Time Series Forecasting with Minimally-Structured Neural Networks

지원철 (홍익대학교 산업공학과)

Time series analysis describes the underlying processes or phenomena as a mathematical model which can effectively capture the sequence of actions taken by the time series. From this viewpoint, it is natural that the neural network can be an alternative to the conventional linear and polynomial predictive methods because the multi-layered feedforward neural networks (MLNN) can be universal approximators (Hornik et al, 1989). In the pioneering work by Lapedes and Farber (1987), the MLNN have demonstrated an impressive ability in approximating funtion and forecasting.

However, We must address some difficulties in adopting the neural network approach for managerial forecasting:

1. Limited Number of Observations:
2. Noisy Environment:
3. Size of the Network:

When the MLNN is used as a fitting function of a time series, it seems that the larger size of MLNN performs better. However, although any time series can be fitted arbitrarily well by the MLNN, it does not necessarily lead to optimal prediction. In other word "overfitting" problem may be very serious. Therefore, the purpose of this study is to confirm whether the MLNN can perform reliably as a managerial forecasting tool with relatively small amount of noisy data. This requires us to find the minimal structure of MLNN for a time series. The key research issues are:

1. To alleviate the overfitting problem, what are possible aiternative structures of MLNN ?

2. What are the comparative performance differences among the alternative structures of MLNN ? Can the MLNN outperform the ARMA model in forecasting accuracy ?

First, We tested the performance of the various sizes of MLNN using real time series which were fitted by ARMA models in the literatures. Second, to achive better forecasting accuracy, we adopted two alternative structures of MLNN. One structure seeks to fine the minimal networks by eliminating unnecessary processing elements(PE's) or weights to improve the generalization power of MLNN. The other structure adopts the recurrent network which uses the feedback connections in MLNN. Finally, We tested the prediction performances of these two alternatives in comparison with real time series showed that recurrent network gives the best results in terms of forecasting accuracy when time series include much noise.