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Automated Trading with Genetic-Algorithm Neural-Network Risk Cybernetics: An Application on FX Markets

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Abstract

Recent years have witnessed the advancement of automated algorithmic trading systems as institutional solutions in the form of autobots or black box. However, little research has been done in this area with sufficient evidence to show the efficiency of these systems. This paper builds an automated trading system which implements an optimized genetic-algorithm neural-network (GANN) model with cybernetic concepts and evaluates the success using a modified value-at-risk (MVaR) framework. The cybernetic engine includes a circular causal feedback control feature and a developed golden-ratio estimator, which can be applied to any form of market data in the development of risk-pricing models. The paper applies the Euro and Yen currency rates as data inputs. It is shown that the technique is useful as a trading and volatility control system for institutions including central bank monetary policy as a risk-minimizing strategy. Furthermore, the results are achieved within a 30 second timeframe for a intra-week trading strategy, offering relative low latency performance. The results show that risk exposures are reduced by four to five times with a maximum possible success rate of 96%, providing evidence of further research and development on this area.

KEY WORDS: automation, autobot, genetic-algorithm neural-network, risk cybernetics, risk-pricing

1. Introduction

There is a growing group of investors and professionals who believe that financial failures are due to poor risk management. In the area of trading and money management, traders and fund managers require risk management systems that are reliable, which means reference to timely information so as to put an appropriate price to risk exposures. Hence, automation in trading algorithmic systems has received strong interest in recent years so as to minimize human errors and poor judgement.

One of the first research in the direction of trading automation is by Jacobs et al (1991) who introduced expert neural networks that provide positive results in adaptive computational mixtures. In the same year, Hornik (1991) produced multi-layer feed-forward networks with new approximation capabilities, which explained and operationalised feed-forward artificial neural networks (ANNs). These studies provided automation procedures in general and these concepts are applied to forex data.

However, Carpenter et al (1991) introduced a real-time learning environment of non-stationary data such as rates using a self-organizing neural network with some success. Mackay (1992) applied computer methods with Bayesian interpolation which assists in rate estimation. These methods serve as the basis of expert systems.

Mizrach (1992) used a multivariate technique in nearest-neighbour forecasts of rates, while Taylor and Alien (1992) compared technical analysis methods for rates. Both studies proved to provide evidence of the positive forecasting abilities of technical methods. Weigend et al (1992) attempted to predict sunspots and rates using connectionist networks. Although these studies provided some success, they were not convincing to the trading community.

Fransconi et al (1992) expanded ANN methods by introducing multi-layer networks by local feedback. Pictet et al (1992) offered real-time trading models for rates, which was one of the first papers on real-time models. Refenes et al (1993) offered rate prediction with neural network design strategies, which again gave direction to the research community that ANNs could provide positive results for forecasting performance and hence for risk management techniques. Nachne and Ray (1993) modelled rates from the frequency perspective and provided forecasts. These models from the early 1990s provided forecasting strategies but lacked in risk management applications.

Kuan and Liu (1995) forecasted rates using feed-forward and recurrent neural networks, which was a new application of ANNs to rate prediction. The early 1990s turned attention to ANNs and Wei and Jiang (1995) used standard ANNs for rate forecasting with some success. Later on, Episcopos and Davis (1996) used a combination of ANN and an expanded and modified GARCH model to predict returns in rates. Tenti (1996) applied recurrent neural networks in forecasting rates. We expand these methods with genetic optimization and in some ways the recurrent and feedback strategies are similar to the cybernetic strategies that are introduced in this paper.

Further to the above research, Shanker et al (1996) analysed the effect of data standardization on neural network training, which provided foundations to today's ANN setup. Hann and Steurer (1996) attempted to forecast monthly and weekly rates using neural networks and linear models with some success. Neely et al (1997) utilized a genetic-programming approach to determine if technical analysis in rates was profitable with mixed results.

This research presented here uses a genetic optimization approach in an ANN framework so as to forecast rates. The process involves the use of a developed golden-ratio estimator and causal feedback loops which are the foundations of cybernetics.

2. Related Literature

El Shazly and El Shazly (1997) compared the forecasting performance of neural networks and forward rates, which evidently pointed to the usefulness of forward rates for *ex ante* results. Jamal and Sundar (1998) modelled rates with neural networks, which provided more evidence for positive ANN applications. Zhang et al (1998) used state-of-the-art ANN forecast models and again in Zhang and Hu (1998), used neural network forecasting which was tested on the Pound/Dollar rate. Both studies provided ANN applications in the positive direction.

With the advent of more modern estimation approaches, Alien and Karjalainen (1999) used genetic algorithms to find technical trading rules, which is among the first appearances of using GA for technical rules which relates to our current study.

Moving forward, El Shazly and El Shazly (1999) used genetically-evolved neural networks to forecast rates for four currencies, which was designed to forecast the 3-month spot rate and compared to forward and futures rates, then evaluated with accuracy and direction of change. The performance of their attempt was positive and supported the advancement of similar techniques.

Lisi and Schiavo (1999) compared neural networks and chaotic models for rate prediction, and concluded that both models outperformed the random walk. Shin and Han (2000) create an optimal signal multi-resolution by GA to support ANN for rate forecasting. They use wavelet analysis for feature detection useful in describing the signals with discontinuous or fractal structure in financial markets. They propose an integrated thresholding design of the optimal or near-optimal wavelet transformation by GAs to represent a significant signal most suitable in ANN models. They conclude that their integrated approach using GAs has better performance than the other wavelet thresholding algorithms.

Dempster and Jones (2001) developed a real-time adaptive trading system using genetic programming. They create a genetic program that could 'drop' trading rules as soon as they become loss-making or when more profitable rules are found. They attempt to emulate such traders by developing a trading system consisting of rules based on combinations of different indicators at different frequencies and lags. Their method shows that despite the individual indicators being generally loss-making over the data period, the best rule selected by the developed system is found to be modestly, but significantly, profitable in the presence of realistic transaction costs. This study serves as a good basis for development of a more robust system as we look at creating a signal-producing framework for risk measurement.

Qi and Zhang (2001) operationalise time series forecasting using neural network and investigate model selection criteria. Walczak (2001) empirically analysed data requirements for forecasting with neural networks. It became apparent that the turn of the century increasingly focused on ANN studies which is the foundation of automated trading and risk management applications.

Lawrenz and Westerhoff (2003) modelled rate behaviour with a GA by constructing a model where heterogeneous, boundedly-rational market participants rely on a mix of technical and fundamental trading rules applied according to a weighting scheme. Traders evaluate and update their mix of rules by genetic algorithm learning. The study focused on the human element, where interaction between the traders produces a complex behaviour of exchange rates. Their model simultaneously produces several stylized facts: high volatility, unit roots in the exchange rates, a fuzzy relationship between news and exchange-rate movements, cointegration between the exchange rate and its fundamental value, fat tails for returns, a declining kurtosis under time aggregation, weak evidence of mean reversion, and strong evidence of clustering in both volatility and trading volume. This is one of the first studies that attempt to provide a comprehensive risk profile of rates for risk and trading management.

Neely and Weller (2003) performed intra-day technical trading on the forex market with interesting results. They used a genetic program and an optimized linear forecasting model. When realistic transaction costs and trading hours are taken into account, they find no evidence of excess returns to the trading rules derived with either methodology. Thus, results are consistent with market efficiency. However, they do find that the trading rules discover some remarkably stable patterns in the data. This result provides some evidence that genetic learning with appropriate trading rules, uncovering hidden patterns in data is a possibility, which could be capitalized on by market participants.

Austin et al (2004) created adaptive systems for forex trading, which was a collaborative extension of the study by Dempster and Jones (2001), and was a joint effort with HSBC bank and utilized order flow data from the bank to compute trading volume. They find that order flow is an important input for their trading system and encourage more research in the direction. However, order flow data is limited since it will be difficult to compute the total global order flow and volume data since many transactions are private in nature, and so the best effort would be to use a close proxy as a good estimate of the global order flow, which makes the effort an obvious limitation.

Wei et al (2004) provided a comprehensive review of forecasting rates with ANNs. The integration of neural networks with other technologies produces mixed results but is encouraging and a promising tool for forecasting financial time series. They suggest that future research should address self-adaptation to different situations, which in effect are automation procedures.

In the paper where Phillips (2005) wrote on automated discovery processes in econometrics is an important reference to our study. Advances in computer power, electronic communication, and data collection processes have helped to elevate the status of empirical research within the economics profession in recent years and they now open up new possibilities for empirical econometric practice. Of particular significance is the ability to build econometric models in an automated way according to an algorithm of decision rules that allow for heteroskedastic and autocorrelation robust (HAR) inference. Computerized search algorithms may be implemented to seek out suitable models, thousands of regressions and model evaluations may be performed in seconds, statistical inference may be automated according to the properties of the data, and policy decisions can be made and adjusted in real time with the arrival of new data.

Brandl et al (2006) created an automated econometric DSS to forecast rates, which enables the extraction of essential information indispensable to set up accurate forecasting models based on a genetic algorithm and applies the resulting models to forecast daily EURUSD exchange rates. The genetic algorithm optimizes single-equation regression forecast models. The approach discussed is new in literature and, moreover, allows flexibility in automated model selection within a reasonably short time.

Lee and Wong (2007) created a multivariate neuro-fuzzy system for currency risk management decision-making and showed evidence of plausible performance for its predictive ability in forecasting the direction and magnitude of future rate movements. They evaluate the predictive performance of a hybrid multivariate model, using multiple macroeconomic and microstructure of foreign exchange market variables, and exploits the merits of adaptive learning ANN and intuitive reasoning (fuzzy-logic inference) tools. Empirical tests with statistical and machine learning criteria reveal plausible performance of its predictive capability.

Yu et al (2007) develop an intelligent system framework integrating forex forecasting, and incorporating IF-and-THEN trading rules, back-propagation neural network (BPNN)-based forex forecasting and web-based forex trading decision support, which is used to predict the directional change of daily forex rates and to provide intelligent online DSS for investors. Oh et al (2007) investigate the relative market efficiency in financial market data, using the approximate entropy (ApEn) method for a quantification of randomness in time series. They used the global foreign exchange market indices for 17 countries during two periods from 1984 to 1998 and from 1999 to 2004 in order to study the efficiency of markets around the market crisis. They found that on average, the ApEn values for European and North American foreign exchange markets are larger than those for African and Asian ones except Japan, and also that the ApEn for Asian markets increased significantly after the Asian currency crisis. Their results suggest that the markets with larger liquidity have higher market efficiency.

One of the last studies with relevance to our study was by Kiani and Kastens (2008) who analyse forex futures for the British pound, Canadian dollar, and Japanese yen against the USD. They model relationships between exchange rates in these currencies using linear models, feed forward artificial neural networks, and three versions of recurrent neural networks (RNN1, RNN2 and RNN3) for predicting these rates. They perform forecast evaluations based on a suite of forecast error tests and find mixed results for model selection.

We introduce in the next sections the various components of the genetic algorithm neural-network developed.

3. Golden-Ratio Estimator

We develop a golden-ratio estimator (GRE) based on the golden section, which is a line segment sectioned into two according to the golden ratio. The total length (a + b) is to the longer segment *a* as *a* is to the shorter segment *b*. The golden ratio, circa 1.618 can also be expressed as its inverse or 0.618.

The reason for using the golden ratio is that the ratio postulates that it includes the way humans behave, i.e. the ratio reflects the innate behavior of human thinking towards the treatment of proportions relative to 2-dimensional actions (Plummer, 2005).

Hence, the following is postulated as the basis of an input component of the GANN.

The golden ratio is ϕ , expressed algebraically is:

$$\frac{a+b}{a} = \frac{a}{b} = \phi \tag{3.1}$$

$$\phi = \frac{1+\sqrt{5}}{2} \approx 1.6180339887... \tag{3.2}$$

The following are corrollaries of the GR which are applied to the relationships between minimum, maximum and mean of open-to-close prices on a weekly basis as follows:

a: | min price – mean price | (3.3)
b: | mean price – max price | (3.4)
where a>b : hypothesized ratio=1.618
where b>a : hypothesized ratio=0.618

It is proposed that values out of this range bound above or below are termed as volatility fractures, outliers or extreme values; while values within this bound are known as volatility clusters. We compute the probability statistics for this occurrence for the EURUSD and USDJPY and draw comparisons. Thus the GRE is developed and estimated as follows:

Golden-Ratio Estimator (GRE) = GF/GR (3.5)
where GF is subject to genetic optimization between 0 and the golden ratio (GR).

The GRE is a ratio used as an input to the genetic-algorithm neural network (GANN) signal, which is described in the next sections. The GRE developed can be interpreted as the ratio of the conditionally-optimized GF normalized with the GR, which represents a multiplier to the genetic algorithm. The GRE also serves as an adjustment factor that absorbs or inflates the "gap" to satisfy the algorithm in creating an appropriate signal output.

4. Technical Explanatory Variables as Network Inputs

We introduce a class of technical explanatory variables (TEVs) which are classified into various groups. They are: Return Factors (REF), Return Volatility Factors (RVF), Mean Factors (MEF), Difference Factors (DIF), Range Factors (RAF), and Relative Ratio Factors (RRF).

The TEVs are described below:

There are two REFs which proxy the return function of forex rates.

The Return Factors (REF) are:

$$LNR = \ln(CP) - \ln(OP) = \ln(CP / OP) \tag{4.1}$$
$$LNRM = \ln(MAXP) - \ln(MINP) = \ln(MAXP / MINP) \tag{4.2}$$

where LNR is the logarithm of the closing price (CP) minus the logarithm of the open price (OP). LNR represents the continuously compounded nominal return if one is to buy at the open price and sell at the closing price; and LNRM is the continuously compounded nominal return if one is to buy at the minimum price and sell at the maximum price. LNRM, hence, represents the maximum possible return given this trading strategy.

The two RVFs are proxies to return volatilities of the above two possible return calculations.

The Return Volatility Factors (RVF) are:

$$LNR2 = LNR^2 \tag{4.3}$$

$$LNRM2 = LNRM^2 \tag{4.4}$$

where LNR2 is the square of LNR and LNRM2 is the square of LNRM. Both LNR2 and LNRM2 represent the volalities of the return statistics calculated above. By taking the squares of the returns is a common treatment for converting negative returns into positive numbers to analyse the magnitude of the volatility. The direction of volatility is not the concern here as the trading strategy includes both long and short positions that can realize returns in either direction.

Mean prices serve as a middle point of a series of prices or as in this case, the middle point of two prices. Often, the mean calculation is treated as a representation of an expected value, such as a mean return would equate to the expected return. Below are the two Mean Factors (MEF) that explicitly represent the price value between the open price and close price for the mean price (MEP), and for the MMEP, it represents the price value between the maximum and minimum prices. In equation form, they are:

Mean Factors (MEF):

$$MEP = (OP + CP) / 2 \tag{4.5}$$
$$MMEP = (MAXP - MINP) / 2 \tag{4.6}$$

where MEP is the Mean Price which is the average of the open price (OP) plus close price (CP); MMEP is the Minimax Mean Price which is the average of the maximum price (MAXP) and minimum price (MINP).

Difference factors (DIF) represent the range between various prices. These include 2 types of momentum calculations, one using open prices and the other using close prices; and both upside and downside potential returns. They are calculated as follows:

Difference Factors (DIF):

$$O2 - O1 = OP_t - OP_{t-1} \tag{4.7}$$

$$MOM = CP_t - CP_{t-1} \tag{4.8}$$

$$US = MAXP - OP \tag{4.9}$$

$$DS = MINP - OP \tag{4.10}$$

where O2-O1 is daily momemtum using open prices; MOM is daily momemtum using close prices; O1 or OP_{t-1} is the open price at the previous period or (t-1), O2 or OP_t is the open price at current period or t, hence O2-O1 is the momentum using open prices; MOM is the momentum using close prices, where $CP_t - CP_{t-1}$ is the close price at time t minus the close price at time (t-1). Both momentum calculations represent the range of price variation between periods and are an indicator for the relative momentum or strength of a continuous direction of a market trend. Momentum measures the acceleration and deceleration of prices, indicating if prices are up at an increasing rate or down at a decreasing rate.

The next TEV is Range Factors (RAF), which is similar to difference factors, but in this classification, only the positive values are utilized, i.e. the modulus of the calculations. There are a total of ten RAFs which are range values between combinations of the open, close, maximum and minimum prices. RAFs, however, exclude the values that are included as DIFs. The RAFs are as follows.

10 Range Factors (RAF):

$$O - C = |OP - CP| \tag{4.11}$$

where O-C is the *modulus* or *absolute value* of the open price minus the close price. The value represents the spread between the open and close prices, which indicates the volatility of prices during the time period under study, in this case, the weekly period. O-C can be interpreted as a volatility proxy to the price volatility between open and close prices.

$$O - M = |OP - MEP| \tag{4.12}$$

where O-M is the modulus difference of the open price and mean price, which represents a range value where the larger the O-M, the greater the range volatility.

$$C - M = |CP - MEP| \tag{4.13}$$

where C-M is the modulus difference of the close price and the mean price. This is also a range volatility proxy.

$$MIN - M = |MINP - MEP| \tag{4.14}$$

where MIN-M is the modulus difference of the minimum price and the mean price, which represent a range volatility with reference to the end of period price.

$$MAX - M = |MAXP - MEP| \tag{4.15}$$

where MAX-M is the modulus difference of the maximum price and mean price, which is a range volatility proxy as well.

$$MAX - MIN = MAXP - MINP \tag{4.16}$$

where MAX-MIN is the maximum price minus the minimum price. This represents the maximum range possible in any given time period.

$$O - MM = |OP - MMEP| \tag{4.17}$$

where O-MM is the modulus difference between the open price and the minimax mean price (MMEP).

$$C - MM = |CP - MMEP| \tag{4.18}$$

where C-MM is the modulus difference between the close price and the MMEP.

$$MIN - MM = |MINP - MMEP| \tag{4.19}$$

where MIN-MM is the modulus difference between the minimum price and the MMEP.

$$MAX - MM = |MAXP - MMEP| \tag{4.20}$$

where MAX-MM is the modulus difference between the maximum price and the MMEP. The last 3 calculations represent range volatility proxies with reference to the MMEP.

The final group of TEVs is the Relative-Ratio Factor (RRF) classification. These represent the ratio of the various combinations of open, close, maximum and minimum prices in ratio format. The six RRFs are as follows:

Relative-Ratio Factors (RRF):

$$O/C = OP/CP \tag{4.21}$$

where O/C is the open price divided by the close price.

$$MIN/MAX = MINP/MAXP \tag{4.22}$$

where MIN/MAX is the minimum price divided by the maximum price.

$$O/MIN = OP/MINP \tag{4.23}$$

where O/MIN is the open price divided by the minimum price.

$$O/MAX = OP/MAXP \tag{4.24}$$

where O/MAX is the open price divided by the maximum price.

$$C/MIN = CP/MINP \tag{4.25}$$

where C/MIN is the close price divided by the minimum price.

$$C/MAX = CP/MAXP \tag{4.26}$$

where C/MAX is the close price divided by the maximum price.

5. ANN Iterative Algorithm

This section describes the artificial neural network (ANN) iterative algorithm procedure that is implemented as follows:

1) Create an initial population within possible input variables and network architectures selected from the pool of technical explanatory variables (TEVs). Initial population members are transformed to a binary coded chromosome, which represents the trading signal of 0 or 1, where 0 represents short position or no action, and 1 represents long position.
2) Train and test these networks to determine how fit they are for solving the problem. Calculate the fitness measure of each trained network in the current population. The fitness measure used here is the absolute success rate of the signal output compared to the actual trading signal where an actual buy signal is where price at time t is lower than price at time t+1 and vice versa for the short or no action signal.
3) Rank the networks according to their fitness value and select the best networks through designing a probability experiment with the use of success rate measurements where if implied signal = actual signal, success rate is 1, if not 0.
4) Create the next generation by pairing up the genetic material representing the weights, inputs and neural structure of these networks. Refilling is done by mating the selected members by exchanging genes of chromosomes, where the genes are the various forms of TEVs, while the weights are in the form of the GRE.
5) Apply mutation in a random fashion according to a preassigned mutation probability with the use of evolutionary optimization technique.

6) Go back to stage (2) of the training/testing cycle until the optimum population is reached.

The process is continued generation after generation until an optimum (according to the predetermined criteria described in the next section) network architecture is reached. Through this process, the better networks survive and their features are carried forward into future generations and are combined with others to find better networks for the particular application. This genetic search method is much more effective than random searching, as the genetic process of recombining features vastly improves the speed of identifying highly fit networks. It also has a potential advantage over using only personal experience in building neural networks, as new and potentially better solutions may be found through this process which might otherwise be overlooked because of almost unavoidable assumptions made by the user.

6. Genetic-Algorithm Neural-Network (GANN)

GANN are constructed using both genetic feedforward (GFF) and genetic feedback (GFB) networks. Genetic-Algorithm (GA) is applied to the initial parameter space for optimization. To evaluate the performance of the models, observations are used as 'out-of-sample' testing sample points.

Inspired by the role of mutation of an organism's DNA in natural evolution - an evolutionary algorithm (a subset of GA) periodically makes random changes or mutations in one or more members of the current population, yielding a new candidate solution (which may be better or worse than existing population members). There are many possible ways to perform a "mutation," and the Evolutionary Solver (ES) actually employs three different mutation strategies. The result of a mutation may be an infeasible solution, and the ES attempts to "repair" such a solution to make it feasible; this is sometimes, but not always, successful.

The research deals with a DS-approach which automatically searches for econometric forecasting specifications in multivariate, nonlinear, dynamic models by means of a GA, specifically with the ES application. For an overview of automated attempts in selecting econometric forecast models see for example Pesaran and Timmermann (2005).

Forecasting time series y can generally be described as follows: given a set of explaining time series X, we are trying to find a function f(.), such that

$$y_{t+1} = f(X, y_t, y_{t-1}, y_{t-2}, \ldots) + \varepsilon_{t+1} = \hat{y}_{t+1} + \varepsilon_{t+1} \tag{6.1}$$

where the time series ε is statistically independent or patternless and $\hat{y}_{t+1}$ is the forecast for y_{t+1}.

An FX-trading decision g(.) can be seen as the mapping,

$$g : \hat{y}_{t+1} \rightarrow \{buy, sell\} \quad (6.2)$$

Coding and Genetic Optimization Procedure

As usual, a population P is a set of individual or chromosomes g_i , i.e.,

$$P_T = \{g_1, \ldots, g_{np}\} \quad (6.3)$$

Since in our GA-application each chromosome has to represent a set of TEVs contained in a regression model as well as the number of observations to be included in the (in-sample) regression, the internal bit-representation of a chromosome g_i is as follows:

$$g_i = \begin{matrix} b_{i01} & b_{i02}, \ldots, & b_{i0n_w} \\ b_{i11} & b_{i12}, \ldots, & b_{i1n_w} \\ b_{i21} & b_{i22}, \ldots, & b_{i2n_w} \end{matrix} \text{ and so on...} \quad (6.4)$$

where b denotes binary variables, i.e. b denotes the number of variables included in the regression model represented by g and n and n denoting the number of bits used for coding a variable index and the number of observations to be included in the model, respectively. Note that the coding mechanism uses variable chromosome length, since in our case a chromosome is a sequence of variable indices, and the GA is allowed to arbitrarily set the number of variables between some user-defined lower and upper bound.

The objective function is to maximize the success rate which is the sum total of the efficiency output. The success rate measures the percentage success where the model predicts the price movements of the actual signal i.e. where implied signal equates to actual signal. The contraint function is the GR-Factor (GF), which is a user-defined bounded variable subject to GF >= 0 and <= GR. By estimating GF under GANN optimization, the system computes the implied signal that best-fits the actual signal of the price feed which results in an optimized solution for the model.

Optimization with Premium Solver

Microsoft (MS) Excel Solver add-in tool uses the Generalized Reduced Gradient (GRG) non-linear optimization code developed by Leon Lasdon, University of Texas at Austin, and Allan Waren, Cleveland State University. This study uses visual basic for applications (VBA) in MS Visual C++ environment to implement the model.

7. GANN-GRE (GANN1) Optimization

Following the above sections, the developed model is the Genetic-Algorithm Neural-Network with Golden-Ratio Estimator (GANN-GRE or for simplicity just GANN1). It is programmed as an iterative algorithm providing a signal output desribed as follows.

GANN1 is estimated based on the cybernetic concept that all technical explanatory variables (TEVs) within the framework proposed impact decision for trading. It is corollarized that TEVs contribute as a decision coefficient and/or multiplier of the upside potential (US) for a long (buy) decision, and a decision coefficient and/or multiplier of the downside risk (DS) for a short (sell) decision.

In economics, a multiplier is a factor of proportionality that measures how much an endogenous variable changes in response to a change in some exogenous variable. That is, suppose a one-unit change in some variable x causes another variable y to change by M units. Then the multiplier is M. In the case here, the TEVs are endogenous for the determination of the exogenous trading signal.

Both US and DS for both decisions are factorised by momentum (MOM), which represents an indication of the directional strength, and subject to adjustment by the GRE, which acts as a buffer term to "soak" or "inflate" estimates according to the optimization functions. The proposed form for GANN-GRE is as follows.

GANN-GRE signal at time t utilizing all values at (t-1) is estimated as:

If (REF * RVF * MEF * RAF * RRF * MOM * GRE * US)>
(REF * RVF * MEF * RAF * RRF * MOM * GRE * DS), then 1, otherwise 0. (7.1)

where GRE = GF/GR subject to 0<GF<1.618; REF: return-factors; RVF: return-volatility factors; MEF: mean factors; RAF: range factors; RRF: relative-ratio factors; US: upside; MOM: momentum; and DS: downside.

Hence, the GANN1 signal comprises weekly values at time (t-1) that impound the following combinational conditions: US>DS, scale-adjusted by MOM with GRE as a multiplier under constraint and GA optimized. The estimtated outputs of 1 signifies a long signal, 0 signifies a short or inaction position.

The outputs performances are evaluated based on the following designs:

Actual Signal: if close price > open price, then 1, otherwise 0.

Signal Efficiency: if actual signal = GANN signal, then 1, otherwise 0.

Output Parameters: US/DS Signals, One-Day Ahead Long/Short Signals, Modified Value-at-Risk (MVaR).

While other studies have included macroeconomic factors such as the gross domestic product (GDP), interest rates, import/export statistics, cosumer price index (CPI), etc, these are excluded from this study as the data are mostly static on a short-term basis and become a non-dynamic explanatory factor that makes less sense to include in this technically-driven model. The derivative parameters represent calculated proxies for risk and return volatility measures in various forms.

As described in the previous chapter, GRE is GF/GR and subject to constraint $0 \le GF \le 1.618$. The rationale being that the US or DS terms can be scaled to a potential maximum of 1 or 0 with the GRE, which is a range estimate for the risk threshold. Implementing standard evolutionary (a subset of genetic algorithm techniques) optimization derives a set of results. If the adjusted-US is greater than the adjusted-DS, the signal should be long (buy) signal, otherwise vice versa.

In notation form:

If

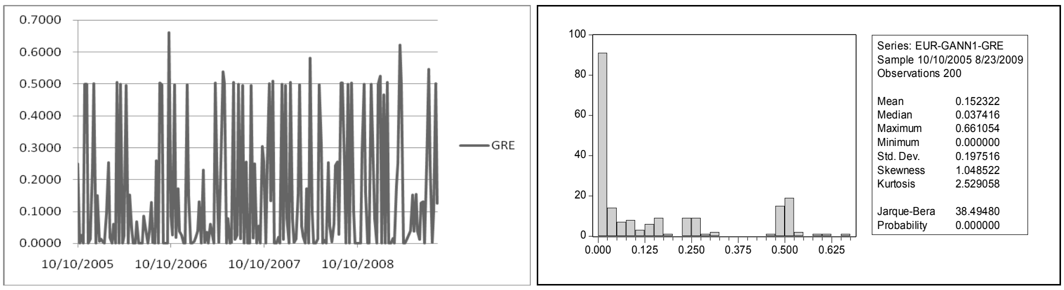
$$(TEV_{n,t} \times MOM_{n,t} \times GRE_{n,t} \times US_{n,t}) > (TEV_{n,t} \times MOM_{n,t} \times GRE_{n,t} \times DS_{n,t}) \tag{7.2}$$

→

$$(REF_{n,t} \times RVF_{n,t} \times MEF_{n,t} \times RAF_{n,t} \times RRF_{n,t} \times MOM_{n,t} \times GRE_{n,t} \times US_{n,t}) > (REF_{n,t} \times RVF_{n,t} \times MEF_{n,t} \times RAF_{n,t} \times RRF_{n,t} \times MOM_{n,t} \times GRE_{n,t} \times DS_{n,t}) \tag{7.3}$$

Then 1, otherwise 0, where GRE = GF/GR, which represents a risk threshold factor.
where TEV: technical explanatory variable; MOM: momentum; GRE: golden-ratio estimator; US: upside; DS: downside; REF: return factor; RVF: return volatility factor; MEF: mean factor; RAF: range factor; and RRF: relative-ratio factor.

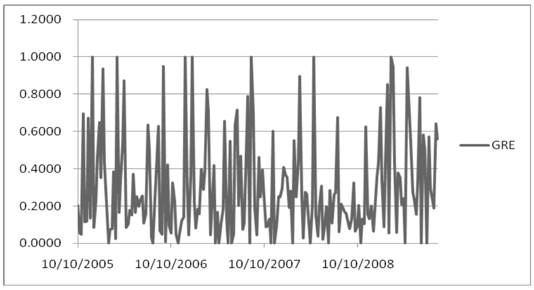
Figure 7.1 - EURUSD-GANN1-GRE Charts

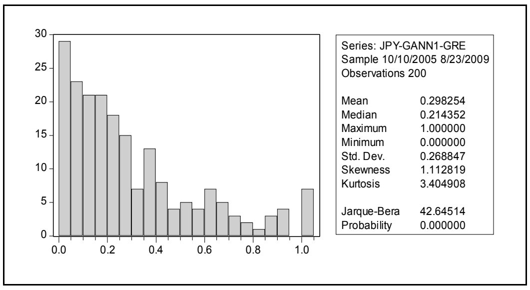


The GRE values for EURUSD under GANN1-optimization are non-normal as expected that is similar to the results for the GF values previously. The important result obtained at the 97% cumulative value is that the range of values are between 0 to 0.5194, which signifies that the GRE values of 0 to 0.5194 represent 97% of the GANN inputs. Since GRE is the normalization of GR, the values are between 0 and 1. GRE represents a percentage multiplier in the optimization procedure. Evidence above shows that the volatility structure of GRE under optimization is of a volatility band within approximately 52% of the maximum allowable estimator (GRE). The histogram also shows there exist a peakedness on the extreme left side of the distribution, implying some evidence of a trend formation.

The GANN-GRE (GANN1) optimization that is performed for EURUSD is also estimated for the USDJPY and presented here as follows.

Figure 7.2 - USDJPY-GANN1-GRE Charts





Likewise, the GRE values for USDJPY under GANN1-optimization are non-normal, and the results are markedly different to those of EURUSD. The values are more dispersed and varying with values ranging the entire spectrum between 0 and 1. It is noted that the GRE values concentrate in a band of 0 to 0.4286, which make up 75.0%. The range of 0 to 0.714 make up 90.5%. This represents evidence that the GRE statistic is less sensitive for USDJPY than for the EURUSD series.

8. GANN-GRE-2 (GANN2) Optimization

GANN-GRE-2 is termed GANN2 and is the same as GANN1 except for a time adjustment, where the operation of the signal function utilizes data from (t-1) in time. In notation form:

If

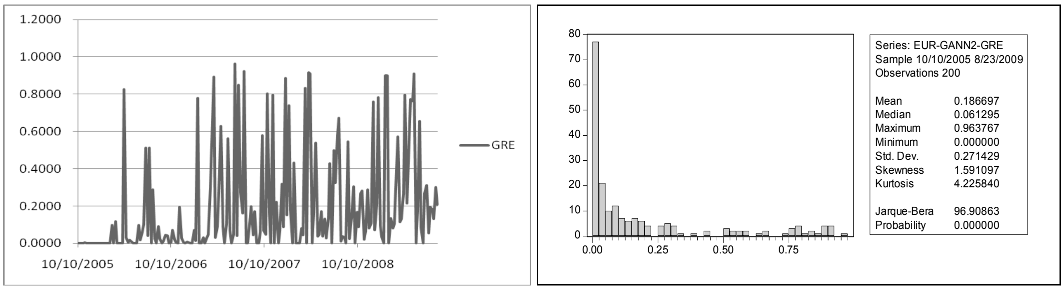
$$(TEV_{n,t-1} \times MOM_{n,t-1} \times GRE_{n,t-1} \times US_{n,t-1}) > (TEV_{n,t-1} \times MOM_{n,t-1} \times GRE_{n,t-1} \times DS_{n,t-1}) \quad (7.4)$$

→

$$(REF_{n,t-1} \times RVF_{n,t-1} \times MEF_{n,t-1} \times RAF_{n,t-1} \times RRF_{n,t-1} \times MOM_{n,t-1} \times GRE_{n,t-1} \times US_{n,t-1}) > (REF_{n,t-1} \times RVF_{n,t-1} \times MEF_{n,t-1} \times RAF_{n,t-1} \times RRF_{n,t-1} \times MOM_{n,t-1} \times GRE_{n,t-1} \times DS_{n,t-1}) \quad (7.5)$$

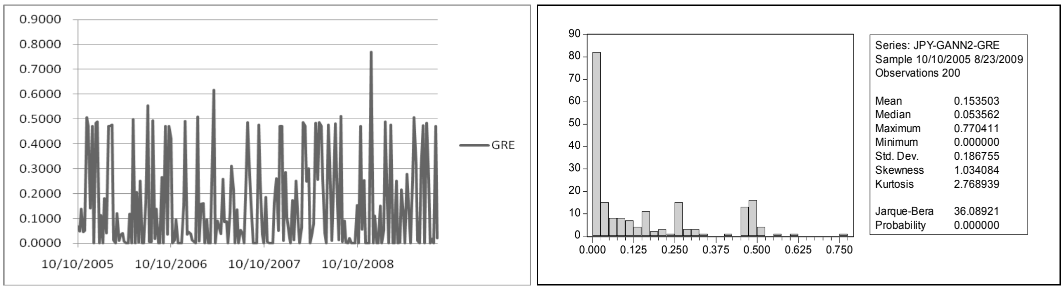
Then 1, otherwise 0, where GRE = GF/GR (risk threshold factor / multiplier).
where TEV: technical explanatory variable; MOM: momentum; GRE: golden-ratio estimator; US: upside; DS: downside; REF: return factor; RVF: return volatility factor; MEF: mean factor; RAF: range factor; and RRF: relative-ratio factor.

Figure 8.1 - EURUSD-GANN2-GRE Charts



The GRE values for EURUSD under GANN2 optimization are non-normal, and values are dispersed and concentrate in between 0 to 0.4130, which comprise 82.5%. GRE values of 0 to 0.757 account for 90% of values, or 76% of maximum possible value. Likewise, GANN2 is performed for USDJPY.

Figure 8.2 - USDJPY-GANN2-GRE Charts



The GRE values for USDJPY under GANN2-optimization presented above are non-normal, but similar to GF values in the previous section, the evidence is clear that the values are regularized between 0 to 0.500, which comprise 90.0%. In other words, the GRE values of 0 to 0.5 account for 90% of the optimization results, which represents 50% of the entire possible spectrum allowed under optimization. This result is meaningful as it means that the estimator used (GRE) is able to explain 90% of the GANN2 results.

9. GANN Summary Results

This section analyses the results for the return volatilities of LNR2 and LNRM2 under GANN optimization and are described below.

EURUSD Return Volatility Analysis

LNR2 and LNRM2 volatilties display instability patterns over the 200 weekly data points for periods August 2005 to August 2009. There is an obvious volatility breakout for the period of mid-2008 to mid-

2009, which is beyond the volatility range of the general trend. Based on the trading algorithms for the period under study, the upside (US) signal for EURUSD is 18.0% and downside (DS) signal is 12.0%.

The EURUSD series reveal the following mean values computed as: a=0.0148, b=0.0153, a/b=1.3624. Under the GF-framework, volatilty fractures (VFs) occur 22.5% for EV@0.618 (where EV: extreme value) and 20.5% for EV@1.618.

VCF-analysis of LNR2 reveals 81.5% is within volatilities (vols) of 0.000% - 0.027%, while LNRM2 reveals 74.5% is within vols of 0.000% - 0.072%. LNR reveals 45.5% are positive, while LNRM reveals 2.21% mean returns with this weekly strategy. There are evidence of volatility clusters in the data series, while volatility fractures occur that are in line with EV@0.618 and EV@1.618.

GANN1 encompasses the technical factors with GRE, and is genetically-optimized to produce same-period forecasting. GANN2 encompasses all technical factors with GRE, and is genetically-optimized but utilizes 1-period before as a circular causal (continuous) feedback loop of data for 1-period ahead forecast (>15,000 iterations are used in the optimization algorithms). The results are reported as follows.

The success rates for GANN1 are: long signal @ 0.30, actual signal (ASIG) long @ 0.54, which means that the efficiency rate is 67%. The partition for efficiency is: long efficiency @ 85%, short efficiency @ 59% (with >16,800 iterations, no further improvements are observed and obtained).

For GANN2: long signal @ 0.31, ASIG long @ 0.54, hence 65% efficiency rate. Efficiency partition is: long efficiency @ 82% and short efficiency @ 58%.

Finally, for GANN1, the mean values of GF=0.2465 and GRE=0.1523. For GANN2: mean values of GF=0.2145 and GRE=0.1326 (see below on GRE for USDJPY for discussion on this).

USDJPY Return Volatility Analysis

The trading algorithms reveal US signal 15.0% and DS signal 8.5%. GR-framework reveals volatilty fractures occur 12.0% for EV@0.618 and 28.5% for EV@1.618. The values of a=1.4837, b=1.2458, and a/b=1.5493 (closer to GR=1.618 compared to EURUSD, implying that the GR algorithm for USDJPY has a stronger tendency or approximation to GR).

LNR2 reveals 76.0% is within vols of 0.000% - 0.040% (27.0% falls out of range). LNRM2 reveals 79.0% is within vols of 0.000% - 0.109% (21.0% falls out of range). LNR reveals 60.0% are positive. LNRM reveals mean returns for a weekly strategy averages 2.555%.

For GANN1: long signal @ 0.47, ASIG long @ 0.48, this represents 61% success efficiency. Long efficiency @ 61%, and short efficiency @ 60% (>18,000 iterations and above, no further improvements are obtained). For GANN2: long signal @ 0.28, ASIG long @ 0.48, 78% efficiency. Long efficiency @ 96%, and short efficiency @ 71%. And finally for GANN1: GF=0.4826, and GRE=0.2983. GANN2: GF=0.2838, and GRE=0.1754 (the GRE value for EURUSD-GANN2 is the lowest, implying that the GRE requires a smaller range for obtaining optimization i.e. GANN2 for EURUSD is most efficient).

LNR2 volatility fractures occur at 18.5% for EURUSD and 24% for USDJPY. Under the GR-risk framework, DS is 22.5% for EURUSD and only 12.0% for USDJPY, implying less downside volatility in the USDJPY.

The GANN2 model for EURUSD in the long transaction achieves signal efficiency of 82%. GANN2 long signal efficiency for USDJPY is a high 96%, implying that the GANN2 models are the most useful in implementing for an automated DSS.

Table 9.1 – LNR2 Summary Results

MEAN or VALUE	EURUSD	USDJPY
LNR	45.5% positive	60.0% positive
LNRM	2.210%	2.555%
US / DS	18.0% / 12.0%	15.0% / 8.5%
a / b	0.0148 / 0.0153	1.4837 / 1.2458
(a/b)	1.3624	1.5493
LNR2-VC	81.5% (0-0.027%)	76.0% (0-0.040%)
LNR2-VF	18.5% (>0.027%)	27.0% (>0.040%)
LNR2-VF-DS @ GR	22.5% @ EV0.618	12.0% @ EV0.618
LNR2-VF-US @ GR	20.5% @ EV1.618	28.5% @ EV1.618
LNRM2-VC	74.5% (0-0.072%)	79.0% (0-0.109%)
LNRM2-VF	25.5% (>0.072%)	21.0% (>0.109%)
GANN1-LSIG / ASIG	0.30 / 0.54	0.47 / 0.48
GANN1-EFF	67%	61%
GANN1-L-EFF / S-EFF	85% / 59%	61% / 60%
GANN2-LSIG / ASIG	0.31 / 0.54	0.28 / 0.48
GANN2-EFF	65%	78%
GANN2-L-EFF / S-EFF	82% / 58%	96% / 71%
GANN1-GF / GRE	0.2465 / 0.1523	0.4826 / 0.2983
GANN2-GF / GRE	0.2145 / 0.1326	0.2838 / 0.1754

Note: US- upside; DS- downside; a=|min-mean|; b=|max-mean|; Sig TEV- Significant Technical Explanatory Variable; LNR2-VC is LNR2 volatility within volatility cluster range; LNR2-VF is LNR2 volatility out of volatility cluster range, i.e. volatility fracture has occurred; EFF-efficiency; While it is apparent that EURUSD possesses more US and DS risks compared to USDJPY, the GR-risk value of (a/b) for both currencies is >1, implying that the downside is larger than the upside.

10. Risk Control with Value-at-Risk

The Value-at-Risk (VaR) measure is commonly used for calculating the risk of loss on a specific portfolio of financial assets. For a given portfolio, probability and time horizon, VaR is defined as a threshold value such that the probability that the mark-to-market loss on the portfolio over the given time horizon exceeds this value (assuming normal markets) at the given probability level.

Value-at-Risk Metric
Given some confidence level $\alpha \in (0,1)$, the VaR of the portfolio at the confidence level α is given by the smallest number l such that the probability that the loss L exceeds l is not larger than $(1-\alpha)$.
In notation form:

$$VaR_{\alpha} = \inf\{l \in R : P(L > l) \leq 1 - \alpha\} = \inf\{l \in R : F_L(l) \geq \alpha\} \quad (10.1)$$

On the left is the symbol of VaR at confidence level α. The right equality assumes an underlying probability distribution, which makes it true only for parametric VaR.

In this study, the VaR statistic calculated has no underlying distribution assumption. Under GANN, the optimization is based on the definition of VaR as the maximum possible loss over a specified time horizon (here, weekly periods are the defined trading strategy) within a given confidence level (95% is used here). The optimization technique solves the problem by finding the market positions that maximize the loss, subject to that all constraints are satisfied within their boundary values.

10.1 MVaR Analysis

The following tables and charts depict the Modified-Value-at-Risk (MVaR) numbers for both long and short positions for the time horizon under study. The VaR is modified in the sense that the probability distribution is not assumed to be normal but rather, the distribution is obtained from the actual long and short transaction calculations.

The MVaR is calculated and reported in percentage terms, as follows:

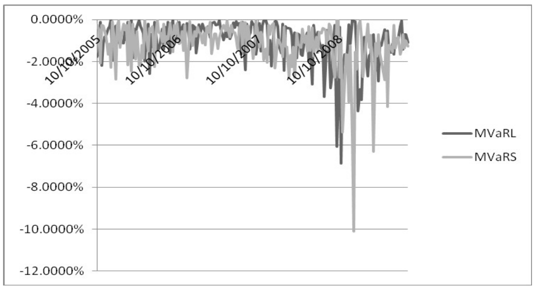
MVaRL = [(Minimum Price – Open Price)/Open Price]% (10.2)
MVaRS = [(Maximum Price – Open Price)/Open Price]% (10.3)

Under GANN, the following MVaR are computed as follows:
MVaRL-G1: if GANN1=1, then MVaRL otherwise 0. (10.4)
MVaRS-G1: if GANN1=0, then MVaRS otherwise 0. (10.5)
MVaRL-G2: if GANN2=1, then MVaRL otherwise 0. (10.6)
MVaRS-G2: if GANN2=0, then MVaRS otherwise 0. (10.7)

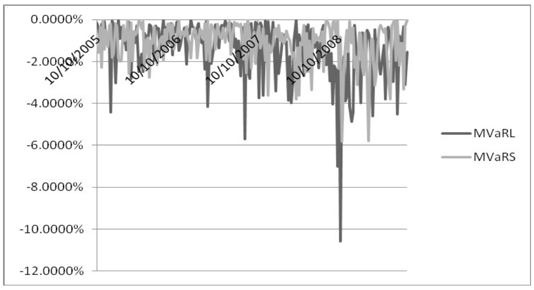
where MVaRL is modified Value-at-Risk for long signal; MVaRS is modified VaR for short signal; MVaRL-G1 is MVaRL under GANN1; MVaRS-G1 is MVaRS under GANN2; MVaRL-G2 is MVaRL under GANN2; and MVaRS-G2 under GANN2.

Figure 10.1 – MVaR Volatiltiy Charts

EURUSD-MVaR Charts



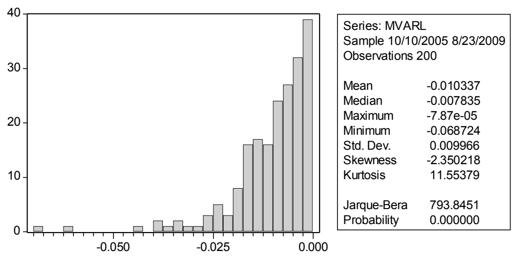
USDJPY-MVaR Charts



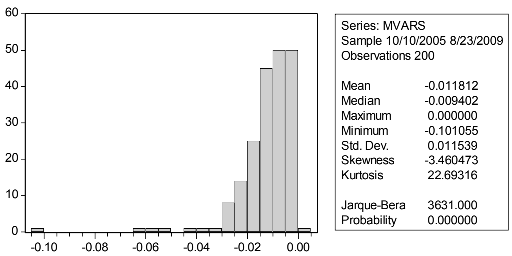
The above charts show the absolute transactional modified-Value-at-Risk for both EURUSD and USDJPY based on a 200-weekly trading strategy; and specifically, the graphs depict for both the MVaRL and MVaRS statistics for both currency series. The charts reveal that for EURUSD, short positions display more volatility, while for USDJPY, the long position is more volatile.

Figure 10.2 – MVaRL and MVaRS Distribution Charts

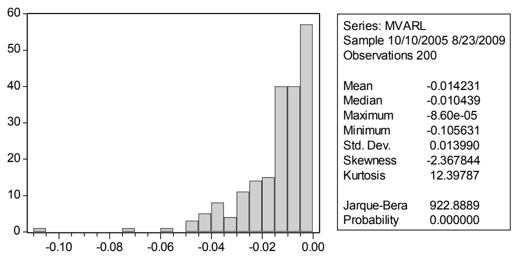
EURUSD-MVaRL



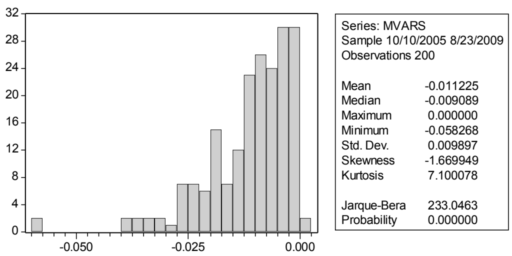
EURUSD-MVaRS



USDJPY-MVaRL



USDJPY-MVaRS



The above four distributions of MVaR are negatively skewed as expected due to the way the values are calculated. Longing the USDJPY and shorting the EURUSD over the period with a weekly trading strategy offers the largest downside risk or potential loss.

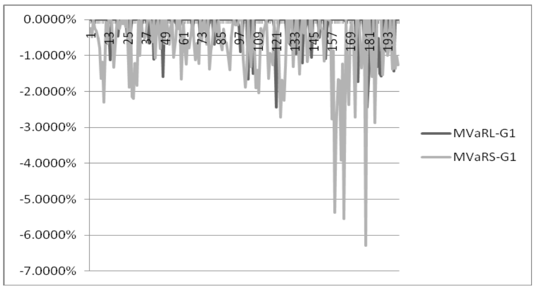
10.2 MVaR Results with GANN1 and GANN2

By implementing a quantitative approach, it is possible to compute precise calculations for risk profiling and characterization of currency series in terms of MVaR. In the risk matrix and framework developed here, the inputs are objective in interpretation and void of judgements since the data is dependent on a predefined criteria.

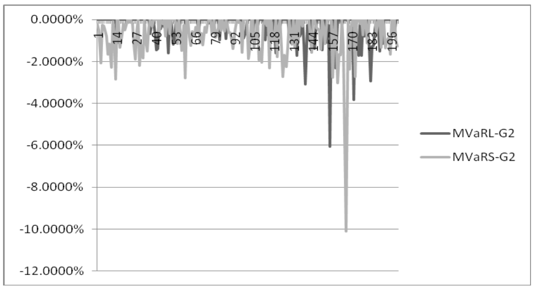
The following MVaR estimates are calculated based on the signals produced by both GANN1 and GANN2.

Figure 10.3 – MVaR@GANN1 and GANN2 Charts

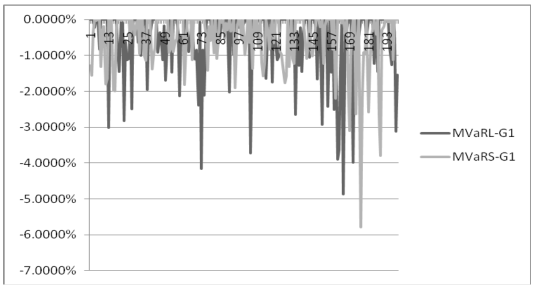
EURUSD-MVaR@GANN1 Charts



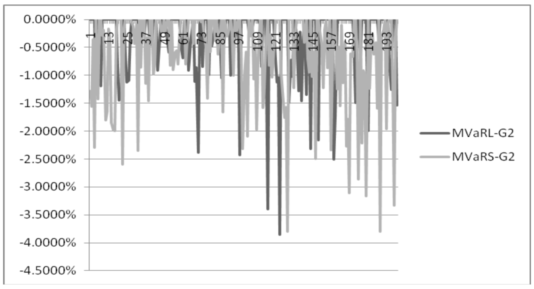
EURUSD-MVaR@GANN2 Charts



USDJPY-MVaR@GANN1 Charts



USDJPY-MVaR@GANN2 Charts



The graphs above show the magnitudes (all are downside) of MVaR for both currency series and for both optimizations under GANN1 and GANN2.

Specifically, the following are the computed results obtained for MVaR under both GANN1 and GANN2 for the EURUSD series:

EURUSD-MVaRL @ GANN1: -0.2111% (minimum)
EURUSD-MVaRL @ GANN2: -0.3297%
EURUSD-MVaRS @ GANN1: -0.7239% (maximum)
EURUSD-MVaRS @ GANN2: -0.6945%

The MVaR estimates for EURUSD reveal that the maximum and minimum MVaR are obtained under GANN1 optimization, which means that the range of MVaR is greater under GANN1. GANN2 optimization results offer a smaller range of downside MVaR, which implies that the use of GANN2 is more favourable for the EURUSD series.

In other words, the above results show that short positions under GANN1 have the highest risk of loss, and long positions under GANN1 have the lowest loss risk. Hence, an investor is able to choose the relevant optimization model for different values of MVaR based on individual risk aversion levels.

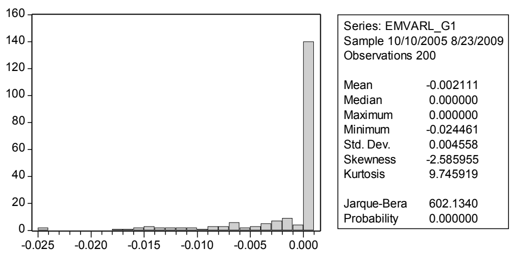
The following are the results for the USDJPY series. MVaR are computed for both GANN1 and GANN2 optimizations.

JPY-MVaRL @ GANN1: -0.5425%
JPY-MVaRL @ GANN2: -0.3433% (minimum)
JPY-MVaRS @ GANN1: -0.5028%
JPY-MVaRS @ GANN2: -0.6156% (maximum)

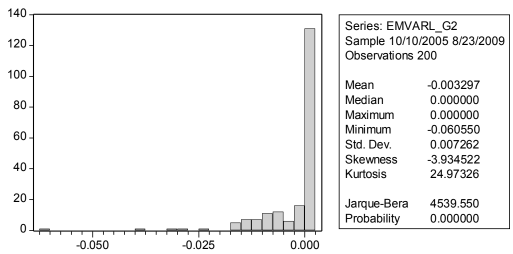
Short positions under GANN2 offer the highest potential loss for USDJPY, while the lowest loss risk is for long positions under GANN2. Hence, GANN1 offers a more risk-averse choice for an investor that is choosing between the optimization models.

Figure 10.4 – EURUSD-MVaR@GANN1 and GANN2 Charts

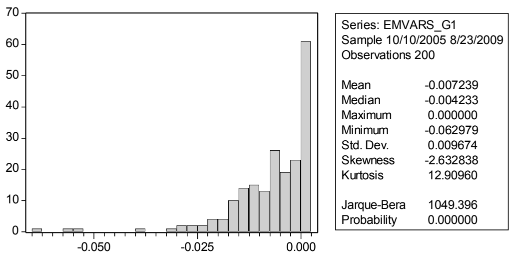
EURUSD-MVaRL@GANN1



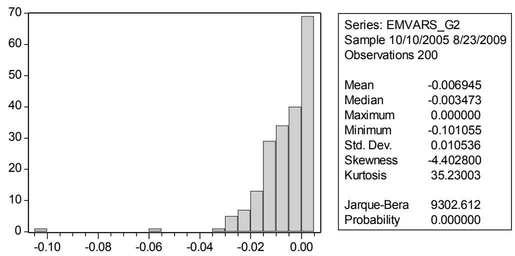
EURUSD-MVaRL@GANN2



EURUSD-MVaRS@GANN1



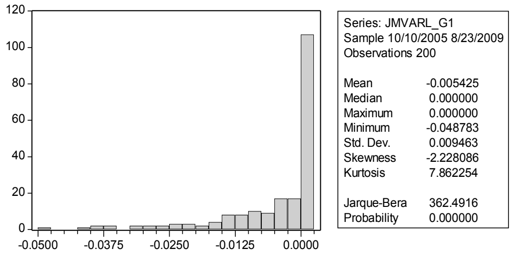
EURUSD-MVaRS@GANN2



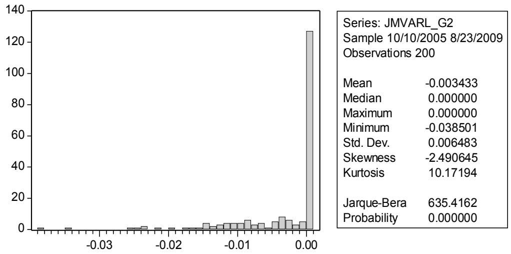
The charts above reveal that long transactions under GANN1 and long transactions under GANN2 are similar in distributional shape, while short positions under GANN1 and GANN2 are also similar in distribution for MVaR. By observation, long positions for MVaR under both GANN optimizations appear to cluster on the extreme right values. This implies that the MVaR is more concentrated for long positions in EURUSD. This peculiar long transactional characteristic is present for the EURUSD data and weekly strategy under study.

Figure 10.5 – USDJPY-MVaR@GANN1 and GANN2 Charts

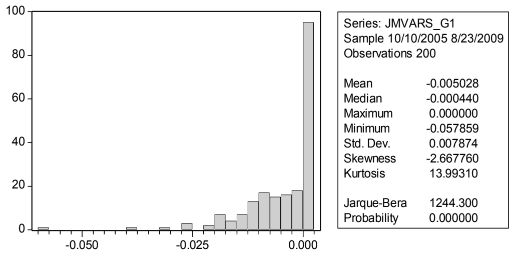
USDJPY-MVaRL@GANN1



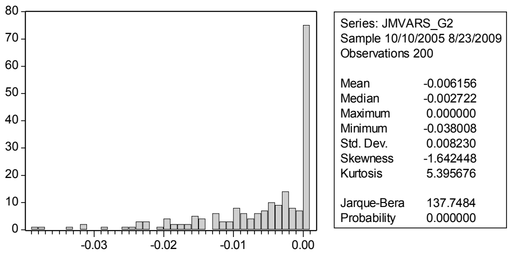
USDJPY-MVaRL@GANN2



USDJPY-MVaRS@GANN1



USDJPY-MVaRS@GANN2



The charts above for USDJPY reveal a more consistent pattern. Both long and short transactions under GANN1 are similar, while both long and short transactions under GANN2 are similar in distributional shape for MVaR. This implies that MVaR for USDJPY has similar long and short transactional risks specific to each GANN optimization output. This is evidence that the USDJPY series has GANN-specific MVaR results, while EURUSD does not possess this feature.

11. Summary and Implications

We provide risk profiles and characteristics of EURUSD and USDJPY in terms of MVaR in both long and short trading decisions under GANN optimizations. Table 13.1 provides the summary results for the MVaR estimates.

The results without GANN optimization (i.e. no DSS) show that EURUSD has a smaller MVaR loss for long transactions while USDJPY has a smaller MVaR for short transactions. In other words, for the period under study, a trader should long the EURUSD and short the USDJPY to minimize MVaR.

A critical result obtained is that the MVaRL values for EURUSD under both GANN1 and GANN2 are the only values that display VCF effects, and are overall lower than values for USDJPY; whereas there are lower MVaRS estimates under GANN1 and GANN2 for USDJPY, implying lower risks for short transactions for the USDJPY, however there is no evidence of VCF effects. Furthermore, the estimates for >90% MVaR values are estimated for both currency series and the results show that GANN1 offers less MVaR for EURUSD, while for the USDJPY, GANN1 is preferred for a short strategy but GANN2 is preferred for a long strategy.

In statistical terms, the lowest risk of loss if an investor uses the GANN system is in adopting a long strategy for the EURUSD is only -0.211% for GANN1 and -0.330% for GANN2. The highest risk of loss is offered on a short strategy on EURUSD for both GANN1 and GANN, while trading the USDJPY offers a risk of loss between these extreme scenarios.

Table 11.1 – MVaR Summary Results

MEAN or VALUE	EURUSD	USDJPY
MVaRL / MVaRS	-1.034% / -1.181%	-1.423% / -1.123%
MVaRL-GANN1/GANN2	-0.211%** / -0.330%**	-0.543% / -0.343%
MVaRS-GANN1/GANN2	-0.724% / -0.695%	-0.503% / -0.616%
MVaRL-GANN1@>90%	> -0.349%*	> -1.045%*
MVaRS-GANN1@>90%	> -1.35%*	> -1.24%*
MVaRL-GANN2@>90%	> -0.865%*	> -0.55%*
MVaRS-GANN2@>90%	> -1.444%*	> -2.172%*

Note: ** symbolizes that VCF exists. VCF exists only for EURUSD-MVaRL under both GANN1 and GANN2; * represents values that are less than 0; MVaRL: modified value-at-risk for long transactions; MVaRS: modified value-at-risk for short transactions; GANN1: Genetic Algorithm Neural Network 1; GANN2: Genetic Algorithm Neural Network 2 1-period ahead feedback loop optimization ; @>90% means that the values represent the cumulative frequency of just being >90% of the total distribution.

12. Concluding Remarks

Forex volatility in all its forms can have a wide repercussion on trading decision making and foreign exchange policy. The aftermath caused by terrorist attacks, financial reporting scandals and the recent subprime mortgage crisis have caused great turmoil to world financial markets and there is clear evidence that there is a tandem increment in forex volatility as shown by the results herein.

For the reason that there is a direct link between financial market uncertainty and public confidence, policy makers often rely on market estimates of volatility as a barometer for the vulnerability of financial markets and the economy. In the US, the Federal Reserve explicitly takes into account the volatility of stocks, bonds, currencies and commodities in establishing its monetary policy. This is also common practice among other governments.

Table below displays the myriad of results obtained in this study and are summarily discussed thereafter for EURUSD and USDJPY currency pair series.

Overall Summary

The study has provided a comprehensive process in developing risk profiles that depict the relevant risk characteristics of two most important currency pairs in the world today. The goals are to offer to traders and policy makers advanced risk management techniques that utilize a suite of technical explanatory variables that are developed.

One of the key outcomes of the research is that RRFs are most the significant technical explanatory factors for explaining both EURUSD and USDJPY return volatilities, while other TEVs do not improve the significance of the overall models herein. This offers an extremely interesting result since prior to this study, RRFs have not been closely studied by the academic world but more by the practising world. The direction of technical analysis should be geared towards quantitative methods that describe with more precision the risk statistics of trading decisions.

LNR2 volatility fractures occur at 18.5% for EURUSD and 24% for USDJPY. Under the GR risk framework, DS is 22.5% for EURUSD and only 12.0% for USDJPY, implying that there is less downside volatility in the USDJPY.

The GANN2 model for EURUSD in the long transaction achieves signal efficiency of 82%. GANN2 long signal efficiency for USDJPY is a high 96%, implying that the GANN2 models are the most useful in implementing for an automated DSS, which can be executed through macros or a repetitive function in MS Visual C++ utilizing live streaming data on a per tick or per customized period basis.

This study postulates the following:

Stylized Fact I: GANN-GRE optimization with feedback control (circular causal or with data-looping as the optimization continuously uses (n-1)-period data for optimizing n-period data) termed GANN2 is most efficient in producing up to 96% efficiency for a weekly long strategy on the USDJPY. This is the basis of risk cybernetics and autobots.

Stylized Fact II: MVaR estimates under GANN provide long and short risk statistics for forex trading signals and decisions. For e.g. a long strategy on EURUSD under GANN1 or GANN2 offer MVaR values of 4 to 5 times smaller than MVaR without either GANN signals.

Contributions of Research

This study can ben implemented in accordance to the latest ISO guidelines, which are useful for corporations keen on risk management for trading decisions. The methods herein are a suggested way of risk management for trading volatility or for hedging decisions.

Risk characterization allows traders to view risk perspectives objectively. For risky portfolios, developing a pragmatic and speedy method for managing risks is essential. As practiced on a daily basis by major financial institutions and investors, volatility management is a routine that never ends. The process repeats itself and is crucial to almost everyone involved in international trade and is exposed to currency risks and fluctuations.

In particular, the study investigates the application of modern financial theory and financial risk management tools and techniques to the case of investment and trading portfolios, which contain vast amount of forex cash securities (between both long and short positions). It also provides an insight on how to measure and report active investment and proprietary trading risk in an innovative and proactive way to senior management in financial and non-financial entities.

Like in every study, there are limitations to this research. As there are enumerous factors that shed light to explain the return volatility performance of forex rates, the study, from the outset, sets the research parameters to include all forms of technical data and indicators only. The exclusion of fundamental factors and other variables is deliberate.

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