

Multi-Agent Simulation of Stock Market with Netlogo

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ABSTRACT

Multi-agent systems representing artificial stock markets are supposed to offer us a mechanism to evaluate the behavior of agents with diverse capacities (traders) in the stock market. The real stock market is a tremendously complicated system, and genuine stock market traders base their present conduct partially on prior experience and partly on perceived market characteristics based on their past individual behavior. Standard analytical and statistical methods struggle to explain and forecast this complex link between behavior and results.

In recent years, using multi-agent-based models to study the stock market has become a promising research area, because this methodology reflects the nature of the stock market, where heterogeneous investors with various expectations and different levels of rationality interact with each other through the market.

In this MS thesis study, the objective is to develop a multi-agent-based simulated stock market where the basic market scenario, such as stock prices and trading volumes, is given extraneously. Inside the simulated stock market, artificial traders will coevolve using individual learning and social learning. In this respect, agents with different capabilities, such as zero-intelligent traders, fundamentalist traders, and intelligent traders, will heterogeneously share the same environment and interact to maximize their objectives.

The expected results of this study can be listed as understanding the role and affected of different agent types in the stock market, market stability, market volatility, and predictability of market prices using the simulation results.

Keywords: Netlogo, Agent-Based Simulation, Stock-Market, Financial Analysis, Clustering, Artificial Intelligence, Multi-Agents

ÖZ

Yapay borsaları tanımlayan çok aracılı sistemlerin, borsada farklı yeteneklere sahip araçların (tüccarlar) davranışlarını analiz etmenin bir yolunu sağlaması bekleniyor. Gerçek borsa çok karmaşık bir sistemdir ve gerçek borsadaki tüccarlar mevcut davranışlarını kısmen geçmiş deneyimlerine ve kısmen de geçmiş bireysel davranışlarına dayalı olarak algılanan piyasa özelliklerine dayandırırılar. Davranış ve sonuçlar arasındaki bu karmaşık ilişkiyi anlamak ve standart analitik ve istatistiksel araçlarla tahmin etmek zordur.

Son yıllarda, hisse senedi piyasasını incelemek için çok etmen tabanlı modellerin kullanılması, bu metodolojinin, çeşitli beklentilere ve farklı rasyonelite seviyelerine sahip heterojen yatırımcıların birbirleriyle etkileşime girdiği hisse senedi piyasasının doğasını yansıtmaması nedeniyle umut verici bir araştırma alanı haline gelmiştir. pazar aracılığıyla.

Bu yüksek lisans tez çalışmasında amaç, hisse senedi fiyatları ve işlem hacimleri gibi temel piyasa senaryosunun harici olarak verildiği çok etmen tabanlı simüle edilmiş bir hisse senedi piyasası geliştirmektir. Simüle edilmiş borsa içinde yapay tüccarlar, bireysel öğrenme ve sosyal öğrenme yoluyla birlikte gelişecektir. Bu bağlamda, sıfır akıllı tüccarlar, köktendinci tüccarlar ve akıllı tüccarlar gibi farklı yeteneklere sahip araçlar, heterojen bir şekilde aynı ortamı paylaşacak ve amaçlarını en üst düzeye çıkarmak için etkileşime gireceklerdir.

Bu alışmanın beklenen sonuçları, simölasyon sonuçları kullanılarak hisse senedi piyasasındaki farklı acente türlerinin rolü ve etkisi, piyasa istikrarı, piyasa oynaklığı ve piyasa fiyatlarının tahmin edilebilirliği olarak sıralanabilir.

Anahtar Kelimeler: Netlogo, Etmen Tabanlı Simölasyon, Borsa, Finansal Analiz, Kümeleme, Yapay Zeka, Çoklu Etmenler

DEDICATION

Dedication to my dear father and mother, for my constant and compassionate support throughout my life, and special thanks to my supportive sister who has always accompanied me on this journey.

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Chapter 1

INTRODUCTION

Because of the significance of financial markets, any changes in these markets will have a significant influence on the economy. On the other hand, many developments, such as economic, social, cultural, and political, will have an impact on markets.

Thus, this issue will create a two-way interaction between the social economy and turnover in communities and the living conditions of people in a particular geographical area on the one hand, and major financial changes in local and global markets on the other.

As can be seen in Figure 1, multi-agent simulation has many and varied uses in scientific research, including:

- To simulate artificial markets
- To simplify complex models by dividing the system into smaller factors
- To simulate interactive agent-centric models
- To simulate competitive agent-based models
- To model complex systems of individual factors and their environment
- To examine the evolution of unit asset prices.

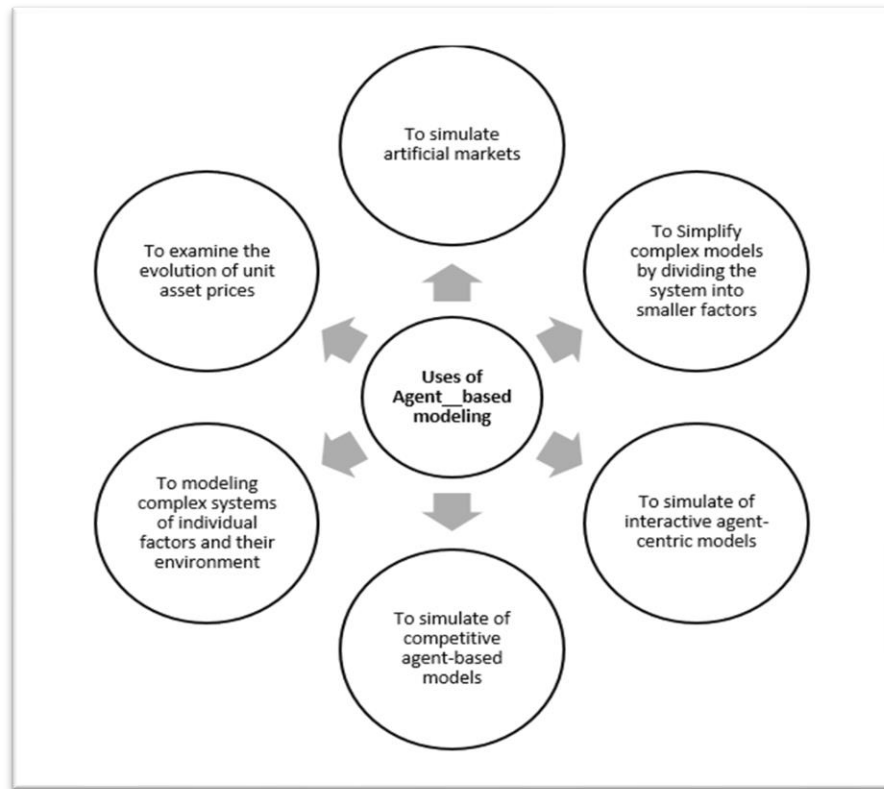


Figure 1: Uses of Agent-Based Modeling

Obviously, in such a situation, the general attention of the world's financial policymakers turns to a better understanding of how the market works and how to predict it to control the economy.

This is where the importance of financial market simulation comes into play. Therefore, in this dissertation, focusing on this goal, a study has been conducted on artificial financial systems, which have several factors that interact with each other and with the market.

Numerous studies have been conducted in recent years to achieve the goal of making significant progress in stock market simulation and performance analysis, and ultimately predicting future market trends.

Several holistic studies have been conducted, for example in the areas of modeling and implementation of new models, and comparison and analysis of the performance of existing models.

The sample examined in this study includes the following:

Modeling of various financial markets [3, 8, 9, 11, 13, and 16], comparative studies of the performance of models according to the method used in their modeling [23, 1], implementation of various simulated models Factor-centered (multi-factor). [4, 6, 17] and analysis of test results [10, 15].

On the other hand, several studies have focused only on one specific aspect. For example, studies on the clustering of investor factors in the market [11,7], the effect of investor factors' behavior in the formation of market trends and prices [23,12], the control and regulatory effect of taxes and transfer costs on the financial stability of the market [19,18] and the formation of network types, etc.

Studies on the formation of network types of influential factors in the process of modeling financial systems include neural networks (artificial neural networks, deep neural networks, transformation neural networks, multilayer advancing neural networks, and frequent neural networks), banking networks, and fuzzy networks, and study the function of systems based on these networks, for example, fuzzy inference system based on adaptive network. [1, 5, 5, 6, 14, 16, 21, 23]

Various tools and methods are used in these studies, which can be technical and fundamental analysis [19,24], log analysis [2,12], performance analysis and sample

analysis [15, 22], statistical analysis including (linear and nonlinear, regression analysis, exponential regression methods, exponential regression, linear regression, correlation coefficient) [2, 16, 24] and time series analysis (Time series, ARIMA, SARIMA) [4.5.7.16], analysis of metrics (dissimilarity criteria) [7], analysis of factors (endogenous factor, exogenous factor [3] influencing the financial market output

In the present model, taking into account the studies conducted so far, we try to simulate an artificial stock market to analyze the behaviors of active agents under the influence of financial fluctuations and ongoing transactions.

It should be noted that the present proposed system is a complex combination of several topics examined in the literature review section that makes the performance of the system more complex than before (networking, clustering, time series, neural network, transaction costs).

For this purpose, 3 kinds of trader models (elementary, technical, and basic) are defined. Each has its group characteristics and communicates with its neighbors to make decisions in the sales process.

Factor clustering and network formation have been used to track and decide on factors. In this model, for simplifying the model, only one stock index is considered for buying and selling. Also, to examine the effect of transaction costs on the activity of agents and the overall market orientation, this cost is included in the performance of traders. The model is flexible in terms of the total number of traders, in other words, in defining the size of the market, and the number of traders can be increased as far as the hardware and executive software used (here the Net Logo-based operating program) allow.

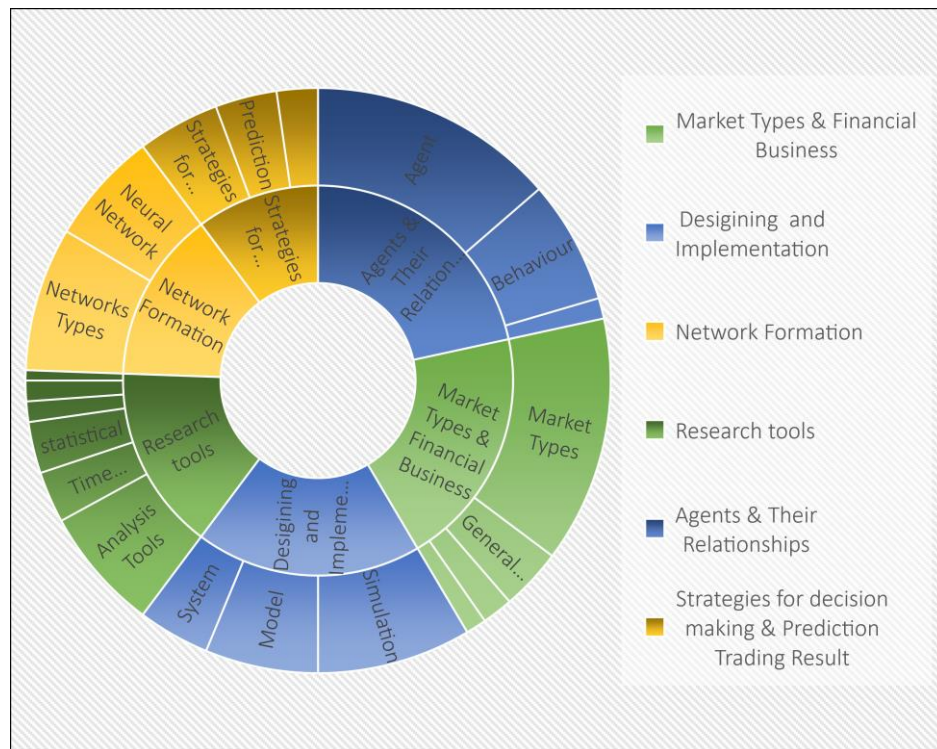
This thesis includes the following sections:

- Literature review
- Methodology including defining the initial assumptions in the model included
 - a Market Agents: characteristics and facilities of traders;
 - b Market environment: market features and facilities;
 - c Governing relationships between simulation Agents (Agents with each other and Agents with the market);
 - d Trading rules (including trading strategy for each trader - transaction costs);
- Mathematic Models definition of mathematical methods and formulas used in the simulation
- Experiments and Results includes tests and experiments performed.
- Conclusion
- Future works
- References.

Chapter 2

LITERATURE REVIEW

In this section, we try to review the literature related to the topic of this thesis, which helps us to gain a deeper insight into the work that has been done in this regard so far.



Abbas Ali Abounoori et al. [1] in their studies try a comparison of two types of stock market forecasting approaches to determine which kind of these models has more explanatory power in forecasting the future processes of the stock. Two static models (Adaptive Neuro-Fuzzy Inference Systems "ANFIS" and Multi-layer Feed-forward Neural Network "MFNN") and a dynamic model (Adaptive Neuro-Fuzzy Inference

Systems "ANFIS") were used in this study (nonlinear neural network auto-regressive model "NNAR"). In this study, only invariable (technical) analysis was employed as the analytical approach, so it does not include all kinds of traders with any strategies. The results show that the method proposed in this article, Adaptive Neuro-Fuzzy Inference Systems) "ANFIS", is more accurate than the other methods. Although this result has already been confirmed by previous studies, it also demonstrated that, when compared to other models, the ANFIS model had a substantially better predicting ability based on the Mean Square Error and Root Mean Square Error criteria.

Ahangar, R. G. [2] develops a model that can be used to forecast the stock values of firms listed on the Tehran Stock Exchange (TSE) during the Global Financial Crisis (GFC).

This was accomplished using linear and exponential regression methods, as well as Artificial Neural Networks (ANNs). After that, a comparison was made between the techniques to see which one was the most effective in predicting TSE stock prices. The results of prior studies in the prediction of stock price had less error. Of course, they just studied specific industries, and this study is especially for the Iran stock market. Their findings cannot be extended to other industries. The findings of this study show that investors may utilize scientific methods to anticipate stock values, allowing them to make profitable stock market investments. Using the model of this study, an investor can predict the stock prices of all companies which have been listed in the Iran Stock Exchange (TSE) since. Neural networks can be used to simulate the behavior of stock prices. They offer a model which is closer to reality than classic methods, according to new research by Tech School. Non-linear methods can decrease the prediction errors more than the linear model because the stock price behavior in the market is non-linear

(Tan et al., 2005). This study shows the superiority and priority of the non-linear models to linear models.

The purpose of the research of Amino Susi et al [3] is to utilize multi-agent modeling to replicate a stock market activity. It will be feasible to investigate the evolution of liquidity in such an environment through the model's many endogenous and exogenous factors.

For simulating the stock market's dynamics based on the actions of investors, they utilized NetLogo, a free, mature, reliable, and fast program with a 22-year development history (from 1999) that is also used to simulate financial markets. The model can be expanded to simulate some other aspects of the financial market, as well as different types of funding. The strong point of their study is to identify and determine the factors affecting market instability, such as the existence of zero intelligent traders (speculative traders), and also to determine the effective mechanisms in the bankruptcy of the traders, like the imitation mechanism. Finally, they show that the stability of the market is strongly impacted by the distribution of trader types and the introduction of the imitation mechanism. The researchers realized the impact of herding behavior on the market stability, as well as the bankruptcy rate.

In this study, the correlation coefficients for linear and exponential regressions are 30.5 and 35.1 percent, respectively, whereas the correlation coefficients for ANNs are 86.041 percent. This demonstrates the ANNs' clear advantage over traditional approaches for forecasting stock values. This means that, especially during the Great Recession, investors must utilize scientific methods to anticipate stock values, rather than traditional approaches.

The major goal of the research conducted by researchers at the Faculty of Mathematics of the University of Barcelona [4] was to use an agent-based model to simulate the evolution of a single asset price. The return series output will be looked upon as a finance time series and an ARCH model comparison. They try to comprehend a few economic principles, as well as some frequent investment habits. They got the help of NetLogo to create simulations with many agents acting independently. They created a simulated time series of log returns using the stock market model. Because of the large number of variables involved, simulating the stock market is difficult. We may make assumptions that are not always correct, or we may oversimplify certain parts. For example, acquiring further assets, even if they sing the stock market model, they had produced a simulated time series of log returns. Because there are so many variables at play, modeling the stock market is difficult. We could make assumptions that are not always accurate or oversimplify some aspects. For instance, their model did not take into account increasing an investor's asset portfolio while still losing money. The importance of model parameters, which determine the dynamics of the model, might also be examined, although it is a less crucial topic. The investor is losing money, which was not considered in their model. The importance of model parameters, which determine model dynamics, might also be covered, although it is a less crucial topic. The presented basic agent-based stock market has a surprising realism feature: the simulated returns series can usually be fitted to an ARMA-ARCH model. As a result of their research, the succession of output returns displays numerous characteristics of actual financial time series, including a heavy-tailed distribution, correlation, and volatility. The primary aim of time series modeling is to predict patterns, periodic effects, observational dependency, and volatile variation.

Based on the study by Colliva, A et al [5] the main issue is that of trying to identify the different results due to the performances of the agents involved in the stock market. The model also includes a special kind of agent, which is endowed with a (supposedly) major forecasting skill. This agent can exploit an Artificial Neural Network (ANN) to predict the future stock price. The ANN has been trained on the time series of prices the agents are looking to and makes predictions based on an information set. Although some procedures that are common in the increasing literature on Artificial Stock Markets, such as price creation and market clearing, as well as any discussion of the accomplishment of a benchmark rational expectation equilibrium, are missing from the program. The impact of predictions and the usage of ANNs on the behavior and performance of agents using ANN models implemented with NetLogo are the subjects of this paper. This study is specifically referring to the extremely contentious random walk theory for stock prices, which has grown into one of the most disputed and intriguing topics in finance since its first breakthrough, courtesy of Bachelor (1900). They discovered that the chances of obtaining a benchmark rational expectation equilibrium were greater than predicted in their research.

Gao, P. et al [6] tried to forecast the index price for the following day using previous data with the help of 4 different methods, and compare results from them to find the method to predict. This study introduces four distinct machine learning approaches in this study, including three common machine learning models: Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), and Convolutional Neural Network (CNN), as well as one attention-based neural network. The basic goal is to forecast the index price for the following day using previous data. The UUA model, which is an attention-based deep learning method, has the best performance in stock index prediction. It could explain the non-linear relationships between various variables, and

also this model has the least MAPE in all of the four models, allowing it to devote more resources to more relevant variables in financial time series while also predicting the long-term. However, this model could not extract vital information in many indicators to reduce the dimension in the inputs and reduce the parameters for training. The results demonstrate that among the different models, the attention-based model performs the best. Furthermore, all of the models presented are more accurate in mature financial markets than in developing markets.

Financial time series clustering is an important area of research and finds wide applications in noise reduction, forecasting, and index tracking. Gupta, K et al [7], in their study, offer two novel dissimilarity metrics that demonstrate improved clustering outcomes when compared to previous approaches. The findings might be used to improve the accuracy of financial time series projections, according to the researchers. The linkage method includes single linkage, and ward linkage is an important aspect of the hierarchical clustering algorithm. It used the 'k', which maximizes cross-correlation between the two-time series X_T and Y_T . This k is defined as the integer 'k', where K is the integer that maximizes the number of times it takes to get X from Y. Financial time series clustering is an important area of research and finds wide applications in noise reduction, forecasting, and index tracking. The paper proposed two new dissimilarity measures that outperform existing dissimilarity measures.

Halaška, M. et al [8] looking into the benefits and drawbacks of agent-based modeling and simulation in the field of BPM in simulation experiments tried to understand whether ABS is required in the field of BPM. For, this has been employed the MAREA simulation framework, which is an integrated simulation environment with an ERP system, and also have been employed automated process discovery approaches to

verify the model. The key limitations and potential barriers to ABS involvement are related to the approach's complexity and robustness, as well as the requisite expertise for its successful implementation.

ABS is a valuable tool for both scholars and enterprises since it eliminates the criticized simplicity in resource modeling. Traditional techniques such as DES and SD have their advantages, but ABS appears to be far more suited and stronger. According to simulations evaluating the influence of changes in resource behavior on the outcome of a company's order-to-cash process (O2C), even slight changes in resource behavior can have a statistically significant impact on process outputs and decisions based on those outcomes.

to demonstrate the movement of price safety development in the financial market, Kanzari, D et al [9], designed and simulate a novel approach of traders' models that modify their actions to the market situation (stable vs. volatility) change. This model took three categories of investors into account: logical (fundamentalist), noise traders, and imitation. There are three categories of decisions: logical decisions (DR), psychosocial decisions (DB), and imitation decisions (DM). It recommended researching the dynamics of asset values in the financial market under two different systems. This study uses Netlogo for modeling. Some shortages in this mode include: the fundamental value (F_t) varies over time; experiments have not been performed with real data; the relations between the factors α , β , γ have not been considered; and the dynamics of the stock market.

experiments back up theoretical assumptions on the importance of mimetic behavior and noisy traders in explaining excess volatility and the development of bubbles.

Marković, A, et al [10] tried to demonstrate how the Internet consumer decision-making process may be modeled and analyzed. The model's goal is to establish a connection between customers and merchants (Internet sales sites) on one hand and to decide how they communicate on the other. Consumers go through the stages of problem awareness, information search, alternative evaluation, purchase choice, and post-purchase evaluation as part of their decision-making process. NetLogo is a piece of software that helps them to keep track of the primary exchanges between the online market's major participants. It is a realistic tool for evaluating B2C online sales systems more accessible. It has the potential to improve the speed and quality of decision-making in electronic trading. However, the observed model does not take into account all of the real factors influencing customer choice, necessitating a careful selection of utility function components, to sum up, all of the important factors that might influence consumers' attitudes and decisions. The study demonstrates that the agent-based simulation and modeling technique may be successfully used for the modeling and simulation of processes on online markets. The findings may be used to analyze the behavior of such markets and track the consequences of various online seller business tactics. A new technique may be utilized to gain a better understanding of the problem of online customer behavior. The interactions of important topics in online sales may be tracked using an agent-based simulation model designed specifically for this study's needs: site users, sellers with various business strategies, and suppliers.

The agent-based approach is a novel perspective on how to simulate consumer behavior. Simple variations at the consumer level led to diverse emergent marketplace behavior, which may be easily simulated using the agent-based technique. Martinho, C. R. et al [11] research provides a few simple instances of markets with a single representative agent (simulated with a C# program) that display varied economic

behavior in this section. It should be noted that the development of direct interaction processes between the agents, such as imitation and word-of-mouth processes, was not part of this project. In this research, consumers engage by influencing one another through their consumption actions. In terms of the degree of realism and complexity of the market simulation, agent-based models of consumer behavior give up new possibilities. Compared to standard modeling methodologies, this strategy has several advantages. The model can be used to simulate a dynamic environment with a variety of deliberative consumers. It demonstrates that the model can easily simulate a variety of marketplaces and economic phenomena, such as pricing, income, substitution, and complementary effects. The agent-based approach is a novel perspective on how to simulate consumer behavior. It allows a more realistic simulation of the behavior of markets. Simple rules describing the micro behavior of consumers can simulate the complex emergent behavior of markets. The proposed model provides the designer of the artificial market more freedom to conceive the simulation. The architecture presented here can serve as a valuable learning and research tool.

Martinovic, J. et al [12] did examinations of log files that can be used to extract useful information about agents and their behavior from an agent-based simulation in a virtual company model. The proposed method builds on the original social network technique by modifying it to focus on agent behavior. The change is based on a definition of the agent-agent relationship. The common attributes that characterize the agents' behavior in the system establish their relationship. Euclidean similarity [20] and cosine similarity can be used to measure how similar two profiles are. The problem was that it couldn't do to find out about the same patterns using the cosine similarity method. Because the agents with no identical sequences will be in separate clusters (groups of agents' behavior) using cosine similarity. So, the issue was that they couldn't identify

small variations in the frequency of sequences in agent profiles because they were too coarse. To remove this disadvantage, the SOM method was used, and the SOM output map was transformed into a graph. Such an approach resolved the problem with the detection of tiny changes in agent behavior. However, this representation had a problem that in the relation between totally different profiles could be constructed. This was caused by the reduction to lower dimensions represented by the SOMM map.

So, in this study, the approach for agent network construction based on agent profiles is described. The construction of the agent network was done using two separate ways. For agent relations, one method employs cosine similarity and graph partitioning, while the other uses self-organization maps and Euclidean similarity.

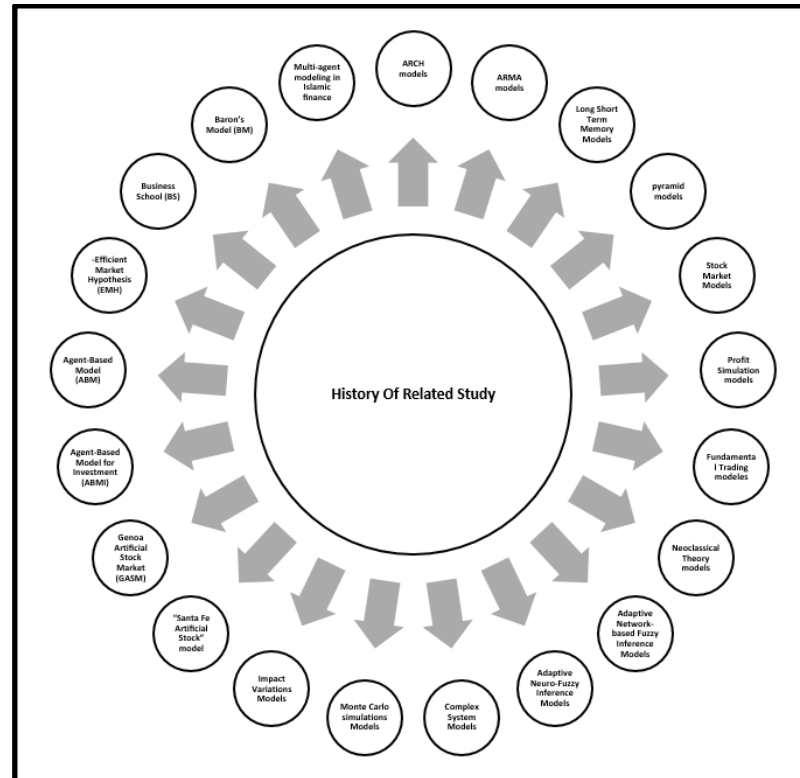


Figure 3: The History of the Related Study Is Brief

Nica, I. et al [14] are investigating the impacts of financial contagion that can spread via a banking network, using the “NetLogo” IT solution to simulate the development of this effect. This study utilized the modeling environment provided by the “NetLogo” 6.0.4 program to show the dynamics of contagion in this financial network and to examine the regulation and self-regulation of banking institutions in a chaotic environment. The financial-banking system's examination of contagion effects is still a relevant and timely topic. This work has been done based on Allen and Gale's model, which illustrates how a regional liquidity shock might cause bankruptcy not just in that region, but also in neighboring regions under specific conditions. This is feasible because of the interconnectedness of the areas, which is made possible by the ties that exist between banks in various regions.

Oldham, M. et al [15] in their study give insights into the factors that drive financial market returns by creating an artificial stock market that uses an existing model-based agent-based model (ABM). Information flows in both directions between neighbors in this model. Intuition implies that this process can turn any network structure into a scale-free network as investors flock to the better-performing investor, culminating in a herd and bubble. Regardless of any initial bias to any of the information sources, there is substantial evidence that a bubble will emerge when investors have created a scale-free network. Investors exhibit a stronger initial prejudice toward their neighbors' activities. If a period of exceptionally high returns attracts new investors to the market, they will seek to join the herd. The mechanics of bubbles in the price of a risky asset are examined in this article. Bubbles are produced when agents with various degrees of confidence in the source of information for distinct assets have different levels of trust in the source of information. Given the greater compatibility of multi-asset models with the real-world considerations faced by investors, this article does not

cover some issues, for example, the impact sufficiency of many assets is sufficient to change market dynamics. Investigating the factors affecting the market efficiency, such as network topology formed by agents, how interaction with neighbors is formed by agents, and consequently, mechanisms of herd formation and bubble formation that are the result of inefficient behaviors of representatives in the stock market. A novel expansion of the behavioral finance model will examine how investors react when their confidence and returns rise and fall. The study sets the groundwork for better informing regulators and investors to reduce wasteful conduct. It will allow much of what behavioral finance has to offer to be incorporated into the model.

For investors, a realistic stock market prediction may be highly beneficial. Making a workable model for this forecast is tricky, due to the stock market's inherent complicated financial data. This issue becomes more challenging when a large range of financial issues influence the stock market index. Pashaei, Z. et al. [16] have made an effort to research this issue and offer a workable approach to address this difficulty. For this, the stock market in Tehran has been used as a real-world case study. To forecast the daily stock market value of Tehran's stock market, the suggested technique uses intelligent nonlinear systems, such as Artificial Neural Networks (ANNs) and Adaptive Network-based Fuzzy Inference System (ANFIS). Finally, the performance of these models was evaluated and compared to that of the linear classical models ARIMA and SARIMA. These time-series data are imposed on non-linear ANN and ANFIS models in the comparison phase; subsequently, using mutual information (MI) and correlation coefficient (CC) criteria, feature selection is performed on the data to extract the most influential characteristics.

The positive point of this study is increasing prediction results of the stock market by up to 55 percent by using MI and CC techniques to pick features in both ANFIS and ANN models. In addition, ANFIS has the potential to outperform ANN in all five assessment criteria. As a consequence, the stock market value is predicted using those variables that have the greatest influence on prediction. This task removes unnecessary data and reduces the rate of errors. Finally, all models are compared against one another using similar assessment criteria to get a comprehensive picture of the exploited models. The results show that using MI and CC techniques to pick features in both ANFIS and ANN models improves stock market forecast accuracy by up to 55 percentage points. In addition, ANFIS has the potential to outperform ANN in all five assessment criteria.

Roman Šperka ET AL [17] tried to help with the ability to undertake trials, which is generally difficult in economics, and using agent-based modeling provides significant tools for minimizing risks in uncertain scenarios. The proposed model is a sophisticated system of trading companies made up of interacting, autonomous individuals in simulation studies. This model is stochastic, dynamic, and discrete in nature. Simple rules govern agent behavior, and their interactions with the environment have an impact on it as well. An agent-based simulation in a multi-agent system is the method employed in this article. It's a simulation environment with a built-in ERP system that uses the REA ontology. MAREA is the framework that is used. Simulation designer is a program that allows you to create a simulation model and tweak the simulation parameters. Because MAREA does not employ double-entry bookkeeping, it differs from ERP systems used in real businesses.

Researchers frequently have difficulty deciding when and when to apply ABMS, as well as understanding the issue itself. Another issue is the validation and testing of those extremely complicated models, which is typically a difficult undertaking. The study discussed the ABMS approach's primary benefits and drawbacks for modeling and simulating complex systems in general. Examining how sales reps' quality of service influences a company's KPIs reveals that the simulation and modeling capabilities of the MAREA framework may be employed.

The overall impact of education and services has a positive influence on KPIs in a changing environment. The quality of sales service is a component of overall service quality, and it has an impact on brand perception and client loyalty. According to simulations, the quality of services has generally beneficial effects on firm KPIs. Findings and added value: Is worked with two categories of clients in simulations: long-term customers and new consumers.

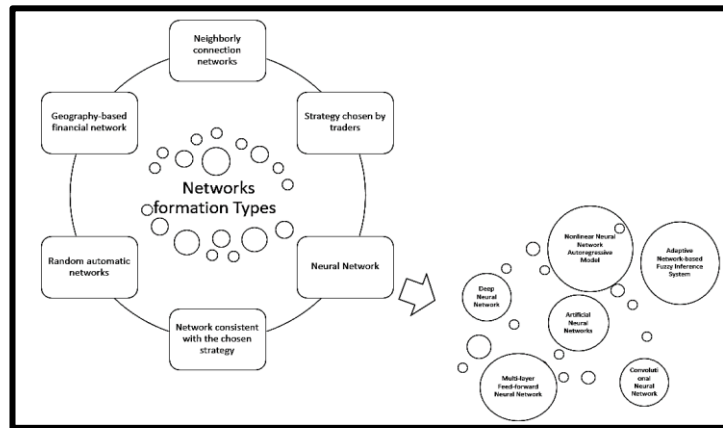


Figure 4: Networks Formation of Agents Investigated

Shi, Y., et al [18] propose a model to explain the financial phenomenon of pyramid schemes in financial markets, developing trading rules for regulators, and developing trading techniques for investors. This study presents an agent-based model to simulate

a type of financial phenomenon with pyramid scheme characteristics. Herd behavior in financial markets is akin to the financial phenomenon with pyramid scheme features. Their findings can be used to design trading rules for regulators and develop trading strategies for investors. Investors can use this model to develop effective investment strategies after evaluating the structure of investors in the market. The relationships between the main fund's rate of return and the proportion of trend investors in all small investors, the small investors' taking profit and stopping loss parameters, the main fund's order size, and the strategies used by the main fund are revealed by simulation results and theoretical analysis. They discovered that when the primary fund employs the method of buying a specified quantity of securities via a single market order in the first trading period and selling them again in the second trading period, the fewer trading periods of buying and selling, the greater the yield.

The study done by Šperka, R et al [19] looked at the impact of transaction costs in particular. Transaction costs may increase as a result of off-market regulation (such as taxes) that affects the stability of the financial market, the overall amount of trade, and other market characteristics. The study illustrates that appropriate transaction fees have a long-term positive influence on financial market stability. In this research, agent-based simulation approaches were utilized to simulate the financial market. The model assumes a generally stable market, with occasional bubbles and crashes. Real-world financial market behavior deviates significantly from the efficient-market concept (Siegel 2003; Allen, Gale 2002). As a result, rather than the efficient-market hypothesis, it is more reasonable to suppose that agents are simply confined to rational judgments. After monitoring pricing fluctuations by including transaction expenses (Tobin tax) in the model, it was found that the negative point occurs when the transaction costs are excessively large (3 percent or more), causing the system to

collapse and the price to rise indefinitely. If the basic trading rules outweigh the technical trading technique. The financial model utilized in this study's agent-based simulation tends to stabilize over time. Although bubbles and collapses will happen in this scenario, their propensities will be less dangerous, since the price will tend to revolve around the underlying value and volatility will be reduced. This explanation is very close to the present financial market position. After monitoring pricing fluctuations by including transaction expenses (Tobin tax) in the model. The Tobin tax was set at a rate of 1.5 percent. While technical traders overrun the market, the price rises in tandem with the transaction expenses to the bubble. However, the price begins to decline in line with the rise of technical analysis. At this point, the market has stabilized and the volatility has decreased. This is the major benefit of the Tobin tax's entry into the financial market. This study shows that appropriate transaction fees (Tobin tax) have a favorable influence on financial market stability in the long run.

Štěpánek, J ET AL [20] tried to investigate the impact of transaction costs on financial market stability, in the long run, using basic commercial and technical rules in transactions by agents has been used agent-based methods of simulation in the case of the financial market. That financial market is a relatively balanced market with bubbles and busts. The model described in this paper is based on some assumptions. Agents are limited to rational; they are heterogeneous and insensitive to the news of market developments, and also their decision is related to their neighbors' decision. Although bubbles and collapses are not eliminated in this model, their tendencies will be less hazardous, since the price will be closer to the underlying value and volatility will be lower. If the basic trading rules outweigh the technical trading technique, the agent-based simulation of the financial model used in this study has the propensity to stabilize over time. Agents employ technical and fundamental trading methods to

determine their speculative investment positions. Appropriate transaction fees have a long-term positive impact on financial market stability, according to the study.

The topic of tools used for research, in the articles whose numbers are displayed here, can be seen in the form of a hierarchical graph in this slide.

As you can see here, the used tools in the first level were divided into 5 main topics. The tools used for research can be seen in the form of a hierarchy in figure 5, The used tools in the first level are divided into 5 main topics, and every one of them has some subtopic.

1. Log analysis
2. Performance analysis
3. Portfolio Analysis
4. Statistical Analysis
 - a. Regression Analysis
 - i. Exponential Regressions
 - ii. Linear Regressions
 - b. Linear Analysis
 - c. Non-Linear Analysis
 - d. Correlation Coefficient
5. Time Series Analysis
 - a. ARIMA
 - b. SARIMA

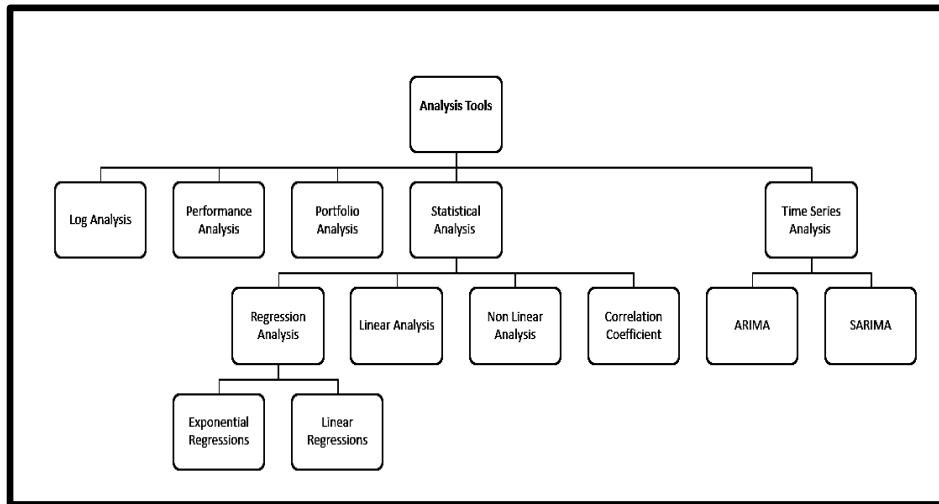


Figure 5: Analysis Tools Used in Related Studies

Suryani, I et al [21] conducted a study on predictive/forecasting algorithms using the non-linear model, Long Short-Term Memory Model (LSTM), for predicting the identified stock future prices. This purposed model has trained four types of networks with models of LSTM. The data set includes information on the previous closing, opening, high, low, and volume of Inf ratel's stocks. Only two months of data are extracted from these databases. This information will be used to train a model for forecasting a company's stock market price on the 61st day. As we know, linear series models such as ARIMA and Auto Regression are univariate time-series-based prediction models. They are incapable of recognizing the underlaid dynamics with the help of multivariate time series, but with different kinds of neural networks, it is possible. For example, ANN proved a better performer when compared to the other three networks (RNN, CNN, and MP). This shows that there lies underlying dynamics, which are very common to all the stock markets. So, the LSTM approach is utilized in this model for forecasting the identified stock future prices, which is trained by providing 60 days of data for a particular business stock. Then the 61st-day stock price may be predicted. The results demonstrate that these neural networks outperform linear models.

In the research done by Su, Z. et al [22] the implementation of a Complex Adaptive System-based agent model in stock trading signaling is described. The model was tested using historical Bank of America stock movement, and random decision rules are used to initialize the system's agents. Also, to decrease the sample space and enhance the decision criteria, genetic algorithms, and machine-learning approaches are used. Monte Carlo simulation is used to create the final rules, which are then tweaked with a market momentum estimate. In this model, momentum is generated by the agents' desire to conduct transactions. The weak point is the lack of a key momentum component for improving the performance of the model. The enhanced CAS model may be highly useful in defining distinct parameters that best define agents' trading strategies, identifying and proposing appropriate positions for different stocks at different periods, and determining the elements that influence an optimum portfolio management approach. The new approach will also have practical applications in portfolio management. This study offers an agent-based model for determining the best times to trade stocks. Between 1987 and 2014, the system was tested in the context of Bank of America. The model outperformed S&P 500 and a buy-and-hold strategy.

In this study, Thakkar, A. et al [23] review the significance and need for a "Deep Neural Network" (DNN) in the field of stock price and trend prediction. To predict the stock market, a variety of NN methods based on deep learning that focus more on CNN, RNN, and other DNN approaches and their subsequent changes to stock market forecasting have been investigated. The emotional, event-oriented, attention-based, and transcendental aspects have also been analyzed to show the appropriateness of NNs in time-series predictions. Nine deep-learning NN models and their predictive performance have been evaluated for several different ICA components. Investment in the stock market may be affected by economic, psychological, as well as social

aspects. For a robust or near-optimal stock prediction model, it may be possible that all the users trade as per the model's suggestions, which may lead to equal profit for all. However, hybrid methods can be used to overcome the inherent limitations of any approach in isolation. These include the identification of suitable dataset duration to analyze the market trend, selection of appropriate functions to derive useful predictions, hyper-parameter tuning, and preparation of the network settings. The analysis showed the importance of model progress, and it can be seen that the model prediction parameters can have a significant impact on the forecast result.

Udagawa, Y. et al [24] tried to apply the definition of both candlestick patterns and price zones where the patterns occur, to apply that information to predict short-term stock price trends. Simulations to estimate market profits are run using historical daily stock data from the US and Asian stock markets, with parameter values for the six-parameter model and exit criterion in terms of standard deviation in almost identical statistics. The suggested stock trading method's profitability is statistically tested using linear regression analysis, which reveals that the time of stock sales is strongly connected to profits for all three exit criteria. Because the study primarily looks at bullish reversal patterns in downtrends, the weak point of their study is that locating the most profitable market in the globe to fulfill the profit needs has certain limitations. The study's findings are primarily concerned with the negative side of the market (downtrend). As for the profitability of international markets, the popular trailing stop criterion gives the best result among the three exit criteria. A six-parameter model for recovering comparable candlesticks is proposed in this work. To detect price trends, the model uses the 5-day and 25-day moving averages, as well as a price zone where a stock price happens. Because a successful stock trade relies heavily on a selling opportunity, three criteria are presented, and the profits generated by each criterion are

simulated. The empirical findings demonstrate that the Dow Jones and NASDAQ are more profitable than the Nikkei 225, Hang Seng, and Shanghai markets in the United States.

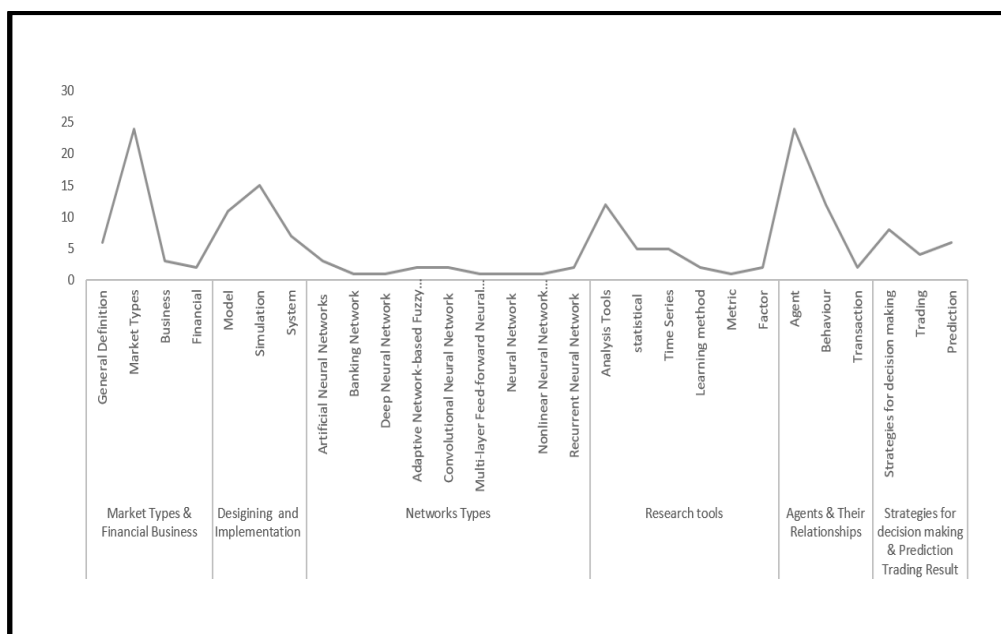


Figure 6: The Effectiveness of the Articles Used In Terms of Number in the Present Case Studies

In Figure 6, you can see how to use articles in terms of the number of topics. Here we have 4 peaks related to 4 main topics that have the highest number of reviewed articles in that field. Two of them are more numerous and two of them are in the next stage.

For example, for topics like network types, the number is less than 5, while for market types the number is near 24.

Chapter 3

METHODOLOGY

Frank Westerhoff created a mathematical model (Westerhoff 2009) that was used in this study. This is a financial market simulation model based on agents.

3.1 Market Investors, Characteristics, and Features of Traders



Figure 7: Topics Covered About "Agents" In the Market

In figure 7, the basic issues in the formation of this simulation are examined. which includes the following

- Understand of characteristics of agents
- Study of the activities and abilities of agents
- Study of how to choose trade rules by representatives
- Investigate how representatives interact with each other (direct or indirect)
- Understand how agents' commands affect each other

- Investigating the effect of interference between heterogeneous agents on the market
- Examining the theory of "rational expectations" on agents (in which factors act under the influence of excessive, fear and peer pressure, is known as behavioral economics).
- A review of the agents against the change of technical mindset with the current price trend.

The basic assumptions of the model include software representatives representing three main categories of investors (shown in figure 8).

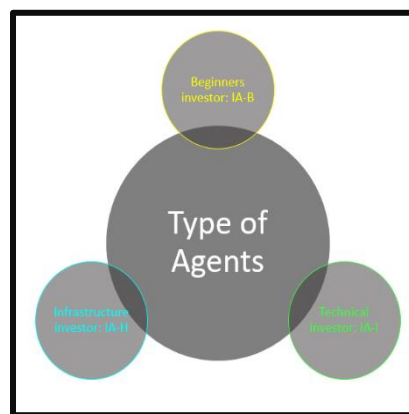


Figure 8: Types of Agents

The novice investor enters the trade randomly and without any logical or emotional thinking. This investor is considered an active trader who interacts with his neighbors and can affect the stability or instability of the market.

Technical investors are those who make decisions based on technical analysis. According to them, prices follow trends.

Fundamental Investors; make judgments based on fundamental research. They believe that the price of assets will eventually return to its original level. When the price of an asset falls below its original value, they buy it.

you can see in figure 9, that the relationships between the agents are defined in this way. Each agent is either a neighbor to other agents or not.

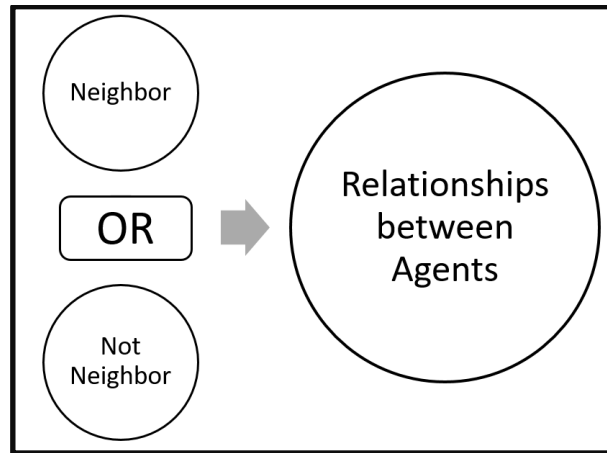


Figure 9: Relationship between Agents in Market

3.2 Agents Types and Abbreviations

NIAP: Total Number of the investor agent population. this symbol represents the sum of the types of investors and is entered only at the initial of the market by the observer as the input of the model, since first the total number of investors must be known and then the number and percentage of each type must be determined. Therefore, it means that there is a relationship between the representatives that if the number of one type of investor decreases, the other types should increase so that the sum of the numbers returns to the initial equilibrium state entered by the observer. For example, we enter

$$NIAP = IA-B + IA-I + IA-H \quad (3.1)$$

the number 40 and assign 35 to the random trading group and assign 5 to the

fundamental trading group, so the remaining number for assign to the technical trading group will be zero unless the number is reset and adjusted again.

$$40 = 35 + 0 + 5$$

- a Beginners' investor: IA-B
- b Technical investor: IA-I
- c Infrastructure investor: IA-H

3.3 Market Environment: Market Characteristics and Facilities

Dominant relationships between simulation investors (investors with each other investors to the market).

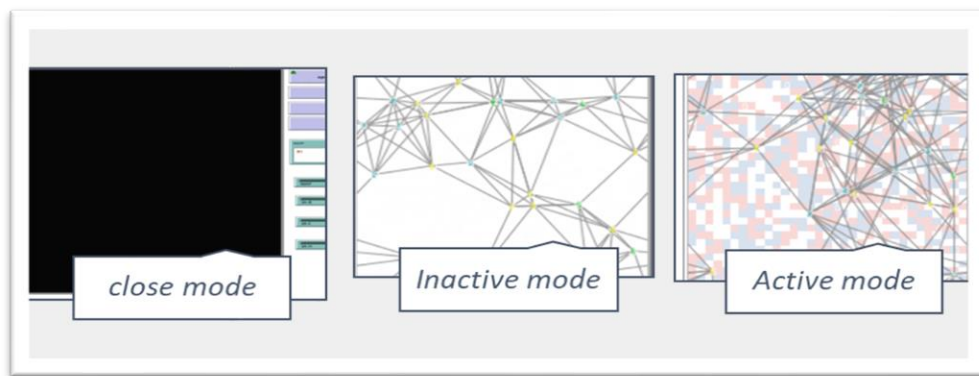


Figure 10: The stages of market formation

The market is initially considered a black environment, which indicates that the market has not yet started operating and is so-called closed, after the initial settings and specified number and percentage Each type of trader in the simulation program (in the form of input by the observer) changes color to white and inactive mode. So, the white color of the display is the beginning of the market but its inactivity (is shown in figure 10).

Investors' relationship with each other: In the next stage, each trader communicates with 7 of the nearest neighbors, which can be seen by the links drawn in figure 11. In this connection, the criterion is only the nearest neighbors and no k-mean methods are used in which the number and distance of neighbors are manually estimated. After establishing these connections, a cohesive dynamic initial network of investors is formed.

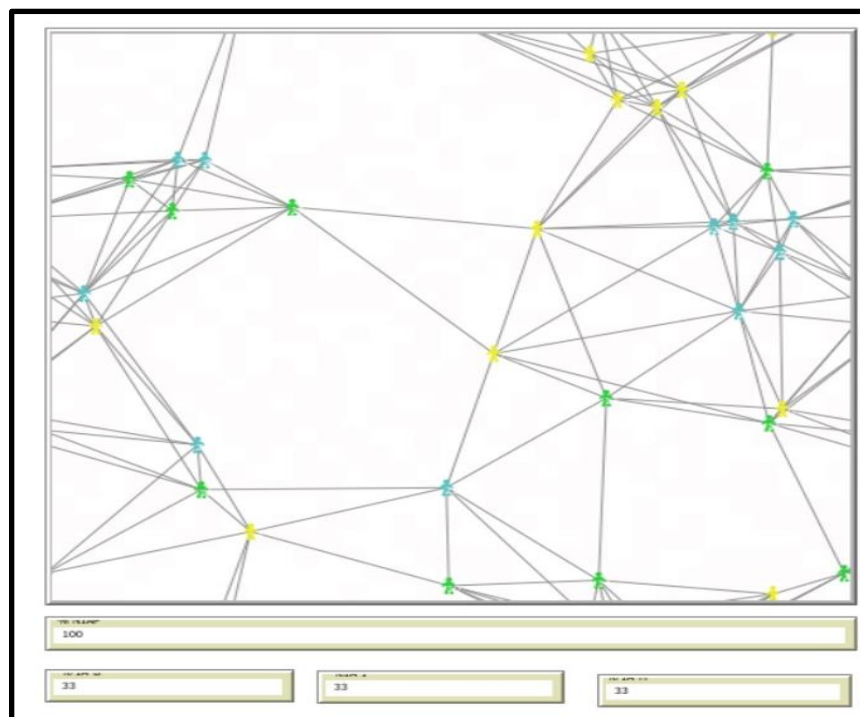


Figure 11: All Types of Investors and Their Relationships with Neighbors

Investors' relationship with the market: In this section, by making any decision by an agent (under the influence of the factors that have been explained in the "decision-making" part) He enters into a transaction of buying or selling, or holding shares, or do not operate in general.

3.4 Trading Rules

Trading rules is including trading strategy and market failure for each trader - transaction costs), The purpose of our work is to simulate the behavior of the stock market according to the behavior of investors: their knowledge of the market and their intelligence, which determines the type and extent of their impact with effective variables such as macroeconomic liquidity, banking deficit, risk aversion or investment capacity. Analytical models generally do not allow us to consider several factors, especially the weight of imitation in decision-making.

3.5 Risk (Prospect Theory)

People's conduct differs in the areas of profits and losses, In financial decisions, the disposition effect is an unreasonable habit and Investors prefer risk-free gains over a riskier choice [32] (shown in figure 13).

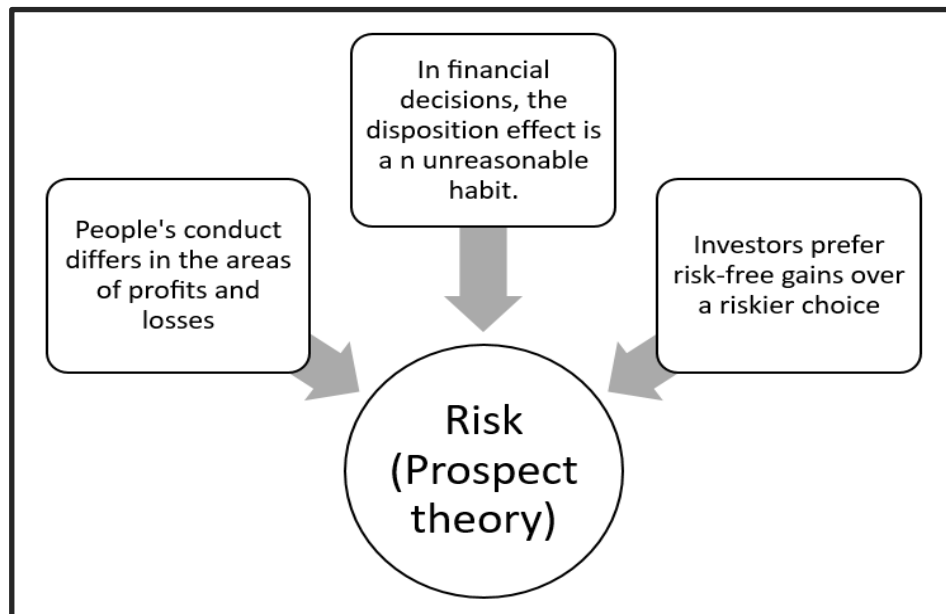


Figure 12:Risk (Prospect Theory)

3.6 Rules of Decision Making

To use multi-factor modeling, investor behavior rules such as the following should be considered:

- Interactions results obtained in past transactions, etc.
- Avoidance of risk
- Personal decisions of each trader according to the type of trader
- Market sentiment and emotions of other investors' behavior
- Risk-taking
- Influence from neighbor's investor
- Compatibility.

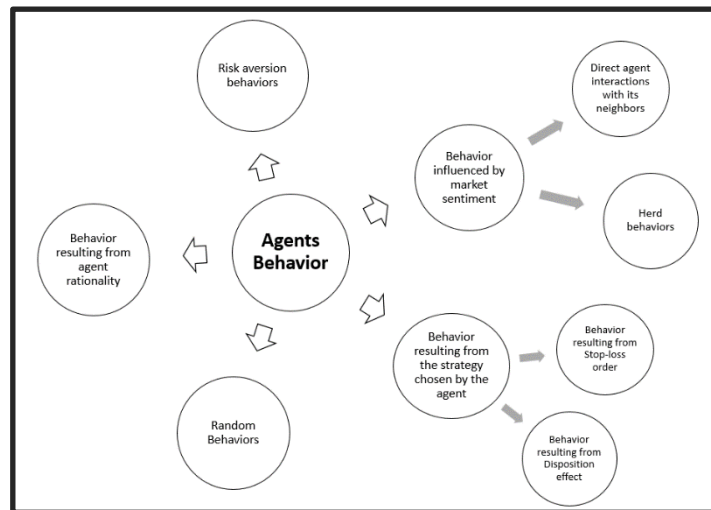


Figure 13: Agents' Behavior

According to figure 13, the Agent's Behavior can be affected by:

1. Behavior resulting from agent rationality
2. Risk aversion behaviors
3. Random Behaviors
4. Behavior influenced by market sentiment

- a. Direct agent interactions with its neighbors
 - b. Herd behaviors
- 5. Behavior resulting from the strategy chosen by the agent
 - a. Behavior resulting from Stop-loss order
 - b. Behavior resulting from Disposition effect

Systems with a high degree of complexity are formed by interactions between units that produce characteristics that are not units in themselves. According to Tesfatsion (see Reference [4]), to offer a more precise description of factor-based computation. A complex system is also compatible if it comprises reaction units, or units that may respond to changing external conditions with various behaviors.

Agent units are regarded as the model's sophisticated adaptive systems, software that integrates both data and behavioral approaches surrounding each one. Agent data, for instance, might be its characteristics, whereas agent behaviors, for example, could be its strategies or method for updating strategies. The goal of this assault on investors is to gain a more accurate picture of real-world systems.

The modeler must modify the starting data and behavioral techniques of each element after implementing the model to identify the system's initial state. Because this model is very dynamic the simulated process has to have the capacity to change over time. as a result of investor interactions without additional modeling involvement.

We created and implemented a basic, factor-based stock market model that replicates the evolution of a company price based on Silva's (2014) collective behavior.

Representatives make individual judgments about which investors to purchase and sell.

The basic premise is that Investors pursue profits under this market concept. As a result, if investors believe the price will climb, they will buy the company's shares in anticipation of this gain and sell it once the price has reached its projected return objective. A lengthy purchase plan is what it's called. Similarly, if investors believe the price is falling, borrow stocks, sell them at a profit, and then buy them again at a loss. Short selling is another name for this approach.

Investors' beliefs, on the other hand, may be incorrect, and their prices may fall (raise) when they anticipate them to rise (fall). When this occurs, it is up to each representative to determine his or her immediate disadvantage.

3.6.1 Agents' Strategies for Trading

Investors have three strategies for making decisions (shown in figure 14):

- Random investment in which investors trade randomly.
- Investors are affected by the effect “disposition effect”
- “Stop Loss Investment”, means that the investor uses stop loss orders depending on the closing time of the positions.

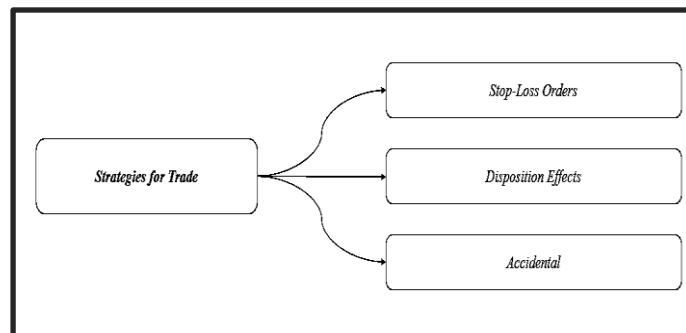


Figure 14: Agent's Strategies for Trading

It should be noted that all investors, regardless of the group to which they belong, try to make a profit by buying long and selling short.

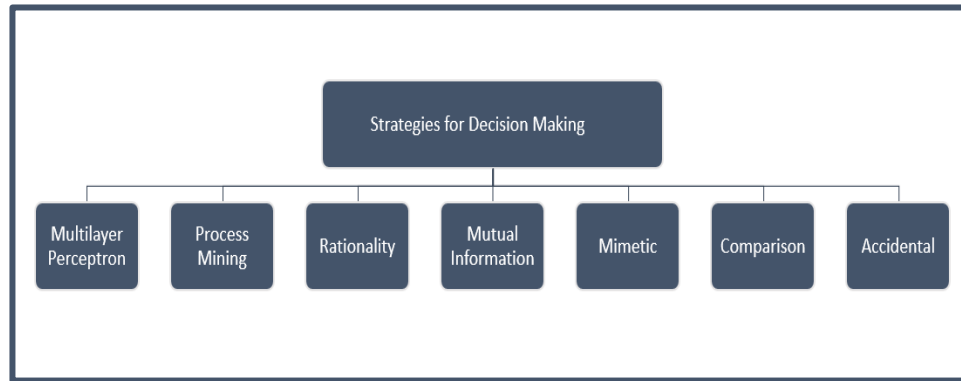


Figure 15: Strategies for Decision-Making by Agents in Market

At any given time, agents either have a long or short stake, or they obtain information from both surroundings and the marketplace mood to enter the market. Long-term dealers close their shares based on the cost. If selling at current prices generates more revenue than one expects, they do sell. The decision to close a losing trade is dependent on the investor's personality. To avoid incurring losses that are greater than the stop-loss, investors sell the orders. Investors hurt by the divestment will sell more if they suffer a loss of 2.25 times their expected return. Finally, if the price does not reach this range, both kinds of financiers will continue to maintain their holdings. Short-term investors, likewise, close based on the price. If purchasing at present pricing provides more money than anticipated, one should purchase.

3.6.1.1 Investors Affected by The Disposition Effect

According to the disposition effect, Investors invest in losing holdings for too prolonged and sell profitable stocks too quickly. A risky alternative that delivers either higher or lower rewards is preferred by investors, according to prospect theory. Researchers Kahneman and Tversky found that when it came to profits and losses,

people behaved differently, with profit-aversion dominating the former and risk-seeking dominating the latter (1979).

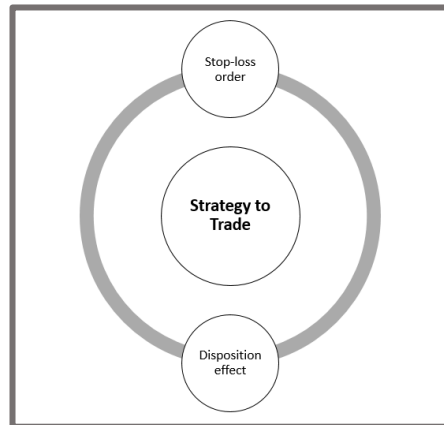


Figure 16: Strategies to Trade

3.6.1.2 Investors Using Stop-Loss Orders

Investments are protected by stop-loss orders, which activate market orders if the price rises over a particular threshold. Both sell-stop orders and buy-stop orders safeguard long holdings, respectively. After reaching a particular price point, the price may fall (or climb) much farther, minimizing the loss by concluding the sale. Assumed in our scenario, the agents who utilize this method always use the same technique.

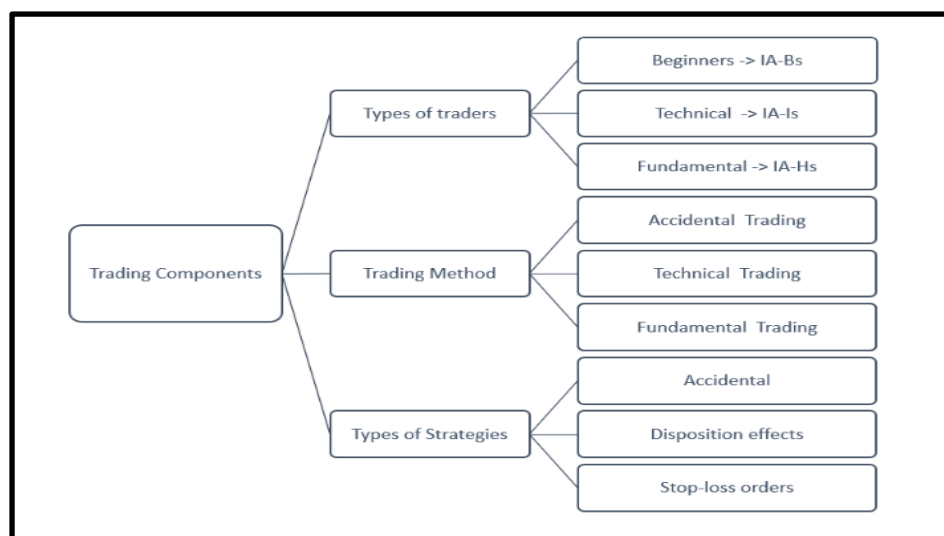


Figure 17: Trading Components

3.6.2 Thinking Methods Doing Trade by All Kinds of Agents

Beginner traders are those who trade randomly. Technical traders are those who make decisions based on technical analysis. According to them, prices tend to follow trends. Fundamental agents make judgments based on market conditions. They believe that asset prices will eventually match their underlying pricing. They acquire an asset when its price falls below its intrinsic value.

The current demand excess is reflected in price fluctuations. Each turn, this excess represents the total quantity of orders issued by technical and fundamental traders. The rate at which their orders are fulfilled changes over time. Agents meet regularly to discuss their trading results. If one agent's relative performance is lower than the others, the others may encourage him to modify his trading technique. The term "communication" refers to direct communication between agents. There is no unique link between communicating agents; they encounter at random.

Profitability, both current and past, is a measure of a rule's success. The approach relies on traders' ability to determine an asset's intrinsic worth. The actors' actions are reasonable.

The price demonstrates the relation between assets bought and sold in a given round, as well as the price movements caused by these orders. The following is a formalization of a basic log-linear price impact function:

The transaction charges are represented by the letter TC. TC remains constant throughout the experiment. While the tax is an out-of-trade component, it will affect

all agents equally. In addition to taxes, there might be other types of transaction costs, such as the cost of getting information. The rise in TC has the following effects.

The price increase will encourage the use of technical regulations. The impact of a price rise on projected future profit opportunities (as the asset's intrinsic worth) is immaterial since they are determined by the company's current condition rather than transaction expenses.

The price rise will attract technical traders in a short period. However, if they start to make money, their interests will wane, and fundamental traders will take over. This will result in financial market stability (price movements are decreasing - price volatility is decreasing).

Chapter 4

MATHEMATIC MODEL

4.1 Mathematical Formulation of Model Hypotheses

With Silva's (2014) collective behavior in the stock market model, we created and implemented a basic agent-based stock market simulation that tracks the price movement of a specific stock as it changes over time. An agent represents the interests of investors who buy and sell based on their criteria. A company's stock may be purchased by investors in anticipation of a gain, and then sold once the price reaches its target return. The Wiener process can accurately recreate the stock price trend that the agents would use to make decisions. The random Traders are agents who, using a Bernoulli extraction, may select their trading position at each time step in a completely random manner. They may be used to simulate the source of price trend uncertainty in the market. In the situation of equal probability, we get the basic distribution form $P = X^n$ for a single binomial distributed variable $p = 1$.

If their close neighbors are purchasing (or selling), Based on this information, they may be prepared to purchase (or sell). Furthermore, an investor j may have additional knowledge advising a buy or sell at any time. To model this situation, we use some auxiliary variables for agent j and buy (or sell) time step t .

4.1.1 Auxiliary Variable

We use an auxiliary variable O^{jt} for agent j in period t that may have additional information at any moment and recommend to the investor j to buy or sell. We take into account both the effect of his/her chosen option and his/her environment's behavior when calculating the influence $O_{buy}^{jt}=1$ means that the agent possesses extra information advising to buy him to buy, and $O_{buy}^{jt}=0$ the agent possesses extra information advising to sell him to sell.

We also use the term ω^{jt} to indicate the investor's trust in his knowledge; as ω^{jt} rises, the weight assigned to his knowledge rises, resulting in a sense of overconfidence. Assumedly that ω^{jt} has the range $[0, \omega_{max}]$ where ω_{max} is a previously defined as much as possible, has a uniform distribution. $\omega^{jt} = 0$ Indicates that the agent pays no heed to the information he has, whereas $\omega^{jt} = 1$, indicates that his knowledge that is equal to the weight of his/her neighbors.

Global Market Sentiment is another issue to consider. I shock, a constant variable linked to extra information, is associated with positive news about the firm if $I \text{ shock} > 0$, despite awful news regarding $I \text{ shock} < 0$. Finally, if $I \text{ shock} = 0$, there is no significant information.

$$I = D_t + I_{\text{Shock}} \quad (4.1)$$

Where;

$$D_t = \frac{s^t - b^t}{n} \quad (4.2)$$

In the above equation; n is the sum of all number of agents (includes IA Bs, IA_Is, IA_Hs so in other words $n = NIAP$). b^t is the total number of buyers in period t and s^t is a total number of sellers in period t .

The β_j is the random parameter $\beta_j \in [0, 1)$ and captures the market sentiment in mind to make decisions. Market sentiment does not affect agent $j=0$, but market sentiment affects agent j when $j=1$.

P_{jt}^{buy} The probability of buying stocks by agent j in a given period t is equal:

$$P_{jt}^{buy} = \frac{b_{jt} + \omega_{jt} O_{jt}^{buy}}{8 + \omega_{jt} O_{jt}^{buy}} + \beta_j I, \text{ if } I > 0 \quad (4.3)$$

Where b^{jt} is the number of purchasers around agent j , there are a maximum of eight purchasers surrounding agent j , and $(\beta_j I)$ is not taken into account if I is less than zero.

P_{jt}^{sell} The likelihood (Probability) of selling stocks by agent j in a given period t is equal:

$$P_{jt}^{sell} = \frac{s_{jt} + \omega_{jt} O_{jt}^{sell}}{8 + \omega_{jt} O_{jt}^{sell}} + \beta_j I, \text{ if } I < 0 \quad (4.4)$$

Where s^{jt} is the number of sellers surrounding agent j (up to 8) and $(\beta_j |I|)$ is ignored if I is bigger than zero.

Maximum value return “ r_{max} ”, is a maximum value previously established. Expected returns follow a uniform distribution on the interval $[0, r_{max}]$

P_t , The surplus demand has a hyperbolic tangent functional form.

$$P_t = P_{t-1} (1 + \tanh D_t) \quad (4.5)$$

If $D_t > 0$ iff $b^t > s^t$, there are more buyers than sellers, and prices rise.

If $D_t < 0$ iff $s^t > b^t$, there are more sellers than buyers, and prices fall.

4.2 Mathematical Formulation of Original Model Transaction Cost

The price reflects the relation between assets that have been bought and sold in a turn and the price change caused by these orders. This can be formalized as a simple log-linear price impact function:

$$P_{t+1} = P_t + a(W_t^C D_t^C + W_t^F D_t^F) + a_t \quad (4.6)$$

The phrase “ a ” is a normal random variable with such a value between 0 and a uniform variance “ σa ” that brings the randomized term to Eq. (4-6) which is independent and identically distributed. A positive price adjustment coefficient is denoted by the letter D_t^C , which are orders generated by technical agents while factor b is not negative, indicating that the agent is sensitive to price fluctuations. The trend is reflected in the difference in brackets.

The phrase “ β ” is a normal random variable with such a value between 0 and a uniform variance “ $\sigma \beta$ ”, that brings the randomized term to Eq. (4.7) which is independent and identically distributed.

Technical analysis elaborates on price patterns, and when they rise (the price rises), agents purchase the assets. So, for technical order rules, formalization may look like this:

$$D_t^C = b(P_t - P_{t-1}) + \beta_t \quad (4.7)$$

D_t^F , are the orders of fundamental ones. The fundamental analysis permits the difference between price and fundamental value for short time only. In long run, there is an approximation of them. So, if the price is below the fundamental value – the assets are bought and vice versa – the orders according to fundamentalists are formalized. Parameter c is a positive parameter and presents agent sensitivity to reaction. represents fundamental value – we keep a constant value to keep the

implementation as simple as possible. The “ γ ” is the random term and it is a normal random variable with a mean of zero and a constant standard deviation σ^γ that is independent and identically distributed.

Weight: The present ratio between the accidental, technical, and fundamental agents is reflected in the weight. W_t^C weights of agents who use technical rules, and weights of technical traders

$$W_t^C = K_t/N \quad (4.8)$$

W_t^F the weights of agents using fundamental rules and the weight of fundamental traders:

$$W_t^F = (N - K_t)/N \quad (4.9)$$

$N=n=NIAP$ is the sum of all traders in the market and K is the sum of technical traders. At each phase, two traders meet and discuss the success of their guidelines. If the second agent's rules seem to be more effective, the first agent alters its action with probability $K_t(1-\delta)$ is the probability of a transition. There's also a chance that the agent will alter his mind on his own. The formula for transition probability is:

$$K_t = (K_{t-1} + 1) \text{ with , probability } P_{t-1}^+ = \frac{N - K_{t-1}}{N} \left(\varepsilon + (1 - \delta) \frac{F \rightarrow C}{t-1} \frac{K_{t-1}}{N-1} \right) \quad (4.10)$$

$$K_t = (K_{t-1} - 1) \text{ with , probability } P_{t-1}^- = \frac{K_{t-1}}{N} \left(\varepsilon + (1 - \delta) \frac{F \rightarrow C}{t-1} \frac{N - K_{t-1}}{N-1} \right)$$

Where the probability of a fundamental actor becoming such a technical actor is:

$$\begin{aligned} (1 - \delta_{t-1}^{C \rightarrow F}) &= 0,5 + \lambda, \text{ for } (A_t^C > A_t^F) \\ (1 - \delta_{t-1}^{C \rightarrow F}) &= 0,5 - \lambda, \text{ otherwise} \end{aligned} \quad (4.11)$$

, And vice versa

$$\begin{aligned} (1 - \delta_{t-1}^{F \rightarrow C}) &= 0,5 - \lambda, \text{ for } (A_t^C > A_t^F) \\ (1 - \delta_{t-1}^{F \rightarrow C}) &= 0,5 + \lambda, \text{ otherwise} \end{aligned} \quad (4.12)$$

Success (efficiency of the rule) is measured by past profitability of the regulations that are codified as follows:

For The Technical regulations

For the fundamental regulations

The most recent performance (after the A_t^C formula respectively A_t^F) is used by the

$$A_t^C = (\exp[P_t] - \exp[P_{t-1}])D_{t-2}^C + dA_{t-1}^C \quad (4.13)$$

$$A_t^F = (\exp[P_t] - \exp[P_{t-1}])D_{t-2}^F + dA_{t-1}^F \quad (4.14)$$

agents, and orders placed in period $t - 2$ are executed at prices that were in effect in period $t - 1$. My optic earnings are computed in this manner. Memory is a feature of agents, and it is represented by the parameter d . $0 \leq d \leq 1$ are the values. If $d=0$, the agent has no memory; otherwise, it has a considerably greater value. Profits have a far greater effect on rule fitness.

4.3 Mathematical Formulation of Customize Model Transaction Cost

The introduction of transaction fees will have a strong influence on the pricing of the asset. Market participants will profit from the price gain, but once they realize profits, their interests will fade, and fundamental traders will take over. The impact of a price rise on projected future profit opportunities is immaterial since they are determined by the company's current condition rather than transaction expenses.

$$P_{t+1} = P_t + a(W_t^C D_t^C + W_t^F D_t^F) + TC + a_t \quad (4.15)$$

Chapter 5

EXPERIMENT AND RESULT

5.1 Interface of Simulation

The user interface is very important for understanding the simulation and providing visually understandable output and graphs, and therefore its user-friendliness is one of its notable priorities. (See figure 18). In this section, we will introduce the components of this section.

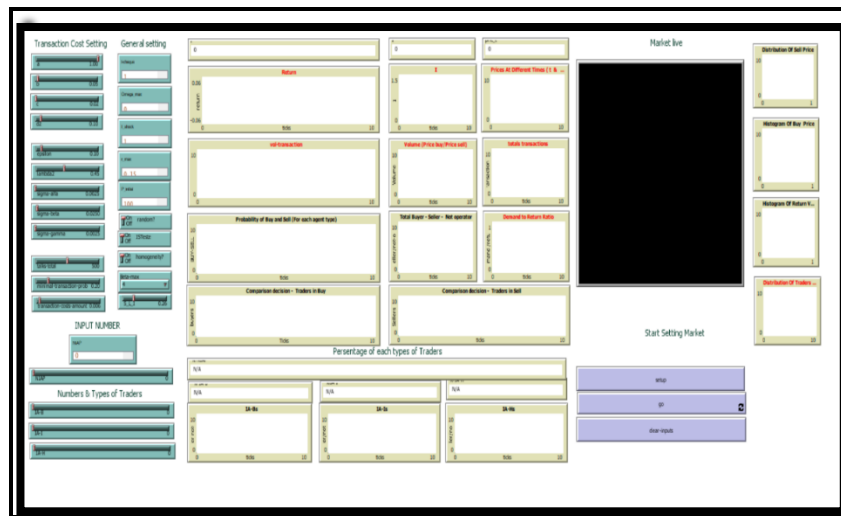


Figure 18: Interface of Stock Market Modeling

5.1.1 Outputs Monitors Includes

- r : Output of return value in period t
- I : Value of I variable in period t
- $Pric_t$: the real-time value of price in the Market

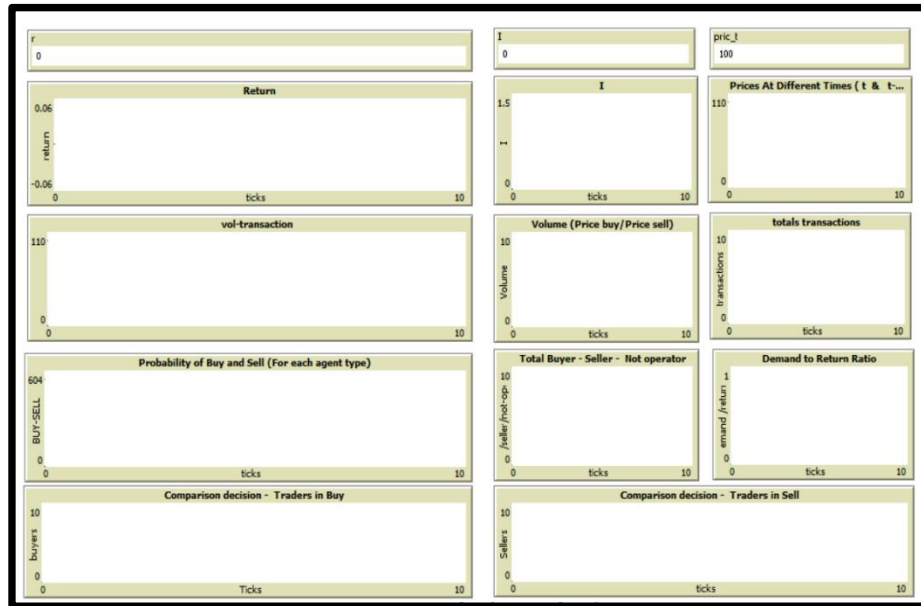


Figure 19: Interface of Stock Market Modeling - (Plots and Monitors)

5.1.2 Plots and Histograms

The best tool for statistical analysis of time series is the use of customized plots (see figure 19 for row graph and plot), so graphs have statistically valuable information in our work

- Return
- I
- Prices at the different periods (t, t-1)
- Vol-transaction
- Volume price ratio (the price of buy/price of sell)
- Total transactions in the market (includes sell and buy)
- Probability of buying or selling
- Total number of sellers, and buyers, not-operate in market
- Demand on return ratio
- Comparison decision – traders in buy
- Comparison decision – traders in sell

- Histogram;
- Histogram distribution of selling price

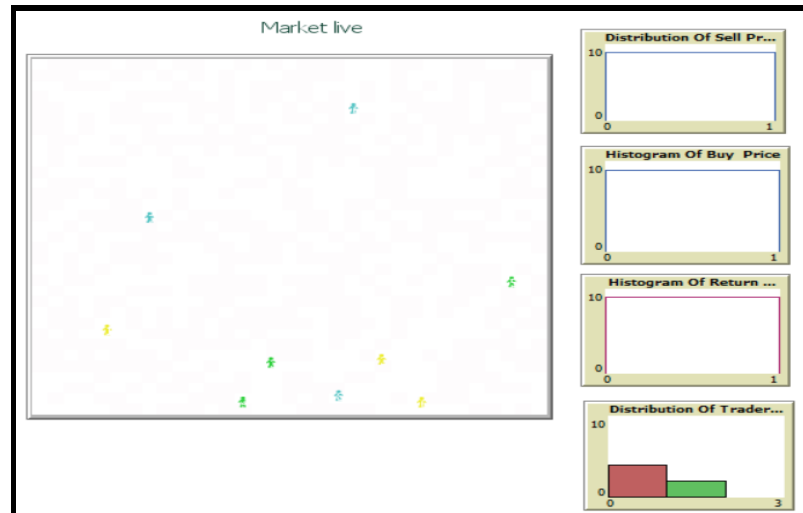


Figure 20: Interface of Histogram

5.1.3 Initial Setting

The initial parameters are set in the same way in all experiments (Figure 21) because each experiment focuses on the changes of one factor and the interaction of other factors with the variable factor.

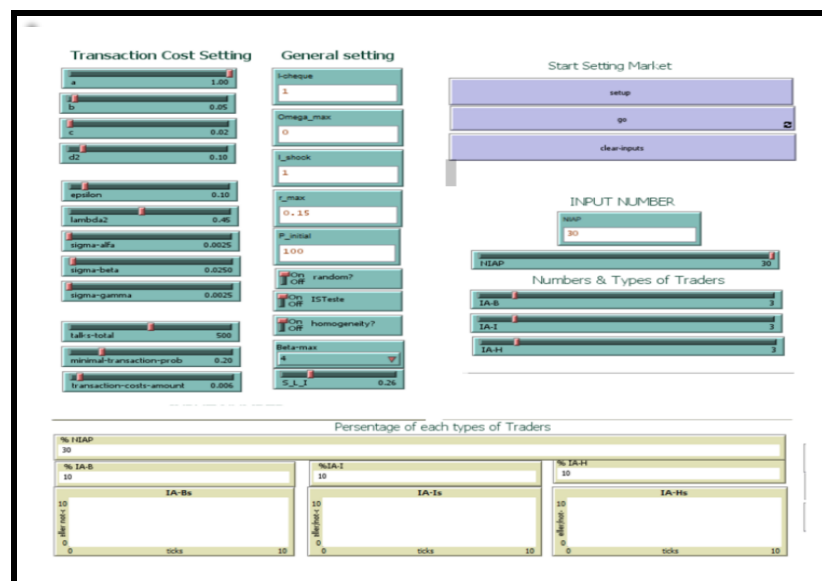


Figure 21: Interface Input of Stock Market Model

5.2 Experiments: Experiment A

5.2.1 Assumption A1

- The number of all three types of traders is equal to each other
- Accidental traders: IA-B=10
- Technical traders: IA-I=10
- Fundamental traders: IA-H=10
- Total number of traders: NIAP= 30
- The cost transaction factor is not calculated.
- Traders trade from 3 main strategies (Random Trading, Disposition Effects, and Stop-Loss Orders Losses).

The results of each trade include buying, selling, or inactivity. The results can be seen in the figure below.



Figure 22: Plot Related to Experiment Number A1

5.2.2 Assumption A2

- The number of each trader is as follows:
- Accidental traders: $IA-B=30$
- Technical traders: $IA-I=0$
- Fundamental traders: $IA-H=0$
- Total number of traders: $NIAP= 30$
- Weighting of accidental trading is 1 and another trading is 0.
- The cost transaction factor is not calculated.
- Traders trade from 3 main strategies (Random Trading, Disposition Effects, and Stop-Loss Orders).

The results of each trade include buying, selling, or inactivity. The results can be seen in the figure below.

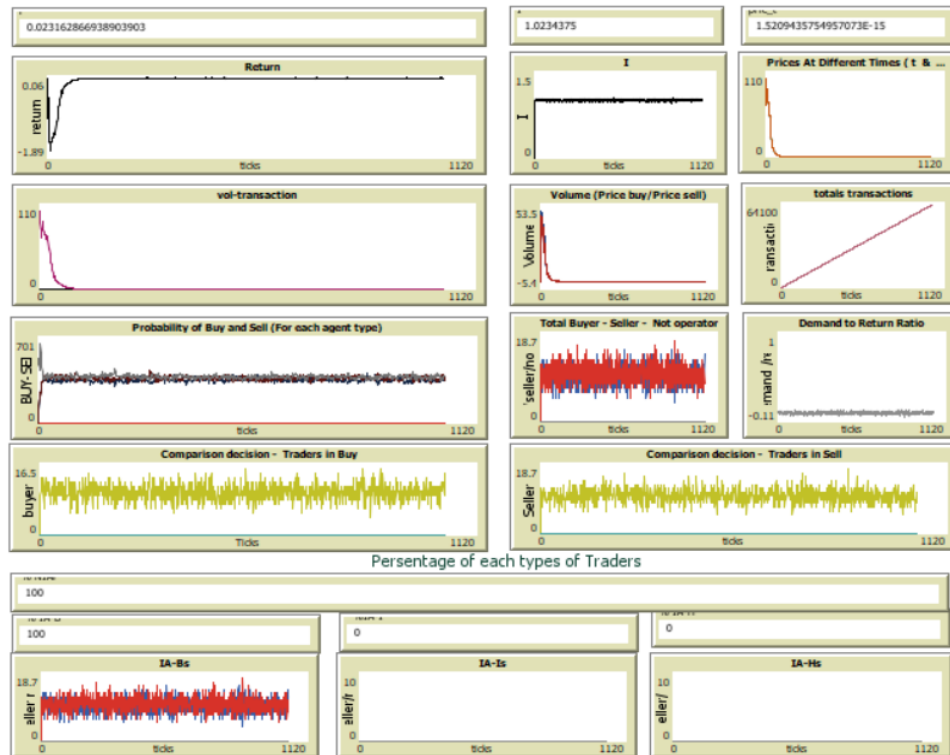


Figure 23: Plot Related to Experiment Number A2

5.2.3 Assumption A3

- The number of each trader is as follows:
- Accidental traders: $IA-B=0$
- Technical traders: $IA-I=30$
- Fundamental traders: $IA-H=0$
- Total number of traders: $NIAP= 30$
- Weighting of technical trading is 1 and another trading is 0.
- The cost transaction factor is not calculated.
- Traders trade from 3 main strategies (Random Trading, Disposition Effects, and Stop-Loss Orders).

The results of each trade include buying, selling, or inactivity. The results can be seen in the figure below.



Figure 24: Plot Related to Experiment Number A3

5.2.4 Assumption A4

- The number of each trader is as follows:
- Accidental traders: $IA-B=0$
- Technical traders: $IA-I=0$
- Fundamental traders: $IA-H=30$
- Total Number of traders: $NIAP= 30$
- Weighting of fundamental trading is 1 and another trading is 0.
- The cost transaction factor is not calculated.
- Traders trade from 3 main strategies (Random Trading, Disposition Effects, and Stop-Loss Orders).

The results of each trade include buying, selling, or inactivity. The results can be seen in the figure below.

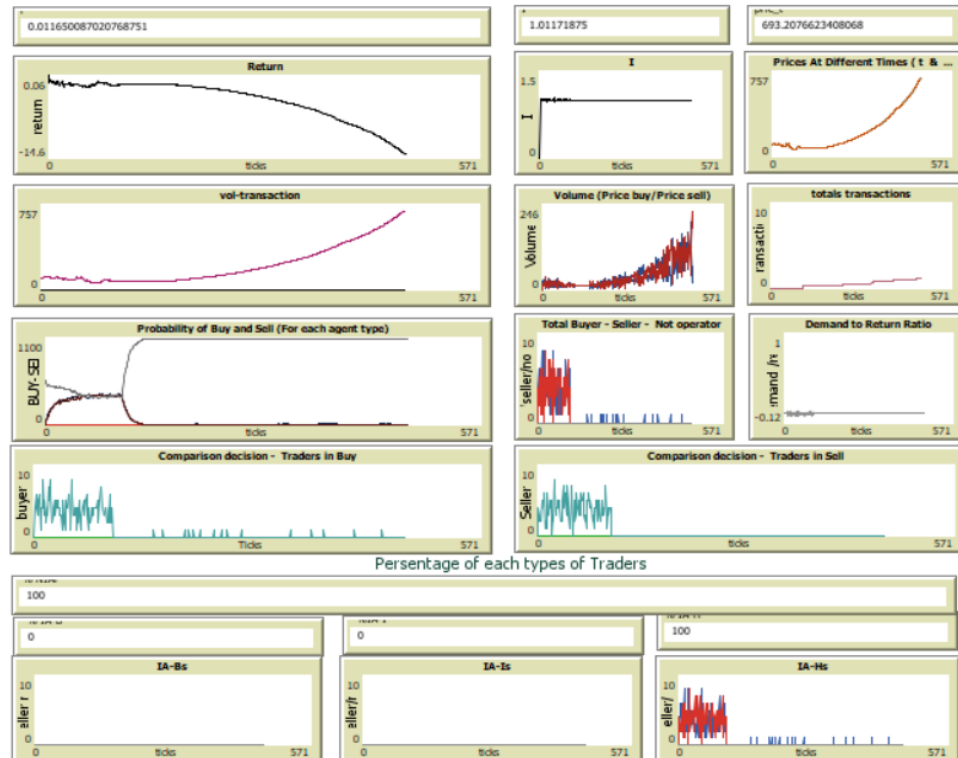


Figure 25: Plot Related to Experiment Number A4

5.2.5 General Result of Experiment A

In experiment A, we removed the entire TC (Transaction Cost) factor from the transactions and in the absence of the controlling factor, we examined the market situation according to the distribution of factors in terms of trading expertise (types of random, technical, and fundamental trade).

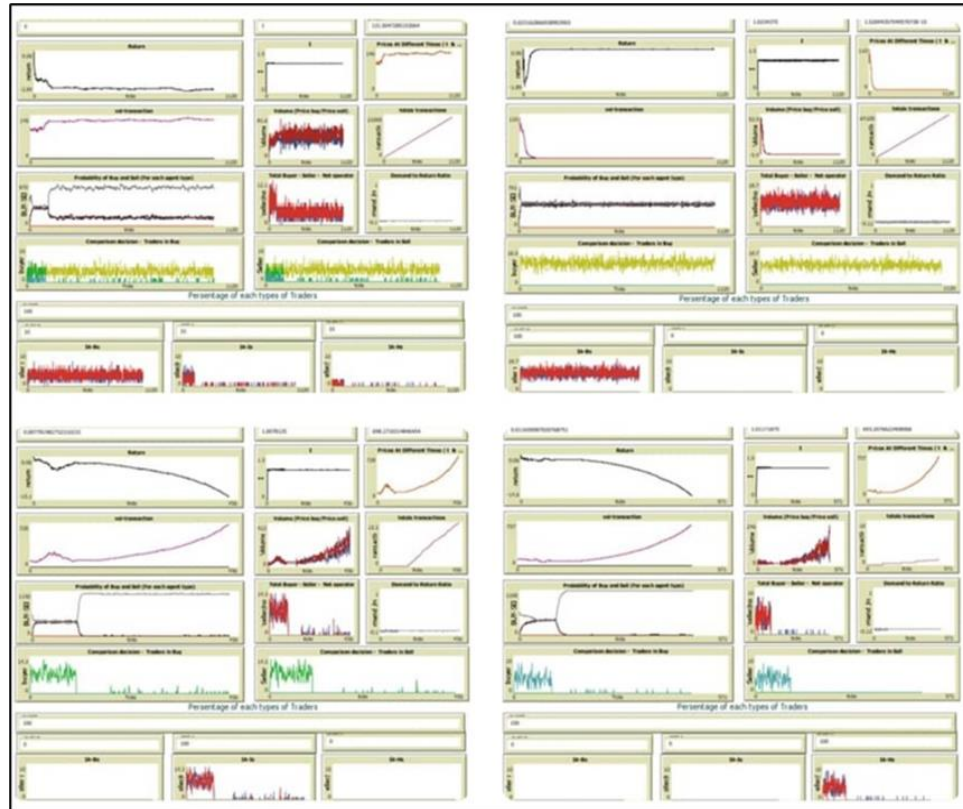


Figure 26: Comparison of result experiments (A1, A2, A3, A4)

To summarize, we can say, without considering transaction cost this result is obtained; In the case of an even distribution of traders in the market, we reach stability in the price and stop trading by professional traders and the number of active traders in the market decreases, the Return decreases, but the volume of transactions is almost constant. The presence of more professional traders in the market, such as technical and fundamental traders, will lead to a decrease in Return and a price increase, while more random traders will cause a decrease in price and an increase in Return.

In the market, stop loss strategies or disposition effects, are behavioral similar and follow similar trends but when the distribution of traders is uniform, such as in figure 22 or there is only one type of trader with a specific strategy, the shape, and inclination of graphs are completely different and trends are sometimes opposite directions. From this experiment, it can be concluded that when the market control agent such as TC (Transaction Cost) is not available, the way traders are distributed in the market and the diversity and inconsistency of traders (even random type or without strategy) cause instability as a result of market outputs such as (Number of buyers and sellers, purchase and sale prices, the total volume of transactions and market sentiment, and even the amount of return in the market.

5.3 Experiments: Experiment B

5.3.1 Assumption B1

The number of all three types of traders is equal to each other

- Accidental traders: $IA-B=10$
- Technical traders: $IA-I=10$
- Fundamental traders: $IA-H=10$
- Total number of traders: $NIAP= 30$
- The cost transaction factor is calculated and exists.
- Traders trade from 3 main strategies (Random Trading, Disposition Effects, and Stop-Loss Orders).

The results of each trade include buying, selling, or inactivity. The results can be seen in the figure below

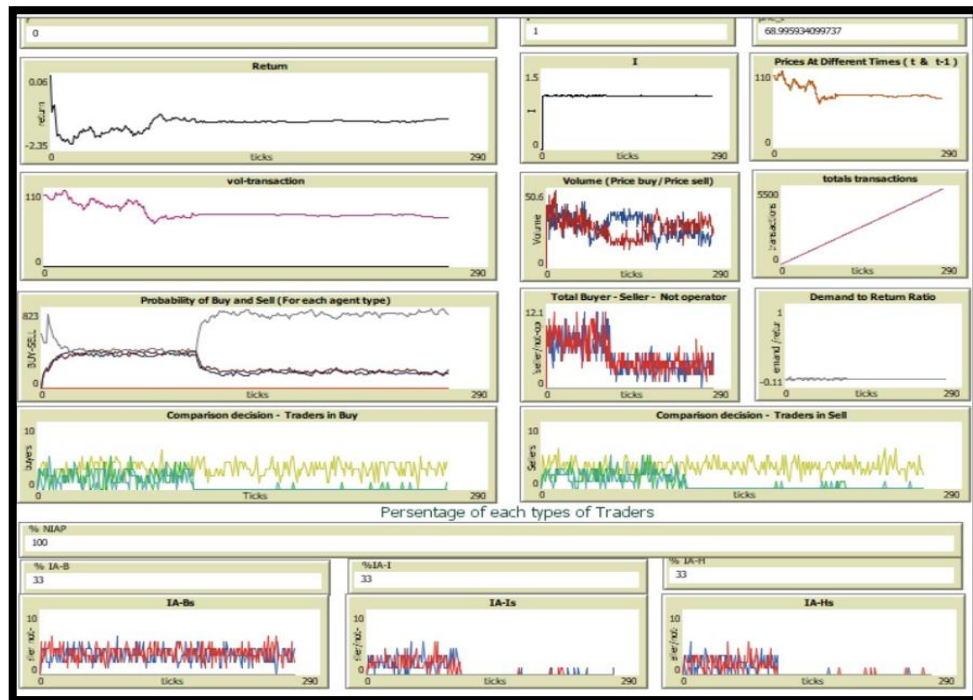


Figure 27: Plot Related to Experiment Number B1

5.3.2 Assumption B2

- The number of each trader is as follows:
- Accidental traders: IA-B=30
- Technical traders: IA-I=0
- Fundamental traders: IA-H=0
- Total number of traders: NIAP= 30
- Weighting of accidental trading is 1 and another trading is 0.
- The cost transaction factor is calculated.
- Traders trade from 3 main strategies (Random Trading, Disposition Effects, and Stop-Loss Orders).

The results of each trade include buying, selling, or inactivity. The results can be seen in the figure below.

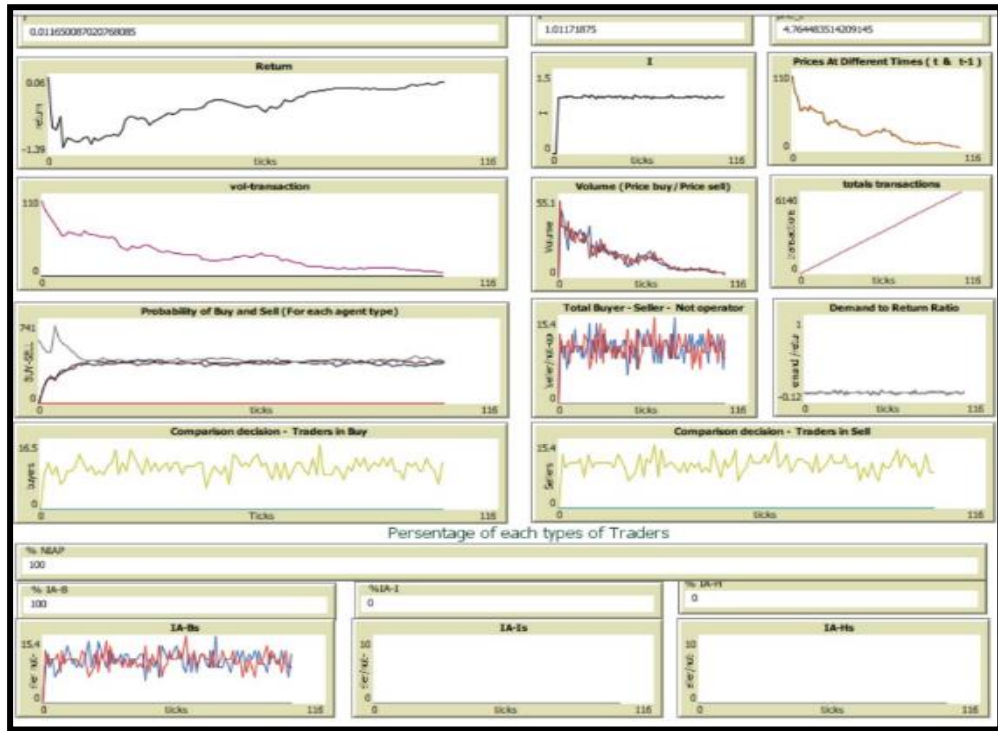


Figure 28: Plot Related to Experiment Number B2

5.3.3 Assumption B3

- The number of each trader is as follows:
- Accidental traders: $IA-B=0$
- Technical traders: $IA-I=30$
- Fundamental traders: $IA-H=0$
- Total number of traders: $NIAP= 30$
- Weighting of technical trading is 1 and another trading is 0.
- The cost transaction factor is calculated.
- Traders trade from 3 main strategies (Random Trading, Disposition Effects, and Stop-Loss Orders).

The results of each trade include buying, selling, or inactivity. The results can be seen in the figure below.

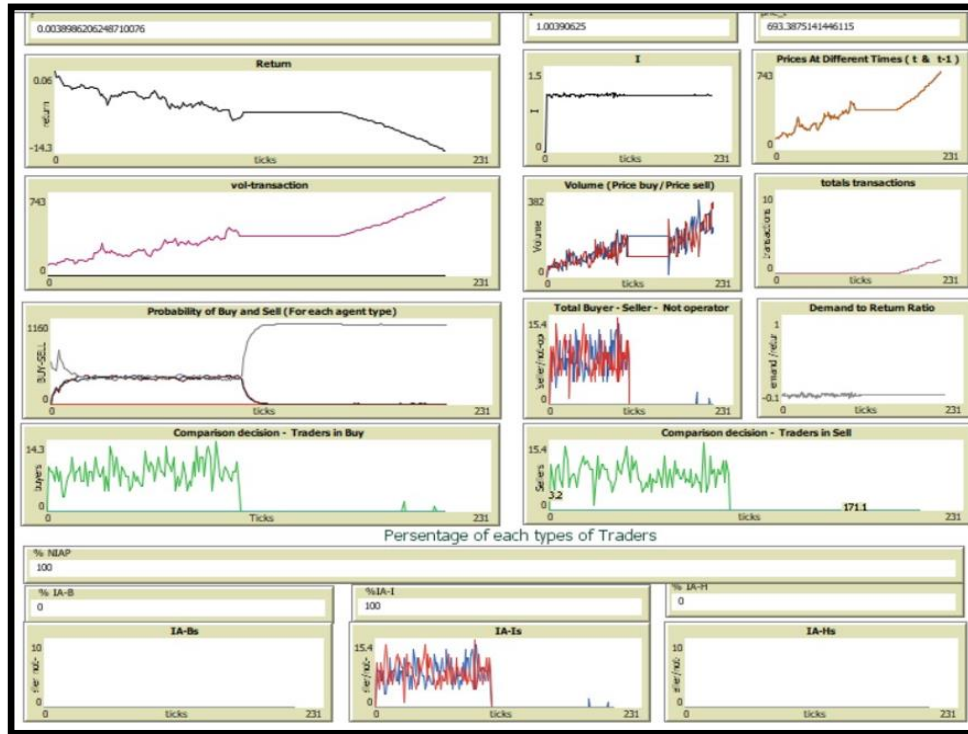


Figure 29: Plot Related to Experiment Number B3

5.3.4 Assumption B4

- The number of each trader is as follows:
- Accidental traders: IA-B=0
- Technical traders: IA-I=0
- Fundamental traders: IA-H=30
- Total number of traders: NIAP= 30
- Weighting of fundamental trading is 1 and another trading is 0.
- The cost transaction factor is calculated.
- Traders trade from 3 main strategies (Random Trading, Disposition Effects, and Stop-Loss Orders).

The results of each trade include buying, selling, or inactivity. The results can be seen in the figure below.

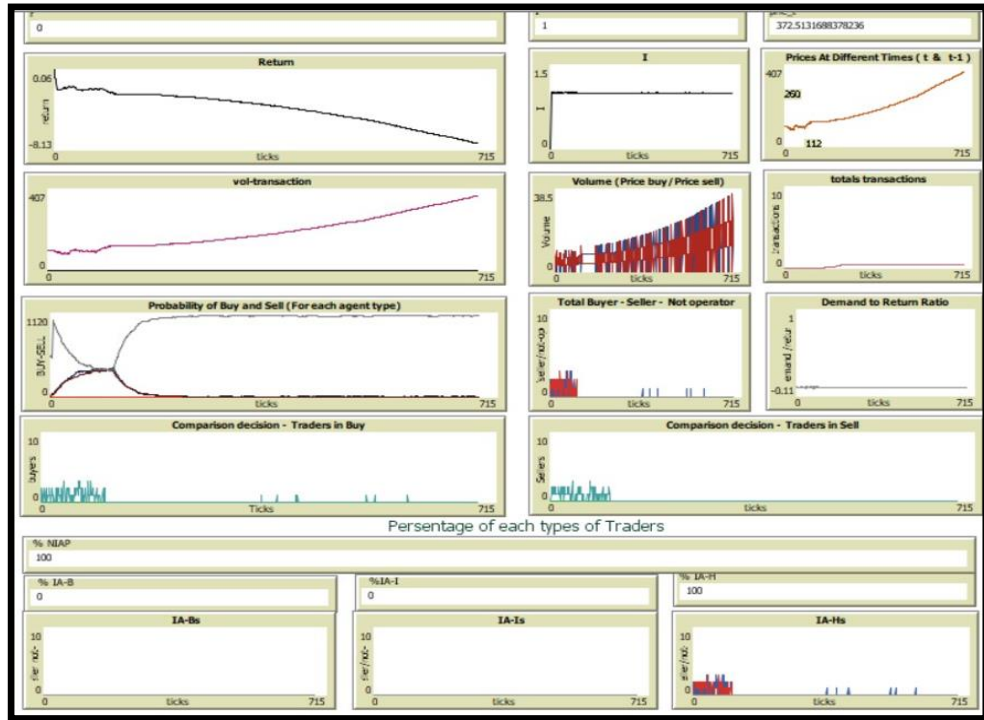


Figure 30: Plot Related to Experiment Number B4

5.3.5 General Result of Experiment B

In experiment B, we applied a market control agent such as TC (Transaction Cost) to the system, we examined the market situation according to the distribution of factors in terms of trading expertise (types of random, technical, and fundamental trade).



Figure 31: Comparison of result experiments (B1, B2, B3, B4)

To summarize, we can say, by considering TC (transaction-cost) this result is obtained; In the case of an even distribution of traders in the market, we reach stability in the price, return value, and volume of transactions.

Trading by professional traders decreases and consequently the number of active traders in the market decreases, and the Return decreases, but the volume of transactions is almost constant. The presence of more professional traders in the market, such as technical and fundamental traders, will lead to a decrease in Return and a price increase, while more random traders will cause a decrease in price and an increase in Return.

By applying a market control agent such as TC (Transaction Cost) to the system, as seen in the market, loss-stopping or decomposition strategies are similar and follow similar trends, but when the distribution of traders is uniform, As in Figure 27, the market trend is almost constant in all respects, for example, prices, returns and trading volume change with a very gentle slope close to zero, and the market is practically stable. But if there is one type of trader with a random strategy, the shape, and inclination of the charts are completely different. In this case, the return increases and the price falls, and also the willingness of traders to continue trading decreases.

Chapter 6

CONCLUSION

6.1 Conclusions and Future works

With the comparison of experiments (A- B) 's results, we reach these points; Technical and basic traders have a similar function if they are one-handed in the market and cause reduced returns, increase prices, and increase the willingness of traders to trade. Of course, this change is also considered a kind of instability.

Therefore, after applying a controlling factor such as TC (transaction cost), to maintain market stability, it is necessary that a uniform market controller factor by imposing restrictions on the entry of a limited number of each type of trader into the market.

In fact, in addition to TC (transaction cost), the factor of uniform distribution of traders is an important and influential factor in market stability, and it is suggested to be defined as a complementary factor next to TC (transaction cost).

Future work after performing multivariate analyses on linear and nonlinear models and identifying the strengths and weaknesses of these analyses, the optimal use of this information in structuring a strong model with low and optimized error rates, for It is stock market forecasting. Recently, very promising work has been done in this field, especially in fuzzy, meta-innovation, and neural networks, which can inspire us in our

future works. This method can necessarily be used for all patterns that behave similarly.

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