Regression and Bee optimization to select Colombia investment portfolio

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Abstract

Making decision to select investment portfolio is very complex and it is based on the risk and the profit. There are multiple studies about investment portfolio, however, it is an open research field due to the complexity of the prediction of the market. In this paper are compared support vector regression models and Long short term memory- Artificial Neural network applied on a database of Colombia stock-exchange of 18 enterprises with 2631 instances for the period 2010-2020. Their results are used to obtain an optimized investment portfolio which is carried out using bee algorithm optimization in order to minimize the risk and maximize the profit with constrain levels based on expected return. The results demonstrated the capability of the decision support system to select portfolio.

Keywords: Data fusion, Adaptive Neuro inference system, Autoregressive model, Portfolio investment, Support Vector Regression

1. Introduction

Portfolio theory was proposed by Markowitz, who carry out deep analysis of the investment risk and profit relationship, becoming a support for investors, establishing how their portfolio can be favored with diversification (Markowitz, 1952). Currently, the traditional form of investment is based on "more traditional compositions and that is used as a reference at a global level is the well-known 60/40 portfolio. This is a classic composition that allocates 60% of the portfolio to equities and 40% to high quality fixed income" [1]. On the other hand, several mechanism portfolio investment support decision have been development from 1997 and the major are focus on value market forecasting models and nowadays, it is an open field of research with multiple challenges [2] [3][4][5].

The main objective of investors is to get the best possible return with the minimum risk. Investment portfolio is the most relevant task for investor but very complex due to the return on risk assets is fuzzy and uncertain [6]. Therefore, the performance of portfolio must be estimated before investment decision and it is carried out using prediction models applied on time windows to support decision which allows minimize risks. So improve these support systems it allows minimize loss investment and maximize profits Lesmana et al. [7]. There are multiple models to select portfolio investment, which are focus on mathematical models, statistical models (autorregresive), machine learning, and hybrid (combinations of two or three). Some of them forecast financial risk considering future economic changes as approach of portfolio investment. In (Novikov, 2018) was proposed a hybrid model using Hidden Markov models and artificial neural networks (Multi-layer perceptron – MLP) to predict macroeconomic situation development to obtain an optimized investment portfolio achieving a performance of 70% of accuracy to quarterly periods. In [8] was proposed a risk model based on mean and volatility of the stock return, which are calculated using autoregressive models (moving average to estimate the mean and conditional heteroscedastic to estimate the non-constant volatility and the portfolio investment is optimized applying Lagrange multiplier technique and the Kuhn-Tucker method, obtaining results from a comparative between two portfolios. In [9] was proposed an approach based on Recurrent ANN (RNN) and high–low distributions to forecast financial markets and select investment portfolio. Similar study was presented by [10]. In [11] was applied Copula theory for selecting the optimal investment portfolio from SP500 stock market and CBOE Interest Rate 10- Year Bond obtaining minimum risk value in the financial market with results that demonstrated its functionality. In Tian et al. [6] is presented an approach to select fuzzy portfolio invest based dynamic optimization on multi-period investment. Other approaches are based on multifactor portfolio using Factor Risk Parity Strategies as presented in [12].

To develop a portfolio investment support decision system depend on the market context so their generalization can be very complex. Particularly, Colombia is an attractive country for investment and limited by laws or agreements such as the one presented in (LAW 1720 OF 2014, 2014). However, the research in portfolio for developing models in this context is very limited [13] especially using machine learning models. Therefore, in this work are analyzed, builded and proposed different portfolio investment models using autorregresive model, machine learning, and a fusion of them in the Colombia context using a database of Colombia market. This study is carried out in five steps as follows: i) Preprocessing: series are preprocessed in order to eliminate outlier and apply imputation. ii)

Multivariate autorregresive models are builded. iii) Multivariate forecasting models are builded using machine learning techniques. iv) Optimization based on bee optimization algorithm. The main contributions of this work are: A methodology to develop a decision support system based on market forecast and optimization considering the aversion of investor.

The remainder of this paper is organized as follows: Section 2 mathematical methods addressed here, Section 3 defines the proposed system, Sections 4 and 5 detail the experiments and results, Section 6 presents the discussion, and Section 7 draws the conclusions.

2. Literature review

Different approaches and applications have been carried to predict time series in the field of economy, risk of the investment portfolio, and stock market such as Linear regression, k- nearest neighbor adaptive neuro-fuzzy inference system, artificial neural networks (recurrent, backpropagation, deep learning), support vector regression, random forest, decision tree, autoregressive models, hybrid methods [14], and differential equations as approach presented in [15] where was propose a securities portfolio optimization method of the stochastic diffusion stochastic differential equation adjusting different parameters which have high time cost. Despite multiple studies of models based on different strategies and their relevant results, achieve a reliable stock portfolio is a challenging task and it is still an open research topic in quantitative investment [16].
In [17] is discussed the lack of methods of prediction and assessment of diversification effectiveness and it was proposed a portfolio theory where Sales risk was measured in terms of the expected error of sales forecast. In real environments the use of stock market prediction systems is limited, due to they depend on information quality, distribution of the data ("non-independent identical distribution in financial data") and the complexity of time series [16]. These problems have addressed using different techniques. In [16] these problems were addressed using a novel deep matching algorithm (TS- Deep-LtM) and which applied on stock selection and tested long-only portfolio strategies highlighting its capability compared with other approaches. similar approaches have been carried out using neural networks. In [18] a market forecasting was carried out using Elman recurrent neural networks with stochastic time effective function (ST-ERNN) was developed and compared with BPNN, STNN, and ERNN forecasting models The proposed model demonstrated the best performance for predicting prices considering measures of MAPE, RMSE, and MAE. The performance of the models

was established using daily data from Shanghai Stock Exchange (SSE) Composite Index, Taiwan Stock Exchange Capitalization Weighted Stock Index (TWSE), Korean Stock Price Index (KOSPI), and Nikkei 225 Index (Nikkei225). Besides an approach based on Efficient complexity, invariant distance (CID) was applied which allow establishing that the prediction performance is better when the CID distance is smaller. In [19] a forecast system of fluctuations of Cryptocurrency trade was developed from analysis over a short-time period and applying multiple-input deep neural network model for the prediction of cryptocurrency price and movement. This approach demonstrated better performance in comparison with fully-connected deep neural networks considering overfitting and computational cost using a mixed of cryptocurrency data. In [20] was compared neural networks and genetic algorithm to predict and analyze stock market investments. The best results were obtained by neural networks of 12 hidden layers, demonstrated the feasibility of short-term forecasting stock market. In [21] portfolio featuring a target risk-return carried out a comparative study of recurrent neural network models (RNNs), including a simple RNN, long short-term memory (LSTM), and gated recurrent unit. LSTM demonstrated the best results. In [19] is applied time-series model based on dropout weight-constrained recurrent neural networks for forecasting cryptocurrency prices and the value of Crypto-Currency index 30.

Other approaches based on different machine learning and game learning have been developed and compared with neural networks demonstrating promising results. In [22] support vector regression, random forest, LSTM neural network, deep multilayer perceptron (DMLP), and convolutional neural network are combined to preliminary predict values of stock before portfolio formation. The predictions are fused using mean-variance and omega optimization. Results demonstrated to SVR with omega and random Forest with mean-variance as the best models. In [23] applied three-game learning algorithms, support vector machine and neural network to predict price fluctuations obtaining the best results with game learning algorithms.

The problems of stock prediction and portfolio selection have also been addressed using information fusion, feature fusion, and model fusion. The literature report from 2011 the application of fusion approaches in the stock market to trend prediction, portfolio management, risk and return forecasting[14]. Other strategies have been oriented to unveil the dynamic of the time series such as presented in [24], who used a Forecasting approach based on spectral time series analysis to predict the Aurubis stock price. In [25] was proposed an approach applied to financial time series forecasting based on Multidimensional KNN algorithm and EEMD with invariance (MKNN–TSPI). Results demonstrated outperforms

EEMD–MKNN model and MKNN–TSPI mode. Other no common strategy is the shown in [26] where is applied a model predictive control to optimize an investment portfolio and multi-period portfolio selection and the presented in [27] was proposed a methodology to improve the profits from mutual fund portfolio, to different works, they predict the price of every stock and then, they carried out a grouping of the stocks to reduce the risk and improve the profits.

3. Materials and Methods

3.1. Database

2630 instances were collected from January 2010 through October 2020. These shares make up the COLCAP stock index, which represents the 20 most liquid shares of the Colombian Stock Exchange. One stock (Terpel) was eliminated since it does not have data available since the period of analysis of this article (it only has information available from 2015). These stocks present stable volatility and liquidity conditions in the Colombian equity market. Each instance has 18 variables corresponding to share values of relevant companies in Colombia as follows: Ecopetrol (V1), Bancolombia PF (V2), Bcolomb (V3), Bogota (V4), Bolivar (V5), Celsia (V6), Cemargos (V7), CNEC (V8), ETB (V9), GrupoArgos (V10), Grupoaval (V11), SURA (V12), COLCAP (V13), ISA (V14), Nutresa (V15), Davivienda (V16), PF Cemargos (V17), Promigas (V18). In Fig. 1 and Fig. 2 are shown the data series for each company and the boxplot of closing price data of all companies respectively. These data has several outliers, but due to the behavior of the variables they cannot be eliminated.

3.2. Support vector machine

Support vector machine (SVM) obtain an optimal hyperplane to separate classes using structural risk minimization to maximize the distance between classes (margins). SVM can be used to binary and linear classification [28], and multiclass classification [29]. SVM was extended to regression (Support Vector Regression-SVR) to predict time series [30][31].

The aim of this method is to use a training data $X = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_l, y_l)\}$ to find a function that satisfies $f(x_l) \approx y_l$. First, $\mathbf{x}$ is mapped to higher dimensional feature space in order to treat non-linear problems as linear problems. The problem is depicted as follows:

$$|f(\mathbf{x};\mathbf{w}) - y| =< \mathbf{w}, \mathbf{\Phi}(\mathbf{x}) > +b \quad (1)$$

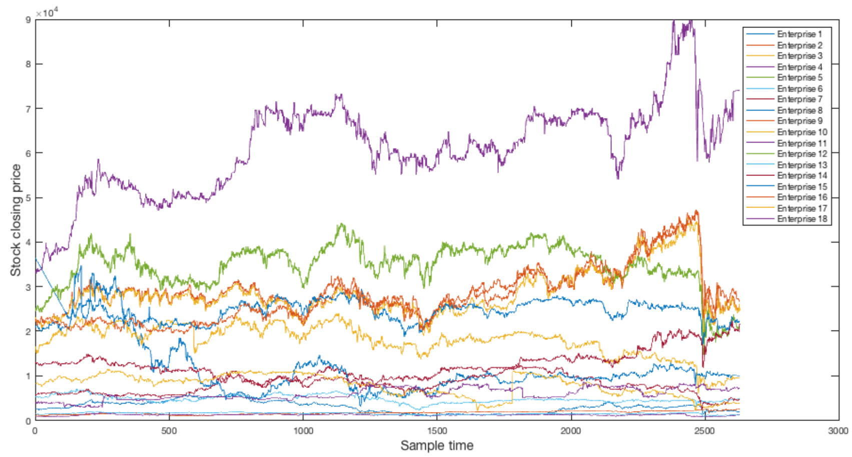

Figure 1: Proposed methodology

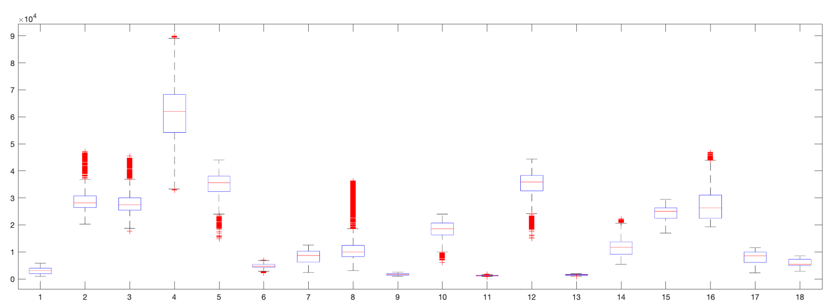

Figure 2: Boxplot of database for all companies

Where, **w** and b results of minimizing the insensitive error (ϵ) between f and the observed values of y, and Φ is the kernel function.

$$|f(\mathbf{x};\mathbf{w})-y|_{\epsilon}\begin{cases} 0 & if|f(\mathbf{x};\mathbf{w})-y|<\epsilon \\ |f(\mathbf{x};\mathbf{w})-y|-\epsilon & otherwise, \end{cases} \tag{2}$$

Kernel functions can be considered as the main potential of support vector techniques, which allow mapping a non-linear problem to linear problem [29]. The most common kernel are:

$$\begin{array}{cc} Gaussian & K(x_i,x_j)=exp(-\|x_i-x_j\|^2) \\ Linear & K(x_i,x_j)=x_i^{\top}x_j \\ Polynomial & K(x_i,x_j)=(1+x_ix_j)^q,\, q=2 \end{array} \tag{3}$$

This technique has other parameters which are widely explained in [32].

3.3. Deep Learning

Artificial neural networks (ANN) can be grouped in Recurrent Neural Networks (RNN) and Feed forward Neural Networks (FFNN). This last are known as backpropagation Neural networks (BPNN) and initially this was limited to one or two hidden layers but the problem was resolved and it is into deep neural network (DNN) and nowadays, they are applied in short-term time series prediction given high accuracy. Likewise, RNN the problem of gradient vanishing was result for this architecture using a Long short term memory (LSTM) cell.

The LSTM network sequence is given by an input time series, a hidden vector sequence and output sequence. They are defined as follows: the input sequence is given by $X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T\}$, the hidden vector sequence is given by $H = \{\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_T\}$ and the output sequence is given by $Y = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_T\}$. The iteration are carried out in the equation $h_t = H(\mathbf{W}_h, [h_{t-1}, x_t] + b_n)$ and $y_t = W_y h_t + b_y$. Where, W is the matrix of weights. The hidden layer function are iterated too. These functions are widely depicted in [33]

3.4. Performance measures

Four performance were applied on forescast models as follows: mean absolute error (MAE= $\frac{1}{N}\sum_{i=1}^{N} e_i$), root mean square error (RMSE=$\sqrt{\frac{1}{N}\sum_{i=1}^{N} e_i^2}$)), Mean absolute percentage error (MAPE=$\frac{1}{N}\sum_{i=1}^{n} |\frac{e_i}{y_i}|$), and fractional bias (FB= $\frac{1}{N}\sum_{i=1}^{n} \frac{2*|e_i|}{|y_i|+|Yi|}$). Where y_i is the real value, Y_i is the predicted value, e is the error, and N is the number of the samples.

4. Experimental Setup

4.1. Methodology

The methodology applied in this study is shown in Fig. 3. First, a database was collected from different sources obtaining 236 instances and 44 variables which was reduced to 54 instances considering completeness criteria. Then, a correlation analysis was carried out using Pearson correlation in order to establish dependence among variables. Then feature selection was applied using Relief-F algorithm and considering a time window prediction of 5 days. SVR regression using Linear, Gaussian, and polynomial kernel were applied to build one model per variable. The same way, LSTM-ANN was applied to predict each variable. The models was builded using all variables and selected variables. Model fusion was applied exploring min, max, mean, median and k-nn techniques. The performance of the models was measured using MAPE, MAE, RMSE, FB. Finally, bee optimization algorithm was applied to select portfolio investment using the predictions given by the best models.

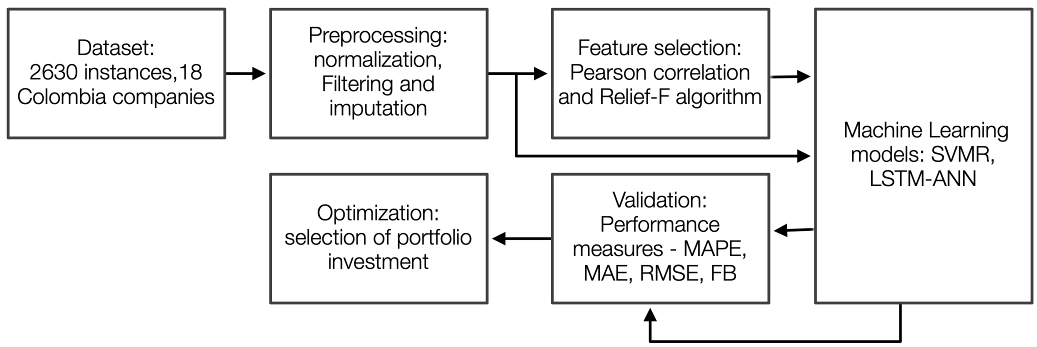

Figure 3: Proposed methodology

4.2. Proposed model

In 3 is shown the methodoly addressed in this study. First, Colombia markets dataset was collected from multiple public database. Then a preprocessing was carried out aplying outlier detection and imputation techniques. Then an uni-variate and multivariate statistical analysis was carried out. Third, three autoregresive models were builded following standar procedures. Fourth, ANFIS, SVMR, and ANN models were builded. All models were builded using time windowing of one week and month. In the fifth step the best models were fused using diferent techniques and validated in the step six using different performance measures. Finally, the proposed model (the best fusion of models) were used for select the portfolio investment applying the Bee algorithm optimization in order to minimize the risk and maximize the profit.

5. Results and discussion

Pearson correlation shows a high correlation (upper to 0.7) to the following variables: V1 and V13 (0.83), V2 and V3 (0.979), V2 and V16 (0.83), V3 and V16 (0.81), V4 and V16 (0.75), V5 and V7 (0.73), V5 and V19 (0.99), V5 and V15 (0.71), V7 and V12 (0.73), V9 and V16 (0.74), V10 and V17 (0.73), V12 and V15 (0.71)

The relevance analysis using Relief-F algorithm show that the most relevance feature for prediction of var 1 ... is ,

In Table 1 is shown the results of RMSE, MAPE, MAE y FB obtained from SVR models using Linear, Gaussian and Polynomial kernels. Analyzing the RMSE measure, the best results was achieved by all variables in exception to V13 with a minimal difference 0.0066. Similar results were obtained for MAPE, MAE and FB measures. Figure Fig. 4

In Table 2 is shown the results achieved by the LSTM-ANN models.

Table 1: Performance of SVR models.

Predicted variable	Technique	RMSE	MAPE	MAE	FB
V1	SVR-Linear	0.1686	0.2411	0.1226	0.2403
	SVR-Gaussian	0.4747	-0.2190	0.3555	3.3606
	SVR-Polynomial	3.5642	5.4384	2.6630	-2.2097
V2	SVR-Linear	0.4183	-0.0205	0.3364	0.2912
	SVR-Gaussian	0.9877	-0.3593	0.7564	0.6670
	SVR-Polynomial	0.7681	0.0804	0.6380	0.5246
V3	SVR-Linear	0.3862	0.1545	0.2658	-0.0227
	SVR-Gaussian	1.9954	0.7979	1.6726	3.2876
	SVR-Polynomial	0.8829	0.3386	0.7266	-0.0931
V4	SVR-Linear	0.3024	0.2578	0.2106	0.0594
	SVR-Gaussian	0.9516	0.4410	0.8118	-0.1390
	SVR-Polynomial	0.3043	0.2544	0.2139	0.0687
V5	SVR-Linear	0.2483	0.6708	0.1694	0.0504
	SVR-Gaussian	0.3336	0.0355	0.2503	0.1529
	SVR-Polynomial	0.2946	2.0448	0.2072	0.1690
V6	SVR-Linear	0.1955	-0.3245	0.1359	-0.0596
	SVR-Gaussian	0.7988	-1.4668	0.7485	3.9789
	SVR-Polynomial	0.2742	-0.6739	0.2073	-0.2161
V7	SVR-Linear	0.1981	-0.2853	0.1572	0.1794
	SVR-Gaussian	1.1947	-1.3056	0.9777	2.5349
	SVR-Polynomial	4.5732	-4.5898	3.4877	-4.0130
V8	SVR-Linear	0.0992	-0.2248	0.0771	0.1419
	SVR-Gaussian	0.1162	-0.2559	0.0880	0.2015
	SVR-Polynomial	6.4456	-7.5590	4.6828	-0.7738
V9	SVR-Linear	0.2148	0.1569	0.1397	0.0543
	SVR-Gaussian	1.6386	1.1905	1.5131	2.9508
	SVR-Polynomial	0.2510	0.1746	0.1748	0.1052
V10	SVR-Linear	0.2345	-0.1184	0.1753	0.0961
	SVR-Gaussian	1.8891	-1.0794	1.7134	2.3516
	SVR-Polynomial	1.0277	-0.5244	0.8731	0.7596
V11	SVR-Linear	0.3377	-0.0329	0.2355	-0.1218
	SVR-Gaussian	2.4324	-1.1033	1.9510	-6.0177
	SVR-Polynomial	0.5491	0.1987	0.4281	-0.3142
V12	SVR-Linear	0.2728	-0.4140	0.1880	0.0821
	SVR-Gaussian	2.9008	-2.1194	2.1056	-44.6037
	SVR-Polynomial	9.1172	1.0817	6.9126	-0.6321
V13	SVR-Linear	0.2860	0.1464	0.2087	-0.2645
	SVR-Gaussian	0.8964	-0.3553	0.6213	1.5616
	SVR-Polynomial	0.2794	0.1915	0.2161	-0.0940
V14	SVR-Linear	0.2418	0.0923	0.1606	0.0409
	SVR-Gaussian	1.9584	1.1119	1.7792	2.9470
	SVR-Polynomial	0.4340	0.2214	0.3125	0.0899
V15	SVR-Linear	0.3449	0.9542	0.2345	0.6987
	SVR-Gaussian	0.8816	0.0749	0.7044	4.0171
	SVR-Polynomial	0.3660	0.8012	0.2474	0.4803
V16	SVR-Linear	0.2770	-0.8258	0.2087	0.0572
	SVR-Gaussian	1.6825	-1.2408	1.3923	2.2307
	SVR-Polynomial	0.9633	-0.6510	0.7958	0.7805
V17	SVR-Linear	0.1202	-0.0932	0.0851	0.0309
	SVR-Gaussian	1.3964	-1.0402	1.2162	2.3532
	SVR-Polynomial	0.5482	-0.4835	0.4768	0.5317
V18	SVR-Linear	0.3750	0.6370	0.3165	-0.3094
	SVR-Gaussian	1.0865	1.8001	0.8500	-0.5225
	SVR-Polynomial	2.5933	3.9255	2.0206	-0.8542

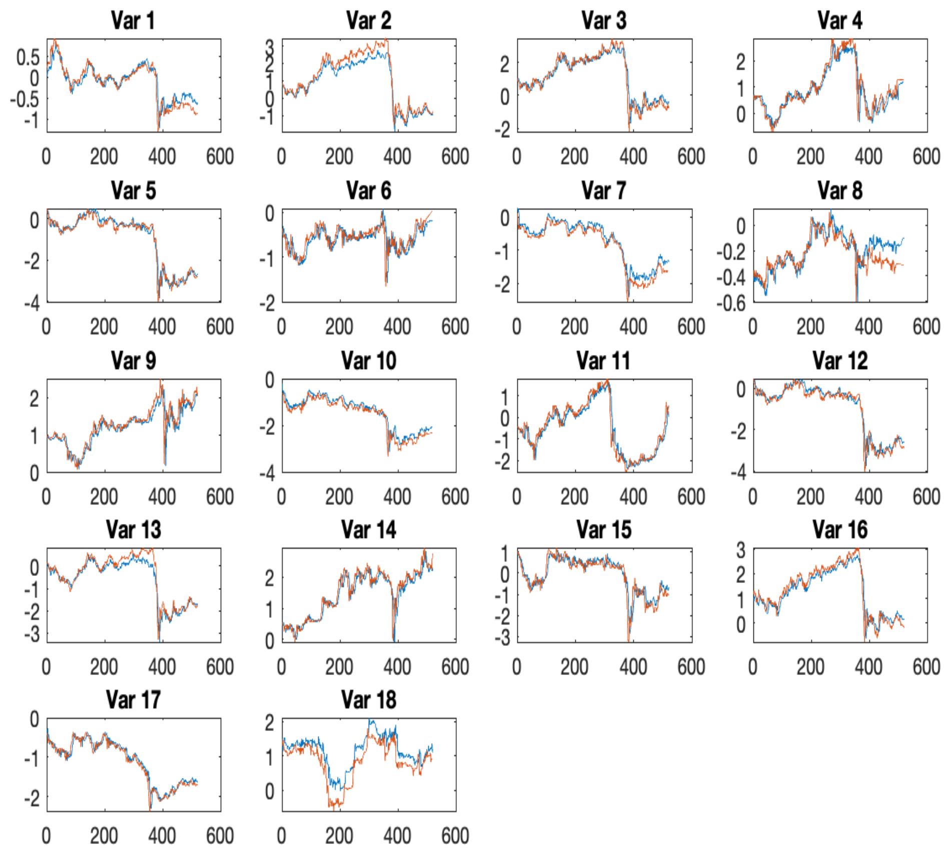

Figure 4: SVR with Linear kernel predictions for each variable vs ground Truth

Table 2: Performance LSTM-ANN models

Predicted variable	RMSE	MAPE	MAE	FB
V1	0.3291	0.2711	0.2533	0.1627
V2	0.9975	0.1977	0.8335	1.0263
V3	0.8746	0.3775	0.7132	0.5561
V4	0.9933	0.9120	0.7704	1.0225
V5	0.6105	4.0346	0.4597	0.5553
V6	0.2600	-0.2922	0.1913	0.2039
V7	0.6814	-0.8912	0.5918	1.0227
V8	0.3345	-0.7351	0.2343	1.4594
V9	0.7827	0.4601	0.5600	0.3647
V10	0.7324	-0.3458	0.5907	0.4475
V11	0.7506	0.6159	0.6038	-0.4386
V12	0.5073	-0.2550	0.3914	0.3725
V13	0.3259	-0.3721	0.2145	0.1581
V14	1.0181	0.4361	0.8017	0.7131
V15	0.6318	2.4229	0.5047	4.0304
V16	0.5612	-0.6475	0.4856	0.4082
V17	0.6632	-0.4832	0.4450	0.2806
v18	1.0640	1.8608	0.9118	-0.2969

In Fig. 5 is shown the results of profit investment portfolio considering real profit, forescast profit and error calculated of both. In Table 3 is shown the means of profit for each aversion.

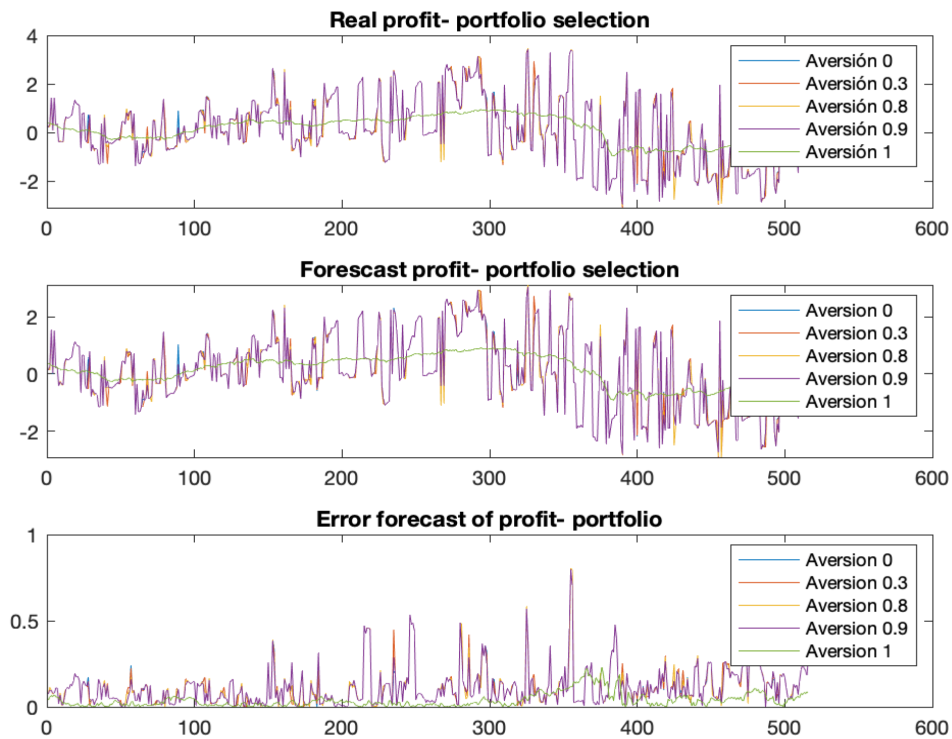

Figure 5: Profit of investment on selected portfolio

Table 3: Mean of profit per aversion

Aversion	0	0.3	0.8	0.9	1
Mean of profit	0.0912	0.0857	0.0848	0.0955	0.1367

6. Conclusions

In this paper a comparative study of forecasting systems for the Colombian stock market was presented. The results demonstrated that the support vector machines with linear kernel present a better performance for forecasts in 5 business days windows compared to the Gaussian and linear kernel SVMs. Likewise, it showed better performance than LSTM Deep Neural Networks.

The selection of the portfolio from the predictions presented by the SVR-Linear proved to be sufficient to obtain positive profit margins with different levels of risk aversion using a metaheuristic optimizer.

An effective decision support mechanism was obtained for investment in 18 different types of shares on the Colombian stock market with the ability to manage aversion levels effectively.

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