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Alternative Output Representation Schemes Affect Learning And Generalisation Of Back-Propagation ANNs; A Decision Support Application

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Abstract: Inherently fuzzy outputs of an Artificial Neural Network (ANN) can be represented by various ways such as, a set of output neurons, one discrete level output neuron, one continuous output neuron. The effect of the aforementioned alternative output representation schemes to performance measures of the ANN, namely convergence of the learning procedure and generalisation capability of the ANN, is studied in this paper. Comparative classification results are presented for a Decision Support Systems (DSS) application, namely the estimation by a ANN trained with Back Propagation, of bull / bear situation of the Athens Stock Market, given the values of a set of technical indicators.

1. Introduction

Decision Support Systems (DSS) need to produce outputs such as the degree of certainty, or the measure of risk associated with a given strategic action. A DSS can be implemented using an ANN model, for various applications as in [1], [2]. Common basic tasks of such ANNs include yes / no classification or qualitative estimation of alternative actions. In this paper, we consider a DSS for Stock Market Current Assessment. This ANN- based model takes as inputs a set of stock market indices and technical analysis indicators, and provides an estimation of the current state of the market. The market state can be interpreted as a general 'BUY', 'HOLD', 'SELL' situation, in natural language terms.

The representation of ANN outputs of inherently fuzzy nature can be carried out using different output schemes. For the application presented herein, three alternative schemes are considered:

- single neuron representation, with three discrete levels, corresponding to 'BUY', 'HOLD' or 'SELL' market state.
- output representation using three neurons, each one encoding one market state
- definition of a composite signal encoding information of bull / bear situation of the market and subsequent representation by one output neuron.

Comparative study of the three schemes mentioned above, shows that output representation affects ANN learning and generalisation, given the model and the training algorithm. Especially, superior results are obtained using the third representation scheme, of a continuous output neuron.

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2. Theory

We consider the class of problems where an ANN has to identify the state of a system, given a set of values from signals of the studied system. Such problems are often encountered in the implementation of ANN-based Decision Support Systems, providing qualitative estimation of alternative actions or strategies. Especially, we study the problem of Stock Market Current Assessment, where it is desired to estimate whether the stock market is in a 'HOLD', 'BUY' or 'SELL' state. This means that the suggested investment strategy corresponds to one of the aforementioned states.

Given the input set of technical indicators and the architecture of the ANN, an appropriate scheme to map market states to neural outputs is seeked. The conceptual configuration of the Current Assessment DSS is depicted in Figure 1, where the alternative state representation schemes are noted as RS-I, RS-II, RS-III.

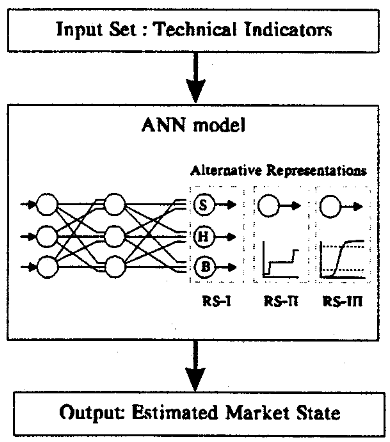

Fig.1. Conceptual Design Of Current Assessment DSS

The ANN model used throughout this paper is feed-forward with one hidden layer, trained with the back propagation algorithm. A standard sigmoid function is used as neurons transfer function. Training of the ANN is carried out using daily data from the Athens Stock Exchange for the last two years. Inputs of the system consist of a set of indicators derived by technical analysis. Training set consists of 350 vectors, of the form of $\mathbf{V} = [\mathbf{I} \mid \mathbf{O}]$, where $\mathbf{I}$ is the inputs' part and $\mathbf{O}$ is the desired outputs' part of the vector.

2.1. Multiple Neuron Representation (RS-I)

According to RS-I, the output level of the ANN consists of three neurons, assigned to each one of the market states. Thus, the outputs' part of training set vectors consists of three numbers, valued at two discrete levels. Technical analysis pre-processing, combined by human expert overview of the training data defines daily market state as 'BUY', 'HOLD' or 'SELL'. Each day's assessment is encoded as in Table I.

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Test set data consist of 45 vectors, derived by historical data from the same period as the training set. Test data include a representative mixture of 'BUY', 'HOLD' and 'SELL' days, in order to ensure valid generalisation results of ANN training.

The final assessment of the ANN is derived by application of the winner-take-all rule, i.e. the neuron with the higher activation level provides the current assessment of the stock market.

Table I. Formulation Of Outputs' Part For RS-I

STATE	O_1	O_2	O_3
'BUY'	0,9	0,1	0,1
'HOLD'	0,1	0,9	0,1
'SELL'	0,1	0,1	0,9

2.2. Discrete Level - Single Neuron Representation (RS-II)

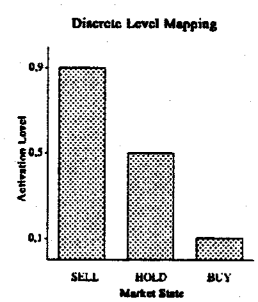

Fig.2. Discrete Level Mapping Of Market States

RS-II is an extension to RS-I, as it encodes the discrete market states in one output neuron. The states are mapped to discrete activation levels of the output neuron, as it is depicted in Figure 2. Nevertheless, the output neuron is continuous, i.e. it may produce outputs with intermediate values.

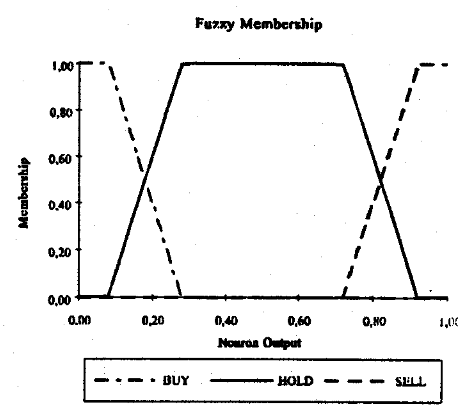

Fig.3. Fuzzy Membership Of Sell / Hold / Buy States

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Training and test set consist of the same input data as in RS-I. Nevertheless, outputs' part, **O**, is for RS-II a single number, corresponding to the day's state, according to the mapping of Figure 2.

Fuzzy membership [3], is used to assess the actual market state. Neuron activation is assigned to the three states with a degree of membership, i.e. the market states are considered as not mutually exclusive. The fuzzy membership functions that have been used in the implementation of the presented DSS, are presented in Figure 3. According to this mapping, an output level of e.g. 0,14 corresponds to a 'SELL' state with membership of 0,7 and a 'HOLD' state with membership of 0,3.

2.3. Single Neuron - Continuous Representation (RS-III)

Further improvement can be expected by defining an indicator to encode information about market's relative position. This way, fuzzy membership is encoded from training phase as a continuous quantity is used to form the outputs' part, **O**, of the training vectors.

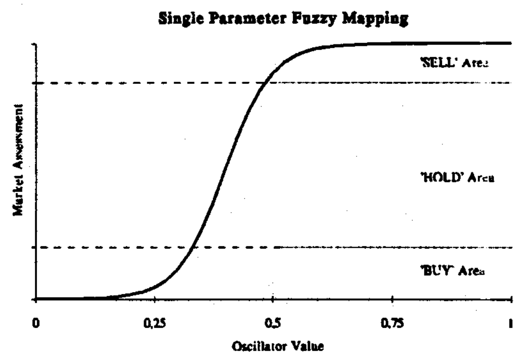

Fig.4. EMACA Fuzzy Mapping

Passing from discrete output to continuous output representation proves very efficient, as 90% of the days the market seems to be in a mostly 'HOLD' state, following though a secondary trend towards either 'BUY' or 'SELL'. This biased distribution often forces the ANN to learn only 'HOLD' states as acceptable and consider 'BUY' and 'SELL' states as noise, if discrete level encoding is used during training.

Furthermore, continuous output representation scheme is analogous to the classical technical oscillators' approach of market assessment. Oscillator approach is important for in-depth market analysis, because it demonstrates market trends apart from discrete state information, fact that adds flexibility when both short or long positions need to be taken.

A market state oscillator, CAO (Current Assessment Oscillator) has been constituted in the form of figure 4. RS-III uses the Exponential Moving Average of CAO, EMACA, as defined by form ‹2›.

$$\text{EMACA}_t = (1-a)\times\text{CAO}_{t-1} + a\times\text{CAO} \qquad ‹2›$$

According to ‹2› the value of CAO of the current and the previous day are

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weighted by a and (1-a) accordingly, where a is defined by form ‹3›,

$$a = \frac{1}{1+days} \quad ‹3›$$

Note that 'days' is a technical analysis parameter, set equal to 4 for the current application. EMACA provides smoothing of output values, aiming to optimise neural training and generalisation. It has been indicated [**4**] that it is generally more effective to train an ANN to learn a smoothed function rather than one with discontinuities.

Training and test set data are the same as for RS-I and RS-II, with the difference that outputs' part are formed with further pre-processing of stock market data. Additional human expertise has been used to assign current market state to values between 0,0 and 1,0 (CAO_t) and consequently, form ‹2› is applied to formulate training and test vectors with $EMACA_t$ as outputs' part, **O**.

3. DSS Application Demonstration

A summary of application results of the ANN-based DSS, to actual data of the Athens Stock Market, is presented on Table II. Production set, that is, a set of data that the ANN had not encountered during the training phase, consists of 45 vectors from actual daily data of the Athens Stock Exchange, from the period of the last two years. Similarly to training and test sets, inputs' part, **I**, of production vectors is derived by pre-processing of the daily data, in order to calculate the corresponding technical indicators. Outputs' part, **O**, correspond to the market state of the particular day, as estimated by technical analysis and by human expertise.

Table II. Results Summary Of Current Assessment DSS Application

Scheme	**Min Avg Error**	**R Sq**	**Mean Sq Err**	**Mean Abs Err**	**Max Abs Err**	**Corr Coef r**	**Cnvg Epochs**
RS-I	0,18656						219
'OUT'		0,4171	0,013	0,035	0,8	0,4171	
'HOLD'		0,3172	0,028	0,082	0,8	0,3172	
'LONG'		0,202	0,016	0,06	0,734	0,202	
RS-II	0,02367	0,3437	0,07	0,04	0,428	0,588	19
RS-III	0,0027485	0,9697	0,001	0,022	0,153	0,986	4

The quantities that appear on Table II, have the following explanation:

Min Avg Error :	Minimum average error among test set vectors, encountered during ANN training; used as a measure of ANN's generalisation capability
R Sq :	Regression analysis indicator of ANN model accuracy
Mean Sq Err :	Mean squared error of actual outputs
Mean Abs Err :	Mean absolute error of actual outputs
Corr Coef r :	Linear Correlation Coefficient between the set of desired outputs (included in production set) and actual outputs
Cnvg Epochs :	Measure of convergence of training procedure - epochs needed until min avg error of training set falls below 0,007 per output neuron

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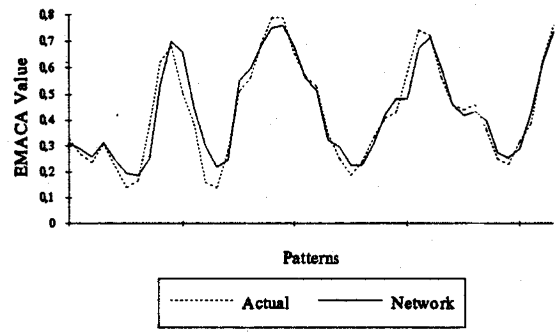

Fig.5. Output Performance Of RS-III For Production Set Data

Figure 5 demonstrates that RS-III provides all the necessary information namely, current state assessment and trend reversals. From Table II superior performance of RS-III over both RS-I and RS-II is statistically verified.

4. Conclusions

The effect of using alternative representation schemes at the output level of an ANN has been examined. A DSS application for Current Assessment of Stock Market indicates significantly different properties in convergence of the training algorithm and generalisation capability of the ANN. Major improvement in training speed has been observed when multiple states are encoded into one discrete level output neuron (RS-II), instead of using separate neurons for each state (RS-I). Further improvement is obtained, with the use of a continuous mapping which encodes market states in a way similar to technical analysis oscillators (RS-III). This approach leads also to significantly better generalisation capability of the ANN. The trade-off for the enhanced overall performance of RS-III is the need of human expertise in defining the current assessment levels of training samples, whereas for both RS-I and RS-II, human intervention can be eliminated by automated technical analysis tools.

Undoubtedly, RS-III can be very useful in building efficient trading tools, capable even of real-time operation. Further research intends to extend RS-III for prediction of the stock market.

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