

Fuzzy Reasoning Inference Model Integrated with Self-Organizing Map for Forecasting Investment Companies under Uncertain Conditions

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Abstract—Forecasting investment companies are used to evaluate based on quantitative and qualitative information under uncertain conditions such as dynamic markets, stock markets and investment portfolios. In our research, we present a new approach which is Fuzzy Reasoning Inference Model integrated with Self-Organizing Map (SOM) using collaborative decision making, together with uncertainties of market conditions to forecast/select the best alternatives from larger number of choices. The proposed approach aims to assist experts to select the right companies for investment and eliminates risky companies. In the proposed approach, the Fuzzy Reasoning Inference Model uses to quantify uncertainties of market conditions, quantitative and qualitative data sets that are integrated by Self-Organizing Map (SOM) in order to select companies and reduce investment risks with dynamic solutions in dynamic environments. To confirm the model's performance, the proposed approach has been tested and performed well in stock markets by dealing with uncertain conditions. Experimental results show that the proposed approach was performed better than other current approaches in terms of investment companies when trading stocks.

1. Introduction

In economics, an investment company is one of segments in financial securities, such as stocks, bonds, commodities, etc. Solving the investment company selection problem means determining the best alternatives in terms of investment to deal with dynamic environments [1]. Company investment selection shows the problems of how to select alternatives from over a large number of securities so that the financial portfolio investment may obtain profitable returns. Investment portfolio is considered trading activities between investment returns and risks. In the recent years, Foreign Portfolio Investment (EFPI), Financial Investment Portfolio (FIP), stock investment portfolio, bonds, and investment companies, are become high-risk markets for investors. The main reasons are that many factors and environments affect the investment company as well as investment returns. Risk management mostly involves utilizing a variety of trading activities in investment portfolios, one of the most complicated stock trading skills for professional investors.

In this paper, the study aims to forecast companies for investment under uncertain conditions in market dynamics. The main purpose of proposed approach is to integrate Fuzzy Reasoning Inference Model with Self-Organizing Map (SOM) using collaborative decision making, together with uncertainties of market conditions to forecast/select the best companies from larger number of choices under uncertain conditions on the stock market. The new contribution in this study is to aggregate uncertain market conditions, evaluated by expert preferences for forecasting companies when investing/trading stocks. The proposed approach has presented in this study as follows: 1) all quantitative and qualitative factors with uncertainty in dynamic market conditions, consisting of company assessments are considered through the model, based on expert preferences; 2) the model is used to quantify uncertainties about various market conditions, evaluated by expert sensibilities and preferences. To confirm this model's performance, we have selected the domains as Vietnam and US stock markets, representing economically developing and developed countries. The proposed system was tested and performed well in real-world investment companies on the HOSE, HNX (Vietnam), NYSE and NASDAQ (US) stock markets through case studies.

The rest of this paper is organized as follows. Section 2 presents a brief overview of the proposed system, consisting of Fuzzy Reasoning Inference model and mechanisms of the proposed approach. The experimental results and evaluations show in Section 3. Finally, Section 4 concludes this paper.

2. Proposed Approach

2.1. Fuzzy Reasoning Inference Model

To invest companies on stock markets, investors may face uncertain conditions in dynamic stock market environments, such as government policies, bank interest rate changes, world stock market prices, financial rule changes and real-time stock trading trends. This is commonly affected by the news published by economic news, websites

and other media. A Fuzzy Reasoning Inference model for the proposed system aims to explain how we evaluate companies in terms of stock trading evaluation and investment risks. This uses uncertainty of quantitative and qualitative factor weights, together with the quantification of expert sensibilities in dynamic market environments. These weights can be transformed through the model, representing in interval values [0,1].

Experts surveys are collected and divided into several groups. Each group of experts makes surveys and provides its experiences using collaborative decision making. Support there is a group of n experts in stock investment portfolio. Let $E = \{e_1, e_2, ..., e_n\}$ be a set of experts, where n is the numbers of experts. Experts may have different degrees of knowledge. Each of these experts collects its preference and a set of $X^S = \{x_1^S, x_2^S, ..., x_k^S\}$ be a set of k alternatives in an environment S. Let $\mu_i(x_j)^S$ be the preference of expert e_i and the expert prefers alternative x_j^S . We consider $\mu_i(x_j)^S \in [0, 1] \forall i, j$ as representing membership values.

To evaluate a company based on qualitative stock-market factors, qualitative factor weights representing in membership value are evaluated by expert preference as defined in Table I.

Table 1: Expert scale representing by membership weights

ID No	μ_{e_i}	Expert scale
1	1	strongly agree
2	0.75	agree
3	0.5	almost agree
4	0.25	almost oppose
5	0	oppose

Note that $0 < \mu_{e_i} < 1$ means fuzzy membership values evaluated by expert e_i .

To quantify expert sensibilities in market conditions, pairs of adjectives called *Kansei* words are collected from dynamic environments. Based on the experts' experiences, Semantic Differentials (SD) method is applied to refine pairwised *Kansei* words. All refined-adjective words use to evaluate alternatives based on expert preferences. In *Kansei* evaluation, expert sensibilities and emotions are quantified in weights, representing in an internal value [0,1] with qualitative factor weights.

To evaluate a company based on quantitative stock-market factors, quantitative factors consist of financial weights obtained from a stock market to normalize these weights in fuzzy weight values [0,1]. For getting quantitative factor weights of each company from a real-time stock market, we apply a Sigmoid function, given by Eq.1.

$$k_j = \frac{1}{1 + \exp\frac{-(D_j - a)}{b}} \tag{1}$$

where k_j (j = 1, ..., l) is the normalized value of quantitative factors of a company; D_j (j = 1, ..., l) is real data in the

stock market, and *a* and *b* are parameters that are assigned values depending on data sets. Parameters *a* and *b* are adjusted by visually checking the Sigmoid function results for the appropriate optimal parameters.

In human reasoning, linguistic expressions represent rules for expert decision situations. To quantify sense human reasoning of expert e_i in dynamic market environments, we use the logical rules as an example of the following:

Rule 1: **IF** JP Yen money exchange rates is higher than USD's **AND** industrial exports are lower **THEN** Stock prices of groups of export companies will be decreased. The system marks negative decision status *exchange risk*-

Rule 2: **IF** GDP (gross domestic product) is good **AND** CPI (consumer price index) is lower **THEN** stock prices of product and food companies may rise quickly. The system marks positive decision status *invest*++

Rule 3: **IF** oil and gas prices on the global market are lower **AND** transportation costs are acceptable **THEN** stock prices of transportation companies rise quickly. The system marks positive decision status *invest*+

Note that investment or risky decision status represents in a positive or negative definition {risk- -, risk-, neutron, invest+, invest++}

Let $f^S = \{f_1^S, f_2^S, ..., f_l^S\}$ be a set of qualitative factors in stock market S, where l is the number of qualitative factors. Factor f_j^S is evaluated by expert e_i^S so that each factor has a different significant factor degree. Let $I_j^S \mid (j=1...n)$ be a set of factor weight states. Let $R^{f_j} = \{R_1^{f_j}, R_2^{f_j}, ..., R_m^{f_j}\}$ be a set of fuzzy rules, where m is the number of fuzzy rules. These fuzzy rules represent by the market environment of the j-th factor f_j^S affected by $R_i^{f_j}$ to evaluate a company based on expert preferences. This represents by the form as follows:

IF $R_1^{f_j}$ AND $R_2^{f_j}$ AND...AND $R_m^{f_j}$ **THEN** Update weights in I_j^S and mark expert reasoning status for company C_i^S

A *Kansei* stock matrix $M_{n \times p}^S$ is constructed, representing in weight values [0,1] for the results of *Kansei* evaluation and company assessments, where n is the number of companies in stock market S and p is the number of *Kansei* words, quantitative and qualitative factors.

A *Kansei* risk matrix $R_{n \times r}^S$ is constructed, representing in weight values [0,1] for the results of *Kansei* evaluation and risk management, where n is the number of companies in stock market S and p is the number of *Kansei* words, quantitative and qualitative factors.

2.2. Mechanisms of the Proposed Approach

Mechanisms of the proposed approach are described in four steps as shown in Figure 1.

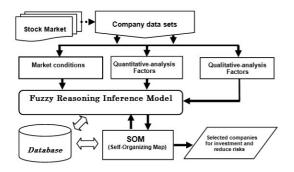


Figure 1: The overview of system

Step 1. Company attribute distance definition

To evaluate company C_j^S in terms of investment company assessment and investment risks, $M_{n\times p}^S$ and $R_{n\times r}^S$ are visualized by SOM. To calculate differences among Kansei stock attributes of companies, the Kansei stock distance $d_{C_i \to C_j}^S$ between two vectors $D_{C_i}^S$ and $D_{C_j}^S$ represents attributes of companies C_i^S and C_j^S respectively as defined by Euclidean distance given by Eq.2.

$$d_{C_i \to C_i}^S = \parallel D_{C_i}^S - D_{C_i}^S \parallel \tag{2}$$

To calculate differences among Kansei risk attributes of companies, the Kansei risk distance $d_{C_i \to C_j}^R$ between two vectors $D_{C_i}^R$ and $D_{C_j}^R$ also represents attributes of companies C_i^R and C_j^R in terms of investment risks respectively as defined by Euclidean distance given by Eq.3.

$$d_{C_i \to C_i}^R = \parallel D_{C_i}^R - D_{C_i}^R \parallel \tag{3}$$

Step 2. Visualizing and updating weights under conditional uncertainties by SOM.

To select superior companies and eliminate risky companies, expert preference distance $d_{e_i \rightarrow e_j}^S$ is represented by m_{ij}^t calculated from the *Kansei* stock attribute distance v_{ij}^t evaluated by expert e_i^S of his/her group at iteration t and the *Kansei* stock weight w_{ij}^t of the expert group.

IF Rule I: *Market Conditions A* **AND** *Other conditions* **THEN** Positive Decisions with collaborative these uncertain preferences, as expressed by Eq.4.

$$m_{ij}^{t+1} = m_{ij}^t + \beta_i^S(||\frac{1}{K} \sum_{\ell=1}^K w_{\ell j}^t - v_{ij}^t||)$$
 (4)

IF Rule f: *Market Conditions B* **AND** *Other conditions* **THEN** Negative Decisions with these distributive uncertain preferences, as expressed by Eq.5.

$$m_{ij}^{t+1} = m_{ij}^{t} - \beta_{i}^{S}(||\frac{1}{K} \sum_{\xi=1}^{K} w_{\xi j}^{t} - v_{ij}^{t}||)$$
 (5)

where $\beta_i^S(i = 1, ..., t)$ is an expert preference and t is the number of iteration assigned; K is the number of uncertainties in market conditions, evaluated by experts.

An expert decision matrix $A_{q \times k}^S$ is updated by its weights given by Eq.4. After that, the Decision matrix $A_{q \times k}^S$ is joined with *Kansei* stock matrix $M_{n \times p}^S$ and its weights are updated to $M_{n \times p}^S$.

To apply similar steps, the *Kansei* risk matrix is trained by SOM using the updating weights, as given by Eq.4 and 5

Step 3. Marking the status of positive and negative expert decisions based on market conditions

Investment, market condition or risky decision status represents in positive decision + or negative decision - in the subset list with a degree {risk- -, risk-, neutron,..., invest+, invest++}

After marking the system, we aggregate multiple uncertainties on the stock market. The updated weights are continuously by SOM training from Step 2 to Step 3 until the expert decision matrix is training completely.

Step 4. Select potential companies and eliminate risky companies by the comparison of the results of *Kansei* stock matrix and *Kansei* risk matrix by SOM visualization

After training process of the *Kansei* stock and *Kansei* risk matrices is done, these SOM results can be presented on a map. Assume that B_i^R and G_i^R are appropriate company groups in SOM results of *Kansei* stock matrix and *Kansei* risk matrix, respectively visualized by SOM. Decision makers eliminate $C_i^S \subseteq G_i^R$ that is not in the list for investment. Based on *Kansei* stock distance among expert preferences with the closest company having similar attributes, the final result on a map is shown in selected superior companies, matching with expert preferences and eliminating risky companies.

3. Experimental Results and Evaluations

We have selected a domain as stock investment portfolios on stock markets with dynamic markets for demonstration. This approach has been tested and performed in case studies for financial investment portfolio on the HOSE, HNX (Vietnam), NYSE and NASDAQ (US) stock markets for the period of April 2010 to March 2011. The proposed approach has been implemented in the C++ programming language. A web-based application is used to connect data based on expert preferences via the Internet. The steps of process in this application is as follows: (1) screen out companies available on the stock markets; (2) Kansei data and real-world stock data sets are obtained from a stock market in order to construct a Kansei stock matrix and Kansei risk matrix; (3) the Kansei stock and Kansei risk matrices are visualized by SOM to screen out the superior and risky companies for investment; (4) Evaluation of forecasting companies using virtual stock trading with successful investment companies; and (5) Selling stocks of these companies based on market conditions to calculate investment returns. Figure 2 shows the overview of a map result.

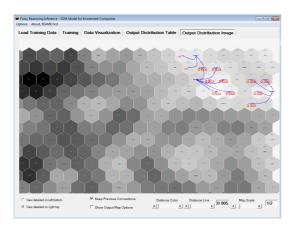


Figure 2: The overview of a map result

Experts 1,2, and 3 selected these companies, matched with appropriate expert preferences by reducing the maximum *Kansei* stock distance of the companies and eliminating those that have the greatest distance. There was no company selected by expert 1. Figure 3 shows companies that expert preferences 2 and 3 transform to investment signals based on the sense human reasoning and expert preference, as shown in the map.

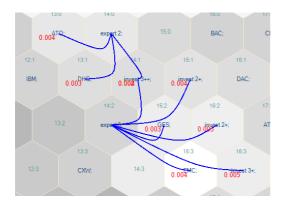


Figure 3: The map result for investment

The system showed risky investment decisions that these companies have removed them from the list of investment, as shown in Figure 4.



Figure 4: The map risky decisions

Recently, the new approach using Rule-based approach [2] is concerned with the synthesis of the fuzzy logics and Dempster-Shafer theory and presented in stock trading naturally based on evident reasoning and testing on an actual stock market. For investment companies using virtual trading system, we have employed these approaches on the case studies on the NYSE and NASDAQ. These results show and 9-11% profits with 80-85% successful investment companies, respectively to deal with various uncertain conditions of overall market prices for the period of April 2010 to March 2011. Figure 5 shows experimental results of successful investment companies and compares with Rulebased and Self-Organizing Map (SOM) approaches which were tested by using real-world data sets under the same conditions for investment on the NYSE and NASDAQ.

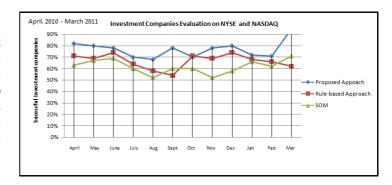


Figure 5: Average percents of successful investment companies for trading

Further testing results show that an average percent profits are between 12-15% on the HOSE and HNX with 84-87% successful investment companies (wining trades) for the period of January 2010 to May 2010.

4. Conclusions

The experiments through case studies show that the new approach, applying Fuzzy Reasoning Inference integrated with SOM model enhances the performance of forecast/selection companies, investment returns and reduce losses to deal with various uncertain conditions.

References

- [1] S. C. Misra, A.Mondal, "Identification of a companys suitability for modelling its corresponding Return on Investment," *Mathematical and Computer Modelling*, vol.53, No.3-4, pp.504-521, 2011
- [2] L. Dymova, P. Sevastianov and P. Bartosiewicz, "A new approach to the rule-based evidential reasoning: Stock trading expert system application," *Expert Systems with Applications*, vol.37, no.8, pp.5564-5576, 2010.