2018

Modeling the Standard and Poor's 500 Index via Wave Analytics: Harnessing Lag for Intraday Utilizations

John Cardenas
University of Central Florida

MODELING THE STANDARDS AND POOR'S 500 INDEX VIA WAVE ANALYTICS: HARNESSING LAG FOR INTRADAY UTILIZATIONS

by

JOHN CARDENAS

M.A. University of Central Florida, 2003

A thesis submitted in partial fulfillment of the requirements
for the degree of Master of Science
in Modeling and Simulation
in the College of Graduate Studies
at the University of Central Florida
Orlando, Florida

Spring Term
2018

Major Professor: Patricia Bockelman Morrow

ABSTRACT

Modeling and simulation of financial instruments is accomplished from multiple approaches but most completely from an engineering perspective. Aeronautical engineering yields a wave model created for stock indices in the 1970s. This comprehensive methodology models stock markets as waves for the intention of trading or investing yet has not been applied on time periods smaller than daily or weekly, known as intraday. Stakeholders trading intraday waves need to utilize wave analysis for price capture, analytics, and profitability.

It is the purpose of this thesis to present a model to harness wave analytics for the needs of traders seeking price capture of the Standard and Poor's 500 Index on an hourly and minute time periods, or intraday. This paper applies wave analytics in time frames never accomplished before for the sufficing the needs of index day traders.

ACKNOWLEDGMENTS

I wish to thank the almighty God for giving me the strength and fortitude to continue when I was tired or wanted to give up. I never felt alone in this endeavor. I want to thank my family members for their kind words and support, and for mottos that were freely given: “Never, never, never give up!” I wish to acknowledge Reverend Albert J. Bowes who always had a word of wisdom when none seemed to be found. I would like to thank my peers who worked tirelessly with me on multiple projects, papers, exam study sessions late into the night to completion. I wish to acknowledge Dr. Patricia Bockelman-Morrow for being my committee chair and constantly guiding me in the right direction with grace, care and patience. I wish to acknowledge Dr. David Kaup who helped me see waves in a mathematical way new to me and for his time and mindful dedication. I wish to acknowledge Dr. Ilhan Akbas for his coursework and expertise which allowed me to view my research from a greater perspective. I wish to acknowledge Professor Zimmerman of Seminole State College who was kind enough to donate hours to help me and his other students understand the math when challenges came about. I also need to acknowledge Dr. Ron Wallace in the department of Anthropology at UCF in his continued support throughout my entire graduate career. I know more because of his coursework and he is a great example of an excellent professor who gives to his students effortlessly and graciously.

TABLE OF CONTENTS

LIST OF FIGURES vi

GLOSSARY vii

CHAPTER 1: INTRODUCTION 1

History and Background: A Literature Search 1

Current State of Moving Average Utilization in Market Analysis 6

Problem 9

CHAPTER 2: METHODS 11

Moving Averages: Digital Filtering Historical Data 11

Regression: Creating a True Central Tendency in Defining the Wave. 14

Model Parameters for digital filtering. 15

Verification and Validation. 17

CHAPTER 3: RESULTS 19

Model parameters in utilizing two moving averages 19

Verification and Validation 20

Data Validity 20

Face validity: A real time example 21

Validation: Reasonable information for the stakeholder 22

CHAPTER 4: CONCLUSIONS 29

Future Directions in Market Modeling: Artificial Intelligence and Quantum Approaches 29

Amplifying the human experience is a side benefit of visually identifying waves 35

REFERENCES 37

LIST OF FIGURES

Figure 1: Gann square root calculator (center moving out in a spiral are the roots of time/price). 3

Figure 2: Displayed is Elliot wave's theoretical 5 wave impulse wave and ABC corrective wave. 5

Figure 3: Simple Cross-over technique of text book moving average combinations. 8

Figure 4: A regressed moving average showing a true central tendency (regression = one half look back period). 12

Figure 5: Model A utilizing a true central tendency (40, -20) and a realtime MA (40). 16

Figure 6: Model A showing convergence of moving averages = potential signal forming (trough or crest). 23

Figure 7: Model A in signals a wave down. 25

Figure 8: Model A showing a wave down followed by a wave up…note moving average crossovers. 26

Figure 9: Model A filters sideways data from 18th-26th = noise. Signifies a failure to dampen noise in data for a clean signal. Until moving averages diverge. 27

Figure 10. Model A filtering data in 3 minute increments for possible signaling…note arrows. 28

Figure 11: Model A shown as a component of a larger system. Note oscillator employment and 31

Figure 12: Theoretical system filtering data on a quantum level with employment of artificial intelligence. 32

GLOSSARY

Index = a basket of stocks where individual values are grouped together of a specific market.

Lag = a falling behind of values of the moving average and the data it summates.

Moving average (MA) = a running total or running mean of data points dependent on look back periodicity.

SPX = Standard and Poor's 500 Index

Real time = an unadjusted or unregressed value, for thesis purposes applicable to moving averages.

Regression = a shifting backwards in space thus time, in this case moving averages.

CHAPTER 1: INTRODUCTION

Late in his career Jim Hurst researched and proposed a model for financial instruments (e.g., stocks, stock indices, bonds) from the perspective of wave analysis (Hurst, 1970). To date no one else has presented a theory or model as complete to Hurst's original work. Hurst innovatively defined markets as waves from an engineering background. The value of modeling market data as waves is to identify inherent characteristics or constants in the waves of stock data. Constants define price in a predictable format and provide a strong foundation from which to study and build models of stock markets.

Waves, studied from the movement and flow of natural events (such as the motion of sound, wind, or water), have inherent properties and characteristics providing constants. Using moving averages in modeling is an effective tool for filtering data and finding reoccurring relationships between the raw data (e.g., price) and their moving averages. Thus, modeling the wavelike structure of price or data is key to identifying wave, structure, and analysis. To consider wave analytics as the only market model is myopic at best. Other methods similar to wave analytics exist and were noted for comparative purposes in the following literature search. The shift of focus here is to examine the differences of market models similar to wave analytics.

History and Background: A Literature Search

Investors and timers of the markets employ both fundamental and technical analysis when seeking financial gains of investments. Fundamental analysis is the *what* to buy, while technical work points to *when* to buy. Technical analysis is therefore timing of markets for the sake of capturing profits utilizing techniques or systems of techniques. (Murphy, 1999).

Theoretical contributors proposed models of how markets move and why. Models of the markets must present some sufficing of the stakeholders needs, such as timing of when to buy/sell. It is not the purpose to examine all market timing techniques or contributors but to focus on other approaches similar to wave analytics, as first proposed by Hurst. Each approach introduced a model of stock markets based on various constants and techniques. The following contributors belong to this unique group of market modelers.

Dilbert Gann proposed a mathematical model in his published books and newsletters for timing the markets, specifically commodities. He believed “nothing new has been created under the sun...” which expressed his belief history is repeatable and cyclic thus predictable (Gann, 1927). After his death, a select few bought his works and destroyed them, which kept a level of secrecy to his exact methods. Historically, Gann was known for his published works being cryptic and challenging to apply. According to Gann (1927), time and space can be mapped in advance of a financial instrument, such as the commodity of cotton, by calculating square roots of the data or price. Figure 1 is an example of a Gann calculator used to define possible future prices. Part of Gann’s work stems from an application of astrology to utilize planetary angles of influence on prices based on the rhythms of force and influence. Esoteric by nature and difficult to understand and yet Gann was considered by many to be the world’s greatest trader, often predicting prices and market crashes (such as the decline of 1929) in advance. Others have tried to decipher and unveil his methods for modern applications (Mikula, 2003).

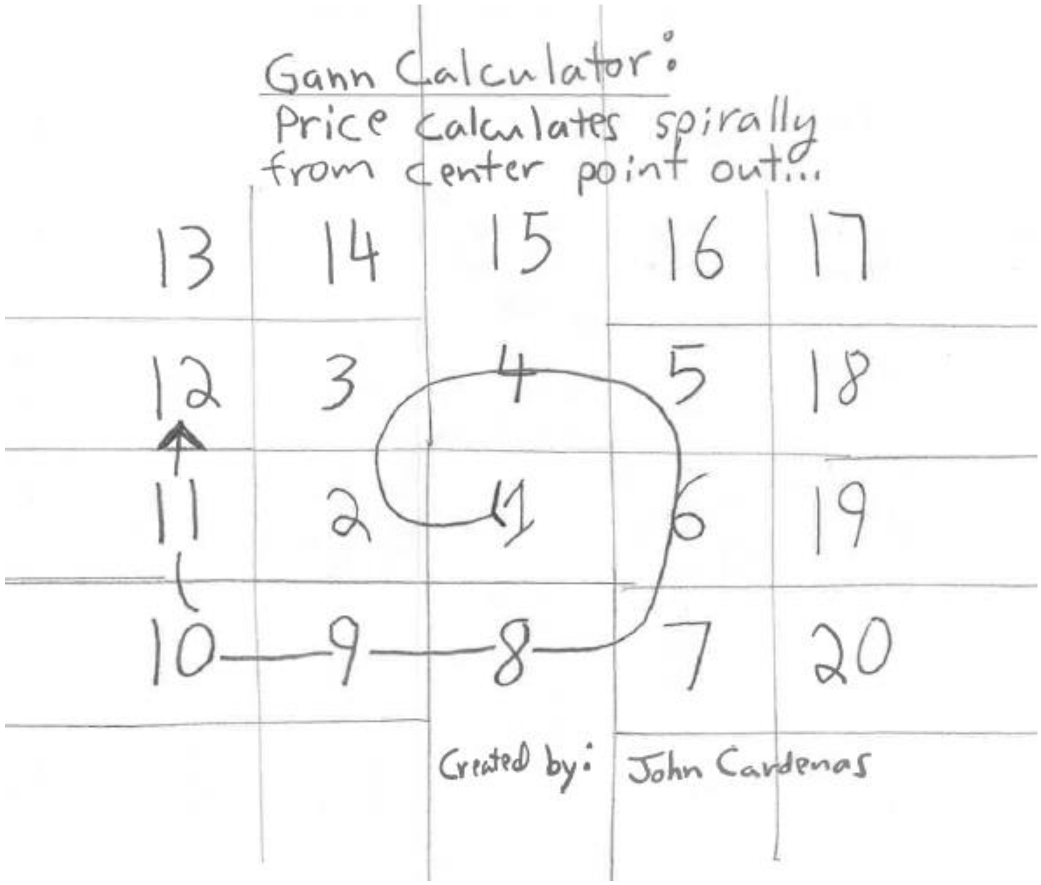

Figure 1: Gann square root calculator (center moving out in a spiral are the roots of time/price).

Source: Image by author

Edward R. Dewey began his work on cycles while employed as chief economic analyst for J. Hoover in the 1930s. Later in his career he established The Foundation for the Study of Cycles. His premise asserted unrelated time series contained similar cycles and can be reflected by powers of 2 and or 3. These cycles recur in human social behavior, such as stock cycles, and in natural events, such as the breeding cycle of feral bobcats and other mammalian life forms (Dewey, 1947). Although critically reviewed, Dewey heavily influenced researchers of the time by proposing cycles as driving forces in many phenomena as repetitive events such as economics reflected in stock prices. Dewey was considered by many researchers of stock market behavior as the "father of cycle analysis." His greatest contribution is that cycles do exist in all flora and fauna therefore human behavior.

Ralph Nelson Elliot also contributed to the modeling of markets by proposing his own original work in 1938: the Elliot Wave. Jim Hurst references Nelson in his 1970 publication. The premise proposed by Elliot is that all markets have an inherent constant found in the price structure. Also that price structures into 5-wave and corrective wave as shown in Figure 2 below. Structure, in Elliot Wave is an expression of ratios based on *pi* or the Fibonacci sequence. Prices advance or decline in these measured ratios and can provide patterns of possible predictive nature. Stock prices can advance or decline in waves of five or three and can have multiple patterns expressed in Fibonacci ratios (i.e., .232, .382, .618, and .786 …). His work is reproduced by modern authors and continues as a methodology for modeling market behavior today. The pattern prediction is often past perfect with limited real time application.

Research into why waves occur in aggregate behavior are the most recent publications by Elliot wave researchers (Pretcher & Parker 2007).

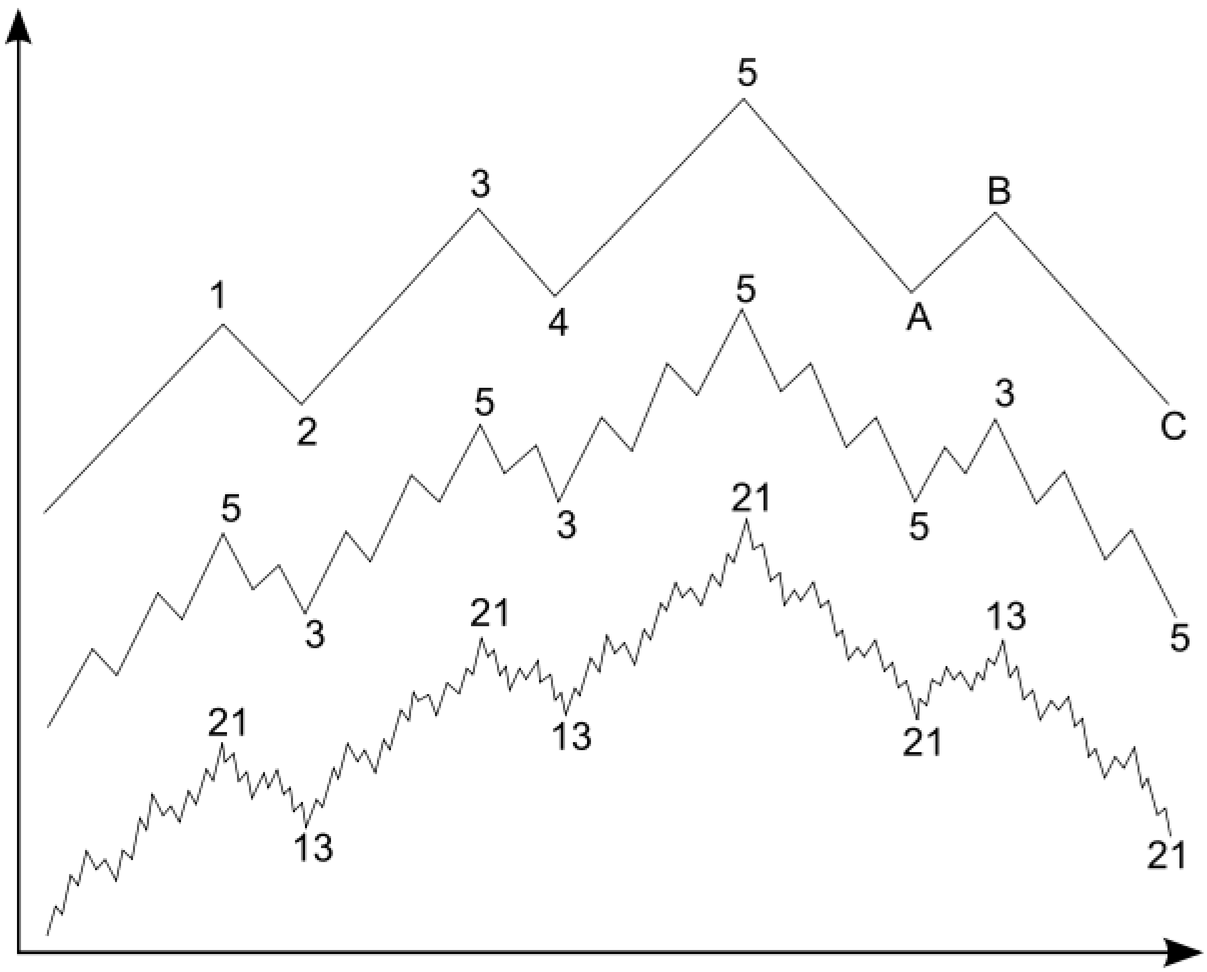

Figure 2: Displayed is Elliot wave's theoretical 5 wave impulse wave and ABC corrective wave.

Source: Public domain

Historically multiple methods for modeling the markets exist. Each proposes a way to structurally map or model markets based on their own respective constants. Gann (1927) proposed time and space as designed in advance of market prices utilizing square roots and planetary influences. Today, Gann practitioners are challenged to use such esoteric knowledge

that lacks completeness or reproducible results. Dewey (1947) proposed that cycles exist in all forms, including stocks, yet a working model does not exist of his work for markets. Elliot (1938) asserts markets move in measured ways in accordance to expressions of *pi*. These golden ratio relationships are sometimes visible after the fact and those that have tried to apply the specifics are often left seeking incomplete patterns so the method lacks efficacy. The most comprehensive market model for investing comes from engineering. Jim Hurst accurately proposed markets exist in waves identifiable with digital filtering. A search of peer reviewed journals yields modern application and utilization of moving averages that do not utilize this application.

It is beyond the scope of this paper to examine all systems proposed for the analysis of markets. Modern applications of moving averages used for trading models or systems in recent journal publications provide a state of the topic update.

Current State of Moving Average Utilization in Market Analysis

A current search of peer reviewed journals for articles covering moving average applications for market analysis presents some common textbook applications and uses. Common uses of moving averages occur in evaluating prices, and finding the trend or general movement of the instrument studied. Moving averages are often a performance measure when examining financial instruments such as commodities (e.g., coffee, gold, currencies), bonds (e.g., municipal, corporate), and stocks (e.g. Apple, Ford, and S&P 500 Index). Found heavily in today's literature is the technique of using moving averages that crossover, when a moving average of a specific look back period that is shorter or longer than another can be used as a means of analysis of investment price. When used to examine investments, these crossovers can

help to create portfolios for investment groups. In examining Australian stocks this proved useful to create a selection strategy to form a rule-based portfolio using moving average crossovers as signals (Pavlov & Hurn, 2012). This technique has also been applied to central and eastern European markets when sampling 15 years of historical data (Zoicas-Ienciu, 2014). Other researchers have applied the crossover to the Dow Jones Index to examine data from the previous 90 years and found similar results (LeBaron, 2000).

The moving average crossover once again proved to be effective in assessing price. Moving averages represent central tendencies of overall price performance and can create positive as well as negative thresholds to gauge performance for profits. This was noted in the following journal publication. Researchers of financial markets (Gurrib, 2014), quantified the profitability of moving average crossovers and applied a simple formula. The efficacy of this strategy is a formula that divides total losses by total gains to achieve a profit factor:

Profit Factor = Final Balance * Total Profit/Total Loss

The usefulness of the strategy was back tested against historical data to further prove its profitability over time. M'ng & Zainudin (2016) researched the same moving average crossover technique in currency markets as a means of timing the markets for increased profits and arrived at the similar results. That study examined trends in exchange rates of currencies (from the Philippines, Malaysia, Singapore, and Thailand), and used moving averages to filter out volatility and find new trends in price for gains. Results again proved to be more profitable than

the buy and hold strategy of the average investor, and demonstrated how well moving averages can filter price data for trend following (i.e., when to buy and when to sell the currency studied).

Another variation of the moving average crossover added a dynamic trailing stop to increase cumulative returns. The moving averages generated buy signals and the trailing stop secured profits (Papailias & Thomakos, 2015). The authors state that the use of averages was critical in smoothing data. This is what Jim Hurst postulated in the 1970s.

In Figure 3 the crossover technique of the above articles is demonstrated in a generalized form: The blue moving average has the shorter look back period of 18 time units (in this case days) and the yellow has the longer look back period of 39. When the 18 MA (moving average) crosses the 39 MA a change in trend of price can be identified in most cases.

Figure 3: Simple Cross-over technique of text book moving average combinations.

Source: Image by author

In another article the performance of moving averages of natural gas futures prices were examined at different time scales (Liu, An & Wang, 2015). The innovation here was the comparison of the same instrument using multiple timeframes. In this case natural gas futures were the focus for seeking fractals or points of price change often associated with peaks and troughs in a sinusoidal wave of price. Most performance measures are evaluated only on one time frame, such as a daily or weekly, but in this study many timeframes are compared and analyzed as a means of improved measurement. Other researchers highlighted positive results of using moving averages to increase profits when trading crude oil futures by employing rule based investing (Pätäri & Vilska, 2014; Wang, An, Liu & Huang, 2016). However, dismal performance for profit generation was found when moving averages were employed in volatile price environments of rapid price change, but the conditions were extreme and focused on the rise and fall of internet stocks of U.S. markets circa the year 2000 (Fong & Yong, 2005). Although much has been explored in the recent past employing moving averages few if any involve *regressing* averages. This technique is the focus of the following section in which the efficacy and application are discussed in defining stakeholders' problems and providing solutions.

Problem

Can moving averages be utilized to trade waves in timeframes of hours and minutes?

Can combining moving averages of varying lengths of lag augment each other to produce a trading signal or a potential signal?

Can wave analytics help day traders of indexes increase profitability?

The stakeholders for these questions are index traders of the Standards and Poor's 500 trading hourly and/or minute charts. Defining waves in stock data aids in defining the trend of the index in general. Digital filtering or the employment of moving averages is common and taught in textbook market analysis (Murphy, 1999). *Regressing* moving averages is a technique Hurst utilizes as a means to define the central tendency of price, identify a wave and determining trend. Profitability in trading equates with the timing of transactions yielding profits. Knowing where to buy/sell in time or space on a wave of changing price is where Model A excels. Model A uses moving averages in determining where and when to buy/sell as waves form and subside.

CHAPTER 2: METHODS

The following methods are employed:

1. Moving average utilization as data filters.
2. Regressing moving averages to defines the wave component thus central tendency.
3. Model parameters utilized in digital filtering.
4. Verification and Validation on two time frames: hourly and minute models.

Defining the basic anatomy of a wave is an important beginning point of study because it is very important for the purposes of investing. Peaks and troughs are the highs and lows of a sinusoidal wave where data, in this case price, changes direction. The premise is to invest in accordance with where the wave is in time and space for price capture of falling or rising prices. Rising prices present places on the wave to buy and falling prices present places on the wave to sell, both can generate profits. Figure 4 below, shows the Standard and Poor's 500 Index with peaks and troughs identified using a particular technique Hurst borrowed from engineering: using pass filters or digital filters known as moving averages.

Moving Averages: Digital Filtering Historical Data

Digital filters, also known as moving averages, can sum up historical data of any sort and smooth data (Musa, 1963). Moving averages are often used in summing up historical data as a type of running tabulation (Ehlers, 2010). Many different moving average types exist and have their own respective specific calculations. For the purposes of this thesis a simple moving average will be used in Model A. The definition and composition of the simple moving average will be discussed in the following section.

Figure 4: A regressed moving average showing a true central tendency (regression = one half look back period).

Source: Image by author

A simple moving average computes data points, in this case historical prices, over a specific number of periods (Murphy, 1999). Periods divide time into units. Units can represent minutes, days, weeks, months, years, or decades. It is important to note that periodicity of the moving average is a designated number of units of time that are included in a summing up process, often referenced as a *look back period*. For example, Model A, presented as the core of this thesis, employs a 40 MA (moving average). This moving average can be used on multiple timeframes of differing time units. For the purposes of this thesis the time units presented will be either 2-hour units or 3-minute units. In Figure 4 through Figure 7 of this thesis the time units are 2-hour units and in Figure 10 time units are of 3-minute units. What the moving average, in

this model a 40 MA, does is to summate a data point from each time unit. Many differing data points can be created but for the purposes of the simple moving averages employed in Model A only the closing price or the last price to print in that specific time unit, is used in the summated calculation of the simple moving average. Model A employs a moving average of a 40 periodicity, so it will add up the previous forty closing prices, summate them, and divide by forty. This also means that as new prices print for new units as time progresses then the last unit is replaced by a new closing price as the MA is only interested in the last forty closing prices to create a running total that is continually changing as time progresses. In some sources on the subject a *moving mean* is identical to a simple moving average, but for the purposes of this thesis the later will be utilized.

A further example of a 5 MA is shown here:

Market Data: (closing prices) Day 1 = 5, Day 2 = 5.5, Day 3 = 5, Day 4 = 6, Day 5 = 6.3

5 MA calculation = 5 + 5.5 + 5 + 6 + 6.3 = 27.8/ 5 = **5.56**

5 MA calculation: Day 1(closing price) + Day 2(closing price) + Day 3(closing price) + Day 4(closing price) + Day 5(closing price) = X /5 = **simple moving average value**

These moving averages provide smoothed representations of summated historical data and have an inherent constant known as *lag*. Hurst stated that the additive work moving averages derive from data lag behind price action by 50% of the look back period. The look back period is the setting on the moving average that designates how many units it is summing up. An example, illustrated above in Figure 1 is of a moving average with a look back period of 18 which adds and averages all the price data of the last 18 units of time; whether days, years,

minutes, or hours; yet lags behind actual data due to the summation process. An 18 moving average lags actual data movement by 9 units of time. This provides lag as a constant employed in Hurst's model for functionality. A constant is a reliable basic building block for further understanding a wave by smoothing data that we can refer to as price. It is important to note lag as a constant is adjusted for modeling in this case, a technique not utilized in the current usage of moving averages.

Regression: Creating a True Central Tendency in Defining the Wave.

As noted, moving averages are a summation of past price data and present visually on stock charts to aid in analysis. Hurst discovered inherent lag in moving averages equal to 50% of their look back or summation period. A useful application of this constant lag is to eliminate it creating a true central tendency. This identifies the wave component in stock price visually at any time period. Hurst advised to attach curvilinear envelopes once the zero-lag moving average is constructed to see the waves of the market being studied. This is useful on large timeframes, like daily and weekly charts, as originally intended. Envelopes surround price and are equidistant from the regressed moving average. The chart above in Figure 4 shows a zero-lag 18 moving average in yellow, curvilinear envelopes in blue, identifies peaks and troughs in white.

This is essentially how Hurst (1970) would structure the very basics of his model to identify a true central tendency. This is an important take away as a regressed moving average identifies central tendency, trends in price and can be utilized on any time period. In Hurst's work this is how one would identify the above on weekly and monthly charts. Unique to this thesis is to apply above technique on periods of hourly and minute increments. It is commonly understood all moving averages have lag inherently (Ehlers, 2010). Combining zero lag moving averages

with moving averages of 50% lag is the basis of this model for intraday (minutes, hours) trading purposes.

Model Parameters for digital filtering.

The focus of this thesis is to illuminate some of the tools by the original works of Jim Hurst and apply them in unique ways. This model creates a central tendency by regressing the moving average by 50% as one component combining it with a moving average that is not regressed. Moving averages (or MA, refer to glossary) are used in combination for the purposes of this thesis model. Two moving averages of differential lag combine from the same dataset to identify trends and generate a potential signal for trading. This model is not intended to generate absolute signals for trade but to yield valuable information to the stakeholder or intraday index trader.

Moving averages regressed define the wave utilizing zero lag or a true central tendency and this is quite useful when combined with a moving average of normal lag of 50%. What can be garnered from this useful combination is a crossover of moving averages.

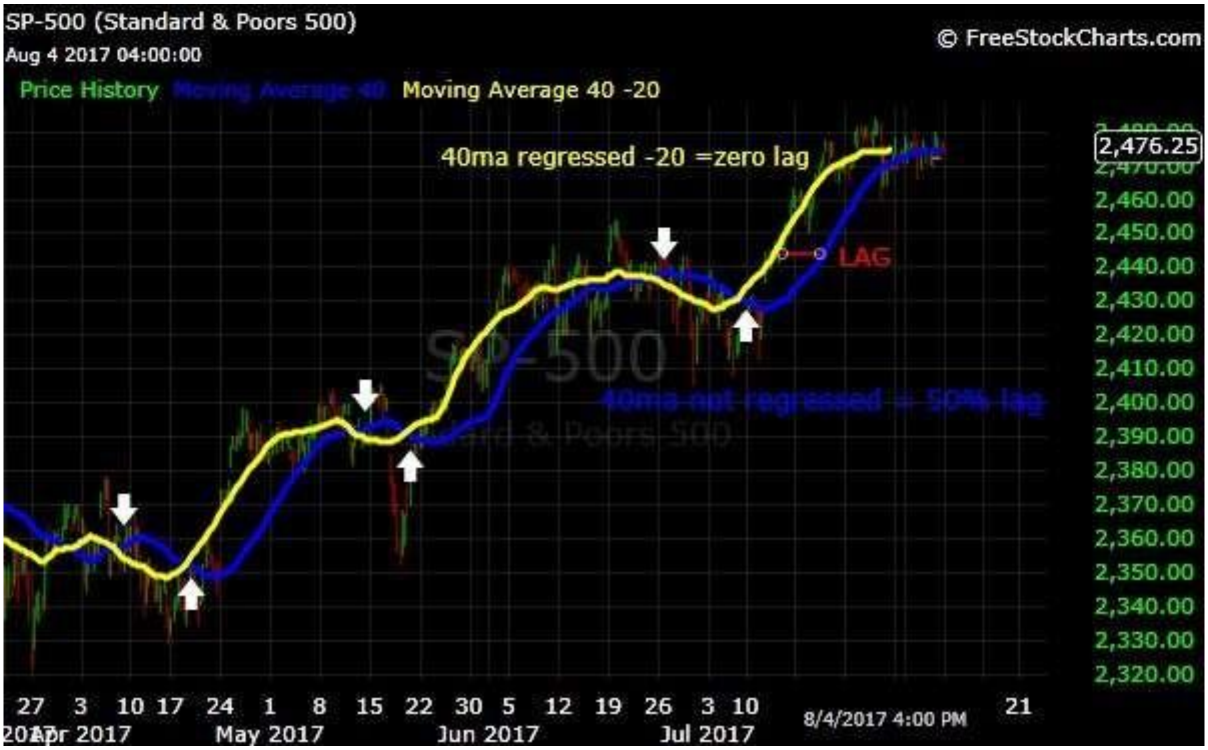

Figure 5: Model A utilizing a true central tendency (40, -20) and a realtime MA (40). Source: Image by author

It is time to narrow the scope to the proposed model in Figure 5. The model shows important indicators to buy or sell in a trending market. This is not absolute because when prices move sideways or do not trend in any direction then noise in the data gives no such indications. What is important to note is that the same technique used by Jim Hurst can be utilized to aid traders of smaller timeframes, such as in units of hours, demonstrated in Figure 5. To say that the model above generates signals for trading alone is incorrect. What the model does accomplish is defining the trend and finding high probability points on the wave where the potential for change can occur in a directional manner. This is invaluable for traders wishing to capture price moves. This model provides valuable wave information for more complex systems when

combined with other technical tools. Signals are *past perfect* but leave the trader to use the information provided and extrapolate what may happen next, a crest or a trough.

As seen in Figure 5, data from August 4, 2017 indicates a peak in the wave is forming. Note the price of the S&P 500 on August 4th is crossing over to the nonregressed moving average. This is how the model can provide awareness of critical junctions in the wave. The nonregressed moving average will be referred to as real time moving average moving forward. The real time moving average acts as a point in space where change in wave structure is possible when breached directionally by the regressed moving average, known as a crossover.

Model limitations were evident when the model was not calibrated or designed to function in an unsupported environment. Models based on moving averages generally are models that focus on trends (Murphy, 1999). Moving averages get lost when noise is too great. The model presented in this thesis is such a model requiring a trending market. It is at this juncture where verification and validation from engineering sources are employed in discerning efficacy, limitations, and flaws.

Verification and Validation.

"Model validation is defined as the substantiation that a model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" (Sargent, 2013). This is part of the validation process. Model A is a financial engineering model of stock indexes intended to aid traders in timeframes smaller than weekly or monthly charts. The stakeholders, index traders, are informed of potential change occurring on hourly charts, specifically in 2-hour increments. The scope of the model is not intended to

generate absolute signals for trading but to inform stakeholders where price can change in space and time. This is accomplished in real time and is reactive only, not predictive.

Change in trend is defined as a move in a new direction. Peaks and troughs signify this change of the sine wave motion in stock indexes. Identifying this point of change is part of the intended application of Model A. The regressed moving average in Model A is the component identifying the central tendency of trend in price data. When this crosses the real time moving average, a change in the wave of price is identified. This can inform stakeholders who may wish to trade based on this information or not. Therefore, the intended purpose to aid intraday index traders is facilitated by Model A by consistently identifying waves for the purposes of trading, analytics, and profitability.

CHAPTER 3: RESULTS

The prior chapter presented Model A's methodology:

1. Moving averages utilized as data filters.
2. Regressing moving averages defines the wave component thus central tendency.
3. Model parameters utilized in digital filtering.
4. Verification and Validation on two time frames: hourly and minute models.

The following results are the employment of the above methods, labeled respectively:

1. Model A employs moving average as a digital filter of historical data
2. A 40 MA was employed for regression thus defining central tendency.
3. Model A regresses a moving average and combines with a real-time MA.
4. The model established efficacy in identification of central tendency patterns and directional price trends in 2 hours and 3-minute timeframes using verified historical data.

Model parameters in utilizing two moving averages

Parameters for Model A include combined moving averages on the same hourly chart of forty (40) MA and is shown in Figure 5 (below): 40 MA regressed 20 units and is combined with a 40 MA that is not regressed or real-time. Figure 5 represents the historical values of data on price of the Standard and Poor's 500 Index. Each individual bar is equal to 2-hour unit's bars of time, thus intraday. Arrows point towards meaningful crossovers of the two separated moving averages. FreeStockCharts is the software used to present these charts and is free to the public in this form.

Verification and Validation

Verification provides a domain of applicability accomplished by utilizing market data vs. contrived data and possesses a satisfactory range of accuracy as it informs the stakeholder of change in wave structure on hourly and minute time frames. Waveform from the data within the stock indexes provides enough information for a trader to discern where price action can change or pause and where respective trading strategies can be employed by the stakeholder. It is not the purpose of this thesis to present trading strategies, but to present the useful information Model A provides for stakeholders on multiple intraday timeframes. Limitations of Model A present themselves when prices have no clear direction and noise becomes a factor. Model A illustrates in the above examples efficacy useful in providing information for stakeholders on timeframes smaller than a day (i.e., intraday) to demonstrate validity with verification provided by the charts in Figures 4−5.

Data Validity

Model A did not have a simulation associated with it in terms of recreated data. There is a level of validity associated with real world data that is not contrived. This is known as real world and not conceptual (Sargent, 2013). Contrived data from any source other than real time data could invalidate design of the model. The data utilized by Model A is not simulated or randomly generated but is the actual data generated in stock indexes daily. The Standards and Poor's 500 Index generates data or prices every week, specifically from 9:30 a.m. to 4:15 p.m. eastern standard time, Monday through Friday. This data is reported through stock exchanges and could be purchased but was available to the public freely. Stock charting programs access this data and provide access via their respective websites and in their charting software,

sometimes for a fee. For the purposes of this thesis free data was collected by FreeStockCharts.com and issued in both pay and free formats for charting purposes. This is not the only source of stock data available but for the purposes of this thesis data was collected from FreeStockCharts.com. The integrity or validity of the data presented is thus of a professional, accurate, and secure source.

Face validity: A real time example

The results of the model must be determined as reasonable in output for face validity to occur. Does the model accomplish what it was intended to do? Model A informs stakeholders when price is changing or in the process. It did this in a past perfect fashion. In real time, Model A would reactively indicate change as moving averages converge, both the central tendency MA (0% lag) and the real time MA (50% lag). Convergence of moving averages does not guarantee a cross over but implies the possibility is increasing. The opposite may occur with moving away from each other and a continuation of the last past perfect signal. Every trading day adds eight hours of data to the moving averages and they adjust accordingly in real-time. In cases where data or price stalls and prints in sideways clusters, the likelihood of a crossover in real time for Model A increases. Price may churn up and back repeatedly causing the data input to the moving averages to become redundant and over sample the same numerical inputs. Prices unable to trend in an up or down direction begin to stall until establishing a new trend or continuing with the previous trend. If prices simply range sideways in an oscillatory manner, then the trend is sideways. The moving averages will visibly overlap and flatline as the wave pauses before resuming an up or down direction. Price oscillation in a range signifies trend in a

sideways direction and can occur indefinitely. Performance and interaction of moving average components of Model A are of focus next.

Validation: Reasonable information for the stakeholder

Reasonable information for the stakeholder is information to satisfy a need. In this case, more information about the wave for trading purposes on an hourly or minute basis. Need to know information for the stakeholder is where we are on the wave in time and space, are prices waving up or down or trading sideways, and is a trough or peak developing. Model A infers all the above by showing the central tendency

(regressed) and its interaction with a real time moving average (50% lag).

Model A combines two moving averages: 40(-20) MA regressed (0% lag) and a 40 MA in real time (50% lag) combined on one 2-hour chart of the Standard and Poor’s 500 Index. This is represented in Figure 5. Note that in real time the trader has no true signal but a potentiality as moving averages converge. The central tendency is delayed 20 units or bars of time equal to 2 hours each. The regression is equal to 40 hours or roughly five trading days. This crossover is always occurring five days in the past perfectly. Once the crossover has occurred the trader is assured in a late fashion that the wave has changed, and the trend is changing in direction. If the change is sudden and prices increase or decrease rapidly then the real time moving average acts a potential trigger. When prices or data remain right of the 40 MA in real time charts then prices are waving lower. In contrast if price is left of the 40 MA in real time charts then current data is out performing its average to higher levels. This is the point where the late signal will occur in forty trading hours in the future. Although the signaling is past perfect for troughs and peaks in the sign wave much powerful information is gleaned here in real time.

Much like a weather report, the last past perfect signal indicates positive or negative price action from that point in space and time. As long as prices do not violate the last past perfect signal point in space then direction is sustainable from that signal, also capturing price through amplitude. Figure 4 illustrates using real time charts a point of change potential forming in the S&P 500 Index wave occurring Friday August 4.

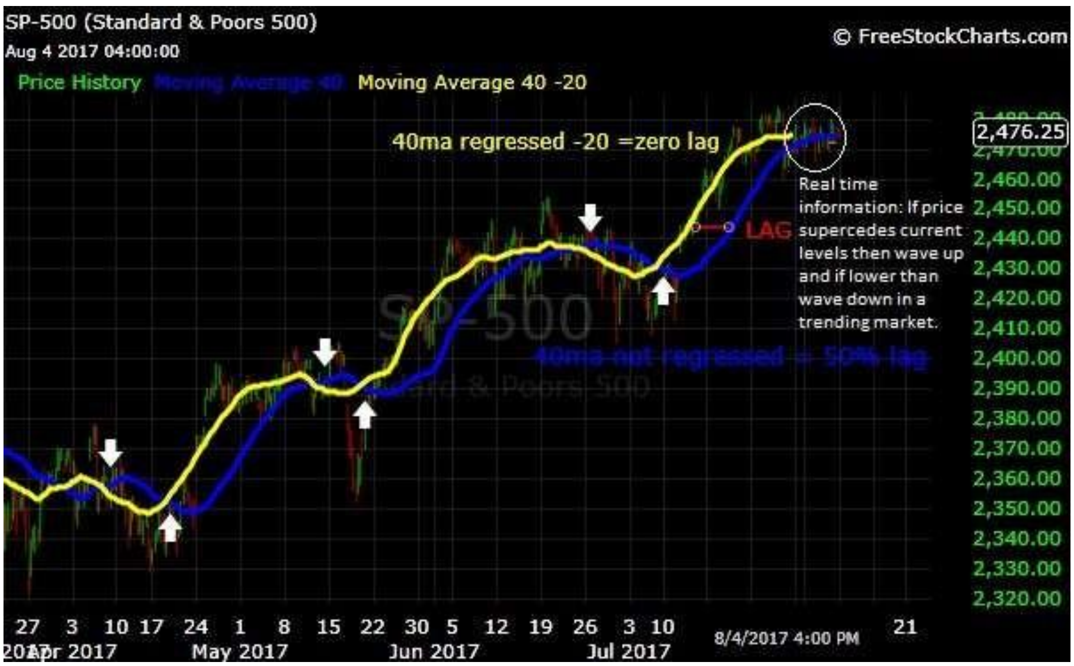

Figure 6: Model A showing convergence of moving averages = potential signal forming (trough or crest).

Source: Image by author

Note in Figure 6 above that prices are trending in a generally positive direction in a wavelike fashion achieving higher values. This is an uptrend in technical analysis (Murphy, 1999). Prices moving from trough to crest, or vice versa, is the amplitude of the wave (Hurst, 1970). Figure 6 is a real time example of data flow implying a peak by the convergence of the moving averages on 08/04/2017. The moving averages in Figure 6 are converging in real time

but will not cross, or separate, in 20 units or bars each bar representing 2 hours, thus a perfect signal is delayed in time. If in the future the moving averages separate then values are increasing, wave up. If the moving averages cross then values will decrease, wave down. To speculate how long into the future prices will wave in any direction is predictive and is not the scope of Model A, which is reactive only. Prices crossing above or below the real time MA and consistently staying to the left or right indicates the central tendency will follow in the future and is reactive in nature.

The following graphs will present real-time price and Model A beginning with Figure 6, which left off in time 08/04/2017. Figure 7 shows the net results of wave action going lower or down. Note in Figure 6 the moving averages did cross with the central tendency moving lower than the real time moving average. This implies weakness in the market, in this case the S&P500 Index, so that stakeholders can adjust trades and investments accordingly. Figure 5 implied weakness by having moving averages converge. Figure 6 confirms the convergence ultimately lead to a crossover of moving averages signifying a wave down. The time stamp for Figure 7 is representing data up to 08/21/2017. This application illustrates how Model A functioned with historical data as it is updated in real time. Although Figure 5, Figure 6, and Figure 7 perfectly represent how Model A works effectively in sufficing stakeholders needs it is important to also present historical situations where the opposite occurs.

Figure 7: Model A in signals a wave down.

Source: Image by author

The following result occurred. As the market signaled weakness by a cross-over occurring prices in Figure 7, the index waved down and recovered. See Figure 8 below.

Figure 8: Model A showing a wave down followed by a wave up…note moving average crossovers.

Source: Image by author

A market that is not trending up or down will often create noise. Moving averages will sum up the directionless market and the noise of a sideways moving market will create a convergence of moving averages. In an up-trending market, the convergence can signal a possible change in direction but does not guarantee a trough or crest but a pause in the uptrend. This still useful for an index trader to know prices or data is in a sideways pattern and the market will reverse direction or continue up, eventually one of the two scenarios in trend will occur. Figure 9 below shows an example of this scenario.

Figure 9: Model A filters sideways data from 18th-26th = noise. Signifies a failure to dampen noise in data for a clean signal. Until moving averages diverge.

Source: Image by author

What is important to note in the above charts each bar represents 2-hour time increments. Model A is also useful in a minute timeframe. The following examples are taken from the most recent stock index data. Day traders need to know as much as possible of wave structure. Below is an example of price data for the Standard and Poor's 500 Index. Each price bar represents 3-minute time increments. The white arrows show crossovers and the last green arrow is signaling a rise in price which has yet to occur.

Figure 10. Model A filtering data in 3 minute increments for possible signaling…note arrows.

Source : Image by author

CHAPTER 4: CONCLUSIONS

Wave analysis and its employment is a valuable tool to address stakeholder needs but must also have a profitable component; which it does. A tool alone cannot insure profitability, but it can increase probability if used properly in combination with other tool sets, such as money management, risk analysis, timing and many other tools. What wave analysis does provide is an invaluable understanding of time and space in a large set of data as a guide or map so that the stakeholder can identify the wave and trade it according to their own individual plan. This could be to trade against the wave or with it and either could be profitable. Profitability is a combination of tools and proper utilization by the stakeholder ultimately. Since wave analysis can be combined with other tool sets easily it is the following section which introduces possibilities and directions.

Future Directions in Market Modeling: Artificial Intelligence and Quantum Approaches

Jim Hurst created a model of stock market indexes and individual stocks using moving averages to find the wave components within price data. This is an oversimplification of his work but delivers the main thrust. Modern publications have proven the usefulness of moving averages in stock market analysis. When used properly they can outperform the basic buy and hold strategy. As modeling of markets increases in complexity, moving averages can play an active role in decision-making. Some of these models are the basis of systems capable of taking advantage of modern computing methods in creating rule-based learning and basic programming. This is somewhat new as some retail trading brokers offer this and have done so as early as the 1990's. Tradestation is a charting and broker provider for those wishing to test and create systems for trading. Using the Tradestation broker platform the average retail trader

or investor can back test their own individual rule-based strategies and even deploy them in real time market conditions. Profit and loss margins are generated without ever investing or trading. The platform can generate simulations using historical price data or simply trade predetermined strategies in real time. Moving averages do not have to be included in all investment decisions or trading systems or models but have been proven useful in market analysis. Figure 11 shows an example of a system including models of the Standard and Poor’s 500 Index, approximating Jim Hurst’s wave analytics incorporating moving averages. In the upper pane, Hurst’s curvilinear envelopes address price via regressed moving averages. In the lower panel price is transduced in a separate model that gauges momentum, or how price changes, via zero based oscillatory indicators tied to measures of volatility based on standard deviations. Combining both models can be described as a system. A system by definition “is defined to be a collection of entities that act and interact together toward the accomplishment of some logical end” (Law, 2007).

Figure 11: Model A shown as a component of a larger system. Note oscillator employment and lines.
Source: Image by author

This simple representation of a system can generate signals to buy and sell. Artificial intelligence (or A.I.) would utilize the transduced data of the above system to act and react to market conditions and learn from a machines perspective. The overall problem to solve is how can the above generated data be utilized to capture price for profit? This the newest application of A.I. to solve problems humans can pose to a computer with an eventual goal.

Research in the private industry exists and is being developed behind closed doors as proprietary intelligent systems. A.I. can be used as a support system to decision-making for stock market models. Sometimes referred to as fuzzy-logic based systems they can take into consideration many factors simultaneously with technical data (such as that provided by moving averages or other indicators) to generate better decision-making or identifying clear buying and

selling points (Fernandez-Rodrıguez, Gonzalez-Martel & Sosvilla-Rivero, 2000; Kuo, Chen & Hwang, 2001). This is the future of models as component parts of larger systems aided by computer decision-making or support. Ultimately, a computer may buy and sell financial instruments on the behalf of their creator and the human acts merely as a manager. As we understand more of A.I. and its uses and limitations, the marketplace will have a new contender, the smart machine. In figure 12 a theoretical system involving wave models is graphically represented. Other unique directions in market analysis may come from the world of quantum physics in defining waves not in the macro way Hurst envisioned.

Figure 12: Theoretical system filtering data on a quantum level with employment of artificial intelligence.

Source: Image by author

Econophysics is a relatively new field in which physicists are applying theoretical frameworks from quantum physics to stock market modeling. This can be accomplished by modeling wave functions and operators in the stock market to fit well established theoretical

equations such as the Schrodinger equation. Here the basic elements (e.g., atoms, electrons) of physics theories and how they are shaped in wave format or solid is described mathematically, this includes energy and how it moves. Part of this theory helped to define atoms and their components electrons, neutrons, and protons; in physical form and as wavelike form. Electrons appear as solid particles when forced to collide and interact with other solid particles but when left undisturbed dynamically take on a wavelike form. In this wavelike form a probability function occurs that can loosely predict where the electron is likely to be found in space in the future. This is known as particle duality. Classical mechanics (physics) states that electrons and other particles stay the same, but experiments seem to prove otherwise. Schrodinger developed his theory as it explains the changes occurring in electrons from solid to waves as a better general understanding of this dynamic process. What theorists are attempting to do is assign values from the stock market to fit within quantum theory, such as the Schrodinger equation.

Others have described cash and other assets investors may own as a wave function (Zhang & Huang, 2010). This can possibly be waiting to transform into a solid particle or a purchase of stock. Others have created a quantum model to explain a relationship that occurs in quantum physics that is similar in describing the relationship of stock price and ownership, what is known and unknown and what can change dynamically (Cotfas, 2012). The dynamic aspect of a wave transforming itself in shape and form is what roughly occurs in the macro world of stocks, so some parallels can be drawn. This field of Econophysics formed its beginnings in the 1990s and has relatively few publications available, mostly for purchase. The general idea is that the stock market and its operators (investors, traders, banks, brokerages, market makers, etc.) are in constant flux as part of a dynamic system and may be modeled as a quantum formula

capable of mathematically explaining the process or even predicting the next process to occur, theoretically.

These future directions for stock modeling are embraced in professional circles. The use of artificial intelligence or neural networks is not new. Banks and trading houses have been hiring *quants* since the 1990s to create models for high speed trading and investing. Some comment that with the playing field being relatively equal as fast computers are available to all the focus must shift in new directions in order to stay competitive. The original premise of this paper was to introduce the efficacy of a model proposed by Jim Hurst in the 1970s using an innovation of wave analytics that is still applicable today. What is unknown to most is that this model is past perfect, a hidden strength based on constants, but in real time the stakeholder is left with a solve for *X* type of scenario. Hurst's original works also include a predictive element he called 'cyclicality' and this addressed the repetitive nature of the markets he called 'nominality' (Hurst 1970), but these concepts fall beyond the scope of this thesis and will be left included. Using only some of the discoveries in above work with newer techniques can promise unique directions. It is here where a modernization of Hurst's model can be combined with neural networks capable of solving the probability for *X* and some of the keys to the macro waves can be usefully contained in a quantum equation, Figure 12 is a theoretical example. Figure 12 represents a concept system of how artificial intelligence would combine empirical factors and the wave model as components to ultimately assist in buying and selling. Unexplored territory but worthy of formal investigation.

Amplifying the human experience is a side benefit of visually identifying waves

This thesis explores tools present in wave analysis and applies these tools to smaller timeframes then the originator intended. Defining the wave and trading the price action is a challenging task. Wave analysis helps inform the stakeholder of vital information in helping increase profitability. In the future directions section of this thesis, coupling wave analysis with other tools to create systems is explored. Wave analysis is not limited to the macro world of standard physics but also has quantum components and applications far beyond the scope of this thesis. If wave analysis can be applied to stock indexes what other fields benefit? Since scientists agree everything is a wave then understanding wave analysis thus may have universal applications. Fields of medicine, human performance, and natural disasters are only some of the applications possible for wave analysis. It is the scientific community's duty to explore these possibilities for the general benefit of all.

Modeling waves in stock indexes provides a visual feedback for the human system to internalize filtered data and patterns. This is a means of experiencing an external reality, the markets, in a format for understanding time and space for human perception as an internal reality. As central tendencies in Model A make meaningful crossovers and waveforms are filtered from data and defined the human system is trained in identifying patterns for profitability, thus survival. Essentially the human interaction with Model A is an augmentation of performance via experience on a psycho-somatic level. As the human interaction increases exposure to wave form patterns then a learning process is occurring which augments perception. Model A can train the human experience visually and eventually human perception will benefit by identifying wave components without intervention of modeling. Our earliest of ancestors

surviving from subsistence patterns of hunting and gathering must have utilized pattern recognition. These patterns may have emerged from watching herds migrate on a seasonal level or even how these herds flowed in recognizable patterns during hunting for energy capture much like trading. The implications of exposure to wave patterns is likely inherent in the human umwelt and has been a staple in our survival or adaptively it would not exist. The question raised here in conclusion is can filtering large waves of data train the human condition or its human factors to better serve survival? Wholeheartedly it is this researcher's opinion and experience that yes is answer to the above question. What is required to prove the above assertion can be accomplished via active experiments, structured scientifically for empirical results but is yet to be explored.

REFERENCES

Averill, M. L. (2007). *Simulation modeling and analysis*. Tucson, AZ: McGraw-Hill.

Cotfas, L.-A. (2012). A quantum mechanical model for the relationship between stock price and stock ownership. *Statistics and Informatics, Academy of Economic Studies*, 6.

Dewey, E. R., & Dakin, E. F. (1947). *Cycles: The science of prediction*. New York, NY: Holt and Company.

Ehlers, J. F., & Way, R. (2008). Empirical Mode Decomposition, A novel approach for cycle and trend mode detection. *Stocks & Commodities,* November, 19−29.

Ehlers, J. F.; & Way, R. (2010). Zero lag (well, almost). *Technical Analysis of Stocks and Commodities*, November, 1−8.

Elliot, R. N. (1938). The wave principle. In R. Prechter, Jr. (Ed.), *The major works of R. N. Elliot.* Gainesville, GA: R. New Classics Library.

Fong, W. M., & Yong, L. H. (2005). Chasing trends: Recursive moving average trading rules and internet stocks. *Journal of Empirical Finance, 12*(1), 43−76.

Fernandez-Rodrıguez, F., Gonzalez-Martel, C., & Sosvilla-Rivero, S. (2000). On the profitability of technical trading rules based on artificial neural networks: Evidence from the Madrid stock market. *Economics letters, 69*(1), 89−94.

Gann, W. D. (1927). *The tunnel thru the air* (pp. 75−76). New York, NY: Lambert-Gann.

Gurrib, I. (2014). The Moving Average Crossover Strategy: Does it work for the S&P500 Market Index? Retrieved from https://ssrn.com/abstract=2578302

Hurst, J. M. (1970). The Profit Magic of Stock Transaction Timing. Prentice-Hall.

Kuo, R. J., Chen, C. H., & Hwang, Y. C. (2001). An intelligent stock trading decision support system through integration of genetic algorithm based fuzzy neural network and artificial neural network. *Fuzzy Sets and Systems, 118*(1), 21−45.

Law, A. M. (2008, December). How to build valid and credible simulation models. In S. Mason, R. Hill, L. Mönch, & O. Rose (Eds.), *Proceedings of the 40th Conference on Winter Simulation* (pp. 39−47). Miami, FL: Winter Simulation Conference.

LeBaron, B. (2000). The stability of moving average technical trading rules on the Dow Jones Index. Derivatives Use, Trading and Regulation, 5(4), 324−338.

Liu, X., An, H., & Wang, L. (2015). Performance of generated moving average strategies in natural gas futures prices at different time scales. *Journal of Natural Gas Science and Engineering, 24*, 337−345.

Mikula, P. (2003). The Definitive Guide to Forecasting Using WD Gann's Square of Nine. Mikula Forecasting Company.

M’ng, J. C. P., & Zainudin, R. (2016). Assessing the efficacy of adjustable moving averages using ASEAN-5 currencies. *PloS One, 11*(8), e0160931.

Murphy, J. J. (1999). Technical analysis of the financial markets. Penguin.

Musa, J. D. (1963). Discrete smoothing filters for correlated noise. *The Bell System Technical* Journal, September, 2121−2151.

Pätäri, E., & Vilska, M. (2014). Performance of moving average trading strategies over varying stock market conditions: The Finnish evidence. *Applied Economics, 46*(24), 2851−2872.

Pavlov, V., & Hurn, S. (2012). Testing the profitability of moving-average rules as a portfolio selection strategy. *Pacific-Basin Finance Journal, 20*(5), 825−842.

Papailias, F., & Thomakos, D. D. (2015). An improved moving average technical trading rule. Physica A: Statistical Mechanics and its Applications, 428, 458−469.

Prechter R. R., Jr, & Parker, W. D. (2007). The financial/economic dichotomy in social behavioral dynamics: the socionomic perspective. *The Journal of Behavioral Finance, 8*(2), 84−108.

Sargent, R. G. (2013). Verification and validation of simulation models. *Journal of Simulation, 7*(1), 12−24.

Wang, L., An, H., Liu, X., & Huang, X. (2016). Selecting dynamic moving average trading rules in the crude oil futures market using a genetic approach. *Applied Energy*, *162*, 1608−1618.

Zhang, C., & Huang, L. (2010). A quantum model for the stock market. *Physica A: Statistical* Mechanics and its Applications, 389(24), 5769−5775.

Zoicas-Ienciu, A. (2014). The performance of moving average rules in the central and eastern European stock markets. Review of Economic Studies and Research, 7(2), 165.