A Fuzzy Cognitive Map-based Stock Market Model: Synthesis, Analysis and Experimental Results

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Abstract

The expansion of advanced modeling tools, such as neural, evolutionary, fuzzy and hybrid systems, has led to a systematic attempt for their applicability in the challenging stock market field. Today, the ensuing results are admittedly far better than those accomplished by models based on linear or typical non-linear mathematical approximators; yet, the related trading risk remains at significantly high levels. In quest of innovative approaches, one interesting research direction appears to be the complete analysis and exploitation of various interrelated quantitative and mostly qualitative agents affecting stock market behavior. Based on this criterion, Fuzzy Cognitive Maps (FCMs) constitute a powerful modeling tool for the development of a stock market forecasting system as they are structured as networks of cause-effect relationships between diverse factors. The subject of this study is aligned with the aforementioned remark; firstly, the recognition of crucial stock market, business and economic agents is attempted, secondly an FCM-based stock market model is designed, and ultimately the feasibility and effectiveness of the real world application is evaluated.

I. INTRODUCTION

The introduction of intelligent techniques in the domain of stock market has caused a significant progress in the design and implementation of forecasting models and trading strategies. At the same time, the exploitation of stock market, financial and macroeconomic data has become particularly analytical and systematic. Admittedly, many researchers have reported significant profits and a large trading risk reduction, but acceptable levels of forecasting accuracy are still under consideration [1]. The reason for the existing restrictions is the nature of stock market itself; numerous interrelated factors act, which represent business status, economic situation, political stability etc., and generally, affect decisively stock prices, either directly or indirectly. The issue regarding qualitative information handling along with quantitative measures has already been investigated, through the implementation of hybrid systems applying fuzzy rules or other similar methodologies, and finally producing satisfactory results. Typical examples are the studies of Yoon and Swales [2] and Kohara, Ishikawa, Fukuhara and Nakamura [3]. However, the development of an integrated stock market system that is able to represent the existing cause-effect relationships between various agents, to manage simultaneously quantitative and qualitative information, and to ultimately estimate the total effect over stock prices, has not yet been published.

FCMs appear as the most appropriate tool for simulating stock market, as FCM theory enables the manipulation of cause-effect relationships, incorporating quantitative and qualitative terms. In this article, the analytical construction of a stock market model and its evaluation with real-world data is attempted. Firstly, clusters of key-factors and their cause-effect relationships are defined; then, an evaluation procedure is followed. Special attention is given in the incorporation of a learning algorithm using Evolution Strategies (ES), which reinforces FCM modeling capabilities and finally renders FCM approach a very promising methodology for applications, including stock market simulation and conducting stock price predictions on it.

II. FCMS: OPERATION, DESIGN & LEARNING

CMs are networks describing systems of interrelated factors (*concepts*), where the relationships have a positive or negative cause-effect form. In such networks, the nodes represent the concepts and the links the existing relationships. Fuzzy Cognitive Maps are CMs incorporating fuzzy logic principles. Nodes and links in a FCM have values in the interval [-1,1]. High (absolute) values in the links between concepts (e.g. 0.8, -0.9) signify strong cause-effect relationships between the concepts while high (absolute) values in nodes indicate significant changes in the corresponding concept states. Detailed analysis of FCMs is conducted in [4]. As plainly declared in [5]: "...*Despite the positive aspect about FCM modeling capabilities, their major weakness is still the intervention of experts for the determination of the structure and the estimation of link values.* ...". This deficiency of FCMs may be eliminated, to some extent, through the development of a learning procedure, which can estimate the causality of each cause-effect relationship in FCMs, just by exploiting predetermined data sets of optimal, or desired, behaviors. One efficient approach solving the problem of causality estimation is the introduction of evolution strategies in FCM theory. Koulouriotis, Diakoulakis and Emiris in [5] have already shed light on the sight of FCM and ES combination. In general, they proposed the concept of structure evolution, as the general framework for design and fine-tuning FCM-based structures, and examined the applicability of evolution strategies on FCM learning, and case testing. The ensuing results proved quite promising for further research. The synthesis and analysis of the stock market model presented in the following sections are based on this novel scheme.

III. STOCK MARKET MODEL STRUCTURE

In this paper, one of the most crucial tasks is the recognition of clusters of determinant factors affecting stock prices. In addition, an evaluation of the cause-effect relationships that are perceived to exist between the specified agents is attempted and, finally, their representation as a whole system of interrelations is highlighted. Such a representation will allow the incorporation of an FCM-based inference engine, which will facilitate the assessments of the overall (direct & indirect) effect of financial, economic, political and other factors over stock prices. The major sources of information eventually used for building the stock market model were not only academics' and experts' knowledge, but also bibliography on economics, corporate finance and portfolio theory. According to the findings of our research, the major factors affecting stock prices can be classified into five core clusters: (a) *National Economic and Political System,* (b) *International Economic and Political System,* (c) *Business Sector Condition,* (d) *Company Profile* and (e) *Fundamental and Technical Analysis Indicators.* As a Cognitive Map, the previous listed clusters of agents affecting stock prices are depicted in Figure 1.

Proceeding to an analytical description of each subsystem, *National Economic and Political System* (Figure 2) mainly encompasses concepts related to the operation of economic system as a whole, such as inflation, interest rates, money flow, bonds and currency exchange market. Additionally, a list of qualitative agents hardly affecting economic operations, such as political situation and diverse economic events are embodied in this subsystem. *International Economic and Political System* includes factors related to international economy and political stability, the condition of international stock markets and the collaboration or/and political proximity with foreign regions. In *Business Sector Condition,* the agents that are taken into account are the growth & development perspectives, the legislative and governmental regulations affecting corporate operations. The subsystem *Company Profile* could not be omitted, as it constitutes the backbone of stock market. It sustains the logic underlying corporate financing through stock market and in general the purpose of securities trading. In detail, *Company Profile* encloses concepts related to financial criteria (profitability, liabilities, capital structure etc.), management efficiency, business strategies (mergers & acquisitions, strategic alliances etc.), business plans and, of course, firms' competitive advantages or core competencies (human resources, know-how etc.). *Fundamental and Technical Analysis Indicators,* to a large extent, express through quantitative terms current stock market situation, signify abnormal conditions, and strongly formulate the behavior and attitude of traders as these indicators are easily assessed or obtained. Therefore, it's wise to incorporate them to a stock market model as a separate segment. For the needs of the specific application, the following technical analysis tools were taken into consideration: price/earnings ratio, price/book value ratio, dividend yield, Relative Strength Index (RSI) and MACD. Additionally, two more parameters were used; the hedge funds position relatively to given firms and the transactions volume that is analyzed not only through the indicators Price-Volume Index (PVI) and On Balance Volume (OBV) but also considering moving averages and the covariance with the aggregate trading volume.

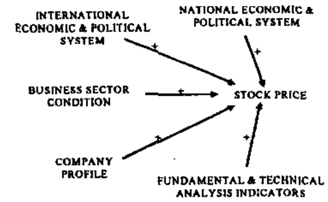

Fig. 1. Stock Market Model

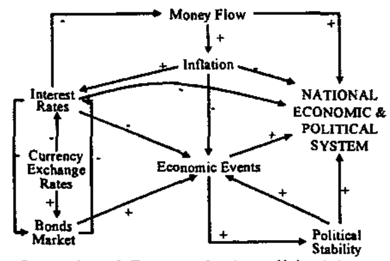

Fig. 2. National Economic & Political System

Considering the whole CM-based stock market model, consisting of the five basic subsystems of interrelated agents, it becomes obvious that it is feasible to test for stock price forecasting purposes. Indeed, setting the values of the constituent concepts, the effect over a given stock price can be estimated. Evaluating the magnitude of the resultant effect, a trading decision can be made.

Several issues arise when a forecasting process is eventually followed. The first one refers to the way through which the concept values will be initially set. In fact, this is an open issue for each different application area. The second matter to consider is the way to enhance the CM-based stock market model to an FCM through an accurate and objective process, which means to avoid analysts' intervention. This topic is another crucial task of the current study. To fulfill such a requirement, the ES-based FCM training algorithm discussed in Section II is activated. The problem here is how to select a convenient data set, on which FCM training will be based on. This issue is also covered in this work. A case study concerning the analysis of economic, business and stock market situation for 8 months in Greece has been attempted, so as to extract the needed information for the implementation and verification of the stock market model. Further details are provided in Section IV. The last matter of concern is the evaluation and mainly the interpretation of the produced output (stock price effect). The common practice is the adoption of a "buy & sell" logic, which means that the produced stock price effect can be used as a trading signal; if output is larger than an *upper* limit then "buy"; else if output is smaller than a *lower* limit then "sell"; else keep current position. In fact, this problem can be faced up as an additional routine in the FCM training algorithm. In other words, the training process may be formulated so as to estimate the optimal *upper* and *lower* limits that maximize trading profits, or minimize false signals or generally optimize a trading-oriented criterion. In order to avoid complexity, this question may be kept separated from the training procedure and analyzed in a subsequent phase, as it happens in the application presented in the following section.

IV. EXPERIMENTAL RESULTS

In this section, an attempt to evaluate the forecasting model presented in Section III takes place. The following issues are considered:

(I) What measures must be used in order to evaluate the model performance?
(II) What is the model performance when the cause-effect relationships (their causality) are user-defined?
(III) Does (or to what extent) the ES-based FCM models (the causality of the cause-effect relationships is estimated through a training process) outweigh a user-defined model (the causality is user-defined)?
(IV) Is the FCM structure extracted in Section 3 correct?

The above questions are discussed in the sequel. For the experimental conduction of the study, a large database was created. The gathered information concerns indicators and events about economic, business and stock market issues for the period Dec. '97-Aug. '98. The conducted analysis focused on ten stocks negotiated in the Athens Stock Exchange. The forecasting process was as follows: at the end of each week, information from economic and stock market databases, newspapers and economic magazines were gathered and afterwards an evaluation of the concepts included in the stock market model was attempted. When the stock price effect was estimated, a decision about to "buy, hold or sell" was made. For the evaluation of the model performance, two measures were selected: (i) the forecasting accuracy of the positive/negative stock price movements in a weekly basis and (ii) the attained profit during the period (Dec. '97-Aug. '98) comparatively to the "buy & hold" strategy (which produces profits equal to the actual stock return). Having defined the performance measurements, the evaluation of the stock market model proceeds. The user-defined model was first considered, that is the causality of each cause-effect relationship of the FCM is user-defined. This task conducted using information of academics and practitioners and, undoubtedly, subjective reasoning underlies all their assumptions. TABLE I presents the achieved forecasting accuracy for each of the 10 tested securities. Measuring the profitability (taking into account 1% transaction cost) of the stock market model, diverse "buy & sell" strategies tested. Practically, all the combinations between the *upper* and *lower* limits in the interval [-0.3,0.3] (with step 0.05) were examined. The maximum observed returns (among all strategies) for each stock are given in TABLE II. Figures in TABLE II are meaningless if they are not compared with the "buy & hold" strategy that is provided in TABLE III (buy 2-1-98, sell 31-8-98). Looking at the achieved accuracy, the user-defined model is at an acceptable, but not satisfactory, level. However, taking into account the produced profits comparatively with the actual stock returns, the FCM demonstrates an exceptional performance.

TABLE I
FORECASTING ACCURACY / USER-DEFINED MODEL

Stock 1	Stock 2	Stock 3	Stock 4	Stock 5
57,6%	*63,6%*	*57,6%*	*60,6%*	*66,7%*
Stock 6	**Stock 7**	**Stock 8**	**Stock 9**	**Stock 10**
66,7%	*57,6%*	*57,6%*	*63,6%*	*54,5%*

TABLE II
MAXIMUM RETURNS / USER-DEFINED MODEL

Stock 1	Stock 2	Stock 3	Stock 4	Stock 5
134,4%	*223,3%*	*76,4%*	*264,8%*	*59,6%*
Stock 6	**Stock 7**	**Stock 8**	**Stock 9**	**Stock 10**
113,4%	*71,3%*	*78,7%*	*44,2%*	*38,8%*

TABLE III
BUY & HOLD STRATEGY

Stock 1	Stock 2	Stock 3	Stock 4	Stock 5
71%	119%	38%	43%	14%
Stock 6	**Stock 7**	**Stock 8**	**Stock 9**	**Stock 10**
66%	15%	25%	-2%	11%

A means to reduce subjective reasoning is the incorporation of the ES-based FCM learning algorithm. Through this procedure, experts are responsible only for the determination of the initial concept values and not the estimation of the causality of each cause-effect relationship. The implementation of the learning algorithm calls for the separation of the available data set into the training and the testing set. For the needs of the specific application, many different pairs of training/testing sets were formed. Each type of set was consisted of a portion of the selected 10 securities. The total amount of examples were 330 (10 stocks for 33 weeks) under this consideration, the analysis of the ensuing results must be separated also into two parts; in-sample and out-of-sample analysis. Obviously, the results related to the out-of-sample performances are the most crucial. It must be cleared up that each training/testing set reflected also different ES-settings (configurations) and therefore a completely new model is extracted each time. Specifically, different ($\mu+\lambda$) Evolution Strategies were followed and the determinants varying among the diverse models were the population size, the number of generations and a strategy parameter ($\Delta\sigma$) adjusting variability in the population. In general, for the implementation of the FCM training algorithm, two cases may be discerned: *Case (1)*: experts give the sign of each cause-effect relationship, while the algorithm fine tunes the value of each FCM link, and *Case (2)*: the signs of the FCM links are unknown and the learning algorithm must approximate the value of each FCM link from scratch.

The achieved forecasting accuracy of the diverse models extracted by applying evolution strategies with different configurations (population, generations, $\Delta\sigma$, number of examples) is given in TABLES IV and V. Comparing these figures with those of TABLE I, the value of the FCM training algorithm becomes evident. Indeed, the average forecasting accuracy extracted by the values of TABLE I is 60.6%, while for cases 1 and 2, in an out-of-sample basis, the average forecasting accuracy is augmented about 5-10%.

Another measure is the improvement of the profits defined as:

$$\text{Profit improvement} = \frac{\text{ES / FCM return} - \text{User / FCM return}}{\text{User / FCM return}}$$

Indeed, the implementation of the FCM training algorithm improves profitability comparatively to the user-defined model at about 10-20% in an out-of-sample basis.

Therefore, this fact is adequate for accepting the assertion that an ES-based FCM outperforms the user-defined FCM. A comparison of the figures displayed on TABLES IV-VII clearly shows that the FCMs extracted from case 2 are better than their counterparts. This observation, combined with the fact that many deviations in the estimated and the predetermined link signs have been observed, indicates the existence of significant deficiencies in the stock market model based on the user-defined structure. This fact necessitates the adoption of a structure evolution scheme that will approximate even from scratch the real stock market FCM [5].

TABLE IV
FORECASTING ACCURACY / CASE 1

Models				In-Sample	Out-Of-Sample	Total
Population	Generations	$\Delta\sigma$	Examples			
20	10	0.1	66	69,7%	64,4%	65,5%
20	30	0.2	66	74,3%	64,1%	66,1%
100	30	0.3	99	75,6%	64,9%	68,2%
10	30	0.3	33	75,8%	58,6%	60,3%
10	30	0.3	66	69,7%	64,8%	65,8%
30	100	0.3	66	72,8%	61,4%	63,7%
10	50	0.3	66	71,2%	67,1%	67,9%
20	20	0.1	132	71,2%	61,6%	65,5%
20	20	0.3	132	69,0%	64,7%	66,4%
Average				**72,1%**	**63,5%**	**65,5%**

TABLE V
FORECASTING ACCURACY / CASE 2

Models				In-Sample	Out-Of-Sample	Total
Population	Generations	$\Delta\sigma$	Examples			
50	30	0.4	132	72,0%	67,7%	69,4%
10	100	0.2	132	70,5%	66,2%	67,9%
30	30	0.6	99	71,7%	64,1%	66,4%
100	10	0.4	99	71,7%	61,0%	64,2%
100	50	0.8	99	73,7%	65,4%	67,9%
30	50	0.25	198	70,2%	63,6%	67,6%
30	50	0.75	198	70,7%	68,2%	69,7%
30	50	1.25	198	69,2%	68,2%	68,8%
10	50	1	198	70,2%	68,2%	69,4%
30	50	1	198	68,2%	67,4%	67,9%
50	50	1	198	67,7%	62,9%	65,8%
Average				**69,9%**	**66,0%**	**67,6%**

TABLE VI
PROFIT IMPROVEMENT / CASE 1

Models				In-Sample	Out-Of-Sample	Total
Population	Generations	$\Delta\sigma$	Examples			
20	10	0.1	66	45,4%	19,2%	24,4%
20	30	0.2	66	45,8%	12,6%	19,3%
100	30	0.3	99	61,6%	19,3%	32,0%
10	30	0.3	33	-5,9%	-11,4%	-10,8%
10	30	0.3	66	18,3%	21,2%	20,6%
30	100	0.3	66	-9,2%	-22,4%	-19,8%
10	50	0.3	66	19,6%	27,1%	25,6%
20	20	0.1	132	50,0%	5,6%	22,5%
20	20	0.3	132	34,6%	26,6%	29,8%
Average				**28,9%**	**10,9%**	**15,9%**

TABLE VII
PROFIT IMPROVEMENT / CASE 2

Models				In-Sample	Out-Of-Sample	Total
Population	Generations	$\Delta\sigma$	Examples			
50	30	0.4	132	29,4%	18,9%	23,1%
10	100	0.2	132	27,8%	32,2%	30,4%
30	30	0.6	99	55,0%	7,4%	21,7%
100	10	0.4	99	32,2%	3,9%	12,4%
100	50	0.8	99	29,6%	8,6%	14,9%
30	50	0.25	198	32,0%	6,3%	21,7%
30	50	0.75	198	34,4%	23,1%	29,9%
30	50	1.25	198	52,6%	24,3%	41,3%
30	50	1.75	198	11,1%	2,8%	7,8%
10	50	1	198	26,9%	24,6%	26,0%
30	50	1	198	37,3%	23,6%	31,8%
50	50	1	198	21,2%	3,9%	14,3%
Average				**36,5%**	**19,6%**	**26,6%**

V. CONCLUSIONS

The goal initially set in this study was the introduction of a new concept about stock market forecasting and trading systems. The necessity to adopt the rationale of different subsystems of interrelated factors was brought into action through the implementation of an FCM-based simulation system. Indeed, fuzzy cognitive maps constitute a powerful methodological framework for underpinning the specific application, especially when developing the FCM training algorithm based on evolution strategies.

Although the attempted application has not ended in completely success, the ensuing results are satisfactory and lead to new research directions. At first, the FCM-model even at its naive shape, which was completely user-defined, it showed a significant forecasting ability, while simultaneously producing exceptional profits. Furthermore, the incorporation of the ES-based training algorithm produced substantial improvements both in the forecasting accuracy of the positive/negative stock price movements and the attained profits. The constant drawback of the proposed scheme is the necessity for experts' intervention for the FCM concept values setting.

Based on the proposed approach, two directions must be followed in order to enhance current forecasting potential. The recognition of accurate and credible measures and the construction of fuzzy rule bases for evaluating qualitative parameters are of major importance. The same necessity is also valid about quantitative factors because their estimation and interpretation usually calls for many criteria. Furthermore, research must focus on the ES-based FCM training algorithm in order to become faster, more effective and robust.

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