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Neural Network Techniques for Time Series Prediction: A Review

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***Abstract*— 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. To solve the time series prediction problem various techniques have been developed over many years to enhance the accuracy of forecasting. This paper presents a review of the prediction of physical time series applications using the neural network models. Neural Networks (NN) have appeared as an effective tool for forecasting of time series. Moreover, to resolve the problems related to time series data, there is a need of network with single layer trainable weights that is Higher Order Neural Network (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. 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 Artificial Neural Networks (ANN). The goal of this research is to present the reader awareness about HONN for physical time series prediction, to highlight some benefits and challenges using HONN.**

***Keywords*— Time series prediction, Neural Network, Forecasting, Higher Order Neural Network, Physical time series.**

I. INTRODUCTION

The data that is collected within a specific time period like daily, hourly, monthly or annually is known as time series data. It appears in many different areas like physical time series, economic time series and marketing and sales time series. From statistical to artificial intelligence, there is a range of neural network techniques which have been used to handle a time series problem [1, 2, 3, 4]. Neural networks (NNs) have appeared as an effective tool for forecasting of time series [5]. 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 [6]. ANNs have the capability to learn [7] and have a non-linear relationship between input and output to approximate any continuous function and it is beneficial for complex data. In the recent development, much progress has been done on the simulations of neural network models [8]. ANNs are also known as neural networks that are motivated from the brain. ANNs are the intelligent based models of the biological neurons [9] and it is also used effectively for time series prediction. From the past decades, significant advancement has been obtained for the brain development [10].

There are many types of neural networks that has been utilized in different fields [11]. Neural networks applied in many applications like regression-based judgmental forecasting, signal and image processing, time series forecasting [12]. 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 [13]. On the other hand, ANN has some drawbacks also like excessive training time, implementation cost, less efficiency and accuracy [14]. There are no well-known methods for designing the best optimal network that depends on data.

To overcome the drawback of NN Higher Order Neural Networks (HONNs) were developed. 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 [15]. 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. There are many different neural network techniques that have been utilized for the prediction of time series.

This paper explains the applications of neural network models for physical time series prediction. The main objectives of this research can be summarized as follows:

1. To review the existing neural network models that explore what and how much work have been done so far in order to get the more accurate prediction of the physical time series.
2. To track the trends of research in this field.
3. To identify the significances of this area.

This remaining part of this paper is organized as follows: Section II describes the overview of neural network techniques for time series forecasting and its motivation behind the use of NN. Section III explains some literature review on the HONN models and its structure. Section IV includes the physical time series and its application for the NN. Section V presents the conclusion and future work of this research.

II. Neural Network Techniques for Time Series Forecasting

A time series is a collection of observations of data items taken sequentially during a specific time period. Time series basically refers to an arrangement of observations over time intervals and measured frequently over successive times [16]. There are some examples of time series like the price of a stock over successive days, sizes of queries to a database system, sizes of video frames and sizes of packets over the network. The time series can be used on the variable that changes over time. To forecast the future activity, the time series utilizes the past information and associated pattern. 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 [17]. The neural network employed in many time series analysis [18, 19]. NN can use a variety of topologies and learning algorithms. The ability of neural network is to nonlinear information processing, function approximation and generalization [17]. Below sub section describes about different types of neural network techniques.

Different Architectures of Neural Networks

It is classified into two different types depends on the NN architecture: Feedforward Neural Networks (FNN) and Recurrent Neural Networks (RNN). Feedforward Neural Networks (FNNs) are mostly used in many time series forecasting applications broadly [20, 21, 23]. 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. Furthermore, FNN was the first and might be the simplest type of ANN [24]. 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 [25] also it can solve nonlinear problems [26, 27]. 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 [28].

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 [29]. 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 widely used for time series prediction [30]. 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 [25, 31]. They can have complicated dynamic and make the network very difficult to train [29].

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 [32]. 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 [33, 34].

III. Higher Order Neural Networks

HONNs are utilized to deal the nonlinear problems that cannot be tackled by any other statistical technique and multilayer perceptron technique [35]. 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 [1]. 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 [36]. 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 [37].

HONN has been appeared as an important tool for prediction of time series and has widely used in many scientific and engineering problems [38]. However, HONN architecture deal with higher-order terms and it requires a huge amount of resources [39]. The following subsection describe the types of HONN.

A. Types of Higher Order Neural Networks

PSNN is the type of HONN and was firstly proposed by Shin and Ghosh [40]. This network is used to predict temperature time series. PSNN is a more better network model than other HONN in approaching computational complexity having highly regular structure. PSNN network has multiplicative neurons in output layer. There are fixed weights in between hidden layer and output layer, this attribute helps to drastically reduce the training time [41]. PSNN model only requires one summing unit to increase the order in order to get the desired level of error. To analyze the effects of network parameters PSNN is used with backpropagation algorithm [42]. The PSNN having j^{th} order consisting of two layers; output and hidden unit layers shown in Fig. 1.

The structure of PSNN shows that 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 kth output unit y_j. 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. It creates the overfitting problem in the structure and needs more training time for learning.

Intended the properties of PSNN another type of HONN was developed called Jordan Pi-Sigma Neural Network (JPSN). The traditional feedforward MLP and the Jordan Recurrent Neural Network is used to addressed for modeling streamflow data from daily time series [43]. The JPSN can be pertained as associative memories, for pattern recovery and pattern completion and also for time-varying behavior due to its properties which can be set to a fixed stable state. Fig. 2 demonstrates the JPSN structure.

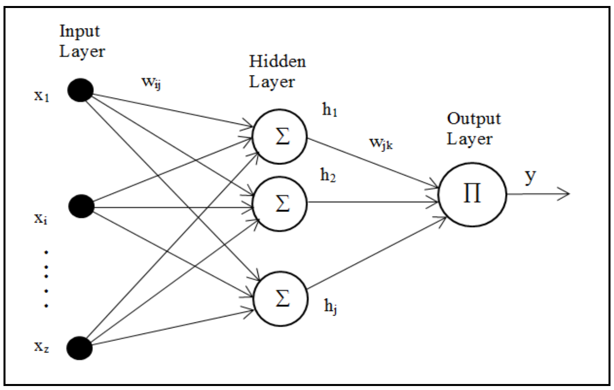

Fig. 1 Architecture of j^{th} order PSNN

JPSN was constructed having an additional link, also there are some specific capabilities in JPSN architecture that do not exist in the ordinary PSNN like reserve the past information for next use and attractor dynamic. Thus, it can be used for the identification of nonlinear dynamic system. For the forecasting of temperature, JPSN used less memory throughout the process of training [44].

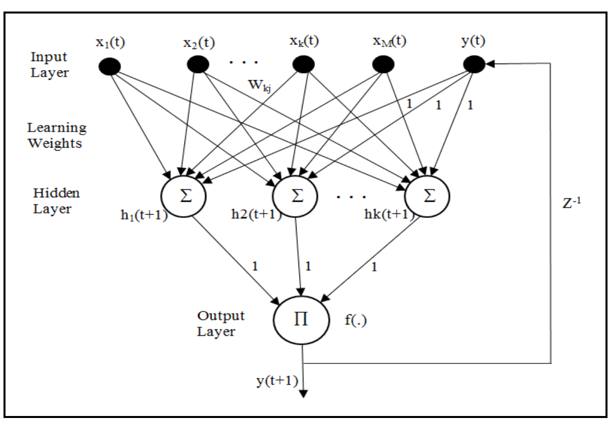

Fig. 2. Jordan Pi-Sigma Neural Network

To overcome the drawbacks of MLP, another network was presented using the PSNN and RNN properties for the prediction of temperature [45]. JPSN initializes weights with small values between [0, 1] which shows very slow training process. The fixed weights found in JPSN, which are between the recurrent node and the hidden nodes, could decrease the performance of the JPSN with some time series. Furthermore, higher order Jordan Pi-Sigma Neural Network (JPSNN) was developed for the purpose of classification [14]. JPSNN is combined with Genetic Algorithm (GA) and trained using back propagation Gradient Descent (GD) learning. GA-JPSNN performs well as compared to the other models for classification and shows higher accuracy [14]. The network output is linked from the input layer through feedback link. Moreover, the Jordan Neural Network (JNN) has been utilized for prediction in model predictive control [46]. Despite that, JPSN model has some drawbacks that slow down the training process and decrease the performance of the network because of the fixed weights.

Moreover, there are many techniques that used recurrent connection in their models. Recurrent networks provide more benefits than feedforward networks for time series prediction because of the behavior of time series in which past input is used for present input. Therefore, Ridge Polynomial Neural Network (RPNN) used recurrent link in its structure. It has three layers input layer, hidden layer and output layer [47]. It consists on different layers of pi-sigma units in hidden layer. RPNN can approximate on any continuous function. The RPNN provides regular and efficient network as compared to ordinary higher order feed forward networks and maintain their fast learning ability. On the other hand, this network has difficulties like it has complex structure that could increase the stability issue. Moreover, to address the stability issue Ridge Polynomial Neural Network with Error Feedback (RPNN-EF) is proposed that utilized the error of the network through computing the desired value from the predicted value. This error is saved in the memory for later use. Hence, the network used that memory to enhance the forecasting results show that this type of network improved the performance of forecasting by using error feedback of the network [48]. Furthermore, another model Pi Sigma Neural Network using Error Feedback (PSNN-EF) that is modified feedback error learning approach using properties of PSNN is proposed to improve the performance and prediction of the time series [49]. Although there are many advantages of recurrent neural networks that lead us to use the properties of recurrent neural networks in the proposed model but still there are some issues like the complexity increase due to the complex architecture and it found difficult to train.

However, HONN reduced the training time by providing the simple structure of NN for all possible higher order multiplicative interactions. These kinds of networks are specially designed to handle the problems that are linearly non-separable by using suitable input representation. Though the HONN have been widely used in the identification of dynamic systems, classifications, pattern recognition, non-linear simulations and other fields, but some improvements on HONN should be done.

IV. Physical Time Series Prediction

There are five data types that are included in physical time series like Oceanography, Hydrology, Astronomy, Earth Sciences and Marine Biology [50,51]. Physical science is the part of natural science that concern with non-living systems that belong to physical time series. Oceanography is the exploration about the biological and physical features of the ocean also it includes the ocean science and its applications. In 1902, the first oceanography international organization was established as an International Council for the Exploration of the Sea (ICES) [52]. Time series of oceanic incident generally consist of periodic components that belong to a huge range of time scales like waves, annual cycles, tides, orbital geometry and tidal currents.

Meanwhile, astronomy is the investigating about the moon, stars, planets, galaxies that are created in the external earth's atmosphere. On the other side, the earth science is recognized as a geoscience that is an acceptable term for the science that is related to the Earth planet. Earth science focused on the study of ocean, atmosphere, biosphere and solid earth. Many researchers have been used various tools to clarify the concepts of earth system that how the system of the earth is working and how it emerges to its current position. This area is also including a look at the effects of earthquake, tsunamis and seismic sources like oceanic, tectonic, explosions and volcanic. From the past decade of the 20th century, the study shows that the cycle of hydrology has significantly changed for the western United States [53]. While hydrology and hydroclimatology is a study about the quality of water and the interaction of the water with other several mediums on the earth. The hydrologic cycle is generally determined as a model that explains the study of storage and circulation of water between hydrosphere, lithosphere, atmosphere and biosphere [50]. However, the hydrology is a geoscience that can predict the circulation and occurrence of the earth's water also it depends upon the basic sciences of physics, mathematics, biology and chemistry. Hence, hydrology science is used for water resource management, hydrologic engineering with economics and its related social sciences [54].

A. Applications on Physical Time Series Prediction with Neural Networks

The data that is collected within a specific time period like daily, hourly, monthly or annually is known as time series data. It appears in many different areas like physical time series, economic time series and marketing and sales time series. Physical time series belongs to physical sciences that include the study of natural science and its phenomena. In the analysis of physical time series, the data contain random noise which generally creates the difficulty for a pattern to identify. Therefore, in order to make the pattern more eminent, there is a way to filter out the noise in physical time series techniques. These patterns described by model-based components like trend component, seasonal component, cyclic component and irregular component [55]. Basically, physical time series is utilized to study the past behavior of the variable, designing the policy decisions and make a plan for the future operations. Also, to estimate or predict the behavior of phenomena in future that is very necessary for the business planning. The application of physical time series also occurs to predict travel time for urban networks [56]. Physical time series are difficult to be determined and predicted among many time series. To resolve the issues related to prediction of physical time series a special kind of spiking neural network called Polychronous Spiking Network was applied to explore the features of the spiking neural network model [57].

TABLE I
THE SUMMARIZATION OF TIME SERIES FORECASTING TECHNIQUES

Researchers	**Techniques**	**Description**	**Drawbacks**
Martens (2011)	RNN	They are capable to store information for a long time in the hidden state.	RNN controllers are extremely difficult to optimize.
Hussain *et al.*, 2008)	RPSN	This network provides promising results and has the ability of faster learning	This model is not appropriate to forecast the nonstationary and highly non-linear signals
Husaini et al. (2011)	JPSN	JPSN is used to predict temperature, which required less memory during the network training. The result is compared with PSNN and MLP.	Not guaranteed to improve the prediction of future temperature events for more than one meteorological parameter.
Ghazali et al. (2012)	JPSN	This 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.
Huang et al., (2014)	Polychronous Spiking Network	Capable to resolve the issues related to prediction of physical time series	Difficult to utilized for every type of time series.
Husaini et al. (2014)	PSNN	PSNN can reduce the training time, it has a high feasibility and provides accurate temperature prediction.	No recurrent link to make the network more generalize.
Nayak *et al.* (2015)	JPSNN	GA-JPSNN performs well as compared to the other models for classification and shows higher accuracy.	Need more stable network for large scale problems.
Wysocki & Ławry. (2015)	JNN	Jordan network has a very simple recurrent architecture and when used for modeling of dynamic processes of higher order it gives some unavoidable inaccuracy, it can be successfully used in predictive control.	The proposed network is a bit complex network
Waheeb et al. (2016)	RPNN-EF	RPNN-EF uses few amounts of weights as compared to other models and it can be efficient way to enhance the performance of forecasting.	The proposed network setting may not best for all models.

Furthermore, Recurrent Pi-Sigma Neural Network (RPSN) was proposed and its application to the prediction of physical time series is mentioned in [58, 59]. 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. Meanwhile, some statistical tools like an artificial neural network that get attention to the researchers to predict the seismic events by neural intelligence approach [60]. The comparative analysis of different forecasting techniques is shown by the Table 1.

Furthermore, for the better and accurate prediction of non-stationary and physical time-series, another approach was applied called Regularization technique in SMIA network [5]. The proposed network provides the promising results for the prediction of nonlinear time series. Besides this, there is a need for some different approaches that would beneficial to find appropriate initial weights for network structure. Moreover, to predict physical time series artificial neural network by combining the wavelet technique is used. In this regard, monthly rainfall time series data set is used to check the performance and it shows that wavelet neural network provides better prediction than ANN [61]. However, to forecast the wind speed another approach Empirical Mode Decomposition (EMD) with Elman Neural Network (ENN) is proposed. The results of EMD-ENN model show lower error as compared to ENN, back-propagation neural network and persistent model [62]. Furthermore, artificial wavelet neural network is used to forecast the wind time series. The proposed method also reduced the computational complexity [63]. Different models are developed for forecasting of wind speed and power generation. The statistical ARIMA model and linear autoregressive (AR) model were selected for wind speed prediction and also ensure the lowest errors [64, 65, 66].

V. Conclusion and Future work

This paper evaluated the applicability of different NN techniques for time series prediction. To examine the issues related with prediction of time series, there are many types of NN that have been discussed in this paper. 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, nowadays, 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. Although many achievements have been attained using HONN but still there are some issues that need to be solved. Furthermore, in future the HONN models can be hybridizing with other models to increase the reliability of forecasting.

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