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Applications of Artificial Neural Networks in Economics and Finance

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INTRODUCTION

The abilities of the brain, a complex, nonlinear and parallel computer, to learn, memorize and generalize, have motivated research in biological neural systems, referred to as "artificial neural systems" (ANNs) (Engelbrecht, 2007, p. 5). ANNs are a powerful technique for multivariate dependence analysis. The current capabilities of modern computing power and storage space allow for easy solutions of problems with a single objective by means of moderate-sized ANNs (Ibid.). Unlike other traditionally used techniques in economics and finance, artificial neural networks (ANNs) do not necessarily rely on assumptions about the population distribution (Shachmurove, 2003). Furthermore, the universal approximation theorem (Cybenko, 1989; Funahashi, 1989) postulates that an ANN with one hidden layer is capable of approximating any continuous function.[1] Due to these facts, ANNs are becoming an increasingly attractive and flexible analytic tool for applications in the area of economics and finance. The purpose of this article is to present such important applications with an emphasis on recent research trends.

BACKGROUND

Please see the Artificial Neural Networks entry, this volume for further discussion on ANNs basics. A frequently used ANN in economics and finance is the feedforward ANN. In this architecture, information stringently flows from the neurons situated in the input layer to the neurons in the subsequent layers without any feedback connections. Each node is a neuron except for the input nodes. Rather than moving directly from input to output, new neurons as weighted combinations of input variables located in a hidden layer are created. This is a common ANN feature that ensures the achievement of modelling flexibility. When all neurons of a preceding layer are fully connected with all neurons in the subsequent layer, the ANN is referred to as "a multilayer perceptron" (MLP).

Similarly to MLPs, ANNs of a radial basis function type (RBF) (Broomhead & Lowe, 1988) are universal function approximations (Haykin, 1998) that have been a frequent choice in business applications. The difference between MLP and RBF ANNs consists in the type of approximation to non-linear mapping they deliver. The RBF delivers a local approximation while the MLP – a global one (Haykin, 1998). The detailing of contributions focused on the technical specifics of ANNs concerning optimization and architecture is beyond the scope of this article. Instead, the interested reader is referred to their comprehensive coverage in the books of Haykin (1998), Engelbrecht (2007), Haykin (2009) and Rojas (2013), while McNelis (2005), Zhang (2008), and Alexandridis and Zapranis (2014) contain applications in the area of economics and finance.

MAIN FOCUS OF THE ARTICLE

The purpose of this section is to survey important applications of ANNs in economics and finance. Emphasis has been laid on recent research trends in contributions in which ANNs are the main em-

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pirical method or are combined with alternative research tools.

Applications of ANNs for Prediction

A major part of the ANN contributions in the area of economics and finance is dedicated to predictions. The implemented input data are either technical (for example, historical data of assets' statistical distribution moments) or fundamental (for example, data on the current economic activity). A tendency to focus on robustness checks is followed by some authors: (1) to compare the performance of ANNs to alternative methods, such as ARCH/GARCH models, which are appropriate for financial and economic data that frequently exhibit volatility clustering; (2) to combine them in hybrid models, or (3) to implement several ANN architectures in order to encourage the choice of the optimal one. In this section, such contributions are given priority over works that implement a single ANN model because of their goal of finding the best solution from several alternatives.

Falat et al. (2015) studied the volatility dynamics of the EUR/GBP currency with the traditionally applied in such research setting statistical approach that relies on ARCH and GARCH models, as well as several RBF ANN architectures. The authors reported higher but not considerable accuracy for the statistical approach. However, Falat et al. (2015) attributed this to factors such as their non-ideal but improvable optimization strategy. Kristjanpoller et al. (2014) combined ANNs and a GARCH model in a hybrid ANN-GARCH model for predicting the volatility of three emerging Latin American stock markets. On the basis of several robustness checks, the authors reached the conclusion that the hybrid model improved the performance of the GARCH model with respect to their sample. Kristjanpoller and Minutolo (2015) obtained analogous results concerning the spot and future volatility of gold. They also proposed an algorithm that incorporated variables in their model only if they improved it, assessed in terms of a measure of the model error.

Abrishami and Varahami (2011) implemented, for the prediction of gas prices, the popular in financial and economic research multilayer feedforward ANN and a group method of data handling (GMDH) ANN. The latter architecture is based on pattern recognition and can be used as a refined alternative to the traditional technical analysis (Abrishami & Varahami, 2011). The authors proposed a hybrid ANN containing GMDH and rule-based expert system modules. They reached the conclusion that it performed better during the recent 2008 financial crisis. Similarly, based on a GJR-GARCH ANN model for predicting the volatility of the NASDAQ Composite Index, Monfared and Enke (2014) reached the conclusion that hybrid models were appropriate for forecasting extreme events because the structure of volatility becomes more complex. ANNs should be avoided in low-volatility periods because they bring unnecessary complexity (Monfared & Enke, 2014).

A class of ANN models with a growing number of financial and economic applications is the wavelet ANNs, proposed by Zhang and Benveniste (1992). They combine a wavelet function as an activation function and a classical ANN. Bernard et al. (1998) explained their superior performance with their lower computational cost if wavelets were used instead of other activation functions. At the same time they preserve their approximation capacity due to their ANN component. Alexandridis and Zapranis (2013 a,b) demonstrated that wavelet ANNs could be efficiently used for weather derivative pricing and modelling as well as for the prediction of the prices of financial weather derivatives. Alexandridis et al. (2008) also reported accurate performance of wavelet ANNs for predicting crude oil returns. The interested reader is referred to the book of Alexandridis and Zapranis (2014) for a comprehensive account of the model identification framework for utilizing wavelet ANNs in various applications.

Sermpinis et al. (2016) proposed two hybrid ANNs: an adaptive evolutionary multilayer per-

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