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A comparative study of neural network and Box-Jenkins ARIMA modeling in time series prediction

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Abstract

This paper aims to investigate suitable time series models for repairable system failure analysis. A comparative study of the Box-Jenkins autoregressive integrated moving average (ARIMA) models and the artificial neural network models in predicting failures are carried out. The neural network architectures evaluated are the multi-layer feed-forward network and the recurrent network. Simulation results on a set of compressor failures showed that in modeling the stochastic nature of reliability data, both the ARIMA and the recurrent neural network (RNN) models outperform the feed-forward model; in terms of lower predictive errors and higher percentage of correct reversal detection. However, both models perform better with short term forecasting. The effect of varying the damped feedback weights in the recurrent net is also investigated and it was found that RNN at the optimal weighting factor gives satisfactory performances compared to the ARIMA model. © 2002 Published by Elsevier Science Ltd.

Keywords: Box-Jenkins autoregressive integrated moving average model; Multi-layer feed-forward neural network; Recurrent neural network

1. Introduction

The objective of time series prediction can be stated succinctly as follows: given a finite sequence X_1, $X_2, X_3, \ldots, X_t$, find the continuation $X_{t+1}, X_{t+2}, \ldots$. For example, in repairable system failure analysis, $\{X_t\}$ can be viewed as the stochastic inter-failure time or the number of failures per time interval. The ability to predict the time, or at least the range within a specific confidence interval, of the next impending failure is important as it provides a better base from which effective planning on maintenance, decision making on spares provisioning and replacement policies can be carried out.

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The highly popularized Box-Jenkins autoregressive integrated moving average (ARIMA) model has been successfully applied in not only economic time series forecasting, but also as a promising tool for modeling the empirical dependencies between successive times between failures (Walls & Bendell, 1987). It also results in satisfactory predictive performances (Ho & Xie, 1998]. Similarly, the emergence of various neural network topologies and efficient learning algorithms have also led to a wide range of successful applications in pattern recognition (Hwarng, 1997) and forecasting; notably in financial markets time series (Azoff, 1994). However, the use of neural networks for reliability analysis is not widespread. Liu, Sastri, and Kuo (1995) demonstrated that feed-forward networks showed promising results in identifying the underlying failure distribution and estimating its parameters. This work had further motivated us to explore the feasibility of neural networks for predicting failures in repairable systems.

Conceptually, both approaches are nonparametric techniques and are very similar in that they attempt to discover the appropriate internal representation of the time series data. Few assumptions are needed and no a priori postulation of models is required. Furthermore, by iteratively adjusting the weights in the modeling process, the autocorrelation between the data can be explored and better estimates can be obtained. This paper explores the potential application of ARIMA model and neural networks to reliability data in repairable systems. An overview of the essential features and some technical characteristics of the proposed methodologies are first discussed. This is followed by a case study on the compressor failures of a process plant and finally, the predictive performances of the proposed models are summarized.

2. Box-Jenkins ARIMA models vs artificial neural networks

For more than half a century, the Box-Jenkins ARIMA linear models have dominated many areas of time series forecasting. In general, a nonseasonal time series can be modeled as a combination of past values and past errors, denoted as ARIMA (p, d, q) or expressed as

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q}$$

where $\{\phi_t\}$ and $\{\theta_t\}$ are the coefficients, p and q are the orders of autoregressive and moving average polynomials, respectively. The basis of this approach consists of three phases: model identification, parameter estimation and diagnostic testing. Similarly, a seasonal model can be represented as ARIMA (p, d, q)(P, D, Q).

Neural networks are essentially a nonlinear modeling approach that provides a fairly accurate universal approximation to any functions. Its applications for model fitting are closely associated with statistical techniques (White, 1989). Besides, it is a very versatile technique due to its learning, generalization and prediction capabilities. For time series forecasting tasks, the prediction model has the general form

$$X_t = f(X_{t-1}, X_{t-2}, \ldots, X_{t-p}) + e_t$$

Appropriate neural network architectures can be trained to predict the future values of the dependent variables. If the network paradigm and parameters are appropriately designed, these can result in satisfactory forecasting performance (Kohzadi, Boyd, Kermanshahi, & Kaastra, 1996). One of the best known neural models is the multi-layer feed-forward neural network (MFNN) consisting of an input layer, one or several hidden layers and an output layer. On the other hand, the partially recurrent neural network (RNN) can learn sequences as time evolves and responds to the same input pattern differently at different times, depending on the previous input patterns as well. This model can

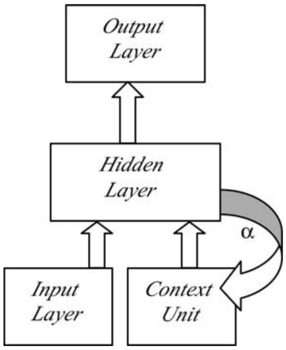

Fig. 1. The recurrent neutral network.

sometimes lead to an improved forecasting performance as compared to the MFNN. As shown in Fig. 1, the proposed architecture consists of additional feedback connections through a set of context units and these are not trainable. Instead of unity feedback weights to the context units (Elman, 1990), this model consists of damped feedbacks α (ranging from 0 to 1) and it possesses the characteristics of a dynamic memory (Pham & Liu, 1992).

3. Simulation results on compressor failures

The failure time data for a repairable compressor system at a Norwegian process plant was investigated (Hoyland & Rausand, 1994). A total of 90 critical failures occurred in the time period between

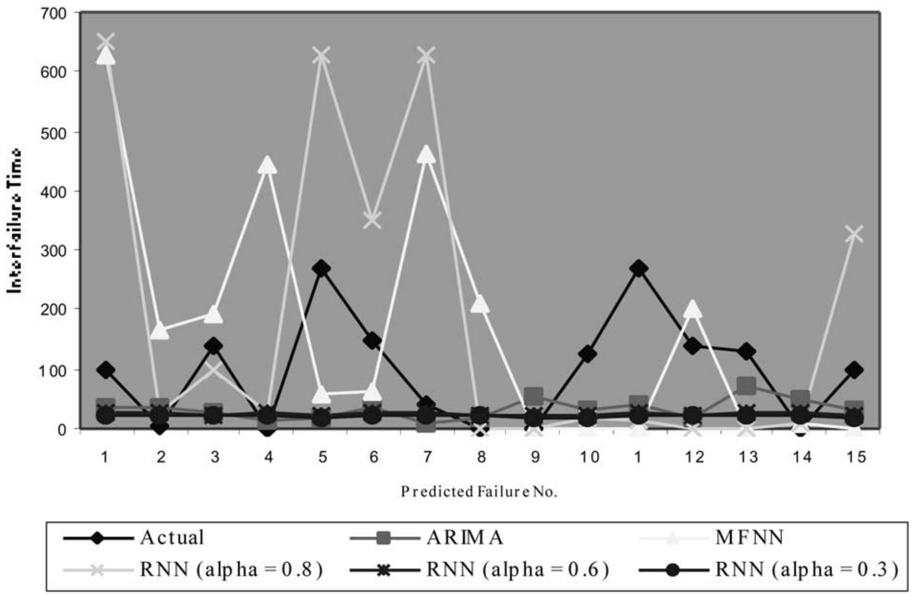

Fig. 2. Forecasting performances of fitted models.

Table 1
Results of the fitted models

	MAD		MSE	Detection (%)	
	Short term	Long term		Short term	Long term
RNN ($\alpha = 0.3$)	58.7	89.5	4.68	50	46.7
RNN ($\alpha = 0.6$)	58.5	88.7	4.59	50	60
RNN ($\alpha = 0.8$)	161.2	177.6	5.91	75	53.3
MFNN	297.6	187.2	11.38	50	40
ARIMA	54.1	86.7	–	75	60

1968 and 1989; and caused process shutdown. The inter-failure data was fitted by suitable ARIMA model and compared with the feed-forward and RNN models. It was found from the model adequacy check that the most appropriate Box-Jenkins model is the ARIMA (1, 1, 1)(0, 0, 1). In our MFNN topology, it consists of three input nodes, 10 hidden neurons and one output neuron. The learning and momentum rates are set to 0.05 and 0.5, respectively. As for the RNN design, it has additional context neurons and weights due to the feedback connections. For both models, back propagation algorithm (Rumelhart & McClelland, 1986) has been adopted in the training process. Furthermore in RNN, the effect of different damped feedback weights α on the predictive performances are investigated and depicted in Fig. 2. A summary of the results is then tabulated in Table 1. Assessment of the models is made solely on two considerations: the relative comparison of prediction accuracy via mean absolute deviation (MAD), and the correct percentage detection of reversals or turning points. From the results, the following observations can be made:

(a) The comparatively lower prediction errors achieved suggest that both the ARIMA and the recurrent models perform better with short term forecasting.
(b) Amongst the three classes of models evaluated, feed-forward neural network generates not only poorer short term (predicting next four failures) and long term (predicting next 15 failures) forecasts, but also the lowest percentage of correct reversal detection.
(c) Generally, depending on the values of the feedback weights α, the predictive performances of RNNs can be comparable with ARIMA models. A smaller range of values for α is preferred.
(d) Based on the mean squared error (MSE) criteria for the out-of-sample testing patterns, an optimal feedback weighting factor $\alpha = 0.6$ can be found. However, with more hours of training the neural network, setting $\alpha = 0.3$ can achieve almost similar results (for both short and long term predictions).
(e) By comparing the correct reversal detection percentage, ARIMA model still performs better. This is closely followed by the recurrent network at the optimal setting. As highlighted in point (a), feed-forward network has poor detection capability.

4. Conclusion

The theoretical underpinnings described by both ARIMA and neural network models are sophisticated, but the advent of computing technology and simulation tools have made the understanding of the methodologies much easier. In this paper, we explored the feasibility of applying neural network models; in particular the recurrent architecture with damped feedback weights, in predicting compressor failures of a repairable system. The short term and long term forecasting errors obtained with the optimal feedback weighting factor, at $\alpha = 0.6$, is comparable with the fitted ARIMA model. However, the lower prediction errors suggest that both models perform better with short term forecasting. Similar conclusions can also be drawn for the percentage of correct reversal detection; again in favor of both the ARIMA and the recurrent networks. Furthermore, the simulation results highlighted that the feed-forward neural network did not perform well and are generally inferior to the ARIMA and the recurrent models. Its predictive performances are poor and have lower reversal detection capability. It is thus concluded that both the ARIMA and the RNN (with appropriately chosen α values) approaches are promising time series modeling tools in predicting failures of repairable systems.

References

Azoff, E. M. (1994). *Neural network time series forecasting of financial markets*, (1st ed). New York: Wiley.

Elman, J. L. (1990). Finding structure in time. *Cognitive Science*, *14*, 179–211.

Ho, S. L., & Xie, M. (1998). The use of ARIMA models for reliability forecasting and analysis. *Computers and Industrial Engineering*, *35* (1–2), 213–216.

Hoyland, A., & Rausand, M. (1994). *System reliability theory: models and statistical methods*, (1st ed). New York: Wiley.

Hwarng, H. B. (1997). A neural network approach to identifying cyclic behaviour on control charts: a comparative study. *International Journal of System Science*, *28* (1), 99–112.

Kohzadi, N., Boyd, M. S., Kermanshahi, B., & Kaastra, I. (1996). A comparison of artificial neural network and time series models for forecasting commodity prices. *Neurocomputing*, *10*, 169–181.

Liu, M. C., Sastri, T., & Kuo, W. (1995). An exploratory study of a neural network approach for reliability data analysis. *Quality and Reliability Engineering International*, *11*, 107–112.

Pham, D. T., & Liu, X. (1992). Dynamic system modelling using partially recurrent neural networks. *Journal of Systems Engineering*, *2* (2), 90–97.

Rumelhart, D., & McClelland, J. (1986). *Parallel distributed processing: exploitations in the micro-structure of cognition, 1 and 2*, Cambridge: MIT Press.

Walls, L. A., & Bendell, A. (1987). Time series methods in reliability. *Reliability Engineering*, *18*, 239–265.

White, H. (1989). Learning in artificial neural network: a statistical perspective. *Neural Computation*, *1*, 425–464.