APPLYING NEURAL NETWORKS AND GENETIC ALGORITHMS TO TACTICAL ASSET ALLOCATION

YPKE HIEMSTRA

Tactical asset allocation (TAA) adjusts the strategic diversification of an investment portfolio among asset classes in order to respond to fluctuating short term market conditions. TAA involves the prediction of asset class returns and adjustment of the strategic portfolio. The paper claims that by its very nature the return generating process is nonlinear, and presents a neural network that applies a fundamental approach to predict the S&P500. An optimization model using genetic algorithms exploits the predictions to adjust the strategic portfolio. Performance analysis on the basis of simulations using historic data show that the TAA system significantly outperforms a passive rebalancing policy. The system is useful for any investor active in more than one asset class. The investor can use the system to beat the S&P500 or to outperform passive management of a particular asset mix.

1. INTRODUCTION

Tactical asset allocation (TAA) adjusts the diversification of a strategic (i.e. long term) investment portfolio among stocks, bonds and cash in order to respond to fluctuating short term market conditions. Asset allocation is very important as it explains over 90% of portfolio performance (Brinson, Singer and Beebower, 1991).

This paper presents a system for TAA that applies adaptive systems. Adaptive systems include neural networks (see for example Haykin, 1994) and genetic algorithms (see for example Goldberg, 1989). The system decomposes TAA to prediction and optimization subtasks. A neural network predicts the S&P500 using a fundamental approach. The optimization model uses these predictions of the S&P500 to adjust the strategic portfolio. The optimization model uses genetic algorithms to solve complex optimization problems by requiring that any short-term adjustments impact long-term investment objectives. The overall system seeks to improve upon long-term investment objectives by generating maximum additional return for a sustained level of active risk (the risk of underperforming the strategic portfolio) under the constraint that the strategic risk exposure is not violated. The system is useful for any investor active in more than one asset class to beat the S&P500 or to outperform passive management of a strategic asset mix.

Section 2 discusses TAA, and section 3 briefly discusses applying adaptive systems. Section 4 presents the neural network developed to predict the S&P500 and section 5 discusses the optimization model and the application of GA. Section 6 presents the results of trading simulations. Finally, conclusions are presented.

2. TACTICAL ASSET ALLOCATION

Sharpe (1987) presents an integrated view of strategic asset allocation, tactical asset allocation, and dynamic asset allocation. Strategic asset allocation adopts a long-term view and determines a strategic asset mix. TAA adjusts the strategic diversification among asset classes on a monthly or quarterly basis. Figure 1 presents a general view of TAA. Short-term market behavior and the investor's risk attitude determine the optimal portfolio, under constraint of the strategic portfolio. Confidence in TAA is limited due to the risk associated with predicting short-term market behavior. Using the strategic portfolio as a constraint limits the deviation from the long-term optimal portfolio, ensuring that adjustments correspond to the confidence assigned to TAA. The TAA policy is evaluated by comparing the optimal portfolio's performance to the performance of the strategic portfolio.

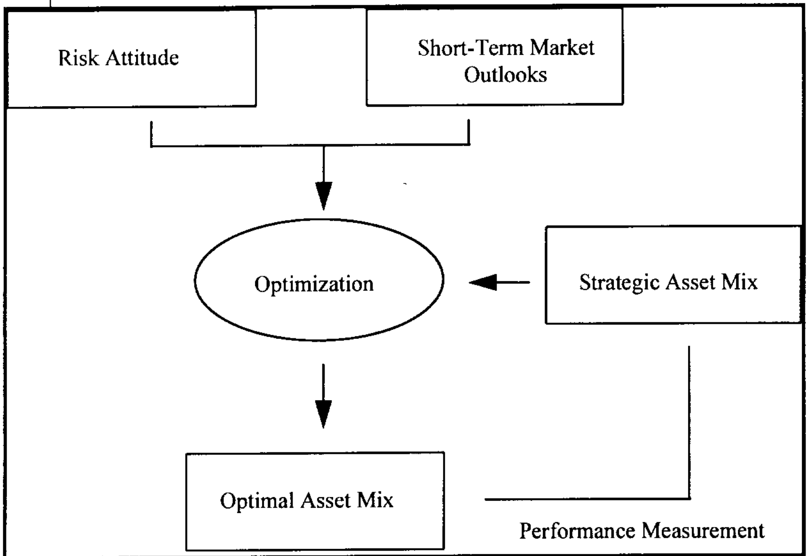

Figure 1. General view of tactical asset allocation.

studies adopting the fundamental approach have produced evidence that a significant part of the variation in monthly, quarterly, and annual excess returns can be predicted using fundamental information, e.g., Campbell [1987], Chen, Roll and Ross [1986], Fama and French [1989], Ferson and Harvey [1991], Pesaran and Timmermann [1994], and Solnik [1993]. These studies invariably apply linear modeling methods, with a limited number of independent variables. In particular, evidence has been accumulated which indicates that ex ante information on inflation, interest rates, the business cycle, and valuation measures such as the dividend yield, can be used to predict monthly, quarterly, and annual excess returns.

3. Applying Adaptive Systems

TAA is difficult because excess-return prediction and TAA optimization are complex problems. We apply a neural network to predict the S&P500. In the next section we will present a fundamental approach to predicting the stock market, and claim that it involves nonlinearity. The motivation for utilizing neural networks is that they can approximate any function (Hornik, Stinchcombe and White, 1989), are parameter-free (i.e., learn without a functional specification of the relation to be learned) and are robust estimators when distributions are non-Gaussian (Lippmann, 1987).

TAA optimization is difficult because of the many variables that require consideration and the complex relationships between these variables. Genetic algorithms (GA's) are inspired by the evolution of biological systems and apply operators to a population of potential solutions. By repeatedly applying operators that mutate, combine, or select potential solutions, the population converges towards a solution, producing an efficient and robust search. In section 5 we apply GA's to TAA optimization. The motivation for utilizing GA's is that they do not rely on mathematical properties of the objective function, e.g., that the objective function be differentiable.

4. Predicting the Stock Market

4.1. The Fundamental Approach to Stock Market Prediction

A basic distinction between approaches to predicting excess returns exists in the whether or not the approach makes predictions based on the dynamics of the market (i.e. price movements and trading volume), or by capturing fundamental forces that drive the market. Finance

4.2. A Nonlinear Return Generating Process

Nonlinearity implies asymmetry in the market's response to positive news versus negative news, which is clearly a characteristic of market behavior. For example, a rise in the interest rate affects the net present value of future dividends less than a decrease of the same magnitude pushes the net present value up. A high degree of nonlinearity implies context sensitivity (i.e., the meaning of news depends upon the economic context), which is also clearly the case. For example, an increase in inflation can be good news or bad news. It may be an indication of increased demand and economic activity, or of a lack of supply, depending upon the business cycle. Finally, the size of a news shock can induce disproportionate effects. Pesaran and Timmermann (1994) experiment with various nonlinear terms and find statistically significant results in their monthly and quarterly regressions. Renshaw (1993) also claims significant nonlinearity.

This paper adopts the fundamental approach to stock market prediction. It does so by using three factors (the business cycle, interest rates, and inflation) to characterize investment conditions and the dividend yield to represent market valuation.

4.3. Applying Neural Networks

The basic challenge in applying neural networks is to find the optimal model complexity, the complexity that has the best tradeoff among extracting signals present in the data and fitting noise. Too low a complexity results in a failure to sufficiently extract all signals from the data, while too high a complexity produces overfitting of the model to noise in the data. Sample size and the signal-to-noise ratio of the data are the prime constraints on model complexity. Elder and Finn [1991] present a general discussion on se-

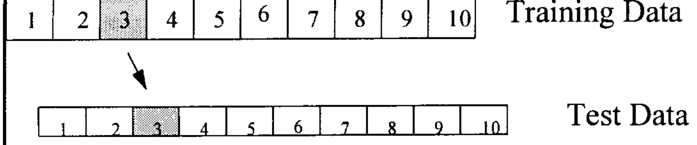

Figure 2. Cross-validation. In this case, the data was divided into 10 subsets. A subset is removed from the training data and serves as the test set for the model that is trained on the remaining subsets. This procedure is repeated 10 times to use all data for training as well as testing.

lecting optimal model complexity.

Neural networks have two dimensions of complexity: size and saturation. The larger the neural network (i.e., the larger the number of hidden neurons), the higher its representational power. The more saturated the network (i.e., the larger the absolute weight magnitudes associated with the links in the network), the more the activation functions operate outside the range that produces the most linear mapping, and the more complex the representation.

Constructive learning algorithms (e.g., Optimal Brain Damage, Le Cun et al. [1990]) address the issue of overfitting in the context of network size. A rule of thumb is that there should be several training examples for each weight. Early stopping refers to a method that addresses the issue of saturation. The early-stopping procedure begins with an arbitrary (nearly) linear model and stops training before the in-sample minimum on the error function is reached. This is based on the assumption that, during the initial stages of learning, the network learns the patterns that generalize best. To select the optimal complexity (i.e., saturation), Weigend et al. [1990] suggest that one should reserve part of the data for cross-validation, and stop training at the point where the error function on the cross-validation set has its minimum. Generalization is then estimated by the performance on the original test set.

We applied backpropagation and early stopping to training the neural network, and the method of Weigend et al. to estimating model complexity. The iterative character of backpropagation provides the opportunity to stop learning if, at a certain stage during the learning process, the network begins to fit to noise (i.e., performance on the cross-validation set deteriorates). To apply early stopping, it is necessary to select the number of hidden nodes in advance. Following Ripley's suggestion that the number of nodes in the hidden layer should approximate the average of the number of nodes in the input and output layer (Ripley [1993]), we train a neural network with 2 hidden neurons. The architecture we use is the standard neural network architecture for nonlinear regression (Haykin [1994]), with bias weights and one hidden layer. The hidden units use hyperbolic tangent activation functions, the output unit has a linear activation function. Inputs were normalized to have zero mean and unit variance.

	Correlation	Error Rate	NMSE	RMSE
BPN2	0.290	0.419	0.951	8.041
OLS	0.265	0.430	0.965	8.102

Table 1. Out-of-sample results (1976-1993) of the neural network model (BPN2) and the linear Ordinary Least Squares (OLS) model.

4.4. Generating Out-of-Sample Predictions

We focus on predicting quarterly excess returns using four inputs: dividend yield on the S&P500 (YSP), the three-month T-Bill rate as the short-term interest rate (SIR), the inflation rate based on the consumer price index (CPI), and the change in the 12-month moving average of the industrial production index (DIP), (Hiemstra and Haefke [1996]). YSP and SIR are instantaneously available, and so the latest observations prior to the forecast period were used as input to the neural network predictor, i.e., the values at the end of the preceding month. Macroeconomic information is available typically on a monthly basis with a lag of some 20 days, and so the DIP and CPI were used with a 2-month lag. The input data set consists of 93 quarterly observations covering the period 1970-1993, of YSP(t-1), SIR(t-1), DIP(t-2), and CPI(t-2). The desired output is the S&P500 quarterly excess return, defined as total return (price movement plus dividends related to the initial investment) minus the risk-free rate of return, the 3-month T-Bill rate.

Given the small sample size at the quarterly frequency, and the noisy character of the data, it is crucial to produce sufficient out-of-sample results to reliably estimate generalization. Pesaran and Timmermann [1994] apply a recursive approach to predicting excess returns, in which case all data available at time t is used to forecast the excess return at time $t+1$. Cross-validation and bootstrapping are examples of resampling techniques that use observations for twice, for training as well as testing (Weiss and Kulikowski [1991]). Cross-validation (see Figure 2) uses all data for testing, and consumes considerably fewer resources than recursive prediction or bootstrapping. We apply 10-fold cross validation to estimate generalization. The 10 resulting test sets were combined to form out-of-sample estimations on the entire data set.

Table 1 shows the out-of-sample results of the neural network model (BPN2) and the linear Ordinary Least Squares (OLS) model. The correlation between forecasts and actual values, the error rate (fraction of incorrect sign predictions), the Normalized Mean Square Error (NMSE, obtained by dividing the Mean Square Error by target variance) and Root Mean Square Error (RMSE) all show that the neural network predicts the S&P500 more accurately.

Figure 3 shows the out-of-sample forecasts of the neural network versus actual excess returns. Note that the sign prediction of the four steepest downturns is correct.

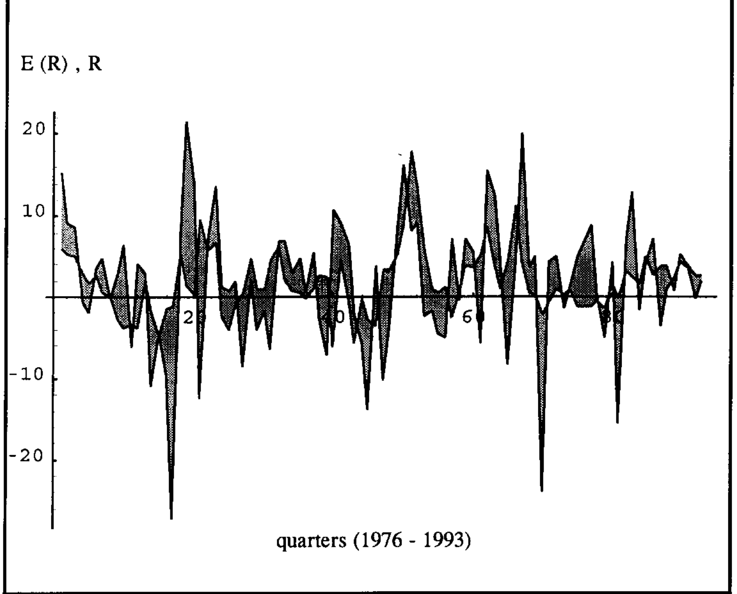

FIGURE 3. Actual and predicted S&P500 excess returns (1976-1993).

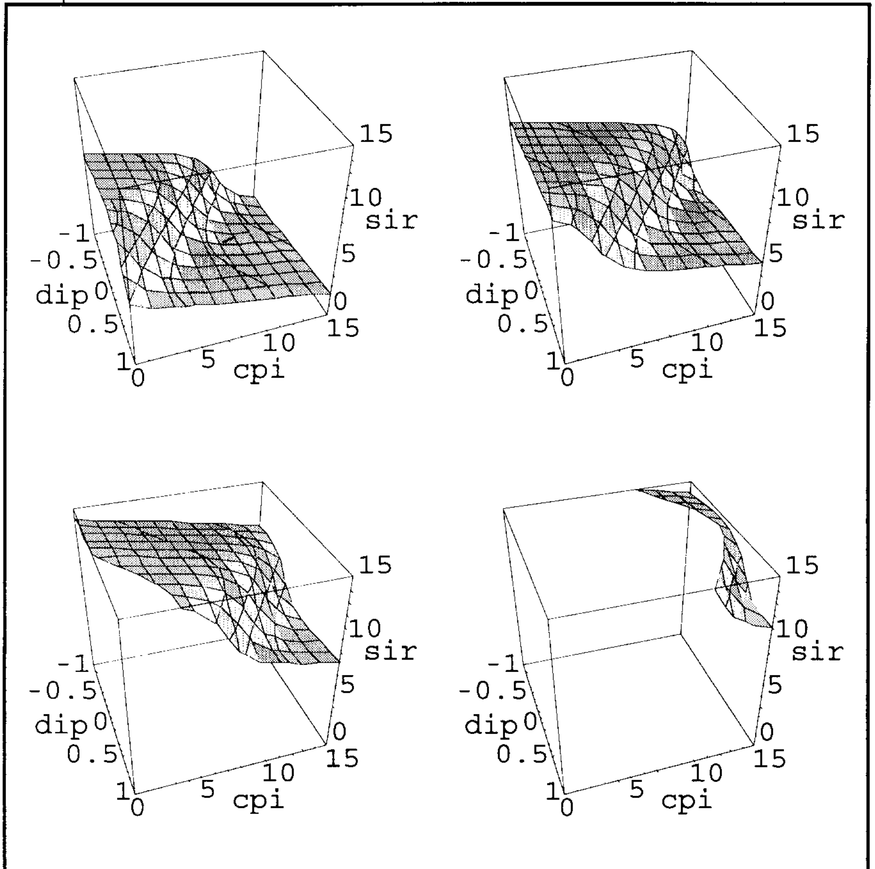

FIGURE 4. Sensitivity Analysis. The surfaces represent input combinations that produce a predicted excess return of 0 for YSP = 3, 4, 5, 6, respectively. The combinations above the surface represent negative excess returns, the combinations below the surface represent positive predictions. In the first case, for YSP = 3, many input combinations produce a negative excess return. In the last case, nearly all input combinations produce a positive forecast.

4.5. Sensitivity Analysis

Visualization can be used to interpret the model's behavior. Figure 4 shows four 3D-contour plots. The 3D-contour plots show the decision surface (excess returns = 0) in the input space, with YSP fixed at a particular value and the other inputs along the axes. YSP increases from the top left figure to the bottom right figure. These graphics represent the impact of the macroeconomic investment conditions. On-screen animation of the 3D-contour plot (as the values for YSP are varied over time) provide a technique for comprehensively visualizing the behavior of the neural network predictor.

5. Tactical Asset Allocation Optimization

5.1. Tactical Frontier Optimization

Given excess-return predictions, an optimization model is used to adjust the strategic portfolio in order to determine the optimal portfolio. Tactical Frontier Optimization (TFO) adapts the mean-variance framework to select the optimal tactical portfolio (Hiemstra [1994]). The mean-variance framework, the traditional approach to portfolio selection, is attractive because of its explicit tradeoff between risk and return (Elton and Gruber [1991]). The mean-variance framework derives its name from the basic tenet that an investment alternative is fully characterized by the mean and variance of its return distribution, the mean representing the expected return and the variance representing risk.

The central concept of mean-variance optimization is the efficient frontier. On the efficient frontier lie the portfolios with the highest expected return for the various risk exposures. In the context of TAA, the efficient frontier is the short-term efficient frontier (SEF) that reflects the short-term properties of the asset classes. Fluctuating short-term risk-return characteristics of the asset classes change the shape and locus of the SEF, and the strategic portfolio will usually lie below the SEF. TFO determines, in three steps, how to move from the strategic portfolio to the SEF in order to optimize the asset mix.

The first step is to consider only portfolios that dominate the strategic portfolio, since the objective of TAA is to generate higher returns, but not at the expense of higher risks. A portfolio is said to dominate another portfolio when it has a higher expected return and no additional risk. The portfolio's risk should never exceed the risk of the strategic portfolio

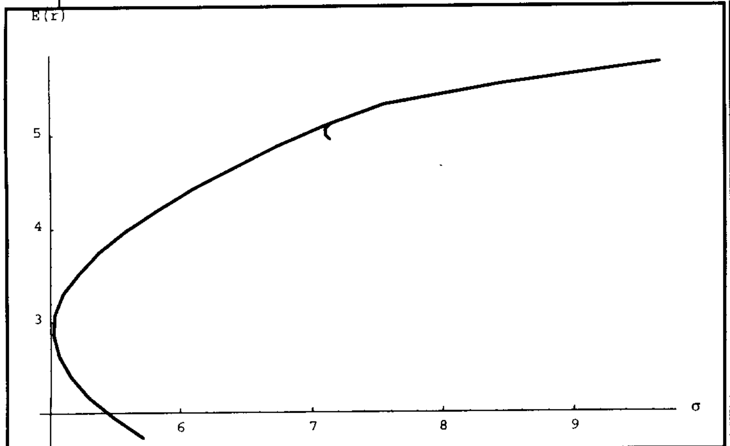

Figure 5. Efficient frontier (the large curve) and tactical frontier (the very small curve). E(r) is the expected return, σ is the standard deviation of returns. The mean-variance input used for the calculations is for U.S. data. Given this input, a portfolio of 70% bonds and 30% stocks plots below the efficient frontier. If this portfolio is the strategic asset mix, and the efficient frontier represents the short-term efficient frontier (SEF), the question is how to adjust the strategic mix, i.e., how to move from the strategic portfolio to the SEF. The answer to this question is the tactical frontier, which represents all potentially interesting portfolios between the SEF and the strategic portfolio.

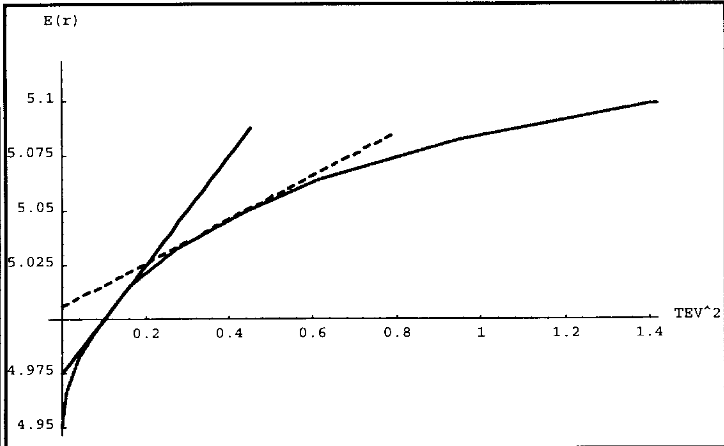

Figure 6. The payoff of active risk and selection of the optimal portfolio. The steepest line represents ARA = 0.25, the other line ARA = 0.1. Calculations are based on the same mean-variance input as Figure 5.

because, if it does over any single period, there would be no guarantee that it would not exceed the risk exposure of the strategic portfolio over other periods. The second step is to measure active risk (i.e., the risk of underperforming the strategic portfolio) using tracking error volatility (TEV, the standard deviation of the difference between the portfolio's return and the return on the strategic portfolio), and to consider from the set of portfolios that dominate the strategic portfolio only those with the highest expected return for the respective levels of active risk. These portfolios form the tactical frontier, which runs from the strategic portfolio to the SEF (see Figure 5).

The last step is to select one of the portfolios on the tactical frontier. Figure 6 shows the tradeoff between active risk and expected return of portfolios along the tactical frontier. The curved line represents the expected return as a function of variance of tracking error (TEV^2) starting at the strategic portfolio (where $TEV^2 = 0$). The risk attitude as to active risk, expressed in terms of active risk aversion (ARA) determines the optimal portfolio. ARA is the required compensation for the last unit active risk that is accepted, as measured by TEV^2. The optimal portfolio exists where the line is tangent to the payoff curve. The more active risk averse the investor the steeper the line and the closer the optimal portfolio is to the strategic portfolio.

TFO integrates TAA with the strategic asset allocation, and ensures that the tactical policy adds to the long-term investment objectives. Since TFO only considers those portfolios that dominate the strategic portfolio, expected returns increase, but not at the expense of additional risk. In this way, TFO respects the strategic decision regarding risk exposure. TFO generates the maximum additional expected return that can be achieved without violating the strategic risk exposure for the sustained level of active risk across multiple periods.

5.2. Applying Genetic Algorithms

The formal specification of the TFO optimization problem is (in matrix notation):

With respect to x, $\mathrm{Max}(x'r - ax'Vx)$

subject to the following constraints:

$$(q+x)'V(q+x) \leq q'Vq \quad (1)$$
$$(q+x)_i \geq 0 \text{ for each } i \quad (2)$$
$$x'1=0 \quad (3)$$

where
x is a vector of weight adjustments,
r is the vector of expected asset class returns,
a is the active risk aversion,
V is the covariance matrix of asset class returns, and
q is the vector of strategic portfolio weights.

The objective function balances expected return ($x'r$) and active risk ($x'Vx$) as illustrated by Figure 6. Constraint (1) is the constraint that the risk of the portfolio should not exceed the risk of the strategic portfolio ($q'Vq$). Constraints (2) and (3) ensure that each portfolio weight is positive and that the sum of portfolio weights is 1. Figure 7 illustrates the optimization problem. The dot at coordinates {0.7, 0.3} represents the strategic portfolio, the dot

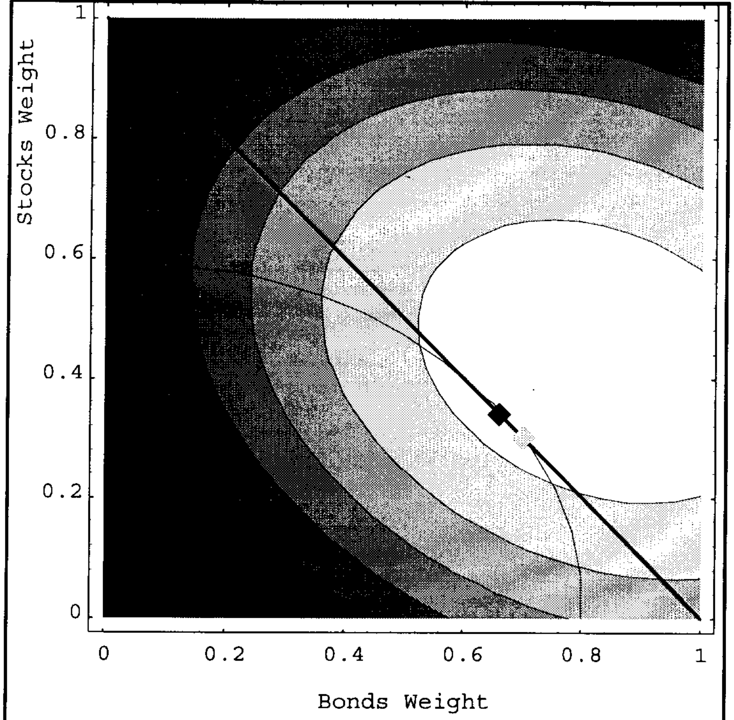

Figure 7. TFO optimization. Bonds and stocks weights along the axes, the closer to the origin the higher the weight in cash. The contours represent the score on the objective function, the lighter the shading the higher the score. The diagonal represents the constraint of no short-selling. The curved line represents constraint (1), the constraint that the risk of the portfolio should not exceed the risk of the strategic portfolio. Note that portfolios extremely overweighted in stocks or bonds do not meet this constraint. The dot at coordinates {0.7, 0.3} represents the strategic mix, the other dot represents the optimal mix if ARA=0.1. Calculations based on the same mean-variance inputs as Figure 5.

at coordinates {0.66, 0.34} represents the optimal portfolio for this particular input set, assuming ARA=0.1.

The TFO optimization problem is a complex quadratic optimization problem that includes nonlinearities in both the objective function and the constraints. Introducing transaction costs significantly complicates the optimization task, unless we opt for a solution method that does not rely on a mathematical description. A GA does not require particular mathematical properties (e.g., that the objective function is differentiable or convex) since it relies exclusively on evaluating the objective function to guide its search. The TFO problem can be mapped to a GA solution by including constraint (1) in the objective function to form an evaluation function, and by applying a crossover procedure which automatically ensures that constraints (2) and (3) are met. A straightforward crossover procedure is to mix portfolios with weight w according to:

childPortfolio = w*parentPortfolio1 +
(1-w)*parentPortfolio2

	Rebalancing	Timing	TFO
Return	14.01	14.21	14.53
Volatility	10.50	9.96	9.90
TEV	0	1.54	1.57
Sharpe Index	0.29	0.31	0.33
Information Ratio	not defined	0.06	0.15
Turnover	0.02	0.11	0.17

Table 2. A comparison of a rebalancing policy of a strategic 40% bonds, 60% stocks asset mix to two active policies with identical active risk. The timing policy increases return and reduces risk. Applying the TFO methodology (with ARA = 0.05) further improves performance.

The easiest way to implement the mutation operator is to simply swap weights. A more sophisticated technique is to randomly select a weight w near 1 and to produce a mutated portfolio as a child portfolio by mixing the portfolio with either a portfolio that is fully invested in one asset class or a portfolio that has equal weights for all asset classes apart from one in which it is not invested. For example, assume a {0, 0.4, 0.6} portfolio, and $w = 0.9$:

$$0.9\{0, 0.4, 0.6\} + (1 - 0.9)\{0.5, 0, 0.5\} =$$
$$\{0, 0.36, 0.54\} + \{0.05, 0, 0.05\} =$$
$$\{0.05, 0.36, 0.59\}$$

6. Performance Analysis

Performance analysis evaluates the added value of the system by simulations on the basis of historic data. We simulated three policies for the period 1976 - 1993. The strategic portfolio consists of 60% stocks and 40% bonds. Transaction costs were assumed to be 0.1% of turnover, which can be achieved by applying synthetic futures instead of physical trading. The first policy simulated was a passive rebalancing policy that restores the 60/40 portfolio weights at the end of each quarter. Secondly, we simulated a timing policy. The timing policy exploits the neural network's predictive power by reducing the stocks weight to approximately 10% when the predicted excess return is negative. Table 2 shows that the timing policy adds 20 basis points to the annualized mean return, while reducing volatility. The third policy simulated also exploits the neural network's predictive power, and in addition applies the TFO methodology. The TFO policy (with ARA = 0.05) has equal active risk as the timing policy (TEV = 1.57, versus TEV = 1.54 for the timing policy) but adds at least 52 basis points while also reducing overall risk. Active risk of a policy operating on a strategic asset mix is calculated as the standard deviation of its return in excess of the return obtained by rebalancing the strategic asset mix. The

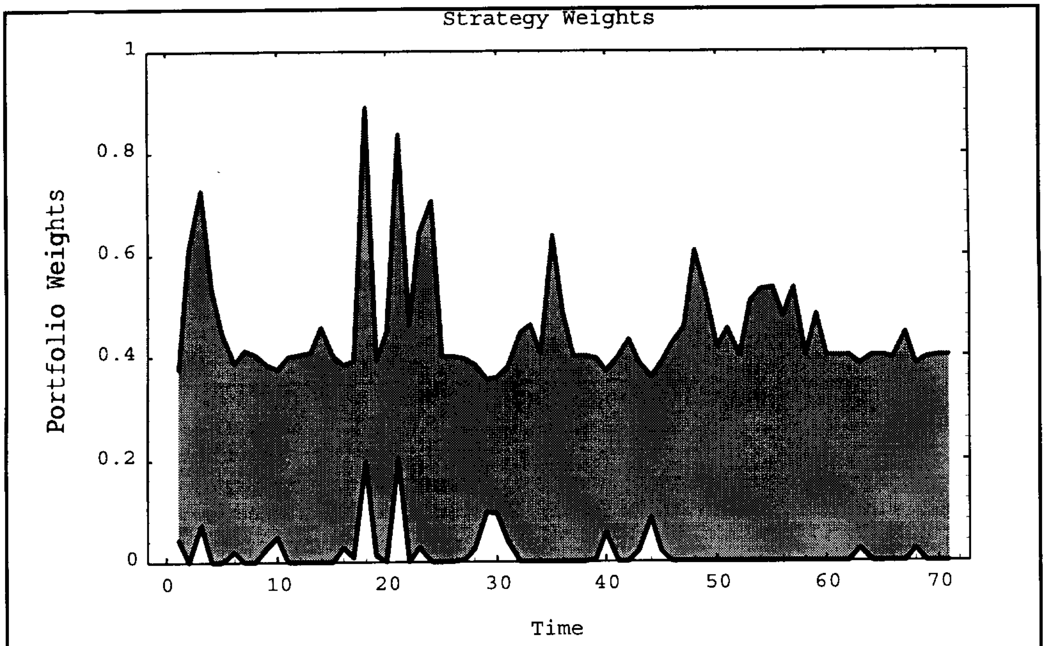

FIGURE 8. Portfolio weights using TFO, given a strategic 60/40 stocks/bonds mix (1976 - 1993).

Information Ratio is computed as the mean quarterly return in excess of the rebalancing policy, divided by its standard deviation. The table shows that TFO generates much higher return per unit of active risk than does a simple timing policy. The Sharpe Index is calculated on a quarterly basis, and shows that this TFO policy produces approximately 10% more return per unit risk than the rebalancing policy.

Figure 8 illustrates changes to portfolio weights using this TFO policy over the period 1976 to 1993. The x-axis represents time in months. The y-axis represents portfolio weights for each point in time. The lower region represents the cash weight; the shaded region represents the bonds weight; and the upper region represents the stocks weight.

Figure 9 shows the relative value over time of an initial investment in 1976 for the three policies, given a strategic portfolio of 100% stocks. The bottom line represents the rebalancing policy; the upper line represents TFO results; and the line in between represents a timing policy with similar active risk as the TFO policy. The TFO policy produced an end value over 50% higher than rebalancing.

CONCLUSION

TAA is a difficult problem. We argued that index prediction involves nonlinearity, and we discussed TFO, a portfolio adjustment model based on the mean-variance framework, that has complex mathematical properties.

We showed that adaptive systems can successfully manage the complexities that occur in TAA. The neural network model discussed produced significant predictive power, and outperformed the alternative linear model. We proposed that GA can successfully manage the complexities of TFO, and that this model outperforms simple rule-of-thumb adjustment of the strategic asset mix. Performance analysis over nearly 20 years of market data show the potential for added value using adaptive systems. The adaptive system dramatically outperforms a passive rebalancing policy by adding on average 131 basis points per year, while reducing overall risk.

The system can be applied by any investor active in more than one asset class. For example, a mutual fund can use the system to beat the S&P500, and a pension fund can use the system to outperform passive management of a particular strategic asset mix.

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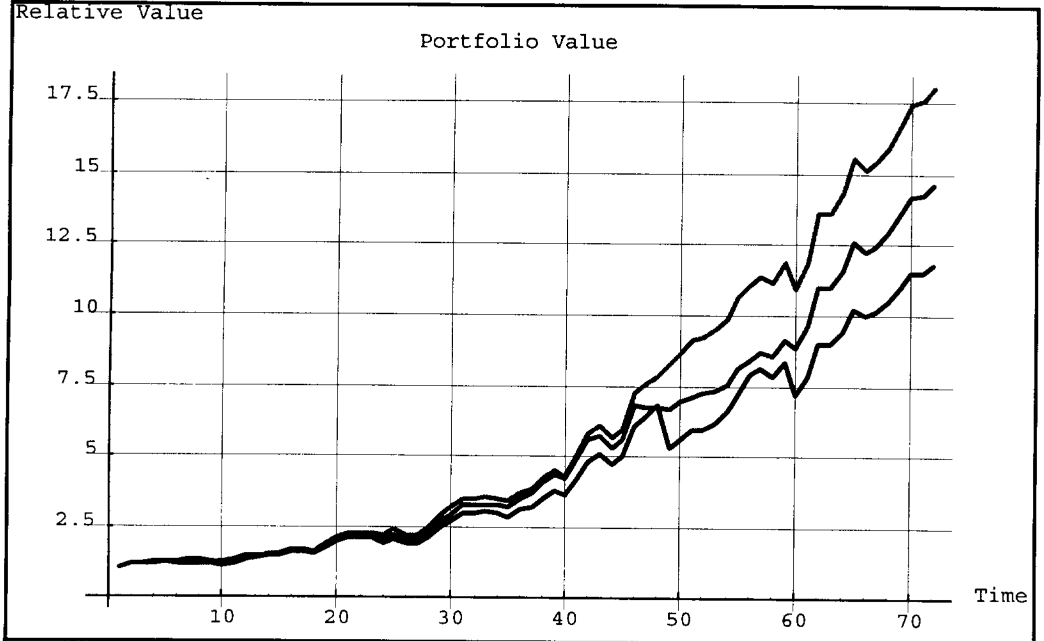

Figure 9. Portfolio value growth (1976-1993). Relative value is computed as the portfolio value divided by the initial investment.

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