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Cellular automata based financial market

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Abstract
Cellular automata are discrete, abstract computational systems that have proven very useful as general models of complexity and as more specific representations of non-linear dynamics. They can be used directly to create visual or acoustic multimedia content and possibly make parallel computers. However, much of its potential remains un-explored as of now, including modelling financial markets. This includes trading stocks, currency, and other financial instruments. We choose financial aspect to explore because financial market is the perfect example of unpredictability. Even if we spend hours looking at statistics and base our game plan on it, the way financial market moves can never be perfectly mapped out. Even though we have made impressive progress in Machine learning and AI, even they fail here because they only work where the past, present, and future remain consistent. In a few words, we can say that financial market is a chaos, it all depends on how well a particular stock does at a particular time frame. Even this fluctuates constantly. Cellular automata help bring sense to this chaos, by giving deeper insights on the patterns and forces that drive financial market. It can give us simulations that can help us study different aspects of financial market without it being based on existing data to free it from the constraints of past and its unpredictability.

Keywords: Cellular automata, financial market, market theory

1. Introduction
Cellular automata (CA) is a deterministic finite-state machine (DSM) concept invented by the British mathematician John Horton Conway in 1970. A CA has an initial configuration of discrete neighborhoods, or cells, that have discrete neighborhood neighbors. The neighborhood may also be called a universe of discourse, as it is the granularity at which the roles played by all of its cells are defined. Neighbors are what distinguish different cells within the same neighborhood. To an observer, these can be seen as distinct states of a CA state. Each cell has a specific role to play, corresponding to that cell's neighborhood.

Conway's initial work concerned evolving cellular automata evolving according to simple rules without changing the underlying grid boundaries or initial conditions. The most widely used cellular automata are the "classical" cellular automata, whose cells evolve on a regular Cartesian grid. Each cell's state is not directly affected by the states of its non-neighboring cells, except that its state can change if it has fewer than two neighboring cells. This is known as a Moore neighborhood. The set of rules applied to each cell is known as its transition function or transition rule. The initial configuration with each cell normally in an arbitrary state can be considered to be a black box whose contents are unknown. A CA with all cells in the unknown state is said to be white or empty.

A CA can simulate complex systems, particularly Conway's Game of Life. A CA is also a convenient computational modelling tool, as it can be used to simulate finite state machines or other computation systems operating on binary words (bits).

When we talk about works in respect to financial markets, capital market theory has been set, which has rational investor hypothesis, efficient market hypothesis and random walk of yield rate as its basic concepts. It tries to predict the movement of financial and capital markets using different mathematical models. However, when we try to compare the results of calculations using this theory and the real data, it usually doesn't match. Financial market is rendered as a complex system which consists of masses of investors. The movement of investors is completely random as they make investments one the basis of public and private information they receive about the market. This is where cellular automata come.

The Santa Fe Artificial Stock Market is the first artificial stock market made. It was developed in the 1970s and all the subsequent markets are a variation of this model. SF-ASM uses agent-based financial market technique. They try to simplify the complexity of individual interactions. Investors first try to predict the movement of stocks and based on their predictions; they make a decision. SF-ASM uses capital market theory and its concepts to deal with the information provided to it.

However, there is more to stock market than public information. There is a lot in insider information and insider trading that goes on behind the scenes whose nature is unpredictable. This increases the complexity of stock markets as insider information reaches different people at different times unlike public information. Artificial markets increase their efficiency in this aspect by simplifying the nature of information by adopting cellular automata.

One of the most important issues in futures markets is how to predict future prices and movement in the markets. Traders often use technical analysis or fundamental analysis to predict future movements of financial instruments. The common way of doing this is through computer programs, which receive data from forums and news and use it to predict movements and values. There are several problems with doing this: traders will only be able to make use of a small amount of information, sometimes limited by what they are willing to spend on information; it is also possible that the predicted movement may not correspond to the actual movement in the market; if there are many traders using computers, there is a chance that there will be no consensus on the trends being predicted [1, 2].

Even though SF-ASM and other artificial financial markets introduce cellular automata to simplify the complexity of financial markets, the neighbourhood they introduce is fixed in its nature and is not flexible to situations as much as it should be. Hence a new model called CAFM – Cellular Automata Financial Market is discussed in this paper.

CAFM is intended to become a basic framework or foundation for all the types of AFM out there in which aspects like investors, pricing, time, market etc., can be modified with respect to different AFMs. This will lead to artificial markets resembling real markets and hence provide accurate results and amplify the purpose of AFM.

2. Financial Markets

Financial markets are an integral part of today's economy and have been since decades. Despite this, very few have complete knowledge of its workings. Financial markets in its essence are exchanges between two parties. These exchanges are variable in nature. They can be of stocks or commodities. Capital markets are a segment of financial markets that deal with long term financial exchanges [3, 4]. They contain stock markets, bond markets, money markets, foreign exchange markets etc. As discussed earlier, financial markets are complex systems and there hasn't been any capital market theory which can explain the inner workings from start to end. The capital market theories already present are far too restraining for a complex system like this. Since thoughts and decisions of real people affect the financial market in a great manner, a theory with constraints fail. Statistics can give a rough idea about the progress of financial markets for the next few years based on previous data, but a theory driven by statistics cannot essentially give accurate results. The movement of market is not static, it is dynamic, and the complexities can be explained in terms of time and space. The complexity of financial markets stems from its structural complexities and hence any approach that constraints the basic elements of financial markets is not a solution. When we view financial markets on a large scale, we realize the amount of people interacting with each other via financial markets. It's a quantity not easily put into words. All these individuals affect the outcome of financial markets, whether it's on a large scale or a small scale, when all of it is accumulated, the result surely changes. But even if the actions of these individuals are unpredictable, they are not random. It is still within the limits of financial markets and by learning this we can find an "order" behind the complexity of markets. The interactions of individuals within a system can also be simplified. Even though financial markets are global, majority of individual interactions are local, that is, they are bound to an area. By breaking down this global interaction that happens on a large scale into small areas of local interaction, the patterns become more discernible.

If we speak about the actions of individuals investing in a stock market, there is also a major driver that is common for almost all of them. Many people are looking for long term investments that lead to a gain or profit. So, investments are made on the basis of prediction regarding how well a stock is going to do in the future. These predictions come from past experiences of the investor, information they have and influences from other sources. These influences are primarily insider information that passes on from one investor to other. The accuracy of this insider information varies as it goes from one to another but is still reliable.

The present AFM are a culmination of different theories or hypotheses that satisfy one or more aspects of real markets. These include rational market hypothesis, random walk of yield, Markowitz efficient portfolio and many more. However, there is much to explore and the conversation and developments regarding AFM are not complete.

CA systems have been used in the financial markets. One such example is that of Binomo.com, where trends and price movements can be found and evaluated using their platform. This is only one application and only uses one type of cellular automata for this purpose, however there are many uses of CAs in the financial markets.

After studying about AFM and financial markets in general, we realize that the current approach towards financial markets is in the right direction. Treating them as complex systems is the best way, we can expand our research and understanding of the financial market. Taking the best parts of the current models, we can create a new model that goes one step further in making an AFM that coincides with the real market. With the equipment we have now and combining it with the knowledge we have gained over the years since the introduction of SF-ASM, we believe such a model can be successfully synthesized. For this, we will first discuss the current AFM.

3. Artificial Financial Market

3.1 Santa Fe Artificial Stock Market

In late 1980s, professors at Santa Fe Institute came up with a model for AFM which went on to be known as SF-ASM. This was one of the earliest attempts to construct an AFM model. Even though there are many inconsistencies with this model, it provided a breakthrough in this field. It is a relatively simple model that solved many questions in financial economy. This model's main objective was to provide a test-bed for Rational Expectations Hypothesis (REH) [5, 6].

It is a discrete-time model instead of a continuous one.

$t = 0,1,2,\ldots.$

SF-ASM has N traders and an auctioneer to conduct the exchange who can also be referred to as the stock market. Initially, each trader is identical in nature, but they change over time and they have same initial wealth. A time period will start from 't' and last till 't+1'. Financial assets are available for purchase at the beginning of each period.
There are risk free assets 'F' in infinite supply, where traders pay a constant amount and get a return rate r for each period.
There are also shares of risky stock 'A', where trader pay an uncertain amount (d_{t+1}) at the end of each period and receive an uncertain return rate R_t for each period.
To calculate R_t, p_t is taken which is the price of A at time t.

$$R_t = [p^e{}_{t+1} - p_t + d^e{}_{t+1}]/p_t$$

$$p_t = [d^e{}_{t+1} + p^e{}_{t+1}] / [1 + R_t]$$

Traders have an identical wealth function U(W) and a portfolio with record of their F stock and A stock. Each time period, the traders aim to maximize their gain [EU(W_{t+1})]. In the beginning of each time period, each trader sets a number of rules that predict the expected sum and generate expected gain.
From the above scenario, we see that SF-ASM is a general form of model with condition-forecast rules. Traders use their sets of rules to predict the future price and then make investments based on that. After the auctioneer receives the investments made by traders, he decides the price for the next period. Oversupply indicates price drop and short supply indicate price hike.
The major shortcoming with this model is its portrayal of information flow. Since this model is correlated to efficient market hypothesis, it portrays information like EMH does- as basic as price of stocks. But in real markets, information is highly complex. Apart from price of stocks, there are other public information and insider information. Even the psychology of traders comes into play as their emotions can make them more inclined towards one stock. Since real markets are also time complex, the reaction time of different investors also add to the complexity. So, a straightforward model with no delay is not highly accurate and that is how SF-ASM was modelled.

3.2 Use of CA in Artificial Market

Macroeconomics is not easy to predict. One way to try and do this is through the use of CAs. It has been shown that there are relationships between different macroeconomic factors, e.g., if the GDP goes up then the stock index will go up as well. If variables can be simplified into binary variables that take on states of 1 or 0, then these can be represented by CA rules which are applied to a lattice or grid according to the rules in the CA model. By doing this, it means that market information can be used to feed into a CA model, which will evolve according to the rules used in the CA model gradually reaching equilibrium when it conforms to real market trends and values. This is a more direct method of predicting future movements in the markets.
Sometimes it is necessary to know not just the direction a market will move, but also how quickly it will move. In financial markets, there are often periods of high volatility which have to be dealt with. One way to handle this is through stochastic volatility based on the Ornstein-Uhlenbeck process, however this is still limited to the short term and the longer-term trends still remain a mystery. CAs can provide another method of approaching this by using a model which predicts not just one movement but several movements of different magnitudes at different instances in time based on the rules that govern that particular CA model, which has been fed with historical market data. By doing this, it is possible to make predictions out of a long-term trend and magnitudes of movement which would otherwise be impossible using other methods [2, 3].
CA models also allow traders to analyze the history of market prices and analyze trends as well as establish what is likely to happen next in the market. This has been shown to be useful in predicting future movements and whether there will be further movement in a given market.

3.3 Cellular Automata Based Financial Markets

In the more recent models, the flow of information is treated as a complex system of its own. Human interactions are also considered as a part of the system. To work with this complex system, cellular automata was considered the best approach and the results also show the same. "The cellular automaton model of investment behavior in the stock market" was developed in 2003 and is a typical cellular automata based artificial market. The neighbourhood in this model follow Moore's definition.
This model went in a completely different direction than SF-ASM by only taking into consideration the local interactions and disregarded the public information. It gave a new insight to AFM but by ignoring all other factors of a stock market, it proved to be less insightful than SF-ASM.
Capital market is one of the most dynamic and happening systems where large number of people interact and associate with each other and every individual has a clear vision and target of their own. The mannerisms and behavior of the individuals are majorly dependent on the predictions made from data and information. However, there's a fine line of difference between the capital market theories and models in terms of differing viewpoints related to data/information category, its spread and methods of handling it. The complexity and sophistication of the capital market dynamic rises from the which is curated during the process of establishing an organization. It can also be observed that multi-agent and cellular automata are equally suitable for modelling this extensive market. On extending the essence of classic cellular automata, it can be learned that it consist of a heterogenous mixture of cells and socially related neighbors, providing a higher chance to develop artificial financial market based on cellular automata [4].
For this we have to extend the quadri-tuple system of cellular automata:

$$\wedge = \left(Z^d, S, N, \delta\right)$$

To a six-tuple system:

Ù= (*Z*, *S*, *N*, *P*,d,s)

Considering the inclusion of neighborhood transformation function in the cellular automata, it now concerns a six-tuple set. In this new definition, Z replaces the conventional Z^d, which implies that the space occupied by this automata doesn't necessarily have to be the Euclidean Space and can be a network or a graph structure instead. And hence *N* in the above tuple set implies the graphs neighborhood definition. To add on, *N* doesn't need to be stable. s*: N→N* refers to the transformation function of the neighbourhood and is capable of changing the neighbourhood in every evolutionary phase of the cellular automata and *P* indicates the public information involved. Accordingly, the state transition function becomes $\delta: P, Sn+1 \rightarrow S$.

Despite the extension involved in defining the cellular automata, the remaining essential features and grass root characteristics remain intact and the newly evolved cellular automata are time-space discrete systems where each of the cells decides its state during the next step as per the states of the neighbours and itself. The dynamics involved is purely due to the emergence of massive groups of cells with adaptive behaviour. The conventional cellular automata is often considered to be an instantiation of the newly evolved definition as the cells can be heterogenous and also a multiagent in the new definition of the same.

The novel definition of cellular automata actually provides the foundation to create and develop a cellular automata based on artificial financial market due to the presence of many such markets under various assumptions and categories. In such kind of a cellular automata, the cells represent the investors involved in the financial market. The main aim here is to extract the essence of the capital market and emphasise more on the heterogenous behaviour of each individual involved. In fact, this information is a governing and decisive factor for a predictive system.

4. The Cellular Automata Financial Market

Based on the above discussion, we get a clear idea on what we need to achieve with AFM and hence we can start building CAFM under those conditions. For this, we take patches of successful parts from other models and build around it. The main target of this model will be to fill in the missing gaps in current models like the relation between dynamics and structure of a financial market and focus on verification of different capital market theories. We keep in mind the previous works in this field and also their shortcoming while we attempt to design a new model based on cellular automata.

CAFM, as its name suggests, will be cellular automata based artificial financial market and we will design its framework using c++ language. This is because c++ allows generic programming and parallel framing. The main problem that we are dealing with is how we treat information. So, the starting point of our library will be abstraction of personal and public information. For this we will use parameterized function available in c++ template. The base classes of cell, cells' container, neighbourhood, are provided in the library and are both template classes. The parameters involved in these templates are of abstract data types of the cell state and other acquitted data and information. The parameter State Type is the type used to describe the cell states and it can be defined as per user needs. The class CellBase<StateType> contains pure virtual functions used for state transition and any derived class from CellBase must overwrite the transition function as per its own rule. The library used consists of two derived classes of CellBase of which, synchronous and asynchronous executions were targeted by each. On developing a cellular automaton, the main steps to be carried out include defining the necessary data types, creating classes and providing relevant transition functions to the derived class.

The cells in the cellular automata library are majorly managed by the cell container classes and these containers have specific design targets. The cell container should offer various modes of traversals so as to access all cells in the automaton. Further, the random access of cells needs to be ensured as a bland assumption of the structure of the automaton cannot be made and the cells need to be accessed through their neighbors. The neighbors of the automaton must have an inner expression within the container which implies that accessing a cell, gives us the access to its direct neighbors too. It is also important to note that the container must offer serial as well as parallel accesses. In detail, when different threads access different cells without mutex at the same time, the container should be thread safe. When different threads access the same cell at the same time, a mutex would be provided.

The cellular automata library should also consider the option of satisfying the concurrency requirements through the class called concurrent_Vector. Using this library to build the automata model will ensure that all classes are derived from CellContainerBase<StateType> which is a thread safe container to store cells. And this allows random access of cells through index. The CellContainerBase class has member pointers which usually point to the derived classes in the neighborhood and the neighborhood classes consist of two standard abstract functions – *AppendItem* and *Neighbors.* The *AppendItem* function is used to create a new cell's index into the structure while the *Neighbors* function is used to return the index of the neighboring cells. The derived class of neighborhood are mainly needed to instantiate the above two functions. The motive of using index to handle neighborhood cells is to separate the design and structure of the container and neighborhood classes respectively. Two derived classes of CellContainerBase<StateType> are provided to perform the evolution of the cellular automata in serial or parallel way.

By using this type of framework, we have treated AFM as a cellular automaton model. Through this framework, we have simulated investments, interactions, and all other basics of a financial market. But we have not fixed any assumptions that is left for designers to input. Designers can decide the structure and future of a neighborhood, they can classify the datatype of information and even choose how price behaves. But in case a designer wants to simulate a pre-designed neighborhood, a series of sample templates with all the different variables defined will be available to all users. They can use them as reference for their own model or can take a template and further build on it.

5. Simulation of CAFM

Simulation of an AFM is also evolution of the cellular automata. We can run parallel simulation as it gives higher performance but also ensures that the evolution and simulation run close to real markets. One simulation can run over many days and will stop when the user wants to or in an unlikely event of market crash. After each trading day, AFM will be closed and accounts settled, just like a real market.

After a simulation cycle is over, a report of the simulation will be generated. CAFM has tools that can analyze this report and compare it with real markets to test its accuracy. The report analysis will give insights to the simulation and even point out the things a designer may have missed. One of the main tools of analysis is the Hurst exponent.

In order to analyze the financial time series, Hurst exponent was first introduced by Mandelbrot and he considered this exponent to be better than variance analysis, spectral analysis and autocorrelation. This parameter is used to approximate the memory time of the series in long term. R/S analysis is one of the most commonly used estimation techniques of Hurst exponent. And Edgar E. Peters used this analysis technique to determine the fractal feature of the time series and also developed the Fractal Market Hypothesis.

Consider a time series of length T. Firstly, the series is divided into N adjacent sub periods of length v such that $N*v=T$. Each individual sub-period is stored as I_n, $n = 1,. N$ and each element I_n is stored as $r_{t,n}$, $t= 1,2,v$. M_n is the arithmetic mean value of I_n. The accumulated deviation $X_{t,n}$ from the mean is calculated using following equation:

$$X_{t,n} = \sum_{u=1}^{t} X_u - M_n$$

Let:

$$R_n = \left(\max(X_{t,n}) - \min(X_{t,n})\right)$$

R_n is the range of I_n. Let S be the standard deviation of I_n. Then the Rescaled Range is defined as:

$$E(R_n / S_n) = (aN)^H \quad \text{as N} \rightarrow \infty$$

H, which is the slope, is the Hurst exponent and it can be calculated using the least square method or other methods.

One of the main tasks of E-AFM is to compute how the microstructure and organization of the capital market can lead to complexity. For example, the graph structure of neighborhood cells can lead to the spread of personal/private data and information in the market. We use the degree distribution to measure the complexity of the networks, and use the clustering coefficient to measure the dependency level within the investors.

In the last, researchers are suggested to refer articles [6-15] to know more about raised issues in the current era/ in various sectors/ applications and how technology overcome these challenges in an efficient way.

6. Conclusion

As it has been with previous attempts at making a model for artificial financial market, it is difficult to include all the aspects of a real market in this model. But the way information is intercepted and the way it travels across the neighborhood in CAFM is an insightful approach that can become a steppingstone for further research in this field. The response to the data by investors and the data produced by them are carried out at the same time and this makes the capital market a self-feedback system. This self-feedback procedure and strategy can get quite complex and the behavior of the individual plays an important and essential role. The artificial financial market based on cellular automata provides a possibility to describe and elaborate on these parameters such that the self-organization n process can be simulated on it.

Cellular automata is the best tool we have right now to build an artificial market that resembles a real market. However, cellular automata alone cannot be used to accurately design an artificial market. As we have seen in this paper, cellular automata can be used to simplify the flow of information, which is a complex model of its own. This goes on to say how cellular automata can be used for particular aspects of a financial market but it alone is not effective enough to create a long-lasting stable model.

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