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# Modelling and trading the English stock market with new forecasting techniques

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## Abstract

The motivation of this paper is to introduce a short term adaptive model (Partial Swarm Optimizer) combined with linear and nonlinear models when applied to the task of forecasting and trading the daily closing returns of the FTSE100 exchange traded funds (ETFs). This is done by benchmarking its results with a higher order neural network (HONN), a recurrent neural network (RNN), an autoregressive moving average model (ARMA), a moving average convergence/divergence model (MACD), plus a buy and hold strategy. More specifically, the trading performance of all models is investigated in forecast and trading simulations on the FTSE 100 ETF time series over the period January 2000 to June 2016 using the last two years for out-of-sample testing. As it turns out, the proposed adaptive models do remarkably well and outperform its benchmarks in terms of correct directional change and trading performance.

*Keywords*: particle swarm optimization; genetic algorithm; multi-layer perceptron; radial basis function; confirmation filters; FTSE100; day trading
*JEL Classification Codes*: G15, G17

## 1. Introduction

The novelty of the proposed approach lies in the application of a sliding window ma-chine learning approach for forecasting and trading the FTSE100 and at the superiori-ty of the proposed machine learning technique. To the best of our knowledge this is one of the first times that this adaptive PSO algorithm is combined with an RBF neu-ral network to model and forecast an equity index. Moreover, our proposed machine learning method also applies the

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PSO algorithm to select the more relevant inputs at each step. This is different from many other existing non-linear models as most neural networks provide a prediction in the form of a weighted computation of all inputs which are fed into the network during the training process. Therefore, the proposed model has an ability to locate the optimal feature subset which should be used as in-puts. This enables the practitioner to introduce a more expansive universe of inputs without having to worry about a noticeable reduction in training times or a redundan-cy of features. Moreover, the feature selection is a dynamic procedure and not a stat-ic one with different feature subsets being selected in different time steps. This also helps remove the risk of survivorship bias when back testing older data as all major equities can be included as inputs. Furthermore we found that the mixed inputs in the radial basis function neural network are producing better results comparing to auto-regressive inputs. Finally the back test shows the correct sliding window of 200 days in the whole out of sample period. The performance of the proposed methodology is compared with numerous linear and adaptive methodologies. To allow for a fair comparison, all non-linear methods included in the comparative analysis were trained with the same sliding window approach. Moreover, the deployed Particle Swarm Optimisation (PSO) algorithm was also deployed to optimize the autoregressive and moving average terms in an Autoregressive Moving Average (ARMA) model.

## 2. Literature review

The FTSE100 is an index which has been modelled and forecasted by many who focus their research on conventional, statistical and machine learning methods. Some of the earliest re-search was conducted by Weigend et al. (1990), Lowe (1994), Tamiz et al. (1996), and Omran (1997). More recent research conducted by Lee and Ko (2009) focuses on Radial Basis Function (RBF) NNs. Lee and Ko (2009) proposed a NTVE-PSO method which compares existing PSO methods, in terms of prediction the different practical load types of Taiwan power system (Taipower) in terms of predicting one-day ahead and five-days ahead. Yan et al. (2005) con-tributes to the applications of RBF NN by experiments with real-world data sets. Experimental results reveal that the prediction performance of RBF NN is significantly better than a tradi-tional back propagation neural network models. Marcek et al. (2009) estimate and apply ARCH-GARCH models for the forecasting bond price series provided by VUB bank. Cao and Tay (2003) compare a support vector machine model with an RBF and a generic Back Propa-gation Neural Network model. In their methodology Cao and Tay (2003) analyse five futures contracts which are trade on the CME. Empirical results from this analysis conclude that the RBF NN outperforms the BP NN while producing similar results to the SVR NN. As an overall summary the predictive ability of an RBF is significantly stronger when compared to any of the aforementioned benchmark models. With the emergence of newer technology and faster pro-cessing power finance has seen numerous advancements in the area of artificial intelligence. As a result, the accuracy and practicality of such models has led to AI being applied to different asset classes and trading strategies. Enke and Thawornwong (2005), Karathanasopoulos et al (2013a) Karathanasopoulos et al(2013b), Karathanasopoulos et al (2014), Karathanasopoulos et al (2015a) and Karathanasopoulos et al (2015b) suggest that machine learning methodologies provide higher returns when compared to a buy and hold strategy. De Freitas et al. (2000) pro-pose a novel strategy for training NNs using sequential Monte Carlo algorithms with a new hybrid gradient descent / sampling importance resampling algorithm (HySIR) forecasting the FTSE100 closing prices. The HySIR model outperformed all the other benchmarks in terms of trading performance. Tino et al. (2001), Jasic and Wood (2004), Bennel and Sutcliffe (2005), Karathanasopoulos et al (2012a), Karathanasopoulos et al (2012b) and Karathanasopoulos et al (2013c) show results which indicate that for all markets the improvement in the forecast by non-linear models is significant and highly accurate. Moreover, Eldeman (2008) presented a hybrid Calman filter - Radial Basis Function model used in forecasting one day ahead the FTSE100 and ISEQ. The RBF model outperform all the other seven traditional recurrent neural network. Moreover, Nair et al. (2011) propose a hybrid GA neural network which, when compared with benchmark models, outperforms displaying superior accuracy and overall performance. Nair et al. (2011) forecasts one day ahead and uses closing prices from the FTSE100, BSE Sensex, Nikkei 225, NSE-Nifty and DJIA as inputs for his models. Lastly, Karathanasopoulos et al. (2013b) have used a sliding window approach which combines adaptive differential evolution and support vector regression for forecasting and trading the FTSE100.

## 3. Related financial data

The FTSE 100 ETF index is a weighted according to market capitalization which currently comprises of 101 large cap constituents listed on the London Stock Exchange. Trading signals are generated based on the forecast produced by each of the models. When the model forecasts a negative return then a short position (sale) is assumed at the close of each day and when the model forecasts a positive return a long position (purchase) is executed. Profit / loss is determined by daily positions and in circumstances were consecutive negative or positive changes are forecasted the position is held as a trading decision for the following day. Arithmetic returns are used to calculate daily returns and they are estimated using equation 1. Given the price level $P_1$, $P_2$, … , $P_t$, the logarithmic return at time t is formed by:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

*Table 1.* Total dataset.

| *Name of Period* | *Trading Days* | *Beginning* | *End* |
|---|---|---|---|
| *Total Dataset* | 3500 | 1 January 2000 | 14 June2016 |
| *In sample Dataset* | 2900 | 1 January 2000 | 14 June 2012 |
| *Out of Sample Set* | 600 | 15 June 2012 | 14 March 2016 |

The inputs for the nonlinear models has been divided in two categories, one is the category with only autoregressive returns and the other category has a combination of autoregressive returns, moving averages, fixed income returns, commodity returns, equity returns, equity index returns and a volatility time series where all included. In total the numbers of inputs used in this paper are 1000. (for the autoregressive inputs the number is 200 and for the mixed inputs the remaining) Summing up the data has been divided after optimising the models in the in-sample period and out of sample period thought the back test procedure. In the out of sample period after automated 500 back tests we came to the unique best of 200 days sliding window which gives the best and most profitable results. This is first time that academic research has been tested with more than 500 back-tests.

## 4. Proposed method

In this algorithm the adaptive Particle Swarm Optimization was proposed by Kennedy and Eberhart (1995), which has been used to locate the parameters Ci of the RBF NN while in parallel locating the optimal number for the hidden layers of the network. This methodology is extended to the proposed algorithm to allow its application in a sliding window approach, to optimize the feature subset. In our example as mentioned before the sliding window is for 200 days as was the best window in the out of sample period, providing the best results. The performance of an RBF NN highly depends on its structure and on the effective calculation of the RBF function's centres Ci and widths σ and the network's weights. In this approach the PSO searches only for optimal values of the parameters Ci and the optimal feature subset which should be used as inputs. A sliding window approach is used and this enables for a prediction which is based on daily re-optimisation of the model's parameters and input dataset. For the number of hidden neurons (the RBF NN structure) no further optimization procedure was followed but simple 10 node architecture was selected. This simple topology enables us to alleviate the computational cost of the optimization procedure and to maintain the simplicity in the derived models to achieve better generalization performance. Each particle i is initialized randomly to have 10 hidden neurons (within a predefined interval starting from the number of inputs until 1000 which is the maximum hidden layer size that we applied). The algorithm is a multi-objective algorithm which addresses two main elements. The first is an error minimisation algorithm and the second is employed to optimise and improve the trading performance through optimising annualised returns. In few words the PSO optimizes the inputs in the RBF NN and maximize the annualised returns.

## 5. Empirical results

### *5.1. Benchmark models*

Four linear benchmark models and three non-linear models were used to gauge the effectiveness of the proposed PSO RBF model. The linear models: the MACD strate-gy, the ARMA model, the ARMA-PSO and the Buy and Hold strategy plus the three non-linear models: the generic HONN model, the generic RNN and the PSO RBF model were all used to generate next day trading signals. With the Buy and Hold strat-egy the practitioner simply buys the index at the beginning of the in sample period and then sells it at the end of the sample period. The MACD strategy used is quite simple. Two moving average series are created with different moving average lengths. The decision rule for taking positions in the market is straightforward: If the short-term moving average intersects the long-term moving average from below a 'long' position is taken. Conversely, if the long-term moving average is intersected from above a 'short' position is taken. The forecaster must use judgement when determining the number of periods n on which to base the moving averages. The combination that per-formed best over the in-sample sub-period was retained for out-of-sample evaluation. The model selected was a combination of the FTSE100 and its 8-day moving average, namely n = 1 and 8 respectively or a (1, 8) combination. The AR and MA terms in the ARMA model are re-estimated based on a window of 200 days to produce a forecast. The PSO ARMA is optimized by a PSO algorithm to find the optimal combination of AR and MA terms. The HONN and the RNN model is estimated using a traditional back propagation algorithm to adjust the weights when forecasting next day returns. Finally as mentioned before the PSO RBF neural network uses a PSO algorithm to select the optimal inputs from a set of autoregressive returns and secondly maximise the annualized returns of the FTSE100 index. Neural networks exist in several forms in the literature. The most popular architectures are the Higher Order Neural Network (HONN) and the recurrent neural network. Their most important problem is that they require a feature selection step and their parameters are hard to be optimized comparing with the proposed methodology. For these reasons outline by Karathanasopoulos et al. (2012) Genetic Algorithms (Holland, 1995) were used to select suitable inputs. The Levenberg–Marquardt back propagation algorithm (Roweis, 2013) is employed during the training procedure which adapts the learning rate parameter during this procedure.

### *5.2 Statistical performance*

In table 2 the statistical performance in the out-of-sample period of all models is pre-sented. For the Root Mean Squared Error (RMSE), the Mean Absolute Error (MAE) and The mean absolute percentage error (MAPE). Interpretation of results is such that, the lower the output, the better the forecasting accuracy of the model con-cerned. The Pesaran-Timmermann (1992) (PT) test examines whether the directional movements of the real and forecast values are in step with one another. Furthermore, it checks how well rises and falls in the forecasted value follow the actual rises and falls of the time series. The null hypothesis is such that the model under study has ‘no predictive power’ when forecasting the ETF return series. The Diebold-Mariano (1995) DM statistic for predictive accuracy statistic tests the null hypothesis of equal predictive accuracy. Both the DM and the PT tests follow the standard normal distribution.

By observation, it can be seen that the proposed mixed input RBF-PSO model is the strong est statistically.

*Table 2.* Statistical performance (out of sample period).

| | *Buy and hold* | *MACD* | *ARMA* | *ARMA-PSO* | *RNN* | *HONN* | *RBF-PSO autoregressive* | *RBF-PSO mixed* |
|---|---|---|---|---|---|---|---|---|
| *MAE* | 0.0240 | 0.0220 | 0.0200 | 0.0135 | 0.0165 | 0.0132 | 0.0127 | 0.0119 |
| *MAPE* | 301.67% | 300.75% | 256.60% | 180.78% | 232.23% | 223.11% | 189.21% | 161.22% |
| *RMSE* | 0.0421 | 0.0419 | 0.0376 | 0.0195 | 0.0222 | 0.0203 | 0.0161 | 0.0155 |
| *PT-Stat.* | 11.91 | 11.77 | 12.00 | 14.03 | 14.10 | 14.44 | 16.15 | 16.51 |
| *DM* | -3.21 | -3.13 | -3.08 | -2.56 | -2.12 | -2.01 | -2.00 | -1.97 |

### *5.3 Empirical trading results*

In this section we present the results of the proposed methodology applied to trading the FTSE100 English index. These results are compared with the results of the retained benchmark models. The trading performance of all the models considered in the out-of-sample subset is presented in the table below. Our trading strategy for the proposed methodology is simply the output of the best classifier found. Specifically, we go or stay long if the forecasts have a positive movement and go or stay short when a negative direction is forecast. The trading strategy applied in benchmark models is simple and identical for all of them: go or stay long when the forecast return is above zero and go or stay short when the forecast return is below zero. Because of the stochastic nature of the proposed methodology a simple run is not enough to measure its performance. This is the reason why 1000 runs where executed and the mean results are presented in the next tables.

As it was expected the proposed methodology clearly outperformed the existing models wit h leading results across all the examined metrics. Another unique output observation is made w hen comparing the proposed PSO RBF model (mixed inputs) with the PSO RBF model (autor egressive inputs), it is clearly beneficial for the trader to examine a larger and more expansive universe of explanatory variables as it reduces volatility, maximum drawdowns and improved annualised returns.

*Table 3.* Out-of-sample results without transaction costs.

| | *Buy and hold* | *MACD* | *ARMA* | *ARMA-PSO* | *RNN* | *HONN* | *RBF-PSO autoreg.* | *RBF-PSO mixed* |
|---|---|---|---|---|---|---|---|---|
| *Information Ratio (excluding costs)* | 0.39 | 0.40 | 0.44 | 0.78 | 0.60 | 0.67 | 0.92 | 0.96 |
| *Correct Directional change* | 52.21% | 51.23% | 50.78% | 58.45% | 59.23% | 50.44% | 60.00% | 64.22% |
| *Annualised Volatility (excluding costs)* | 18.73% | 19.53% | 20.31% | 19.33% | 20.23% | 19.89% | 20.44% | 20.91% |
| *Annualised Return (excluding costs)* | 7.44% | 8.00% | 9.00% | 15.21% | 12.23% | 13.34% | 18.91% | 20.12% |
| *Maximum Drawdown (excluding costs)* | -23.39% | -23.94% | -23.21% | -21.72% | -25.49% | -22.09% | -23.49% | -21.00% |
| *Positions Taken (annualised)* | 4 | 17 | 18 | 24 | 28 | 21 | 19 | 20 |

## *5.4 Trading costs*

Up to now, we have presented the trading results of all our models without considering transac tion costs. Since some of our models trade quite often, taking transaction costs into account mi ght change the whole picture. According to the English Stock Exchange, transaction costs for f inancial institutions and fund managers dealing a minimum 1 million pounds gives us an avera ge transaction cost of 17 basis points or 0.17% per position.

In the filtered trading simulation, the PSO RBF maintains its ranking as the best model. Thi s threshold filter is optimized during the in sample and applied to the examined dataset. Result s are improved under the supervision of a trading filter as overall annualized returns are increa sed. Furthermore, overall volatility and maximum drawdowns are also improved.

*Table 4.* Out-of-sample results with transaction costs

| | *Buy and hold* | *MACD* | *ARMA* | *ARMA-PSO* | *RNN* | *HONN* | *RBF-PSO autoreg.* | *RBF-PSO mixed* |
|---|---|---|---|---|---|---|---|---|
| *Annualized Return (excluding costs)* | 7.44% | 8.00% | 9.00% | 15.21% | 12.23% | 13.34% | 18.91% | 20.12% |
| *Position Taken (annualized)* | 4 | 17 | 18 | 24 | 28 | 21 | 19 | 20 |
| *Transaction Costs* | 0.64 | 2.72 | 2.88 | 3.84 | 4.48 | 3.36 | 3.04 | 3.2 |
| *Annualised Return (including costs)* | 6.8 | 5.28 | 6.12 | 11.37 | 7.75 | 9.98 | 15.87 | 16.92 |

## 6. Conclusion

This paper introduces a novel methodology for acquiring profitable and accurate trading results when modelling and trading the FTSE100 index. The proposed PSO RBF methodology is a sliding window combination of an adaptive PSO with a RBF neural network. It not only addresses the limitations of existing non-linear models but it also displays the benefits of using an adaptive hybrid approach to utilizing two algorithms. Furthermore, this investigation also fills a gap in current financial forecasting and trading literature by imposing input selection criteria as a pre-selection system before training each of the neural networks. Furthermore, the application of a PSO algorithm to a traditional ARMA model is also a novelty of this paper. Lastly the multi-objective approach to optimising statistical and trading performance is applied to an equity index for the first time. Experimental results proved that the proposed technique clearly outperformed the examined linear and machine learning techniques in terms of an information ratio and net annualized return. This technique is now a proven and profitable technique when applied to forecasting a major equity index.

**References**

Bennell, J. and Sutcliffe C. (2005) Black and Scholes Versus Artificial Neural Networks in Pricing FTSE100 Options, *Intelligent Systems in Accounting, Finance and Management: An International Journal*, 12(4), 243-260.

Cao, L.J. and Tay, F.E.H. (2003) Support Vector Machine with Adaptive Parameters in Financial Time Series Forecasting, *IEEE Transactions on Neural Networks*, 14(6), 1506-1518

De Freitas, J.F.G., Niranjan, M., Gee, A.H., and Doucet, A. (2000) Sequential Monte Carlo Methods to Train Neural Networks Models, *Neural Computation*, 12(4), 995-993.

Diebold, F. and Mariano, R. (1995) Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 20, 133-144.

Ding, H., Xiao, Y. and Yue, J. (2005) Adaptive Training of Radial Basis Function Networks Using Particle Swarm Optimization Algorithm, *Lecture Notes in Computer Science*, 3610, 119-128

Enke, D. and Thawornwong, S. (2005) The Use Old Data Mining and Neural Networks for forecasting Stock Markets Returns, *Expert Systems with Applications*, 29(4), 927-940.

Edelman, D. (2008) Using Kalman-Filtered Radial Basis Function Networks for index Arbitrage in the Financial Markets, in *Natural Computing in Computational Finance Studies in Computational Intelligence*, 187-195, Springer Berlin Heidelberg.

Holland, J. (1995) Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, *Control and Artificial Intelligence*, MIT Press, Cambridge.

Jasic T. and Wood, D. (2004) The Profitability of Daily Stock Indices Trades Based on Neural Network Predictions: Case Study for the S&P 500, the Dax, the Topix, and the FTSE100 in the Period 1965-1999, *Applied Financial Economics* 14(4), 285-297.

Karathanasopoulos, A., Laws, J., Sermpinis, G. and Dunis, C. (2012a) Forecasting and trading the EUR/USD exchange rate with Gene Expression and Psi Sigma Neural Networks, *Expert Systems with Applications*, 39(10), 8865–8877.

Karathanasopoulos, A., Theofilatos, K., Sermpinis, G., Amorgianiotis, T., Georgopoulos, E., and Likothanassis, S. (2012b) Modelling and Trading the DJIA Financial Index Using Neural Networks Optimized with Adaptive Evolutionary Algorithms, in *Engineering Applications of Neural Networks*, 453-462, Springer Berlin Heidelberg.

Karathanasopoulos, A., Sermpinis, G., Theofilatos, K., Georgopoulos, E. and Dunis, C. (2013a) Forecasting Foreign Exchange Rates with Adaptive Neural Networks Using Radial-Basis Functions and Particle Swarm Optimization, *European Journal of Operational Research*, 225(3), 528-540.

Karathanasopoulos, A., Dunis, C., Likothanassis, S., Sermpinis, G. and Theofilatos, K. (2013b) A Hybrid Genetic Algorithm-Support Vector Machine Approach in the Task of Forecasting and Trading, *Journal of Asset Management*, 14, 52-71.

Karathanasopoulos, A., Vasilakis, G., Theofilatos, K., Georgopoulos, E. and Likothanassi, S. (2013c) A genetic programming approach for EUR/USD exchange rate forecasting and trading, *Computational Economics*, 42(4), 415-431.

Karathanasopoulos, A., Sermpinis, G., Laws, J. and Dunis, C. (2014) Modelling and Trading the Greek Stock Market with Gene Expression and Genetic Programing Algorithms, *Journal of Forecasting*, 33(8), 596-610.

Karathanasopoulos, A., Stasinakis, C., Sermpinis, G. and Theofilatos, K. (2015a) Modeling, forecasting and trading the EUR exchange rates with hybrid rolling genetic algorithms—Support vector regression forecast combinations, *European Journal of Operational Research*, 247(3), 831-846.

Karathanasopoulos, A., Sermpinis, G., Stasinakis, C. and Theofilatos, K. (2015b) Forecasting US Unemployment with Radial Basis Neural Networks, Kalman Filters and Support Vector Regressions, *Computational Economics*, 47(4), 569-587.

Kennedy J. and Eberhart R.C. (1995) Particle Swarm Optimization, *Proceedings of International Conference on Neural Networks*, 1942-1948, Orlando.

Lee, C.M. and Ko, C.N. (2009) Time Prediction using RBF Neural Netwoks with nonlinear time-varying evolution PSO algorithm, *Neurocomputing*, 73(1-3), 449-460.

Lowe, D. (1994) Novel Exploration of Neural Network Methods in Financial Markets, *IEEE World Congress on Computational Intelligence*, 6, 3623 3428.

Marcek, D., Marcek, M. and Babel, J. (2009) Granular RBF NN Approach and statistical Methods Applied to Modelling and Forecasting High Frequency Data, *International Journal of Computational Intelligence Systems*, 2(4), 353-364.

Nair, B., Gnana Sai, S., Naveen, A.N., Lakshimi, A., Venkatesh, G.S. and Mohandas, V.P. (2011) A GA Artificial Neural Network Hybrid System for Financial Time Series Forecasting, *Information Technology and Mobile Communication*, 147, 499-506.

Omran, M.F. (1996) Non Linear Dependence and Conditional Heteroscedacity in Stock Returns: UK evidence, *Applied Economics Letters*, 4(10), 647 650.

Pesaran, M. H. and Timmermann, A. (1995). Predictability of stock returns: Robust-ness and economic significance, *Journal of Finance*, 50(4), 1201-1228.

Roweis. S. (2013) Levenberg-Marquardt optimization, available at http://www.cs.toronto.edu/~roweis/notes/lm.pdf (retrieved on 30.9.2013).

Tamiz, M., Hasham R., Jones., Hesni, B. and, Fargher E.K. (1996) A Two Staged Goal Programming Model for Portfolio Selection, *Lecture Notes in Economics and Mathematical Systems*, 432, 286-299.

Tino, P., Schittenkopf, C. and Dorffner G. (2001) Financial Volatility Trading using Recurrent Neural Networks, *IEEE Transactions on Neural Networks*, 12(4), 865-874.

Vapnik, V.N. (2000) *The Nature of Statistical Learning Theory*, Springer, USA.

Weigend, A.S., Huberman B.A. and Rummelhart E.D. (1990) Predicting the Future: A Connectionist Approach, *International Journal of Neural Systems*, 1(3), 345-346.

Yan, X.B., Wang, Z., Yu, S.H. and Li, Y.J. (2005) Time Series Forecasting with RBF Neural Network, *Machine Learning and Cybernetics, Proceedings*, 8, 4680-4683.