terms of convergence speed and root mean squared estimation error, as compared to the conventional Bayesian algorithms. Aharon *et al.,* [10] introduced a class of Bayesian lower limits for parameter valuation using random test-point conversion. A Bayesian estimation is one type of estimation that uses a statistical method to predict the best data from the sensor reading. Previously, it was demonstrated that the Bayesian regularisation algorithm outperformed the Levenberg-Marquardt algorithm in a variety of application techniques [17-19]. The Bayesian regularisation method does away with the need for extensive cross-validation. It provides an effective criterion for terminating training and avoids network overtraining. The Bayesian regularisation training method is capable of producing localization algorithms for wireless communication systems such as speech and audio processing, multimedia processing, underwater acoustic, biological signal processing, and other applications, making it a more flexible and durable backpropagation network [17-19].

This paper proposed to use a Bayesian Training (BR) algorithm to restore the signal losses. The objective of this project is to study signal restoration using data estimation, to apply Bayesian Neural Network (BNN) in signal restoration, and to validate the performance by comparing the result with other algorithms. This signal restoration method will estimate the best value for the loss signal. Thus, the output of signal restoration will have accurate data and be comparable with the original signal.

1.1 Signal Restoration

Signal restoration is the practise of leveraging previous knowledge from the process or the desired output signal to forecast the original input signal that was impacted by noise. The signal may be impacted by noise in a number of ways, including during the signal's capture, storage, transmission, processing or conversion. Because there will always be some undesirable signal present with the transmission, a pure clean signal cannot be produced [11]. The noise from the signal needs to be minimised or reduced in order to fix this issue. As shown in Figure 1, the signal restoration method includes estimate of the random input e and the model parameter vector θ for the loss signal sample.

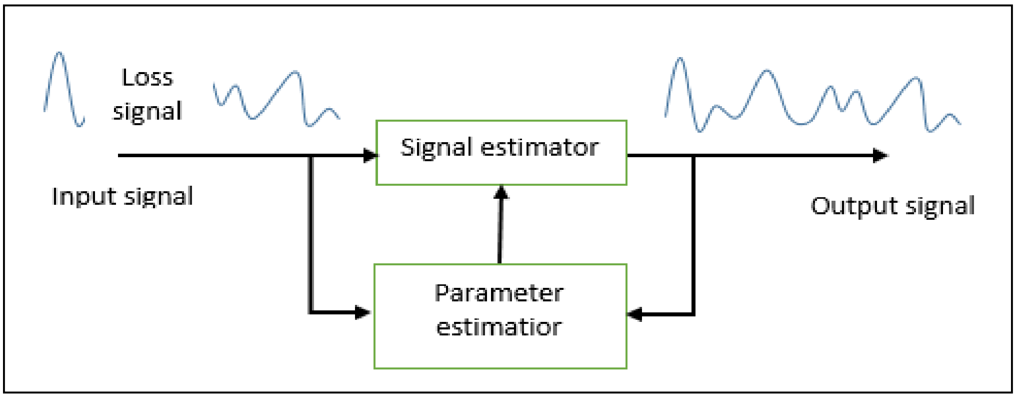

Fig. 1. Signal restoration process

1.2 Bayesian Learning Algorithm for Estimation

One of the statistical ideas that can be used in network learning is Bayesian estimation. The purpose of statistical decision theory is to offer an alternative framework for handling such circumstances when solving problems from a state of uncertainty. Data will be analyzed using statistical techniques by estimating distribution parameters. Bayes' rule shows that probability distribution can be written as [10,13] in Eq. (1).

$$PD(DS,\alpha,\beta, NM)= \frac{PD(DS|w,\beta, NM)PD(w|\alpha,NM)}{PD(DS|,\alpha,\beta,NM)} \tag{1}$$

Where, DS represents the dataset, NM represents the network model and w is the network weights. PD (w|α, NM) is the prior distribution, which represents the knowledge of the weights. PD (DS|w, β, NM) is the likelihood function which indicates the probability of the data occurring, given the weights w. PD (DS|,α,β,NM) is a normalization factor that guarantees that the total probability is 1. The advantages of using a Bayesian regularization algorithm are improving the unstable condition during the training dataset and reducing the variance. This algorithm is usually suggested as the norm in regression. It calculated the best combination of weights and squared errors for constructing an appropriately specialized connection [7-9].

1.3 Lavenberg Marquadt Learning Algorithm

The Levenberg-Marquardt algorithm was designed to approach second-order training speed without requiring the Hessian matrix to be computed. When the performance function is a sum of squares (as is common in training feed-forward networks), the Hessian matrix is based on Eq. (2).

$$H = J^T J \tag{2}$$

The gradient can be computed as in Eq. (3).

$$g = J^T e \tag{3}$$

Where, J is a Jacobian matrix containing the first derivatives of network errors with respect to weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed using a typical back propagation technique, which is far less difficult than finding the Hessian matrix. The Levenberg-Marquardt algorithm employs this approximation to the Hessian matrix in the Newton-like update given by Eq. (4).

$$X_{k+1} = X_k - [J^TJ+\mu I]^{-1} JT_e \tag{4}$$

A sigmoid function is a computation function that produces an S-shaped sigmoid curve. The sigmoid function is differentiable and real-valued, with either a non-negative or non-positive first derivative or exactly one infection point. There are two asymptotes as well, $t \rightarrow \pm\infty$. Eq. (5) defines the Sigmoid Function:

$$P(t)=\frac{1}{1+\lambda^t} \tag{5}$$

This algorithm is commonly recommended as the norm in classification; however, the user should note the drawback that it requires more storage than other algorithms.

1.4 Gradient Descent Learning Algorithm

Gradient descent (also known as steepest descent) is a first-order iterative optimization process used to determine the local minimum of a differentiable function. The goal is to take repeated steps in the opposite direction of the function's gradient (or approximation gradient) at the current point, because this is the steepest descent. The weight related between the *j*-neuron of the (*k*-1) layer and the *i*-neuron of the *k*-neuron layer is updated based on Eq. (6) to Eq. (9) as shown below [16]:

$$w_{ij}^k(t)= w_{ij}^k(t-1)+ \Delta w_{ij}^k(t) \tag{6}$$

$$b_i^k(t)= b_i^k(t-1)+ \Delta b_i^k(t) \tag{7}$$

$$\Delta w_{ij}^k(t)= \eta_w\, \rho_i^k(t) v_j^{k-1}(t)+ \alpha_w\, \Delta w_{ij}^k(t-1) \tag{8}$$

$$\Delta b_i^k(t)= \eta_b\, \rho_i^k(t)+ \alpha_b\, \Delta b_i^k(t-1) \tag{9}$$

Where, the *w* represents the weight, *b* represents the threshold, α_w and α_b are the momentum constants, η_w and η_b represent the learning rates, and ρ_i^k is the error signal of *i*-th neuron of the *k*-th layer which is back propagated in the network. Then the activation function of the output neuron is normally linear. The steepest decent type algorithm suffers from a slow convergence rate because the search for global minima could become trapped at local minima and the algorithm can also be sensitive to the user selectable parameters [16].

1.5 Artificial Neural Network (ANN)

An ANN is widely used in the machine learning process which is to train the machine as desired need. It has many advantages such as the capability to incorporate the dynamic changes in the systems, adept to solve non-linear problems, and reliability and accuracy depending on the training [12,16].

2. Methodology

The flow of methodology in this study is shown in Figure 2. Data was taken from the Machine Learning Repository [15] specifically as Energy, Air Quality and Combined Cycle Power Plant.

The Energy data sets are chosen as the simplest data set among the comparison but with a direct current (dc) shift effect. The Air Quality data set is the moderate data set among the comparison but also with a direct current (dc) shift effect. The combined Cycle Power Plant data set is the heaviest data set among the comparisons but without a direct current (dc) shift effect. These three (3) types of data selections are based on categories of difficulties starting from the simplest data, the moderate data, and the heaviest data for signal restoration purposes. The first data set is Energy (A) dataset. Energy dataset is a collection of data for monitoring the house temperature by using ZigBee wireless network. The data is set at 10 minutes period for about 4 months. Temperature outside the building in degree Celsius (˚C) dataset is used for signal restoration experiment for Energy Prediction. The second data set is Air Quality (B) dataset. Air Quality dataset is the collection of gas reading. The dataset contains 9358 instances of hourly averaged responses from an array of 5 metal oxide chemical sensors embedded in an Air Quality Chemical Multisensory Device. Data were recorded from March 2004 to February 2005 (one year) representing the longest available recordings of on field deploy air quality chemical sensor devices responses. Tin oxide dataset that records the concentration of metal oxide in milligram per meter cubic is used for signal restoration experiment for Air Quality Prediction. The third dataset is Combined Cycle Power Plant (C) dataset. This dataset consists of 9568 data points collected over 6 years (2006-2011) when the power plant was set to work with full load. The hourly average ambient variables temperature of the plant in ˚C is used for signal restoration experiment for Combined Cycle Power Plant Prediction.

In general, the performance of signal restoration for Energy Prediction in Figure 3 reflects that LM and BR training algorithm are quite good in terms of signal restoration. The trained signal using LM and BR are able to follow the actual signal, however trained signal using GD is bad for signal restoration.

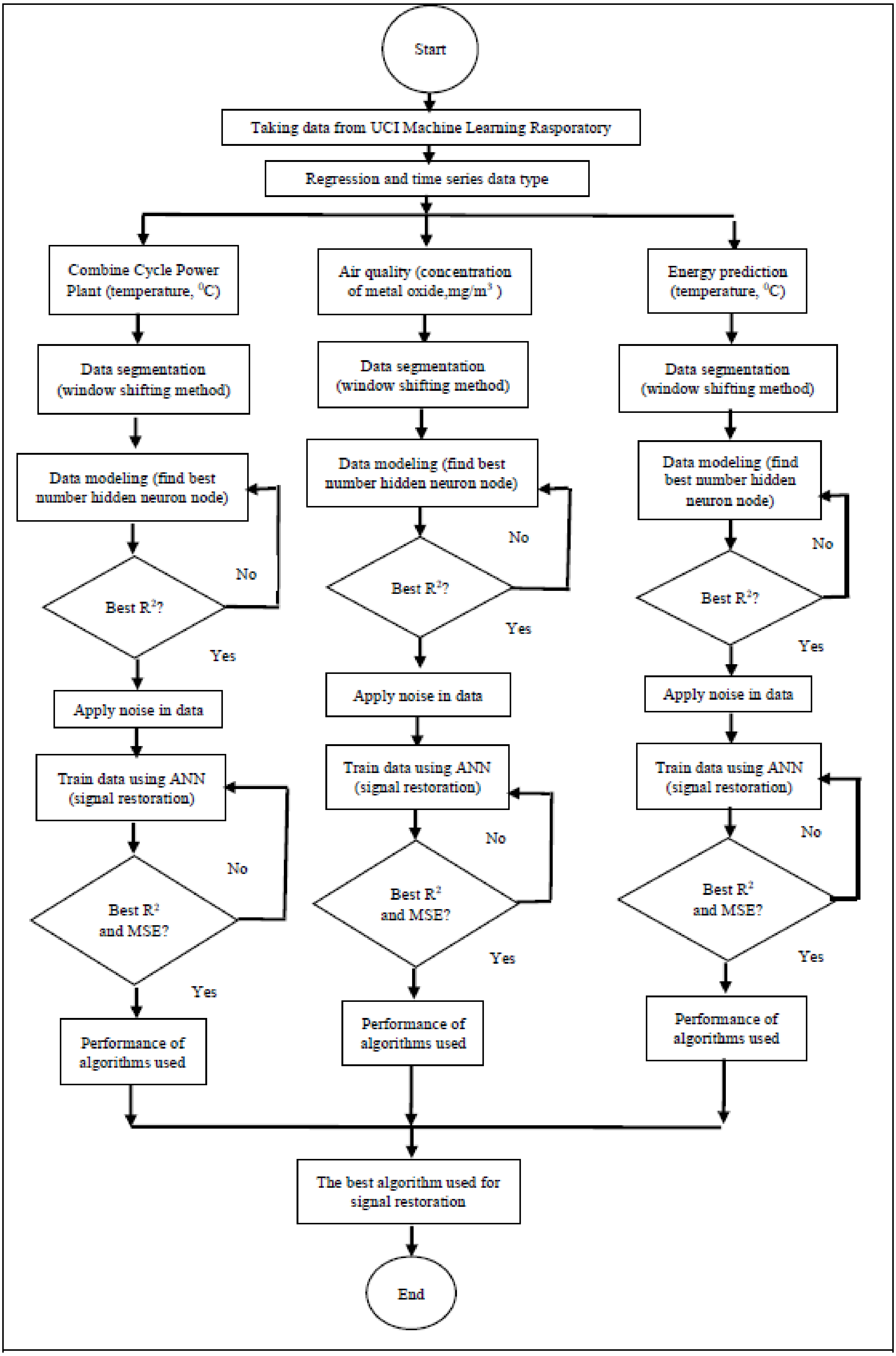

Fig. 2. Flow chart of the study

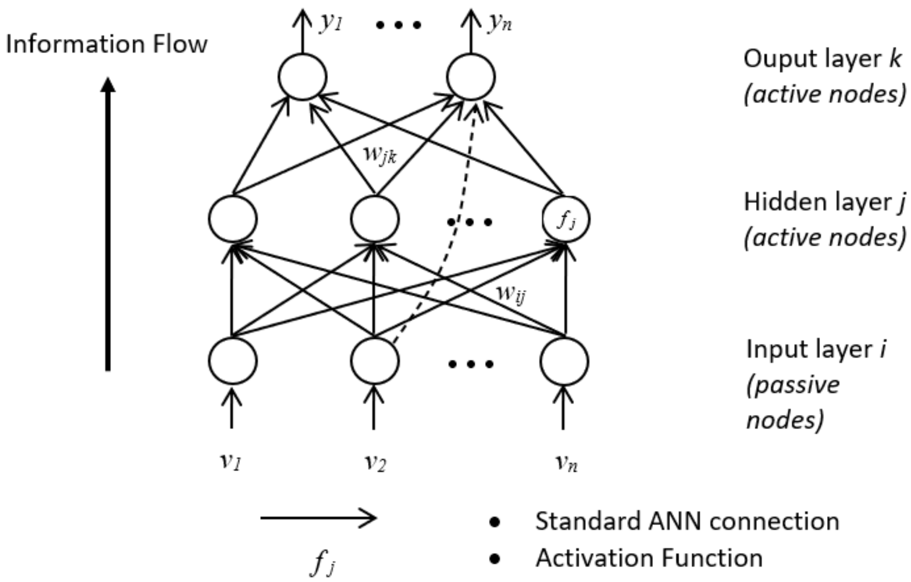

Fig. 3. Basic construction of neural network [12,16]

2.1 Data Pre-Processing

All the data set mentioned above was processed as follows in order to provide investigated losses in the original signal for example the Energy signal. The original signal is shown in Figure 4, followed by the altered signal that represented losses of 2, 6 and 10 data in Figure 5, Figure 6 and Figure 7 accordingly.

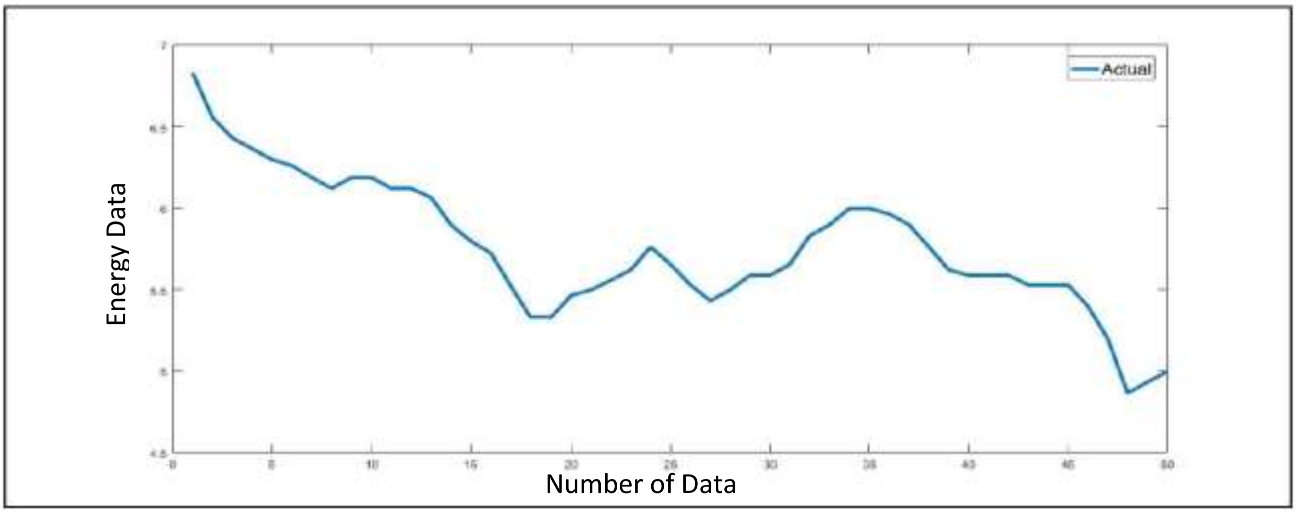

Fig. 4. Original signal of energy prediction

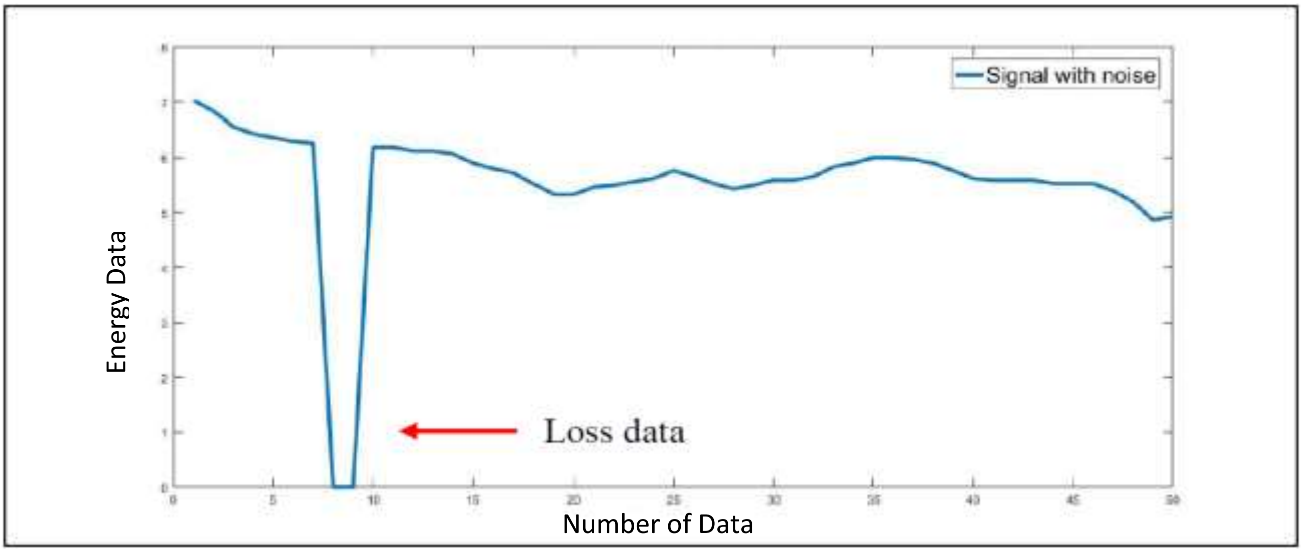

Fig. 5. Signal for energy prediction with loss of 2 data

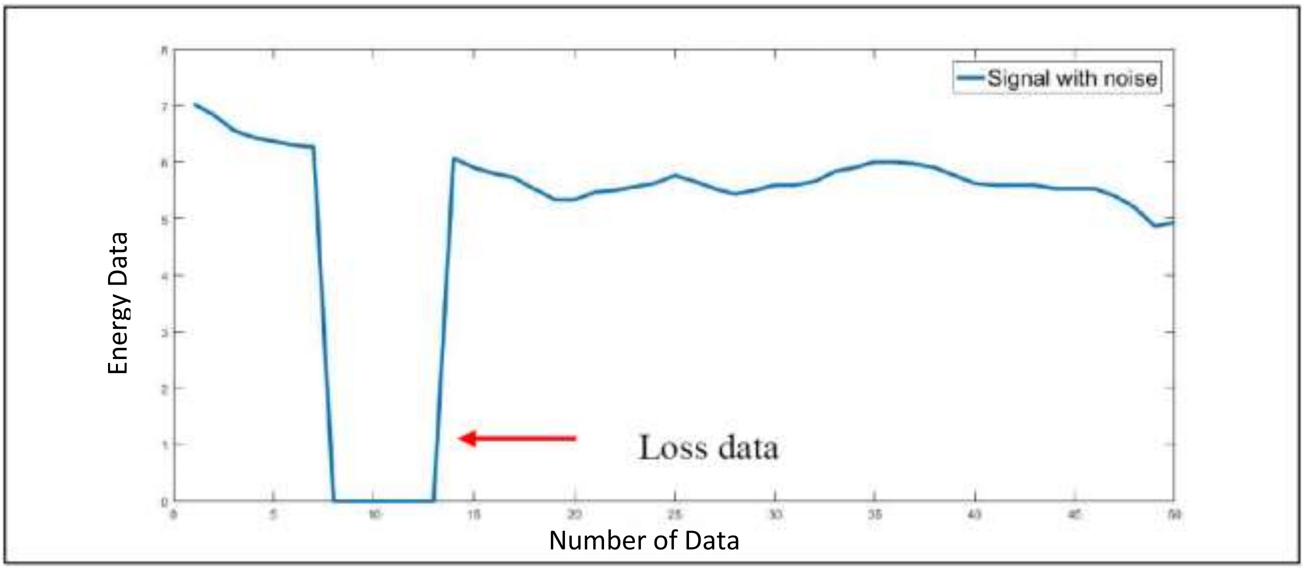

Fig. 6. Signal for energy prediction with loss of 6 data

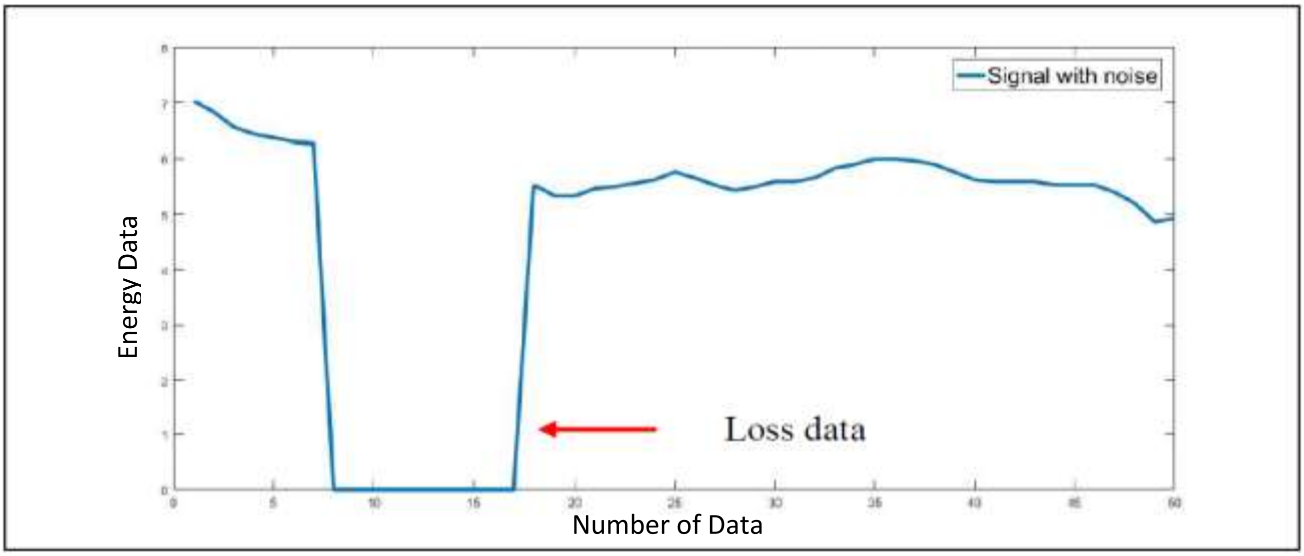

Fig. 7. Signal for energy prediction with loss of 10 data

Air Quality and Combined Cycle Power Plant data set will be similarly pre-processed as an Energy data set.

2.2 Data Training and Testing

After the best number of hidden nodes in Multilayer Perceptron (MLP) Network was identified, the test was conducted using 20 to 80 number of data and with different number of hidden nodes which is from 10 to 70. This test was conducted using Bayesian Regularization (Trainbr), Lavenberg Marquardt (Trainlm) and Gradient Descent (Traingd) training algorithm. The numbers of input data used were 20, 50 and 80 with data losses of 2, 6 and 10. The results from the output of MLP after training were analysed to see how possible it follows the desired data. The loss of data represents noises that disturb the original signal in collecting the data. The loss data were set as zero which means the data is totally loss. MLP will train, validate, and test the loss data by referring to the desired output data or target data. All dataset was set as follows: training is 70%, validation is 15% and testing is 15% of the total dataset. The training dataset is used to supervise the learning of the data by comparing the result with the target data. The parameters of learning will be adjusted along with the learning process. The validation dataset will evaluate the model fitness on the training dataset while tuning the model hyperparameters. The testing dataset is used to make a final evaluation of model fitness on the training dataset.

2.3 Performance Evaluation of Signal Restoration

The performance of signal restoration was evaluated using the Coefficient of Determination (R^2) and Mean Square Error (MSE) referring to the output signal after the testing process.

3. Results

This section shows the simulation results for the testing data using Bayesian, Levenberg-Marquardt and Gradient Descent algorithm. Data were examined multiple times with different size of data and different size of loss data from the real one. The purpose of these project is to see the performance of training algorithm whether can be used for different size of data and how precisely it follows the desired data. The number of data which were used 20, 50 and 80. While the loss data are count as number of data removed from the actual data, the losses data are 2, 6 and 10. However this paper only shows the data size of 50.

3.1 Performance of Energy Prediction

Performance of Energy Prediction in Table 1 shows R2 values for all training algorithms (BR, LM dan GD) produce values in the range of 0.7 to 0.9. BR training algorithm shows the best value for R2 and MSE. BR produce R2 value of average more than 0.99 for 2, 6 and 10 data losses and the smallest MSE value of average -30 dB among the comparison. LM produce R2 value of 0.97 for 10 data losses where the performance is degraded after the losses is increased. LM produce the second best MSE value among the comparison. GD produce R2 value of 0.7 for 10 data losses where the performance is the worst among the comparison. GD also produce the worst MSE value among the comparison. GD (represented by purple line in Figure 8) is able to follow the actual signal (blue line), but GD provide amplitude that is a bit larger than actual signal. The output of prediction trained by GD signal follow the target or actual signal, whereas there is still some error found between prediction and target signal.

Table 1
Performance of energy prediction

Training algorithm	Coefficient of determination, R^2			Mean square error, MSE in dB		
	2	6	10	2	6	10
BR	0.9968	0.9936	0.9957	-32.8759	-29.8108	-31.5814
LM	0.9920	0.9871	0.9728	-28.8429	-26.7685	-23.5466
GD	0.8578	0.8175	0.7060	-16.3572	-15.2755	-13.2041

3.2 Performance of Air Quality Prediction

Performance of Air Quality Prediction in Table 2 shows R2 values for all training algorithms (BR, LM dan GD) produce values in the range of -31 to 0.9. BR training algorithm provides the R2 values from 0.96 to 0.98 with MSE values are the lowest compared to the others training algorithm which are around 30. LM produce R2 value of 0.74 to 0.82 where the performance is degraded after the losses is increased. LM produce the second best MSE value among the comparison which are around 40. GD produce R2 value of -31.3 for 10 data losses where the performance is the worst among the comparison. GD also produce the worst MSE value among the comparison which are around 60.

Table 2
Performance of air quality prediction

Training algorithm	Coefficient of determination, R^2			Mean square error, MSE in dB		
	2	6	10	2	6	10
BR	0.9830	0.9783	0.9653	30.4331	29.3753	32.4684
LM	0.8247	0.8097	0.7475	41.0892	39.8604	39.5055
GD	-23.9567	-25.9418	-31.2617	61.0384	62.1534	61.3708

3.3 Performance of Combined Cycle Power Plant

From Table 3, it shows that most of training algorithm have a worse value for R2 and MSE except for TrainBr. Traingd have negative value for all of its R2. While Trainlm is near to zero (0) which not good in terms of signal regression. This type of signal has a sharp change of its state from maximum point to minimum point. This is difficult for signal restoration to estimate and follow the actual signal. Only Trainbr is able to follow the actual signal with R2 range is about 0.3 to 0.6. Traingd has a large error for signal restoration. This algorithm is the worse compared to Trainlm.

Table 3
Performance of combined cycle power plant prediction

Training algorithm	Coefficient of determination, R^2			Mean square error, MSE in dB		
	2	6	10	2	6	10
BR	0.7428	0.6135	0.4081	11.8967	13.6656	15.5160
LM	0.0037	0.3114	0.2215	17.7775	16.1733	16.7065
GD	-12.5860	-40.0418	-50.2160	29.1247	33.9260	34.8878

Figure 8 to 10 demonstrate how effective Trainlm and Trainbr are at signal restoration. The trained signal is capable of keeping up with the real signal. While the signal restoration is poor for Traingd. The R^2 value for Traingd is negative. The discrepancy between the learned signal and the actual signal in the training signal is very high. When compared to other training algorithms, Traingd's trained signal's amplitude is also bigger. The best training algorithm for this air quality signal is Trainbr.

Trainbr is the best for predicting the loss of data, according to all signal restoration performance for various signal types (energy prediction, air quality and combined cycle power plant). Trainbr can estimate and track the actual signal. The red line (Trainbr) in the entire figure indicates that it is followed by the blue line (actual signal). It also shows that the level of difficulty for signal restoration using all training algorithm. The easiest signal type is an energy prediction dataset, followed by an air quality dataset and a combined cycle power plant dataset. Trainbr can estimate and track the actual signal. The red line (Trainbr) in the entire figure indicates that it is followed by the blue line (actual signal). It also shows that the level of difficulty for signal restoration using all training algorithm. The simplest signal type is an energy prediction dataset, followed by an air quality dataset and finally a weather prediction dataset.

From the results, the Bayesian method is able to restore the signal which affected by noise or some loss of data with higher accuracy compared to others training algorithms. Signal restoration for Energy Prediction dataset shows that the best number of hidden nodes used for the training is 15 with R^2 values in the range of 0.4 to 0.99. Table of performance shows that Trainbr is the best training algorithm to be used for signal restoration with R^2 value about 0.99, then followed by Trainlm with R^2 values in the range 0.6 to 0.9 and lastly Traingd with R^2 value the lowest which are in range of 0.5 to 0.9. MSE for this type of signal shows all of its values are negative and Trainbr has the lowest value compared to the other training algorithm. Therefore, Trainbr is the best training algorithm to be used for this type of signal.

While, for Air Quality dataset, the size of hidden nodes used is 25. Trainbr and Trainlm shows that the R^2 values in the range of 0.4 to 0.9 for hidden neuron node size of 20 and 30. Therefore, an average value is used, which is 25. Result of training signal for the size of data 50 (Table 2) shows that the Traingd have all of its R^2 values are negative and MSE is the bigger compared to other training algorithm. Trainlm have R^2 values in the range of 0.6 to 0.8 with MSE value around 40. This performance is quite good. However, Trainbr shows the best performance for restored this signal. The values of R^2 for Trainbr in the range of 0.8 to 0.9 with lowest value of MSE compared to those two-training algorithms.

The size of hidden neuron node used for train Combined Cycle Power Plant dataset is 70 with R^2 values in the range of 0.4 to 0.9. This value is best compared to other size of hidden node. Since this signal is the difficult to be train only Trainbr have a positive value for R^2. The performance of signal restoration using Trainbr shows the R^2 values in the range of 0.3 to 0.7 and MSE values is the lowest. While, Trainlm have R^2 values near to zero which mean bad in term of signal regression. R^2 value for Trainlm are in range of -0.08 to 0.3. Traingd has the worse value for R^2 and MSE compared to other training algorithm. All R^2 value for Traingd are negative with MSE value is the bigger one. For this type of signal, Trainbr is the best training algorithm to be used for signal restoration.

From the results of all type of signal being used for this study, it shows that the Trainbr is the best training algorithm to be used for signal restoration. Most of R^2 values is above 0.5 and near to 1 which is good for signal regression. While the values for MSE are the smallest compared to other training algorithm. Since the restoration of the signal is successful, the objectives of this study are achieved.

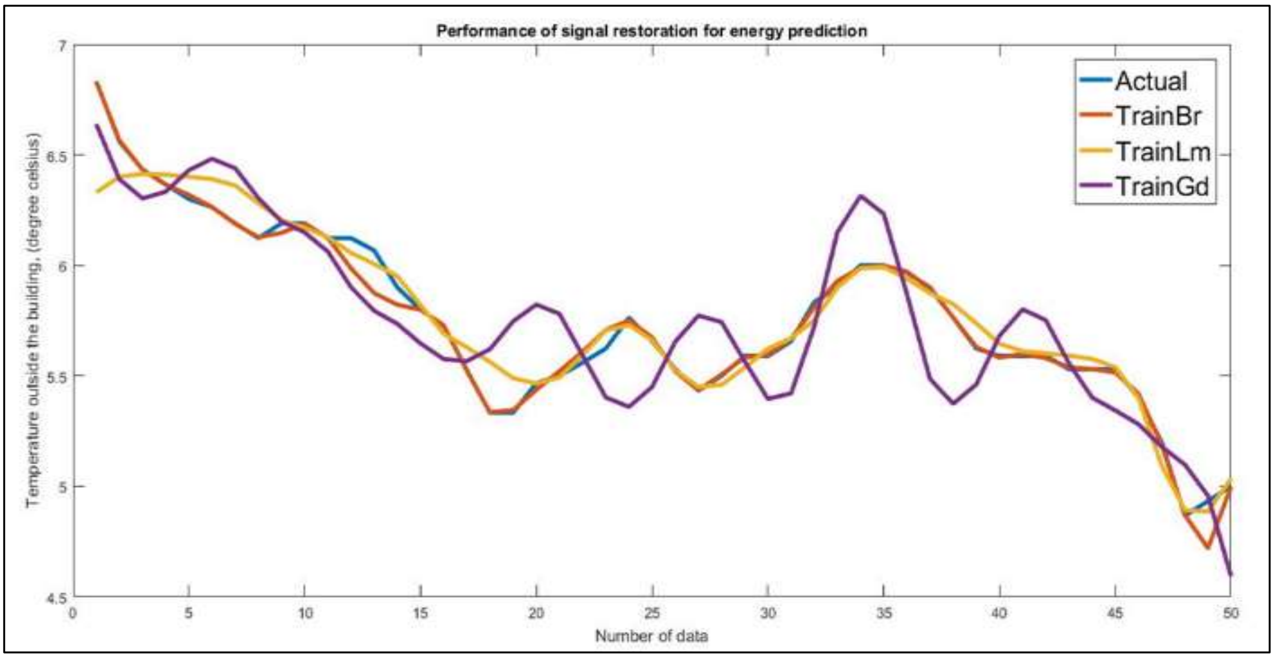

Fig. 8. Performance of signal restoration for energy prediction

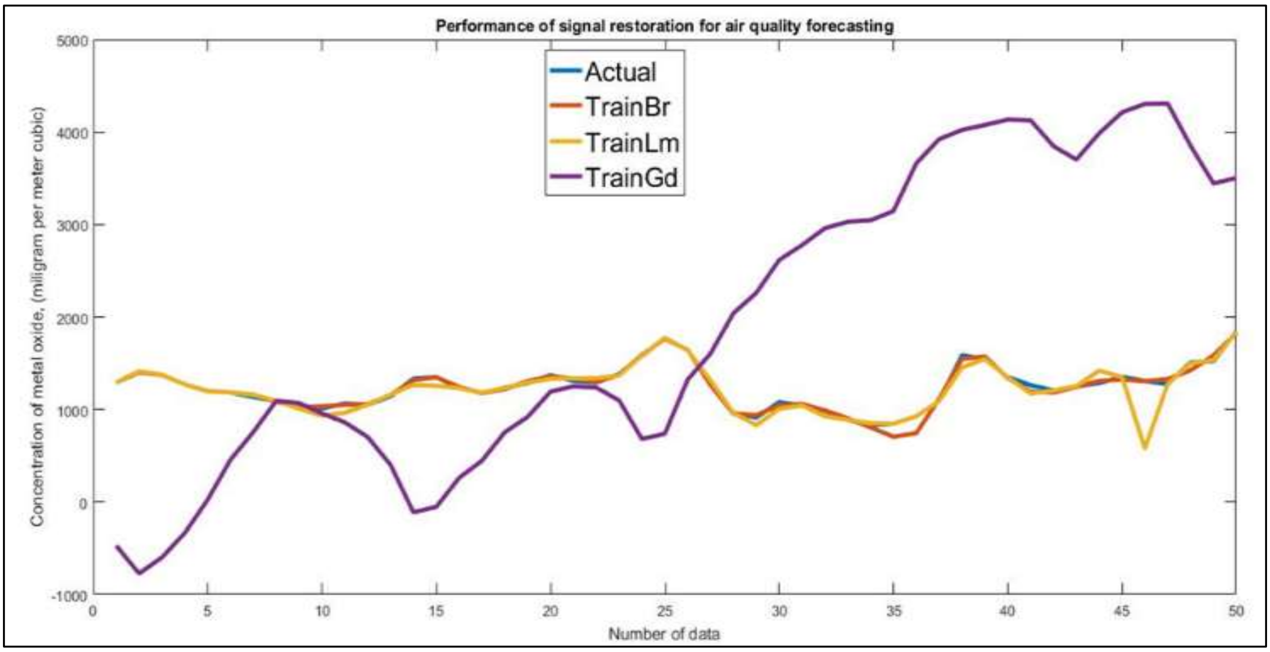

Fig. 9. Performance of signal restoration for air quality prediction

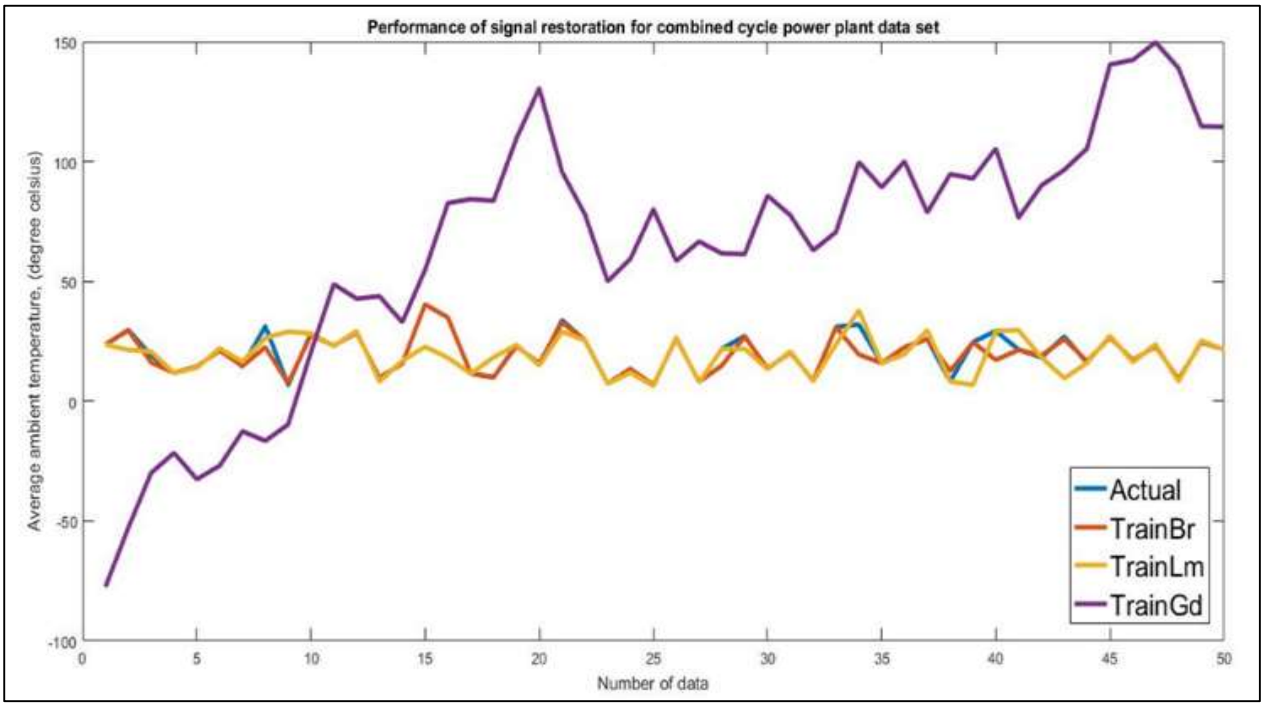

Fig. 10. Performance of signal restoration for combined cycle power plant prediction

4. Conclusions

Aiming at the use of signal restoration to predict the original input signal affected by noise using some prior information from the desired process or output signal, this paper proposed a signal restoration using estimation by applying a Bayesian Neural Network. Based on the general model of Artificial Neural Network and learning algorithms under the condition of off-line estimation, this study proposed a comparison of Bayesian Regularized (BR), Levenberg-Marquardt (LM), and Gradient Descent (GD) training algorithms in MLP network as the model estimator. Perform off-line neural network parameter estimation to obtain the best network for predicting the original input signal from the distorted or noisy version of the original signal. Compared to traditional LM and GD, the results demonstrate that Bayesian Regularized is the most effective training algorithm for signal restoration. In comparison to the LM and GD training algorithms, the majority of R^2 values for BR are close to 1 (0.7 to 0.99) and the MSE value is the lowest (-32.9387 dB). This proposed BNN model can be apply in the signal restoration and prediction for practical wireless communication system such as speech and audio processing, multimedia processing, underwater acoustic, biological signal and others.

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