5
Experiments and Results

In this chapter, we present the performed experiments to assess the forecasting quality of the proposed predictors.

In the performed experiments, regardless of the chosen predictor algorithm, neither forecasting task nor simulation task have spent more than 5 minutes. The most time consuming part is the training of the predictors, but it is worth mentioning that once trained, they has its weights calibrated and any prediction made during the simulation task is almost instantly.

In section 5.1, we describe the available dataset and how the feature engineering is conducted to select the best fit feature template set for each predictor. And the quality assessment for both forecasting and simulation tasks are reported in section 5.2, where we report the experiments results, by comparing our predictors with the selected benchmarks.

5.1
Dataset and Feature Enginneering

The available dataset contains 513 consecutive days, including 343 trading days of observations of the BM&FBOVESPA stock prices. It presents the stock's opening, highest, lowest and closing prices every minute from December 18^{th}, 2008 to May 14^{th}, 2010. To perform the predictions focusing on Pairs Trading, we calculate the spreads from this raw data.

We use about 85% of this dataset for the predictors training and validation, keeping the last 50 days for the trading system experiments. Thus, the test period falls between March 4^{th} 2010 and May 14^{th} 2010.

5.1.1
Feature Enginneering

Some previous models for stock market forecasting use only the preceding days opening, highest, lowest and closing values of the target feature as input features [12, 76, 77]. These values are here called base values.

When testing our predictors, we include both the base values and also some indicators from a very influential school of stock market analysis: the Technical Analysis. Technical Analysis believes that the current price of a given stock fully reflects all its significant information [78]. And therefore, it implies that all the necessary information about the stock market future trends can be found in the past values. Thus, historical data about the stock values have to be analyzed in order to estimate future trends [2].

In our experiments, we test several input feature sets. We vary the number of preceding days, the base values and the selected indicators.

Regarding the number of preceding days, we test the forecasting by using both a 5 and a 10 days input window.

Among the tested indicators are: the Simple Moving Average (SMA), the Triangular Moving Average (TMA), the Exponential Moving Average (EMA), the Bollinger Bands (BB) and the Relative Strength Index (RSI). These indicators are widely used by the followers of Technical Analysis and are well known to be very informative for day trading.

SMA, TMA and EMA are variations of moving averages. SMA is the simplest one and refers to the classical arithmetic mean. TMA is a weighted average, whose result is equivalent to a double smoothed SMA, which is a SMA calculated twice. The re-averaging makes this kind of moving average even smoother and more wavelike. EMA is a type of infinite impulse response filter that also applies weighting factors to the values, so that the weighting for each older data point decreases exponentially, never reaching zero.

The other two indicators are slightly more complex. Developed by John Bollinger, BB are volatility bands placed above and below a moving average based on the standard deviation of the values. It can be used to measure the highness or lowness of the values or to estimate the upper and lower boundaries that limit their range. Finally, RSI is classified as a momentum oscillator, measuring the velocity and magnitude of the directional movements of a trend. It intends to chart the current strength or weakness of a trend based on its values in a recent trading period.

For both time windows, we test all possible sets by considering the five indicators and the base values. The best predictions obtained by all predictors use a 5 days time window, but the considered indicators are not the same for all predictors.

Below, we present the best input features set for each predictor and the training error achieved by them. To measure the error achieved by the predictors during the training step, we calculate the MAPE of predictions performed over the training dataset defined by:

$$\varepsilon = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{(cv_i - dv_i)}{dv_i} \right|, \tag{5.1}$$

where cv_i and dv_i are respectively the calculated and desired values, corresponding to the i-th of the n predictions performed.

PLSR Input Features

In PLSR predictor, the best results are obtained when we consider in the input features the SMA, the EMA and the BB indicators, the current day opening value, and only the previous 5 days lowest or highest base values, when predicting the minimum or the maximum value, respectively. The following matrix shows the format of PLSR dataset matrix used to predict the lowest value either of price or spread.

$$\begin{pmatrix}
\substack{D-5\\ Day\\ Lowest\\ Value} & \substack{D-4\\ Day\\ Lowest\\ Value} & \substack{D-3\\ Day\\ Lowest\\ Value} & \substack{D-2\\ Day\\ Lowest\\ Value} & \substack{D-1\\ Day\\ Lowest\\ Value} & \substack{SMA\\ of\ 5\\ Lowest\\ Values} & \substack{EMA\\ of\ 5\\ Lowest\\ Values} & \substack{High\ BB\\ of\ 5\\ Lowest\\ Values} & \substack{Low\ BB\\ of\ 5\\ Lowest\\ Values} & \substack{D\\ Day\\ Open\\ Value} & \substack{\textbf{Target:}\\ \textbf{D Day}\\ \textbf{Lowest}\\ \textbf{Values}} \\
. & . & . & . & . & . & . & . & . & . & . \\
. & . & . & . & . & . & . & . & . & . & .
\end{pmatrix}$$

Figure 5.1: PLSR Dataset to Lowest Value (D is the Current Day)

Considering the average of the performed experiments, the PLSR training for the interday forecasting obtains a MAPE of 2.35% and 2.31% for the minimum and maximum predicted values, respectively. And as expected, in the intraday forecasting, the PLSR training presents a better performance obtaining a MAPE of 1.80% and 1.76%.

SVR Input Features

The SVR predictor reaches its best results in the experiments where it disregards additional indicators and use only the previous 5 days lowest or highest base values, when predicting the minimum or the maximum value, respectively, besides the current day opening value. The matrix below presents the format of SVR dataset matrix used to predict the price or spread lowest value.

$$\begin{pmatrix} \begin{matrix} D-5 \\ Day \\ Lowest \\ Value \end{matrix} & \begin{matrix} D-4 \\ Day \\ Lowest \\ Value \end{matrix} & \begin{matrix} D-3 \\ Day \\ Lowest \\ Value \end{matrix} & \begin{matrix} D-2 \\ Day \\ Lowest \\ Value \end{matrix} & \begin{matrix} D-1 \\ Day \\ Lowest \\ Value \end{matrix} & \begin{matrix} D \\ Day \\ Open \\ Value \end{matrix} & \begin{matrix} \textbf{Target:} \\ \textbf{D Day} \\ \textbf{Open} \\ \textbf{Value} \end{matrix} \\ . & . & . & . & . & . & \\ . & . & . & . & . & . & \end{pmatrix}$$

Figure 5.2: SVR Dataset to Lowest Value Prediction (D is the Current Day)

The SVR training for interday forecasting obtains an average MAPE of 2.58% and 2.49% for the minimum and maximum predicted values, respectively. And, such as PLSR, presents a better performance in intraday forecasting, obtaining an average MAPE of 1.99% and 1.95%.

ANN Input Features

In our ANN model, we obtain the best results when considering the input layer with the EMA and the BB indicators, the current day opening value and only the lowest or the highest base values of the previous 5 days, if we are estimating the minimum or the maximum value, respectively. Similarly, the output layer has one forecasting neuron, for the minimum or the maximum value. Finally, to calculate the number of neurons in the hidden layer, we use the geometric mean of the number of neurons in the input and in the output layers [73]. In the figure 5.3, we show the topology of ANN used to predict the lowest value either of price or spread.

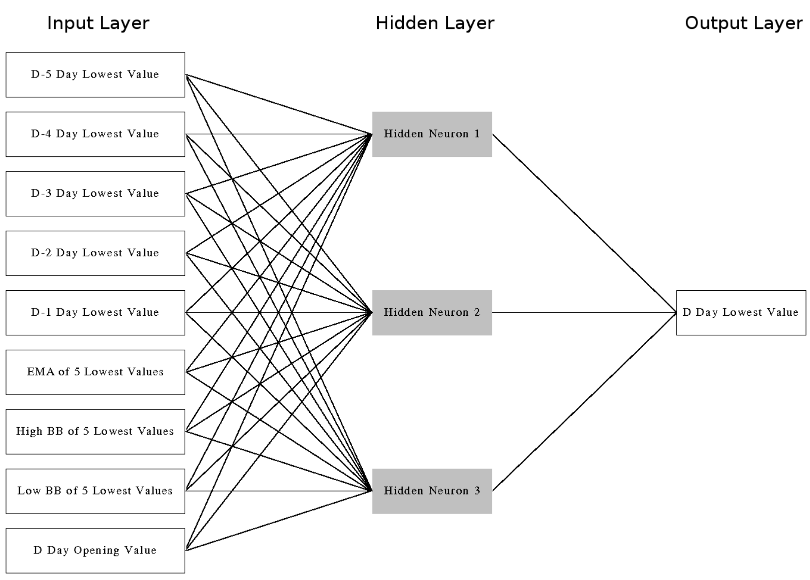

Figure 5.3: ANN Topology to Lowest Value Prediction (D is the Current Day)

The ANN experiments for interday forecasting present average MAPE of 1.53% and 1.36% respectively for the minimum and maximum predicted values. And those for intraday forecasting also have a better performance with average MAPE of 0.93% and 0.88%.

5.2
Forecasting and Simulation Results

When assessing the forecasting quality through the trading system, we consider two metrics: the maximum drawdown (MD) and the return on investment (ROI) [79].

Maximum drawdown is one of the most popular risk indicators employed in trading systems. It calculates the maximum possible percentage loss in the considered period, caused by the greatest relative decline of the invested capital from a historical peak. Algorithm 3 shows how our trading system calculates the maximum drawdown.

Algorithm 3 Maximum Drawdown Calculation Algorithm

```
current_drawdown ← 0
maximum_drawdown ← 0
peak ← −inf
for i=1 to n do
   // updating peak
   if current_rentability[i] > peak then
      peak ← current_rentability[i]
   end if
   // calculating the current drawdown
   current_drawdown ← 100.0 ∗ (peak − current_rentability[i])/peak
   // updating the maximum drawdown
   if current_drawdown > maximum_drawdown then
      maximum_drawdown ← current_drawdown
   end if
end for
```

Return on investment is a performance measure used to evaluate the profitability of an investment, defined as the ratio of money gained relative to the amount of money invested. It is a very popular metric because of its versatility and simplicity [80]. To facilitate the comparison between the investments here and other types of investments, we also present the annual return on investment (AROI), which is the projection of return on investment in one year.

$$AROI = \left(\frac{FC}{IC}\right)^{\frac{247.6}{50}} - 1, \tag{5.2}$$

where IC and FC are respectively the initial and final capitals, 50 is the number of tested trading days and 247.6 is the average number of trading days in a year on the BM&FBOVESPA, taking into account the last 10 years.

To analyze the effectiveness of evaluating the performed predictions by using either classical prediction error metrics or the trading system metrics, we present both types of metrics, by presenting also the MAPE relative to the predictions performed by all predictors.

We present the results separately according to the type of trade concerned. Subsection 5.2.1 exhibits the results obtained by the experiments focusing on buy and sell operations. And the results of the experiments for Pairs Trading are shown in subsection 5.2.2. We separate the results obtained by the two different forecasting schemes in both sections.

In order to avoid potential discrepancies in the results due to peculiarities of a particular asset, we consider the same assets in all experiments. We select assets of important Brazilian companies from the oil, steel and banking sectors.

Representing the oil sector, we choose the Petrobras stocks: the preferential one, Petrobras PN (PETR4), and the ordinary one, Petrobras ON (PETR3). Petrobras, or Petróleo Brasileiro S.A., is a semi-public Brazilian multinational oil company. It is the largest company in Latin America by market capitalization and revenue. Moreover, it is the largest company headquartered in the Southern Hemisphere and the 8^{th} in the world, according to its market value [81, 82, 83].

To represent the steel sector, we select the preferential stocks of two among the most important companies of this sector in Brazil: Usiminas PN (USIM5) and Gerdau PN (GGBR4). Usiminas is a large producer of steel in the Americas. With the major steel mills in Brazil, the company accounts for 28% of total steel output in the country [84]. Gerdau is the world's 14^{th} largest steelmaker and the largest producer of long steel in the American continent, with steel mills in Brazil and in thirteen other countries [85].

Finally, representing the banking sector, we pick the preferential stocks from Bradesco bank and its controlling company: Bradesco PN (BBDC4) and Bradespar PN (BRAP4). Bradesco is one of the top four biggest banks in Brazil. It was the largest private bank in Brazil until the merge of two other banks in 2009 [86]. Bradespar is its controlling company, a Brazilian investment company formed in 2000 by Bradesco in order to allow the bank to spin off some of its industrial investments [87].

5.2.1
Buy and Sell Operations

This section presents the results obtained in the experiments focusing on buy and sell operations. Every table shows the MAPE relative to the minimum and maximum predicted prices and the trading system metrics calculated in the simulations guided by these values.

In tables 5.1 to 5.6, we present the results achieved by the interday predictions for all considered stocks.

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	2.39%	1.94%	9.26%	-1.41%	-6.79%
10-SMA	3.33%	2.99%	11.13%	-8.32%	-34.96%
15-SMA	4.09%	3.80%	17.38%	-14.20%	-53.16%
CCS	1.50%	1.08%	4.75%	8.25%	48.08%
PLSR	0.89%	0.61%	9.39%	14.16%	92.67%
ANN	**0.88%**	**0.62%**	**10.22%**	**17.04%**	**117.97%**
SVR	0.97%	0.62%	10.94%	8.00%	46.39%
ORACLE	0.00%	0.00%	0.00%	157.05%	$10*10^3$%

Table 5.1: PETR4 - Buy and Sell Operations - Interday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	2.13%	1.85%	12.30%	3.54%	18.80%
10-SMA	3.20%	2.84%	9.36%	-7.76%	-32.97%
15-SMA	3.94%	3.57%	15.10%	-12.76%	-49.13%
CCS	1.30%	1.03%	4.71%	12.10%	76.05%
PLSR	**0.85%**	**0.68%**	**11.43%**	**21.97%**	**167.38%**
ANN	0.84%	0.68%	6.78%	21.68%	164.24%
SVR	0.88%	0.69%	9.03%	17.68%	123.93%
ORACLE	0.00%	0.00%	0.00%	160.94%	$11*10^3$%

Table 5.2: PETR3 - Buy and Sell Operations - Interday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	2.70%	2.63%	8.00%	-2.52%	-11.87%
10-SMA	4.05%	4.03%	12.15%	-10.17%	-41.20%
15-SMA	5.56%	5.43%	13.46%	-13.46%	-51.12%
CCS	1.86%	1.68%	4.26%	4.64%	25.18%
PLSR	**0.81%**	**0.83%**	**16.91%**	**17.29%**	**120.28%**
ANN	2.88%	2.24%	10.74%	10.07%	60.82%
SVR	3.36%	3.62%	11.31%	11.33%	70.15%
ORACLE	0.00%	0.00%	0.00%	246.69%	$47*10^3$%

Table 5.3: USIM5 - Buy and Sell Operations - Interday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	2.87%	2.46%	16.98%	-4.06%	-18.56%
10-SMA	4.01%	3.71%	17.92%	-15.30%	-56.06%
15-SMA	4.94%	4.56%	21.10%	-19.41%	-65.65%
CCS	1.77%	1.38%	9.86%	-2.00%	-9.52%
PLSR	0.96%	0.92%	9.36%	10.95%	67.29%
ANN	**1.02%**	**0.93%**	**10.22%**	**16.12%**	**116.86%**
SVR	1.18%	1.02%	11.79%	15.46%	103.78%
ORACLE	0.00%	0.00%	0.00%	229.98%	$37*10^3$%

Table 5.4: GGBR4 - Buy and Sell Operations - Interday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	1.69%	1.38%	10.93%	10.17%	61.55%
10-SMA	2.13%	1.80%	12.55%	1.92%	9.88%
15-SMA	2.37%	2.01%	10.59%	-1.54%	-7.40%
CCS	1.09%	0.92%	6.17%	-2.28%	-10.79%
PLSR	**0.73%**	**0.66%**	**16.78%**	**14.29%**	**93.76%**
ANN	0.76%	0.68%	10.60%	9.92%	59.74%
SVR	0.81%	0.74%	11.49%	11.62%	72.35%
ORACLE	0.00%	0.00%	0.00%	142.19%	$8*10^3$%

Table 5.5: BBDC4 - Buy and Sell Operations - Interday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	2.71%	2.13%	9.87%	0.98%	4.95%
10-SMA	3.65%	3.25%	14.56%	-8.22%	-34.61%
15-SMA	4.94%	4.42%	19.30%	-19.30%	-65.42%
CCS	1.84%	1.25%	5.48%	4.28%	23.06%
PLSR	**1.05%**	**0.67%**	**14.74%**	**17.39%**	**121.21%**
ANN	1.28%	1.21%	11.77%	15.10%	100.65%
SVR	1.88%	1.29%	12.80%	12.37%	78.16%
ORACLE	0.00%	0.00%	0.00%	235.58%	$40*10^3$%

Table 5.6: BRAP4 - Buy and Sell Operations - Interday Forecasting

These first results show the superiority of the interday predictions performed by our proposed predictors over those performed by the benchmarks, when we consider the trading system metrics.

However, the remoteness from the Oracle's solution points to a long road of improvements until the optimal solution.

In tables 5.7 to 5.12, we expose the results related to the intraday predictions performed for all considered stocks.

Predictor	**Min MAPE**	**Max MAPE**	**MD**	**ROI**	**AROI**
5-SMA	2.02%	1.97%	9.77%	-0.52%	-2.55%
10-SMA	2.96%	3.08%	11.03%	-8.22%	-34.61%
15-SMA	3.75%	3.94%	15.99%	-13.44%	-51.07%
CCS	0.75%	0.52%	7.90%	-2.37%	-11.20%
PLSR	0.64%	0.45%	13.67%	20.04%	147.07%
ANN	**0.64%**	**0.46%**	**12.24%**	**23.24%**	**181.45%**
SVR	0.74%	0.56%	14.84%	14.70%	97.22%
ORACLE	0.00%	0.00%	0.00%	244.88%	$45*10^3$%

Table 5.7: PETR4 - Buy and Sell Operations - Intraday Forecasting

Predictor	**Min MAPE**	**Max MAPE**	**MD**	**ROI**	**AROI**
5-SMA	1.79%	1.88%	12.30%	4.81%	26.19%
10-SMA	2.79%	2.95%	9.18%	-5.66%	-25.06%
15-SMA	3.56%	3.72%	15.09%	-12.68%	-48.90%
CCS	0.68%	0.53%	7.88%	16.47%	112.76%
PLSR	0.61%	0.47%	11.25%	25.33%	205.89%
ANN	**0.61%**	**0.48%**	**12.60%**	**29.39%**	**258.21%**
SVR	0.63%	0.52%	9.24%	21.58%	163.17%
ORACLE	0.00%	0.00%	0.00%	253.70%	$52*10^3$%

Table 5.8: PETR3 - Buy and Sell Operations - Intraday Forecasting

Predictor	**Min MAPE**	**Max MAPE**	**MD**	**ROI**	**AROI**
5-SMA	2.47%	2.51%	8.19%	-1.28%	-6.18%
10-SMA	3.90%	3.92%	11.52%	-9.23%	-38.09%
15-SMA	5.47%	5.31%	13.27%	-13.27%	-50.59%
CCS	0.93%	0.80%	11.54%	6.09%	34.01%
PLSR	**0.77%**	**0.67%**	**7.25%**	**15.83%**	**107.03%**
ANN	2.37%	2.10%	10.67%	11.59%	72.12%
SVR	3.23%	3.26%	13.09%	13.27%	85.34%
ORACLE	0.00%	0.00%	0.00%	405.89%	$306*10^3$%

Table 5.9: USIM5 - Buy and Sell Operations - Intraday Forecasting

Predictor	**Min MAPE**	**Max MAPE**	**MD**	**ROI**	**AROI**
5-SMA	2.64%	2.42%	18.71%	-3.11%	-14.48%
10-SMA	3.86%	3.70%	18.17%	-15.55%	-56.70%
15-SMA	4.87%	4.56%	20.97%	-19.28%	-65.38%
CCS	0.94%	0.71%	4.74%	0.53%	2.65%
PLSR	0.83%	0.64%	11.56%	10.50%	63.96%
ANN	**0.99%**	**0.76%**	**9.75%**	**19.10%**	**137.64%**
SVR	1.10%	0.89%	14.58%	17.20%	119.45%
ORACLE	0.00%	0.00%	0.00%	423.38%	$362*10^3$%

Table 5.10: GGBR4 - Buy and Sell Operations - Intraday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	1.48%	1.34%	11.11%	8.80%	51.84%
10-SMA	2.01%	1.81%	12.55%	3.41%	18.06%
15-SMA	2.23%	2.02%	10.64%	-1.20%	-5.80%
CCS	0.58%	0.45%	8.61%	-3.07%	-14.31%
PLSR	**0.52%**	**0.40%**	**12.28%**	**18.82%**	**134.88%**
ANN	0.54%	0.44%	14.81%	16.55%	113.49%
SVR	0.62%	0.52%	12.07%	11.94%	74.81%
ORACLE	0.00%	0.00%	0.00%	226.97%	$35*10^3$%

Table 5.11: BBDC4 - Buy and Sell Operations - Intraday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	2.39%	2.11%	6.33%	1.29%	6.55%
10-SMA	3.41%	3.23%	15.18%	-9.49%	-38.97%
15-SMA	4.78%	4.36%	19.10%	-19.10%	-64.99%
CCS	1.00%	0.66%	7.96%	5.67%	31.40%
PLSR	0.83%	0.60%	15.74%	18.79%	134.59%
ANN	**1.08%**	**0.99%**	**18.54%**	**21.29%**	**160.08%**
SVR	1.65%	1.35%	12.75%	14.36%	94.35%
ORACLE	0.00%	0.00%	0.00%	367.82%	$208*10^3$%

Table 5.12: BRAP4 - Buy and Sell Operations - Intraday Forecasting

The intraday forecasting results reinforce the superiority of our proposed predictors over the four selected benchmarks. In comparison with the interday forecasting, we must emphasize the improvement in predictions caused by the input features added to the predictors input.

5.2.2 Pairs Trading

In this section, we present the results obtained in the experiments focusing on Pairs Trading. The tables presented here have the same columns of those seen in the previous section, and the MAPE refer to the minimum and maximum predicted spreads.

The experiments are performed considering three stock pairs. In all of them, a very strong relationship can be identified.

The first pair contrasts the Petrobras preferential and ordinary stocks: Petrobras PN (PETR4) and Petrobras ON (PETR3). This pair represents the most common type of Pairs Trading, known as PN *versus* ON. The purpose of this type of Pairs Trading is to contrast two stocks of the same company. It presents a low risk, but generally provides a not very attractive return.

The second pair is composed by the preferred stocks of two companies of the Brazilian siderurgy sector: Usiminas PN (USIM5) and Gerdau PN (GGBR4). This pair is based on another type of Pairs Trading, known as Intrasectoral, whose purpose is to contrast stocks of two companies within the same economic activity sector. Give how these companies belong to the same economic activity sector, it is expected that they reflect the same economical fundaments and behave similarly to the same market changes. Intrasectoral is the riskiest type of Pairs Trading tested here, but in return, is also that with the greatest profit potential.

The last tested type of Pairs Trading considers the preferred stocks of a company and its controlling company. It is known as Controller *versus* Controlled and presents moderate risk and profitability. For this type of Pairs Trading, we consider the preferred stocks of Bradesco and its controlling company: Bradesco PN (BBDC4) and Bradespar PN (BRAP4).

In tables 5.13 to 5.15, we present the results achieved by the interday predictions for all considered stocks. And the tables 5.16 to 5.18, exposes the results of the intraday predictions.

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	0.35%	0.32%	1.89%	1.79%	9.18%
10-SMA	0.36%	0.33%	1.88%	2.39%	12.41%
15-SMA	0.38%	0.34%	1.88%	2.19%	11.32%
CCS	0.24%	0.35%	1.42%	2.15%	11.11%
PLSR	0.23%	0.26%	2.33%	7.54%	43.33%
ANN	**0.25%**	**0.24%**	**5.59%**	**12.11%**	**76.13%**
SVR	0.22%	0.25%	3.12%	9.52%	56.88%
ORACLE	0.00%	0.00%	0.73%	84.35%	$2*10^3$%

Table 5.13: PETR4 x PETR3 - Pairs Trading - Interday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	1.69%	1.78%	11.04%	-1.46%	-7.02%
10-SMA	2.17%	2.21%	15.00%	-6.00%	-26.39%
15-SMA	2.66%	2.74%	13.83%	-10.82%	-43.28%
CCS	1.05%	1.05%	9.82%	-1.13%	-5.47%
PLSR	0.61%	0.86%	7.16%	14.29%	93.76%
ANN	**0.62%**	**0.76%**	**9.17%**	**25.33%**	**205.89%**
SVR	0.65%	0.77%	6.13%	22.21%	169.99%
ORACLE	0.00%	0.00%	0.00%	149.86%	$9*10^3$%

Table 5.14: USIM5 x GGBR4 - Pairs Trading - Interday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	2.02%	1.96%	7.45%	-4.47%	-20.26%
10-SMA	2.58%	2.59%	17.19%	-17.19%	-60.70%
15-SMA	3.17%	3.23%	24.15%	-24.15%	-74.56%
CCS	1.17%	1.37%	4.06%	2.27%	11.76%
PLSR	0.73%	1.06%	8.48%	14.10%	92.17%
ANN	**0.76%**	**1.05%**	**6.23%**	**17.32%**	**120.56%**
SVR	1.02%	1.77%	8.34%	18.27%	129.55%
ORACLE	0.00%	0.00%	0.00%	146.67%	$9*10^3$%

Table 5.15: BBDC4 x BRAP4 - Pairs Trading - Interday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	0.34%	0.30%	1.94%	1.52%	7.76%
10-SMA	0.33%	0.34%	1.88%	2.39%	12.41%
15-SMA	0.36%	0.36%	1.88%	2.27%	11.76%
CCS	0.21%	0.17%	4.13%	0.05%	0.25%
PLSR	0.17%	0.17%	1.89%	6.89%	39.09%
ANN	0.18%	0.17%	5.04%	16.49%	112.94%
SVR	**0.19%**	**0.18%**	**6.71%**	**17.09%**	**118.43%**
ORACLE	0.00%	0.00%	1.71%	75.47%	$2*10^3$%

Table 5.16: PETR4 x PETR3 - Pairs Trading - Intraday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	1.59%	1.75%	7.80%	-4.56%	-20.64%
10-SMA	2.10%	2.20%	18.98%	-6.38%	-27.85%
15-SMA	2.65%	2.77%	13.94%	-10.93%	-43.63%
CCS	0.63%	0.64%	3.80%	1.57%	8.02%
PLSR	0.55%	0.59%	8.22%	21.42%	161.46%
ANN	**0.54%**	**0.57%**	**11.39%**	**33.41%**	**316.80%**
SVR	0.59%	0.59%	9.69%	19.13%	137.93%
ORACLE	0.00%	0.00%	0.00%	180.60%	$16*10^3$%

Table 5.17: USIM5 x GGBR4 - Pairs Trading - Intraday Forecasting

Predictor	Min MAPE	Max MAPE	MD	ROI	AROI
5-SMA	1.94%	1.83%	6.51%	-6.51%	-28.35%
10-SMA	2.56%	2.54%	16.90%	-16.68%	-59.49%
15-SMA	3.14%	3.23%	24.06%	-24.06%	-74.41%
CCS	0.58%	0.72%	11.46%	-11.46%	-45.27%
PLSR	0.55%	0.65%	10.45%	16.18%	110.15%
ANN	**0.87%**	**0.88%**	**9.04%**	**23.43%**	**183.61%**
SVR	1.01%	1.28%	8.13%	13.98%	91.17%
ORACLE	0.00%	0.00%	0.00%	172.17%	$14*10^3$%

Table 5.18: BBDC4 x BRAP4 - Pairs Trading - Intraday Forecasting

The results obtained by the predictions focusing on Pairs Trading confirm the superiority of the proposed predictors over the four presented benchmarks, but also reiterate how they are far from the optimal solution.

Furthermore, these results show the evident improvement provided by the inclusion of intraday features in the predictors input. The figure 5.4 ilustrates this improvement, by comparing the average MAPE evolution of the minimum spreads predicted by PLSR to the Pair Trading USIM5 x GGBR4 either in interday or intraday forecasting scheme.

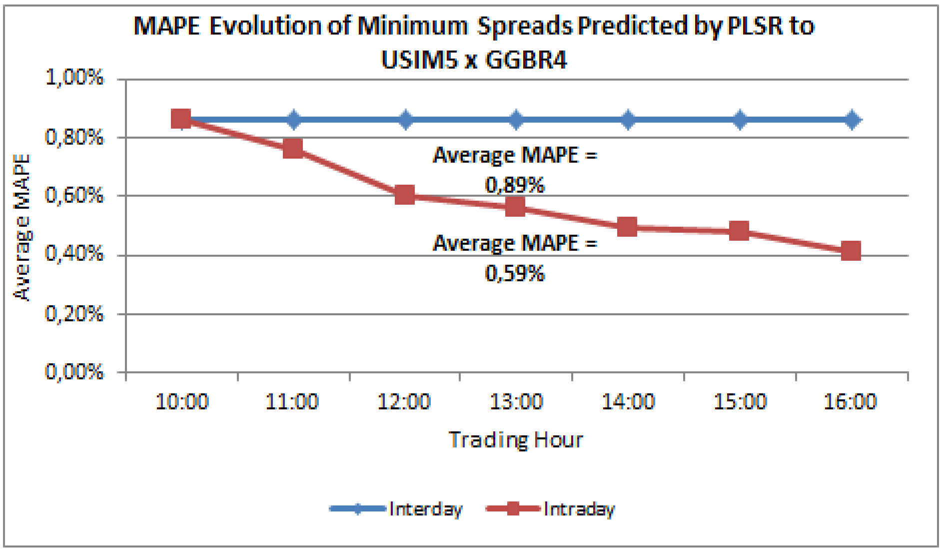

Figure 5.4: Average MAPE Evolution of Minimum Spreads Predicted by PLSR

Our experimental findings indicate that, despite the similar results when considering the MAPE, the tested predictors show very different results at the trading system simulations. These results show the importance of a system like the one proposed here to assess the stock market forecasting quality, by simulating the focused trades and presenting to the investor metrics closer to its reality.

However, despite the performed simulations represent all market rules with full fidelity, they must be used only to estimate the effectiveness of the tested indicators, once there will be distortions between past markets simulations results and the strategies performance when they are applied in the real-time market.