A Comprehensive Survey on Pi-Sigma Neural Network for Time Series Prediction

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***Abstract*—Prediction of time series grabs received much attention because of its effect on the vast range of real life applications. This paper presents a survey of time series applications using Higher Order Neural Network (HONN) model. The basic motivation behind using HONN is the ability to expand the input space, to solve complex problems it becomes more efficient and perform high learning abilities of the time series forecasting. Pi-Sigma Neural Network (PSNN) includes indirectly the capabilities of higher order networks using product cells as the output units and less number of weights. The goal of this research is to present the reader awareness about PSNN for time series prediction, to highlight some benefits and challenges using PSNN. Possible fields of PSNN applications in comparison with existing methods are presented and future directions are also explored in advantage with the properties of error feedback and recurrent networks.**

***Index Terms*—Higher Order Neural Network Time Series Forecasting; Pi-Sigma Neural Network; Recurrent Networks.**

I. INTRODUCTION

Forecasting natural occurring phenomena has been addressed and analysed by many researchers and it 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 include a time component. These problems are ignored due to its time component which makes time series issue more difficult to manage. A time series is a collection of observations of data items taken sequentially during a period of time [1]. Time series basically refers to an arrangement of observations over time intervals and measured frequently over successive times [2]. 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 [3].

The importance of time series forecasting investigates from the facts that has a large series of applications containing environmental systems, control systems, economics and engineering processes [4-6][4, 5, 6]. Also, decisions about the economic policy of governments, investments and trading of large companies depend on computer modelling forecasts. To handle time series forecasting researchers and public investigators experienced with many challenges [7]. Neural networks (NN) have appeared as an effective tool for forecasting of time series [8].

Artificial Neural Networks (ANNs) are the intelligent based models of the biological neurons and it is also used effectively for time series prediction [9]. To get the desired level of accuracy, NN or ANNs based models are utilized to approximate any non-linear or continuous function and it is completely data driven, which is especially useful for complex data of unknown nature. Furthermore, to forecast the exchange rate, ANNs based models and time series econometric models are utilized [10]. However, developers used classical statistical and econometric models for prediction but these models cannot be treated as superior to forecast in financial time series. Failure of this will result is cannot handle uncertainty nature of foreign exchange data series [11]. NN have the advantages that it is highly flexible in the approximation of nonlinear function in time series forecasting.

A feedforward ANNs in time series forecasting that are most commonly used is Multilayer Perceptron (MLP) [12]. The MLP has been applied in terms of useful mechanism for prediction, classification, function approximation and pattern recognition [13, 14]. However, for solving complex nonlinear mapping problems MLP requires a large number of units due to its multilayered structure. It consequences poor generalization and low learning rate [15]. Furthermore, training an MLP is often quite slow and often reach in computationally intensive training [16].

The selection of appropriate model has been considered by many developers and researchers to resolve the issues related to prediction of time series problem [17]. 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 consider to developing the input representation spaces broadly [18]. The type of HONN is PSNN that is used for forecasting [19]. Therefore, it ensures minimum error in training and testing as compared to MLP. Moreover, the PSNN is used to provide better forecasting result it needs less training time and use smaller number of weights mentioned in [20]. Furthermore, for the training of PSNN a hybrid genetic learning algorithm is presented and proved that algorithm can overcome PSNN converges speed problem and accomplish more better performance [21]. Moreover, inspired from HONN and Recurrent Neural Networks (RNN) a new type of network called Recurrent Pi-Sigma Neural Network (RPSN) is considered [22] and its application to physical time series prediction are mentioned in [23]. RPSN accomplished fast training and convergence when compared with another feedforward and RNN. Furthermore, network error feedback is used rather than network output feedback and it was used in the network as additional input in different models for time series prediction [24, 25, 26]. In another work a new model Ridge Polynomial Neural Network with Error Feedback (RPNN-EF) was proposed for prediction [25]. So, we can say that using error feedback in this model we get minimum error and increase the reliability of forecasting. Moreover, the existence of the recurrent link enhance the capability of the network for attractor dynamics and storing information for future use [27].

Another forecasting tool Jordan Pi-Sigma Neural Network (JPSN) is presented by [28, 29] that is the combination of PSNN and RNN. It is used to handle time series problem. The fixed weights found in JPSN are between the recurrent node and 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. Furthermore, another model was considered that is inspired from Genetic Algorithm (GA) and Gradient Descent (GD) learning algorithm called JPSNN [30]. However, when using some large data sets, GA-based models stuck in local trapping and premature convergence. The main focus of this study is to emphasize on the advantages of PSNN, to provide a comprehensive survey about the literature to examine how much work is done for the purpose of better prediction of time series signals, to review the gaps faced by many researchers.

This remaining part of this paper is organized as follows: Section II describes some preliminaries which includes the overview of PSNN and its structure and motivation behind PSNN. Section III summarizes some literature review and reviews on the gaps that are explored during the development of proposed model. Section IV presents the conclusion and future work of this research.

II. PRELIMINARIES

This section explains some basic concepts of pi-sigma neural network and its structure.

A. Pi-Sigma Neural Network (PSNN)

PSNN consist on regular structure which demonstrates fast learning process. It is amenable to achieve the desired level of complexity by using incremental addition of units. The network structure of PSNN includes indirectly the higher order network's capabilities employing product cells as output units and less number of weights [31]. The basic concept of this network is that the polynomial of input n^{th} order variables is represented by product ("pi") of n linear combination ("sigma") of input variables. That's the reason this network is known as pi-sigma instead of sigma-pi [20]. To analyze the effects of network parameters PSNN is used with backpropagation algorithm [19]. After training and testing, the result of PSNN shows lower errors which proves that this network can represent non-linear function very well unlike MLP.

PSNN is the type of HONN and was firstly proposed by Shin and Gosh [31]. The PSNN has capability of fast learning which reduces the network complexity by using efficient polynomials for many input layer variables. The number of summing units found in hidden layer of PSNN which indicates the network order. PSNN is more efficient than MLP because it may avoid the over fitting problems of MLP. The architecture of PSNN is fully connected with two layered (hidden and output layer) feedforward network. In the hidden layer, the sigmoid function is used and linear function is utilized in the output layer. The input layer is connecting with the hidden layer and the output of the hidden layer is feed to the output unit. PSNN contains weights fixed to unity lies between the hidden layer and output layer which reduce the training time [16, 32, 20]. The architecture of PSNN having j^{th} order consisting of two layers; output and hidden unit layers shown in Figure 1.

The architecture of PSNN shows x is N dimensional input vector and x_i is the i^{th} element of x. These weighted inputs are feeding into a layer of j^{th} linear summing units utilizing for the k^{th} output unit y_j.

$$y_j = \sigma\left(\prod_j\left(\sum_k w_{ijk} x_i + \theta_{jk}\right)\right) \tag{1}$$

where σ is the non-linear transfer function and w_{ijk} and θ_{jk} are adjustable co-efficients.

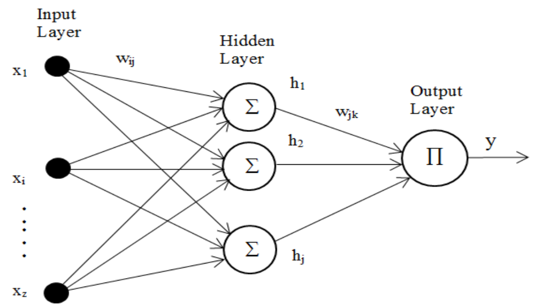

Figure 1: Architecture of j^{th} Order PSNN

B. Why Pi-Sigma?

Recently researchers are focusing to HONN due to fewer units having nonlinear mapping ability. The ability of HONN is to increase the input representation space that is used in many complex data mining problems. It also achieves high learning abilities which require less memory in respect of nodes and weights. HONN are types of feed-forward neural network, multiplicative and summing units are combine in the networks and comparison with conventional ANNs that determines more accurate forecasting [33]. Moreover, the HONN model have ability of functional mapping which determined through some time series problems and it shows the more benefits using HONN models as compare to conventional ANNs [34]. Furthermore, the development of HONN with less complex network architecture is used to enhance the generalization capability. It needs only one layer for the training of weights to achieve the nonlinear separable as compared to the MLP and other feedforward networks [35].

Several researchers work on NN applications in many disciplines had proved their benefits related to classical methods. The different variations of NN like feedforward neural network, backpropagation neural network and MLP has been commonly used networks. Meanwhile, when dealing with complex and nonlinear problems, MLP appears very slow in some situations because of multilayered framework and it requires excessive training time for learning process mentioned in [16]. To resolve complex non-linear mapping problems in MLP the result shows low learning rate because it desires a large number of processing units [15]. Moreover, there are some major gaps for ordinary NN architectures like dense complexity, long training time, efficiency and implementation cost. To overcome such issues, the objective of this research work is using HONNs to reducing the network's complexity with single layer of trainable weights [15, 12]. However, combinations in higher order for input information are used for the development of several kinds of NN, as well as HONN, product unit neural networks and sigma-pi neural networks. The main aim of PSNN is that it has fast learning capability which reduces the overall network complexity and provides more generalize network structure. PSNN is better as compared to MLP because the parameters used in PSNN are fixed to unity from hidden layer to output layer and it protects from over-fitting problems that exist in MLP. Also, PSNN ensures the minimum error in training and testing [32]. Moreover, the PSNN used fewer amount of weights and lesser training time as compared to other neural network models [20]. The PSNN has been strongly preferred to solving several difficult problems including zeroing polynomials [36], classification [37], time series forecasting [29, 38, 39].

III. Literature Review

The Neural network is like a biological neural network and inspired by the NN single brain. That is composed by a huge amount of fully inter-connected processing units (neurons). It is used to solve complex problems efficiently that contains many inputs. NN is a machine that is developed to find the way how the brain plays a specific task [40]. NN is largely parallel distributed processor and having ability for learning (store information and make it for future use). In this section, some important papers of investigators that struggled on different models are go through that can be beneficial for future work.

A. Techniques for Time Series Prediction

To predict the future happenings for financial time series data an application namely Ridge Polynomial Neural Network (RPNN) was presented by [32]. The proposed network is trained with a constructive learning algorithm. RPNN utilized less epochs to learn the data, that is almost 2-60 times faster.

Meanwhile, to overcome the slow learning problems containing in MLP and to provide a network for multi-step ahead for financial time series prediction Ridge Polynomial Neural Network (RPNN) is presented by enhance the order of pi-sigma units. From the benchmark results it is concluded that RPNN provide high profit return with fast convergence on different financial time series signals.

Furthermore, to predict financial time series, two networks are concatenated with each other and proposed a new network model called higher-order polynomial pipelined neural networks [33]. The properties of recurrent pi-sigma network and pi-sigma network is used in this network. In this study, this proposed method is utilized to enhance the prediction level of exchange rate between the US dollar and other currencies. This model provides more accuracy in the forecasting in term of exchange rate time series and improvement in the signal to noise ratio.Meanwhile, for the purpose of better prediction, a new type of recurrent neural network (RNN) called RPSN was presented by [23]. This network has a regular architecture that having link between the units, it forms a directed cycle or looping. It is a development in the network of feedforward pi-sigma. In this paper, this technique has been implemented for physical time series prediction that are the number of sunspots and the mean value of the AE index to check the network performance increases. RPSN exhibit superior performance. Results showed that it requires small training set, shows more fast training and convergence as compared to MLP, SLRNN and the SOSLRNN.

In order to predict non-stationary physical time series a new type of technique namely self-organized multilayer perceptrons network that is motivated by the immune algorithm (SMIA) is proposed [8]. This algorithm is implemented to expand the generalization capability for time series prediction. The datasets that are used in this research are the Lorenz and Solar data.

Another type of HONN is JPSN that combines the characteristics of PSNN and the RNN is dealing with time series problems [28, 29]. The contributions of their research work consist on to overcome the weaknesses of MLP and to observe the next-day temperature prediction. They conducted expansive experiments for training, testing and validation sets. This network results are compared with PSNN and MLP. JPSN need less memory during the network training in terms of Mean Squared Error (MSE), Mean Absolute Error (MAE), Normalized Mean Squared error (NMSE) and Signal to Noise Ratio (SNR). Genetic algorithm (GA) has been joined with JPSNN for enhancing the efficiency of network and the result shows better performance as compared to Pi-Sigma network [30].

PSNN is utilizing for one-step-ahead forecasting presented by [20]. The ANN techniques were implemented with 5-years historical data daily temperature measurement of period 2005-2009 for Batu Pahat, Malaysia. The aim of this research is to analyze the consistency of PSNN on the temperature measures. The network data must be pre-processed before used for training and to remove the non-linearity, they normalized the input and target vectors. Using this system, they certified that PSNN showed small errors in training and testing. PSNN provides more accurate result than MLP in terms of MSE, SNR, MAE, NMSE and CPU time.

PSNN based on Genetic Algorithm (GA) is proposed by [41] which is more effective and efficient forecasting tool used for the prediction of the five real stock market. Gradient Descent (GD) and Genetic Algorithm (GA) are used to train the network. To overcome the problems of GD based back propagation, they engaged the GA with PSNN which is a common global search development. Their observations show that GA based Pi-Sigma network structure presented less prediction error signals as compared to GD based model.

Moreover, Ridge Polynomial Neural Network with Error Feedback (RPNN-EF) is addressed by [26] to improve the forecasting performance for one-step ahead and multi-step ahead forecasting. This network model is a combination of HONN and error feedback recurrent neural network. Their target was to predicting time series such as IBM common stock closing price, heat wave temperature and Mackey–Glass differential equation. When compared with other existing models like RPNN, DRPNN the proposed technique is found to be much faster for one-step ahead forecasting and it shows quite lower prediction error for multi-step forecasting.

Another powerful technique of Higher-order neural network with recurrent feedback connection is used for better prediction. For this purpose, the Ridge Polynomial Neural Network with Error-Output Feedbacks (RPNN-EOF) model was presented [42]. The minimum and maximum normalization method used for data pre-processing for time series forecasting. This model gives better understanding for the Mackey–Glass time series and show less error when compared to other models.

As mentioned above the overview of some researcher's work in-terms of models or techniques, compared techniques, evaluation criteria and datasets used are shown in Table 1.

The overview of the time series prediction model explains the methodology and evaluation criteria for the following time series forecasting techniques. Furthermore, the comprehensive summary of these different techniques that involves results, pros and cons for time series prediction that extract the research gap in the field of time series signal are presented in Table 2.

Table 1
Overview of Time Series Prediction Models

Researchers	Models/ Techniques	Compared Techniques	Evaluation Criteria	Datasets
Ghazali et al. (2006)	RPNN	MLP, FLNN, PSNN	AR, NMSE, SNR	US/EU, UK/EU, JP/EU exchange rate, and the IBM closing price
Ghazali et al. (2008)	RPNN	FLNN, PSNN, MLP	AR, NMSE, SNR	IBM closing price, US/EU, JP/EU, JP/US, JP/UK exchange rate, CBOT-US government bond
Hussain et al. (2008)	PPNN	FLN, MLP	MSE, SNR, MD, AR	EUR/USD, YEN/USD, POUND/USD
Hussain et al. (2008)	RPSN	MLP, SLRNN, SOSLRNN	Results showed an average improvement in terms of SNR, ARV	The mean value of the AE index and the number of sunspots
Mahdi et al. (2010)	SMIA and R-SMIA	MLP, R- MLP, FLNN	NMSE, MSE, SNR, CDC	Lorenz time series signal and Solar signal for 1-step ahead and 5-step ahead
Husaini et al. (2011)	JPSN	PSNN and MLP	Less memory required during the network training in terms of MSE, MAE, NMSE, SNR	5-years daily measurement of temperature
Ghazali et al. (2012)	JPSN	PSNN and MLP	The evaluation is on the base of MAE, NMSE, MSE, and SNR over the temperature data demonstrated	Temperature Dataset
Husaini et al. (2014)	PSNN	MLP	Provide more accurate result in regard of MSE, SNR, MAE, NMSE, CPU time	5-years historical data daily temperature measurement of period 2005-2009 for Batu Pahat, Malaysia
S.C. Nayak et al. (2015)	PSNN based on Genetic Algorithm	MLP	Less complex network, APE	BSE, NASDAQ, TAIEX, FTSE and DJIA closing prices of 2012
Waheeb et al. (2016)	RPNN-EF	RPNN, DRPNN	Performance is evaluated by RMSE, NMSE, MAE, SNR	IBM common stock closing price, daily heat wave temperatures and Mackey–Glass differential delay equation
Waheeb et al. (2016)	RPNN-EOF	RPNN, DRPNN, RPNN-EF	RMSE	Mackey–Glass time series

Table 2
Comprehensive Summary of Time Series Prediction Model

Researchers	Results	Pros	Cons
Ghazali et al. (2006)	Experimental results show that RPNN has strong capabilities to provide better prediction and take less time for training	RPNN provide fast and quick training	Difficult to get the appropriate parameter for adding new pi-sigma unit in the network
Ghazali et al. (2008)	To resolve the slow learning problem of MLP, another type of RPNN is constructed.	RPNN show fast convergence and provide superior performance	For take more advantages of RPNN no recurrent link found
Hussain et al. (2008)	The network provides more accurate forecasting and improvement in the signal to noise ratio	nonstationary signal shows best SNR results	No improvement gets in forecasting
Hussain et al. (2008)	The network has a regular structure, In RPSN connections between the units form a directed cycle or looping, Results showed an average improvement in terms of SNR	Require small training set, achieved fast training and convergence as compared to other feedforward and recurrent neural networks	Problem of selecting the appropriate order of the RPSN
Mahdi et al. (2010)	The prediction of one step and five steps ahead using non-stationary physical time series data is presented	R-SMIA and SMIA networks shows better prediction than the other networks	SMIA model does not proficient on the entire Solar signal.
Husaini et al. (2011)	JPSN as an alternative mechanism to predict the temperature, which required less memory during the network training	Less memory required during the network training	Not guaranteed to improve the prediction of future temperature events for more than one meteorological parameters
Ghazali et al. (2012)	The proposed JPSN has shown to outperform the ordinary PSNN and MLP on the prediction errors and convergence time	The network is capable of representing nonlinear function better than the other models	The fixed weights found in JPSN could decrease the performance of the JPSN with some time series
Husaini et al. (2014)	To overcome the issues of the MLP, PSNN can reduce the training time, PSNN has a high feasibility and provide accurate temperature prediction for one-step-ahead	Provide better prediction as compared to the MLP	No recurrent link to make the network more generalize
Nayak et al. (2015)	The performance of the proposed GA- JPSNN is quite better than all the other models in terms of accuracy	It is observed that proposed method is able to overcome the nonlinearity factor	However, in some large data set cases, GA-based models stuck in local trapping and premature convergence.
Waheeb et al. (2016)	RPNN-EF uses few amounts of weights as compared to other models and it can be efficient way to enhance the performance of forecasting	Enhance forecasting performance	The proposed network setting may not best for all models
Waheeb et al. (2016)	RPNN-EOF uses the properties of error and output feedbacks. It is concluded that this model shows small error for forecasting	Increase the capability of forecasting and provide less error	Due to the complex network structure, it takes long time for training and testing

B. Review on the gaps

The attention of the authors is obtaining by numerous reviews about PSNN, many successes have been attained by researchers and till now there are some gaps that need to be filled. We summarize some of the issues that motivate to further improve PSNN for time series prediction, as follows:

i. The different variations of NN like feedforward neural network, backpropagation neural network and MLP has been commonly used networks. However, there are some major deficiencies for ordinary NN architectures such as dense complexity, more training time, efficiency and implementation cost [30]. Multi-layer Perceptron (MLP) has widely used in many applications like signal processing [43] and pattern recognition [14]. Input structure of MLP is not capable to produce high combination of inputs. However, solving complex nonlinear mapping problems in MLP requires a large number of units due to its multilayered structure, it consequences poor generalization and low learning rate [15].
ii. To overcome such issues of MLP, researchers used HONNs to reducing the network's complexity having single layer of trainable weights [15, 12]. PSNN utilized the properties of HONN that provides the minimum error in training and testing. It also needs the lesser number of weights and can reduce training time [19, 20]. The problem with PSNN is that it has no recurrent link in order to increase the forecasting performance for the network.
iii. JPSN is proposed which is alternative mechanism of PSNN. It uses a network structure like PSNN and additional recurrent connection in its structure having with fixed weights. The limitations in this model are (1) very slow training process due to initializing weights with small values between 0, 1 [28], (2) due to the fixed weights performance of the network could decrease [29].
iv. Higher order Jordan Pi-Sigma Neural Network (JPSNN) is proposed which combined with Genetic Algorithm (GA) [30]. The network is trained using backpropagation Gradient Descent (GD) learning can be better alternative for JPSN. It is observed that proposed model has the ability to modify the nonlinearity factor. However, when using some large data sets, GA based models stuck in local trapping and premature convergence.
v. Considering the deficiency of PSNN, recurrence and error feedback can be added in PSNN in order to get efficient method of prediction for time series. Adding error feedback connection may fill the gap that found in PSNN. Recurrent networks are more suitable as compared to feedforward networks because the dynamics of the time series collected and stored in the memory of recurrent network.

IV. Conclusion and Future Work

This paper evaluated the applicability of HONN for time series prediction. A short discussion of observations produced from this survey in order to examine the issues related with time series prediction. In this review, the reader can observe the characteristics of PSNN. Recently researchers are focusing to HONN due to nonlinear mapping ability. For this purpose, PSNN is recycled that reduces the overall network complexity and provides more generalize network structure. Although many achievements have been attained using PSNN but still there are some issues that need to be solved. Some of the real-world problems like to forecast the future happening values with subsequent time steps, dynamic changes over time and the time series prediction based on past values for the time being requires recurrent network. Recurrent networks are dynamic state having the feedback path which directs the network to enter new state. Network error feedback need to utilize as an input which helps to minimize the network error as compared to network output feedback which enhances the accuracy of forecasting. Looking for the future investigation, we will be delighted to consider the effectiveness of the PSNN model with the combination of recurrence and error feedback connection by testing it on many time series prediction with different lengths to ensure the significant prediction performance. Further, the future works for best settings will be made to enhance the network structure than other higher order networks.

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