REAL-TIME ANALYSIS OF THE ELLIOTT WAVE PRINCIPLE UTILIZING HISTORICAL MARKET DATA

by

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Dedication

This thesis is dedicated to my wife Kelly. Without her continual support and motivation, I would not have been here and would not have been able to complete this work.

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I would like to thank Dr. Gary D. Boetticher. His mentorship and guidance have been invaluable not only to this research and to my career as a student, but to my professional and personal life as well. His love of learning is infectious and is something I will carry with me for the rest of my life, and I am forever grateful for it.

I would also like to thank my family – my mother, father, and sisters – for their continued support and encouragement.

Finally, I would like to thank Dr. Feagin and Dr. Drake for their support and belief in this project.

ABSTRACT

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University of Houston-Clear Lake, 2021

Chair: Gary D. Boetticher, Ph. D.

The Elliott wave Principle is a theory developed by Ralph Nelson Elliott which describes a pattern of movement in financial markets. When drawn correctly, Elliott waves provide an opportunity to make profitable buy and sell decisions. An Elliott wave consists of 5 waves or lines. There are many varieties of formations depending upon various rules (e.g., line length). Creating an Elliott wave with historical data can be relatively easy for several reasons. Since all data is known, it is possible to construct a complete wave and assess the wave in terms of profitability. Constructing Elliott waves in real-time is a considerable challenge compared to finding Elliott waves within historical data. The primary problem is that once a complete wave (all 5 lines) is identified, an investor cannot go back retroactively and enter a trade. Furthermore, the dynamics of real-time data can impact the identification of respective waves. This research first identifies Elliott waves using historical financial data. Various Elliott wave formations are characterized.

After grouping similar waves, their respective formations are statistically analyzed and described in terms of probabilities. This information will provide insight into the assessment of Elliott waves using real-time data. Waiting to identify a complete Elliott wave in real-time is not very fruitful. Thus, this research examines the partial formation of Elliott waves.

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CHAPTER I:

INTRODUCTION

In the 1930's, Ralph Nelson Elliott discovered patterns in certain stock market price charts. He codified these findings into a set of rules called *The Wave Principle* [3]. If applied correctly, these rules identify profitable trade patterns. Elliott believed that the *The Wave Principle* patterns captures the natural order which occurs in nature. It models the Fibonacci series and the Golden Ratio which occur throughout nature in flowers, seashells, and even the formation of galaxies [1]. Elliott waves have a fractal nature, and so as a chart is zoomed in or out, the same pattern can be seen repeating, just on a different time scale. Close observation reveals waves within waves down to the smallest observable scale.

Like many of the natural formations mentioned, Elliott waves have a well-defined structure that follows specific rules and guidelines. They have a recognizable shape, structure, and pattern. However, interpreting Elliott waves and related formations can be quite subjective in nature and two people may not necessarily agree on how a formation is applied to a chart. Accurately predicting an Elliott wave as it is forming could lead to a profitable model. Achieving this requires a tool that removes the subjective nature of finding Elliott waves and instead provides a reliable and repeatable methodology.

Effective investing requires a tool that consistently provides profitable results and the Wave Principle has the potential to provide such guidance. The shape of an Elliott wave presents a clear location – the end of sub-wave 2 – as the ideal location for an investment opportunity. A tool that can only show Elliott waves after they have occurred provides no value in a real-time investment situation. So it is critical that a real-time investment tool shows the creation of each segment of a full Elliott wave.

CHAPTER II:

BACKGROUND

2.1 Technical Analysis vs. Fundamental Analysis and Technical Indicators

The Wave Principle falls under a type of investing called technical analysis. The technical analysis methodology observes patterns and trends in price, volume, and other statistical measures of a stock or commodity. Technical analysis consists of two methodologies – technical indicators and chart formations. Technical indicators use mathematical formulas to determine market trends and when changes in those trends occur so trades can be placed. A technical indicator may overlay a price chart or exist within its own chart. When triggered, an indicator identifies a buy or sell opportunity. They can be used alone or in conjunction with other technical indicators to provide more informed methods of making buy and sell decisions. An example would be an indicator crossing a certain pre-determined value or if one indicator crosses another. A second major pillar of technical analysis are chart patterns or formations. There are specific patterns and formations that tend to occur in price charts that indicate a probable change in the current trend, or at times a sideways movement. Thesechart formations have specific names and features and occur throughout various price charts. Formations can be sketched out by hand on a printed price chart or by a computer program that allows the user to draw lines on a chart.

2.2 The Wave Principle

The Wave Principle describes market movements as a series of patterns that occur in predictable directions. The shape and direction of these waves result from human psychology and emotions. The Wave Principle hypothesizes that waves occur independent of current events, supply and demand, company management, and other traditional barometers used to predict the movement of stock prices [1]. The waves that make up the Wave Principle consist of specific features and rules that help the analyst to recognize them.

2.2.1 What makes up an Elliott wave?

The most basic structure of the Wave Principle is the five-wave structure called the motive wave. The motive wave structure consists of three waves that are moving in the direction of the general trend and two waves that move opposite the trend in a corrective manner as can be seen in Figure 2-1. Waves 1, 3, and 5 move in the direction of the trend and waves 2 and 4 move opposite the trend in a corrective fashion. Waves 1, 3, and 5 capture the overall movement and progress of this wave.

The structure of the motive wave can be described by three important rules. Assuming a bullish wave, they are:

1. The trough of wave 2 may never move below the beginning of wave 1.
2. Out of waves 1, 3, and 5, wave 3 may never be the shortest wave.
3. The trough of wave 4 may never cross below the peak of wave 1.

Rules 1 and 3 describe the corrective nature of these waves. If they were to be violated, waves 2 and 4 are no longer simply corrective and could indicate a different trend or a different formation which will be discussed in the next section.

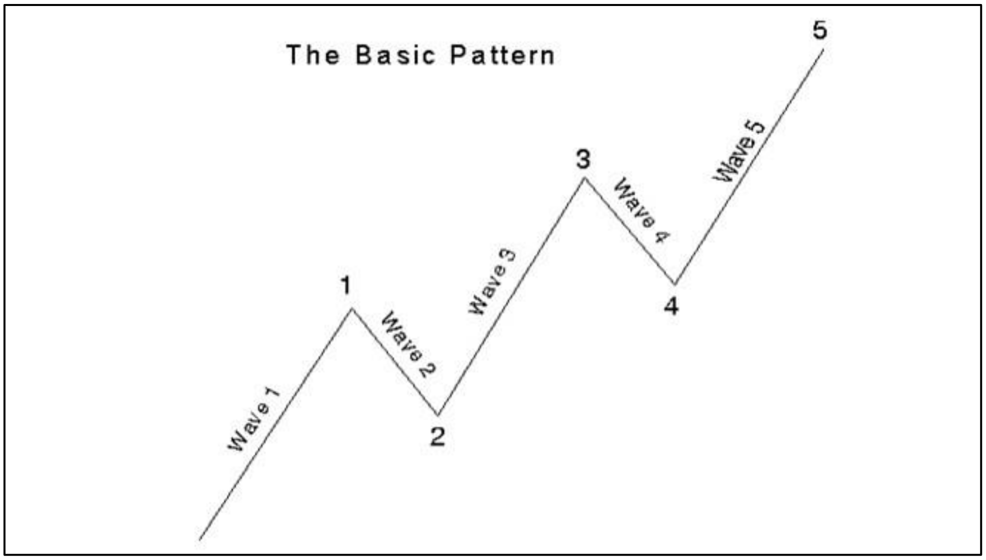

Figure 2-1: A basic wave [1]

Upon conclusion of the motive phase, a phase of three waves that act as a correction to the motive phase will occur. These three corrective waves are labled A, B, and C, and can be seen occuring after the motive wave in Figure 2-2. Waves A and C move opposite the general trend of the motive wave while wave B acts as a correction to A and C and moves with the trend of the motive phase. There are no explicit rules for this set of waves but Frost and Pretcher do present a set of guidelines. Some of these guidelines are listed below [1].

- “Wave C is often about the same length as wave A.”
- “Wave C almost always ends beyond the end of wave A.”
- “Wave B typically retraces 38 to 79 percent of wave A.”

The A-B-C wave can be seen as a correction to the 1-2-3-4-5 wave and so just as the trough of wave 2 may not cross below the start of wave 1 as rule 1 states, the end of wave C should not cross below the beginning of the 1-2-3-4-5 wave [1].

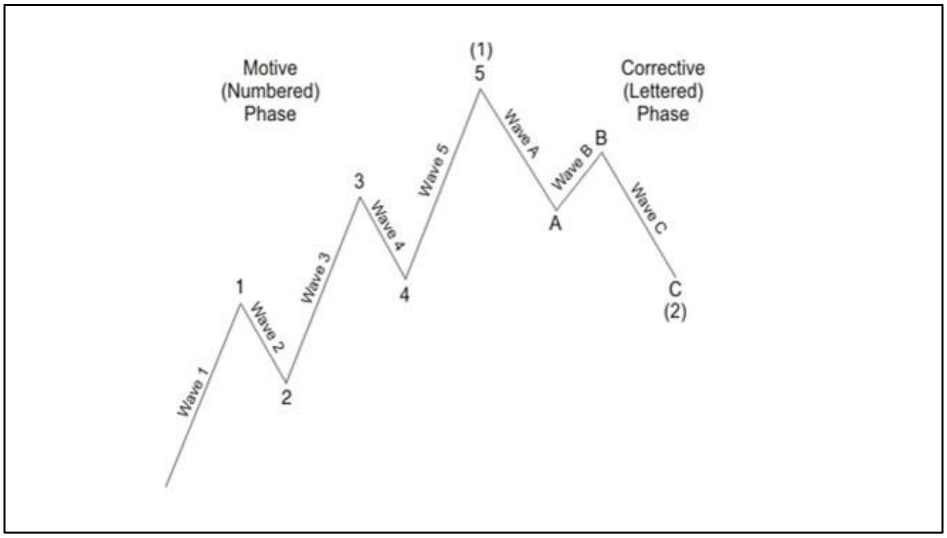

Figure 2-2: Eight wave cycle [1]

The combination of the previous eight waves describes a single cycle in the Wave Principle. While the motive wave in Figures 2-1 and 2-2 show the market trending upward and the corrective ABC wave trending down, an Elliott wave with the motive wave trending downward and the ABC wave trending upwards is equally valid.

At the end of this full eight wave cycle it would be reasonable to expect another eight wave cycle starting with the 1-2-3-4-5 motive wave.

An interesting observation is how motive waves recursively occur within each other. Figure 2-3, shows each 1-2-3-4-5 wave actually makes up either wave 1, wave 3, or wave 5 of a larger 1-2-3-4-5 wave. The ABC corrective waves after each smaller 1-2-3-4-5 waves becomes either wave 2 or wave 4 of the larger 1-2-3-4-5 wave. This figure illustrates the fractal nature of the Wave Principle. Each wave is itself made up of smaller wave structures. A larger scale shows that a larger 1-2-3-4-5 wave is actually wave 1 in an even larger wave structure. Within a single Elliott wave, it can be seen that sub-waves make up this larger wave.

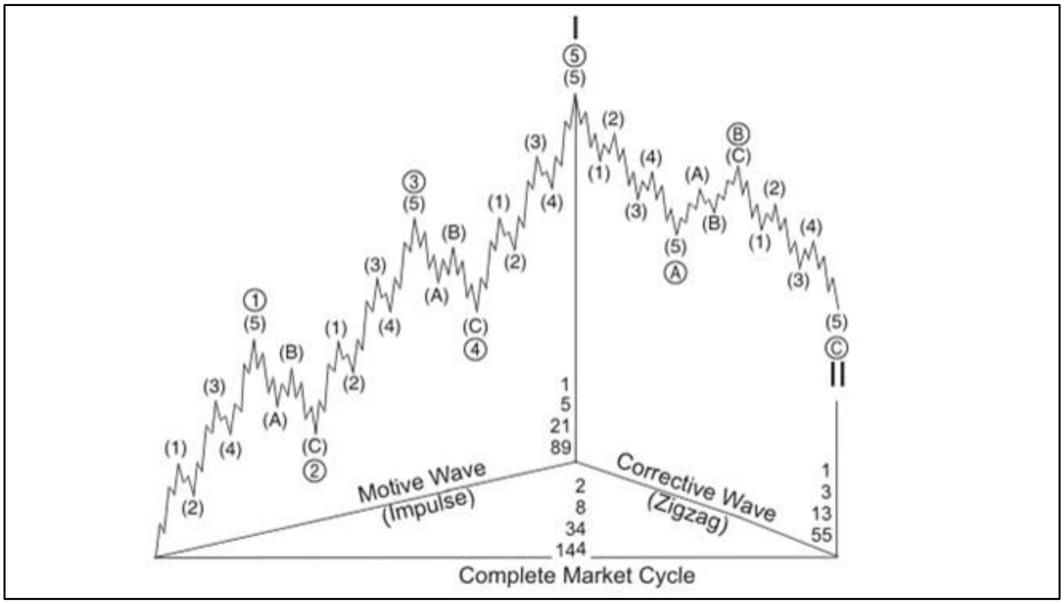

Figure 2-3: Complete Market Cycle [1]

2.2.2 Elliott wave Formations

The formations of a price chart fall into two categories: motive waves and corrective waves. Motive waves move in the direction of the trend while corrective waves move against the trend. Motive waves are groups of five waves while corrective waves are never groups of five and frequently occur as groups of 3 [1]. Within these two types of waves exists five types of motive waves and four types of corrective waves that can be viewed as formations. These formations help a technical analyst, who is using the Wave Principle, to properly describe the trend of the market and make more accurate predictions. The next section describes of each of them.

2.2.2.1 Impulse

The simplest type of motive wave is the Impulse wave and is illustrated in Figure 2-1. The impulse wave has already been described in section 2.2.1 and they must adhere to the three listed rules. These waves are generally easy to find in a chart and play a key role in the Wave Principle.

2.2.2.2 Extension

An extension is a motive wave that contains erratic behavior and cannot be classified as an Elliott wave because it violates one of the three foundational rules. Figure 2-4 shows extensions in various positions on a wave. Extensions account for what might appear to be noise in the price chart and it is common to find extensions within an impulse wave and even within other extensions [1].

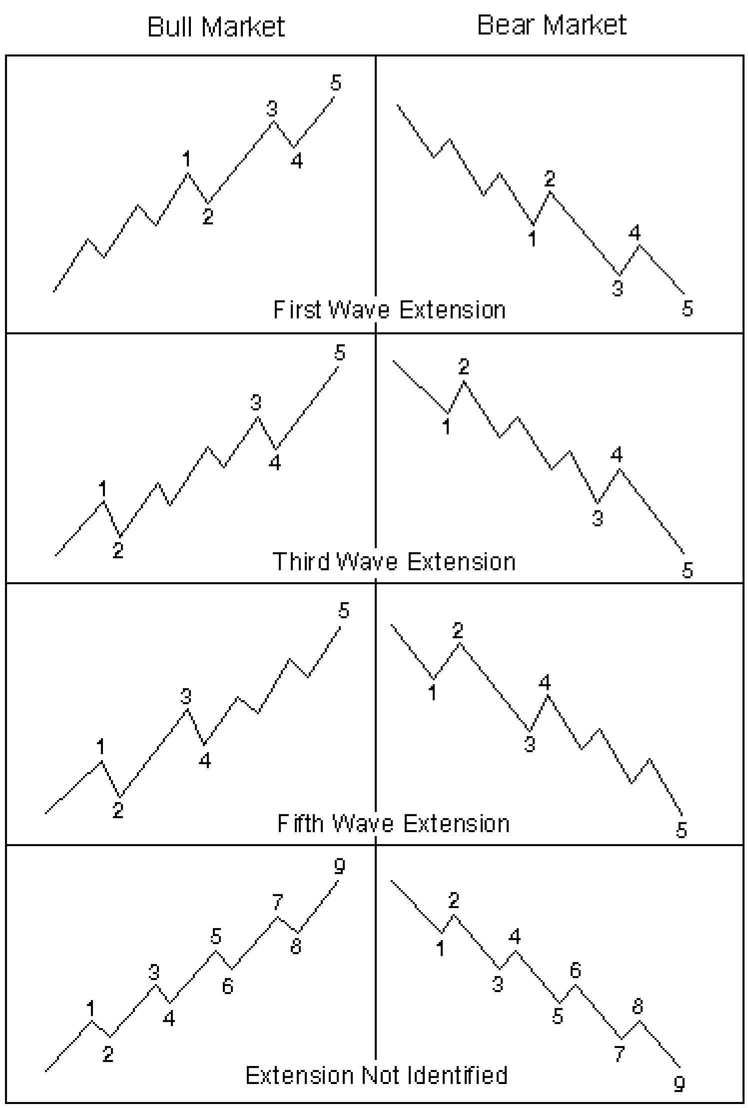

Figure 2-4: Extension waves [1]

2.2.2.3 Truncation

When an Elliott wave's fifth wave does not move beyond the end of wave 3, this is referred to as a truncation. Figure 2-5 demonstrates the fifth wave failing to move beyone wave 3 in what is referred to as a Bull Market Failure or Bull Market Truncation. There are two significant elements of a truncation that can help an analyst. First, it is often found after a strong third wave, and second, it typically indicates a strong impending reversal in the trend of the market [2].

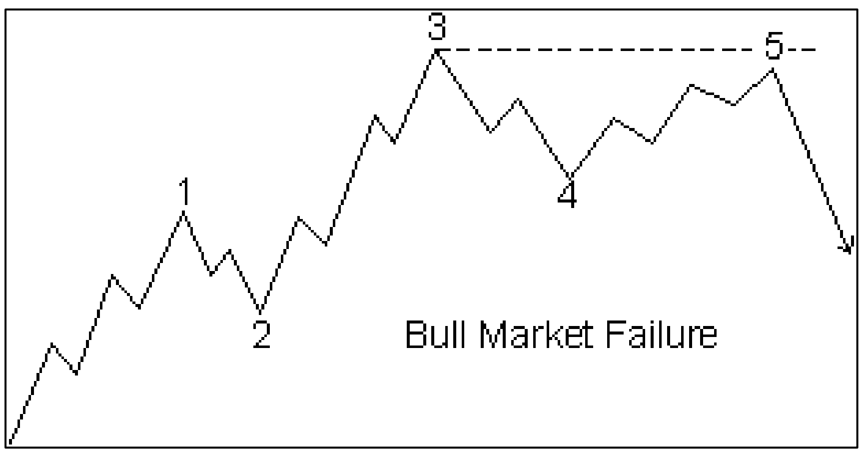

Figure 2-5: Tuncation [1]

2.2.2.4 Diagonal

The diagonal motive wave follows the first two rules but it does not follow the third rule. This means that the trough of wave 4 will cross below the peak of wave 1 as can be seen in Figure 2-6. In the most typical type of diagonal, a contracting diagonal, converging trend lines can be drawn above and below the formation. A reversal of the current trend typically follows a contracting diagonal [2].

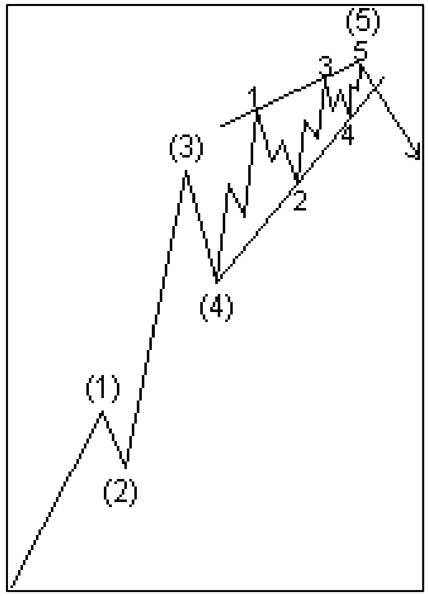

Figure 2-6: Diagonal [1]

2.2.2.5 Zigzag

The first corrective wave is the zigzag. It consists of three declining waves and is labeled ABC as seen previously in Figure 2-2. It can also move in an upward motion and in that case is referred to as an inverted zigzag [1]. The peak of wave B can never go beyond the start of wave A. Zigzags can repeat after each other, seemingly up to a max of three. This potential repeatability can make them difficult to interpret. The sub structure of a zigzag is a 5-3-5, meaning that if an ABC corrective wave is observed on a larger time scale it would become apparent that wave A is made up of 5 waves, wave B is made up of three waves, and wave C is again made up of 5 waves [2]. This structure can be seen in Figure 2-7.

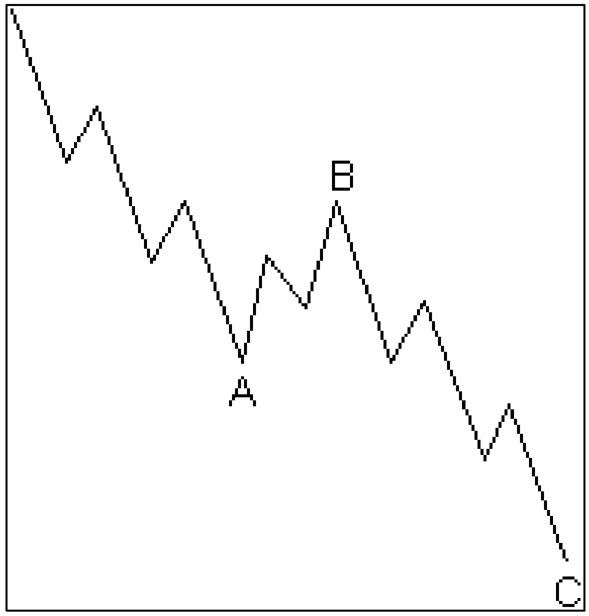

Figure 2-7: Zigzag sub-wave structure [1]

2.2.2.6 Flat

A flat correction will appear similar to a zigzag except that it will have a 3-3-5 sub-structure and will not show any significant progress up or down in the chart. A flat can typically be found in a market with a strong underlying trend. It can be described as a sideways formation with wave B typically making up 90% of the progress of wave A and wave C terminating near the end of wave A [2]. Figure 2-8 demonstrates an expanded flat in a bull market.

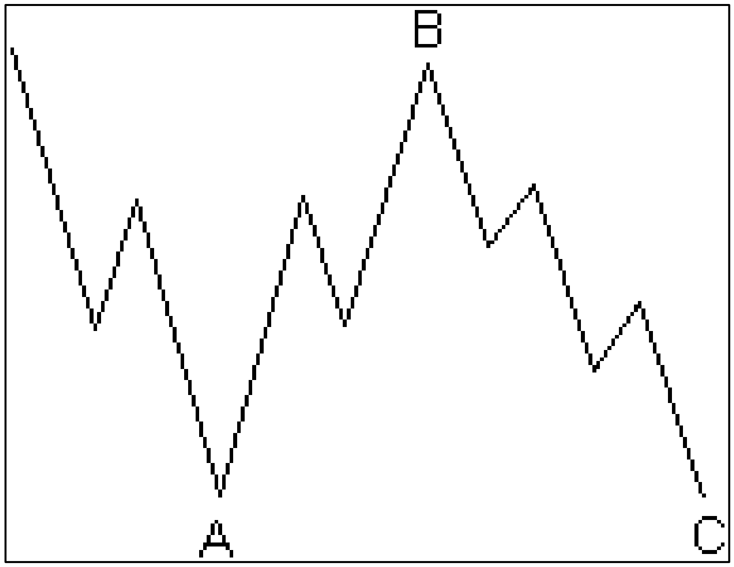

Figure 2-8: Flat correction [1]

2.2.2.7 Triangle

A triangle is a sideways moving 5 wave corrective formation. It has a unique structure of 3-3-3-3-3 and is labeled A-B-C-D-E [1]. When trend lines are drawn above and below the formation, a triangle formation begins to appear. The triangle formations can be ascending, descending, expanding, or contracting and will typically indicate a sharp change in the current trend of the market at the end of the formation. Figure 2-9 shows examples of each of these in both bull and bear markets.

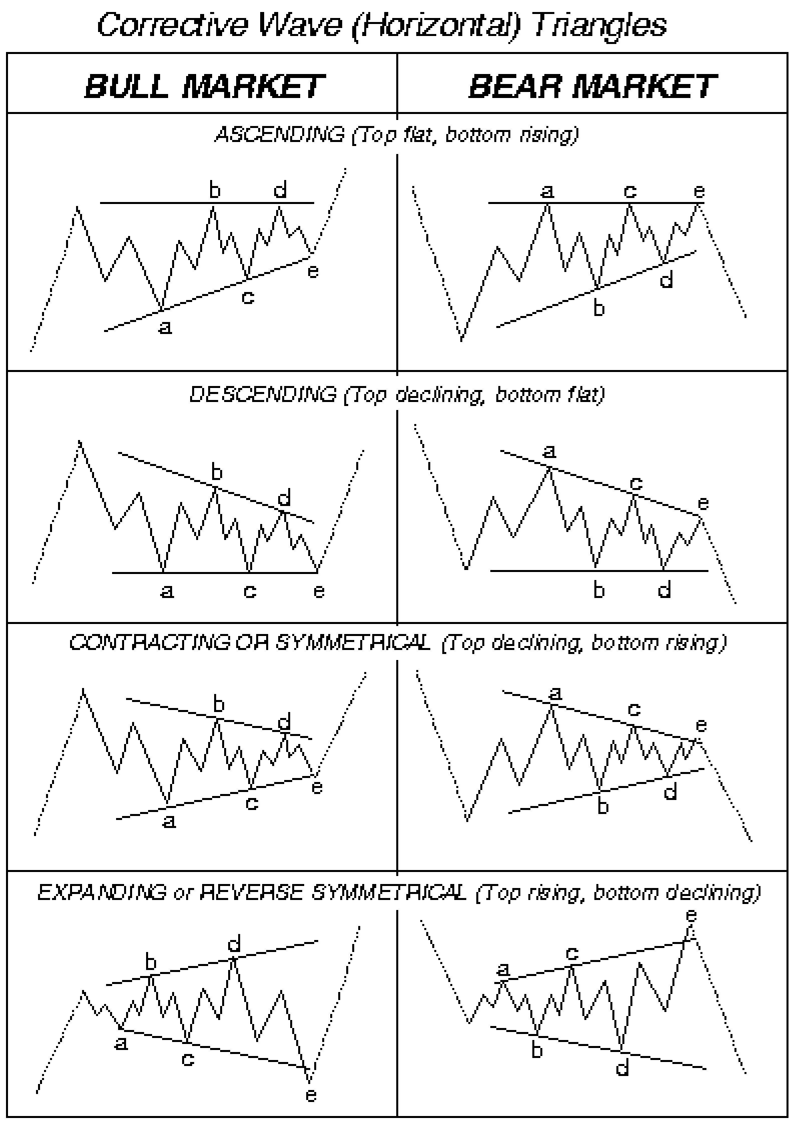

Figure 2-9: Various triangle corrections [1]

2.2.2.8 Combination

When two or three corrective waves are concatenated they are referred to as a combination. Combinations will be found in pairs of two or three and are named double three's or triple three's respectively. Typically, combinations are extension of sideways action in the market [1]. However, a double three may contain a triangle as it's second formation after which would likely follow a trend reversal. Within a combination, the first corrective wave is labeled W, the second is labeled Y, and if the combination is a triple three the third wave is labeled Z. In between each corrective wave there is a transition wave that is labeled X. The X wave can be any corrective three wave structure.

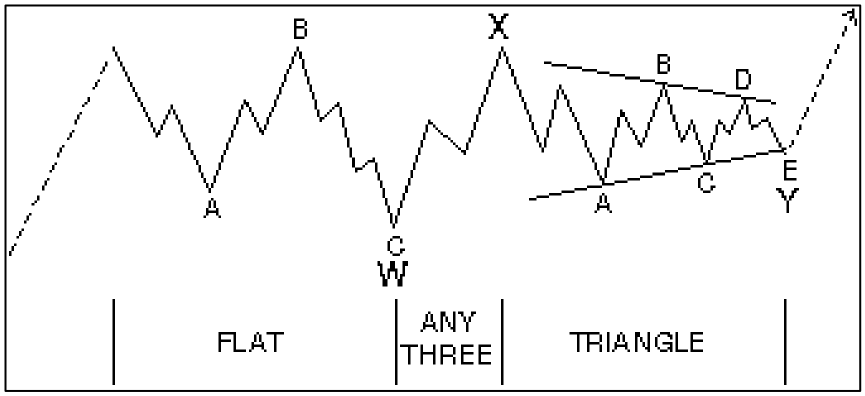

Figure 2-10: Combination of flat and triangle [1]

CHAPTER III:

LITERATURE REVIEW

3.1 General Discussion

Research on Elliott waves primarily focuses on the identification of Elliott waves after they have formed[1..3, 7..10, 12..16, 18..22] . These waves are often observed on time scales of days or months with very little focus on intra-day time intervals.

This serves as a useful academic exercise but provides little to no value to a trader who must make trade decisions in real-time. The data used in these experiments often fails to accurately portray real-world situations. In many cases, the data is not described in enough detail for a reader to attempt to replicate the experiments. With sparse data and Elliott waves found after they have formed, it is often difficult to ascertain if a model would be able to make money in a real world trading environment.

Table 3-1: Classification of Papers

Classification	Citation
Machine Learning used	[4], [9], [10], [14], [6], [17], [18], [19]
Data Description given	[4], [12], [15], [17], [18], [19], [20]
Money Management	[4]
Image Classifier	[9], [10], [14], [17], [19]
Predictive Trading	[4], [5], [6]

Money management techniques are lacking in the majority of papers that were read for this research [1..3, 5..10, 12..16, 18..22]. Trading is unlikely to be a profitable endeavor without good money management techniques. If Elliott waves are to be used as a trading method, money and risk management must be employed. In [4], the authors utilize a breakout analysis as their money mangagement technique. This analysis triggers a buy or sell order when the current price reaches a certain price. A buy order is triggered if the current price is higher than what has been seen in the last 20 bars. Conversely, a sell order is triggered if the current price moves below the lowest price seen in the last 20 bars. While this technique can help a trader avoid some losses, a lot of change can occur in 20 bars. This can be especially important in a highly leveraged commodity such as futures markets where large sums of money can be gained or lost in 20 bars. A more conservative approach would be ideal.

Two papers presented models that could be used to place trades in real-time. In [5], Elliott wave analysis predicts the exchange rates between the U.S. dollar and the Euro. The authors used the ProRealTime trading platform on historical data of the foreign exchange (FOREX) rate between the U.S. dollar and Euro over a period of 8 years. This analysis presents several possible scenarios that may occur. This is an impressive analysis of historical data that gives some insight into how the market may move in the future but does not offfer enough concrete evidence for trading. Additionally, it does not offer any intra-day analysis.

In [6], a Wave Analysis Stock Prediction (WASP) system was described that utlizes neuro-fuzzy architecture in conjunction with Elliott waves to make predictions about the stock price of the National Bank of Greece. The WASP system uses nine different models developed via their neuro-fuzzy architecture that combine to give a final prediction that can be used to make a buy or sell decision. The results of their model are compared to a buy and hold strategy and appear to perform significantly better.

Methods used to find Elliott waves include Fibbonacci analysis, mathematical models, different software packages with built-in and custom functions, and various machine learners.

3.2 Individual Paper discussion

In [Marañon 7], the authors apply Elliott waves to predict the prices of precious metals and a metal price index in the context of a Monte Carlo simulation.The simulation tests the probability that the advance and retracement between waves correspond to Fibonacci ratios. The simulation found a large range of possibilities which made an accurate prediction difficult. A more traditional fundamental analysis was discussed in an attempt to explain the price action of these commodities. While potentially useful, this type of analysis should not be necessary if an investor is utilizing the Elliott Wave Principle. A fundamental idea behind the Elliott Wave Principle is that patterns occur regardless of current events or news. Therefore, attempting to correlate current events and news to price fluctuations runs counter-intuitive to the ideas behind the Elliott Wave Principle. The authors also acknowledge that metal commodities are not ideal candidates for an Elliott wave analysis because they are not aggreagate commodites. An aggreagate index contains a mass volume of trades made by large groups of people making market decisions which can reduce the noise that might be introduced by current events. While metal commodities are not aggregations, they do trade at high volume, and so Elliott waves may provide some useful insight. The Monte Carlo analysis used in this paper found some trends between waves and when they form as shown in Table 3.2-1. While some situations show a high probability of an outcome, the findings for the most useful wave, wave 3, do not rise above 45%.

Table 3.2-1: Probability of Wave formation based on Fibonacci Ratio [Marañon 7]

Price amplitude waves link through FR and probability of scenarios.

Wave	Connected to price of	Price amplitude section	PDF within section	move	Section probability
W1	Not applicable	Not applicable	Not applicable	Not applicable	Not applicable
W2	W1	0.23–0.38	Triangle(0.23,0.38,0.38)	Retracement	12%
	W1	0.50–0.61	Triangle(0.50,0.61,0.61)	Retracement	73%
	W1	0.61–0.78	Triangle(0.61,0.78,0.78)	Retracement	15%
W3	W1	0.78–1.00	Triangle(0.78,1.00,1.00)	Advance	2%
	W1	1.00–1.61	Triangle(1.00,1.61,1.61)	Advance	15%
	W1	1.61–1.78	Triangle(1.61,1.78, 1.78)	Advance	45%
	W1	1.78–2.61	Triangle(1.78,2.61,2.61)	Advance	30%
	W1	2.61–4.23	Triangle(2.61,4.23,4.23)	Advance	8%
W4	W3	0.23–0.38	Triangle(0.23,0.38,0.38)	Retracement	15%
	W3	0.38–0.50	Triangle(0.38,0.50, 0.50)	Retracement	60%
	W3	0.50–0.61	Triangle(0.50,0.61,0.61)	Retracement	15%
	W3	0.61–0.78	Triangle(0.61,0.78,0.78)	Retracement	10%
W5, if W3 > 1.61W1	W1	0.78–1.00	Triangle(0.78,1.00,1.00)	Advance	2%
	W1	1.00–1.61	Triangle(1.00,1.61,1.61)	Advance	16%
	W1	1.61–2.61	Triangle(1.61,2.61,2.61)	Advance	82%
W5, if W3 < 1.61W1	W1-W2 + W3	0.50–0.61	Triangle(0.50,0.61,0.61)	Advance	2%
	W1-W2 + W3	0.61–1.00	Triangle(0.61,1.00,1.00)	Advance	16%
	W1-W2 + W3	1.00–1.61	Triangle(1.00,1.61,1.61)	Advance	82%

In [Satari 8] the price of copper is predicted by combining Elliott wave analysis, Ichimuko clouds, and Fibonacci analysis. The historical data analyzes the global price of copper from 2008 through 2018. The author's analysis of this chart shows a resistance line and what the authors believe are waves 1 and 2 with waves 3, 4 and 5 yet to form. If this prediction is true, this would be an ideal location to place a trade. Primary waves 1 and 2 are subdivided into smaller Elliott waves that consist of complete Elliott waves with sub-waves 1 through 5. Each of the sub-waves one through five are then summed up to determine the proportion of movement that they account for in the primary wave. So, in Table 3.2-2, it can be seen that wave 1 makes up 34% of the movement of the primary wave. This data provides the authors with an expected rise for the upcoming wave 3 that should complete in 2022. The analysis is well thought out and executed. However, this analysis was performed on only this commodity and so does not provide a reliable or repeatable method of prediction. .

Table 3.2-2: Proportion of movement in parent wave

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
Ratio to parent	34%	16%	57%	14%	39%

Kotyrba [9 Kotyrba] utilizes an artificial neural network (ANN) to identify Elliott waves. Their network consists of the input layer, one hidden layer, and the output layer. The training set used for the neural network consists of images of Elliott waves. The data used for testing were images from the EUR/USD FOREX pair. The ANN did detect some Elliott waves; however this represents an image recognition and cannot be used to help predict when a new Elliott wave will occur.

Volna [10 Volna] also uses a neural network with historical data to find Elliott waves. This neural network uses back-propagation to determine if a pattern is one of twelve Elliott wave patterns categorized into four types – an impulse, a correction, a triangle, or an Elliott wave. The data used was from the EUR/USD FOREX pair and consisted of daily, hourly, 10-minute, and 1-minute charts. The daily data spans from 5/8/2008 to 3/12/2010. The hourly, 10-minute and 1-minute charts appear to also span this time frame but are not clearly labeled. All of the charts highlight pattern 4 recognition but it is not clear what pattern 4 represents or how it might be used in trading. In each chart the neural network was able to find patterns in the data, but it was not clear how accurate the neural network was. Very general statements are made about predicting the trend of the market, but no testing was done to prove the accuracy of these predictions.

D'Angelo [5 D'Angelo] examines the EUR/USD FOREX pair between the years 2009 and 2017 on a weekly basis. He uses ProRealTime software to analyze price charts and perform Elliott wave analysis. The analysis relies on visual analysis of historical EUR/USD to make buy/sell decisions. While a prediction is made for the future price of this commodity, there was no unique model or new technique utilized. The analysis did not focus on the intra-day trading that this paper explores.

Patel [13 Patel] analyzes three securities from the Indian stock market. The first commodity was Adani Port and Special Economic Zone Shares data from September of 2013 through January of 2016. Second, was Axis Bank from July 2013 through January of 2016. Third, is Tata Motor Share from 2009 through 2016. A visual analysis using Elliott wave methodology shows a primary Elliott wave in each of the three cases. No unique methods or techniques were employed. While some insight was given about the future prices of these commodities, there was no meaningful method of prediction.

Jabbur[15 Jabbur] designs three Elliott wave based models and evaluates them using five stocks from the Brazilian stock market. OHLC data for 1, 5, 10, and 15-minute intervals are analyzed using three different agents. Agent one intends to find a breakout point before wave 3 or 5 occur. The second agent looks for a corrective move at the end of an Elliott wave or Elliott formation. The third agent looks for a downward trend after a zig-zag formation. These agents were run on historical data and the results of their investments were recorded. It is not clear what software platform was used to deploy the models. The returns did not appear to be very profitable.

Ilalan [16 Ilalan] utilizes Elliott wave analysis along with Brownian motion to describe the motion of the Nikkei 225 index. Due to the fractal nature of Elliott waves, the authors are able to calculate it’s Hausdorff dimension and the authors observe that the pattern of Elliott waves seems similar to Brownian motion graphs.

Volna [17 Volna] explores three variations of neural networks as a means of identifying Elliott waves. These variations include a multilayer artificial neural network (ANN), a variation of an ANN that utilizes analytical programming, and a synthesized pseudo neural network. The training data consists of up to 12 patterns showing what various Elliott formations should look like. The testing data is the EUR/USD FOREX pair for 11/03/2010. Their methods found Elliott waves in historical data but more in the context of image recognition instead of a prediction using historical or current data. This research is similar to what was done in [10 Volna] with the key difference being the types of neural networks used.

Vantuch [18 Vantuch] attempts to find Elliott waves using an algorithm from the book “Trading Chaos” by Dr. Bill Williams. After Elliott waves are found, a support vector machine (SVM) and random forest (RF) are used to try and detect patterns trends in the data. The data used included the price of gold, silver, and the EUR/USD FOREX pair. The data on the price of gold and silver is from 01/01/2011 through 12/31/2015 in 1-minute intervals. The data on the EUR/USD FOREX pair is from 01/01/2015 through 12/31/2015, also in 1-minute intervals. There are no trades made or analyzed. The focus of the research is on Elliott wave identification and statistical analysis in historical data. They describe the quality and amount of Elliott waves found in 10-minute data. As a result, it is difficult to make any conclusions as to whether this would be a valuable system in a real-world trading environment.

Kotyrba [19 Kotyrba] is focused on finding patterns in historical data using neural networks combined with analytical programming. This work is very similar to that found in [9 Kotryba] with the biggest difference being that Fibonacci retracement levels are incorporated into this research. The training set for the neural network consists of waves that closely follow Fibonacci levels of retracement within Elliott waves. The dataset description indicates the experiments were performed on eBay stock. Ten different datasets were examined, each with 300 values [19 Kotyrba]. The authors did not provide dates and time frames for the data. This research focuses on recognition of Elliott waves in historical data but does not present an effective method of finding them in real-time so that actual trades could be placed.

Magazzino [20 Magazzino] uses the software package ProRealTime to study the S&P 500 with Elliott Wave Principle. The analysis relies on the interpretation of the author. There is no algorithmic model that finds Elliott waves or predicts when they might form. While their predictions may well be accurate, the lack of a system that can be rapidly applied in real-time makes this research only mildly useful to the reader seeking a more reliable and repeatable method of finding and applying Elliott waves.

Antunes [12 Antunes] examines the Portuguese stock market index, PSI20 using Elliott wave analysis. This analysis is performed without the aid of any algorithmic or financial model. In part the study was done using fundamental analysis – observations about current events and other traditional financial indicators. While an Elliott wave analysis was utilized it does not expand or help the research being done in this thesis.

Tirea [4 Tirea] creates a multi-agent system that uses various techniques to find a consensus about future trends of a stock or commodity. The coordinator agent attempts to generate buy and sell signals to maximize profit. The coordinator agent is fed data from the Elliott wave agent, a neural network prediction agent, and a technical analysis agent. Each agent sends either a buy or sell signal and is equally weighted. If 2 of the 3 agents indicate the same action, then it takes this action. The technical analysis agent uses four indicators – GAP analysis, BreakS analysis (which refers to a breakout from a channel), Market's Mode (MM) analysis, and Momentum Precedes Price concept (MMP). The details on how the Elliott Wave and neural network agent generate their signals are not disclosed. This paper uses data from two stocks on the Bucharest Stock Exchange, symbols OLT and TLV. OLT is a chemical company based in Romania but the stock is currently delisted. The data used is monthly data from March of 2012. TLV is the Banca Transylvania out of Romania. This stock is still currently trading, and the data used in the paper is monthly data from March of 2012. They document when buy and sell signals were received and seem to show good returns on possible investments. They also utilize money management techniques via a simple Stop-Loss mechanism.

Walker [21 Walker] provides valuable information on applying Elliott wave analysis to make actual trades. Key foundations to this style of analysis and trading involve observing waves at different degrees or time frames. It is recommended to group intra-day waves into larger degrees to find the overall trend. The author believes that Elliott waves at larger degrees more accurately represent the trend of the market. Central to the methodology is finding highs and lows on the chart that signify the potential beginning and end of a wave. By properly locating these extremes, an analyst will be able to accurately define Elliott waves on a chart. Another central theme to the methodology presented in this book is the “C Wave Method” which involves trading at the end of an ABC corrective wave. If the market is impulsive, as shown in Figure 3.2-1, the idea would be to stay with the trade until the analyst receives an indicator that the impulse is correcting. If the current trend is corrective, as shown in Figure 3.2-2, the analyst should look for the end of wave C and then enter the market [21 Walker]. The author includes a large number of examples of price charts for various securities along with wave counts and how they are used to place trades in real-time. Money management is discussed in the form of profit taking and protective stop measures. No results from actual trades are discussed in this book but there are examples that show how an Elliott wave analysis would inform buy and sell decisions in different scenarios.

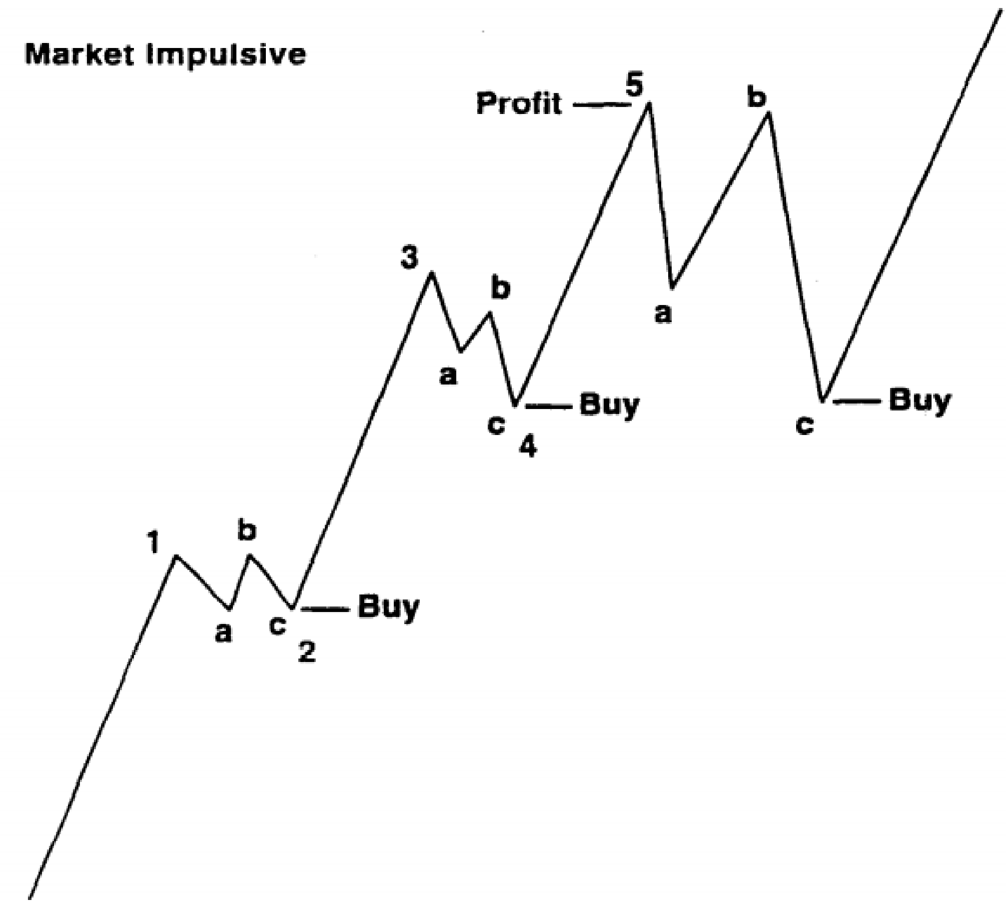

Figure 3.2-1: C Wave Method Impulsive trades

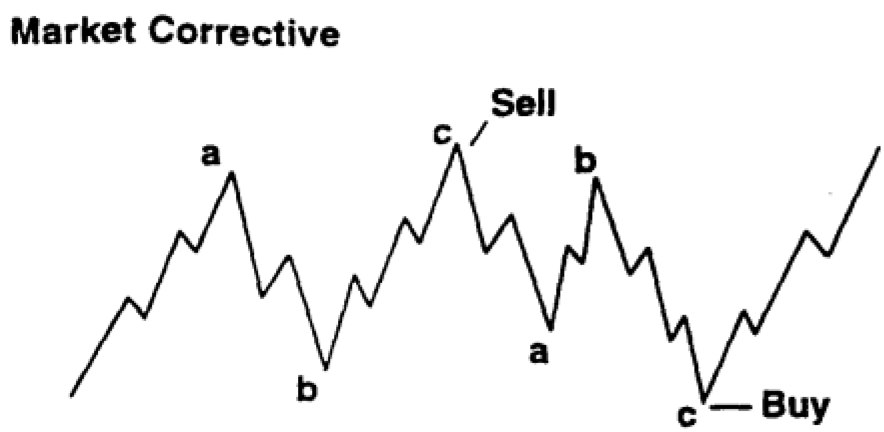

Figure 3.2-2: C Wave Method Corrective trades

Poser [22 Poser] provides the reader with a comprehensive breakdown on the basics of Elliott wave Theory and its core principles. He then gives insight into his method of identifying Elliott waves. In addition to the rules set by Elliott, he adds that volume should be strong and impulse waves should be easily recognizable. Considerable effort is spent distinguishing between impulse waves and corrective waves. This ability is important because an analyst would enter or exit the market at different times based on a wave being either impulsive or corrective. In the later chapters of his book, he covers several examples of different types of markets, how he would count Elliott waves on their respective charts, and when he might enter or exit a trade.

Poser describes the Fibonacci retracement levels, advice on when to use them, and which ones he prefers to utilize. He believes that too many retracement levels can lead to incorrect Elliott waves being drawn. Instead, he advises to only use 23.6%, 38.2%, 50.0%, 61.8%, and 76.4%, primarily focusing on 38.2%, 50.0%, and 61.8%. Periods of high volatility seem to be the ideal times to use Fibonacci retracement [22 Poser]. He also adds that determination of the beginning and end points from which you calculate your retracement levels are vital. Several examples of how to correctly find these beginning and end points are provided.

Poser includes various pieces of trading advice and money management techniques to help a trader and/or analyst. For example, if trading on an intra-day time cycle, he advises looking at larger time cycles for long-term trends. Examples of trading in different markets – futures markets included – are included for the reader. Charts with Elliott waves and Fibonacci retracement levels show how he would analyze a security and when he would enter or exit trades.

At the time of writing this book in 2003 he is aware, but somewhat wary of computer models to find Elliott waves. He feels that computer models can be useful but cannot account for the “human element” [22 Poser]. His trading style ultimately relies on fundamental analysis in conjunction with Elliott wave analysis. He clearly states that Elliott waves are a tool he uses, but not the only one. He argues that fundamental analysis is equally important and should be used in conjunction with Elliott wave counts. Poser uses real-world market data to provide examples of how he would have performed his analysis. He shows ideal buy and sell locations but does not give real world examples of trades that were made.

After careful review of books and papers regarding Elliott waves, it is clear that key elements are missing from the body of knowledge. There are very few examples of actual trades being placed with documented results, detailed data descriptions are lacking, and trading results are theoretical or not included. The analysis of historical data is a useful exercise in helping to determine investment methods, money management techniques, and investment models or algorithms. Unfortunately, most of the research available does not present a model that can be used to help make buy and sell decisions. It is certainly possible that the authors achieved success but did not wish to reveal their methods and/or model. However, this was never stated and is pure speculation.

CHAPTER IV:

STATEMENT OF PROBLEM

As stated earlier, the Wave Principle describes a predictable pattern that is believed to exist within financial markets. If Elliott waves are drawn correctly, then, in theory, they could be used to make profitable buy and/or sell decisions. Since the Wave Principle is open to wide interpretation, this can lead to results that are not easily replicated. The paper aims to find Elliott waves programmatically against real-time data and the various formations that make up the Wave Principle in order to arrive at a more consistent and reproducible method of finding Elliott waves. The ability to reproduce Elliott waves consistently and rapidly will allow for an analysis that can be performed on multiple time frames at a rapid pace so that profitable decisions can be made in real-time and in the short term instead of only identifying trends over long periods of time. A programmatic method of finding Elliott waves also means that various settings can be iterated upon in order to more effectively find waves.

When attempting to find Elliott waves programmatically, there exists a dramatic difference in working with historical data versus real-time data. Historical data is fixed and so is easier to analyze. Real-time data is more challenging because as the data streams in, the current price can have dramatic effects on how previous data was analyzed and classified, thus potentially altering buy and sell signals. In a historical dataset, the data points in the future can be used to make more profitable buy and sell decisions. While not realistic, this historical analysis can help us to find patterns that might be useful in making decisions in real-time. With real-time data, a program cannot peek into the future and so the methods for finding Elliott waves, chart patterns, and other technical analysis methods must be applied differently. Finding a way to manage this difficulty is also a focus for this paper.

In traditional Wave Principle analyses such as those found in [1] and [2], predictions are made over long periods of time – years or months and occaionally days. This research uses much smaller time frames – five minutes or less. While typical Wave Principle analysis aims to make longer term buy and hold type trades this paper explores how Elliott waves can be used for intraday-trading. Being able to accurately analyze real-time data is central to being able to do this.

Additonally, the software uses major peaks and troughs of varying scope as the points that constitute the Elliott wave formations as opposed to the traditional method of using every data point on the chart. Scope is a term used to find more useful peaks and troughs. The scope value corresponds to the number of bars that the software will look forward and backwards in time when looking for a peak or trough (in a real-time analysis only data looking back in time will be used). By using this method, less peaks and troughs will be found overall, but each peak and trough will have greater significance when finding Elliott waves. This provides for more meaningful data and ideally, more descriptive Elliott waves and formations. Finding waves programmatically also allows for a more systematic method of finding formations in historical data which can help us to study live data..

In order to identify Elliott wave formations more accurately, historical data will be utilized to describe the details of formations as they often appear. This taxonomy can then be used as a guideline to help find these formations more accurately in live data. This kind of breakdown of these formations does not exist and would be a useful tool to aid in finding Elliott waves.

CHAPTER V:

PROPOSED TECHNICAL INNOVATIONS

The following technical innovations are proposed for this thesis:

- Utilize datasets that are larger than previous studies and show that the algorithm works in a variety of different market conditions.
- Analyze data in the most realistic manner possible. Include applicable commissions, trading delays to mimic real-world conditions, and trading within realistic hours.
- Show that partial Elliott waves contain enough information about the trend of the market to make profitable investment decisions.
- Collect and export data about each element of an Elliott wave that provides the basis for research in this paper and future research.
- Similar to [11 Bulkowski], this work shows statistical data about elements of the Elliott wave formation and derive the most profitable investment strategies from this data.
- Optimize different Elliott wave parameters to improve trading models.
- The development of an algorithm that can find Elliott waves in historical datasets and in real-time. The ability to find Elliott waves in real-time with enough time for the user to make a trading decision is a key focus of this paper.

CHAPTER VI:

STATEMENT OF WORK

6.1 Overview

The primary goal of this research is to find Elliott waves in real-time and then generate buy and sell decisions. This will be accomplished programmatically using Amibroker and the Amibroker Formula Language (AFL). Initially, Elliott waves will be identified using historical data. These waves will be verified according to their adherence to the Elliott wave rules outlined in Chapter 2, Section 2.2.1. If, at any point, a wave violates a rule, the current wave search will end, and a new search will begin at the next bar starting from wave 1.

Financial assessment of Elliott waves will consist of back testing in Amibroker using six different datasets. Each dataset is treated independently of each other. To mimic real-world conditions as accurately as possible, the following trading conditions will be utilized:

- Trading occurs on weekdays within regular market hours from 8:25 AM to 2:35 PM.
- For each dataset, the initial equity is $100,000.
- Every trade will constitute 3 S&P E-Mini contracts.
- Every trade uses a stop loss of 5 points.
- Commission fees are $4.10 round trip per contract.
- A trade delay of 1 bar will be used to accurately represent where trades will be placed in real-time
- Both long and short trades are considered.

Verification of Elliott waves within historical data, combined with a statistical analysis of these results allows for better prediction in a real-time situation. Real-time Elliott wave experiments will utilize results from the historical analysis to show more accurate real-world results and improve trading techniques in real-time. Ideal Elliott wave identification would allow for trades to be placed between the end of the second wave and the start of the third wave which often shows the most action in the direction of the trend.

6.2 Process to find Elliott Waves

The first step finds peaks and troughs within a dataset and stores these values in an array. This is performed on both live and historical datasets. Figure 6.2-1 highlights two data points. A red arrow indicates a peak, and a green arrow indicates a trough. These points are located and plotted in the entire dataset up to the most current peak in a live setting and form the basis for finding Elliott waves.

The peaks and troughs are found by scanning a range of data points within the window in Amibroker and determining if a bar should be marked as a peak or trough based on the scope variable. The scope variable determines how far back from the current bar the software will look to determine if this is the highest or lowest point within the scopes range. Live trading requires information in real-time and for this reason, only one bar forward is examined. When examining a bar as a possible peak or trough, the program scans backwards a number of bars indicated by the scope variable and forward one bar. An example of looking for a peak transpires as follows: If $High_x$ is 1000 with a scope of 2, the software checks that $High_{x-1}$ and $High_{x-2}$ are lower than 1000. Lastly, if $High_{x+1}$ is lower than $High_x$, $High_x$ will be marked as a peak. The process is similar for finding a trough, except the search is for the lowest price in a set of bars instead of the highest. The scope variable defaults to 1 but can be adjusted dynamically in real-time to find Elliott waves at varying scope values. Increasing the scope finds more accurate peaks and troughs, but fewer Elliott waves. Figure 6.2-1 uses a scope variable set to 1.

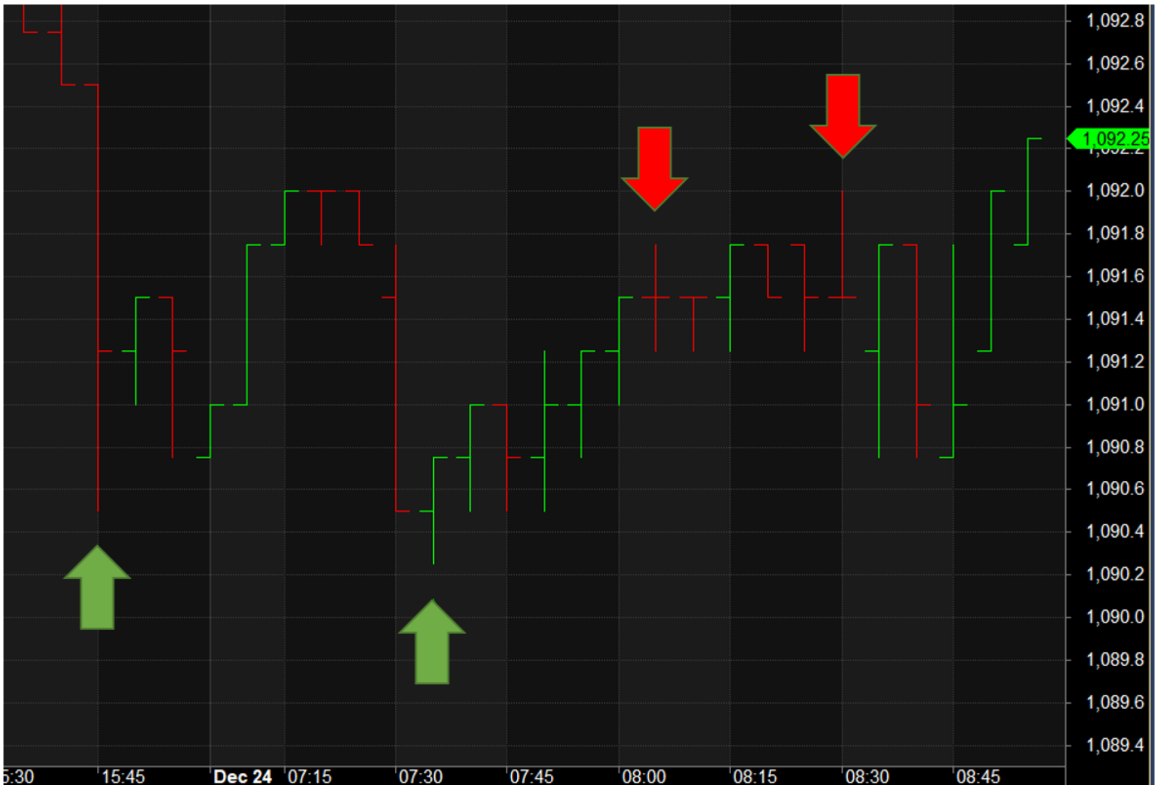

Figure 6.2-1: Peaks and Troughs with scope of 1 in 2001-2003 dataset. Arrows enlarged for clarity.

After collecting all the peaks and troughs, we start to identify Elliott waves. The first step finds a possible beginning for a bullish wave 1 – simply any trough. Once found, the software begins to look for a peak in subsequent bars. If a peak is discovered, then this is considered to be bullish wave 1, the points are recorded, and a line is plotted. As more bars enter the chart, the software scans for peaks that are higher than the current peak at wave 1. If a higher peak is found before a trough, it replaces the previous wave 1 peak and the line representing wave 1 is updated.

After finding the first wave, the software scans each bar for a potential second wave. A second wave would start with a trough that connects from the peak of wave 1.

Any trough that occurs after wave 1 will be inspected. If a trough is found it is checked to see if it is less than or equal to the trough at wave 1. If it is, then this is not an Elliott wave, all previously recorded points are cleared, and the search must restart. If the trough is greater than the wave 1 trough, then wave 2 of an Elliott wave has been found and the points are recorded and plotted. If a trough is found after wave 2 and this trough is lower, then this is not an Elliott wave, and the search must restart from wave 1. Once a completed wave 2 has been found, a long position is entered. The peak and trough search looks one bar into the future, so for a proper trade to be placed, the position should not be entered until the bar after a wave 2 has completed.

If a peak is found in a bar that follows the trough at wave 2, it is possible that wave 3 has formed. If this peak is greater than the wave 1 peak, it is a wave 3. Wave 3 is plotted and saved. However, if successive peaks occur without an additional trough that dips below the wave 2 trough, the wave 3 peak is readjusted to the higher peak, recorded, and re-plotted. This is demonstrated in Figure 6.2-2. The top of this wave 3 is an ideal location to exit our long position. It is not uncommon for higher peaks to be found after the initial wave 3 peak. Using historical analysis results for data from 2001-2003, the average number of bars between wave 2 trough and wave 3 peak was found to be 5. This number is used as an indicator for when to close a trade and is described in more detail in the Experiments section. As a result of this finding, a long position is not closed until at least 5 bars have transpired and a suitable wave 3 peak is found.

Figure 6.2-2: Wave 3 formed using highest available peak. Peaks 1, 2, and 3 were replaced as higher peaks were found.

With wave 3 found, the search for wave 4 starts by looking for a trough in the bars that follow the wave 3 peak. This trough must be greater than the peak at wave 1. If this check is successful, the points are recorded, and a line is drawn that indicates a wave 4. Lastly, a check is performed to be sure that a lower trough does not occur after the one that was recorded. If that does happen, and the new trough is also greater than the peak at wave 1, the recorded variable for wave 4 is replaced and the line for wave 4 is re-drawn.

If, in the bars that follow the trough at wave 4, a peak is identified before a trough, this may be a wave 5. If the peak found after wave 4 is greater than the peak at wave 3, this is a valid wave 5. The appropriate variables are recorded, and a line is drawn for wave 5.

As part of money management, two failsafe checks have been added that allow us to exit a long position outside of a wave 3 formation. There are cases where a wave 2 occurs, a long position is entered, and the check for wave 3 fails. When this happens, the search for Elliott waves restarts with wave 1 and we remain in a long position. In order to be sure that no trade is held for an extended period of time, when a wave 1 is found, the software checks to see if a long position exists. If the long position check is true, the position is closed. This condition is shown in Figure 6.2-3 below.

Figure 6.2-3: Long position entered at (1). Wave 3 fails at (2). Failsafe sell at wave 1 peak (3) to exit long position.

The second check occurs as follows: A long position is entered at the Open of the bar that follows a wave 2 as shown in Figure 6.2-4 at location 1. Wave 3 is found and connects to the previous wave 2. However, the wave 3 peak, shown at location 2 in Figure 6.2-4, does not meet the user defined *wave 3 bar count mean* of 3 in order to close the position. If wave 4 and 5 are found, a check is performed to see if a long position exists. If this check is true, the long position is closed at the open of the bar that follows wave 5. This is shown in Figure 6.2-4 at location 3.

Figure 6.2-4: Long position entered at (1). Wave 3 did not meet wave 3 bar count mean of 3 at (2). Long position closed at (3) via failsafe check.

This process for finding a bullish Elliott wave is simultaneously being performed for bearish Elliott waves. The logic works the same with the search for peaks and troughs reversed at each point.

6.2.1 Chart indicators

Within Amibroker, several chart indicators have been created that appear in real-time to aid the user in placing trades and understanding the current progress of an Elliott Wave search. The notation shown below in Figure 6.2-5 show the wave indicators for bullish waves 1 through 5 and corrective waves A, B, and C. These indicators appear at the start of a wave.

Figure 6.2-5: Bullish wave labels. Only bullish waves shown.

The next set of indicators, Figure 6.2-6, overlayed on this chart tell the user when to buy or sell. A buy indicator is represented by a light blue filled square. An indicator to sell is indicated by a light blue hollow square.

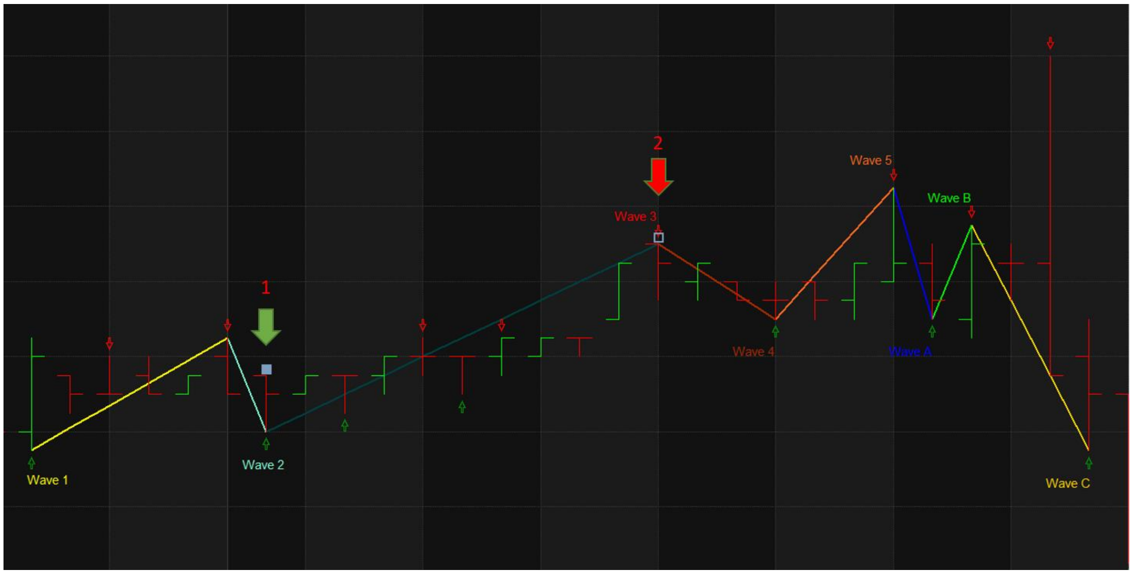

Figure 6.2-6: Buy indicator shown at (1). Sell indicator shown at (2). Only bullish waves shown.

Similarly, wave labels are shown for bearish waves as shown in Figure 6.2-7. Bearish waves 1 through 5 are shown and labeled. For bearish waves the lines are shown as dashed to distinguish between bullish when all waves are being shown.

Figure 6.2-7: Bearish wave labels. Only bearish waves shown.

Different indicators are shown on the chart to indicate when to short and when to cover. For a short entry, a light orange circle is shown on the chart. When the algorithm determines that the short should be covered, a light orange hollow circle will be shown. These indicators are shown in Figure 6.2-8.

Figure 6.2-8: Short indicator shown at (1). Cover indicator shown at (2). Only bearish waves shown.

6.3 Statistical Analysis of Historical Data

Elliott wave formations are found within each dataset and used as a trading strategy for back testing in Amibroker. The results are exported to a CSV file format for analysis in Microsoft Excel and Python. Other statistical analysis packages can analyze this data in future experiments. Both bullish and bearish Elliott waves are extracted, analyzed, and the following properties are logged:

- Number of occurrences of waves 1 through 5.
- The average number of bars that each wave occupies.

- Standard deviation and variance for the number of bars in each wave.

These values shall be recorded for each setup at scope values ranging from 1 through 5. Each setup will wait three bars after a buy or short before a sell or cover can be executed. Understanding these conditions provides valuable data to better place buy and sell orders and create money management techniques to avoid losses.

6.3.1 Analysis of 2001-2003 dataset

The charts below provide wave statistics for the 2001-2003 dataset for 5-minute data bullish waves.

Table 6.3-1: Scope 1 Statistics – Bullish Waves

Wave	Count	Number of Bars Mean	Number of Bars Variance	Number of Bars Std. Deviation
1	4428	2.95	4.52	2.13
2	2184	1.93	1.13	1.06
3	1381	3.90	10.05	3.17
4	349	2.53	2.94	1.71
5	189	2.49	2.57	1.60

Table 6.3-2: Scope 2 Statistics – Bullish Waves

Wave	Count	Number of Bars Mean	Number of Bars Variance	Number of Bars Std. Deviation
1	2913	4.56	11.76	3.43
2	1546	2.66	1.77	1.33
3	840	5.61	19.76	4.45
4	242	4.06	6.97	2.64
5	100	3.38	4.38	2.09

Table 6.3-3: Scope 3 Statistics – Bullish Waves

Wave	**Count**	**Number of Bars Mean**	**Number of Bars Variance**	**Number of Bars Std. Deviation**
1	2211	6.00	20.35	4.51
2	1260	3.46	2.66	1.63
3	561	7.32	32.74	5.72
4	173	5.18	10.78	3.28
5	72	3.46	4.00	2.00

Table 6.3-4: Scope 4 Statistics – Bullish Waves

Wave	**Count**	**Number of Bars Mean**	**Number of Bars Variance**	**Number of Bars Std. Deviation**
1	1803	7.42	29.82	5.46
2	1048	4.08	3.38	1.84
3	425	8.80	43.78	6.62
4	127	6.34	13.60	3.69
5	55	4.11	3.54	1.88

Table 6.3-5: Scope 5 Statistics – Bullish Waves

Wave	Count	Number of Bars Mean	Number of Bars Variance	Number of Bars Std. Deviation
1	1512	8.62	39.79	6.31
2	916	4.76	4.95	2.23
3	314	11.30	72.71	8.53
4	105	8.05	31.93	5.65
5	36	3.89	4.16	2.04

In order to further help visualize this data, violin plots have been created in Python. These plots provide a visual representation that shows the distribution of bars per wave for each scope value. These plots are contained in the following Figures 6.3-1 through 6.3-5. Of note in these graphs and the data in tables 6.3-1 through 6.3-5 are the fact that wave 3 consistently contains the most bars on average. Elliott Wave Theory predicts that wave 3 will, on average, be the longest wave with the most potential for profitability and this data helps to confirm this.

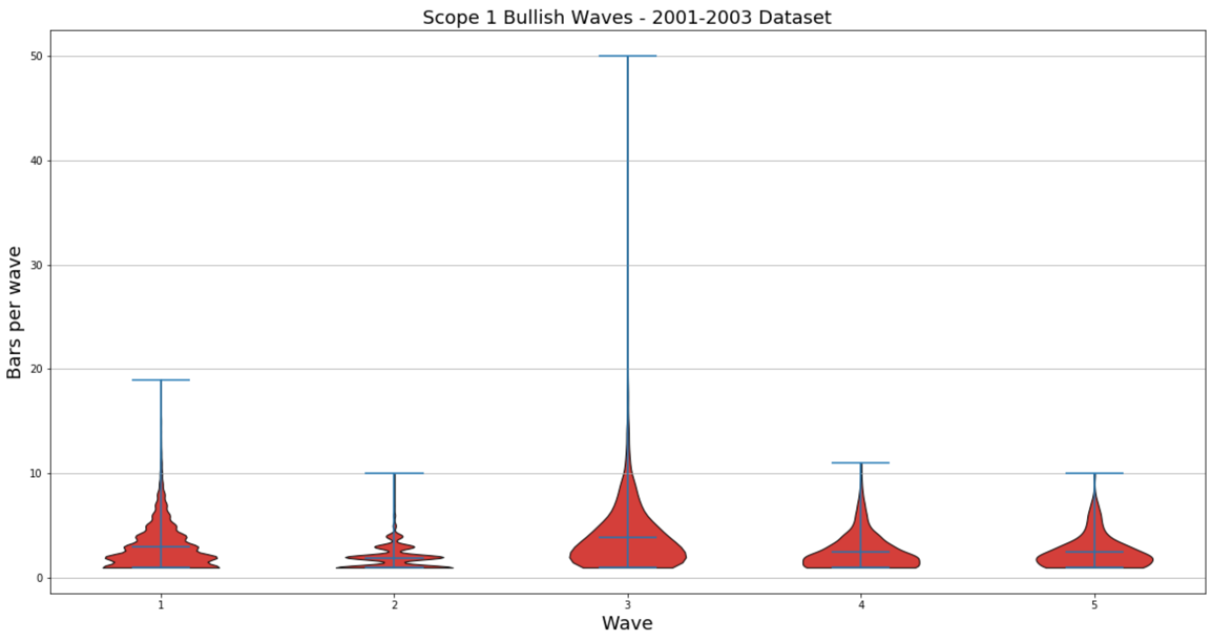

Figure 6.3-1: Violin plot showing bars per wave for scope 1.

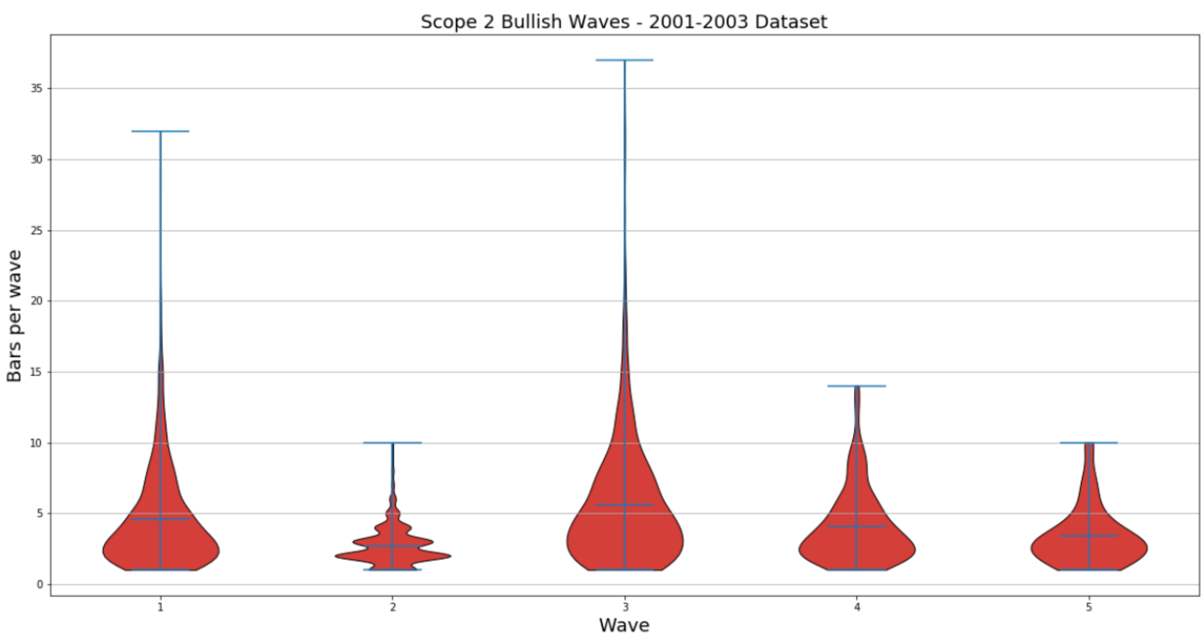

Figure 6.3-2: Violin plot showing bars per wave for scope 2.

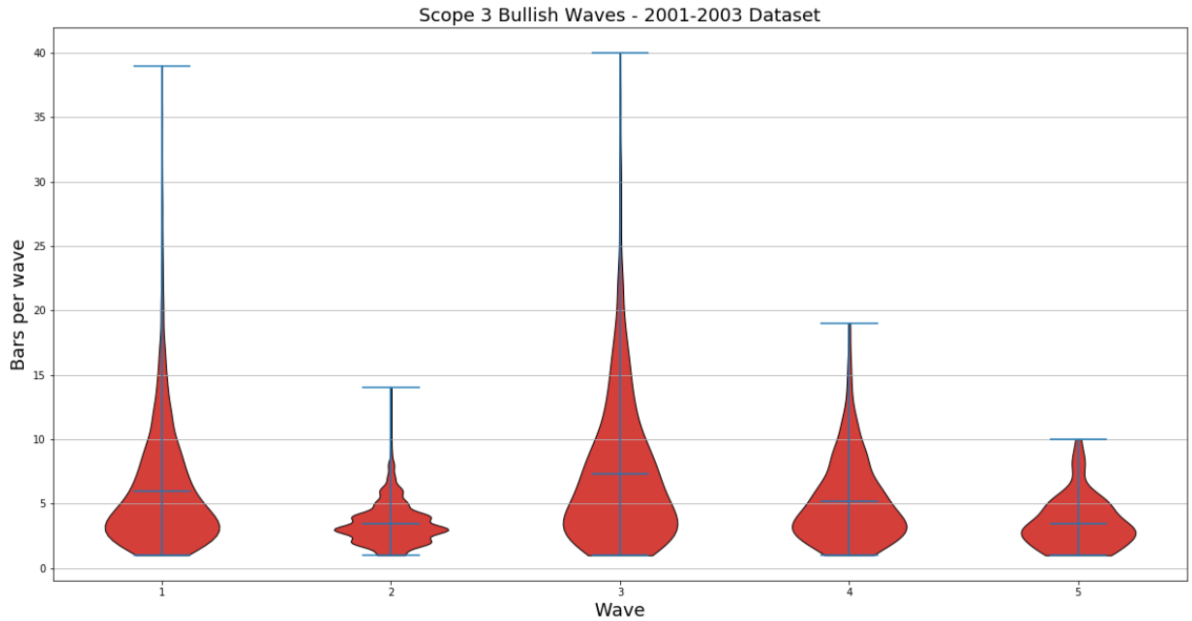

Figure 6.3-3: Violin plot showing bars per wave for scope 3.

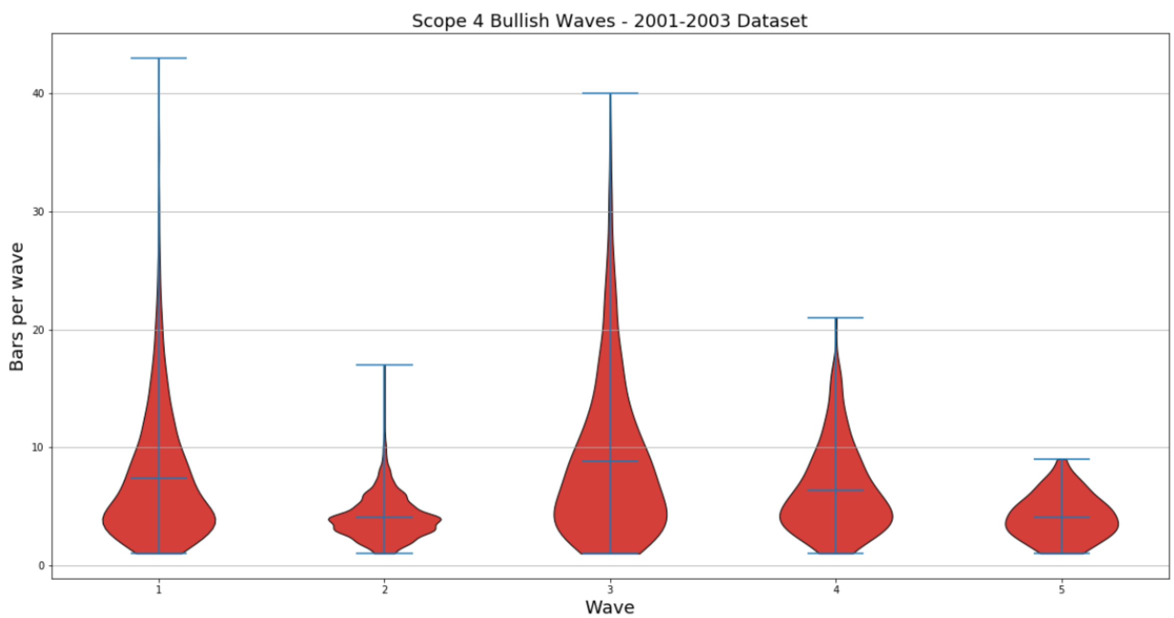

Figure 6.3-4: Violin plot showing bars per wave for scope 4.

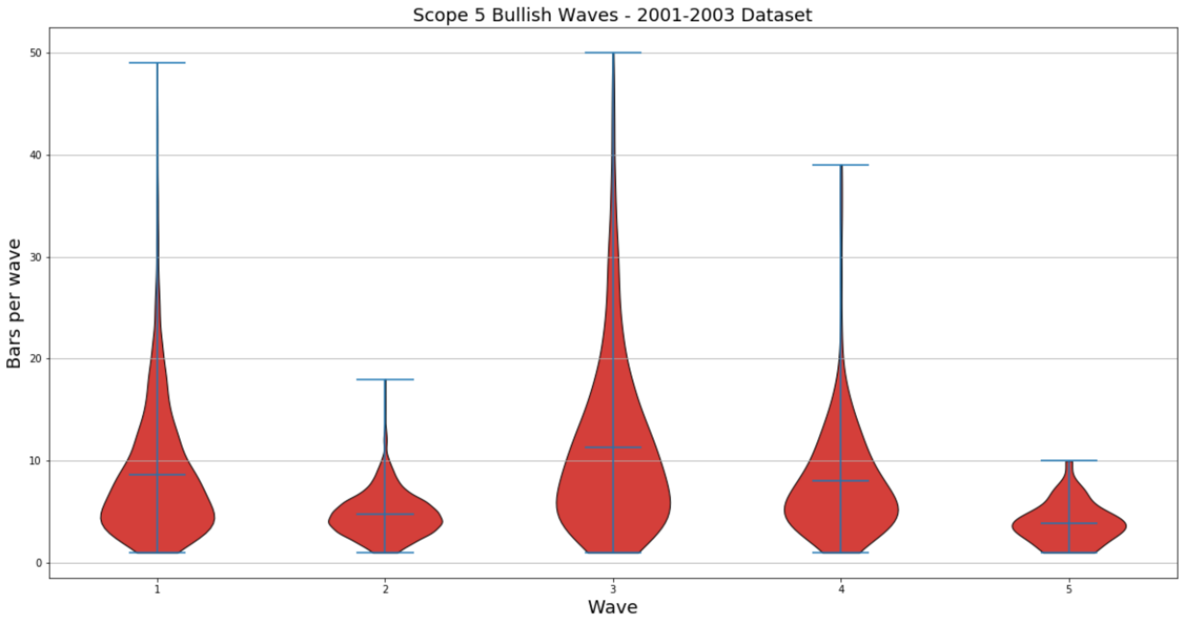

Figure 6.3-5: Violin plot showing bars per wave for scope 5.

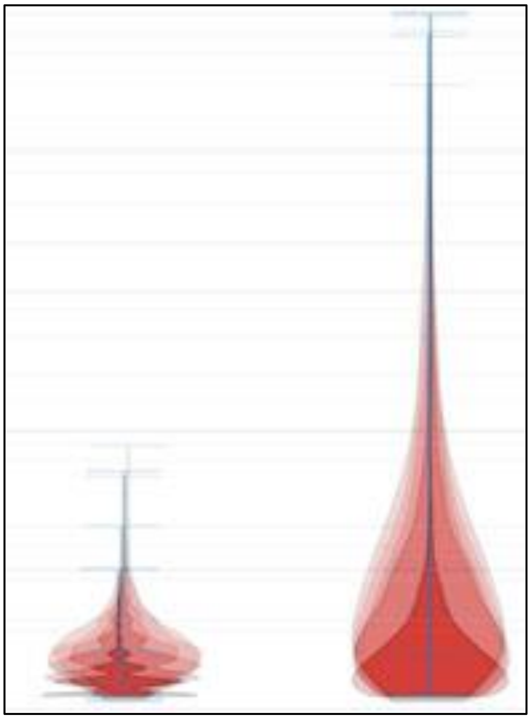
Figure 6.3-6: Overlay of Wave 3 violin plots.

6.4 Real-Time Analysis

The statistical analysis serves as a basis for deploying buy/sell orders and money management techniques when applying Elliott waves to a real-time situation. The data that is extracted from historical experiments and analysis will be the driving factor behind the real-time experiments. The success of the real-time experiments will be evaluated based on the number of profitable trades they make and the magnitude of their profitability.

These experiments will be tested using actual real-time data on live markets within Amibroker. Additional real-time testing will be conducted using tools within Amibroker that allow for a simulated real-time environment. The Amibroker feature called *bar replay* will be useful for this type of testing. Bar replay plays back all the data from a price chart at a desired speed with the option to start and stop at will. Observing the data in this fashion creates a real-time simulated environment that requires buy and sell orders to be placed with only information that is available at that moment in time. Figure 6.2-5 provides a visual example of the design flow for this paper.

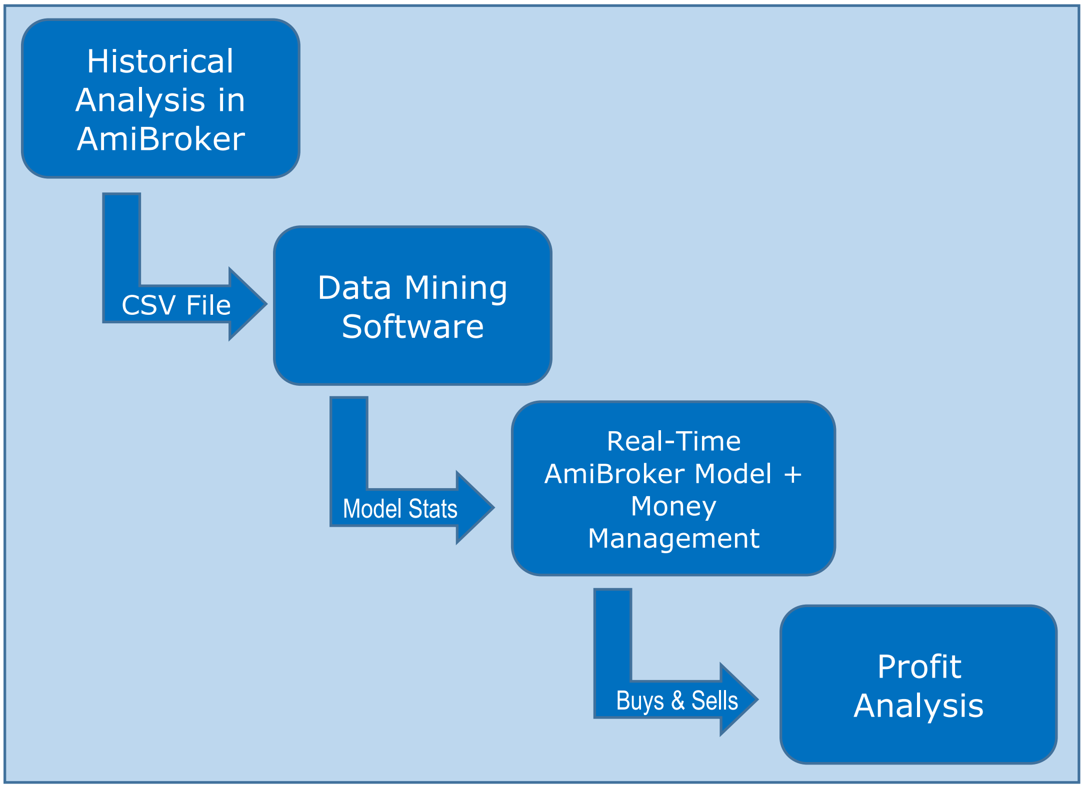

Figure 6.2-5: Design Pipeline

CHAPTER VII:

DATA

7.1 General Data Description

All back testing uses five-minute interval OHLCV data based on various S&P E-mini futures contracts. E-mini contracts expire quarterly. As a result of this, data for successive contracts was obtained through Interactive Brokers and manually pieced together in Excel to create a continuous set of data. This resulted in six different datasets. They include the following ranges: 2001 through 2003, 2015, 2016, 2017, 2018, and 2019. The following table contains information on each dataset.

Table 7.1-1: Dataset descriptions

Dataset	Number of Rows	Time Interval
2001-2003	64,412	5-minute
2015	74,837	5-minute
2016	75,540	5-minute
2017	71,991	5-minute
2018	72,675	5-minute
2019	72,312	5-minute

It should be noted that the 2001-2003 dataset has fewer rows than the other datasets despite covering a larger time frame. In the 2001-2003 dataset only, the weekends were filtered out. No trades are placed on weekends in any of the analyses performed in this paper so this has no effect on the overall results.

As compared to other papers, the datasets used in these experiments offer significantly more data. In [4], the datasets used include daily data for the month of March in 2012, yearly data for 2011 that appears to be weekly (though no time interval is given), a 100-day dataset in a daily time interval, and a 60-day dataset also shown in daily time intervals. [12] contains a large range of data – from January 1993 through June 2012. However, there did not appear to be an algorithm run on this dataset and it was instead used by the author to identify Elliott Waves "by hand". In [15] the dataset includes 26 days from September to October 2013 and uses time intervals ranging from 1, 5, 10, and 15 minutes. In [17], the dataset is the EUR/USD from November 3, 2010 shown in 10-minute time intervals. [18] appears to have the largest dataset in the papers reviewed with the price of gold and silver from January 1st, 2011 through December 31st, 2015 and the EUR/USD from January 1st, 2005 through December 31st, 2015. The data was broken into time intervals of 1-minute, 10-minute, 15-minute, and 1-hour. [20] examined 10 datasets, each with 300 values. No information was given on the dates or time intervals used.

The real-time analysis examines the same datasets used in the historical analysis so that a comparison can be made. Each dataset includes the Open, High, Low, and Close, Volume, Time, and Date attributes.

The S&P E-mini futures contract was chosen for several reasons:

- As an index it includes many stocks. This minimizes the impact of news and current events on price movement.
- The spread (price between and bid and ask) is minimal. This reduces gaps within the data.
- It trades at high volume. This makes it an ideal candidate for an Elliott wave analysis as it captures a large amount of market sentiment.

CHAPTER VIII:

EXPERIMENTS

8.1 Analysis of Historical Data

Elliott waves and formations are identified using large historical datasets. They will be recorded and analyzed with the intent of finding commonly occurring features or trends that lay the foundation for modeling in real-time. The following experiments are performed:

8.1.1 Elliott wave Proof of Concept: Initial model and results

The first iteration of this software utilizes a different algorithm for finding Elliott waves. This algorithm first found peaks and troughs in the same fashion as the current algorithm. The first step in a search for a bullish Elliott wave was to find a trough followed by a peak. From this point forward, peaks and troughs would be found in-between the first pair. From the initial trough, a peak would be identified in subsequent bars, and this would constitute a wave 1. From the initial peak, a trough would be identified in subsequent bars, and this would constitute the line for wave 5. This process of finding alternating peaks and troughs continues until the search met in the middle to form a wave 3.

This method finds Elliott waves but finds fewer waves than the current algorithm. It cannot identify partially-formed waves – only fully-formed waves. After a few tests in a real-time environment, it became clear that this model cannot be used to trade in real-time. The ideal time to enter a trade is at the start of a wave 3 which often has the largest jump in price. This initial model finds a peak and trough that represent the start of wave 1 and end of wave 5. Since the full Elliott wave will have transpired before it finds the wave, this cannot be used to enter a trade at wave 3.

This older model ultimately provides a unique way of finding Elliott waves but it was clear that a different direction needed to be taken in order to create a successful model.

Table 8.1-1: Old and new model comparison showing total number of full Elliott Waves – waves that contain waves 1 through 5.

Model	**Dataset**	**Scope**	**Bullish wave count**
Old Model	2001-2003	10	88
Old Model	2015	10	83
Old Model	2016	10	78
Old Model	2017	10	55
Old Model	2018	10	69
Old Model	2019	10	65
New Model	2001-2003	1	189
New Model	2015	1	119
New Model	2016	1	131
New Model	2017	1	98
New Model	2018	1	141
New Model	2019	1	140

8.1.2 Historical Experiment 1: In winning trades, how many bars on average occur between a wave 2 trough and wave 3 peak?

The software exports a large amount of data to a .csv file so that further study can be conducted on historical data. One of the variables recorded is the number of bars between a wave 2 trough and a wave 3 peak. This variable is of particular interest in live trading. As live data enters the chart, a peak will often form 1-3 bars after a wave 2 trough which would indicate that a long position should be closed. However, through observation of live data and replaying historical data as though it were live, it became apparent that the initial wave 3 peak is often not the final peak that ends up making up wave 3. For example, a peak might occur 2 bars after a wave 2 trough, and this will be labeled as a wave 3 peak. If a long position is closed here the profit would be minimal as a long position would have only recently been entered at the bar after the wave 2 trough. What was often observed was that several bars after the initial wave 3 peak, a higher peak would form and create a more profitable location for a sell order. This was demonstrated in figure 6.2-2.

Using the data extracted from the CSV file for the 2001-2003 dataset, the mean value for bars between wave 2 and 3 was calculated and can be seen in Table 8.1-2. This value – referred to as the mean of the wave 3 bar count is used to determine when a sell order should be placed in real-time trading and is explored further in the experiments section. A check is created that makes sure at least a number of bars equal to the mean of the wave 3 bar count have passed between the wave 2 trough and wave 3 peak. Figure 8.1-1 is a box plot of the number of bars between the wave 2 trough and wave 3 peak on long trades for all the datasets. Table 8.1-2 shows the mean values for long trade wave 3 bar counts for each dataset. Figure 8.1-2 and Table 8.1-3 show the data for short trades.

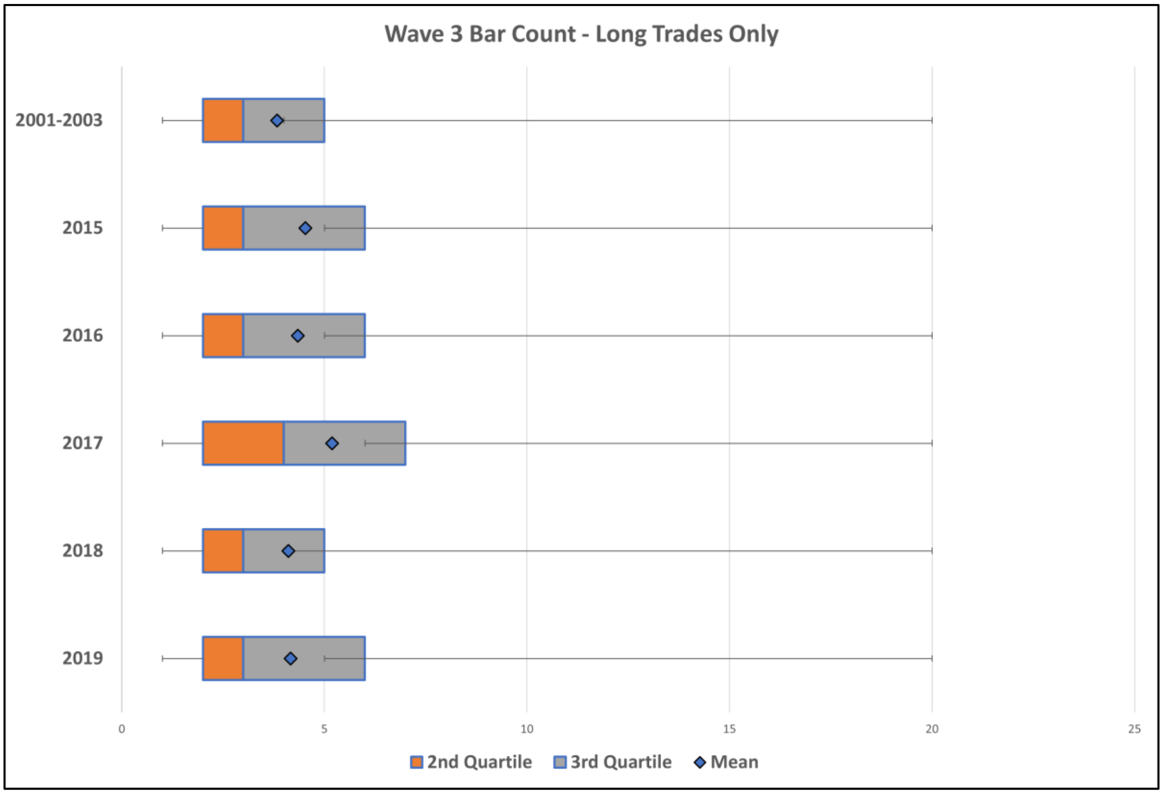

Figure 8.1-1: Box plot showing number of bars between wave 2 trough and wave 3 peak for long trades using a scope of 1. Values beyond 20 are considered outliers and have been filtered out for clarity.

Table 8.1-2: Mean Values for Long Trades with Scope Value 1.

Dataset	Mean Number of Bars (5-Minute)
2001-2003	3.90
2015	4.85
2016	4.83
2017	5.71
2018	4.34
2019	4.35

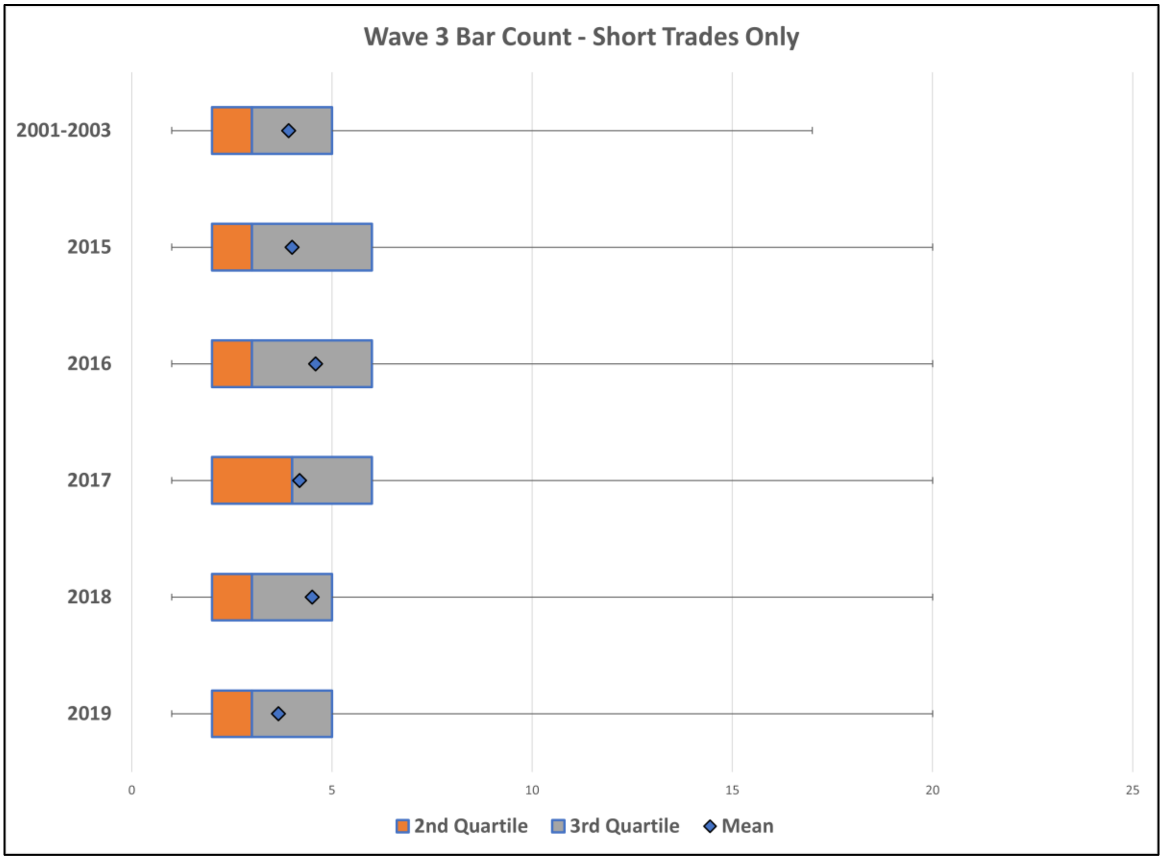

Figure 8.1-2: Box plot showing the number of bars between wave 2 peak and wave 3 trough for short trades using a scope of 1. Values beyond 20 are considered outliers and have been filtered out for clarity.

Table 8.1-3: Mean values for Short Trades with Scope Value 1.

Dataset	**Mean Value**
2001-2003	3.72
2015	4.71
2016	4.52
2017	7.89
2018	4.13
2019	6.70

Table 8.1-4 displays data when the algorithm runs for different *wave 3 bar count means*. An important statistic is the number of trades that occur within the same Elliott wave which will be referred to as intra-wave trades. In a long trade scenario, an intra-wave trade is one where a buy order is transmitted at the bottom of wave 2 and a sell

order is transmitted at the top of wave 3 in the same Elliott wave. A trade that is not classified as intra-wave would be a buy order transmitting at the bottom of a wave 2 and a wave 3 fails to form. In this case, failsafe checks will exit the buy position at an ideal time, but it cannot occur within the same wave where the buy order was placed as that wave failed to fully form.

In this historical analysis, the ideal value at which to set our *wave 3 bar count mean* will be 0. This achieves the highest theoretical net profit percentage and the highest percentage of winning trades.

It is important to note the values for long trade and short trade wave shifts. For all scenarios, there are 308 long trade wave shifts and 247 short trade wave shifts. These totals indicate the number of times in which a wave 3 peak shifted position. In a long trade, this would occur because of a higher peak being discovered shortly after a current wave 3 peak. In a short trade, the software would detect a shifting trough instead of a peak. Trading in a live environment with these shifting values becomes problematic without a *wave 3 bar count mean* to help maximize profit. This will be explored further in a live data experiment.

Table 8.1-4: Intra-Wave Trades with scope of 1 for 2001-2003 dataset

Wave 3 Bar Count Mean	**Net Profit**	**Winning Trades**	**Intra-Wave Bull trade %**	**Intra-Wave Bear trade %**
0	510.8%	68.2%	64.0%	59.2%
1	510.8%	68.2%	64.0%	59.2%
2	501.9%	67.0%	55.2%	48.6%
3	492.8%	63.8%	45.7%	36.4%
4	483.1%	61.4%	36.9%	27.0%
5	483.5%	60.4%	31.5%	20.0%

This experiment provides valuable insight into the behavior of wave 3. Wave 3 is the most crucial data point described in this paper as it describes ideal trade entry and exit points. Analysis of the historical back testing data shows that out of all the waves, wave 3 occurs over the longest period of time (bars). This is important as it not only provides time for more positive price action to occur, but it also corresponds to what Elliott predicted. In addition, having this information from a historical analysis allows us to create a variable to aid in real-time trading – the wave 3 mean count. This variable gives us insight into what to expect from the third wave and how to best time our exit trades in real-time.

8.1.3 Historical Experiment 2: Variation of scope and the results on trading.

The scope is an important variable in how the algorithm makes trading decisions. A large scope value produces fewer Elliott waves since there will be fewer points. What will be of interest is optimizing the scope value. Can we find less waves but with a higher wining trade percentage? The results for this analysis for the 2001-2003 data are summarized in Table 8.1-5. Table 8.1-6 shows the total number of each wave found in the datasets. The more waves that are found, the more trades can be placed.

A *Buy and Hold* strategy is not considered for the following reasons:

1. Futures contracts for the E-mini expire every three months which means an investor would need to close their position before expiration or settle the contract at expiration which can be costly.
2. Futures contracts are highly leveraged instruments and holding for extended periods of time can expose the investor to very high levels of risk.

Table 8.1-5: Scope Analysis for 2001-2003 dataset

Scope	***Wave 3 Bar Count Mean***	**Net Profit**	**Long Profit**	**Short Profit**	**Annual Rate of Return**	**Winning trade %**
1	5	483.50%	231.60%	252.24%	98.36%	60.36%
2	5	375.70%	177.86%	197.83%	83.23%	62.5%
3	5	239.03%	117.34%	121.7%	60.65%	59.96%
4	5	165.37%	87.91%	77.46%	48.08%	60.26%
5	5	134.02%	78.68%	55.34%	39.12%	58.88%

Table 8.1-6: Wave count for each dataset

Scope	***Wave 3 Bar Count Mean***	**Wave 1 count**	**Wave 2 count**	**Wave 3 count**	**Wave 4 count**	**Wave 5 count**
1	5	4428	2184	1381	349	180
2	5	2913	1546	840	242	98
3	5	2211	1260	561	173	72
4	5	1803	1048	425	127	55
5	5	1512	916	314	105	36

These tables clearly show that as scope increases, fewer waves are found. With less peaks and troughs, there are fewer opportunities to find Elliott Waves. It can also be seen that as we have fewer waves to trade, the profitability, in absolute terms, decreases. While there is a slight increase in winning trade percentage for a scope of 2, the difference is marginal and winning trade percentages remained within a margin of 4% for all the years studied.

Figure 8.1-3 below shows a profit chart for the 2001-2003 dataset. This shows the growth of an account starting with $100,000 and trading 3 contracts at a time. The value indicated in the chart is total account value.

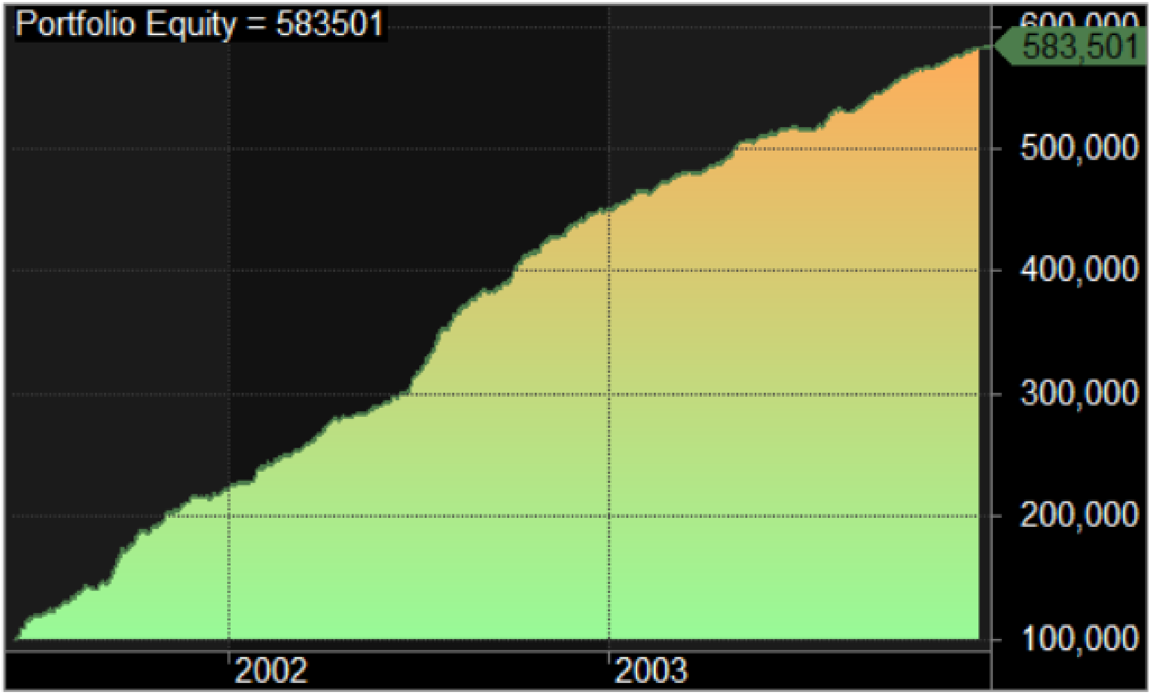

Figure 8.1-3: Profit chart for 2001-2003 dataset with scope of 1 and threshold of 5. Y-axis values are in dollars.

8.1.4 Historical Experiment 3: Optimization of scope and *wave 3 bar count mean*

Experiments 1 and 2 show how scope and the *wave 3 bar count mean* affect the profitability of a model. Experiment 3 uses the AFL function "Optimize" to find the ideal settings of scope and *wave 3 bar count mean* that will allow for the highest possible net profit percentage. Optimize allows the user to specify a parameter with a default value, a minimum value, a maximum value, and step size. Once set, Amibroker runs in Optimize mode which back tests every combination of variables specified over the desired dataset. The results are presented in a matrix that allows for comparison of different aspects of each test.

This optimization uses three variables: the scope, *wave 3 bar count mean* for long trades, and *wave 3 bar count mean* for short trades. The *wave 3 bar count mean* provides a specific number of bars that must pass during a wave 3 before the algorithm is allowed to sell. The scope optimization settings were a minimum setting of 1, a maximum value of 5, and a step size of 1. For the wave 3 bar count means, they were both set to a minimum value of 0, a maximum value of 10, and a step size of 1. Table 8.1-7 shows the top 10 settings on the 2001-2003 dataset.

Table 8.1-7: Optimization Results Sorted by Net Profit. Starting Capital of $100,000, 2001-2003

Rank	**Net Profit[A]**	**Avg. Profit[B]**	**% of Winners**	**Scope**	**Wave 3 Mean – Long**	**Wave 3 Mean - Short**
1	$512,276	$152.74	67.99%	1	2	0
2	$512,276	$152.74	67.99%	1	2	1
3	$510,763	$151.11	68.22%	1	0	0
4	$510,763	$151.11	68.22%	1	1	0
5	$510,763	$151.11	68.22%	1	1	1
6	$510,763	$151.11	68.22%	1	0	1
7	$507,351	$150.1	66.21%	1	3	1
8	$507,351	$150.1	66.21%	1	3	0
9	$507,238	$150.07	64.14%	1	8	1
10	$507,238	$150.07	64.14%	1	8	0

A: Net Profit is: Ending capital – Initial capital.

B: Avg. Profit represents the ratio of total profit and number of winning trades.

Figures 8.1-4, 8.1-5, and 8.1-6 show 3D plots of the optimization results. In each plot, one variable was set to the rank 1 value and the other two variables were optimized.

The value of CAR/MDD refers to the *Compound Annual Return % (CAR)* divided by the *Max system Draw Down % (MDD)*. The Max system Draw Down refers to the largest decline from peak to valley in the analysis.

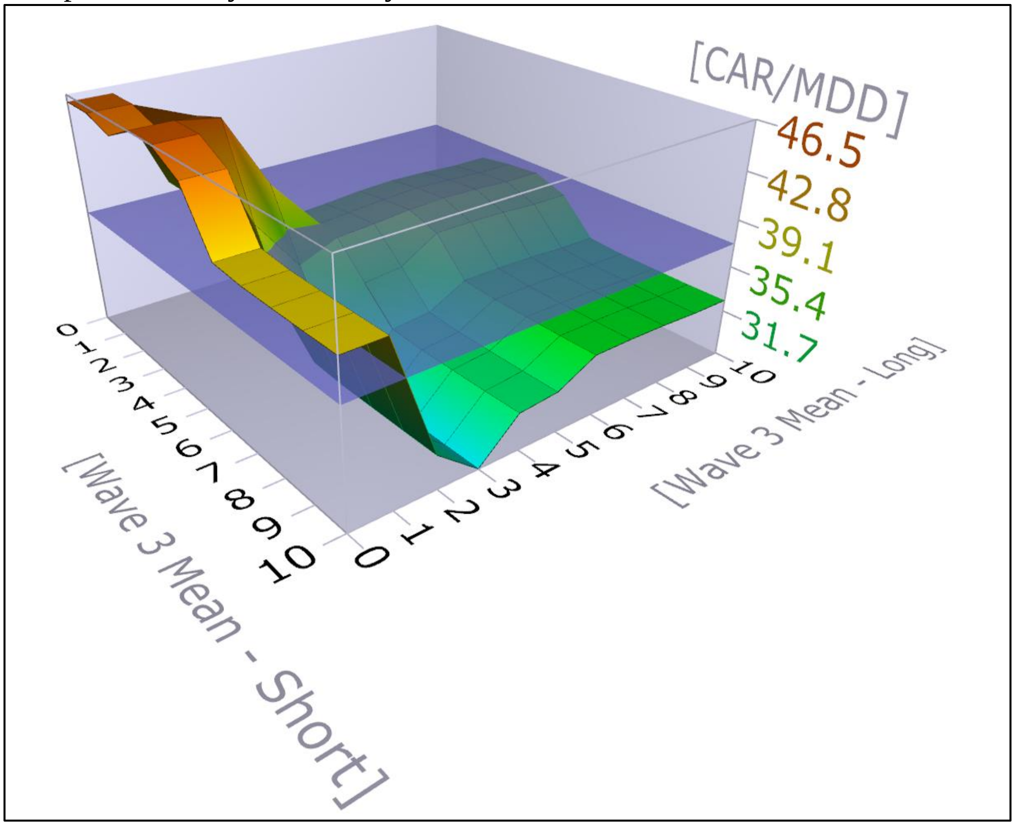

Figure 8.1-4: 3D optimization plot. In this plot, scope was set to 1 and wave 3 mean for long and short were optimized.

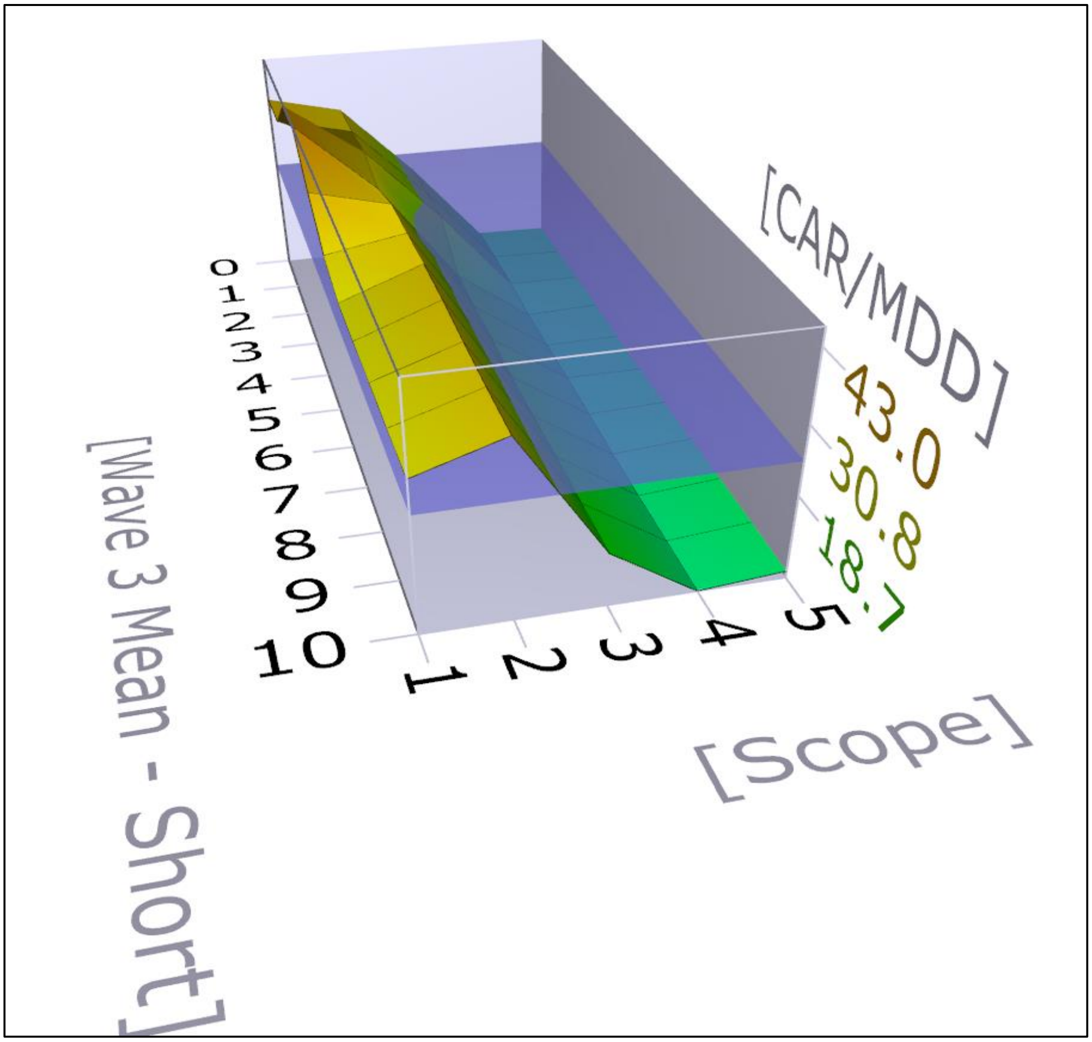

Figure 8.1-5: 3D optimization plot. In this plot, wave 3 mean - long was set to 2 while wave 3 mean - short and scope were optimized.

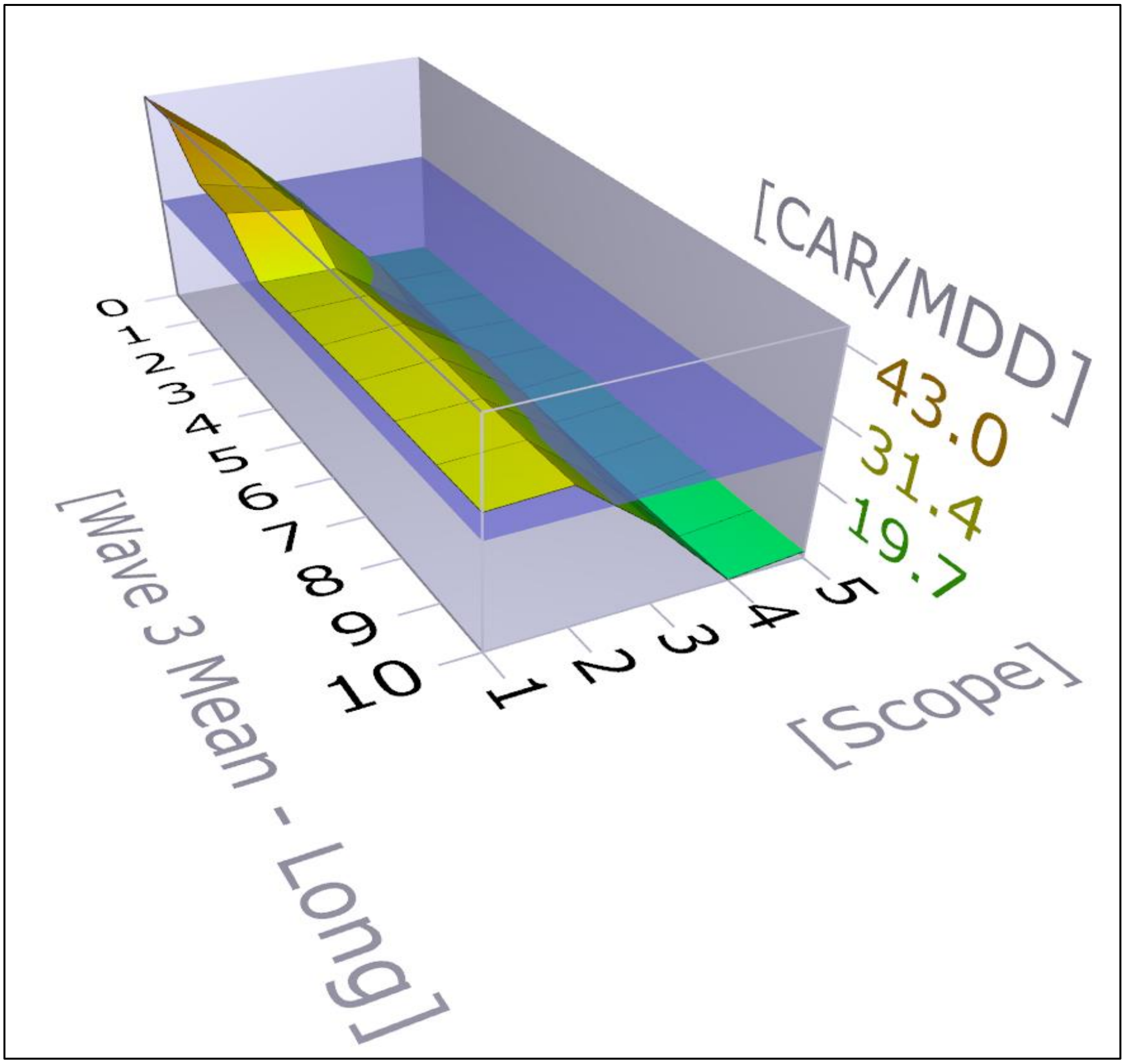

Figure 8.1-6: 3D optimization plot. In this plot, wave 3 mean - short was set to 0 while wave 3 mean - long and scope were optimized.

The results indicated the ideal setting would be a scope value of 1, *wave 3 mean* for long trades of 2, and *wave 3 mean* for short trades of either 0 or 1. When used in live trading, this optimization should be run with the most current set of historical data to produce results that most accurately align with current market trends.

8.2 Live Data Experiments

Live data experiments use actual real-time data or simulated using bar replay in AmiBroker to replicate real-time conditions. Finding Elliott waves in live data requires a different approach than historical data. It is possible to find the absolute highest peaks and lowest troughs in historical data because all data points are visible. This allows for accurate prediction of Elliott waves. In a live environment, the next data point is always hidden from the investor's view. The only data available to make a decision with is historical data. Naturally, this reduces the accuracy of predictions as compared to a historical analysis. The information gained from the historical analysis is therefore intended to aid in improving the predictions that can be made in real-time.

The experimental model must produce Elliott waves and formations without looking forward in time. Experiments on historical data are intended to inform the real-time model and produce more accurate results. A real-time model must make money to be successful. Minimizing the impact of losses using a stop is one key component of a real-time model. A stop is a rule that indicates when to exit a trade to minimize losses. All the experiments and tests use a 5-point stop. This means that if a trade moves in the opposite direction then desired by 5 or more points, the algorithm exits the trade. The live data experiments are detailed below.

8.2.1 Real-Time Experiment 1: Utilizing *the bar count mean for wave 3* makes more profitable real-time trades

In Historical experiment 1, the profitability of a model based on the *wave 3 bar count mean* was shown in Table 8.1-2. From the table, it can be seen that a *wave 3 bar count mean* of 0 provides the most valuable and accurate trading model. This experiment shows how in a real-time situation, these theoretical values are difficult – if not impossible - to achieve. This is due to wave 3 shifting as mentioned in section 8.1.2. The bar replay function within AmiBroker will be utilized to simulate trading in a real-time environment and demonstrate wave 3 shifting.

Figure 8.2-1 shows a historical snapshot in time from the 2001-2003 dataset in 5-minute bars with a *wave 3 bar count mean* setting of 0. A buy signal, represented by a solid light blue square, appears on 12/17/03 at 1:15 PM shown at location (1) in Figure 8.2-1. Location (2) shows a sell signal indicated by a hollow, light blue square. The open of the bar after this sell indicator is where a sell order is placed in real-time – clearly a lower peak than what is shown at location (3). The sell order at location (2) occurs due to a setting of 0 for the *wave 3 bar count mean* and a shifting of the wave 3 peak from location (2) to location (3). A recounting of how this plays out in real-time using bar replay illustrates this point.

Figure 8.2-1: In this image, (1) indicates a buy signal. Without wave 3 bar count mean, a sell indicator appears at (2), missing out on a higher peak at (3). 5-minute bars shown.

Figure 8.2-2 shows the first step of the bar replay. When the bar at 1:15 PM completes, a buy indicator appears, and a trade is entered at the open of the bar at 1:20 PM at 1071.5.

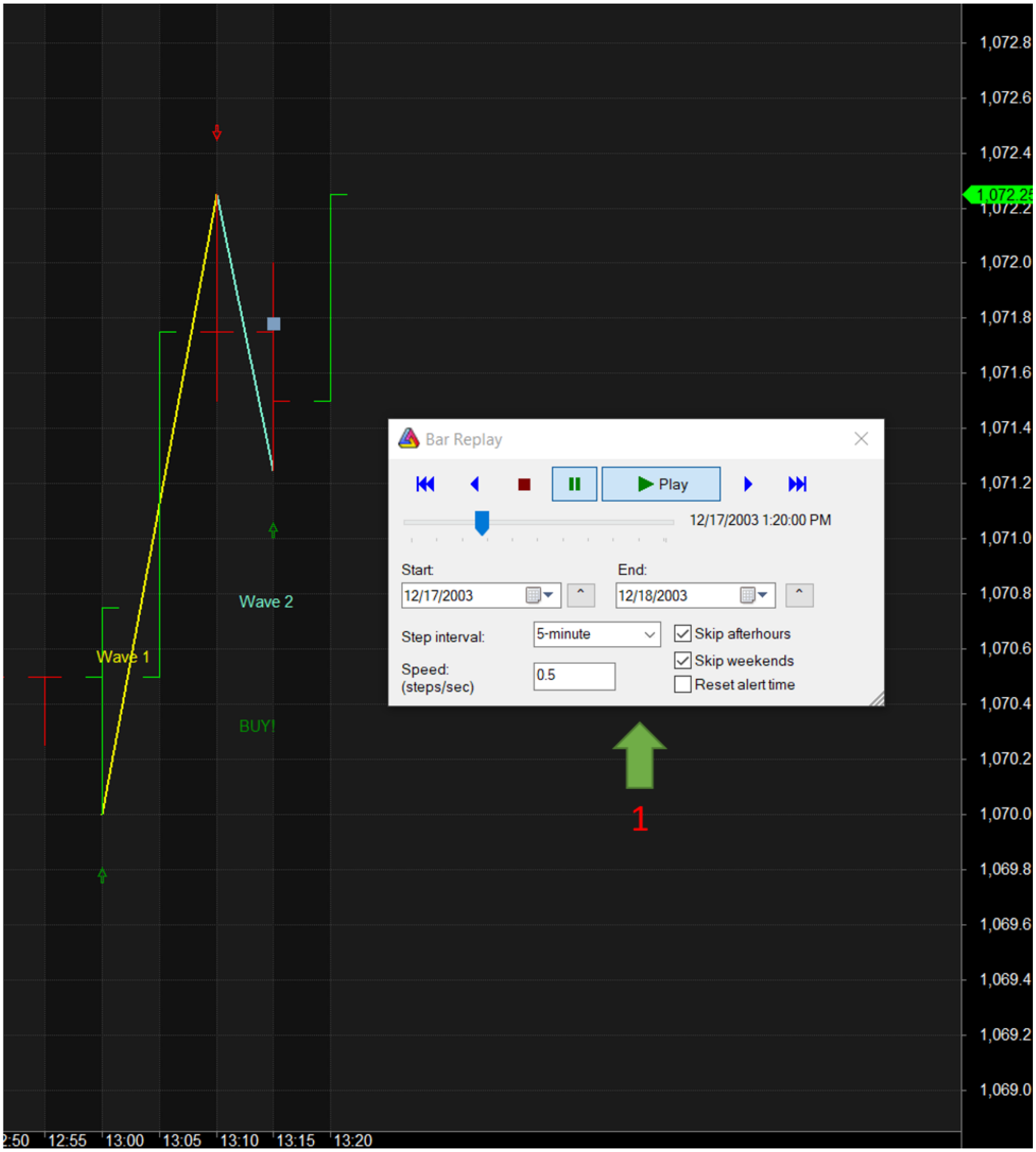

Figure 8.2-2: Stepping through 5-minute bars using bar replay. This step is showing the 2001-2003 dataset paused on 12/17/03 at 1:20 PM. (1) highlights the control interface for bar replay.

Figure 8.2-3 shows the next important step at 1:30 PM. At 1:25 PM, a peak is found, and this corresponds to a valid wave 3 endpoint. With a *wave 3 bar count mean* of

0, a sell indicator appears at 1:25 PM. In real-time, this would translate to a sell order at the open of the bar at 1:30 PM at 1072 – a profit of only half a point.

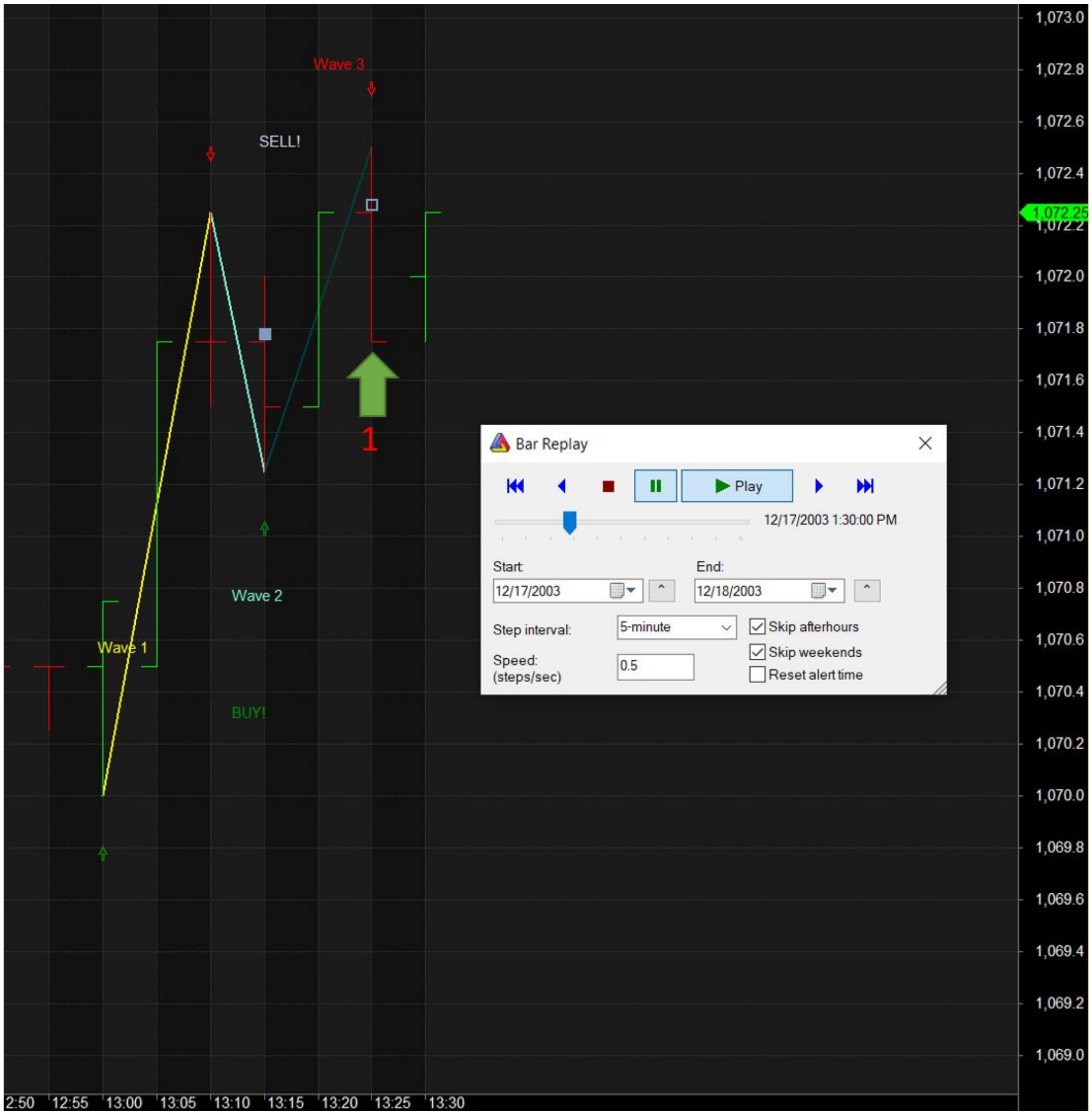

Figure 8.2-3: Stepping through 5-minute bars using bar replay. This step is showing the 2001-2003 dataset paused on 12/17/03 at 1:30 PM. (1) highlights bar at 1:25 PM showing a sell indicator. Wave 3 bar count mean is set to 0 in this case.

As the user watches the chart continue to unfold in real-time, it becomes clear that exiting the trade at 1072 was not an ideal time to do so. Figure 8.2-4 demonstrates a wave 3 shift occurring at location (1) - a higher peak than what was previously thought to be the end of wave 3 is found. A sell indicator at 1:40 PM would have allowed the user to exit the position at the open of the bar at 1:45 PM at 1073.5 – a point difference of 2.

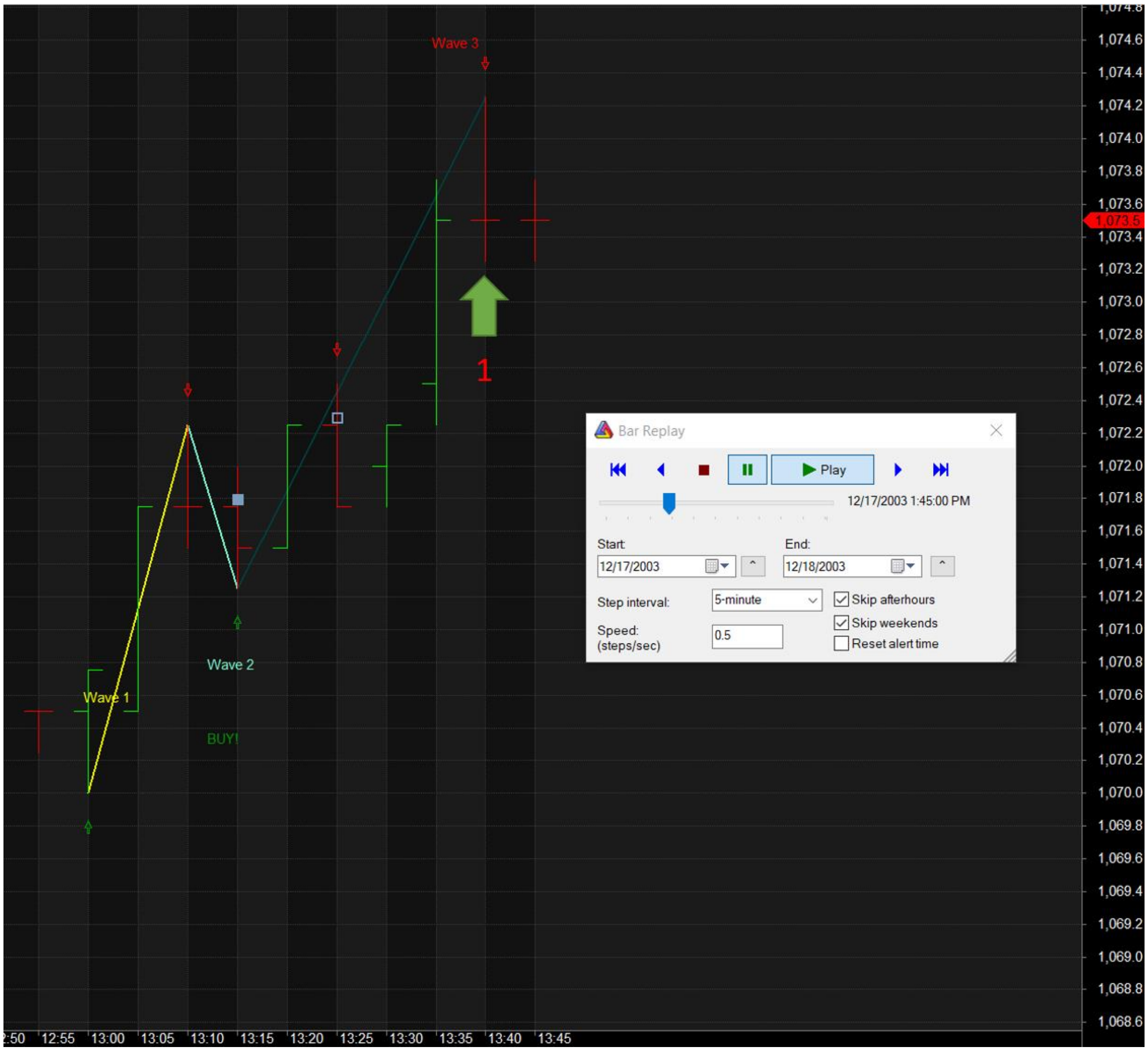

Figure 8.2-4: Stepping through 5-minute bars using bar replay. This step is showing the 2001-2003 dataset paused on 12/17/03 at 1:45 PM. (1) highlights bar at 1:40 PM showing a higher peak. Wave 3 bar count mean is set to 0 in this case.

Figure 8.2-5 shows how this trade can unfold if the *wave 3 bar count mean* is set to 5. This variable instructs the algorithm to wait for 5 bars before deciding to close a position. The initial sell indicator shown in Figure 8.2-3 no longer appears because only 2 bars transpired between the buy indicator and sell indicator. With *wave 3 bar count mean* set to 5, wave 3 shifting can be accounted for, and more profitable trades can be placed in a real-time scenario.

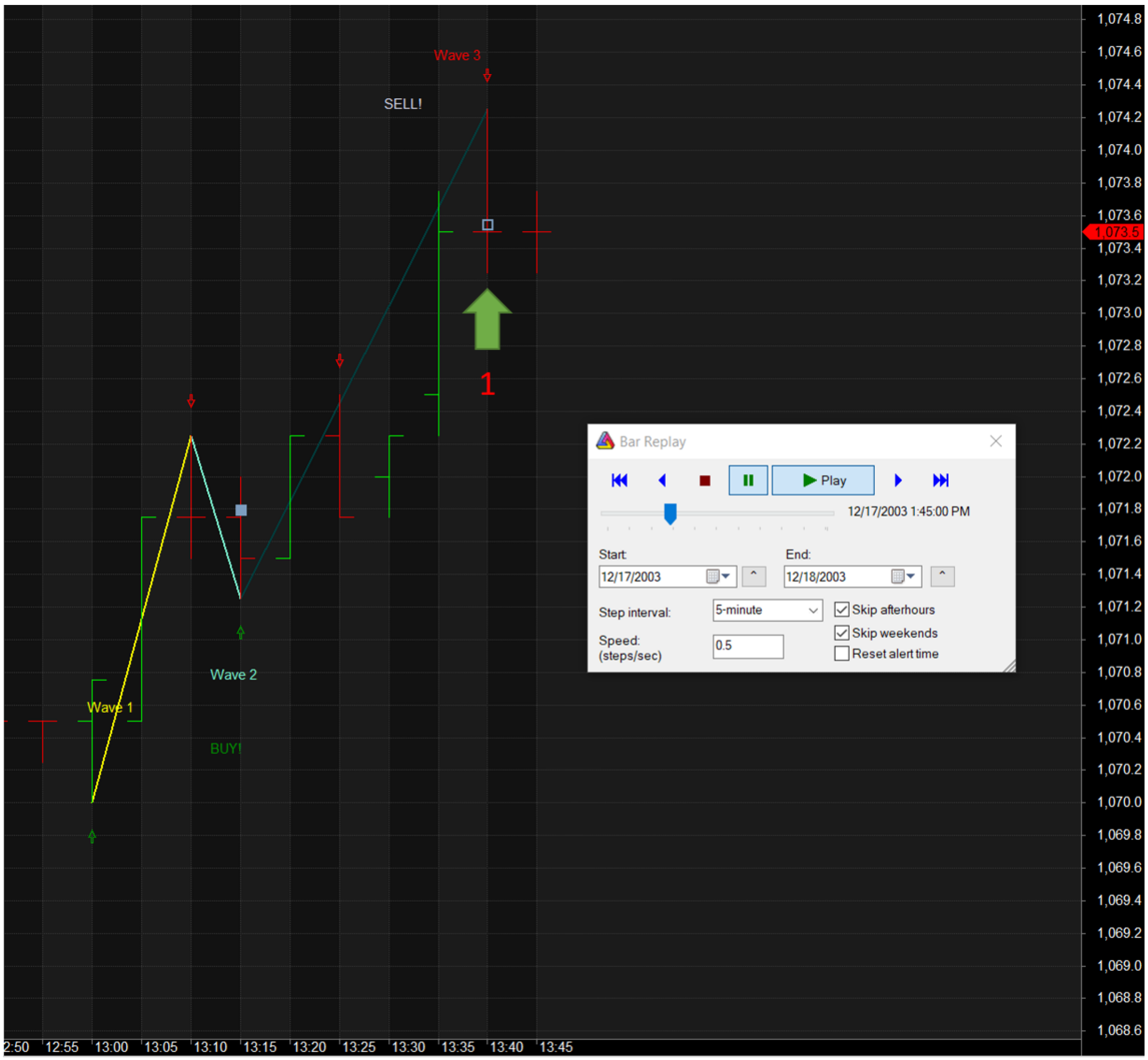

Figure 8.2-5: Stepping through 5-minute bars using bar replay. This step is showing the 2001-2003 dataset paused on 12/17/03 at 1:45pm but with wave 3 bar count set to 5. With this setup the trade exits at (1).

This experiment highlights the utility of *wave 3 bar count mean* when trading in a real-time environment. Within the 2001-2003 dataset, 22.3% of wave 3 occurrences display an early sell signal that ends up shifting to a higher peak. These early signals are not the ideal time to exit a trade. Figure 8.2-1 highlights how this can happen, and it shows how *wave 3 bar count mean* helps the user achieve more profitable trades. The data from historical analysis 1 show us that we can expect nearly 4 bars in a winning wave 3 trade. This observation should make the user wary of selling too soon after a buy order has been placed. This experiment examines each bar as a wave unfolds and shows how waiting to sell as the *wave 3 bar count mean* tells the user to do will result in a more profitable trade.

Money management techniques and a defined strategy are key ingredients in becoming a successful investor. This algorithm encapsulates important techniques such as money management, patience, exit strategies, and emotional control into a program that handles all of those aspects for the user. There is no guesswork involved – simply waiting for the correct signal. However, if the program the user relies on is not sending reliable signals investing can become difficult and frustrating. This experiment highlights how this can happen with a wave 3 shift and offers a solution that reduces the impact of wave 3 shifting and help ensure profitable trades.

8.2.2 Real-Time Experiment 2: Modifying scope look-ahead for trade entry

With live trading, the entry signal for a trade entry – either a buy or a short – can shift on the user of the software when scope is looking ahead 1 bar. This occurs because a trough may exist on bar x_i but bar x_{i+1} ends up slightly below bar x when it completes. When this happens the trough at x disappears and shifts to bar x_{i+1}. While this is a more accurate location for a trough, in a real-time trading environment the movement of the buy or short indicator can produce confusion when trying to place orders. This also means a historical back check would not accurately represent the potential trading gains in real-time. This experiment details how trading is affected when the forward-looking check is removed from trough entry points only.

In order to visualize what is happening, a special marker is placed on the chart showing where a trough once existed but then moved due to the bar at x_{i+1} having a lower price. Figure 8.2-6 highlights a situation on a chart that would be problematic in real-time. If a trade was entered at the initial buy signal shown at (2), the price at entry would have been 1108. A buy entered at the ideal location shown at (1) would net an entry price of 1107.25 – better than what would likely happen when trading in real-time. A historical analysis uses this ideal location and can therefore skew the historical back testing results.

Figure 8.2-6: 2001-2003 dataset showing 5-minute bars on 12/30/2003. Location at (1) is where the buy indicator appears on the chart. Locations (2) and (3) show where troughs and buy indicators appeared previously.

A solution to this real-time trading problem removes the 1 bar look ahead for troughs. This negatively impacts profits but creates buy signals in real-time that do not shift, making trading easier for the user. It also results in a more accurate historical back testing. Figure 8.2-7 shows how the chart shown in Figure 8.2-6 would look without a 1 bar look ahead.

Figure 8.2-7: 2001-2003 dataset showing 5-minute bars with no trough look ahead on 12/30/2003. Location at (1) was previously shown buy indicator. Location (2) shows buy indicator that would be executed in real-time.

Figure 8.2-8 illustrates a second example of trough lookahead causing issues in real-time trading. This image shows a series of disappearing troughs starting at location 1 depicted by a hollow gold star. With an algorithm looking ahead, a trade entry at location (1) would be avoided in back testing. However, this is not a realistic simulation of what a user sees.

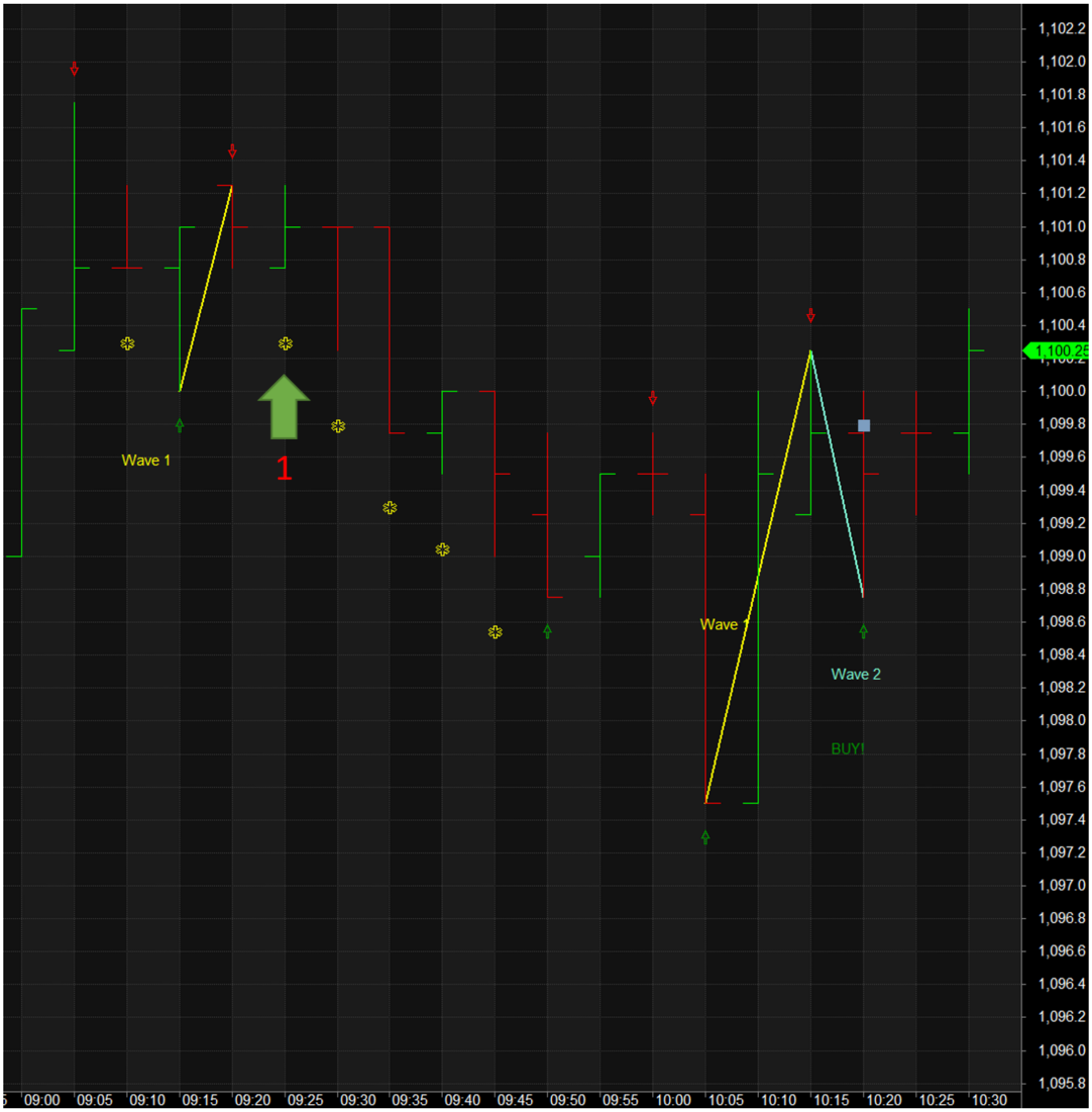

Figure 8.2-8: 2001-2003 dataset showing 5-minute bars with 1-bar trough look ahead on 12/29/2003. Starting at location (1) several troughs appear and disappear in real-time.

Figure 8.2-9 provides a realistic view of what happens in real-time trading. At location (1) a buy signal is sent, and the system enters a long trade. This is clearly not an ideal trade and results in a loss when the sell signal appears at location (2). This highlights the tradeoff in making buy signals stable and more realistic – reduced performance in the model.

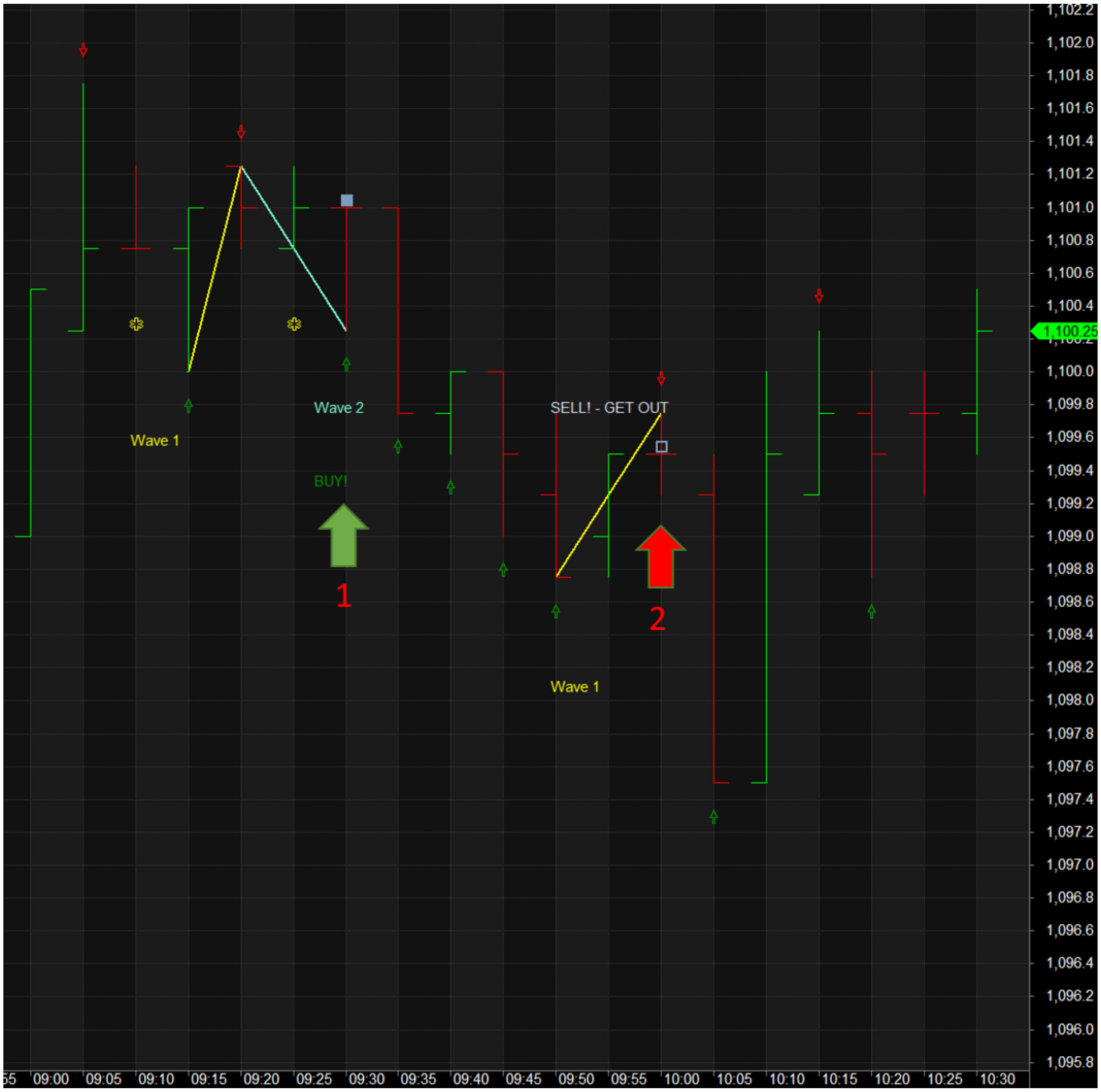

Figure 8.2-9: 2001-2003 dataset showing 5-minute bars with no bar trough look ahead on 12/29/2003. Location (1) shows real-time buy signal and location (2) shows real-time sell signal.

Table 8.2-1 below shows the difference in long and short trading when removing the look ahead feature. Results perform worse than the theoretical historical back testing but still do very well while also representing what the user can expect when trading in real-time.

Table 8.2-1: Profitability comparison between 1-bar and 0-bar lookahead for long and short trades. Scope set to 1. Wave 3 bar count mean set to 5 for long trades and 1 for short trades.

	Net Profit % - Long		**Net Profit % - Short**	
Dataset	1-Bar Lookahead = Y	1-Bar Lookahead = N	1-Bar Lookahead = Y	1-Bar Lookahead = N
2001-2003	238.76%	128.20%	274.44%	157.49%
2015	127.51%	75.73%	146.50%	54.42%
2016	112.29%	104.14%	102.09%	64.73%
2017	73.29%	50.10%	66.36%	30.43%
2018	157.28%	100.07%	275.12%	205.40%
2019	155.20%	111.55%	166.64%	73.17%

The following figures show a comparison of total portfolio equity for the 2001-2003 and 2018 datasets. The data in the figures below correspond to the data shown in Table 8.2-1.

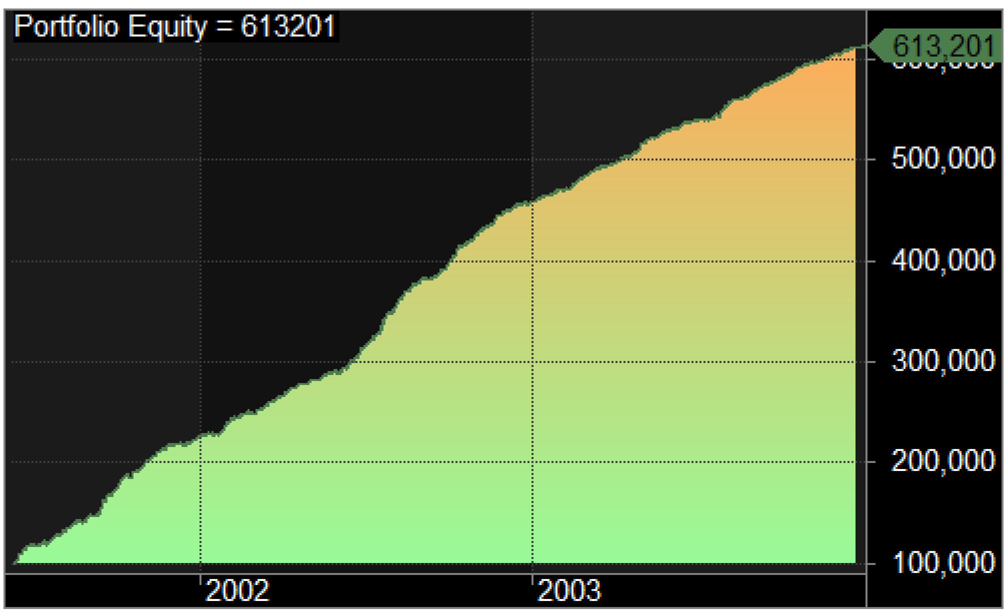

Figure 8.2-10: Total portfolio equity for 2001-2003 for both long and short trades. Scope set to 1 and 1-bar lookahead is enabled.

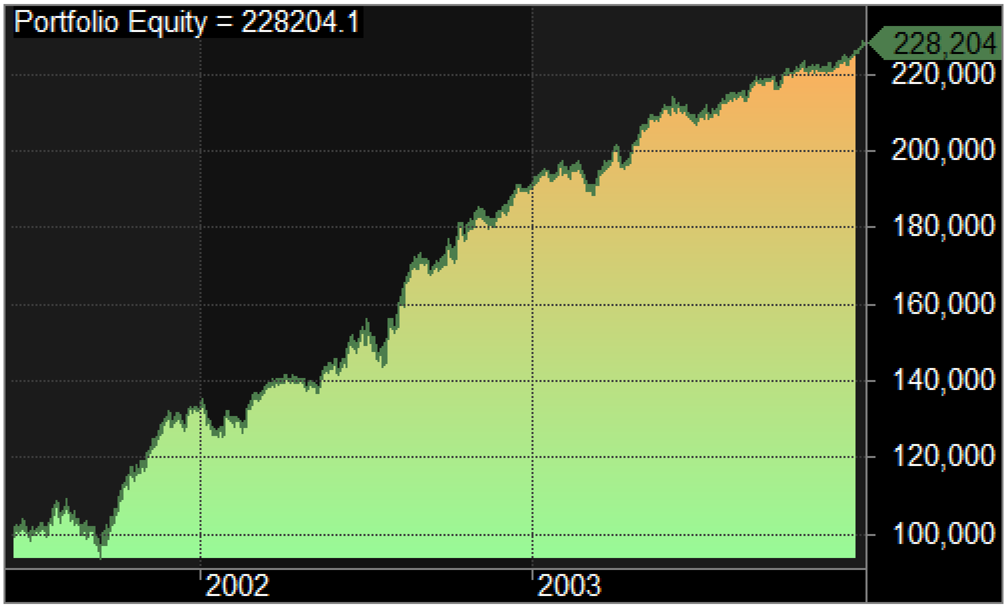

Figure 8.2-11: Portfolio equity for 2001-2003 for long trades only with scope of 1 and 1-bar lookahead disabled.

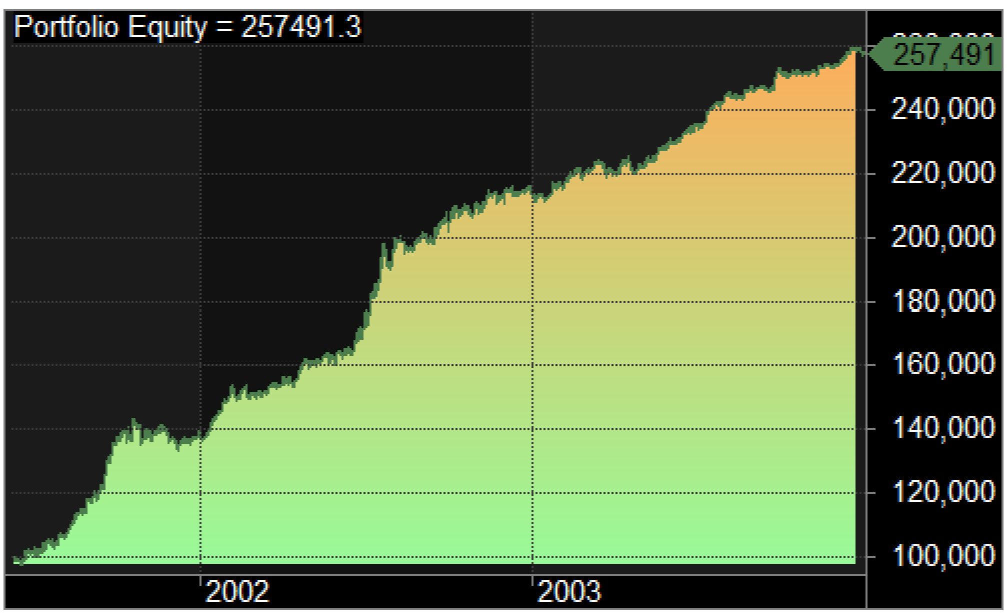

Figure 8.2-12: Portfolio equity for 2001-2003 for short trades only with scope of 1 and 1-bar lookahead disabled.

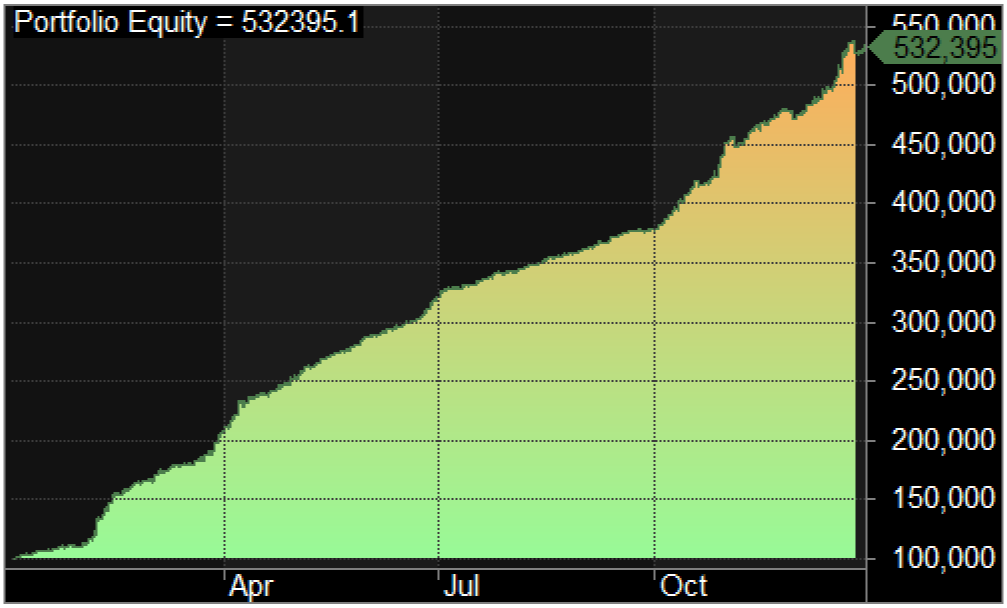

Figure 8.2-13: Total portfolio equity for 2018 for both long and short trades. Scope set to 1 and 1-bar lookahead is enabled.

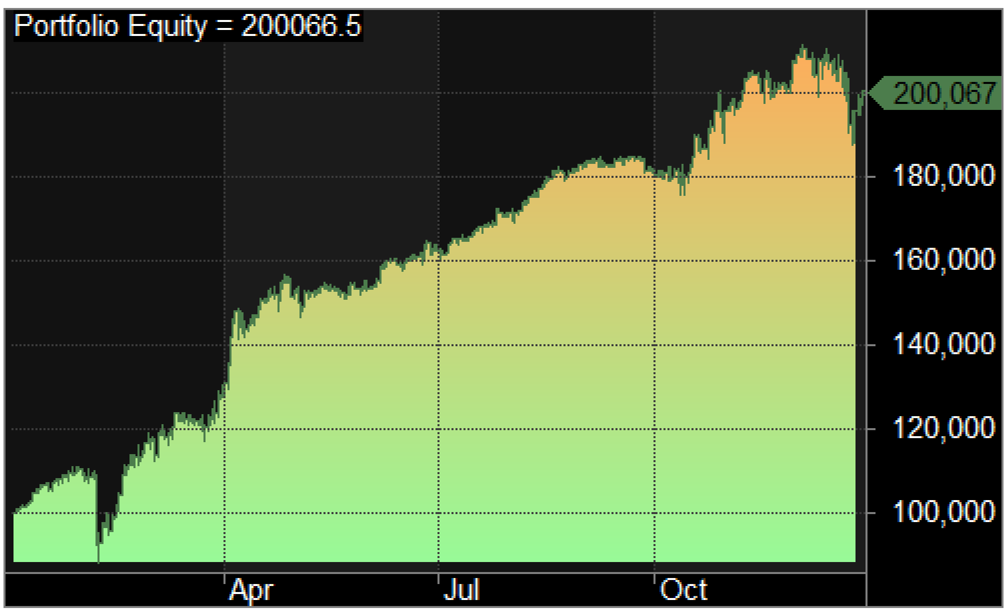

Figure 8.2-14: Portfolio equity for 2018 for long trades only with scope of 1 and 1-bar lookahead disabled.

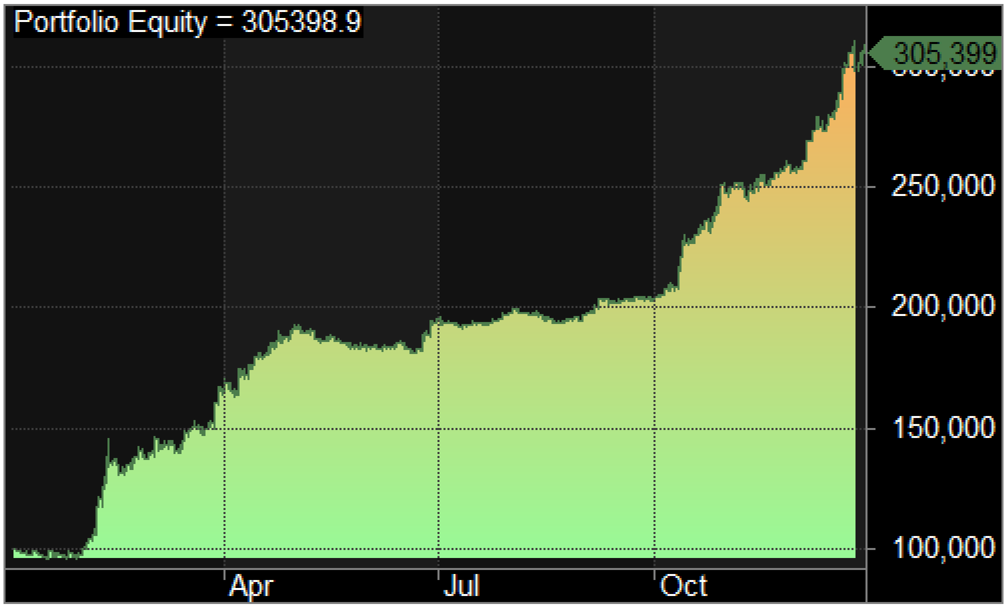

Figure 8.2-15: Portfolio equity for 2018 for short trades only with scope of 1 and 1-bar lookahead disabled.

The goal of this experiment is to ensure that the results we get historically are as close to what we can expect in real-time. With scope looking ahead one bar, signals can sometimes appear and disappear for the user in real-time as demonstrated in this experiment. This can put the user into trades that ultimately end up as a loss. To account for this scenario and make the algorithm more user-friendly, the look ahead was disabled. As expected, the net profit was affected negatively as shown in Table 8.2-1. However, the trade results also represent more accurate real-world conditions and are still quite positive.

An important step towards real-time trading is the *bar replay* feature of Amibroker. Amibroker does not place a trade until the completion of a bar. During the 5-minute duration of the current bar, a trough may appear as the price drops lower below the other bars around it within its scope. At this point a buy signal would appear for the user. However, if before the completion of the bar the price rises above the bars within its scope, the trough disappears along with the buy signal causing confusion. This puts the user into a position of being in a trade with no clear exit strategy.

This issue arises in part due to how Amibroker places trades in back testing along with how peaks and troughs are identified in the algorithm. The algorithm is making decisions on peaks and troughs in real-time while Amibroker makes back testing decisions at the end of each bar. The changes recommended in this experiment prevent the scenario described above. The excellent results on historical models suffer a slightly negative impact as a tradeoff for results that more accurately represent actual trading and provide the user stable trading signals. A model that creates confusion for the user is problematic and eventually the user will give up on using such a model.

CHAPTER IX:

DISCUSSION

The trading models created throughout this research are profitable across a variety of market conditions. The large datasets chosen contain up, down, and sideways market conditions. The back testing is designed to mimic real-world conditions as closely as possible to provide confidence that Elliott waves can be programmatically identified and create profitable trades in real-time.

The initial challenge in this work involves effectively finding Elliott waves. The original model could find waves, but only after they occurred. Once an algorithm to find waves in real-time was developed, a methodology could be followed to help create useful experiments that maximize trading success both historically, and in real-time. This is outlined in Figure 9.1-1.

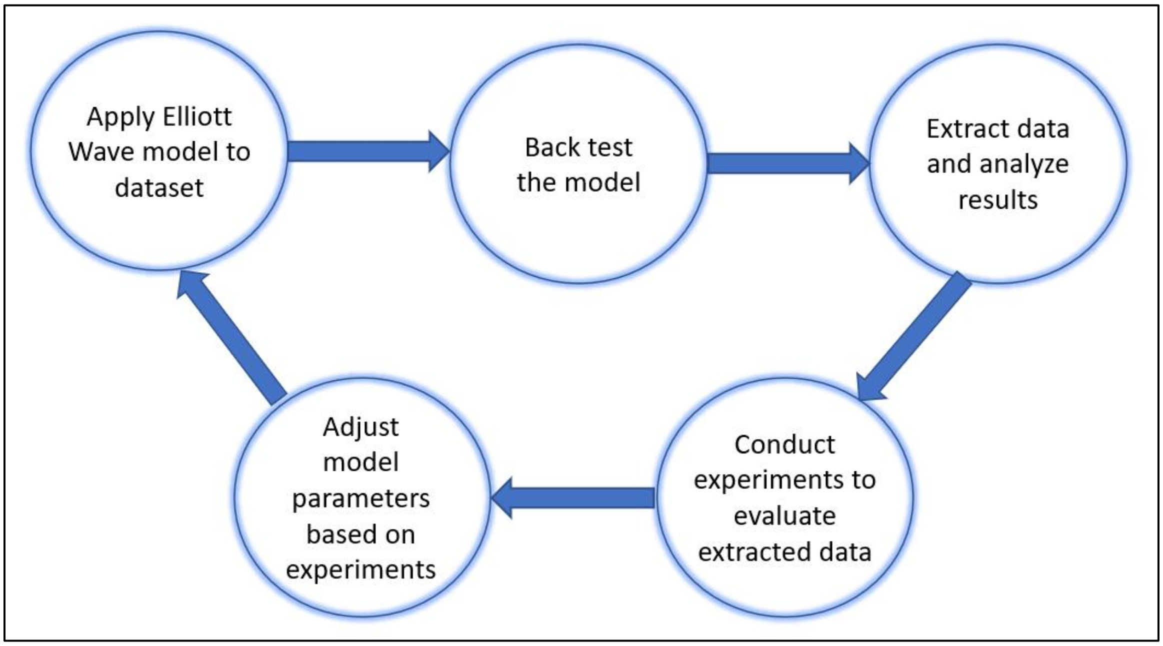

Figure 9.1-1: Experimental process.

The Elliott Wave Principle states that wave 3 should generally be the longest of the five waves [1][Citation?]. Using this knowledge, an initial model was created that enters trades at the end of wave 2 and exits trades at the end of wave 3. The results from this initial back testing generated waves 1 and 2 but did not always produce wave 3. Therefore, an exit condition would not always trigger. This led to the development of the failsafe rules described in section 6.2. These rules are important so that trades can be closed at appropriate times and so that open trades are not held so long that they prevent the algorithm from opening new trades.

Upon visual inspection of historical charts, it was apparent that sell orders were sometimes being placed before the full development of wave 3. This observation indicated that further study of wave 3 might yield useful results. Features were added to the model that would export the large amounts of data being generated about each wave. With the knowledge that wave 3 serves as a crucial data point, and large datasets that described the behavior of wave 3, experiment 1 was developed. This led to the concept of *wave 3 mean* as a tool to help improve trading.

To further optimize historical trading, experiment 2 evaluated how scope would affect profitability. The concept of scope was then optimized together with *wave 3 mean* for both long and short trades in experiment 3. These values provide an effective baseline of settings for the user to try out in their own trading.

Once a variety of statistics and information are acquired from the historical study, this data is used to help create more accurate real-time analysis. The goal is to improve the timing of entering and exiting trades. In real-time experiment 1, w*ave 3 mean* was deployed as a money management tool that improves and stabilizes trade exit signals to the user. Real-time experiment 2 evaluates scope look-ahead and details why this should be turned off so that realistic back testing can be done. This gives the user confidence in trade entry signals that are sent while working in real-time.

As a summary, the following table provides insight on key statistics about the analysis of Elliott waves for the 2001-2003 dataset.

Table 10.1-1: Elliott wave summary of 2001-2003 data.

	Long Trades	**Short Trades**
Net Profit %	238.76%	274.44%
Wave 1 occurrences	4428	4543
Wave 2 occurrences	2184	2334
Wave 3 occurrences	1381	1359
Wave 4 occurrences	349	364
Wave 5 occurrences	189	180
Mean bars in Wave 3	3.90	3.72

CHAPTER X:

CONCLUSION

This thesis demonstrates the utility of the Elliott Wave Principle and its ability to show trends on intra-day data. The size of the datasets used for the experiments are substantially larger than any published studies involving Elliott waves that were found for this thesis. The datasets also represent a variety of different market conditions – all of which contain Elliott waves that can be used for profitable trading in simulated real-time. Tables 10.1-2 and 10.1-3 show expected profit totals for historical and real-time analysis.

Table 10.1-2: Historical back-testing results. Scope set to 1. Wave 3 bar count mean set to 5 for long trades and 1 for short trades.

Dataset	**Net Profit % - Long**	**Net Profit % - Short**	**Total Profit %**
2001-2003	238.76%	274.44%	513.20%
2015	127.51%	146.50%	274.01%
2016	112.29%	102.09%	214.38%
2017	73.29%	66.36%	139.65%
2018	157.28%	275.12%	432.40%
2019	155.20%	166.64%	321.84%

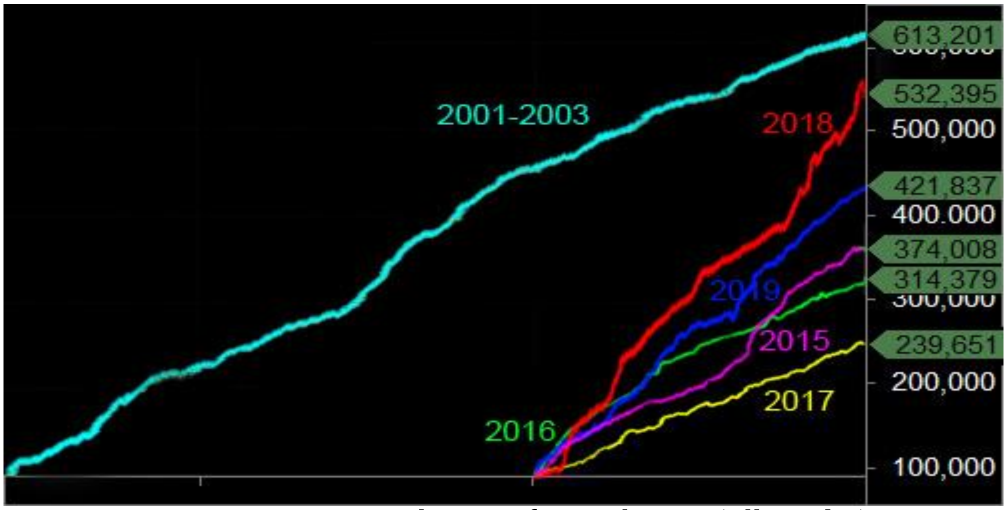

Figure 10.1-1: Final Equity for Each Year (All Trades)

Table 10.1-3: Real-time back-testing results. Scope set to 1. Wave 3 bar count mean set to 5 for long trades and 1 for short trades.

Dataset	**Net Profit % - Long**	**Net Profit % - Short**	**Total Profit %**
2001-2003	128.20%	157.49%	285.69%
2015	75.73%	54.42%	130.15%
2016	104.14%	64.73%	168.87%
2017	50.10%	30.43%	80.53%
2018	100.07%	205.40%	305.47%
2019	111.55%	73.17%	184.72%

Many of the published studies reviewed in this research seek to find visual patterns of Elliott waves. Visual identification of Elliott waves does not provide any trading opportunity. Thus, these papers have no pragmatic value. The methodology utilized in the algorithm in this thesis adheres to the rules of The Elliott Wave Principle but finds patterns programmatically instead of visually. This allows for more consistent and reliable results while also generating a large set of data that can be inspected and analyzed for improvement of the algorithm. The statistical analysis and historical experiments show how this data helps to describe successful conditions that predict Elliott waves and can then in turn be used for accurate and successful real-time trading.

This approach finds full and partial Elliott waves that provide very profitable trading opportunities for real-time trading. It also contains variables such as *scope*, *wave 3 bar count mean*, and *scope look ahead* that the user can alter in order to ascertain ideal trading locations. The successful trading demonstrated - even when finding partial Elliott waves - shows how The Elliott Wave Principle can detect general trends in the market. This thesis shows how to properly find peaks and troughs on a chart that can then be used to identify waves as dictated by the rules of The Elliott Wave Principle.

The experimental results on historical data being applied to real-time data provide examples that mimic real-world trading as closely as possible. This work programmatically finds Elliott waves and utilizes the information about them to trade in real-time with real data – no other research was found with this capability. It also shows that Elliott waves need not be fully formed and/or connected in order to make profitable trades. While traditional methods of finding Elliott Waves try to find trends that span an entire chart with various waves, sub-waves, and sub-formations, this research shows that the basic Elliott wave is enough to indicate the trend of the market. This information can then be utilized to make profitable trades in real-time with little to no effort from the user.

CHAPTER XI:

FUTURE WORK

This project utilizes large datasets and generates large amounts of data which provide great opportunity for future work.

A machine learning algorithm can be utilized on the output data to possibly generate exceptional results. A reinforcement learning algorithm using a deep neural network is the ideal choice. The data from each historical run will be used to train a reinforcement learner and develop a set of rules for trades with even higher winning percentages. Data such as number of bars between waves, volume, and moving averages are ideal candidates.

Currently, the algorithm only looks for Elliott waves. Expanding the code to identify the various Elliott formations will help improve trading possibilities and identify additional trading opportunities.

The experiments in this paper are intended to be used on intra-day trading. However, The Elliott Wave Principle is often applied to long term forecasting. An exploration into using this algorithm for long term forecasting could yield valuable information.

Elliott waves are one of many existing technical indicators. They all provide different interpretations on the current market status. Combining the results of other indicators with Elliott waves as found in this thesis could provide for valuable trading opportunities not yet identified here.

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