# AN IMPROVED PI-SIGMA NEURAL NETWORK USING ERROR FEEDBACK FOR TIME SERIES PREDICTION

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I would like to dedicate my Master's degree thesis to my beloved father (late), mother, brothers, sisters and husband whose sincere prayers and efforts make it possible for me to fulfill their utmost desire.

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# ABSTRACT

Time series prediction grabs much attention because of its effect on the vast range of real-life applications. Traditional time series forecasting tools have some limitations like slow training process, less efficient training methods that decrease the performance of the model. Higher Order Neural Network (HONN) using recurrent feedback appeared as a powerful technique in the domain of time series prediction and it has the ability to expand the input space, making them more efficient for solving complex problems and perform high learning abilities in time series prediction. This study proposed a model called improved Pi-Sigma Neural Network using Error Feedback (PSNN-EF) which combines the properties of Pi-Sigma Neural Network (PSNN), recurrence and error feedback. PSNN-EF uses backpropagation gradient descent algorithm for training purpose and is tested with physical time series signals of humidity, evaporation and wind direction datasets that are collected from Malaysian Meteorological Department (MMD). The prediction result is compared with Jordan Pi-Sigma Neural Network (JPSN) and the ordinary PSNN. The results clearly showed that the PSNN-EF significantly improved the computational efficiency of the training process and has been developed to produce more realistic and acceptable results. The average improvement of the proposed model on evaporation dataset is 2.06%, humidity is 7.45% and wind is 3.51% as compared to other models. The benefit of using error feedback is that it generates more accurate and promising results of prediction. Therefore, from the performance of the proposed method, it is noticed that PSNN-EF can provide better solution to JPSN for one-step-ahead prediction of those three datasets.

# ABSTRAK

Ramalan data siri masa meraih banyak perhatian atas kesannya terhadap pelbagai aplikasi di dalam kehidupan sebenar. Alat peramal siri masa tradisional ini mempunyai beberapa batasan seperti proses latihan yang perlahan, kaedah latihan ini kurang efisien juga mengurangkan prestasi model. Rangkaian Neural Pesanan Tinggi (HONN) menggunakan maklum balas berulang, berfungsi sebagai salah satu teknik penting dalam ramalan domain data siri masa dan ia mempunyai keupayaan meningkatkan ruang input, menjadikannya lebih efisyen untuk menyelesaikan masalah kompleks dan melaksanakan kebolehan pembelajaran yang tinggi dalam ramalan data siri masa. Kajian ini mencadangkan satu model yang dipanggil Rangkaian neural Pi-Sigma yang menggunakan Maklum Balas Kesalahan (PSNN-EF) yang telah ditambah baik serta menggabungkan sifat-sifat Rangkaian Neural Pi-Sigma (PSNN), maklum balas berulang dan kekeliruan. PSNN-EF menggunakan algoritma turunan latar belakang *backpropagation* untuk tujuan latihan dengan isyarat siri masa kelembapan fizikal, penyejatan dan *dataset* arah angin yang dikumpul dari Jabatan Meteorologi Malaysia. Hasil ramalan dibandingkan dengan Rangkaian Neural Jordan Pi-Sigma (JPSN) dan PSNN biasa. Hasilnya dengan jelas menunjukkan bahawa PSNN-EF meningkatkan kecekapan pengiraan proses latihan dan telah dibangunkan untuk menghasilkan hasil yang lebih realistik dan boleh diterima. Peningkatan purata model yang dicadangkan pada dataset penyejukan adalah 2.06%, kelembapan adalah 7.45% dan angin adalah 3.51% berbanding dengan model lain. Manfaat menggunakan maklum balas kekeliruan dan kesilapan adalah bahawa ia menjana hasil ramalan yang lebih tepat dan memberikan hasil yang lebih tepat. Oleh itu, dari prestasi kaedah yang dicadangkan, PSNN-EF dapat memberikan penyelesaian yang lebih baik untuk meramalkan satu-langkah ke hadapan dari ketiga-tiga *dataset* tersebut.

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| | | |
|---|---|---|
| NN | - | Neural networks |
| HONN | - | Higher Order Neural Networks |
| MLP | - | Multi-Layer Perceptron |
| PSNN | - | Pi-Sigma Neural Network |
| JPSN | - | Jordan Pi-Sigma Neural Network |
| JMN | - | Jordan Neural Network |
| PSNN-EF | - | Pi Sigma Neural Network using Error Feedback |
| ANNs | - | Artificial Neural Networks |
| RPSN | - | Recurrent Pi-Sigma Neural Network |
| FNN | - | Feedforward Neural Networks |
| RNNs | - | Recurrent Neural Networks |
| RBF | - | Radial-basis Function |
| ART | - | Adaptive Resonance Theory |
| SOM | - | Self-Organising Maps |
| RMNM-ANN | - | Recurrent Multiplicative Neuron Artificial Neural Network |
| MA | - | Moving Average |
| AR | - | Autoregressive |
| FLNN | - | Functional Link Neural Network |
| RPNN | - | Ridge Polynomial Neural Network |
| ICES | - | International Council for the Exploration of the Sea |
| GA | - | Genetic Algorithm |
| GD | - | Gradient Descent |
| JPSNN | - | Higher order Jordan Pi-Sigma Neural Network |
| BP | - | Backpropagation |
| RPSNN | - | Recurrent Pi-Sigma Neural Network |
| EMD | - | Empirical Mode Decomposition |

| | | |
|---|---|---|
| ENN | - | Elman Neural Network |
| ARMA | - | Autoregressive Moving Average |
| ARIMA | - | Autoregressive Integrated Moving Average |
| MMD | - | Malaysian Meteorological Department |
| SNR | - | Signal to Noise Ratio |
| MSE | - | Mean Squared Error |
| MAE | - | Mean Absolute Error |
| NMSE | - | Normalised Mean Squared Error |
| $w_{ij}$ | - | Vector of weights |
| $f$, σ | - | Activation function |
| $o_j$ | - | Actual value |
| $d_j$ | - | Targeted value |
| $x(t)$ | - | Input nodes |
| $y(t+1)$ | - | The network output at time $t+1$ |
| $w_{kj}$ | - | The trainable weights |
| $h_k(t+1)$ | - | The summing unit |
| $\alpha$ | - | Momentum |
| η | - | Learning rate |
| $y_j$ | - | Output |
| $e$ | - | Error |
| $d(t)$ | - | Desired output |
| $d(t)$ | - | Predicted output |
| E | - | The error function |
| max $X$ | - | Maximum value |
| min $X$ | - | Minimum value |

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# CHAPTER 1

# INTRODUCTION

## 1.1 Background

Forecasting natural occurring phenomena has been addressed and analyzed by many researchers and which is a general issue in many domains of science. It is important to predict a time series because many problems that are related to prediction such as health prediction problem, climate change prediction problem and weather prediction problem include a time component. These problems are ignored due to their time component which makes time series issue more difficult to manage. The importance of time series forecasting investigates from the fact that has a large series of applications containing environmental systems, control systems, economics and engineering processes (Sapankevych & Sankar, 2009; Shumway & Stoffer, 2011; Al-Jumeily *et al.*, 2014). A time series is a collection of observations of data items taken sequentially during a period of time (Brownlee, 2016). To find out the accurate forecasts for rare weather is a difficult task in the science of modeling. Much work has been done by many scientists to forecast the atmospheric issues and to estimate the potential cost of forecasting methods (W.Zhu & Pi, 2014). To predict future happenings or future incidents, time series forecasting tools are used in which some phases of historical or present events will proceed into the future. In this process, a certain set of past variables generates a set of outputs (Ballesteros *et al.*, 2014). Time series forecasting tools can be categorized into two different approaches: intelligent-based and statistical-based. The nonlinear nature of intelligent-based approaches in time series forecasting gives better performance than statistical approaches (Al-Jumeily *et al*., 2014).

From statistical to artificial intelligence, there is a range of neural network techniques which have been used to handle a time series problem (Hussain *et al*., 2008; Ghazali & Al-Jumeily, 2009; Sewell, 2012; Adhikari & Agrawal, 2013; Oancea & Ciucu, 2014; Chaudhuri & Ghosh, 2016). Neural networks (NN) have appeared as an effective tool for forecasting of time series (Mahdi *et al*., 2010). The selection of appropriate model has been considered by many scholars and researchers to resolve the issues related to the prediction of time series problem (Zhang *et al*., 2001). Therefore, much struggle has been done to improve the quality of prediction so, the developers are focusing on Higher Order Neural Networks (HONN) that has recently considered to developing the input representation spaces broadly (Hassim & Ghazali, 2013a). Researchers examine the ability of HONN that can use to predict the upcoming trends of time series data. It is capable to learn the dynamics of the time series and maintains fast learning process. The type of HONN is Pi-Sigma Neural Network (PSNN) that is used for forecasting (Husaini *et al.*, 2012). Therefore, it ensures the minimum error in training and testing. This network utilized less memory in the form of weights and nodes then it means it resolve the space complexity problem as compared to the other higher order neural networks. Moreover, the PSNN needs the lesser number of weights and can reduce training time (Husaini *et al*., 2014).

On the other hand, PSNN faced some problems like conjunction increase in this network because this network minimized the space complexity and assigned less memory. This network needs more time for learning. Furthermore, Recurrent Pi-Sigma Neural Network (RPSN) is proposed and its application to the prediction of physical time series is mentioned in (Hussain & Liatsis, 2002; Hussain *et al*., 2008). This network structure utilized the properties of HONN. The structure of the network is regular and has a recurrent connection between the output layer to input layer employed to store the information for later use. This network provides promising results and has the ability of faster learning as compared to existing feedforward networks. In contrast, the structure of RPSN is not appropriate to forecast the nonstationary and highly non-linear signals. To overcome the problems of PSNN, another network Jordan Pi-Sigma Neural Network (JPSN) is proposed that utilized the properties of PSNN. It is used for the prediction of temperature time series. Despite that, JPSN model has some drawbacks that slow down the training process and decrease the performance of the network because of fixed weights. Consequently, the purpose of this research is to predict the physical time series with the more accurate result which is the first motivation in developing a modified model, an improved Pi-Sigma Neural Network using Error Feedback (PSNN-EF) for time series prediction by combining the properties of PSNN and error feedback.

## 1.2 Problem Statements

Time series basically refers to an arrangement of observations on a quantity over time intervals and measured frequently over successive times (Hussain *et al.*, 2016). In handling time series forecasting, researchers and public investigators experienced many challenges (Schwaerzel & Bylander, 2006). Moreover, forecast the future value and understanding the nature of and modeling the evolution of the time series is the most difficult to be determined. These are the problems in which classical linear statistical methods are not sufficient and where more advanced machine learning algorithms are required. That is why there was a need for such algorithms that could perform nonlinearity mapping of input-output. Currently, most of the techniques are involved to find sophisticated mathematical models to improve the efficiency of the prediction of physical time series. To solve the time series prediction problem various techniques have been developed over many years to enhance the accuracy of forecasting. Nowadays, Neural Networks (NN) have appeared as an effective tool for forecasting of time series (Mahdi *et al.*, 2010). Furthermore, Artificial Neural Network (ANNs) are the intelligent based models of the biological neurons and it is also used effectively for time series prediction (Malik, 2005).

To resolve the problems related to time series data, there is a need of network with single layer trainable weights that is HONN which can perform nonlinearity mapping of input-output. So, the developers are focusing on HONN that has been recently considered to develop the input representation spaces broadly. PSNN is the type of HONN and it has the capability of fast learning which reduces the network complexity by using efficient polynomials for many input layer variables (Shin & Ghosh, 1991). Based on PSNN structure a new technique JPSN having abilities of the higher order was developed which includes the characteristic of PSNN used for time series problems (Husaini *et al*., 2011; Ghazali *et al*., 2012). The value of the weights is fixed with 1 that are found in JPSN are between the recurrent node and the hidden nodes that could decrease the performance of the JPSN with some time series. Also, JPSN initializes weights with small values between [0,1] tends to the very slow training process.

To overcome the limitations and looking into the benefits of PSNN and RPSN, this research work proposes an improved network model that is utilized for training and testing for time series forecasting. This model is called an improved Pi-Sigma Neural Network using Error Feedback PSNN-EF for time series prediction that is a combination of the properties of PSNN, recurrence and error feedback. Recurrent networks are dynamic state having the feedback path which directs the network to enter a new state. Error feedback is capable to handle complex structure output spaces naturally and it is also capable to store information for later use and attractor dynamics. This is the first motivation to use the error feedback in our proposed model. In this regard, backpropagation algorithm is used in this network for the purpose of learning from error. Hence, by using the proposed PSNN-EF this research lead to enhance the prediction accuracy for physical time series.



## 1.3 Aim and Objectives of Research

The goal of this study is to improve the PSNN for time series prediction and to enhance its prediction accuracy.

In order to complete the goal of this research, few objectives have been set:

1. To improve a Pi-Sigma Neural Network using Error Feedback (PSNN-EF) for time series prediction which includes the characteristics of PSNN and error feedback.
2. To simulate the PSNN-EF for the prediction of physical time series datasets.
3. To evaluate the out-of-sample performance of the PSNN-EF for time series prediction and benchmark the results with the ordinary PSNN and JPSN.

## 1.4 Scope of Research

This research majorly focuses on the construction, implementation and testing of PSNN-EF for physical time series prediction. This network model is trained with the backpropagation learning algorithm for the three datasets wind direction, humidity and evaporation (Malaysian Meteorological Department, 2010). The results are compared with ordinary JPSN and PSNN in terms of Mean Squared Error, Signal to Noise Ratio, Normalized Mean Squared Error, Mean Absolute Error, and epoch.

## 1.5 Significance of Research

PSNN-EF is important to be used in this research to forecast the upcoming trends by comparing the performance of the network with the JPSN and PSNN model. This research may support in time series like wind direction, humidity and evaporation to predict future improvements and developments which can be beneficial for human life. Accurate forecasting model has drawn much attention to academic and decision maker's interest. Besides, the PSNN-EF will be suitable for hydrology departments which apply the nonlinearity relationship in forecasting. Simulation results can be utilized to construct a vigorous and reliable time series model for prediction and can be a better solution for JPSN and PSNN in terms of flexibility and accuracy. Besides, this work has the capability of assisting the daily prediction event for the Malaysian Meteorological Department (MMD).

## 1.6 Thesis Organization

The remaining thesis is comprised as follows: Chapter 2 explains the related background information regarding the existing techniques in time series prediction. In addition, the introduction of ANN's architecture, the use of HONN and its advantages and to solve the problems regarding time series. Chapter 3 illustrates the research framework for time series prediction and the proposed PSNN-EF model. This chapter continues to explain the implementation of a proposed model that is starting from data selections to the complete process of prediction. Chapter 4 describes the simulation of

PSNN-EF. Analysis of the result related to prediction is shown in graphs and tables. The comparison of the simulation results with different models like JPSN and PSNN is presented. Acquired results were examined through different parameters. Chapter 5 presents the conclusion and useful suggestions for expanding the proposed model in future.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1 Introduction

Artificial Neural Networks (ANNs) obtained a big attention in various fields of science and engineering. ANNs are the intelligent based models of the biological neurons and it is also used effectively for time series prediction (Malik, 2005). Models of neurological networks were proposed by McCulloch and Pitts in 1943 (Mcculloch & Pitts, 1943). In the recent development, much progress has been done on the simulations of neural network models (Stergiou & Siganos, 2016). ANNs are also known as neural networks that are motivated from the brain. From the past decades, significant advancement has been obtained for the brain development (Stiles & Jernigan, 2010). Neural networks applied in many applications like regression-based judgmental forecasting, signal and image processing, time series forecasting (Shen *et al.*, 2013). This chapter provides the necessary background on neural networks that will make this thesis relatively self-contained.

## 2.2 Neural Networks

ANN is the model of processing information that is established on biological nervous systems like a brain. The brain has the ability to learn from its previous experience. It consists of interconnected processing units in a complex network. Each unit is called a neuron which sends a signal when it receives an input from the other nodes (Maind

& Wankar, 2014). ANN can change its architecture depending on the internal stimuli and external input that flows in the network throughout the learning stage (Singh & Chauhan, 2009). It is a machine learning technique that consists of human brain and number of neurons. Neurons in ANN tend to have fewer connections than biological neurons. An ANN is composed of interconnected processing neurons that interact with one another and its function is utilized to transform the neuron's activation level into an output. The activation function is used to simplify the network and introduce nonlinearity into the network.

The human brain integrates 10 billion of neurons and has 60 trillion connections with each other. The brain can handle so many neurons more parallelly and communicate with them rapidly as compared to the fastest computers. The main components of a network are neurons, bias, activation function and connection weights. Some details of these components are described here. A network is combined with many different elements. The basic unit for the development of the network is neurons, they are connected in each layer. Every neuron has an independent computational unit. However, every connection contains their own weights and the connections of neurons are not similar. The neuron has three basic elements that are input, hidden and output and the neuron's input is a product by their weights (Mcculloch & Pitts, 1943). Every neuron contains $n$ input signals denoted as '$n$'$xi, i = 1,2, \dots . n$ having weight $w$, $wi, i = 1,2, \dots . n$. At $i^{th}$ input the signal is multiplied by its corresponding weights to get an output. The neuron combines the signals from the weighted connections $w_{ij}$ towards the summing layer and calculates its activation function from input of the network. Then network will send the output signal depend on its activation function.

ANN is highly parallel, complex, nonlinear information-processing system and a distributed control. It has the ability to arrange neurons for performing actions like perceptron, pattern recognition, and motor control (Pagariya & Bartere, 2013). The importance of brain-style computation became a very basic principle of neural network development. The neural network employed in many time series analysis (Moustra *et al*., 2011; Zamani & Sorbi, 2013). The next section describes different neural network architectures.

## 2.3 Different Architectures of Neural Networks

Neural Networks (NN) can use a variety of topologies and learning algorithms. There are several models of a neural network, but all networks have three common components like a neuron, the connection between the architecture and learning algorithm. It is classified into two different types depends on the NN architecture: Feedforward Neural Networks (FNN) and Recurrent Neural Networks (RNN).

### 2.3.1 Feedforward Neural Networks

Feedforward Neural Networks (FNN) are mostly used in many time series forecasting applications broadly (Abdulkarim & Garko, 2015; Sharma *et al*., 2013; Wu *et al*., 2016). FNN model is a network that has no recurrent link which means the signals can pass in one direction only. The data is passed from the input layer to further process. Every processing elements produce its computation depends on the weighted sum of its inputs. The calculated values become the input values for the next layer and this process continues until the output generated.

FNN was the first and might be the simplest type of ANN (Singh & Chauhan, 2009). There are several types of FNN like Adaptive Resonance Theory (ART), Self-Organizing Maps (SOM), Radial-basis Function (RBF) and Multilayer Perceptron (MLP). The most common type of feedforward neural network is MLP that is a useful technique which is used for solving complex problems when suitable data is available to train them. MLP is capable of learning from input-output signals (Güldal & Tongal, 2010) also it can solve nonlinear problems (Sibanda & Pretorius, 2011; Mishra *et al*.,2013). An MLP consists of several numbers of units that are connected through a weighted link. These units have different layers like input layer and hidden layer that can be one or more layers and an output layer (Gales, 2015). Furthermore, to accomplish the required input-output relationship of the network, the adjustment of weights during the training in MLP through minimizing the error function (Rumbayan & Nagasaka, 2011).

Although there are many advantages of using MLP but due to its multiple layer structure it requires a great number of units for solving complex nonlinear problems, it consequences poor generalization and low learning rate (Yu *et al*., 2014). Moreover, MLP is very slow because it needs much more training time for learning and training with high computational complexity (Ghazali & Al-Jumeily, 2009). MLP has broadly used in different applications like signal processing (Nielsen *et al*., 2009) and pattern recognition (Mat Isa & Mamat, 2011).

### 2.3.2 Recurrent Neural Networks

The Recurrent Neural Networks (RNNs) were proposed in the 80's for modeling the time series. They are capable to store information for a long time in the hidden states. A recurrent network has iterative cycles in their architecture and they get the output using feedback from its units (Martens, 2011). The representation of dynamics internal feedback loops are provided by the recurrent neural network to enhance the learning efficiency and to store information for future use. RNN is very powerful network because it combines the properties of distributed hidden state and non-linear dynamics. Distributed hidden state which enables them to efficiently store large amount of information regarding the past and non-linear dynamics which allows updating their hidden state in complex ways.

RNN is widely used for time series prediction (Güldal & Tongal, 2010; Jaeger, 2013). Furthermore, RNN gives the opportunity to represent a computational network to forecast the time series that depends on the number of persistence components by the number of feedback loops (Guldal & Tongal, 2010; Qin *et al*., 2017). They can have complicated dynamic and make the network very difficult to train (Martens, 2011). Moreover, a new Recurrent Multiplicative Neuron Artificial Neural Network model (RMNM-ANN) is proposed for forecasting of non-linear time series (Egrioglu *et al*., 2015). This network is used particle swarm optimization algorithm for the training purpose. In this network, Moving Average (MA) and Autoregressive (AR) terms are employed by using the error of the model as feedback. The performance of this proposed network was evaluated by using real-life time series. Results clearly show that RMNM-ANN shows better performance and provides accurate forecasts. The next section will define another type of neural network called Higher Order Neural Networks (HONN).

## 2.4 Higher Order Neural Networks (HONN)

To solve business problems much research has been done and applications of neural network have proved their benefits with classical methods, also neural network is capable to modeling linear time series (Ahangar *et al*., 2010). However, if the network having large number of inputs and long training cycles then the training becomes extremely slow. To solve these time-consuming operations, the researchers are focusing to the HONN that have a single layer of learnable weights and fewer units having nonlinear mapping ability and reducing the network's complexity (Yu *et al.*, 2014; Ghazali *et al.*, 2008). Moreover, HONNs are utilized to deal the nonlinear problems that cannot be tackled by any other statistical technique and multilayer perceptron technique (Giles *et al.*, 1988).

The ability of HONN is to enhance the input representation space that can be used in different complex data mining problems. It also required less memory in terms of nodes and weights. Due to the combination of multiplicative and summing units in HONN, they demonstrate more accurate forecasting (Hussain *et al.*, 2008). Moreover, the HONN model has the ability of functional mapping which determined through some time series problems and it shows the more benefits as compared to conventional ANNs (Yadav *et al.*, 2007). The main advantage of this network is that its architecture is less complex with only one layer for the training to achieve the nonlinear separable as compared to the MLP and other feedforward networks (Misra & Dehuri, 2007).

Different types of neural networks like Feed-forward and Multilayer perceptron (MLP) have been widely used by many researchers. However, due to some gaps like implementation cost and efficiency, dense complexity and long training time of these networks, it is preferred to use HONN in the network selection (Nayak *et al.*, 2015). HONN has been appeared as an important tool for prediction of time series and has widely used in many scientific and engineering problems (Hassim & Ghazali, 2013b). However, HONN architecture deal with higher-order terms and it requires a huge amount of resources (Akram *et al*., 2017). There are some types of HONNs which are Functional Link Neural Network (FLNN) (Giles & Maxwell, 1987; Dehuri & Cho, 2010), Ridge Polynomial Neural Network (RPNN) (Shin & Ghosh, 1995), Dynamic Ridge Polynomial Neural Network (DRPNN) (Ghazali *et al*., 2011), Ridge Polynomial Neural Network with Error Feedback (RPNN-EF) (Waheeb *et al*., 2016), Pi-Sigma

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