Dynamic Hedge Funds Allocation – An Adaptive Neuro-fuzzy Inference System (ANFIS) Approach

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Background and Aims

Funds (inclusive of superfunds, hedge funds, etc) management firms constitute a multi-billion dollar industry in Australia. Supported by the recent meltdown of the major equity markets, hedge funds now form an integral part of the asset allocation of most major institutional investors (recent data using the Eurekahedge database puts the assets under management by Australian hedge funds at $15 billion). Given the sizable hedge fund industry in Australia, along with the considerable growth potential (with the asset managed by hedge fund globally being over US$1 trillion), it is very important to understand the risk profile of hedge funds as well as the important on investors' portfolio when hedge funds are included.

Over the last decade, extensive empirical analyses had been carried out to determine the statistical properties of hedge fund and fund of hedge fund returns. The conclusion is that such returns are generally more skewed and leptokurtic than expected if the underlying distribution is normal. Fung and Hsieh [2000] has documented that hedge funds have fat tails resulting in a greater number of extreme events than one will normally anticipate. Brooks and Kat [2001] have found that hedge fund index returns are not normally distributed. They have argued that while hedge funds may offer relatively high means and low variances, such funds give investors third and fourth moment attributes that are exactly the opposite to those that are desirable.

Mean-variance analysis is appropriate when returns are normally distributed or investors' preferences are quadratic. The reliability of mean-variance analysis therefore depends on the degree of non-normality of the returns data and the nature of the (non-quadratic) utility function. While the utility function may not be a serious problem, the non-normal distribution of returns presents an issue. While some hedge funds may have low standard deviations, this does not mean they are relatively "riskless". In fact, they harbor skewness and kurtosis, which makes them "risky". Kat [2003] discussed the issue of non-normality of return distributions of hedge funds and stated that modern portfolio theory is too simplistic to deal with hedge funds. Brunel [2004] demonstrated that a mean-variance optimization model is not likely to produce a successful allocation as mean-variance optimizers do not recognize the higher statistical moment issues.

Hence, where return distributions are markedly non-normal and cannot be uniquely described by their mean and variance, reference has to be made to other parameters (such as skewness and kurtosis) of the return distribution. One important result is that when a return distribution is skewed, the minimization of variance (or risk) is no longer equivalent to the minimization of downside risk resulting in the indicated portfolio weights associated with any given selected points (portfolios) on the Markowitz efficiency frontier being inappropriate.

The aims of the proposed research are twofold. First, it proposes an alternative risk measure framework which has accounted for non-normality hedge fund return data distribution. Based on the proposed risk measure, an adaptive hedge funds portfolio choice approach is established based on an adaptive neuro-fuzzy inference system (ANFIS). This line of enquiry is novel and with potential of real-time (i.e. for faster speed and with set accuracy) implementation.

We propose an alternative model known as Semi-Variance model (Grootveld & Hallerbach, 1999), is employed to overcome this non-normality problem:

Min $$SV^{-} = \frac{\sum\left[Max(0, M_P - r_P)\right]^2}{N} \quad (1)$$

Subject to $$\sum_i w_i E(r_i) = M_P$$
$$0 \le w_i \le 1$$
$$\sum_i w_i = 1 \quad \forall i$$

Where: M_p represents the mean or expected portfolio return and r_p denotes portfolio return, SV^{-} represents downside portfolio semi-variance and all remaining symbols have been previously defined.

When the efficient frontier for the semi-variance model is charted, it is the square root of the downside semi-variance or the portfolio semi-standard deviation (SSD_P) against which mean portfolio return is plotted.

A measure that is related to SV^{-} is the up-side semi-variance, SV^{+}.

$$SV^{+} = \frac{\sum\left[Max(0, r_P - M_P)\right]^2}{N} \quad (2)$$

An important relationship exists among SV^{-} and SV^{+} namely that their sum always equals the variance, that is,

$$V = SV^{-} + SV^{+} \quad (3)$$

When the ratio of SV^{-} to SV^{+} (semi-variance ratio (SVR)) equals unity, the distribution is expected to be symmetrical. If SVR exceeds unity, negative skewness is likely to be present. Conversely positive skewness is most likely to be accompanied by an SVR less than unity.

This project will employ the semi-variance model as a risk measure.

Significance and Innovation

This research is significant with three innovations.

1) Contrary to the use of classical mean-variance framework, we propose a standardised risk aversion factor ($0<\gamma<1$) based hedge funds return model that hybridises the lower semi-variance (SV^{-}) risk measure of historical hedge fund return (R_h) and the forecast near term future hedge fund return (R_f), given in equation (4), (Ranaldo and Favre, 2003).

$$E(R) = \gamma R_h + (1-\gamma) R_f$$

2) To our best knowledge and belief, the use of machine intelligent learning tool (Self-organisation Feature Map Neural Network) to perform clustering of hedge fund returns, using the market beta of hedge fund as a criterion, is a pioneering approach.

3) The use of adaptive neuro-fuzzy inference system (ANFIS) for optimising the hedge funds' weights is also novel in investment decision making. ANFIS is a six layer neural network architecture and our context with a uniquely chosen quadratic utility membership (in the fuzzy set discourse) function

(concave normalised risk aversion (vertical axis)- wealth (horizontal axis) function, i.e decreases risk aversion when wealth increases) for hedge fund manager.

The significance of this project will ultimately lead to an unbiased assessment of hedge fund performance. From the fund regulators' point of view, the outcomes of this project would help define hedge fund management styles for formulating investment risk policies to the general public.

Description of Approach

A) Data:

Hedge funds return data and qualitative descriptive reports available from Eurekahedge .

B) Research Methodology

Our proposed new methodology is an application of state-of-the-art intelligent data and text mining techniques to find the best matched investment portfolios based on a set of investor specified criteria. The main steps of our approach are:

Step 1 - Investor to specify investment criteria
This first stage allows the investors to specify their investment criteria in terms of risk and return (Back et al, 2001).

Step 2 - Clustering of available hedge funds in the market
We will use the Self-Organising Feature Map (SOFM) Artificial Neural Network (ANN) (Negnevitsky, 2005) to cluster the hedge funds using our model (4). The number of hedge funds clusters (Tibshirani, Walther and Hastie, 2000) will be used for hedge fund asset allocation. The subsequent clusters in the hedge funds portfolio are then identified as different styles of managed funds, from which the respective fund performance indicators are extracted. The extracted clusters are transformed using fuzzy logic for matching with investors' specifications, with the matching process outlined in Step 3 (Brown and Goetzmann, 1997, 2003).

Step 3 – Optimising investor preference with hedge fund performance
The obtained clusters of existing hedge funds (Step 2 above) are matched to the investment criteria (Step 1) such that the funds best matching the investor preference are picked and the weights of each hedge fund are optimised using ANFIS (Glaffig, 2004; Negnevitsky, 2005). This is achieved by the intelligent computing technique of fuzzy logic, where linguistic variables representing the normalised risk aversion versus wealth membership function. These variables are then matched to the investment criteria of the closest levels as specified by the investor. As the whole matching process is computerised with artificial intelligence, the investor can specify a more extensive list of investment criteria, according to which the best possible matches are then found from a large pool of existing hedge funds in a very short time.

In order to develop and implement the matching process and to achieve optimal hedge funds' weights allocation described above, the following two key tasks are to be carried out:

Task 1 - Development of computer code to compute model (4) using the SOFM-ANN system
This involves coding process using MATLAB, C++ language and Visual-Basic programming to form the core computational engine of the automatic analysis system.

Task 2 - Empirical tests
The data collected from Eurekahedge and hedge fund company reports will be pre-processed to remove the unwanted noises. The clean data, quantitative and qualitative, are then used as inputs to the SOFM-ANN for clustering and visualisation processing to determine the number of fund styles. Descriptive statistics of the clean data are reported while the inferential statistical tests are used to test the out-of-sample clustering and Monte-Carlo simulations will be implemented to validate the prediction accuracy of future fund performance.

Nature of Expected Outcomes

The outcome will be an innovative and user friendly solution for automating investment decisions which curbs the limitations of existing non-intelligent tools, which are too time-consuming and costly. Our approach increases breath and depth of hedge funds allocation while saving time: hundreds of hedge funds can be analysed both quantitatively and qualitatively for the purpose of matching investor specified criteria to formulate the optimal hedge fund portfolio.

We expect the project results to justify for high quality DEST publications (i.e. Social Science Citation and Science Citation Index journals). As this project forms an integral part of a much larger scale innovative project, we will anticipate applying an ARC Linkage project (through subsequent funding support from the Melbourne Centre for Financial Studies) and some parts of the innovative discovery will also form an ARC DP application.

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