**SYNOPSIS**

**STOCK MARKET PREDICTION USING ANN**

**Submitted By-**

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**INTRODUCTION**

Prediction of stock market returns is an important issue infinance. Nowadays artificial neural networks (ANNs) havebeen popularly applied to finance problems such as stockexchange index prediction, bankruptcy prediction andcorporate bond classification. ANN model is a computer

model whose architecture essentially mimics the learningcapability of the human brain. The processing elements of

an ANN resemble the biological structure of neurons and theinternal operation of a human brain. Many simpleinterconnected linear or nonlinear computational elementsare operating in parallel processing at multiple layers. Insome applications it has been specified that ANNs havelimitations for learning the data patterns. They may

perform inconsistently and unpredictable because of thecomplex financial data used. Sometimes data is sovoluminous that learning patterns may not work. Continuous

and large volume of data needs to be checked for redundancyand the data size should be decreased for the algorithm towork in a shorter time and give more generalized solutions.

**ARTIFICIAL NEURAL NETWORK APPROACH**

Machine learning approach is appealing for artificialintelligence since it is based on the principle of learningfrom training and experience. Connection models, such asANNs,are well suited for machine learning where connectionweights are adjusted to improve the performance of anetwork. An ANN is a network of nodes connected withdirected arcs each with a numerical weight, w i , j ,specifying the strength of the connection. These weightsindicate the influence of previous node, ui,on the nextnode, uj, where positive weights represent reinforcement;negative weights represent inhibition. Generally the

initial connection weights are randomly selected.

Feed-forward networks were first studied by**Rosenberg**.Input layer is composed of sate of inputs that feed inputpatterns to the network. Following the input layer therewill be at least one or more intermediate layers, oftencalled**hidden layers**. Hidden layers will then be followedby an output layer, where the results can be achieved .Infeed-forward networks all connections are**unidirectional**.

ij

W

Node ui Node uj

**Multi Layer Perceptron**(MLP) networks are layered feed-forward networks typically trained with static back-propagation. These networks, also known as back-propagationnetworks, are mainly used for applications requiring staticpattern classification. The back-propagation algorithmselects a training example, makes a forward and a backwardpass, and then repeats until algorithm converges satisfyinga per-specified mean squared error value. The mainadvantage of MLP networks is their ease of use andapproximation of any input/output map. The maindisadvantage is that they train slowly and require lots oftraining data.

**Generalized feed-forward**(GFF)networks are a generalizationof them networks where connections can jump over one or

more layers, but these networks often solve problems much

more efficiently

**Training Algorithm**

Training is the process by which the free parameters of thenetworks (i.e. the weights) get Multi Layer Perceptron

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Training is the process by which the free parameters of thenetworks (i.e. the weights) get optimal values. Supervisedlearning models, that are used for MLP and GFF networks,train certain output nodes to respond to certain inputpatterns and the changes in connection weights, due tolearning, cause those same nodes to respond to more generalclasses of patterns. In these models input layer unitsdistribute input signals to the network. Connection weightsmodify the signals that pass through it. Hidden layers and

output layer contain a vector of processing elements withan activation function. Usually the**Sigmoid function**isused as the activation function. Every unit uicomputes itsnew activation ujas a function of the weighted sum of theinputs to unit ui( uj) from directly connected cells.Therefore, the output of each processing unit for theforward pass will be defined as:

Si=ΣWi,j\* uj

ui= f(Si) where f(x)= 1/(1+e-x)

The backward pass is the error back-propagation andadjustment of weights. Gradient descent approach with aconstant step length, also referred to as learning rate, isused to train the network. This method minimizes the sum ofsquared errors of the system until a given minimum or stopat a given number of epochs, where epoch is the termspecifying the number of iterations to be done over thetraining set. The error is multi-dimensional and maycontain many local minima. A momentum term may be added toavoid getting stuck in local minima or slow convergence.The output of each processing unit for the backward pass isdefined as:

f′(Si) = ui\*(1 − ui)

Weights are then updated by the formula where ε is the meansquared error and ρ is the

step size:

∂i=-(∂E/∂Si)

w\*i,j= wi,j+ ρδiui

After the training process is completed, the network withspecified weights can be used for

testing a set of data different than those used fortraining. The results achieved can then be

used for generalization of the approximation of thenetwork.

**System Model**

In this study the following input variables were consideredto ultimately affect the stock

exchange market index value.

Previous day’s index value (according to closing price)(ISE\_PREV)

Previous day’s TL/USD exchange rate (average of buying andselling values) (TL\_USD\_PREV)

Previous day’s Simple Interest Rate Weighted Average

Overnight (ON\_PREV)

Var1 representing Monday (M)Var2 representing Tuesday (T)Var3 representing Wednesday (W)Var4 representing Thursday (TH)Var5 representing Friday (F)

Considering the input variables, the following system modelwas considered for the prediction stock exchange marketindex value:

F= f(ISE\_PREV,TL\_USD\_PREV,ON\_PREV, M, T, W, TH, F)

**Data Sets**

Experimental data will be gathered directly from thecertain Stock exchanges for a period of time. From thisdata set some data will be taken as as testing examples.

**Network Parameters**

For the system model described before, two different ANNmodels (MLP and GFF) were applied with different number ofhidden layers (HL = 1, 2,3,4…) for certain minimum meansquared error value for the data set.

**CONCLUSION**

It is possible to use Artificial intelligence (AI) todevelop models that can be used in prediction. Such modelsare applicable to the financial markets such as the stockexchange. The AI method that was found suitable for thesemodels was the Artificial Neural Network(ANN), whichexploits parallel computing to gain intelligence from inputdata as a basis of predicting future values.