Deep Science Publishing
https://doi.org/10.70593/978-93-49910-98-0_10

Chapter 10: Real-time financial decision systems for trading, investment planning, and risk management

10.1. Introduction

Decision-making in financial trading, investment planning, and risk management requires considerable analytical, qualitative, or quantitative decision support. Such tasks can be carried out using logical rules, portfolio-theoretic or market-attribution analysis, as well as various econometric or statistical models with single or several variables. Traders and investment managers make decisions based on user drafts or suggestions that include a combination of scheduled reports, alerts, risk/return matrix, and forward planning horizons (Bhattacharyya & Chen, 2019; Li et al., 2020; Zhang & Zhou, 2021). The impact on the planned trading strategy of the selected decision systems and operating mode is not transparent. Therefore, expensive services are offered by large investment firms and banks to assist investment managers. Some are made available to investors at competitive prices. Financial markets and their various segments are under the constant scrutiny of traders and analysts either working for investment firms and banks or acting as independent contractors or commentators. As a result, there is a substantial body of literature covering a variety of systems that investors can use for guidance: market, technical, fundamental, and momentum trading systems and rules, as well as economic models to predict changes and regional-level or firm-level models to predict changes in stock prices and financial ratios. More recently, especially after the meltdown, there is also an increasing body of work on credit-default swaps and extreme events and the models that predict their impact (Park & Lee, 2022; Nguyen & Kim, 2023).

10.2. Overview of Financial Decision Systems

Financial Decision Systems (FDSs) and their computer implementation discussed in this work constitute a new class of real-time systems. They make automatic financial decisions in an open-ended and highly dynamic environment. Expert Systems (ESs), currently the most developed class of Expert Decision Systems (EDSs), and their computer implementation constitute a concentrated and advanced form of Decision Production Systems (DPS). In spite of their advanced level, ESs form the class of systems with the narrowest scope, which are limited to specific areas of activity. FDSs are decision-oriented for a broad spectrum of industrial, commercial, and government applications.

Fig 10.1: Financial Risk Management Strategies

They are modeling, assessing, and advising design-oriented, but they can also measure and control, in an operating sense, a limited number of variables. FDSs fuse and integrate advanced analysis, forecasting, estimation, and advising capabilities of mathematical models and advanced decision making capabilities of the synthetic expert and accomplish Advanced Decision Assessment, Advanced Decision Making, and Risk and Control in Real Time. FDSs constitute a new class of automated systems going beyond the capabilities and present conceptual development of concentrations of various types of Decision Production Systems, Expert Systems, Database Systems, Advanced Decision Support Systems, Simulation-Driven Workstations, Decision Assembly Systems, and Knowledge-Based Expert Systems. FDS can acquire, access, digest, and evaluate the knowledge, experience, and expertise of internal and external decision makers well beyond the capabilities of ES. FDS is a decision-oriented for a broad spectrum of applications.

10.3. The Role of Real-Time Data

Real-time data are computer-based streams of some input variable(s), which are made available almost instantaneously after they were generated or measured, i.e., with minimal latency. Development of technology has made possible capturing, transmitting, recording, and processing huge amounts of real-time data of various types and sizes at ever-cheaper costs. Samples of real-time data are "observed" at a non-uniform rate over time. That is, while real time is a continuous-time variable, its associated index concerning the sampled variable has a unit increment between successive samples. Consequently, one is not working with a uniform dataset over a fixed time horizon, generated by a random process that is a stationary or globally non-stationary stochastic process. Throughout this text, we will use the terms "real-time data" and "streaming data" interchangeably.

Surveillance systems monitor events that trigger changes in data feeds that are generated from various real-time data sources. Process control systems receive real-time data to help regulate processes and modify their parameters. Real-time trading systems receive real-time streaming data feeds from multiple financial market data providers and event-driven alerts from data surveillance systems. The data feeds are processed, and the trading signals to be executed are generated, in real-time. In such systems, the differentiating features are high-frequency market data, ultra-low latency, and applications that seek to profit from fleeting trading opportunities involving instantaneous execution of orders.

10.4. Trading Strategies

Trading strategies can be classified into trend-, momentum-, and value-based strategies. All of these strategies can consider portfolio approach and their construction can use multifactor models. When trading in portfolios, factor sensitivities are estimated for individual stocks and not portfolios. Selection of individual stocks for portfolios is also based on criteria derived from factor models. In construction of long-short strategies, portfolio neutrality can be imposed or not. In the latter case, shorts apply to ‘overvalued’ stocks and longs apply to ‘undervalued’ ones, where over- and undervalued are defined by factor models. In the case of current or intended portfolio neutrality, shorts contribute to lowering portfolio risk and costs.

As a result, net dollar position of the strategy can be small compared to dollar positions in long or short positions. In the case of long-neutral strategies, the short portfolio should be the most liquid and cost-effective one. In the case of short-neutral long strategies, the long portfolio should be the most liquid or otherwise cost-effective. Specific shorting constraints on given stocks can also ease trading. It is well-known that analysts estimate target prices for stocks they cover and the estimates are used by funds and other investors.

Unlike buy-and-hold or longer-term holding strategies, trading strategies by definition do not involve conversion of capital to a stock position and investors should be able to continuously hold cash. Trading is done intraday, daily, and weekly or less frequently and strategies are selective or systematic. The holding period can also be different for long and short portions of the strategy.

10.4.1. Algorithmic Trading

Algorithmic trading, also known as algo-trading, is the use of computer algorithms to automatically specify orders (time, price, volume) for financial assets in trading venues in order to achieve pre-defined trading strategy during the trading session. Algorithmic trading can involve the trading of any type and combination of financial instruments, including equities, exchange-traded funds, futures and options, contracts for difference, forex and cryptocurrencies. Algorithmic trading can occur on different market venues and can employ different trading styles, from buying and holding assets for long periods of time to executing thousands of trades within a few seconds.

The idea of algorithmic trading is not new, as first algorithms were developed in the early 1970's. The first financial instruments traded by a computer were stock options using a model. Broader usage of algorithmic trading by banks and professional asset management firms occurred in the late 1980's and early 1990's. Among important milestones were the introduction of a Fast Automated Execution System and a Major Automater. The first computerized high-volume order-driven stock market was created in 1984 when a stock exchange introduced a Computerized Quotation System. First algorithmic trading systems released commercially were designed for institutional investing. Another wave of IT progression in financial technology produced more simple-to-use algorithmic trading solutions by the middle of the first decade of the twenty-first century, making them available to retail customers. Rapid growth of electronic trading priced algorithms was initiated by the practical availability of APIs from exchanges, ECNs, market makers, and Forex brokers.

10.4.2. High-Frequency Trading

High-frequency trading (HFT) refers to a set of trading techniques that are characterized by very short investment time horizons, extreme execution speed and, often, high execution volumes. HFT is indisputably the most innovative, controversial and, possibly, important asset management strategy nowadays. It has been an early large scale application of algorithmic trading, catching the attention of virtually everybody involved in capital markets due to its recent success and expanded influence on liquidity and price efficiency. With HFT, the execution speed of orders is on par with the time horizon that separates two subsequent trades of a single identical instrument. HFT has come close to minimizing this micro-continuity in trading, especially during normal market conditions. Quantitative high-frequency traders generally employ sophisticated computer clusters that reside in co-location facilities as near as possible to market data feeds and order execution gateways.

Smaller packets of intraday market microstructure information, which other types of traders would bundle over large periods of time for observable anomalies to be detected, are at instant disposal of automated market makers due to continuous access to order book depth information and hundreds of permanent connections to execution gateways. These traders attempt to electronically front-run any scheduled or unexpected information release, reacting arbitrarily fast, reducing market impact and almost creating new markets out of thin air while trying to win a tiny bid-ask spread at lightning speed. However, in reality, their profits could be a small fraction of a basis point per transaction times enormous volumes per relatively transient investment horizon. Assuming a flat prior is a guideline for certain biases, unpredicted asymmetric exogenous shocks and possibly moment loving metrics could predict their future activity.

10.4.3. Market Making

Market makers, also known as liquidity providers, play a vital role in maintaining the liquidity and efficiency of financial markets. They are typically specialized firms that post both buy and sell limit orders to exploit the bid-ask spread. Market makers effectively guarantee continuous market presence by automatically conditioning their orders on the anticipated arrival of marketable orders. When no marketable orders are in the quotation system, market makers determine the width of the bid-ask spread, thus providing a service for a fee. When marketable orders are sent to the market, market makers' orders are triggered and they become temporarily exposed to the risk of holding a private stocks inventory. By adjusting their limit orders before they are triggered, market makers manage this risk, a process that involves both algorithmic pricing the bid and ask limits and making use of predictive models of the dynamic behavior of joint market order flow. Algorithms and models of this specific type are both conditional and predictive, thus providing the market maker with the tools to become a fully informed part of the decision system of trading.

Market making systems in capital markets and foreign exchange play a major role in providing continuous liquid markets. Significant inter- and intra-market price differences can cause substantial losses for market order submitters, particularly those who execute in dark pools away from the visible market, while providing an opportunity for arbitrageurs who are both fast and sophisticated enough to exploit such inefficiencies. Market makers provide a valuable service by taxing such differences. However, market making is not a riskless trading strategy. In the case of rapid changes in market valuation, market makers can suffer major losses. It is therefore important that market making systems use sophisticated econometric algorithms for managing trading risks, such as those associated with rapid changes in investor sentiment.

10.5. Investment Planning

Investment planning, in the broadest sense, is an organizing framework, a tool for making logical choices and decisions about long-term finances across multiple domains — savings for retirement, savings and planning for major expenses, and so on. Making a good investment, in this sense, means making an investment that meets the goals established in the planning process.

In financial planning, a client's financial situation is analyzed in detail, both from a short-term and a long-term perspective. Money flows are tracked day by day and year by year, so exact dates for planned expenses can be established. The client's entire portfolio is investigated, including tax considerations, pensions, fringe benefits, insurance, etc.

Investment planning is an important step in the financial planning process. The main objective is to ensure that the investor will have sufficient funds at the time they are needed. In practice, this usually involves setting financial goals, quantifying these goals and exploring the trade-offs involved in the various savings solutions available. By their very nature, the more distant goals are more sensitive to the rate of return from the investment portfolio. Investment risk and return become critical variables in these cases. If income and expenditure forecasts indicate that the investing period stretches into years, then the rate of return from the investment portfolio is paramount because a minor variation in this variable can yield huge differences in the final result.

10.5.1. Portfolio Management

Investment is a task with an uncertain payoff structure; it is reasonable for it to be treated as a task in real-time financial decision systems. Investments, like trading systems, want rapidly varying states of the world, but they are acting on a large timescale. Many features are to be considered so that they become tasks at the speculation planning level of the architecture: investor attitudes towards different sources of risk, how to assess risk, useful models for making forecast decisions, variations in asset time profiles, transaction costs and limited liquidity, availability of additional assets, and the selection of payoffs of derivative securities. Portfolio management is an area of financial decision-making that is traditionally not treated as a real-time system. Portfolio decisions are usually made infrequently, while market conditions can change quickly. Optimization techniques from mathematical programming, complex systems, or even game playing or military planning are often applied to the construction of portfolios.

Real-time systems often maintain and act upon an internal wish list of desired decisions over various horizons, inspecting it frequently for small-horizon wishes that have risen to the top. This involves the combining and filtering of many different systems with different time profiles. In real-time systems, there is often a sequence of several low-priority decisions with very short edges between them on the way to making a higher priority decision that may extend well out into the future. For portfolio management, such very short-horizon decisions could involve fast variations in the expected returns for the portfolio component assets or conditions that make the current portfolio very nearly out of balance. Candidate internal filters need not be fancy; they could just use simple models for risk and return measures, set thresholds early for such fast systems, and allow more balance-awareness to come back in as the decision horizon gets longer. High-frequency portfolio management systems are often tempted to use simple rules that make portfolios either follow the expected returns for the component assets. These portfolio filters would be one index of the timing systems' importance to the proxy portfolio management.

10.5.2. Asset Allocation

Asset allocation is the process of developing a tactical or dynamic allocation policy that is optimal for an investor's expected returns and acceptable risk level. While an investor may have an optimal long-term allocation strategy, their short-term tactical asset allocation may differ from that. Most investors do not have the expertise or professional experience to form a reliable tactical or even long-term asset allocation strategy. Current portfolio management technologies assist in solving tactical asset allocation methods in asset selection and investment horizon.

There are several different approaches to the asset allocation problem: mean-variance optimization, risk parity, and a specific model, among others. Modern portfolio theory shows how to construct an optimal portfolio of risky assets by making assumptions about the investors' risk preferences and using estimators of the means and covariances of the component assets' returns. This theory argues that investors consider only two factors when choosing the mix of risky assets in their portfolios: their rational expectations of future returns on the component assets and their assessment of the risk, as represented by the variances and covariances of those expected returns. If the actual distribution of future returns is not multivariate normal, then this theory is not able to find the optimal portfolio. It shows how to create a risky portfolio with the highest return and allocates investors between this portfolio and the risk-free asset depending on their degree of risk aversion. Risk budgeting emphasizes the risk allocation rather than the capital allocation, implying that investment risks, volatility, and discomfort should be allocated evenly across both asset classes in a diversified portfolio.

10.5.3. Investment Risk Assessment

Investment risk assessment is a crucial area of research and development in the broader area of financial decision support. As the contemporary assets have higher potential to cause interest-losing events, stronger fluctuations occur in the risk levels. This creates a need to develop tools that are, on one hand, effective and fast enough to produce reliable models of risky behavior of assets. On the other hand, they have to be able to take dynamic behavior of this risk into account while preserving some prediction power. This is fundamental for investment risk management. In investment risk assessment, it is usually assumed that some volatility measure is a representation of the risk level.

The VIX index, VXN index and so on are two well-known implied volatility indexes. Although options are usually largely traded on stocks of companies included into the indexes, and Futures are largely traded on the indexes on which the indexes are based, there are no empirical studies concerning the relationship between the implied volatility indexes and the underlying assets or asset portfolios. Deviation of true volatility from the implied one may be an early warning marker of trend reversals. Moreover, to analyze asset portfolios or assets as hindered by their volatility measures is indirectly reducing reliability of the analysis results. This is due to the risk dependence of both the underlying indexes and the sunk asset volatility. Empirical studies of the relationship would give us these two fundamental tools as well as extend their usability providing a clear way to what extent underlying assets risk behavioral model is reliable. The empirical analyzes we propose would be valuable from both the practical and the methodological point of view.

10.6. Risk Management Techniques

Risk management in trading is unique to the broad range of investment and trading techniques. Upon the wide variation of trading horizon, liquidity needs, and accepted risks, specific techniques need to be used for different styles of trading and investing. Moreover, investment may collide with trading. A trader shooting at some novelties should be careful if investment prohibits shorting stocks. On the other hand, investment could be more successful if traders on the same team shoot for volatility spikes to make positions more exposed.

There are some standard risk management techniques that are being used in trading systems. Value at risk has long been popular for risk management. Stress testing is a method that becomes stronger due to big events in relation to short event-driven trading horizons. Scenario analysis is a recommended method for longer trading horizons. Mainstream usage by risk managers, as well as an external examination of risk-committed businesses, suggested the greater usage of scenario analysis compared to basic VaR. Although value at risk is absolutely part of mandatory reporting exercises of risk-committed companies by banks and other companies via reporting by the financially responsible party, scenario analysis provides much deeper insight.

Value at risk is a method that rises and falls with changes in the short-term observed return distribution, thus possibly on-the-move transactions and portfolios. Strong back-testing of forward VaR obtained by sliding calendars is suggested by the ease of VaR computation and disclosure compared to any other equally effective alternative. Any other proposed method should not be numerically stronger for back-testing than VaR, as more sophisticated modelling would have a lesser chance of being right, and more technical risk modelling would require users to admit their doubts. The doubt may additionally add refinement by non-parametric VaR vs. observed net portfolio return distributions.

10.6.1. Value at Risk (VaR)

Value at Risk (VaR), the most popular risk measure, originated in the trading departments of financial institutions in the 1980s. In the banking environment, VaR was primarily used to set capital reserves, and for determining the potential loss on a trading desk at the 1st or 99th percentile. The level of reserves was determined as a weighted sum of the VaR results for different risk factors over various time horizons. The weights were designed to consider the liquidity of the specific asset class. They were largely based on probabilities from stress periods, and had been judged to be significant but reasonable enough not to consider a shift from an expected return to loss unbearable. Because an eventual loss occurring at the top quantile is undesirable, financial institutions continually try to improve their VaR estimation process.

Fig 10.2: Trading in the financial markets

Since VaR is not sub-additive (the joint loss of a portfolio can be higher than the sum of losses of its components), financial institutions have extensive experience at looking at the risks they are taking rather than merely computing VaR as a function of portfolio financial data alone. These banks also have the resources at their disposal to implement more sophisticated dynamic techniques for estimating the changes in VaR as new information comes in. In addition to predictive models which they use to forecast the parameters of the underlying probabilistic process, these institutions typically also have very elaborate proprietary models that aim at estimating which of the potential large loss events are especially likely to occur over the next week or so, and what the likely losses would be.

10.6.2. Stress Testing

Stress testing is a risk management technique that estimates how a financial institution's key variables would change as a result of the occurrence of a particular shock or shock scenario or adverse development in a key risk, macroeconomic, or other factor. In stress testing, the key financials or decision objectives of the institution are evaluated for severity with selected adjustments on the key risks. In many cases, stress testing is performed to provide additional information on estimates. In this situation, selected key financials, decision objectives, and underlying risk management objectives are bad debts, net charge-off ratio, net portfolio, provisions for loan losses, allowances for credit losses, and profitability.

Stress testing can be performed for an unregulated financial institution to none or minimal regulatory requirements, but stress testing of financial institutions that have significant trading or capital risk, systemic risk potential, and risk exposure in excess of established size limits is typically required to be performed periodically, using some specific criteria, by regulators. Financial institutions are required to have an independent validation process in place for ensuring integrity of the selected stress testing methodologies, assumptions, key parameters, input data, employee transparency and disclosure, final results, and documentation. Stress testing relies heavily on subjective estimates, typically with benefits that are difficult to quantify and that must be weighed against the costs involved. The majority of the benefits of stress testing typically accrue from retail and lower middle-market entities.

10.6.3. Scenario Analysis

Scenario analysis modifies the minimal VaR dimensionality assumption that risk factors act independently and can be used to evaluate the impact of some correlated economic change, however, it should be done very carefully. Scenario analysis can address the fat-tail problem of VaR in some particular cases since it is not conditional on the remaining moves. It also can remedy some of the shortcomings of stress testing by going beyond a single stress factor. The attractiveness of scenario analysis is that it is simpler and can be more easily explained to management than many other risk measures. The risks lying beyond the statistical confidence level such as Ömega and CVaR are actually risk discounts, which are given a priori guesstimates derived from managerial judgement called scenario analysis. Scenario analysis is in fact the output of the scenario exposure system which should be linked to the input of some VaR system in order to continuously test predicted VaR numbers against the actual results so that the scenario risk discounts or loss exceedances get validated.

Scenario analysis basically amounts to displaying the changes in pre-tax earnings, equity, and VaR as interest rates change. These changes sum to the changes in leveraged pre-tax earnings since no funds flows into the bank except for capital subscriptions by the stockholders. The summed VaR change is composed of two components: the change in VaR due to the net interest rate position and the change in VaR for federally uninsured deposit liabilities and the rest of the balance sheet. The first component is triggered by a small VaR change in the net interest position since this change is at least an order of magnitude larger than all other changes combined. As for interest rate changes, the correlation with bond returns diminishes as industry beta increases because the greater cash flow should lead to stable intrafirm interest rate patterns despite fluctuation in the general industry beta since enough time passes between firm cash flow's correlation with bond returns being negative and switching positions.

10.7. Technology in Financial Decision Systems

The current revolution in financial decision systems derives from the application of several emerging technology areas and breakthroughs recently developed in artificial intelligence, big data, and cloud computing. As the volume, size, and speed of data collection have reached unprecedented levels, many companies and people have been left behind, failing to notice the effects these developments can have in shaping the new economic scene. Many of these results are focused on recommender systems: technology that provides data-driven suggestions for decision makers. Perhaps this is because for most people, looking for the most suitable choice among several options available in a financial or economic market means a practical and objective way to subscribe to the quest for utility maximization.

Decision systems in finance are, however, much broader than that, since they also serve to help decision makers decide when and how to act under uncertainty and risk. This research area is having huge recent development and results thanks to the increasing access that people and corporations have been getting to new tools and technologies for machine learning and data driven computation, namely deep learning neural networks, big data analytics, and cloud computing solutions. The fact that they can be freely accessed and used has also contributed to make these technologies grow, evolve, and improve very rapidly. These tools have made it possible to address questions that could lead to an effective resolution of the financial decision systems' problem. However, the financial domain is restricted to a few financial specific laws. A non-interactive amalgamation model that reflects society and economy while optimizing a limited amount of personal resources underlines all interactions.

10.7.1. Machine Learning Applications

Decisions from the financial domain are too valuable and too important to not take advantage of the most advanced technological means available, especially in our days, when innovation runs ahead at an incredible pace and enables novel and powerful financial decision support system solutions. We focus here on some of the most promising directions of technological utilization: Machine Learning, Big Data Analytics, Cloud Computing. All of these domains come from general computing technology but have been significantly improved and perfected in directions with direct financial domain benefits.

Machine Learning is probably the most remarkable computational innovation, which – although known for some time – has reached society's business's and researchers' attention more recently. Machine Learning refers to a series of mathematical methods, which allow computers and researchers' objectives to discover very complex patterns and associations in data, much more complex and subtle than what any human being or more classical computational means could uncover. The applications of Machine Learning in all domains of Life, Economy, Society have been phenomenal from a type of model perspective, discovery of new classes of tools such as Deep Learning Neural Networks and from results performance.

The automated transactions from computers and algorithms at high volumes and velocities started using more and more complex and powerful Machine Learning-based decision support systems, notably in informing buy/sell decision at each moment, to profit from the small and temporary price inefficiencies that characterize the market at ultra-low time scales. They were aided in their commotion and breakthrough by the parallel computing potential offered recently by Graphic Processing Units, that made the training of extremely large Deep Learning Neural Network architectures computationally feasible and extremely performant as well.

10.7.2. Big Data Analytics

This section addresses the growing importance of Big Data analytics in helping trading, investment planning, and risk management decisions.To successfully attract more investors or keep existing investors, asset management companies need to have a more complete investor profile. This entails data stacking and processing on all the media, like social networks, email communication reports, online public opinion, etc. The data must also be adaptable to the methods to be used. In general, there are two main methods, quantitative method and qualitative method, while qualitative method is rather information-and-time sensitive. Algorithms for quantitative methods also need adaptation for the two types of data, information-oriented or value-oriented performance. Algorithms for performance evaluation are unable to work on qualitative data, and yet qualitative data is significant in that it bridges differences across markets, geographical range, and developmental stages. Results on using only the quantitative method are only partially satisfying, and suggest a general bias.

While this approach is being used by global investors, manipulating massive data on qualitative aspects is still very much in its infancy stage, or maybe too aggressive for some to start with. Manipulating the qualitative data factor-enriched for quantitative methods could be a more prudent approach for researchers, scientists, or industry professionals. Generating unique factors from qualitative data is now much more intricate and complicated due to imperfections in data quality at the essence of qualitative data.

10.7.3. Cloud Computing Solutions

This chapter surveys various types of cloud computing applications developed to provide virtual, scalable, interactive solutions to real-time financial decision systems. Technical, scheduling, and financial aspects of cloud decision systems are reviewed. These real-time planning systems developed on demand offer more cost-effective and quicker solutions than conventional onsite systems. Cloud computing is new in the sense that it captures the essence of outsourcing but is available on demand for all types and sizes of firms as needed. We discuss new features of decision systems available from on-demand, virtualized cloud computing.

Cloud computing is a technology that provides a number of servers, storage, data management, and other resources from the Internet to individuals and firms on demand. The key feature of cloud technology is that it offers an on-demand, pay-as-you-go, provisioned outsourcing option. Cloud computing has emerged as a potential solution to many design challenges posed in information technology. Its modular, integrated approach to rapid scaling of applications is the newest way to deploy and sustain business and social processes and the infrastructure for decision support. With cloud computing, every type and size of firm has access to immense computing resources that take significant initial and ongoing investment to create and manage onsite.

Cloud computing is a consolidated resource management, storage, and application platform incorporated into decision systems and processes as needed. The general features of cloud computing systems include ubiquitous network access, pooled resources and allocation from a pool on a real-time basis, demand-based model, stabilization, and virtualization of design systems to exploit the available resources. The extraordinary feature of cloud computing systems is that they allow interactive applications to respond more rapidly to dynamic consumer demand than conventional onsite systems without requiring online resources to support peak consumption.

10.8. Regulatory Considerations

The increasing use of automated trading systems has raised a number of regulatory concerns. Regulatory authorities have implemented regulatory requirements relating to trading, including those relating to the registration and compliance of all market participants to minimize their chances of failure with a financial shock as well as avoid an adverse impact on the market, such as market manipulation with fake or spoof orders, or market disruptions, such as trading on erroneous low-latency orders. In this context, market participants, including exchanges and electronic communication networks, are required to retain records of all electronic trading activity adequate for audit trail purposes, whether initiated by an algorithm or a trader manually entering order data into the system. Such recording requirements are designed to allow easy visual or electronic reconstruction of events, including circumstances surrounding significant volatility in the market and failover to enforced trading rules, such as cross market circuit breakers stopping major exchanges triggering a market wide halt.

Beneath the trading and order recording regulations, trading also falls under the vast compliance requirements for holding or managing an investor’s account. Wealth managers managing their clients’ wealth and broker-dealers executing trades for clients are obligated to achieve the best possible price in buying or selling instruments for their customer as well as preferably choosing the broker dealer with the least commission charge, but always informing their customers of the commissions due for such trades. Compliance burden entails even prohibitive penalizations in case of committing regulatory wrongful actions for repeat offenders.

10.8.1. Compliance Requirements

Trading has always been scrutinized by tax authorities, with a variety of transaction tax regimes, procedures, agents for particular types of products, and so forth. Regulations often differ at the country and regional levels, and trading different products can lead to different regimes being invoked. However, the information provided is not exhaustive – e.g., we do not have trading firms that take proprietary positions in other firms' products.

Additionally, numerous regulations for principal traders and proprietary trading firms instruct and monitor transaction execution times during the trading process while ensuring integrity, security, and financial stability. There are requirements about acceptable fills or aggressive and passive liquidity-taking during the trading process. These requirements vary from region to region and can be altered by the issuing authority without prior notice. Moreover, after a trading session or session expiration, various reporting duties and other compliance requirements must be fulfilled.

Apart from direct regulators, there are also other entities acting in a capacity that governs the ethical operation of the transaction. Practically, every exchange is also its owner who issues a clear code of ethics and rules that guide the trading and financial decision-making process. It is therefore of cardinal importance for a trader to feel the pulse of the internal rules of transaction engagement and successful trading practice of every single exchange and act accordingly in the roles of its trader and watcher.

10.8.2. Impact of Regulation on Trading

Modern trading and markets amounts to an entire industry underpinning the operation of any market-centric economy. The growing complexity and sheer size of financial markets has led to, and is the result of, somewhat reduced trust and confidence in the operation of markets, combined with the increased damage that can be done by a few bad apples. It is, therefore, no great surprise that regulators have been, or are in the process of being, created in an attempt to assure the public and the economy that the level of trust and reliance has the chance to be respected. The introduction of regulations imposes an added cost to the allocation and functioning of capital in the economy, which can dissuade some actors from participating and affect the price formation involved.

The downside effect of regulations is a direct and indirect cost of doing business. Historically one could argue that 'doing business with a government-based monopoly' - as indirect regulation is often labelled - would be less efficient and less able to provide the costs benefits and efficiencies that market participants could provide. The future, however, lies in a pragmatic appreciation of the realities imposed by operating agents, and regulations, in a highly connected world and economy. Specifically, future developments regarding the dressing code and manner of activities imposed by the modern agents for the provision of trading and trading systems, could be dictated both by addiction to return and rates of returns reflection - profit motive inherited through several generations - as well as the specificities such as risk of firm failure, concern for brand and reputation, contagion effects of correlated value informational mirroring, as well as capital charge implications of balance sheet mismatching.

10.9. Case Studies

Perhaps one of the difficulties of writing about automated financial decision systems is that, at least to the present time, there is relatively little in known case study form. Given that what is being explored here is complex, sophisticated and far from trivial, it seems probable that most of those who have attempted to do what is being proposed, if they have succeeded, either consider the information they have thus assembled to be too valuable to share, or have chosen, for whatever reason, not to document the experience. What is written here is meant to serve at least as a guide to those who may at some later time attempt what we talk about here.

The systems and/or applications discussed in this section comprise systems that meet a number of criteria. These criteria include: they must have been developed with the intent to operate semi or fully autonomously; they must demonstrate the application of Trading, Investment Planning or Risk Management knowledge by Computer; and they must be sufficiently advanced that they merit discussion in a document such as this. Thus, implementations such as broker-specific automated trading applications, which automatically execute basic pre-programmed trading tasks utilizing technical indicators in a simplistic manner, are not included. The diversity of approaches reflected in the following sections may require an explanation. Some sections talk about systems in relatively greater or lesser detail, ultimately reflecting both a less than complete knowledge of what should be shared for some systems and the desire to strongly emphasize some aspects of other systems.

While the reader may be left wondering why such a list of implementations would be of any interest, the reason is simple: many present day and proposed innovative approaches and techniques for automated trading systems, investment planning systems, or risk management systems are not technically unique. Thus, some of the implementations summarized may be of interest in that they demonstrate detailed technical approaches, ideas, or concepts that the reader may not have previously encountered.

10.9.1. Successful Implementations

For the last 8 years, we have been successfully employing such systems for trading "to make a living" on a number of different asset classes, including commodity futures, equity index futures, equity options, stock pairs, currency options, currencies, stocks – domestic and international ones, and for investment planning in foreign currencies. The systems for both trading and investment planning use averaged closed solutions to solve the associated financial decision problems with the closed formulas used as components for system and strategy evaluation, automatic rule creation and selection, and for results adjusting, and on-line updating. We run a few systems for different tasks in parallel, but for the majority of the time only one of the working systems produces the trading signals.

The trading systems take automated signals for their core decision-making (whether to trade and in which direction) from the averaged closed solution based on the optimality principle. An experienced user can easily select a specific sensor for the whole day session or adjust them several times during the day session for better results, if needed, to react to any drastic market behavior changes or to satisfy specific phases of different market participants.

10.9.2. Lessons Learned from Failures

There have been several real-time systems for financial decisions which turned out not to be very successful. The well known failures of many hedge funds should primarily be blamed on the growing focus on statistical efficiencies, mainly due to the abundance of data and improved econometric methods. A rigid, narrow, and often simplistic modelling framework based on the assumption of stationary volatility are often what actually led traders, funds, and investors to losing huge sums of money because downside market dynamics, the so-called fat tails, were incorporated in the wrong manner, or even, were ignored. In recent years, we have entered a world where well-documented high market volatility is actually being statically modelled by volatility playbook traders, usually hedged third party agents, who exacerbate volatility clustering in stock markets of weaker names, meaning that latent volatility is not being modelled at all using ordinary leverage. New highs are being reached much more slowly in low volatility spells than new lows because latency in volatility doesn't leave sufficient room for non-systematic volatility playbook trader positions at new highs. A special class of proprietary high-frequency trading firms are also market makers in extremely short time frames but seem to be relatively non-adaptive to qualitatively different market states associated with kick-off or kick-end of latent volatility clustering. It is these trading and decision systems in particular which have limited decision-making support because they are mainly incapable of capturing the calamitous lower-dimensional monetary aspects that arise from periods of latent volatility clustering as driven by the volatility playbook mentioned. As a result, principles from the functional and rational finance paradigm are often overruled on such a very short timescale.

10.10. Future Trends in Financial Decision Systems

The next two decades will witness technological advances and new applications in financial decision systems for risk management, trading, and investment planning. Sophisticated hardware and software technologies for improving speed and size will reach new levels that will enable the development of new financial decision systems and improve the existing ones. Hardware and software will continue to develop rapidly. Special hardware chips will provide speed enhancement in performance-critical systems. Developments in multiprocessing parallelism will continue to impact many areas of financial decision systems. On the software side, there will be continued advances in development environments and libraries for all areas of financial decision systems. Algorithms developed and improved based on heuristic and metaheuristic various approaches will continue to make an impact in financial decision systems. Further, developments in wireless technology will enable secure mobile access to financial decision systems anywhere at any time, allowing a new mobility dimension for investors, traders, brokers, and financial analysts.

There are, however, two possible scenarios for the development and improvement of financial decision systems in the next two decades, both with unique risks and concerns. The first scenario continues the historical view that the financial system is stable, and that new design systems allow financial participants to better react to and manage changes in return and risk through developments during normal market conditions. The second scenario is one where market dynamics change radically, and financial decision systems that only function during times of market stability are not useful when needed most. Long periods of stable markets are punctuated by infrequent but often extreme events. Continued development of systems, algorithms, and models based on historical experience is jeopardized by changing markets where financial decision systems may not work as intended.

10.10.1. Emerging Technologies

Over the last several decades, the introduction of computers, networks, and their critical supporting tools have brought a profound transformation within and outside developed economies. None of us can fully understand how the new financial order is likely to shape our lives in the future, yet we certainly have an interest in making sure that it does so for the better. To do this, we must try to understand how it works and how the fundamental dynamics of the new financial order interact with our long-standing physical, psychological, and social natures. This is an initial step in our attempt to profit from the new financial order. We will follow this approach and try to understand the emerging new financial system in the future by exploring today's computer and network technologies. This is in line with the assertion that genuine design innovation is rather unusual in the typical setting of a market economy; it is usually the product of a corporate laboratory, a group of highly talented and appropriately supported designers, or a single visionary entrepreneur. The contribution of creative individuals, however, is a necessary, although not a sufficient, condition for genuine technological innovation. Even though machine learning, disruptive blockchain, and quantum computing are at the core of the most transformative technologies that everyday more shape diverse businesses and their respective value chains, they will continue to be disruptors in the coming decades of the financial decision systems that leverage algorithms.

10.10.2. Evolving Market Dynamics

Real-time financial decision systems exist in the context of a complex, dynamic market environment. More generally, our prototype systems are designed to assist users to manage the analysis, choice, and coordination of all business policies relative to the feedback information daily generated by the operation of their economic agents in markets and by the evolution of public policies. The economic agent is the firm or company, but its place in the market structure, its competitive behavior and the derived hedonic valuation of its asset price by the given level of indirect taxation of corporate capital, are totally market dependent. The supportive information relative to the market structure generally comes from specialized banks that carry out primary market activity on behalf of companies; particularly in capital structure, dividend distribution, mergers and acquisitions.

In considering the future development of firms and their future linkages, we illustrate the case of corporate resistance of differentiated products and its estimated significant effects on degree of market integration and detriment of either agents' market share in the party's law of motion. We find evidence that a price elasticity of demand exists which entirely absorbs the existence of several other random effects inducing price changes of either product in the presence of asymmetrical market shares. Policy decisions by market participants can alter the dynamics of financial processes and markets. Agent market shares in stimulus and external business cycle rollings followed, so that market activity. Note that the policies have different effects on marketability than different correlations. Due to the interlinked nature of these systems, careful design is required to ensure that balance is maintained and, if desired, attained.

10.11. Challenges and Limitations

Real time financial decision systems, like any other technology, are subject to limitations and challenges that can limit their practical application. Some of the important challenges and limitations are mentioned below:

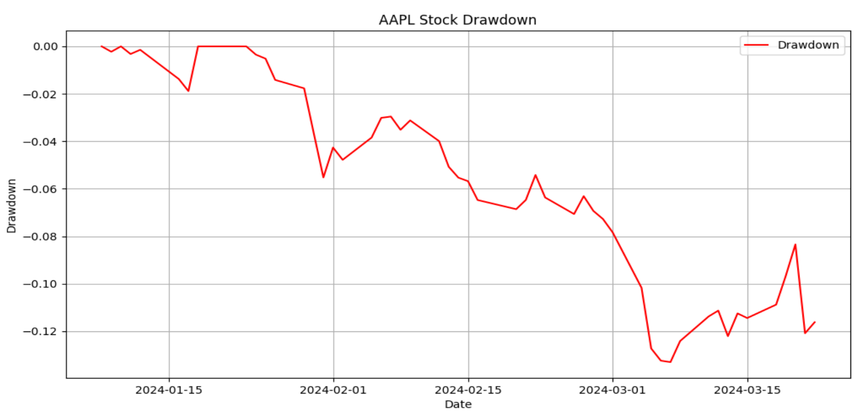

Fig : Real-time Risk Management in Algorithmic Trading: Strategies

The main challenge related to the development of a scientific approach is related to the difficulties in gathering a dataset that can be representative of the problem to solve. In finance, analysts often face several data issues. They have to deal with noisy data with non-negligible amounts of errors, missing values, and irrelevant features. In particular, in the field of machine learning, the amount of available data plays a crucial role in the performance of the model. In finance, models that use real price data are often trained on small datasets.

Given the volatility of the financial markets compared to other contexts in which machine learning is used, overfitting is a major concern. In addition, the limited amount of available data makes data collection, wrangling, and cleaning particularly difficult. Corporate events such as M&As, spin-offs, and bankruptcies change the structure of companies. Analysts need to consider the different constraints that different companies have. This is even more true in the development of anomaly detection models. The analysis needs to define what an anomaly is, and the users should have domain knowledge about the underlying business. These maintenance tasks require expert domain knowledge. In addition, technological requirements have an important impact on the practical application of the system. Machine learning in the financial domain usually requires specific knowledge about the technology used, from the installation of the hardware and software to the configuration and development of the models. The estimated energy requirements associated with the installation and use of machine learning tools may raise a new concern about the environmental impact of financial machine learning systems.

10.11.1. Data Quality Issues

All data used in decision-making systems must be of high quality. The importance of this fact cannot be overemphasized. Many problems due to data quality, or metadata standards and practices, are likely when (1) decision systems are used at the operational level and employ a variety of third-party data sources; (2) data from different sources must be cleaned, validated and verified before being integrated into a unified database and used for calculations in real-time and historical decision systems or data warehouses. Issues can be grouped in three categories. Statistical problems involve data quality for securities and indices prices and returns, data from nearby markets and data computed from continuous or non-traded assets models, including implied volatility, risk-neutral drift and volatility for some fixed-income options, data for the Heston stochastic volatility model or the Vasicek single-factor interest rate and current account processes. We also include here problems related to heteroskedasticity, the correlation of returns, and missing or revised data for data on non-traded prices in our risk models.

Research studies have proposed decision systems for the estimation and testing of the models mentioned above. Information problems involve corporate governance, cyber security, insider trading, and the informational content of financial analysts' forecasts. We consider any data that falls in the category of hard data – specifically prices, trading volumes, financial analysis forecasts and recommendations, risk models, and dividend data – to be widely known by market professionals. Systems have been developed for metadata research and auditing and for soft data collection. This may make reconciliation and consolidation more demanding and time-consuming. This is likely to create issues in the use of profitability accounting data. For the latter, issues can arise as not-applying formulas leads to non-standard periods.

10.11.2. Technological Barriers

Real-time financial decision systems build upon IT and data management innovations. However, technological advances are more limited for challenging tasks such as real-time analysis of big data, decision making based on fuzzy, predictive databases, analysis and search for all possible structured and unstructured complex patterns with references to economic and market assumptions, and prediction of financial transactions to solve decision-making and optimization tasks in investment planning, trading, and risk management. Because of their very nature, financial prediction, planning, and decision support tasks will always persist due to their inherent complexity, difficulty, uncertainty, and dynamicity under market conditions that are subjected to geopolitical, legal, social, and more recently pandemic and human psychological impacts not easy to assess, predict, and quantify.

Real-time financial decision systems can outlive technological barriers by specifying the tasks for which current technological limits may act as constraints. For example, detection of large-scale changes in regimes with sufficient reliability may currently only be achieved with longer temporal series and longer allowable response times. However, this should not preclude having special-purpose scalable micro-models capable of providing service for dynamic local points of interest within specific market areas. As a rule of thumb, vertical interest constrained multi-tasking micro-models are advantageous to general-purpose models that monitor multiple tasks across different vertical markets and that can alert an observer when something interesting happens.

10.12. Conclusion

This chapter presented updated ideas and concepts behind enterprise decision systems and financial decision systems and proposed recently developed and implemented active management real-time enterprise decision systems based on the system paired with portfolio selection real-time financial decision systems containing the system. System processes are presented on examples of virtual companies with time level and microstructure of financial market modules extracted from real data. An important feature of the presented systems is that they provide an opportunity to implement active management in cybernetic space of enterprise processes and robotized decision systems presented in parallel cybernetic variable chosen from practical experiences of enterprise efficiency in the past. This chapter presented interesting and complicated idea of need and method of building portfolio selection systems with stock market index or index of portfolios of efficient enterprise processes or of individual company processes included in the period of portfolio forming. Results of implemented processes for active management of financial markets presented in this chapter and being the first practical applications of enterprise decision systems and financial decision systems, have demonstrated better stability and efficiency of functioning at higher than real time frequency of trading and a better dynamic of risk-return ratio than others based on price patterns by similar criterium provided by confirming their concept of trend following with active management.

Active management with interval of trading about 3 hours and portfolio containing more than several securities, depending on practical opportunities of business with empty sets of securities excluded is possible to be implemented with journey of expected return and variance to the expected return to 0,1. It assures about 10 business and less than 3 family trips monthly or only about monthly basis. Much better traditional value and relative price indicators of business are achieved with portfolios of portfolio influence on index or index of efficient portfolios of business processes. Results have been demonstrated, predicted and explained earlier. Thus, enterprise decision systems are much better tomographic tools for practical real-time research and more useful analytic tools for implementation of decision support and decision automation in active portfolio selection and asset and risk management. This chapter holds materials on possibilities of research in these important and dynamic fields using systems and results in uncertainty estimation, risk modelling, prediction, and minimization for enterprises, for families of intercorrelated enterprises, for portfolios of intercorrelated business processes, and for world economy provided by test interaction programs of world economy.

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