RECURRENT ERROR-BASED RIDGE POLYNOMIAL NEURAL NETWORKS FOR TIME SERIES FORECASTING

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ABSTRACT

Time series forecasting has attracted much attention due to its impact on many practical applications. Neural networks (NNs) have been attracting widespread interest as a promising tool for time series forecasting. The majority of NNs employ only autoregressive (AR) inputs (i.e., lagged time series values) when forecasting time series. Moving-average (MA) inputs (i.e., errors) however have not adequately considered. The use of MA inputs, which can be done by feeding back forecasting errors as extra network inputs, alongside AR inputs help to produce more accurate forecasts. Among numerous existing NNs architectures, higher order neural networks (HONNs), which have a single layer of learnable weights, were considered in this research work as they have demonstrated an ability to deal with time series forecasting and have an simple architecture. Based on two HONNs models, namely the feedforward ridge polynomial neural network (RPNN) and the recurrent dynamic ridge polynomial neural network (DRPNN), two recurrent error-based models were proposed. These models were called the ridge polynomial neural network with error feedback (RPNN-EF) and the ridge polynomial neural network with error-output feedbacks (RPNN-EOF). Extensive simulations covering ten time series were performed. Besides RPNN and DRPNN, a pi-sigma neural network and a Jordan pi-sigma neural network were used for comparison. Simulation results showed that introducing error feedback to the models lead to significant forecasting performance improvements. Furthermore, it was found that the proposed models outperformed many state-of-the-art models. It was concluded that the proposed models have the capability to efficiently forecast time series and that practitioners could benefit from using these forecasting models.

ABSTRAK

Peramalan siri masa mendapat banyak perhatian kerana kesannya terhadap banyak aplikasi praktikal. Rangkaian saraf (NNs) telah menarik minat yang meluas untuk menjadi alat yang baik bagi peramalan siri masa. Kebanyakan NNs hanya menggunakan input *autoregressive* (AR) (iaitu ketinggalan dari siri masa) apabila meramalkan siri masa. Input purata bergerak (MA) (iaitu sisihan) bagaimanapun tidak dipertimbangkan dengan secukupnya. Selain daripada input AR, jika MA digunakan sebagai input tambahan dengan memasukkan semula sisihan ramalan kepada rangkaian, ramalan yang lebih tepat boleh diperolehi. Antara banyak seni bina NN yang sedia ada, rangkaian saraf jujukan tinggi (HONN) yang mempunyai satu lapisan pemberat boleh dilatih dipertimbangkan dalam penyelidikan ini. Ini adalah kerana HONN menunjukkan keupayaan yang cekap untuk menangani ramalan siri masa selain daripada seni bina mudah mereka. Berdasarkan dua model HONN iaitu rangkaian saraf polinomial rabung *feedforward* (RPNN) dan rangkaian saraf polinomial rabung dinamik berulang (DRPNN), dua model berasaskan ralat berulang dicadangkan. Model-model ini dinamakan rangkaian saraf polinomial rabung dengan maklum balas ralat (RPNN-EF) dan rangkaian saraf polinomial rabung dengan maklum balas output ralat (RPNN-EOF). Simulasi meluas yang meliputi sepuluh siri masa telah dilakukan. Selain RPNN dan DRPNN, rangkaian saraf *pi-sigma* dan rangkaian saraf *pi-sigma* Jordan digunakan dalam perbandingan. Hasil simulasi menunjukkan bahawa memperkenalkan maklum balas ralat kepada model membawa kepada prestasi ramalan yang sangat baik. Selain itu, didapati bahawa hasil yang diperoleh dari model yang dicadangkan mengatasi banyak model *state-of-the-art*. Disimpulkan bahawa model yang dicadangkan mempunyai keupayaan untuk meramalkan siri masa dengan cekap, dan pengamal dapat memanfaatkan penggunaan alat peramalan ini.

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LIST OF SYMBOLS AND ABBREVIATIONS

ACI	-	ACI worldwide incorporated stock exchange time series
ANFIS	-	Adaptive Neuro Fuzzy Inference Systems
AR	-	AutoRegressive
ARIMA	-	AutoRegressive Integrated Moving-Average
ARMA	-	AutoRegressive Moving-Average
CPU	-	Central Processing Unit
DRPNN	-	Dynamic Ridge Polynomial Neural Network
$DRPNN_{Feedback}$	-	Dynamic Ridge Polynomial Neural Network with Feedback network stability theorem
$DRPNN_{Lyapunov}$	-	Dynamic Ridge Polynomial Neural Network with Lyapunov function
ENSO	-	El Niño-Southern Oscillation time series
EUR/USD	-	Euro / U.S. Dollar exchange rate time series
FLNN	-	Functional Link Neural Network
HONN	-	Higher Order Neural Network
JPY/USD	-	JaPanese Yen / U.S. Dollar exchange rate time series
LASER	-	Santa Fe LASER-generated data time series
MA	-	Moving-Average
MAE	-	Mean Absolute Error
MG	-	Mackey-Glass differential delay equation time series
MLP	-	Multilayer Perceptron
MSE	-	Mean Squared Error
NAR	-	Nonlinear AutoRegressive

NARMA	-	Nonlinear AutoRegressive Moving-Average
NDEI	-	Non-Dimensional Error Index
NMSE	-	Normalized Mean Squared Error
NN	-	Neural Network
PID	-	Proportional-Integral-Derivative
POLAND	-	POLAND electricity load time series
PSNN	-	Pi-Sigma Neural Network
RBF	-	Radial Basis Function
RMSE	-	Root Mean Squared Error
RNN	-	Recurrent Neural Network
RPNN	-	Ridge Polynomial Neural Network
RPNN-EF	-	Ridge Polynomial Neural Network with Error Feedback
RPNN-EOF	-	Ridge Polynomial Neural Network with Error-Output Feedbacks
RQ	-	Research Question
SLP	-	Darwin Sea Level Pressure time series
SLR	-	Systematic Literature Review
STAR	-	STAR brightness time series
SUNSPOT	-	SUNSPOT numbers time series
SVM	-	Support Vector Machines

LIST OF APPENDICES

LIST OF PUBLICATIONS AND AWARDS

Publications:

[1] Waheeb, W., & Ghazali, R. (Under review since October 2018). A Novel Error-Output Recurrent Neural Network Model for Time Series Forecasting. *Neural Computing and Applications*. (SCOPUS & ISI indexing, **impact Factor = 4.213**)

[2] Waheeb, W., & Ghazali, R. (Accepted with revision required). A New Genetically Optimized Tensor Product Functional Link Neural Network: An Application to the Daily Exchange Rate Forecasting. *Evolutionary Intelligence*. (SCOPUS & ISI indexing)

[3] Waheeb, W., & Ghazali, R. (Accepted). Forecasting the Behavior of Gas Furnace Multivariate Time Series Using Ridge Polynomial Based Neural Network Models. *International Journal of Interactive Multimedia and Artificial Intelligence*. (ISI indexing)

[4] Waheeb, W., Ghazali, R., & Shah, H. (In press). Nonlinear Autoregressive Moving-average (NARMA) Time Series Forecasting Using Neural Networks. In *the 2019 International Conference on Computer and Information Sciences (ICCIS)*. IEEE. (SCOPUS indexing)

[5] Waheeb, W., Ghazali, R., Ismail, L. H., & Kadir, A. A. (2018). Modelling and Forecasting Indoor Illumination Time Series Data from Light Pipe System. In *International Conference of Reliable Information and Communication Technology* (pp. 57-64). Springer, Cham. (SCOPUS & ISI indexing)

[6] Waheeb, W., Ghazali, R., & Hussain, A. J. (2018). Dynamic Ridge Polynomial Neural Network with Lyapunov Function for Time Series Forecasting. *Applied Intelligence*, Vol. 48, Issue 7, pp. 1721-1738. (SCOPUS & ISI indexing, **impact Factor = 1.904**)

[7] Waheeb, W., Ghazali, R., & Herawan T. (2016). Time Series Forecasting Using Ridge Polynomial Neural Network with Error Feedback. In *the Second International Conference on Soft Computing and Data Mining* (pp. 189-200). Springer, Cham. (SCOPUS & ISI indexing)

[8] Waheeb, W., Ghazali, R., & Herawan T. (2016). Ridge Polynomial Neural Network with Error Feedback for Time Series Forecasting. *PLoS one*, 11(12), e0167248. (SCOPUS & ISI indexing, **impact Factor = 3.057**)

[9] Waheeb, W., & Ghazali, R. (2016). Chaotic Time Series Forecasting Using Higher Order Neural Networks. *International Journal on Advanced Science, Engineering and Information Technology*, Vol. 6, Issue 5, pp. 624-629. (SCOPUS indexing)

[10] Waheeb, W., & Ghazali, R. (2016). Multi-step Time Series Forecasting Using Ridge Polynomial Neural Network with Error-Output Feedbacks. In *the International Conference on Soft Computing in Data Science* (pp. 48-58). Springer, Cham. (SCOPUS indexing)

Awards:

[1] Best paper award in the International Conference of Reliable Information and Communication Technology, 23-24 July 2018, Kuala Lumpur, Malaysia.

[2] Best paper award in the International Conference on Soft Computing in Data Science, 21-22 September 2016, Kuala Lumpur, Malaysia.

Data Science World Competition:

Competition Name: M4 Forecasting Competition.

Organized by: Institute For the Future at the University of Nicosia, with the support of the Forecasting & Strategy Unit at the National Technical University of Athens.

Competition Task: Forecast the future values for 100,000 time series.

Competition Result: Listed among the 17 most accurate methods. Ranked 15 among 50 submissions around the world.

CHAPTER 1

INTRODUCTION

1.1 Research Background

Time series are a set of observations that are recorded sequentially over time (Diebold, 2006; Box *et al.*, 2015; Brockwell & Davis, 2016; Hyndman & Athanasopoulos, 2018). Time series are found in many disciplines such as hourly air temperature, daily foreign exchange rate, and weekly interest rates. Most time series signals are difficult to forecast because they consist of non-linear, complex, and chaotic patterns (Samsudin, Saad & Shabri, 2011). Furthermore, some time series are found difficult to analyse and forecast as they are affected by many unpredictable factors (political, economic, and psychological) that interact with each other in a very complex fashion (Elattar, Goulermas & Wu, 2012). Despite the fact that it is difficult in practical applications, forecasting time series data is still an issue of much interest in a wide range of applications. For example, forecasting water-related disasters to save lives and reduce property and infrastructure damage (Badrzadeh, Sarukkalige & Jayawardena, 2015), financial forecasting to maximize profits (Ghazali, Hussain & Liatsis, 2011), and forecasting power demand for effective power system control and economically efficient operations (Zjavka, 2015).

Various time series forecasting models have been developed. Conventional statistical models have been used to model time series and to forecast future values (Rout *et al.*, 2014; Cadenas *et al.*, 2016; Benmouiza & Cheknane, 2016). However, they do not show fully satisfactory performance as they are linear-based models. Therefore, they assume linear relationships between past time series values, making them unable to capture the non-linear relationships that found in most real time series data (Kayacan, Ulutas & Kaynak, 2010; Wong, Xia & Chu, 2010; Xia & Wong, 2014).

Contrary, non-linear models such as support vector machines (SVM), adaptive neuro fuzzy inference systems (ANFIS), and neural networks (NNs) have been shown better performance than linear models (Ömer Faruk, 2010; das Chagas Moura *et al.*, 2011; Osório, Matias & Catalão, 2015; Ansari *et al.*, 2018; Jiang *et al.*, 2018).

A search conducted using the Scopus database for "neural network" and "forecast" in September 2018 yielded 10,850 results, which means NNs have attracted widespread interest among researchers for forecasting problems. NN is inspired by biological nervous systems. During the training step, NN can learn from historical data (e.g. current and past observations) to build a model that has the ability to forecast future observations. Using NNs, machines can learn complex relationships between input and output variables without the need for a human to specify the nature of the relationship (Reid, Hussain & Tawfik, 2013).

Numerous applications have used different types of NNs to model time series. NNs are employed due to their ability to handle non-linear functional dependencies and because they are data-driven models with few prior assumptions about underlying models (Panda & Narasimhan, 2007; Wong *et al.*, 2010; Zhang, 2012). Furthermore, NNs are universal function approximators that can approximate any continuous function with an arbitrary degree of accuracy (Panda & Narasimhan, 2007; Wong *et al.*, 2010; Zhang, 2012).

Higher order neural networks (HONNs) are a type of NNs used for time series forecasting that have been shown better forecasting performance than the most popular Multilayer Perceptron (MLP) networks (Ghazali *et al.*, 2009; Husaini *et al.*, 2011; Sermpinis *et al.*, 2012a; Sermpinis *et al.*, 2012b; Sermpinis, Stasinakis & Dunis, 2014; Al-Jumeily, Ghazali & Hussain, 2014; Husaini *et al.*, 2014a; Sermpinis, Laws & Dunis, 2015). HONNs utilize high order terms (i.e., multiplicative neurons) besides summing neurons. HONNs are simple in their architecture and need fewer trainable parameters to deliver input-output mappings compared to multilayered NNs. Some examples of HONNs are the functional link neural network (FLNN) (Giles & Maxwell, 1987), the pi-sigma neural network (PSNN) (Ghosh & Shin, 1992), the ridge polynomial neural network (RPNN) (Shin & Ghosh, 1995), and the dynamic ridge polynomial neural network (DRPNN) (Ghazali *et al.*, 2009).

Generally, NNs have been used extensively with only Autoregressive (AR) inputs (i.e., lagged time series values) when modelling and forecasting time series. Moving-average (MA) inputs (i.e., past errors) bave not been taken into consideration, unlike the extensive uses of AR inputs. Feeding back a forecasting error to the input layer of the network is considered an MA input, and it is an alternative to the AR modelling (Connor *et al.*, 1994; Burgess & Refenes, 1999; Egrioglu *et al.*, 2015). Based on the systematic literature review (SLR) conducted in this research work, If MA and AR inputs are used with NNs, more accurate forecasts are obtained. Hence this research proposes the use of recurrent error-based NNs for time series forecasting to increase forecasting accuracy.

1.2 Problem Statements

An MLP network can approximate reasonable functions to any desired degree of accuracy (Cybenko, 1989). However, the number of hidden layers and neurons must be sufficient to deal with the given problem. The number of hidden neurons in the hidden layer directly affects MLP performance. An MLP that is of insufficient size usually fails to approximate the underlying function (Ghazali *et al.*, 2008). Furthermore, an MLP with of more than sufficient size tends to memorize the training data, which results in poor generalization and a low learning rate. Therefore, the determination of the number of hidden neurons is not an easy task (Dehuri & Cho, 2010; Egrioglu *et al.*, 2015). In addition, since the MLP is multilayered, and it uses the backpropagation algorithm (Werbos, 1974; Rumelhart, Hinton & Williams, 1986), which involves high computational complexity, the MLP needs excessive learning time.

An easy way to avoid the aforementioned problems in the multilayered NNs is the replacement of hidden layers with higher order neurons in the input layer (Giles & Maxwell, 1987; Pao, 1989; Dehuri & Cho, 2010). Therefore, HONNs are constructed by taking advantage of higher order correlations among inputs to perform non-linear mappings using only one layer of neurons (Giles & Maxwell, 1987; Dehuri & Cho, 2010).

FLNN is a type of HONN that passes input patterns through a functional expansion unit to produce supplementary inputs to its structure. However, it from the combinatorial explosion in the number of free parameters when its order becomes excessively high from the use of multivariate polynomials (Ghazali *et al.*, 2011). A simple yet efficient HONNs is PSNN (Ghosh & Shin, 1992). PSNN was introduced to deal with the weight explosion problem found in FLNN. However, PSNN is not a universal approximator (Shin & Ghosh, 1995). Moreover, PSNNs order can be determined by trial and error.

A generalization of PSNN is RPNN, which is a universal approximator network (Shin & Ghosh, 1995). RPNN are an NN model that address the problems found in MLP, FLNN, and PSNN. RPNN uses constructive learning to automatically determine the number of hidden neurons. Therefore, RPNN neither needs to determine network order as in the PSNN nor the number of hidden neurons as in the MLP (Ghazali *et al.*, 2011). In addition, RPNN is a universal approximator that utilizes univariate polynomials, which are easy, avoiding an explosion in the number of trainable parameters as the number of inputs increases (Shin & Ghosh, 1995; Ghazali *et al.*, 2011). Furthermore, it was found that RPNN produces more accurate forecasts than MLP, FLNN, and PSNN (Ghazali *et al.*, 2009; Ghazali *et al.*, 2011; Al-Jumeily *et al.*, 2014).

All the aforementioned NNs are classified as feedforward NNs. But, to enable an NN to learn a representation of time in data, a recurrent neural network (RNN) is needed. In the RNN, the network activations produced by past inputs are fed back to affect the processing of future inputs (Thiery *et al.*, 2008). In general, RNNs have a memory of the past inputs because of recurrent connections. This allows them to have knowledge of past behaviour and learn the temporal dependences found in time series data over time. Further, they can respond to the same input pattern differently at different times, depending on previous input patterns (Ho, Xie & Goh, 2002). This makes RNNs more suitable for time series forecasting than feedforward NNs (Connor, Martin & Atlas, 1994; Ghazali *et al.*, 2011; Brezak *et al.*, 2012; Al-Jumeily *et al.*, 2014). For this reason, the dynamic ridge polynomial neural network (DRPNN), which is a recurrent version of RPNN proposed by Ghazali *et al.* (2009) showed better forecasting performance than RPNN and other NNs (Ghazali *et al.*, 2009; Ghazali *et al.*, 2011; Al-Jumeily *et al.*, 2014).

Despite the potential and capability of the DRPNN which comprises the feedback connection, it is subjected to the complexity and difficulty of training which summarized in two main points as reported in (Ghazali *et al.*, 2011). First, calculating gradients and updating DRPNN weights are difficult because the dynamic system variable (*"a set of quantities that summarizes all the information about the past behaviour of the system that is needed to uniquely describe its future behaviour* (Haykin, 2009)") affects both the gradient and the output. Second, learning errors may not be monotonically decreased leading to a long convergence time.

To tackle these problems, Ghazali *et al.* (2011) proposed a sufficient condition for DRPNN convergence based on the feedback network stability theorem proposed by Atiya (1988). The aim of this theorem is to adjust network weights to generate network outputs as close as possible to the desired output (Ghazali *et al.*, 2011). This theorem was used with recurrent networks for problems such as pattern recognition and time series forecasting. However, this solution is restrictive where a large network is necessary (Atiya, 1988) or when working with constructive learning because it stops learning with a few hidden neurons. Furthermore, when working with time series forecasting, only learning trajectories are considered, not learning fixed points (Atiya & Parlos, 2000). Therefore, another solution is needed to solve network size restrictions

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