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Hybrid neurofuzzy approaches for sign prediction and volatility dynamics

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Abstract

To profit from trading or to mitigate market dangers, investors need dependable financial application forecasting methods. When the FTSE100 and the New York Stock Exchange return, this study examines the predictive accuracy of a trading strategy using a neurofuzzy model. Furthermore, empirical evidence supports the premise proposed by Bekaert and Wu (2000) that the inclusion of conditional volatility change estimates substantially improves the predictability of the neurofuzzy model. Consequently, headed into the following trading day—a potentially pivotal juncture—we are armed with reliable data. By continuously surpassing the returns of feedforward neural networks, Markov-switching models, and buy-and-hold strategies, the volatility-based neurofuzzy model yields a superior total return (including transaction costs). Two plausible hypotheses that provide weight to the notion that dependence on indicators results from reliance on volatility are the presence of portfolio insurance plans in the stock markets and the "volatility feedback" idea. Passive portfolio management may be surpassed by an investing strategy established on the suggested neurofuzzy model.

INTRODUCTION

A considerable amount of scholarly literature in the field of finance is dedicated to empirical investigations about the association between the volatility of stock returns and those returns. Return shocks are attributed to fluctuations in conditional volatility, as postulated by the "time-varying risk premium hypothesis." Conditional volatility is revised upwards in response to "negative" news that is introduced to the market, which raises current volatility. As a result of the need to offset this greater conditional volatility with a larger projected return, the market's current value falls immediately. The aforementioned theory introduces the notion that the volatility response to return shocks is asymmetric. A rise in conditional volatility is a consequence of negative news, but the overall effect of positive news remains uncertain. The "leverage effects" [2] provide a further rationale for the asymmetric response of conditional volatility. A decrease in financial leverage resulting from a positive or negative return causes an increase in volatility and a decrease in risk associated with the stock.

In contrast to what the time-varying premium theory posits, the causal relationship in this instance is as follows: return shocks induce variations in conditional volatility. Exchange-rate fluctuations are influenced, at least in part, by adjustments in the assessed conditional volatility attains a predefined threshold. To motivate remaining investors to maintain a greater amount of stock, the exit of portfolio insurers from the market must result in a decline in stock prices. Investors consider the impact of portfolio insurance programmes, and in the context of a rational expectations environment, there is no discernible decline in stock values.

In addition, a considerable number of scholars investigate the concurrent correlation that exists between the returns of one-day stock indexes and the adjustments in implied volatility indices. An empirical association between the implied volatility VIX index, and this relationship is statistically significant and negative. Particularly with regard to index, it has been observed that this association is unbalanced; that is, bigger proportionate increases in implied volatility measures are linked to negative stock index returns than to positive returns. In response to unfavorable returns, opponents' traders increase implied volatility; this peculiar behavior is justified on this basis.

On the contrary, empirical data is starting to converge in regards to the forward signal of the underlying stocks that implied volatility may provide. The sole scholarly work that adequately tackles this issue is a study conducted by the researcher. In this study, 21 dummy variables representing equally spaced percentiles of a rolling two-year history of VIX were utilised to regress the anticipated returns of the index over different time periods. The researcher shows that, long positions with higher levels of implied volatility indices are anticipated to provide good forward-looking returns.

In this scholarly article, Christoffersen and Diebold demonstrate that sign dependence and forecastability are both outcomes of volatility dependence, provided that anticipated returns remain nonzero. Volatility fluctuations will affect the likelihood of detecting positive or negative returns, according to the underlying premise of this connection. To clarify, if projected returns remain positive, an increase in volatility corresponds to a greater likelihood of experiencing an adverse return. Furthermore, they demonstrate that this outcome is completely compatible with eliminating conditional mean dependency and conditionally Gaussian distributions. Long positions are exercised in anticipation of positive returns, whilst short positions are used in anticipation of negative returns. This research investigates the predictive value of return signs generated by trading rules based on a fundamental switching approach. This strategy, which has been shown to be very beneficial, has been used in a number of further research. Profits earned by an active trading technique often, notwithstanding circumstances in which transaction costs are substantial. Furthermore, they note that periods of high volatility enhance the reliability of asset return forecasts. A variety of linear and nonlinear econometric models are used by technical trading strategies to provide buy and sell signals.

Predicting Nonlinear Time Series: Fuzzy Systems and Artificial Neural Networks

Creation of novel models or the adjustment of established techniques that improve the capacity to predict outcomes, especially for time series exhibiting dynamic temporal variation patterns, is the primary obstacle in time series analysis. Financial and economic time series are not always accessible to standard time series analysis methods [11], which rely on stable stochastic processes. This is due to the fact that random walks, white noise, and basic linear structural models are unable to characterise economic data in general. Previous research has made substantial use of these techniques; nevertheless, their predictive accuracy for financial data is often compromised. Nevertheless, despite the incorporation of non-constant variance into generalised autoregressive conditional heteroscedasticity (GARCH) models.

Neural networks essentially enhance financial forecasting via the execution of intricate mathematical and statistical operations, such as function approximation and nonlinear interpolation, Numerous studies have been conducted in the field of nonlinear modelling. Processing units that are weighted connections join and function in parallel to form neural networks. Input and output vectors are sent across these connections. Many writers have also conducted extensive research on the function approximation characteristics of neural networks. With an adequate number of hidden units and well-tuned parameters, feedforward networks may estimate any function with the needed level of precision. Notwithstanding this, traditional time series analysis methods and neural networks only use quantitative input variables. Unstructured expert information must be captured to account for the significant impact that a variety of qualitative elements, such as political or macroeconomic influences and trader psychology, may have on market trends.

Recent uses of fuzzy logic in the financial sector have shown very encouraging outcomes since its original implementation in the control domain. It provides a mechanism for depicting data that is stochastic and unreliable. Fuzzy systems use fuzzy language phrases to represent numeric variables (inputs and outputs). Within the Boolean formalism, a distinct variable is assigned an exact numeric value. However, in the fuzzy set, the estimation of the extent to which a variable is a component of the set is performed by a membership function for each word. To establish a connection between the fuzzy input and the fuzzy output set, fuzzy inference rules are essentially written as if-then statements. Fuzzy systems are capable of representing human expert knowledge, experience, intuition, and more via the use of fuzzy inference rules. As a result, they serve as efficient modelling tools for expert systems. Control, categorization, decision assistance, and process simulation are among the many domains in which fuzzy inference systems are implemented [27–31]. The literature has also shown financial and marketing uses [20]. Linguistic interpretability is a significant benefit of fuzzy inference systems. Modeling fuzziness and linguistic ambiguity via the use of membership functions is a primary concern throughout the implementation of fuzzy systems. The use of the operator's specialised expertise for prediction has been implemented in many forecasting issues using the fuzzy system technique. The best predictions may not always be produced by the inference rules generated in this manner, and the selection of membership functions remains a matter of experimentation.

Empirical evidence has accumulated since 1990 supporting the notion that neural networks are a novel and promising technique. Adjusting and refining fuzzy membership functions is possible by using the learning capability of neural networks. By combining the functionalities of the fuzzy expert system with the learning capabilities of the neural network, a hybrid neurofuzzy model is produced. This model is an amalgamation of the two methodologies.

Presenting a hybrid neurofuzzy technique that generates improved forecasts on the market's direction of change, this article contributes to the body of knowledge on financial forecasting applications. Additionally, it is shown that the neurofuzzy model generates more accurate predictions by including volatility changes with endogenous return delays, as opposed to the current approach which utilises moving averages (MAs), return lags, and other inputs. The purpose of this report is to offer a concrete demonstration of this point via a comparative examination.

Following that, article is organised in the following manner. The subsequent forecasting models used in this study are further upon in Section IV. Conditionsal volatility models are succinctly reviewed in Section V. In Sections VI and VII, closing comments are presented, followed by the empirical findings.

Neurofuzzy hybrid model

An input layer, a rule layer, and an output layer comprise the neurofuzzy architecture. Each variable is converted to fuzzy linguistic phrases inside the input fuzzy layer. Fuzzy membership functions denote each phrase. In this layer, the configuration of membership function types takes place, while train neural networks to optimise the parameters of these functions. "The fuzzy inference rules are composed of two components: "THEN" and "IF." These rules are implemented inside the fuzzy rule layer. A "AND" conjunction is used in the "IF" clause. This operator represents the "IF" sector's minimal validity value, as Zimmermann recommended. The output fuzzy layer includes output fog membership functions. The defuzzification layer converts fuzzy variables to exact values. The mammdani technique to fuzzy inference [18] is implemented in the aforementioned structure. However, the inclusion of linear relationships between each rule and the input variables of the system in Sugeno's approach of fuzzy inference [27] obviates the need for the defuzzification stage. The principal differentiation between Sugeno-type fuzzy inference and Mamdani-type fuzzy inference is in the presence of piecewise constant or linear output membership functions. "Takagi-Sugeno model" [24] guidelines are more generic and are expressed as follows:

$$IF\ x \text{ is } A\ AND\ y \text{ is } B\ THEN\ z = h + cx + dy \quad (1)$$

Sugeno is well-suited for modelling nonlinear systems via interpolation of numerous linear models, in light of the fact that each rule is linearly dependent on the input variables of the system.

In order to include the parameters c, d, k, and h of the nth rule used for forecasting the ascending and descending trends of financial market data, the following first-order polynomial is implemented.:

$$z_n = h_n + c_n x_1 + d_n x_2 + k_n x_3. \quad (2)$$

This model is comprised of two sets of parameters: the polynomial parameters and the membership function parameters. In the suggested architecture, every input is linked to one of two membership functions, represented by the symbols "high" or "low," which are indicative of unique regimes. The hybrid training procedure solves for the polynomial parameters. Earlier than the criteria of the membership becoming updated, a backpropagation of the errors is performed on the polynomial parameters using a least squares algorithm.

$$E = \frac{1}{2}(y - y^{\circ})^2 \quad (3)$$

the system output (y) and the target (y°) for a sample of size N. There are five distinct layers that make up the architecture of the model that has been provided. Each of these levels is denoted by the notation Ll,i. The expression l = 1,..., 5 shows the layer index, I represents the ith node of layer Ll,i, and j is the index.

$$L_{1,i} : \mu_{M_i}(x_j). \quad (4)$$

$$L_{2,i} : w_i = \prod_{j=1}^{m} \mu_{M_i}(x_j) \quad (5)$$

$$L_{3,i} : \overline{w}_i = \frac{w_i}{(w_1 + w_2)}. \quad (6)$$

Here is how the rule outputs are computed in the fourth layer:

$$L_{4,i} : y_i = \overline{w}_i z_i = \overline{w}_i (c_i x_1 + d_i x_2 + k_i x_3 + h_i). \quad (7)$$

The output of the system is a piecewise linear interpolating function that is dynamically calibrated in the fifth and final layer using the input-dependent normalised weights.

$$L_{5,i} : y = \sum_i y_i = \bar{w}_1 (c_1 x_1 + d_1 x_2 + k_1 x_3 + h_1) \\ \bar{w}_2 (c_2 x_1 + d_2 x_2 + k_2 x_3 + h_2). \quad (8)$$

The last equation may be rewritten using the matrix format that is shown in the following sentence:

$$y = [\bar{w}_1 x_1 \ \bar{w}_1 x_2 \ \bar{w}_1 x_3 \ \bar{w}_1 \ \bar{w}_2 x_1 \ \bar{w}_2 x_2 \ \bar{w}_2 x_3 \ \bar{w}_2] \\ \times [c_1 \ d_1 \ k_1 \ h_1 \ c_2 \ d_2 \ k_2 \ h_2]^T = \mathbf{X} \cdot \mathbf{W}. \quad (9)$$

If the X matrix were invertible, the solution to the aforementioned dilemma about the weight vector W may be as follows:

$$\mathbf{W} = \mathbf{X}^{-1} \cdot \mathbf{Y}. \tag{10}$$

But in financial applications in particular, straight inversion would imply that the input data be devoid of serial autocorrelation and/or noise, which is impractical. In regard to underdeterminacy and overdeterminacy, other approaches like triangle or robust orthogonal decomposition show improvement; still, they often generate numerical instabilities and contribute to noise overfitting. Unified value decomposition (SVD) is implemented in this study [28]. The probability of overfitting the function being approximated is reduced by the SVD method's use of primary components to eliminate extraneous information associated with noise. Diagonally oriented singular value matrix D, main component matrix U, and orthogonal normal value matrix V comprise the components of the decomposed X matrix. Final solution is obtained for the weight matrix by5

$$\mathbf{W} = \mathbf{V} \cdot \mathbf{D}^{-1} \cdot \mathbf{U}^{\mathbf{T}} \cdot \mathbf{Y}. \tag{11}$$

Input variable fuzzification is accomplished with symmetric triangular membership functions. "ai" is the value of the bi "support" parameter; the triangular function is included in the ai "peak" parameter.

$$\mu_{M_i}(x_j) = \begin{cases} \frac{(1-|x_j-a_i|)}{(b_i/2)}, & \text{if } |x_j - a_i| \le \frac{b_i}{2} \\ 0, & \text{else.} \end{cases} \tag{12}$$

The following explains the updating rule for the "peak" parameter in the gradient descent algorithm:

$$a_{i,t+1} = a_{i,t} - \left(\frac{\eta_a}{p}\right)\left(\frac{\partial E}{\partial a_i}\right) \tag{13}$$

in where ηα represents the learning rate and p represents the training sample size. The "support" parameter is subject to the same criteria. By using the subsequent chain rule, one may reduce a total derivative to its component derivatives:

$$\frac{\partial E}{\partial a_i} = \left(\frac{\partial E}{\partial y}\right)\left(\frac{\partial y}{\partial y_i}\right)\left(\frac{\partial y_i}{\partial w_i}\right)\left(\frac{\partial w_i}{\partial \mu_{M_i}}\right)\left(\frac{\partial \mu_{M_i}}{\partial a_i}\right). \tag{14}$$

The following recursive equation represents the updating rule for the peak parameter subsequent to a partial derivation:

$$a_{i,t+1} = a_{i,t} - \left(\frac{\eta_a}{p}\right)\left\{\left[\frac{w_i}{\mu_{M_i}(x_j)}\right]\left[\frac{(z_i - y)}{\sum_{i=1}^{n} w_i}\right] \times \left[2 \cdot \text{sign}\frac{(x_j - a_i)}{b_i}\right](y - y^{\circ})\right\} \tag{15}$$

whereas for the support parameter

$$b_{i,t+1} = b_{i,t} - \left(\frac{\eta_b}{p}\right)\left\{\left[\frac{w_i}{\mu_{M_i}(x_j)}\right]\left[\frac{(z_i - y)}{\sum_{i=1}^{n} w_i}\right] \times \left[1 - \frac{\mu_{M_i}(x_j)}{b_i}\right](y - y^{\circ})\right\}. \tag{16}$$

In all, there are two iterations of the hybrid learning procedure. Membership parameters stay constant when the SVD technique is used to generate the polynomial parameters. While the mistakes are backpropagated inside the layers during the inverse pass, the parameters are kept constant. This allows the membership parameter adjustments to be determined.

ADDITIONAL ARTICLES OF FORECASTING

To evaluate the neurofuzzy model's profitability and predictability, it is contrasted with three other strategies: a buy & hold (B&H) approach, a Markovs witching (MSW) model, and a feedforward artificial neural network. An exposition of these models follows.

MSW Model

When there are just two regimes present, such as "low" and "high," it is sufficient to suppose that st may assume two values. In this situation, the AR (1) model for both regimes can be expressed as

$$y_t = \begin{cases} \varphi_{0,1} + \varphi_{1,1} y_{t-1} + \varepsilon_t & \text{if } s_t = 1, \\ \varphi_{0,2} + \varphi_{1,2} y_{t-1} + \varepsilon_t & \text{if } s_t = 2. \end{cases} \tag{17}$$

A first-order Markov process is postulated to be in operation. The research proposes the MSW model, which is the most often used model in this category. To bring the model to a close, it is necessary to determine the changeover probabilities for when transitioning from one state to the next.

$$P(s_t = 1 \mid s_{t-1} = 1) = p_{11}$$
$$P(s_t = 2 \mid s_{t-1} = 1) = p_{12}$$

$$P(s_t = 1 \mid s_{t-1} = 2) = p_{21}$$
$$P(s_t = 2 \mid s_{t-1} = 2) = p_{22} \quad (18)$$

To ensure correct probabilities are defined, they must be non-negative and satisfy the conditions that p11 + p12 = 1 and p21 + p22 = 1. By using the idea of ergodic Markov chains, one can easily demonstrate that the study provides this unconditional probability.

$$P(s_t = 1) = \frac{(1 - p_{22})}{(2 - p_{11} - p_{22})}$$

$$P(s_t = 2) = \frac{(1 - p_{11})}{(2 - p_{11} - p_{22})}. \quad (19)$$

Artificial Neural Network using a Feedforward Protocol

A feedforward network with a single hidden layer, adequately concealed units, and appropriately set parameters may estimate functions theoretically with the requisite precision. Through the implementation of a transfer function, a neural network produces its output. For the purpose of reducing the likelihood of overfitting, it is common practise to separate the sample into three independent sets: training, validation, and testing sections (out-of-sample).The biggest dataset, consisting of the most recent observations processed for predictability testing, is designated as the training set. The neural network use this set to detect patterns within the data.

$$y_t = S\left[\beta_0 + \sum_{i=1}^{q} \beta_i G\left(\alpha_{i0} + \sum_{j=1}^{p} \alpha_{ij} x_{j,t}\right)\right] = f(\mathbf{x_t}, \mathbf{z}) \quad (20)$$

with I = q and j = p, respectively. In the context of hyperbolic tangent sigmoid transfer functions, let z = (β0,...,βq, α11,...αij,...,αqp)T represents the weight vector. By using a subset of the data values, the network solution takes into account the estimate. By using backpropagation, a recursive estimation technique, the weight vector is estimated in the following manner:

$$z_{t+1} = z_t + \eta \nabla f(\mathbf{x_t}, z_t) \cdot [y_t - f(\mathbf{x_t}, z_t)] \quad (21)$$

In this context, η denotes the learning rate and ∇ f (xt,z) represents the gradient vector with respect to z. By minimising the mean square error function.

THE MODELING OF VOLATILITY

The depiction of daily returns of the price of a financial instrument that are equally and independently distributed is an example of a stochastic process. The most important assumption that must be made in order to calculate the conditional variance is represented by the symbol (rt)nt=1.

$$r_t = \mu_t + e_t = \mu_t + \sigma_t \varepsilon_t \quad (22)$$

$$\sigma_t^2 = \left[\frac{1}{(m-1)}\right] \cdot \sum_{j=1}^{m} (r_{t-j} - \mu_t^m)^2 \quad (23)$$

Trading days is denoted by $\mu m_t = (1/m) m^{j=1} r_{t-j}$. Conversely, one of the GARCH models [32] may be used to estimate it. The GARCH(1) model is specifically expressed as

$$\sigma_t^2 = \alpha_0 + \alpha_1 (r_{t-1} - \mu_t)^2 + \beta \sigma_{t-1}^2 \quad (24)$$

$\mu_t = (1/T)\sum_{i=1}^{T} r_{t-i}$. The exponentially weighted moving average (EWMA) specification, which Morgan's risk metrics (RM) model implements, is a particular example of GARCH models.

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1-\lambda)(r_{t-1} - \mu_t)^2. \quad (25)$$

For daily data, the ideal decay factor is 0.89, while for monthly data, it is 0.89.

EMPIRICAL RESULTS

The daily index price is denoted by Pt. Then, rt = log(pt)−log(pt−1) is used to compute the daily returns. In particular volatility daily changes Δσ = σt − σt−1 over the preceding p days. The output (y) is the return anticipated one day in advance (rˆt).Using the 20-day MA, RM, and GARCH (1, 1) models, the daily movement of conditional volatility was computed for the same time periods. In order to generate predictions for each day throughout the defined time frame throughout the assessment period, the models make use of a moving window that is composed of each and every prior observation as the training sample. The validation sample for each instance makes up thirty percent of the training set. This is done so that the model's capacity to generalise can be evaluated, and the danger of overfitting may be reduced. The training set is comprised of the observations that have been processed the most recently for each individual instance. In order to create predictions for particular days during each backtesting period, a moving window that is composed of all past observations is used in both the training samples and the validation samples. First-order, two-rule, three-input enhancements to the suggested interpretability Following fuzzy rules, the Sugeno system is described:

$$\begin{aligned} \mathfrak{R}_1: &\ \text{IF } r_{t-2} \text{ is "low" and } r_{t-1} \text{ is "low" and } \Delta\sigma_t \text{ is "low"} \\ &\ \text{then } \hat{r}_t = h_1 + c_1 r_{t-2} + d_1 r_{t-1} + k_1 \Delta\sigma_t \\ \mathfrak{R}_2: &\ \text{IF } r_{t-2} \text{ is "high" and } r_{t-1} \text{ is "high" and } \Delta\sigma_t \text{ is "high"} \\ &\ \text{then } \hat{r}_t = h_2 + c_2 r_{t-2} + d_2 r_{t-1} + k_2 \Delta\sigma_t. \end{aligned}$$

Specifically, the rule formulation is conducted in accordance with Bekaert and Wu's [1] hypothesis, which asserts that modifications in conditional volatility give rise to fresh return shocks. Inference rules are used by the fuzzy learning algorithm to account for this "fuzzy interaction." Changes in volatility affect the likelihood of witnessing positive or negative returns [1]; this is the underlying premise of this connection. 9

In FNN experiments, a hidden layer with 10 neurons (g) and an output layer with one neuron had the maximum prediction power (y).In the MSW model, the returns associated with an AR(8) model are postponed by two periods in both regimes.

To address the use of nonlinear models, an examination is performed to identify the existence of nonlinear dependency in the series.

$$W_{m,T}(\varepsilon) = T^{\frac{1}{2}} \frac{\left[C_{m,T}(\varepsilon) - C_{1,T}^{m}(\varepsilon)\right]}{\sigma_{m,T}(\varepsilon)} \quad (26)$$

The symbol "σm,T (ε)" denotes the standard deviation of the correlation integral Cm,T (ε) between m-dimensional vectors positioned within a distance ε from one another, given a total sample size of T. The trading rule is implemented in the following manner: The models are re-estimated over a rolling sample of duration equal to the training period each trading day ends. Whenever transaction costs are not taken into consideration, the anticipated total return is

$$R_t = \sum_{n+1}^{n+T+1} s \cdot r_t \quad (27)$$

The advised position is represented by the value of s^rt, while the realised return is denoted by rt. A value of -1 indicates a short position, while a value of 1 (+1) implies a long position. The following formula was used to calculate the percentage of correct predictions or properly predicted signs in order to ascertain the degree of accuracy possessed by the models:

$$\text{Sign Rate} = \frac{h}{T} \quad (28)$$

The number of accurate forecasts is denoted by h. Comparative profitability is also measured by the sharpe ratio (SR). When the standard deviation of the trading strategy is subtracted from the mean return, the SR is calculated. A greater return and less volatility are associated with a higher SR.

$$S_R = \frac{\mu_{R_T}}{\sigma_{R_T}}. \quad (29)$$

HM established that, contrary to the null hypothesis of no market-timing talent, the number of correct forecasts is asymptotically distributed as N and follows a hypergeometric distribution (0,1). Table II presents the empirical outcomes derived from the comparative execution of all models. A clear drawback of the FNN model is the loss of 6.4 percent. Once again, the VNF-MA (21) model exhibits superior predictive performance in the context of the NYSE compared to the

TABLE I

BDS TEST

Index	Corr. Dim.	m = 2		m = 3		m = 4	
	Dim. Dist.	E = 1	ε = 1.5	ε = 1	ε = 1.5	ε = 1	ε = 1.5
FTSE100	Raw data	8.86	10.914	14	16.484	16.775	18.343
	AFR	11.654	10.964	13.774	16.168	15.928	18.328
	NLSSR	6.628	4.347	6.207	5.107	3.484	5.268
NYSE	Raw data	12.514	15.123	16.188	18.877	18.603	31.314
	AFR	11.943	13.804	15.6	17.108	17.844	28.448
	NLSSR	7.882	9.534	12.768	11.753	15.3.5	13.857

TABLE II

The trading models' performance outside of the sample

Index	Model	Sign Rate	HM Test	Total Return(%)	Sharpe Ratio	RMSE	B&H Return(%)
FTSE100	VNF-MA(12)	0.629	4.125	63.1(30.2)	0.773	0.123	-18.4
	MSW	0.939	4.881	204.5(87.9)	2.368	0.113	
	FNN	0.616	2.546	49.2(32.4)	0.701	0.123	
	VNF-RM(0.84)	0.588	0.299	25.7(0.8)	-0.086	0.125	
	VNF-GARCH(1,1)	0.616	2.682	35.4(6.3)	0.484	0.126	
NYSE	VNF-MA(12)	0.598	2.481	53.5(13.3)	0.728	0.111	4.4
	MSW	0.627	3.873	223.8(79.8)	2.757	0.122	
	FNN	0.61	2.887	64.5(45.8)	1.888	0.133	
	VNF-RM(0.84)	0.508	2.194	35.7(-1.8)	1.469	0.144	
	VNF-GARCH(1,1)	0.587	-1.898	3.4(6.3)	1.469	0.155	

When transaction costs, calculated at 0.05 percent for each one-way trade, are accounted for, the same picture emerges. Once again, the trading rule continues to provide substantial profits for both indexes. The superior performance of the VNF-MA (21) model in comparison to the FNN, MSW, and B&H strategies is further shown by the larger percentage of accurately anticipated signs. In light of the fact that it is impossible to achieve perfect accuracy in trading, a sign rate that is much higher than fifty percent indicates that the predictive model has greater performance in comparison to the random walk.

Furthermore, in comparison to the SR (annualised) of the FNN and MSW models, as well as the other two VNF models, it is much greater. Consistent with prior findings reported in [8] and the conclusions drawn in [7], it is shown that all models exhibit superior performance compared to the B&H approach,, excluding transaction costs.The capable of generating sign forecasts that are on par with those generated by more intricate econometric models frequently employed to model conditional volatility, according to a comparison of the various specifications for the VNF models. It is not unexpected that the results obtained from GARCH (1, 1) models closely resemble the predictions of the NASDAQ index as described. Additionally, it is stated in reference [5] that the EWMA volatility projections closely resemble the predictions generated by the researcher. On the two financial time series under examination.In contrast to the probabilistic regime-switching Markov model and the nonlinear neural predictor, The proposed model is a piecewise linear interpolator that is dynamically updated, which results in a more accurate identification of turning points concerning sign prediction. Ultimately, improved classification and prediction outcomes result from this process.

CONCLUSION

This work contributed to the body of knowledge that has examined the capacity of trading rules to anticipate returns using separaeconometric models or B&H methods by introducing a VNF model. Upon considering transaction costs, the results imply that the proposed neurofuzzy model exhibits greater performance in terms of FTSE100 and NYSE index returns when compared to the MSW models, FNNs. Over the course of the market period under review, the profitability per unit of risk was significantly increased by the incorporation of the neurofuzzy model of daily volatility variations of conditional volatility, which were produced from several estimating approaches. Conditional volatility provided dependable insights on a potential turning point that may occur the day after in the trading session. The results of this study show that the volatility-based neurofuzzy model has been optimally "trained" to associate conditional volatility fluctuations with the market's "sign" one day ahead of time. Numerous factors might be involved in this. Increasing volatility is associated with higher anticipated returns, according to the first correlation. If "negative" news causes a rise in volatility, the next trading day will see a decline in prices.

It is uncertain, however, what the overall impact on prices will be when "positive" news generates volatility increases. The second argument relates increases in volatility to trigger techniques that a significant number of portfolio managers use. Each increase in volatility results in the liquidation of some portfolios due to the risk limit being reached, hence exerting pressure on the market. Ultimately, the outcomes align substantially with the deductions made from a "statistical" standpoint, which posit a strong correlation between the signs of asset returns and the volatilities of such returns. The evaluation of the trading models with regard to sign prediction revealed that the proposed model, which functions as a dynamically adjusted piecewise linear interpolator, achieves more accurate identification of market turning points than either the static nonlinear neural predictor or the regime switching Markov model. This was discovered as a result of the evaluation. Additionally, the dynamic adjustment of the inference rules and their parameters acts as a facilitator for the creation of adaptive knowledge and the identification of optimum regimes.

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