A Hybrid Trading System for Defence Procurement Applications

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Abstract: In the aftermath of the actual financial crisis, all the MoDs are preparing severe budget cuts in response to the decline in their national income. The costs of transaction dedicated to military procurement are still very high and the efficiency of using this funds in military capability improvements is altered. A new framework based on hybrid trading system for defence spending applications (HTS-D) that incorporates different ingredients like the chaos theory (CHT), non-linear statistical models (NLSM) and soft computing (SC) methods (Artificial Neural Networks- ANN, Fuzzy Logic- FL and Genetic Algorithms- GA) is proposed. The HTS-D framework can be defined in three phases: time series selection by using chaos theory to identify non-random series; forecasting the time series by using ANNs and NLSM; implementation of a rule-based HTS that may incorporate GAs.

Keywords: Defence spending, military applications, Hybrid trading system (HTS), Artificial Neural Network (ANN), Chaos Theory (CHT).

1. Introduction in soft computing for military applications

The dynamics of real defence spending depends on a wide range of factors that interact (strategic environment, the community’s tolerance of risk, the cost of inputs into defence capability) that are balanced against fiscal constraints.

Recent studies shows that the per-unit costs of successive generations of military equipment have been rising in real terms (Defence Materiel Organisation indicates a 4% growth but this reflects also an improvement in capability).

The introducing of new technology reduce the costs and the savings are reinvested into capability improvements, as nations seek the decisive military advantage over their rivals that technology can provide, but the overall effect has been increased per-unit costs (Kirkpatrick 2004).

There is still a critical debate on the factors that drives the rate of capability growth. Strategic developments that raised the intensity
of international military competition might be expected to increase the rate of capability growth. Macroeconomic conditions should have an impact, as the rate of economic growth influences the rate at which governments can afford to invest in new capabilities.

In the context of the IT developing, the use of soft computing (ANN is fitted to uncertainty) mixed with NLSM in military time series with high probability of providing abnormal returns applications take some advantages regarding the optimization of the resources of computers and HTS represents a strong tool in predicting military future events.

ANNs handle time series problems better than other SC methods because they deal well with large noisy data sets. Unlike expert systems, ANNs are not so transparent, and this fact make them difficult to interpret. A rule-extraction ANN routine may enable the extraction of rules from the ANN model.

Expert systems and ANNs are more efficient than the conventional models in statistics and econometrics because of the complexity in translating the systems into precise mathematical functions. Because of the limits of the traditional artificial intelligence, search methods, predicate calculus, rule based expert systems and game playing theory it was natural to turn to the physical laws and bio-inspiration. The modern tools developed in engineering and natural sciences (wavelet transformations, finite impulse response filters-FIR, from the signal processing, GA and ANN from biology and CHT from the physical sciences. These revolutionary techniques have a common thread in that they attempt to solve problems such as the forecasting and explanation of data in military processes with a strong capability to exploit the tolerance imprecision and uncertainty in real world problems and to achieve tractability, robustness at low costs. SC are also used to find an approximate solution to a imprecisely formulated problem and are often used in combination with one another or with more conventional artificial intelligence methods such as expert systems in order to obtain better solutions. The mixed systems that combine one or more artificial intelligence methodologies are known as hybrid systems (HS). ANN-based decisions are efficient in project management and bidding strategy, military forecasting, detection of regularities in price movements, determining of optimal structure of defense expenditures, default and bankruptcy (Hsieh, 1993, Medsker, 1996).


2. The basic principles used in the design of a HTS-D framework

The basic strategy is to incorporate complementary elements from chaos theory, artificial intelligence/ SC and statistical methods.

The first step consists on data selection based on abnormal returns filtering. We hypothesize that if the time series is not random, but a random-like one, it may be chaotic (hence, deterministic) and thus may be modeled by NLSM or ANN models.

The aim is to identify financial time series that may be deterministic or chaotic. Only the series that exhibit this behavior will be used in the second step. Let assume that the 1D- time series is a projection from a multidimensional system. In this case is necessary to reconstruct the series to its true dimension by using the time delay and the embedding dimension parameters. This step starts with the non-linear system detector part, consisting of various functional criteria. The basic function is to measure the Hurst exponent value (H-exp) to determine whether the number of data set is adequate for measuring H-exp and then calculating the mean orbital period and the overall nature of the time series, or the quality of the persistency. The measuring of the H-exp is based on the selection of a good compressor value (log return is a very high compressor) for the time series, averaging for different N, thus removing the AR residual part, and the first peak from the data set of
log(R/S) and Log(N). From the value of H-exp it results the type of model to use for fitting (a short term ARIMA or a long term FARIMA model). The secondary functions are: average mutual information, calculation of the minimum embedding dimension, time delay to reconstruct the phase space. The simplest manner of measuring the time delay is from the peak-to-peak analysis or time domain auto-correlation function. The system predictability is measured from recurrent analysis, rather than the time delay plot, on the basis of a parameter called spectral entropy. It is a very useful measure for selection of a financial time series from the historical database.

The new framework preprocess the data in variable time window size, window gap and to measure the dynamics of the system. The interest is to fit the appropriate model to that particular time frame. The concept is based on the distinction of different types of time series changes: trending, chaotic, random. The change in the dynamic nature of the system is detected by calculating the largest Lyapunov exponent (L-exp) for different time window size. It is also interesting to investigate how the prediction error can be determined from the value of Lyapunov exponent.

The second step is dedicated to the selection/ developing of forecasting models based on the classification of the selected series behavior. The series with chaotic behavior will be used in this phase and this will involve applying a mix between ANN, GA and NLSM. ANN-AR (Tan, 1995) incorporates the output of an AR model to an ANN to enhance the capability of the model. This idea could be extended to other ARCH/ GARCH models. In statistical analysis, the modeller specify a precise relationship between inputs and outputs but in ANN the analyst simply identifies the inputs and the outputs (no knowledge of ANNs training methods such as BP is required to use ANNs). The strength lies in ANN ability to vary in complexity, from a simple parametric model to a highly flexible, nonparametric model. An ANN used to fit a nonlinear regression curve, using one input, one linear output, and one hidden layer with a logistic transfer function, can function like a polynomial regression or least squares spline, but it has some advantages. Polynomial regression are linear in parameters and thus are fast to fit but suffers from numerical accuracy problems if there are too many wiggles. Smoothing splines are also linear in parameters and do not suffer from the numerical accuracy but pose the problem of deciding where to locate the knots.

3. The principles of construction of ANN by using Tan procedure

The ANN series modeling technique is inspired from Tan’s four step procedure:

a) the data should be defined and presented to the ANN as a pattern of input data with the desired outcome or target;

b) the data are either in the training testing/ validation (out-of-sample) set. The ANN only uses the training set in its learning process in developing the model. The model is tested for its predictive ability and when to stop the training of the ANN.

c) the ANN structure is defined by selecting the number of hidden layers that should be build and the number of neurons for each hidden layer.

d) all the ANN parameters are set before starting the training process.

Because there are no fixed rules in determining the ANN structure or its parameter values, a large number of ANNs should have to be build with different structures and parameters. This complex trial and error process can be tedious and the experience of the ANN user in constructing the ANN is very important.

The finding of the end of the training process needs is very important because if the network is overtrained, a curve-fitting problem may occur whereby the network starts to fit itself to the training set instead of creating a generalized model. This typically results in poor predictions of the test and validation data set. On the reverse, if the network is undertrained, it may settle at a local minimum, rather than the global minimum solution (suboptimality). By performing periodic testing of the network on the test set and recording both the results of the training and test data set results, the number of iterations that produces the best model can be obtained. In this case is
needed only to reset the network and train the
network up to that number of iterations.

4. A simple procedure for portfolio
and risk management in military
applications

Because it is very difficult to achieve
accurate forecasting, the main role of trading
systems is to reduce the reliance on the
accuracy of the forecast in improving returns
by managing the risk-return ratio. The key to
performance is not to anticipate trends, but to
follow them. According to Babcock (1989) a
mechanical approach is an optimal way to
avoid the destructive emotionalism that
permeates trading. Transaction costs could be
viewed as an overhead cost that must be added
to every trade. Tan’s approach take into
account all transaction costs.

The final step of the HTS-D framework
is dedicated to the developing of a procedure
with a set of rules to perform money, portfolio
and risk management, signals the trades that
should be done. The portfolio management
module will combine various economical time
series that give the potential to return abnormal
profits, and could identify optimal risk-return
ratio paths. The Markowitz’s portfolio
selection could be optimized by using GAs.
The role of money management module is to
optimize the amount of funds to be committed
for each trade based on the forecast strength of
the second step, amount of total funds
currently available, the maximum amount of
drawdown that is allowed. The trading rules
modules will be analyze for optimal return and
we is possible to use GAs to select technical
indicators for the rules as well as find the
optimal parameters for those technical
indicators. The technical indicators should
include: moving averages, classical oscillators
(momentum, stochastic), directional movement
indicators. The Tan’s simple rules (1995)
consisted of buying/ selling assets if the
forecast from the models were higher or lower
than the current prices by a certain (critical)
factor that considers transaction costs with a
filter that eliminate trades with small amount
of forecast price movements. The last module
is the record keeping and profit/loss reporting.
The framework should be as flexible as
possible in terms of adding parameters such as
variable transactions costs (as this can vary
depending on the asset that is being traded),
amount of risk tolerance desired (aggressive,
risk averse), number of successive trading
losses to be tolerated, maximum amount of
loss per trade. The reporting module could also
identify other benchmark measurements such
as best/worst trade, profit/loss per trade
(Refenes, 1995).

5. Conclusions and future work

An innovative but capable HTS-D
framework is proposed. The main benefit is
related to the theoretical advances in nonlinear
time series modelling and forecasting. This
HTS-D framework incorporates SC techniques
and NLSM for forecasting high volatility –
huge time series data, with applications in
military processes. The significance is given by
the fact that it offers a new framework for
selecting indicators with higher probability of
providing abnormal performance. It also
contribute to the understanding of how CT and
SC can be applied to time series forecasting,
the assistance in the understanding and the
determination of the appropriate forecasting
methods for military applications based on a
new HTS-D framework.

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