6 Experimental Results

In order to test the trading system we described in the previous two chapters experimentally, I first executed the Test Investor function with different parameter configurations in order to identify promising candidates for high risk and conservative investment profiles. Once these investment profiles were identified, I used them in a “live” simulation to test their performance under realistic circumstances with the “Auto Investor” function in NELION. In this chapter, I present the results of these two steps. Additionally, I show the distribution of the four different model types that were used in the simulation.

6.1 Test Investor Identification

The “Test Investor” function in NELION is designed to identify the optimal investor configuration for a high risk and conservative investor. This option allowed the user to specify a test interval to simulate the actions of investors with specific parameters. I limited the parameter space to [0,1] for the volatility, correlation, volume and error parameters and tested weekly investors for the period from January 1, 1998 to December 31, 1998. A second test included the period of January 1, 1999 to December 31, 1999 with an initial capital of US$ 10,000 and a minimum transaction volume of US$

250.00. The cost of each transaction was set at US$ 9.99, which corresponds to the charges at the online broker Datek.com and exceeds the cost at AmeriTrade.com. The minimum expected return was 6%. The trials included all combinations of parameters with values with an increment of 0.125.

As a measure of the risk profile, I examined the final portfolio of each test investor and discarded parameter combinations, which had more than 75% of the portfolio value invested in one stock. Investors with between 50% and 75% invested in a single stock at the end of the investment period were considered “High Risk” combinations, while those with less than 50% invested in one stock were considered “Conservative” Investors.

This separation resulted in two sets of parameter configurations, which I analyzed to identify a promising combination by creating a cross tab query on every combination with two of the four parameters. The resulting six tables for each set and both test intervals for the subsequent calculations are shown in Appendix A.

From the tables, I identified the parameter combination that occurred the most frequent in each set and used this to define two of the four parameters. This value is highlighted on the tables in Appendix A a dark grey background. The table below summarizes these results.

Investor	Parameter 1	Parameter 2
Conservative 1998	Volume=0.875	Error=0.75
Conservative 1999	Volume=0	Volatility=1
High Risk 1998	Volume=0	Volatility=0.875
High Risk 1999	Volume=0	Correlation=0.25

Table 6.1.1: Sample Investor with two Parameters identified

In a second iteration, I used these two values to identify the parameter combination in the remaining four tables that occurred the most frequently to define the third parameter. To simplify the search, I highlighted all relevant columns and rows in the tables of Appendix A with a light grey background and identified the largest values with dark grey characters. This specifies a third parameter as shown in the following table.

Investor	Parameter 1	Parameter 2	Parameter 3
Conservative 1998	Volume=0.875	Error=0.75	Volatility=0.875
Conservative 1999	Volume=0	Volatility=1	Error=0.625
High Risk 1998	Volume=0	Volatility=0.875	Correlation=0.875
High Risk 1999	Volume=0	Correlation=0.25	Volatility=0

Table 6.1.2: Sample Investor with three Parameters identified

Finally, using the three defined parameters, I identified the combination from the last three tables that occurred the most frequently to set the last parameter. The relevant columns and rows are displayed with a medium grey background in the tables in Appendix A, which had not been used and included a medium grey line at the bottom or the left hand side of the two columns or rows that had already been identified in the second iteration.

For the conservative investor 1998, this did not uniquely define the correlation parameter, because a volatility of 0.875 and a volume 0.875 both had 14 occurrences in the correlation parameter at 0.5 and 0.375 respectively. This seemed to indicate that the maximum is somewhere between these two values. Comparing the number of occurrences at 0.375 and 0.5 for each of these two parameters respectively indicated a score of eleven versus ten occurrences, so that I opted for the 0.375 value. This is supported by the tests for the conservative investor in 1999.

The results from this third and final iteration are summarized in the table below.

Investor	Correlation	Error	Volatility	Volume
Conservative 1998	0.375	0.750	0.875	0.875
Conservative 1999	0.375	0.625	1	0
High Risk 1998	0.875	0	0.875	0
High Risk 1999	0.250	0.500	0	0

Table 6.1.3: Sample Investor Parameters

The results show considerably more consistency for the conservative than for the high-risk investors. The correlation, error and volatility parameters changed only slightly between the tests for 1998 and 1999, while the volume parameter dropped from 0.875 to 0. For the high-risk investors, only the volume parameter remained the same at 0, while the remaining parameters underwent significant adjustments.

This is caused by two factors. Firstly, in 1998 the high-risk investor selection only contained 150 investors, compared to 3774 in 1999. For comparison, the conservative investors in 1998 and 1999 had 1218 and 1360 profiles respectively in their analysis. Consequently, the analysis in 1999 allows for a significantly higher degree of confidence, since it is based on 25 times more investor.

Secondly, the volatility in the markets rose in this period, most notably for the Nasdaq, which had an increase of 17% between 1998 and 1999. As a result, a number of profiles, which had a volatility parameter of 0 in 1998, were spread evenly between all investor profiles, so that the profiles with a volatility value of 0.875 were able to dominate. In 1999, the profiles with a volatility parameter of 0 were concentrated in the high-risk selection and defined this set.

The conservative investor profile shows a consistently strong adversity toward high volatility and stocks where the system cannot effectively predict future movements. At the same time, it does not disregard the need for a well balance portfolio, as exemplified by the correlation parameter. This is to be expected, since the portfolios in that conservative set were chosen so that no more than 50% of the invested value remained in a single stock at the end of the interval.

The high-risk investors disregarded the transaction volume and, in 1999, volatility of the stocks completely. This is consistent with the approach of relying on the raw predictions since that parameter had the biggest weight in the 1999 test. The result was a portfolio, which fluctuated, at times widely, as one might expect.

6.2 Testing the Profiles

Using the results from the previous section, I tested the quality of the system for one year starting May 15, 1999 with the NELION test investor function. I configured a high-risk and a conservative investor with the parameters calculated from the 1998 investor profiles. Each had a starting capital of US$ 10,000, expected a return of at least 6% annually and required a minimum transaction volume of US$ 250. The transaction costs were calculated at US$ 9.99 per trade. On the January 15, 2000, I updated the profiles, which resulted from 1999 test.

Every weekend, the system had the opportunity to automatically perform fictitious but unverified purchases and sales. A detailed list of purchases and sales is included in Appendix B. The portfolio development is shown in the diagram below. The Nasdaq, Dow Jones Composites as well as the S&P 500 indexes are included for comparison.

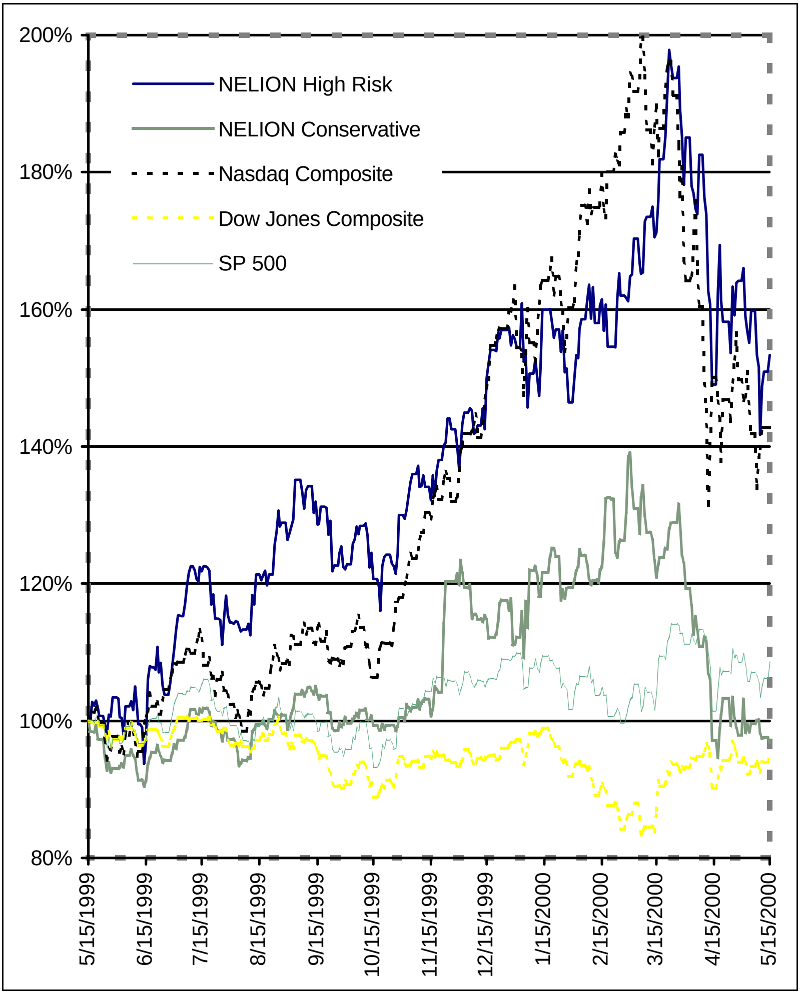

Figure 6.2.1: Comparison of NELION Investors with Major Indexes

This diagram is not adjusted for inflation, which amounts to approximately 1.6% in the test interval. For easy comparison, the return on investment calculation for the interval is summarized in the table below.

	NELION High Risk	NELION Conser-vative	NELION Average	Nasdaq Composite	Dow Jones Composite	S&P 500
5/15/1999	$10,000	$10,000	$10,000	$2,528	$3,306	$1,338
5/15/2000	$15,323	$9,736	$12,530	$3,607	$3,143	$1,452
Return	53.2%	-2.6%	25.3%	42.7%	-4.9%	8.6%

Table 6.2.1: NELION Test Investor Comparison

The results exhibit a pronounced difference between the high-risk and the conservative investor, the former achieving a 53.2% return, while the latter lost 2.6% of the portfolio value. This follows from the portfolio held. The high-risk investor disregarded the model error in the first half of the trial and volatility in the second so that his investment choices gravitated toward stocks traded on the Nasdaq because they tended to exhibit comparatively erratic behavior. This correlation is apparent from Figure 6.2.1, where the portfolio value of the high-risk investor and the Nasdaq remained close during the entire year. NELION beat the index the first six months, trailed it slightly at the beginning of 2000 and regained the edge shortly before the correction in March 2000. Though this adjustment did not pass by the NELION portfolio, the drop was not as pronounced as for the Nasdaq.

The conservative portfolio consistently emphasized good predictability of the stock, as one might expect. Consequently, it chose fewer volatile stocks resulting in a mix between Dow Jones and Nasdaq stocks. The fact that the “old economy” stocks did not perform well is documented by the 4.9% decline of the Dow Jones Composite during our simulation interval.

Two changes in the portfolio value are worth noting here: On November 21, 1999, the conservative portfolio held 1072 stocks of Angeion Corporation at US$ 0.88 a stock. Within two days, the price had jumped to US$ 2.25 and continued climbing up to a peak of US$ 3.94 on February 18, 2000. This increase pushed the value of portfolio up 16% within two days and is clearly visible in on the graph above. On the other hand, the conservative investor purchased 80 shares from Fruit of the Loom on May 15, 1999 for US$ 11.88 each, for a total investment of US$ 950.40. Unfortunately, the company sought protection under Chapter 11 of the bankruptcy law on December 28, 1999 so that this investment was lost completely.

The average of the two NELION portfolios achieved a healthy 25.3% return on investment, well above the S&P 500. Compared to a risk-free investment in government bonds, which returned about 6%-8% annually, these portfolios represent a very attractive alternative. Bearing in mind that the returns already account for transaction costs, they compare favorably to many mutual funds, which state the return on investment without mentioning their charge of between 3% and 5% of the invested value.

6.3 Model Distribution

In the test above NELION selected the weekly trial portfolios from the total list of stocks tracked, which is included in Appendix E. However, since the system is designed for investment horizons of one day, one week and one month, it calculated models for all of these intervals. For the overwhelming majority of the stocks, NELION was best able to predict future values using the k-nearest-neighbor models. For a detailed list, please see the table below.

Model Type	Daily	Weekly	Monthly
ANN	0	1	7
ARN	11	2	1
MM	0	3	5
KNN	96	101	94

Table 6.3.1: Model Type Usage

The low success rate of auto-regressive models is not surprising, given the complexity of stock price movements. The dominance of k-nearest-neighbor models over the Markov and Artificial Neural Network models seems to indicate that the stocks used in this experiment exhibit low–dimensional chaotic behavior, since the complexity that KNN models are generally able to model is lower than the other two non-linear predictors. Hsieh supports this by showing that stock market data is a low-dimensional deterministic system [Hsieh 1990].

The ANN models require considerably more processing time than any of the other models. This poses a challenge, since the algorithm tends to spend as much time calculating these models, as it requires for all the others together. Consequently, the initial model calculation does not search the parameter space of these models as extensively as it does for the remaining model types, which may have further helped the dominance of the KNN models.

6.4 Daily Operation

The application evolved over the months and years in response to the specific requirements of private investors and addresses their immediate needs in its current form. Several distinguishing features were emphasized repeatedly, beside the obvious guidance with specific suggestions.

Overall, the investment recommendations were considered valuable because they helped direct attention to opportunities that are beyond the scope of an individual investor.

The customization of the suggestions instilled a significant amount of trust, because each investor felt that he was getting individual attention. It was clear that the recommendations were not of one mold and independent of the personal goals of the investor, so that there was no cause for suspicion that the recommendations were motivated by NELION's personal gain.

The recommendation and update intervals differ widely between persons who actively participate on a daily basis and investors with a long-term horizon and each appreciate the e-mail frequency.