Journal of Informatics and Mathematical Sciences
Vol. 8, No. 4, pp. 245–251, 2016
ISSN 0975-5748 (online); 0974-875X (print)
Published by RGN Publications

http://www.rgnpublications.com

Special Issue
CRIMSTIC 2016
Current Research in Information Technology, Mathematical Sciences, Science and Technology International Conference 2016
April 13-14, 2016, Melaka, Malaysia

Hybrid Neural Network Model for Metocean Data Analysis

Research Article

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Abstract. Metocean time-series data is generally classified as highly chaotic thus making the analysis process tedious. The main aim of forecasting Metocean data is to obtain an effective solution for offshore engineering projects, such analysis of environmental conditions is vital to the choices made during planning and operational stage which must be efficient and robust. This paper presents an empirical analysis of Metocean time-series using a hybrid neural network model by performing multi-step-ahead forecasts. The proposed hybrid model is trained using a gauss approximated Bayesian regulation algorithm. Performance analysis based on error metrics shows that proposed hybrid model provides better multi-step-ahead forecasts as in comparison to previously used models.

Keywords. Chaotic time-series; Hybrid model; Metocean data

MSC. 62-XX

Received: April 4, 2016 **Accepted:** August 16, 2016

1. Introduction

Meteorological data (wind, pressure, temperature, etc.) and oceanographic data (waves, current, etc.) are often combined together in the term metocean data [7]. Metocean data is obtained through the use of satellites and offshore remote sensors at a particular area of interest, these obtained data is crucial in planning and designing of offshore tower routes and other mega oil drilling installations and structures which are pivotal in the oil and gas industry. Hence, in all stages of any offshore engineering project these study must be performed. Such analysis of environmental conditions which is directly proportional to the choices made during the planning and operational stage which must be efficient and robust [7].

Most of the successful literatures on weather time-series forecasting used neural networks to perform chaotic forecasting [1–3]. Their analyses are solely based on using computational intelligence techniques to perform the forecasts, leaving out the important factor of performing a realiable filtration process [2]. Results have shown that recurrent networks are the most suitable in forecasting [5, 11], but the big question is how to enhance the models performance by providing robust forecasts while addressing the issue of chaos and without jeopardizing model complexity.

The layout of this paper is as follows: a synopsis of related works in the field of time series forecasting is outlined in section 2. In section 3, the proposed hybrid network model is elaborated and an empirical setup and analysis are discussed and analysed in section 4. Lastly, conclusion and future recommendations are detailed in section 5.

2. Related Works

In the domain of forecasting and modelling of time-series, a substantial number of research has been done to analyse and understand the nature of time-series. As a result, a number of models have been developed to solve time-series problems including statistical and non-statistical methods [3, 4, 6, 8–10].

Statistical methods [6, 10] have been successfully employed in time-series forecasting for more than half a century. However, their forecasting abilities are constrained by their assumption of linear behaviour. Thus, the result obtained is unsatisfactory because most of the weather time-series problems are non-linear and complex, in nature [8, 9].

The modeling process of chaotic time-series is pivital to the characteristics of data, hence due to its complex nature the modelling process is not trivial; in such circumstances non-linear forecasting techniques come in handy to enhance forecasting accuracy [3, 9]. Researchers have been provided with a variety of paradigms in artificial intelligence in the form of architectural designs in neural network that can be used to enhance the performance of generating forecasts using chaotic data. Such paradigms include recurrent neural network (RNN) that has been effectively tested on numerous forecasting tasks. However, these types of models are used to generate one-step-ahead forecasts and perform poorly in multi-step-ahead forecasting [3, 4]; hence our work strives to reduce this problem.

3. Hybrid Neural Network Model

In the proposed hybrid model, scaled unscented kalman filter is used to filter and reduce noise in the applied metocean time-series. In the hybrid model, a set of selected points referred to as sigma points represents the state distribution of the data applied for filtering. The difference between UKF and the Scaled UKF is the application of a scaling parameter that controls the distribution of sigma points prior to transformation [2].

The selected sigma points are transformed using a non-linear function $y^{(i)} = g(x^{(i)})$. Posterior distribution of the states are obtained through the following:

For $k = 1, 2, \ldots, \infty$:

(a) *Determine optimal number of scaled sigma points based on the present state covariance*: γ is a scaling parameter given by,

$$y = \sqrt{N + \lambda}, \tag{3.1}$$

$$\lambda = \alpha^2(N + \kappa) - N, \tag{3.2}$$

where α and κ are tuning parameters. The parameter λ, controls the size of the sigma point distribution.

(b) *Time-update equations*: Using the state-update function, apriori state estimate and apriori covariance transform sigma points using:

$$X^x_{i,k/k-1} = f(X^x_{i,k-1}, X^v_{i,k-1}, u_{k-1}). \tag{3.3}$$

(c) *Measurement-update equations*: The generated sigma points are used in transformation through the measurement-update function,

$$Y_{i,k/k-1} = h(X^x_{i,k/k-1}, X^n_{k-1}, u_k). \tag{3.4}$$

The Kalman gain is given by:

$$K_k = P_{x_k y_k} P^{-1}_{\tilde{y}_k}, \tag{3.5}$$

and the scaled Kalman filter estimate and its covariance are generated by:

$$\widehat{x}_k = \widehat{x}_k^- + K_k(y_k - \widehat{y}_k^-), \tag{3.6}$$

$$P_{x_k} = P^-_{x_k} - K_k P_{\tilde{y}_k} K_k^T. \tag{3.7}$$

Filtered chaotic metocean data is then fed into the autoregressive recurrent network. The training process is done in open loop mode and during the testing phase there is no updating of network inputs within the model:

$$\begin{aligned}\widehat{y}(n+1) &= \widehat{f}[y_p(n); u(n)] \\ &= \widehat{f}[\widehat{y}(n), \ldots, \widehat{y}(n - d_y + 1); u(n), u(n-1), \ldots, u(n - d_u + 1)].\end{aligned} \tag{3.8}$$

4. Results and Discussions

4.1 Data

Metocean data consisiting of wind direction, wind speed, total wave energy, peak period, direction, swell energy and sigificant height wave, which are obtained from Petronas Sdn. Bhd are forecasted using the hyrid model. Selected data ranges are from 01/07/1956 to 09/01/1958 (13369 points) of which 9358 and 4010 points were used for training and model testing respectively.

4.2 Multi-step-ahead forecast analysis

The aim of this experimental setup is to perform and evaluate the performance of forecasting chaotic metocean data using a hybrid neural network model. These is achieved by performing an empirical analysis of forecasts generated through short forecasts and increasing the forecasting horizon by generating multi-steps forecasts, and comparative model analysis with existing forecasting models.

Table 1. Selection of appropriate scaling parameters for filtering metocean data

Scaling parameter	Error - NMSE	Scaling parameter	Error - NMSE
$\kappa = 0$	3.6531e-00	$\kappa = 5$	1.5514e-02
$\kappa = 1$	5.0175e-01	$\kappa = 8$	1.1746e-02
$\kappa = 2$	4.1183e-01	$\kappa = 9$	1.6422e-02
$\kappa = 4$	2.1107e-01	$\kappa = 12$	1.7116e-01

To optimize the chaotic time-series input selection, metocean data is first filtered to reduce levels of noise that will have an overall effect on the performance of generating forecasts. As for the selection of appropriate scaling parameter (κ), an empirical analysis is performed by first adjusting the appropriate points in the scale of 0-12, based on the least error obtained through the NMSE value between filtered outputs and original data through the following equation:

$$\mathrm{NMSE} = \frac{\sum_{k=1}^{n}(|m_k - h_k|^2)}{\sum_{k=1}^{n}(|m_k - \bar{h}|^2)}, \tag{4.1}$$

where m_k denotes the unfiltered metocean data, h_k represents the filtered metocean output and $\bar{h}$ is the average of unfiltered inputs. Analysis in selection of best scaling parameter applied to filter metocean data as shown in Table 1. The proposed network structure consists of 10 neurons and a delay of 3 in the hidden and input layers respectively, the network structure is used to generate forecasts as shown in Figure 1. The difference between generating one step forecasts and multi-steps is the performance and updating process of the network loop, for one step forecasts the inputs are updated unlike multi steps forecasts hence the accumulation of errors as forecast period increases.

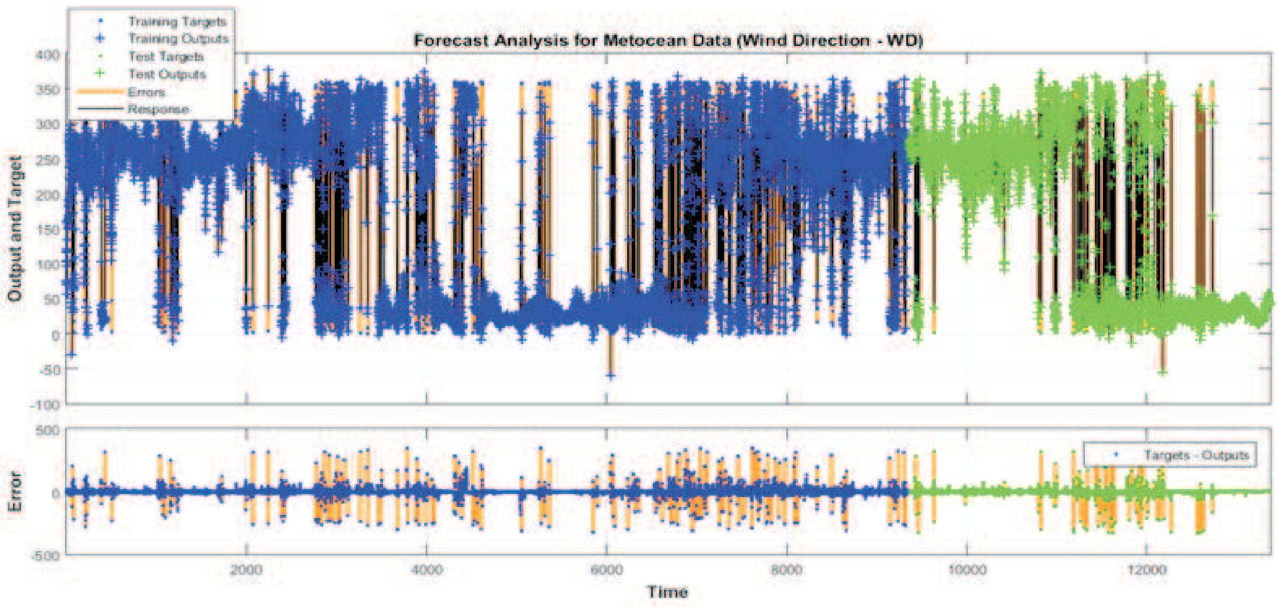

Figure 1. Forecast analysis of metocean data-wind direction

For comparative purposes, Radial basis function and the Elman-NARX networks are selected and the forecast error metrics signifies the dominance of the proposed hybrid model based on forecast analysis between 1 hour and 14 days ahead as shown in Tables 2 and 3. The recurrent network structure for the Elman-NARX hybrid model was set up using the same number of delays as in the applied hybrid network model and trained using modified bayesian regulation algorithm with a learning rate of 0.001.

Table 2. Comparative model performance using NMSE within the range of 1-24 hours

Forecasting Model	1 Hour-ahead	12 Hours-ahead	24 Hours-ahead
Feed-Forward Network	0.8457	1.5861	2.4215
Elman-NARX Network	2.54e-01	0.7854	1.8211
Proposed Network	3.31e-02	5.13e-02	0.1951

Table 3. Comparative model performance using NMSE within the range of 2-14 days

Forecasting Model	2 Days-ahead	7 Days-ahead	14 Days-ahead
Feed-Forward Network	3.3314	7.0142	9.1578
Elman-NARX Network	2.1632	5.0246	7.1578
Proposed Network	0.4331	2.3779	4.2639

5. Conclusion

In this study, the applicability of forecasting metocen data (weather time-series) using a hybrid recurrent model is tested by analysing the performance of generating one-step-ahead and multi-steps-ahead forecasts. Metocean data being a weather time-series is classified as highly chaotic based on the trend and seasonality of the data as shown in experimental setup section, hence the need of accurate and robust forecasts.

Based on quantitative errors obtained through comparative performance, the hybrid neural network model outperformed feed-forward network and the Elman-NARX hybrid network in multi-step-ahead forecasts upto the range of 14 days which is equivalent to 336 time steps. It can be concluded that the proposed hybrid network model has succesfully been applied in testing of time-series and further validated by the forecasting error metrics obtained.

Acknowledgment

This work was supported by YUTP grant (0153AA-A98), funded by Universiti Teknologi Petronas (UTP).

Competing Interests

The authors declare that they have no competing interests.

Authors' Contributions

All the authors contributed significantly in writing this article. The authors read and approved the final manuscript.

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