Engineering Financial Engineering

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***Abstract*—In order to bridge the gap between theory and practice in the Financial Engineering community it is important that financial models demonstrate sound engineering features of reliability and robustness and apply a repeatable process. A review of 47 journal and conference financial engineering papers from 1990 to 2013 reveals a large gap between theory and practice persists. This paper surveys these papers in terms of repeatability, reliability, realism, and robustness. It offers strategies for bridging the gap between theory and practice.**

Keywords—financial engineering, Financial Data Mining, literature survey, Evolutionary Computing, neural networks, genetic programs, genetic algorithms, fuzzy systems, time series analysis, machine learning

I. Introduction

In order for the Financial Engineering discipline to mature, it must adopt a more rigorous approach within the discipline. Aspects of rigor include a applying repeatable process, and producing reliable, realistic and robust models.

Repeatable implies that a paper provides sufficient details so that a reader can replicate the research proposed within a paper. Lack of repeatability makes it difficult to validate an approach, which discounts the credibility of the research.

Developing a reliable model does not compromise the integrity of the modeling process. Using correlated training and test data, building a model with a biased data set, or omitting transaction costs inflate the goodness of a model. Also, building a model with a synthetic data offers is not reliable since it was not created on real data.

A realistic model includes both statistical and financial assessment, manages risk, and considers position sizing. It may even consider scalability. Scalability means that managing $100K would differ from managing $100 million dollars.

A robust approach applies a model to different market conditions. How well does a model handle dramatic changes in the market? How well does a model handle adverse market conditions? Ignoring market conditions can inadvertently overstate the capability of a financial model. An example would be using training and test sets that are highly correlated.

This research examines 47 financial engineering conference and journal papers from 1990 to 2013 with the intent of identifying common issues when formulating financial models. Two criteria served as the basis for identifying papers. First, the paper was published in a previous *Computational Intelligence for Financial Engineering and Economics* conference [1..27]. Second, the citation count for a paper, according to Google Scholar, exceeds 50 [28..47]. This paper ignores books related to financial engineering.

The intent of this paper is not to embarrass any of my distinguished colleagues. The author experienced many of these issues over more than 14 years of building hundreds of thousands of financial models. Rather, the intent is to improve the quality and credibility of research in Financial Engineering by raising awareness in terms of repeatability, reliability, realism, and robustness thereby bridging the gap between theory and practice.

There are numerous benefits by addressing these issues.

- **Repeatability**: Adopting a repeatable process means that other researchers can validate the findings of the original paper. Validating previous research gives credibility to those papers and, in turn, to the financial engineering discipline.
- **Reliability**: Developing financial models using sound conditions gives greater confidence in a particular financial model. This is especially important when one considers migrating from paper trading to trading with real money.
- **Realism**: Applying realistic conditions to a model helps bridge the gap between theory and practice. User would have a greater change of adopting a model created under realistic conditions.
- **Robustness**: Testing models in adverse contexts provides an indication of the extent that a financial model is risk adverse.

Besides these benefits for individual papers, the Financial Engineering community will also benefit. By promoting various financial benchmarks, it will be easier to compare and contrast papers based on their merit.

This paper is organized as follows. Section 2 provides a literature survey of survey papers. Section 3 presents demographic information on the 47 papers surveyed. Sections 4 through 7 examine the papers in terms of repeatability, reliability, realism, and robustness respectively. Section 8, Engineering Financial Engineering, offers suggestions on bridging the gap between theory and practice. Finally, section 9 provides a conclusion.

II. SURVEY OF SURVEY PAPERS

Atsalakis and Valavanis

Atsalakis and Valavanis [48] survey 100 Financial Engineering papers that use neuro-fuzzy and/or neural networks in their modeling process. They provide details regarding input data, forecasting methodology, model comparisons and measures used for performance measures.

There is an overlap of only 7 papers [11, 22, 33, 35, 39, 43, 44], or 15 percent, between the work of Atsalakis and Valavanis [48] and this paper which reviews 47 papers. Atsalakis and Valavanis [48] claim that [35] and [43] use daily data. These claims have been revised to Weekly and Monthly respectively.

The authors claim *The key to successful stock market forecasting is achieving best results with minimum required input data* but do not address any engineering issues associated with any of the papers.

Zhang and Zhou

Zhang and Zhou [49] do a crosscut of 5 data mining approaches (Neural network, Genetic Algorithm, Statistical Inference, Rule induction, and Data Visualization) with six financial applications (Stock Market prediction, Portfolio management, bankruptcy prediction, fx market, fraud detection).

The paper provides a cursory overview of data mining approaches in finance. To there is not in-depth comparison between financial models.

III. PAPER DEMOGRAPHICS

Table one shows the paper demographics in terms of data sample size, time frame for conducting trades/analysis, and the type of financial data used in the experimentation process. Unless specified, it is assumed there are 250 trading days per year. A question mark means the paper did not provide this information.

Table 1: Paper Demographics

Paper	Sample Size	Time Frame	Market/Instrument
1	26	Weekly	Airline
2	?	?	US Stock Market
3	1000	Daily	28 Japanese Stocks
4	500	Daily	30 Stocks
5	5250	Daily?	Macro Econ. Data
6	1750	Daily	Gold
7	NA	NA	Mcky/Glass Simulated
8	None	?	?
9	1667	Daily	Dow Jones Index
10	2250	Daily	27 Dow Stocks
11	2000	Daily	Amsterdam Exch.
12	290	Daily	EcoPetrol (Columbia)
13	756,000	1 Min.	KOSPI (Korea)
14	13,351	30 Min.	Ibovespa (Brazil)
15	200	Daily	10 Stks (Johannesburg)
16	64,440 est.	Bid	FX: Swiss - US
17	Day 1 going public, 875	Daily	Philippine Stocks
18	247	Daily	S&P100, Lehman Bond
19	~125,000	Tick	FX: US - Swiss
20	145	Multiple	33 Hang Seng Stks
21	7564, 3782	Mult,	FX: Dem/USD, S&P
22	500	Daily	Stks:NDQ,NYSE, AMEX
23	2000	Daily	DJIA,Gold,FX:USD-JPY
24	800	NA	Mcky/Glass Simulated
25	1500	NA	ISMARTS Simulation
26	400, 3500	Daily	PS120 (Lisbn), EDP, BCP
27	100	Daily	Aust. Stk, FX:Aus/ US Gld
28	17,000	Daily	S&P Index
29	4775	Daily	ETE(Athens), GE(NYSE)
30	312	Daily	700 Stks (Twan Stk Mkt)
31	2562	Daily?	Taiwan Stck Exch. Index
32	1,440,000	Tick	FX: USD - GBP
33	1000	Daily	WDC, INTC, CPQ, GM
34	731	Weekly	FX: GBP - USD
35	247	Weekly	TOPIX (Tokyo)
36	1000	Daily	FX: USD - GBP
37	379	Daily	Taiwan Stock Mkt.
38	3652	Daily	33 Hang Seng Stks
39	2600	Daily	Bel20 Idx (Belgium)
40	6160	Daily	S&P Futures (US)
41	2003	Daily	14 Stks (Toronto Stk Ex.)
42	2929, 1539, 2155, 2219	Daily	S&P500, MATIF-CAC, EURXBOND, CBOT-US
43	222	Monthly	S&P Index
44	320	Daily	DIA (Diamonds): AMEX
45	1911	Daily	Kuala Lampur: Malaysia
46	58	NA	Bus. Week/Fort. 500
47	239, 239, 239	Daily	FX: YEN-AUS, FX:USD-AUS,Stks: DJIA

Figure 1 shows the papers distributed based on time frame. About two-thirds of the papers use daily data

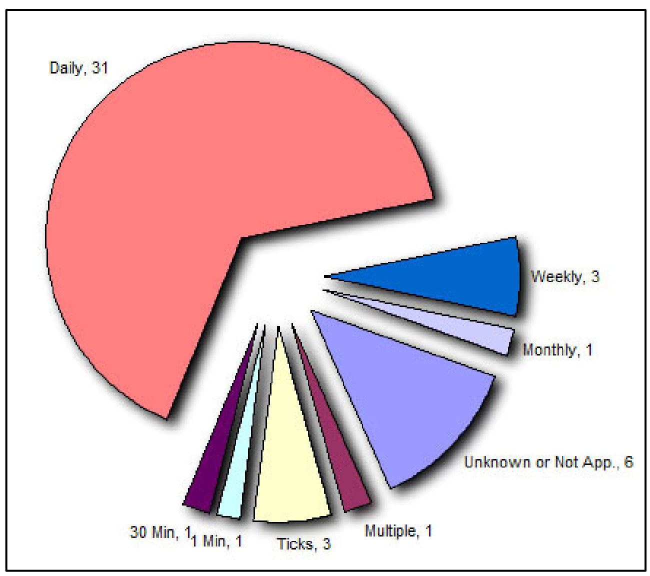

Figure 1: Paper Distribution Based on Time Frame

The sample size demographics is discussed later.

IV. REPEATABILITY: ARE RESULTS REPEATABLE?

Since financial engineering is data intensive it is imperative that authors provide a full description of the data in order for researchers to replicate the original results. Ideally, a paper includes the names of the financial instrument(s) under review, start and stop dates and times for training and test sets respectively, and a link for readers to acquire the data.

Analyzing the 47 papers reveals 5 different levels. At the lowest level a paper is missing the name of the financial instruments, or the start and stop dates/times for when the financial data was reviewed. Thirteen papers fit in this category. One paper [1] referred the reader to another paper.

Data sets for conducting experiments spanned 19 different countries. These include Australia [27, 47], Belgium [39], Brazil [14], Canada [41], China [20, 38], Columbia[12], England[32, 34, 36], Germany [21], Greece [29], Japan [3, 23, 35], Korea [13], Malaysia [45], Philippines [17], Netherlands [11], Portugal [26], South Africa [15], Switzerland [16, 19], Taiwan [30, 31, 37], and the United States [2, 9, 10, 16, 18, 19, 21 - 23, 27 - 29, 32 - 34, 36, 40, 42 - 44, 46, 47].

As shown in Table 2, the authors often describe the data, but did not provide a link to the data source. This may create a repeatability problem when verifying experiments that use data from one's non-native country.

In three cases a link was provided to the financial data. However, one of the links was broken. It is interesting that there is no overlap between sample sets in terms of sample size or financial instruments used. Lack of standardization of data sets and sample sizes makes it difficult to compare/contrast papers.

Table 2: Assessment of Repeatability of Data

Problem	Papers
Data described and Link provided	23, 44
Link provided, but broken	19
Data described, but no link to source mentioned	5, 9, 10, 12, 14, 15, 16, 18, 20, 21, 28, 29, 31, 33 - 37, 41 - 43, 45, 47
Data not described, link to another paper for more info	1
Data Description Missing (e.g. specific symbol, specified time range, or both)	1, 2, 4, 7, 8, 11, 17, 26, 27, 38 - 40, 46

In order to replicate results, it is important to describe trading details. This includes whether a model conducts long or short trades. Also, money management details need to be identified. This could include contracts/shares purchased/sold, stops losses, or maximum number of contracts/shares.

Table 3 describes papers in terms of the amount of information regarding trade details. 43 out of 47 papers did not provide any details in terms of long or short trades. Perhaps the authors did not have sufficient domain knowledge and constructed their models from a *long only* perspective.

Money management strategies are very important to consider when building financial models especially when trading highly leveraged financial instruments. For example, it takes $4,612 to buy an S&P eMini contract (as of 11/3/2013). Thus, with $100K, an investor could purchase 21 eMini contracts. An eMini contract gains (loses) $50 for each point the S&P index moves in (or against) your desired direction. One contract could gain/lose $1,050.

Since January, 1990 there have been 81 days with a difference of 47 points or more between the high and low. A worst-case bad trade would wipe out 50 percent of one's portfolio. A worst-case trade on 7 of those days would wipe out one's portfolio completely.

As depicted in Table 3, several papers [2, 3, 4, 16, 23] provide no mechanism (e.g. statistical or financial) for assessing results. This makes it impossible to verify the results.

Unfortunately, most papers (44 out of the 47) papers ignore money management strategies. This may due to lack of financial domain knowledge, or time needed to incorporate such strategies into their model.

Table 3: Assessment of Repeatability of Trades

Problem	Papers
Trade description missing (e.g. long, or short trades)	1 - 27, 29, 30, 33 - 40, 42 - 47
Money Management Strategies Missing	1 - 12, 14 - 27, 29, 30, 31, 33 - 47
Unknown assessment	2, 3, 4, 16, 23

Papers [28] and [41] do provide details regarding long and short trades.

Dempster and Jones [32] provide the best example of repeatability in terms of long/short description and money management. Their paper was published in 2001 and has received 126 citations. Considering the visibility of the paper and the age, it is surprising that more research had not embraced their rigor.

A special case exists when considering multiple years worth of commodity data such as the S&P eMini contract. In 2007, the amount of equity needed to buy/sell one contract was $2,813. In October, 2013, the amount of equity needed per contract is $4,613. This dramatically cuts the leveraging ability. As a consequence, any modeling that uses historical data prior to the change in equity requirements must use the current definition. Also, replicating results from Financial Engineering papers more than 5 years ago must consider the financial context for that paper.

V. RELIABILITY: ARE RESULTS RELIABLE?

Besides replicating experiments, a reader may consider whether he/she would trade the proposed system. Having enough confidence to invest actual money requires that the financial model demonstrate reliability. This section explores different facets of reliability.

Models correlated to training. A long (short) financial model, based on a bull (bear) market, overstates the profitability of the model. Another variant of this problem uses training and test data that is positively correlated. One solution to temper this situation utilizes excess returns. Excess returns subtracts *buy-and-hold* profits from the financial model profits for long models. Negative buy-and-hold profits are ignored in this situation. Shorting models would add *buy-and-hold* losses to financial model profits.

Range bias means that a data set is selected that optimizes results. It is possible to select a data range that optimizes a financial model. Table 4 shows which papers use only 1 data set. These papers are vulnerable to range bias.

Synthetic data. As mentioned in Table 4, three papers use synthetic data to construct their models. These data sets could also have range bias. Also, given the extent of free financial data available (e.g. http://finance.yahoo.com/), there is no reason to use synthetic data. Constructing a model using actual historical data gives greater credibility than using synthetic data.

Missing transaction costs. As seen in Table 4, 39 of the 47 papers do not include any transactions costs. This certainly inflates the success of a model. In [13] the authors perform two trials on the same financial model. The first trial uses no transaction costs and gains 31 percent. The second version, with transaction costs included, ends up losing 70 percent. Thus, transaction costs dramatically change the outcome of a model.

Table 4: Reliability: Model Formation

Problem	Papers
Only 1 fixed test provided	3, 5, 10, 12, 13, 36, 40
Use Synthetic Data	7, 24, 25
Missing transaction costs	1 - 5, 7 - 12, 14 - 21, 23 - 27, 29 - 30, 34 - 36, 38 - 47

VI. REALISM: WOULD I TRADE THIS SYSTEM?

Another litmus test considers how well the research approaches actual trading. Although there is no guarantee that paper trading success will lead to financial success, it is the closest one can come to actual financial success. The papers have different degrees of realism. Different features are presented below.

No statistical or financial assessment. Table 5 identifies those papers that did not contain any statistical or financial assessment. In certain cases, assessment was based on a fitness value from a Genetic-based approach.

Statistical success does not equal financial success. There are varying degrees for measuring the success of a financial model. The easiest approach determines the percentage of winning trades. However, this ignores the case when one large losing trade negates many small winning trades. Thus statistical success does not guarantee financial success. Table 5 lists 18 papers that rely on statistical measurements only. Most likely an investor may be reluctant to trade a model based only on statistical success. However, extending these papers with backtesting (paper trading using historical financial data) may confirm the merits of these models and thus be a trading alternative.

Managing risk is an important feature of any trading model. This is especially important when trading highly leveraged financial instruments (e.g. S&P futures) or during times of high volatility (e.g. the flash crash of May, 2010). Ignoring risk when formulating a model could lead to disastrous results when performing live trading. Features of managing risk include specifying a starting equity, providing stop loss settings, identifying the number of contracts/shares purchased. As seen in Table 5, 37 of the 47 papers do not use any form of money management techniques.

Position sizing. Several papers provided a starting equity. However, none of the papers indicated that they did any position sizing.

Scalability. None of the papers considered volume for calculating a maximum number of contracts (or shares) for entering or exiting a position.

Table 5: Realism: Measuring Success

Results	Papers
No statistical or financial assessment (could include fitness) (A better than b)	1, 8, 10, 11, 40
Statistics Only. It includes MRAE, RMS, %Accuracy, etc.	5, 7, 9, 12, 14, 18, 19, 24, 25, 27, 29, 34 - 36, 38, 44, 46, 47
No money mgmt techniques	5 - 7, 12 - 26, 28 - 31, 33 - 47

VII. ROBUSTNESS: WOULD I TRUST THE SYSTEM?

Migrating a model from paper trading to real trading will eventually encounter unfavorable market conditions counter to the natural bias of the model (e.g. long model in a bearish market). Thus, it is important that a model be robust to handle such circumstances. There are several features in order to produce a robust model as described below.

Large enough sample set. The larger the sample set, the more confidence can be given for a financial model. Also, larger data sets support longer range technical indicators such as a 200-period Simple Moving Average (SMA). Table 6 shows the average sample size for the reviewed papers. It should come as no surprise that the same size increases as the time frame decreases - due to the availability of data within a time period (e.g. one year).

Table 6: Average Sample for the Reviewed Papers

Time Period	Samples	Average Sample Size
Monthly	1	222
Weekly	3	333
Daily	16	2,382
Tick	4	596,360

Nature of data samples. A trading strategy may go long (buy to enter, sell to exit), or short (sell to enter, buy to exit). Long trading aligns with a bullish market and short trading aligns with a bearish market. It is assumed that if an experiment does not specifying the types of trades, then the financial model places long trades only. More sophisticated models combine financial models consisting of long trades only and short trades only, in order to compound profits.

To insure that a financial model is robust. it tested against 3 different types of markets - a bull, bear, and sideways. None of the papers tested specifically against these types of markets. Some of the papers used a sliding window for training on days 1..10, testing on day 11, training on days 2..11, testing on day 12, etc.

Black Swans. A black swan represents a rare occurrence in nature. These are typically depicted in Finance as major down days. Table 7 shows the 10 worst down days since 1987. The *High - Low* column shows the down day in absolute terms, how big was the drop? The *(High - Low)/Open* column shows the drop in relative terms.

In certain cases, these major drop offs would be ignored by a financial model that only considers the *Close* price. One paper [28] actually explored the possibility of ignoring the Black Swan events from 1987.

Black Swan events cannot be treated as outliers. Otherwise, when they occur in the future, a financial model will be unable to address the event.

Table 7: Black Swans since 1950 for S&P 500 Absolute and Relative Terms

Date	Open	Close	Hi - Low	(Hi - Lo)/Open
10/19/1987	282.7	224.84	57.87	20.5%
10/20/1987	225.06	236.83	29.16	13.0%
10/28/2008	848.92	940.51	95.24	11.2%
11/13/2008	853.13	911.29	94.32	11.1%
10/10/2008	902.31	899.22	96.56	10.7%
10/13/2008	912.75	1003.35	94.18	10.3%
5/6/2010	1164.38	1128.15	101.79	8.7%
9/29/2008	1209.07	1106.42	102.65	8.5%
4/4/2000	1505.98	1494.73	110.04	7.3%
4/14/2000	1440.51	1356.56	101.11	7.0%

VIII. Engineering Financial engineering

It is not the intent of this paper to propose some standard for constructing financial models. This may not be possible considering the various time frames researchers use to create models. Instead, the goal is to help the discipline become more rigorous in the modeling process. The following guidelines are given for generating more realistic, reliable, and robust models along with a repeatable process.

Repeatability: Data. As previously mentioned, it is important to specify start/end dates and time along with providing a link for the data.

Repeatability: Process. By specifying starting equity and identifying money management settings, such as a stop-loss condition, would enable fellow researchers to replicate results.

Also part of the repeatability process would be to specify the maximum number of shares or contracts to consider. This is especially important when trading shorter time frames of 5 minutes or less.

Many worldwide exchanges adopt the Standardized Portfolio ANalysis of risk (SPAN). SPAN is used to establish margins within a trading account. It is used to identify the maximum number of Futures Contracts that may be traded. Margins may vary depending upon the type of account (e.g. regular, or traditional IRA) and length of trade (e.g. intraday versus overnight). Since the SPAN value is subject to change, it is important to include the SPAN Margin in a paper for repeatability purposes.

Including trade details would also be beneficial. This could include winning long/short trades, losing long/short trades, stopped out long/short trades, and commission rates. It would even be better to provide a link to the actual trades.

Realism. Some papers conduct trades over several years, then provide a total profit for the model. A better approach would calculate Annual Rate of Return (ARR). This would make it easier to compare models.

Most papers lacked any money management ideas in their paper. At a minimum, describing and applying stop orders in the modeling process would be very beneficial.

When building models on highly leveraged financial instruments (e.g. eMini Futures), a would most likely not go "all-in." Using position sizing would be more realistic..

The number of contracts/shares that may be bought or sold depends upon the time frame under consideration along with the volume. A general rule is buy/sell no more than 10 percent of the volume for a given time period.

Robust. Consider testing models in bull, bear, and sideways markets. Also, consider testing results in *Black Swan* environments.

IX. Conclusion

This paper presents and analyzes 47 conference/journal papers that use one or more machine learners to build a financial model. The intent of bridging the gap between theory and practice.

Engineering practices/features such as repeatability, reliability, realism, and robustness are explored. Adopting practices/features are very important for producing financial models that may be traded using real money. incorporating these practices/features makes it easier to compare/contrast research results.

This paper also provides suggestions on how to better engineer financial models.

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