

Hybrid Intelligent Decision Support Systems for Selection of  
Alternatives in Stock Trading

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# Abstract

The dissertation presents Hybrid Intelligent Decision Support Systems (DSS) for the selection of alternatives (companies, stocks, and company groups) in stock trading under uncertainty. This study proposes a framework including three models using Hybrid Intelligent DSS. The framework aims to optimize trading decisions in the selection of appropriate alternatives and reduce risky decisions.

This framework is used to quantify qualitative attributes and normalize quantitative attributes of alternatives, together with expert preferences and sensibilities under uncertainty for the selection of alternatives and reducing risks in stock trading. To validate the performance of this framework, the proposed models in the framework have been tested and performed objectively by multiple experts in real-world stock trading through experiments in case studies on the HOSE, HNX and NYSE and NASDAQ stock markets.

In this framework, the first model called a Hybrid SOM-AHP model is a Self-Organizing Map (SOM) integrated with Analytic Hierarchy Process (AHP). This model aims to select short-list investment alternatives in rankings for stock trading. Experimental results of this model showed an average rate from 68% to 70% in stock selection for successful investment. The second model called Hybrid Kansei-SOM (HKS) model is integrated by SOM with Kansei evaluation for quantifying expert sensibilities in trading decisions. The experimental results showed that HKS model obtained successfully stock selection rate from 81% to 85% in investments. The third model called Hybrid Kansei-SOM Risk (HKSR) model aims to reduce risky decisions and alternative risks. Compared to HKS model, HKSR model was reduced risky stocks in investments from 3% to 5% better than that of HKS model. Compared with

Rule-based Evidential Reasoning (RER) model under the same market conditions, HKS and HKSR models showed successful stocks in investments higher from 10% to 15% than that of RER model. In overall evaluation, the proposed framework using Hybrid Intelligent DSS was able to show successful selections of appropriate alternatives and reduction of risky decisions.

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# Chapter 1

## Introduction

### 1.1 Problem Statement

In real-world problems, a selection of alternatives often leads to make a decision under uncertainty in market dynamics. Making right decisions require experts for most approaches under uncertainty how they can deal with complex situations. The following logical issue has become significant when dealing with market dynamics [1]: How decision makers take better decision into account, when making decisions today decision makers may not know about tomorrow. A large number of dynamic problems in selection of alternatives require that either multiple or individual decisions be made in the presence of uncertainty [3, 4].

The main feature of dynamic decision problems is selecting optimal decisions that satisfies appropriate alternatives in interval time. In addition, reasoning about dynamic decision problems involves multiple decision processes since Group Decision Making (GDM) and Decision Making (DM) concern problems in which time and uncertainty are explicitly considered [5]. Group decision makers may dynamically change their decision preferences during the group decision-making processes when selecting alternatives. Dynamic solution problems involve risks that may occur with uncertain timing. This applies to application domains such as dynamic markets, stock markets, and financial investment markets. For the domain of stock trading, decision makers may face uncertain information about stock markets when trading stocks.

When considering alternatives (stocks, companies, company groups) for investment, decision makers make the right decisions at the right time, in order to select appropriate alternatives dealing with uncertain stock market environments. In addition, there are many problems in stock trading that researchers have been investigating advanced approaches under market dynamics.

## 1.2 Background

In recent years, many researchers have investigated a single model of Decision Support Systems (DSS) and intelligent systems have become widely common for a variety of real-world problems [9, 15, 17]. However, many studies are concerned with individual DSS models to solve basic problems from large numbers of DSS applications, employed with simulation results [7–9, 15, 17]. Although these approaches are recently shown to have very good simulation results, the limitation of current approaches is they use partial solutions for basic problems. On the other hand, uncertain values [8, 13] include consequent conditions in dynamic environments such as market dynamics, stock trading, financial investment, and stock investment portfolios.

In stock trading, a large number of single DSS models have been developed as part of stock market investments involved in decision making that can handle a single model of a stock investment system [11, 12]. The main problems in the selection and prediction models have faced uncertain conditions in dynamic stock market environments, such as market dynamics, government policies, world stock market prices, financial rule changes, and published websites. In a case study of stock market investment, experts and investors may feel hard to decide which potential companies at the right time for investment. Furthermore, the decision making under uncertain markets and risks can possibly find companies and groups of companies that occur in risky investment decisions.

The key to successful stock market investment is to achieve the best investment returns in real-world stock trading. Currently, many studies have investigated Decision Support System (DSS) techniques, soft computing models and hybrid systems for stock trading, mostly based on historical data and basic financial

approaches [11, 49–51, 60]. These methods and approaches have been not considered uncertain market dynamics such as macroeconomics, event news, and policies. Recently, the new approach using Rule-base Evidential Reasoning [68] is concerned with the synthesis of fuzzy logic and Dempster-Shafer theory and presented in stock trading conventionally based on evident reasoning and testing on an actual stock market. However, most approaches show incomplete solutions for selection of companies to achieve investment returns since many uncertain conditions that are not considered concurrently in those studies, such as stock prices, technical indicators, macroeconomics, event news, and investor sensibilities for stock trading. In this study, a Hybrid Intelligent DSS has been investigated to select the right alternatives (stocks, companies, stock groups) for investment when dealing with uncertainty and risk.

### 1.3 Study Motivation

The motivation of this study is a new method using Hybrid Intelligent DSS to quantify qualitative and quantitative factors from stock markets, together with experts' sensibilities and preferences using *Kansei* Evaluation to select the right alternatives by dealing with complex situations in stock trading for investment returns. The advantages of this study include addressing these issues:

(1) In order to assist better expert trading decision in the selection of the right companies at the right time for investment, the first issue is to quantify expert's sensibilities using *Kansei* Evaluation about uncertain conditions and risks, together with quantitative and qualitative factors obtained from a stock market and expert preferences that are considered through a framework of the proposed approach.

(2) In order to improve the effectiveness of stock investment model, the second issue is to quantify experts' feelings about trading stocks and their aggregate preferences using Group Decision Support Systems (GDSS) for stock trading by dealing with complex situations in market dynamics.

(3) A framework for selection with alternatives is determined by decomposing the problem into the hierarchy of criteria and stock-market factors to evaluate superior stocks by rankings in terms of the investment portfolio.

## 1.4 Research Objectives and Organization of Dissertation

This dissertation presents an approach using Hybrid Intelligent DSS for the selection of multiple alternatives (companies, stocks, and grouping companies) under uncertainty in stock trading. This framework aims to optimize trading decisions in the selection of multiple alternatives and reduce risky decisions for investment. This framework is used to quantify attributes of alternative selections, together with expert preferences and sensibilities under uncertain market conditions for the selection of alternatives in stock trading.

The proposed framework consists of three models using Hybrid Intelligent DSS for selection of alternatives in stock trading. The first model, called the Hybrid SOM-AHP model, is a Self-Organizing Map (SOM) integrated with Analytic Hierarchy Process (AHP). This model aims to select short-list investment alternatives in rankings for stock trading. The second model, called Hybrid *Kansei*-SOM model, is integrated by SOM with *Kansei* evaluation for optimized trading decisions and selected alternatives with stock market investment strategies. The third model, called Hybrid *Kansei* Risk SOM model, aims to reduce risky decisions and alternative risks under stock-market dynamics. To validate the performance of this framework, these models have been tested and they performed well in real-world stock trading by experiments in case studies on the HOSE, HNX (Vietnam) and NYSE and NASDAQ (USA) stock markets.

This dissertation is divided into seven chapters as well as a bibliography and references. The summaries of chapters and indices are as follows:

**Chapter 1** provides a background of this dissertation which consists of problem statement, motivation, and study objectives.

**Chapter 2** presents some basic ideas of DSS techniques such as SOM, fuzzy reasoning, Analytic Hierarchical Process (AHP), Fuzzy AHP, and *Kansei* Evaluation. Combined these techniques are called Hybrid DSS techniques for new computational techniques to process complex and ambiguous information, which carry out the main roles in the implementation of these models. Further main points of stock market

investments with other current related works are also shown in the detail of this chapter.

**Chapter 3** mainly describes a proposed framework for selection of alternatives under uncertainty and risk in stock trading. The framework aims to optimize trading decisions in the selection of multiple alternatives and reduce risky decisions for investment.

**Chapter 4** presents case studies of Hybrid SOM-AHP model using a Self-Organizing Map (SOM) integrated with Analytic Hierarchy Process (AHP). This model aims to select short-list investment alternatives in rankings for stock trading which shows in experimental results.

**Chapter 5** presents case studies of Hybrid *Kansei*-SOM model, integrated by SOM with *Kansei* evaluation for optimized trading decisions and alternative selections with stock market investment strategies, as shown in experimental results.

**Chapter 6** presents case studies of Hybrid *Kansei*-SOM Risk model which aims to obtain investment returns and reduce risky decisions under uncertain conditions. This model demonstrates an improvement of the stock trading system's performance when applying trading strategies together with risk management under uncertainty and risk. Compared with Rule-based Evidential Reasoning (RER) [68] method under the same market conditions, experimental results show that the profits and winning stocks of this model, are higher than those of RER method.

**Chapter 7** evaluates proposed models with comparisons to the latest approach and DSS methods. This chapter is also concluded in recapitulation of progress made in this research and further research discussions.

**Appendices A,B, and C** present experts' and investors' participations for data collection and survey forms using for data collection of stock and *Kansei* data sets.



# Chapter 2

## Techniques and Research Backgrounds

### 2.1 Introduction

This chapter presents basic concepts of Decision Support System (DSS) techniques. A Hybrid Intelligent DSS including these DSS techniques is used to select alternatives in stock trading. The principal components of Hybrid Intelligent DSS include Self-Organizing Map (SOM), Analytic Hierarchical Process (AHP), Fuzzy AHP, fuzzy reasoning, and *Kansei* Evaluation. This also introduces research background when used in an integration of DSS techniques.

### 2.2 Decision Support System

#### 2.2.1 Characteristics and Capabilities of DSS

A Decision Support System (DSS) helps decision makers or managers to make better decisions that covers and includes various tools, systems and technologies [16]. According to Keen and Scott-Morton [16], DSS is defined as individuals using a computer to improve applications for the quality of decision. In terms of researchers and scientists, DSS is based on a computer-based information system that supports

organizational decision-making activities in order to make better decisions [9, 15, 17].

The main characteristics of DSS are described as shown in Figure 2.1 [15]:

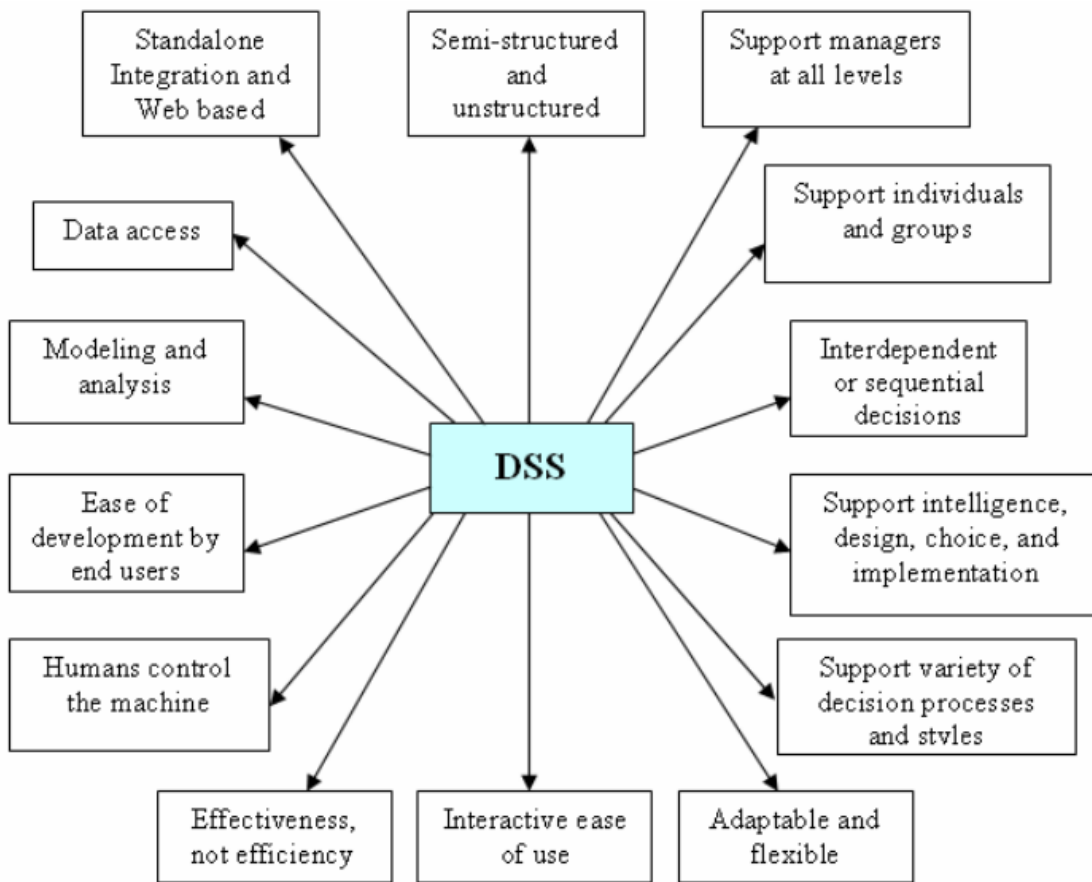


Figure 2.1: Overview of DSS characteristics

- Support for a manager including managerial levels, top executives to line managers.
- DSS supports decision-making processes and styles that improve decision making effectiveness rather than efficiency.
- DSS supports the solution of both structured and non-structured management problems. This allows for the decision maker to make better decisions. DSS also



utilizes models and a knowledge base for supporting all stages in the decision making process.

- DSS also supports semi-structured and unstructured problem in using computerized systems or standard quantitative methods or tools.
- The decision-making process involves main major phases: intelligence, design, choice and implementation.
- Improving managerial effectiveness including control management and performance is to provide decision makers for better analysis, planning, and visualization.
- Support is provided to individuals or groups involving group decision making with DSS model.
- DSS is to develop theory and practice in a methodologies for modeling unstructured problems in the economic, social and management sciences.
- Decision making involves the following features: planning, determining requirements, allocating resources, predicting outcomes, optimizing problems and designing systems.

### **2.2.2 Decision Making in DSS**

A new science of decision making was started in the 1940s. The studies applied problems in the development of new mathematical techniques for decision making [1]. This has produced a set of ideas, approaches, and procedures that can be considered to form a modern framework for decision making. According to Grass [1, 16], a problem is a problem that it has alternative solutions. The problem of decision is the selection from competing alternative solutions. A decision maker is an individual, who dissatisfied with some existing situation or with the prospect of a future situation, possesses the desire and authority to initiate actions designed to alter this situation. Science of decision making is to solve problems, alternative solutions, and decisions.

The science is used in the sense of knowledge or principles obtained by study and practice. A model of decision analysis applies this knowledge to provide decision makers with a quantitative basis for choosing among alternative solutions.

### 2.2.3 Group Decision Making in Group DSS

A Group Decision Support System (GDSS) can be a key strategic combination in group interaction and decision making through expert preferences [15, 41]. In multiple decision making processes, Group Decision Making (GDM) can be applied to coordinate decision making in individuals in order to solve complex business problems [1, 14]. Decision makers can share their ideas and learn how previous decisions have been made. In other words, GDSS can be used in solving problems for decision makers with multiple criteria. This also reduces conflict among members in the decision making results. The conventional GDM is usually a static aggregation of all decision makers. GDSS, which aggregate group expert decisions, are potentially superior to those that use individual decisions for many aspects of domains [16]. When decision involves risks, individuals may make results inefficient as compared with GDSS. In GDM [41], the preferences of a group decision outcome aggregates individual responses into decision making process. Decision making processes have been widely studied in many aspects of social-economic environments. This also reduces conflict among members about the decision making results. GDM can be used in solving problems for decision makers with multiple criteria. Furthermore, GDM is not static over time so it can address dynamic decision situations in which the set of solution alternatives could change throughout the decision making process.

## 2.3 Self-Organizing Maps

A Self-Organizing Map (SOM) is an unsupervised learning algorithm, which was invented by Kohonen as a computational method for the visualization of high-dimensional data [18]. The SOM algorithm is described as follows:

- a. Initialize data matrix  $(a_{ij}^S)$  is randomly visualized by SOM training.

b. Calculate a minimum distance  $p_i$  which is defined by Euclidean distance given by Eq.(2.1).

$$p_i = \sqrt{\sum (x_j^S(t) - w_{ij}^S)^2} \quad (2.1)$$

where  $x_j^S$  is the numbers of input patterns and  $w_{ij}^S$ , which represents vector weights.

c. Select the minimum Euclidean distance. This step finds an index of a "winner" node given by Eq.(2.2).

$$p_i^* = \min\{p_i\} \quad (2.2)$$

d. Update and calculate vector weights given by Eq.(2.3). Repeat the similar steps mentioned above until the SOM has trained completely.

$$w_{ij}^S(t+1) = w_{ij}^S(t) + \alpha(x_j^S(t) - w_{ij}^S(t)) \quad (2.3)$$

where  $\alpha$  is the learning rates, controlled by an expert.

In general, a clustering algorithm is a division of data into groups of similar objects. There are a number of clustering methods for visualizing various data sets, such as K-means, Partitioning Around Medoids (PAM), Support Vector Machine (SVM), evolutionary, hierarchical clustering, and partitioning algorithms [19]. These algorithms have some limitations in complex data sets and integration of expert knowledge during the modeling process. The advantage of SOM is data mapping which is easily interpreted. In addition, SOM is capable of organizing large and complex data sets [18]. However, the disadvantages of SOM are that it is difficult to determine what input weights to use mapping in divided clusters. Uncertain values, market conditions and expert preferences are difficult to aggregate in a conventional SOM model.

In the dissertation, the contribution in this study is to provide a new approach using SOM integrated with other DSS techniques for the selection of alternatives in stock trading. In particular, uncertain values and expert sensibilities including dimension data can be presented in a SOM. The complex data sets can be presented in two-dimensional perceptual space in a map visualization. SOM also uses *Kansei*, quantitative and qualitative data sets in evaluation to quantify interval weight values

[0,1], which are integrated with a SOM model by aggregating multiple expert decisions for the selection of appropriate alternatives in stock trading.

## 2.4 Analytic Hierarchical Process

Professor Thomas Saaty set out to develop a mathematically-based technique for analyzing complex situations which was sophisticated in its simplicity [1,20]. Analytic Hierarchical Process (AHP) was developed in the 1970s and a technique for organizing the information and judgments used in making decisions. This technique became known as the AHP and has become very successful in helping decision makers to structure and analyze a wide range of problems.

AHP helps decision-makers to solve complicated problems through a measurement process within hierarchy and network structures and feed-back models. This method is practical, systematic and effective. It has been commonly used for conducting such undertakings as planning, ranking, selection, and evaluation of alternatives. The structure of AHP model is shown in Figure 2.2.

A summary of the AHP modeling process is basically as follows:

- (1) Set up the decision hierarchy
- (2) Make pairwise comparisons of attributes and alternatives
- (3) Transform the comparisons into weights and check the consistency of the decision maker's comparisons
- (4) Use the weights to obtain scores for the different options and make a provisional decision
- (5) Perform sensitivity analysis to enable a decision maker to examine changes in the ratings of importance and preference

In the AHP structure model, there are some features, as follows [20]:

- To begin with the structure from the top down to specify an overall goal first, then perspectives, criteria, subcriteria and the alternatives to achieve that goal.
- To classify each node, there are no more than nine items under each node of the hierarchy. If more than nine items are needed, consider further decomposition

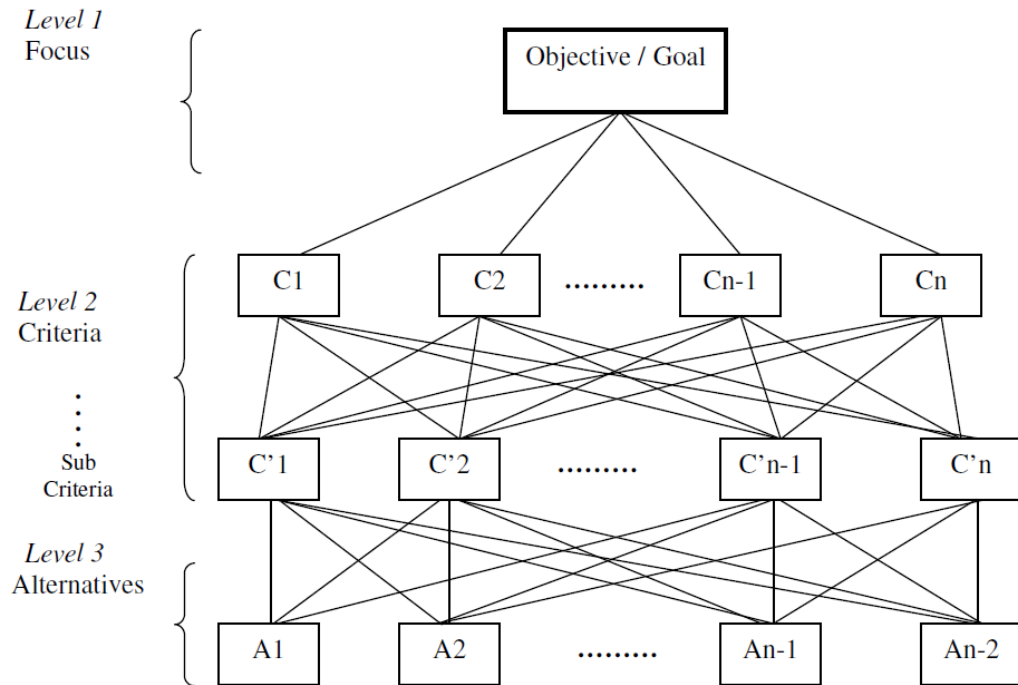


Figure 2.2: Structure of the AHP hierarchy

into levels such as criteria and subcriteria below those main criteria.

- To seek parsimony including all relevant factors but no more than the relevant factors. Too many nodes in the hierarchy cause the analysis to become tedious.

In this study, AHP is applied to either decision making or group decision making for selection of alternatives in rankings under uncertainty in stock trading. In various conditions, AHP also attempts to resolve conflicts and analyze judgment of criteria and provides a comprehensive framework for solving multi criteria in stock markets. AHP is used to rank alternatives in investment portfolios under uncertain market conditions.

## 2.5 Fuzzy Logic and Fuzzy Reasoning

Fuzzy logic is defined as fuzzy set-based methods for approximate reasoning under uncertainty. In particular, Fuzzy logic is to represent expert knowledge in a rule-based

style that reflects this knowledge [22, 23].

Fuzzy reasoning [21] enables approximate human reasoning capabilities to be applied to knowledge-based systems. After the first introduction of the fuzzy sets and fuzzy logic [22, 23], the idea of the reasoning was introduced by L.A. Zadeh [24]. A fuzzy control method was proposed as an application of fuzzy reasoning by D.E. Mamdani [25].

In fuzzy rule-based reasoning, a fuzzy matching step calculates the degree to which the input data match the condition of the fuzzy rules. The fuzzy rules in case of two input variables and one output variable are given by

$$\left\{ \begin{array}{l} R^1 : \text{if } x_1 \text{ is } A_{11} \text{ and } x_2 \text{ is } A_{12} \text{ then } y \text{ is } B_1 \\ R^2 : \text{if } x_1 \text{ is } A_{21} \text{ and } x_2 \text{ is } A_{22} \text{ then } y \text{ is } B_2 \\ \vdots \\ R^i : \text{if } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2} \text{ then } y \text{ is } B_i \\ \vdots \\ R^n : \text{if } x_1 \text{ is } A_{n1} \text{ and } x_2 \text{ is } A_{n2} \text{ then } y \text{ is } B_n \end{array} \right. \quad (2.4)$$

where  $x_1$  and  $x_2$  represent the input variables ( $x_1 \in X_1, x_2 \in X_2$ ) and  $y$  represents an output variable ( $y \in Y$ ).  $A_{i1}$ ,  $A_{i2}$  and  $B_i$  are fuzzy subsets of  $X_1$ ,  $X_2$  and  $Y$ , respectively. When the non-fuzzy input data “ $x_1$  is  $x_1^*$  and  $x_2$  is  $x_2^*$ ” is given, the matching degree  $\omega_i$  is expressed by

$$\omega_i = \mu_{A_{i1}}(x_1^*) \wedge \mu_{A_{i2}}(x_2^*) \quad (i = 1, 2, \dots, n) \quad (2.5)$$

where  $\wedge$  means the minimum operation.  $\mu_A$  is a membership function of the fuzzy subset  $A$ .

In this study, linguistic expressions can be used to represent rules for expert decision situations and uncertain market conditions are represented in fuzzy rules. Common Sense Human Reasoning [2, 77] can be presented by fuzzy reasoning and rules, quantitative knowledge and reasoning evidence.

## 2.6 *Kansei* Evaluation

*Kansei* Engineering (KE) [27, 28] has been developed as a methodology to deal with human feelings, demands, and impressions of business applications. *Kansei* is a Japanese term meaning sensibility, impression, and emotion [40]. In trading stocks, *Kansei* Evaluation makes it possible to quantify investor perception, sensation, cognition, and sentiment about trading actions such as buying-selling decisions and investment risk events.

In *Kansei* Evaluation, we have determined adjective pairs called *Kansei* words: Synonym - Antonym or Synonym - Not Synonym. For instance, the pairs of adjectives *good* - *bad* and *successful* - *unsuccessful* are *Kansei* words. These *Kansei* words are influenced to the hierarchical factor structure [30, 31]. To evaluate companies in terms of stock trading, *Kansei* evaluation is used to quantify expert sensibilities under uncertainty and risks.

### 2.6.1 *Kansei* Words and Stock Market Factor Structure in Company Assessments

In experiments, we have collected 36 *Kansei* words and 19 significant stock-market factors [29, 31, 38, 40], influenced by four criteria for company evaluation and selected appropriately 14 *Kansei* words of the most relevant adjective pairs in stock trading, as shown in Table 2.1.

When trading stocks, professional traders determine appropriate actions (buying/selling) using expert sensibilities for the most suitable stocks matching with trading strategies based on the situations of market conditions. In *Kansei* evaluation, the adjective pairs of trading decision are as follows [29, 31, 38]: Stable-Unstable, Wining-Losing, Expensive-Cheap, Profitable-Unprofitable, Long-term-Short-term, Rising-Falling, and Higher-Lower. Regarding the expert experiences in stock trading, these *Kansei* words for trading decisions are mostly used to evaluate the selected companies for stock trading.

Table 2.1: Pairs of *Kansei* words for *Kansei* evaluation

| No | Negative word  | Positive word | Stock-market factor   | Criteria             |
|----|----------------|---------------|---|----------------------|
| 1  | Not good       | Good          | Structure and management  | Company Assessments  |
| 2  | Unpleasant     | Pleasant      | Organization  |                      |
| 3  | Not famous     | Famous        | Brand name  |                      |
| 4  | Local          | Global        | Planning strategy   |                      |
| 5  | Unsuccessful   | Successful    | Period evaluation   |                      |
| 6  | Cheap          | Expensive     | Market price  | Financial Ratios     |
| 7  | Low            | High          | Profit margin   |                      |
| 8  | Decreased      | Increased     | P/E (price-to-earnings)<br>EPS (earnings per share)                                       |                      |
| 9  | Unsatisfactory | Satisfactory  | P/B (price-to-book)<br>ROE (return on equity)<br>ROA (return on assets)                   |                      |
| 10 | Insufficient   | Sufficient    | Stochastic oscillator   | Technical Indicators |
| 11 | Stable         | Changing      | Moving average convergence  |                      |
| 12 | Standing       | Falling       | Moving average divergence<br>Relative strength index (RSI)<br>Moving average weight (MAW) |                      |
| 13 | Not Confident  | Confident     | Investor confidence index   | Investor Confidences |
| 14 | Risky          | Safe          | Consumer confidence index   |                      |

### 2.6.2 *Kansei* Word and Stock Market Factor Structure in Risk Management

In terms of risk management for an evaluation, *Kansei* words are relevant to investment risks criteria such as company assessments, stock market risks, and environment risks that affect to evaluate companies [29, 35, 69]. We have collected 20 *Kansei* words and 14 significant stock-market factors, influencing to 3 criteria for company evaluation on a stock market in terms of risk management [35]. Table 2.2 shows 14 *Kansei* words, relevant to investment risks for evaluation of companies.



Table 2.2: Pairs of *Kansei* words for risk management

| No | Negative word  | Positive word | Investment Risk factor | Criteria            |
|----|----------------|---------------|------------------------|---------------------|
| 1  | Risky          | Safe          | Finance                | Company Assessments |
| 2  | Low            | High          | Acquisition Risk       |                     |
| 3  | Unsatisfactory | Satisfactory  | Operation              |                     |
| 4  | Unsuccessful   | Successful    | Management             | Stock market Risks  |
| 5  | Uncertain      | Certain       | Business model         |                     |
| 6  | Decreased      | Increased     | Inflation Risk         |                     |
| 7  | Irregular      | Regular       | Market Risk            |                     |
| 8  | Falling        | Rising        | Global market          |                     |
| 9  | Not valuable   | Valuable      | Stock price            | Environment Risks   |
| 10 | Low            | High          | Legislative risk       |                     |
| 11 | Not good       | Good          | Events                 |                     |
| 12 | Not important  | Important     | Political risk         |                     |
| 13 | Unstable       | Stable        | Currency risk          |                     |
| 14 | Uncertain      | Certain       | Economics              |                     |

### 2.6.3 *Kansei* Evaluation by quantification of sensibilities

Let  $X^S = \{X_1^S, X_2^S, \dots, X_m^S\}$  be a set of *Kansei* words which are used to evaluate companies, where  $m$  is the number of *Kansei* words. In order to quantify investor's sensibilities in stock trading, we have refined for the most important *Kansei* words in  $X^S$  to evaluate a company with respect to criteria and stock market factors in stock market  $S$ .

Let  $W_m^S = \{W_m^-, W_m^+\}$  be opposite pairs of *Kansei* words with respect to  $X_m^S$ . Suppose that  $P$  senior investors collect their preferences by surveys. To evaluate company  $C_j^S$ , its *Kansei* weight  $w_{ij}^t$  represents by the  $i$ -th *Kansei* word of the  $j$ -th company evaluated by the  $t$ -th investor. Hence, the average weight of  $i$ -th *Kansei* word of  $j$ -th company is evaluated by  $P$  investors, as given by Eq.(2.6).

$$k_{ij}^S = \frac{1}{P} \sum_{t=1}^P w_{ij}^t \quad (2.6)$$

where company  $C_j^S$  is defined in Section 3.5.1.

## 2.7 Research Backgrounds

### 2.7.1 Stock Trading Basis

The nature of stock market investment problems requires combining knowledge in the fields of both economy and engineering. Stock market investments focus on developing approaches to successfully forecast/predict stock prices, index values, and market trends, aiming at higher profits based on stock trading decisions [37,38]. Most existing approaches to select superior stocks at the right time for investment are broadly classified by trading activities, such as fundamental and technical approaches [37, 39]. Fundamental analysis aims to select potential stocks based on study of the fundamental data of a company such as financial weights, macroeconomics, financial proportions, and stock-market news. Contrary to this approach, technical analysis attempts to predict price by analyzing historical data of the correlation between prices and market behavior volumes for trading stocks.

Regarding the conventional stock market investment strategies [37, 38, 45], there are formal investing strategies, such as value investing, growth investing and technical investing. For example, the value investing strategy focuses on looking for companies selling at a bargain price with fundamental approaches such as price earning (PE), book value, cash flow and profit ratios. The growth investing strategy relies on future potential of a company applied to yield unprecedented stocks for investors. The technical investing strategy focuses on technical analysis looking at the past market activity, price, volume and chart for future movement of stock price. In addition, there are a variety of extra investing strategies such as Income Investing, Growth at a Reasonable Price (GARP), CAN SLIM system, DOGs of the DOW, and others [37, 39]. These investing strategies have been applied to short-term, mixed

and long-term stock trading for investment. In a conventional model of stock market investments, investors/stockbrokers observe the stock market to buy stocks if they tend to gain value, to sell stocks if they tend to lose value or to hold stocks if a current stock price trend is stable. Furthermore, they wish to select potential companies (superior stocks) at the right time for investment.

Even using several commercial trading stock software applications and intelligent systems to make trading decisions, investors may face uncertain conditions in dynamic stock market environments such as government policies, bank interest rates, world stock market prices, financial rule changes, and real-time stock trading trends. A good example illustrating influences on stock market environment is the impact of oil prices on stock prices [74]. Furthermore, the trading behaviors of group/individual investors are commonly affected by the news published by economic news, websites and other publishing news [44]. Suppose that there are stock market conditions influenced by oil prices. Many investors are convinced by the predictability of transportation companies in financial markets and hope to get higher profits through technical and fundamental analysis since the companies provide good financial news. When buying a stock, the investors consider the possibility of the potential companies to invest their funds. In the current stock market environment, oil prices of the country tend to increase the range from 7% to 10% within 3 months so that the company will pay extra oil costs for transportation. The stock price of this company may rise quickly in a short time but trend downward one month later. In particular, several risks affect the stock in market dynamics such as business risks, oil price inflation and policy rules. When selling the stock, the investors consider not only the stock price trends but also the profit or loss incurred by the stock. To control risk management in stock trading, a professional trader usually investigate risks before, during, and after all trading activities. Company assessments together with risk management are considered in trading activities to reduce loss and manage risk. In real-time trading stocks, investor emotion, sensibility and impression in selling/buying stocks on dynamic stock environments may affect uncertain conditions on a stock market. According to the conventional model of stock trading, it is hard to decide which potential companies should be selected at the right time for stock trading in a dynamic

stock market environment. Based on this view point, the study in this dissertation focuses on exploring a new approach to quantify investor's feelings about trading stocks, integrated with DSS models in order to develop a real-world application for selection of alternatives for investment in stock trading.

### 2.7.2 Related Works

Recently, hybrid intelligent systems and soft computing models provide cohesive presentations and classifications for solutions to problems in stock trading for investments [63,64,67]. These systems are used for prediction, analysis, and as comparative methods [49,59–62]. Most studies focus on developing approaches to forecast or predict stock prices based on historical data, aiming at high profits in stock trading. In a stock price model [52–55], option pricing models based on dynamic and general linear investment strategies help investors decide to buy/sell in trading systems. Some approaches [56,57] have investigated analysis models for financial time series forecasting, with many complex features of financial phenomena based on present and past historical data. In other studies, financial market trading systems using fuzzy predictive model and evolving trading rules have been proposed to improve trading strategies based on real-world financial data [59,60,64,65]. In Decision Support Systems (DSS) and Expert Systems (ES) applications [8,9,11,12,66], the approaches are concerned with decision making on stock trading, instead of quantitative and qualitative factors in analysis.

In stock trading, stock markets have become high-risk markets for investors. The main reasons are that many factors and environments affect the stock indices as well as investment returns [45,46]. Risk management is the process of evaluating risk, managing the risk when trading stocks to minimize losses and maximize investment returns [45,69,70]. Risk management mostly involves utilizing a variety of trading activities and financial analysis, one of the most complicated stock trading skills for professional traders [70,71]. Successful investors employ many risk management skills for stock trading, as they know how important it is to avoid mistakes when investing in the stock market. The total risk management is a combination of many

possible sources of risk on stock markets. Financial risk management using the Value At Risk (VAR) method is becoming an international standard method to measure risks in the evaluation of various stock markets [72, 73]. Managing stock market risk starts with identifying the various types of risks, influencing stocks and then taking action to mitigate the impact of risk in an investment portfolio. Each type of risk can affect the investment returns of stock trading. For instance, risks in the stock market may be affected by overall market trends. The trends of the stock market are estimated about 60% - 65% of trends in individual stocks affected by various market conditions so assessing market risk is an important part of risk management. In trading stocks, stock assessments are significant decision-making problems affected by dynamic market conditions, market trends and market risks. According to the related works mentioned above, most research is only concerned with quantitative factors, such as index values, technical indicators, financial factors and volume behaviors based on historical data. Recently, the new approach using Rule-based Evidential Reasoning [68] is concerned with the synthesis of the fuzzy logics and Dempster-Shafer theory and presented in stock trading conventionally based on evident reasoning and testing on an actual stock market. Although this approach is recently shown in an expert stock trading system based on evidential reasoning, the limitation of this approach is that it selects superior stocks at the suitable trading time mostly based on historical data, technical analysis indicators, and trading rules. In particular, in terms of money inflation, political policy and macroeconomics in dynamic market conditions make experts difficult in the trading system. We have employed and tested this approach using Wealth-lab Developer 5 software in daily stock trading with different stock market conditions. The experimental results show that the success of investment performance relies on overall up-trending signals of stock indices and technical indicators mostly based on historical data.

In overall, most recent models, hybrid intelligent systems and approaches mentioned above have been considered historical data in the past or financial fundamental approaches. Most approaches show incomplete solutions for selection of companies to achieve investment returns since many uncertain conditions that are not considered

concurrently in those studies, such as stock prices, technical indicators, macroeconomics, event news, and investor sensibilities for stock trading. This affects the capability for an alternative selection of an investment system to deal with various market conditions. In this study, Hybrid Intelligent DSS has been investigated to select the right alternatives (stocks, companies, stock groups) for investment when dealing with uncertainty and risk.

## 2.8 Conclusion

This chapter described the basic concepts of techniques which uses in a Hybrid DSS model. These basic techniques discussed in this chapter have been developed by many researchers in various engineering areas. In related works, this chapter also provides the latest research news from Soft Computing models, Intelligent Systems, Decision Support Systems, and Hybrid Systems for investments in stock trading. Chapters 3, 4, 5, and 6 discuss methods for applying these techniques to the Hybrid Intelligent DSS models for selection of alternatives in stock trading.

## Chapter 3

# Hybrid Intelligent Decision Support Systems for Selection of Alternatives in Stock Trading

### 3.1 Introduction

Alternatives in a selection are dynamically changing in uncertain environments. When considering uncertainty in processes of multiple decisions for the selection of alternatives in dynamic environments, models that use a single Decision Support System (DSS) have faced limitations for the selection of alternatives in complex situations under uncertainty.

This chapter presents a framework using Hybrid Intelligent DSS for the selection of multiple alternatives under uncertainty in the domain of stock trading. This framework which uses qualitative and quantitative attributes of alternatives, together with uncertain market conditions, aims to find out a short list of alternatives in rankings for investment. In market dynamics, this framework using the aggregation of expert preferences and sensibilities seeks to select alternatives with stock market investment strategies and optimal trading decisions. In addition, risk management is applied to select alternatives at the right time by dealing with complex conditions, with the goal of high investment returns and reducing risky decisions. In this chapter, there are

some conceptual terms and definition, represented in common formulations in stock trading.

## 3.2 Framework using Hybrid Intelligent DSS for Selection of Alternatives in Stock Trading

### 3.2.1 Proposed Framework

According to the related works as mentioned in Section 2.7.2 in Chapter 2, most studies are only concerned with quantitative factors, such as index values, technical indicators, financial factors and volume behaviors based on historical data. In addition, these models have not been considered concurrently uncertain values including market conditions, quantitative and qualitative stock-market factors, together with experts' feelings and preferences about trading decisions. This affects the capability for an alternative selection of an investment system to deal with various market conditions. To solve the problems, a proposed framework is used for the selection of multiple alternatives (companies, stocks, and company groups) under uncertainty and risk in stock trading. Figure 3.1 shows the proposed framework consisting of three integrated intelligent DSS, for selection of alternatives from a large numbers of alternatives by aggregating either individual or multiple expert decisions, aiming for optimized trading decisions and reducing risky decisions.

This framework consisting of its components is described as follows:

- **Data Model:** The data model includes quantitative and qualitative stock-market factors, uncertain market conditions and expert preferences and sensitivities. The data model of stock market investments is used to apply various market conditions on stock markets such as HOSE, HNX, NYSE and NASDAQ.
- **DSS Database:** The database consists of *Kansei* data sets which respond from investors and experts based on their preferences. In a stock market environment, quantitative and qualitative factors obtained from a stock market are evaluated



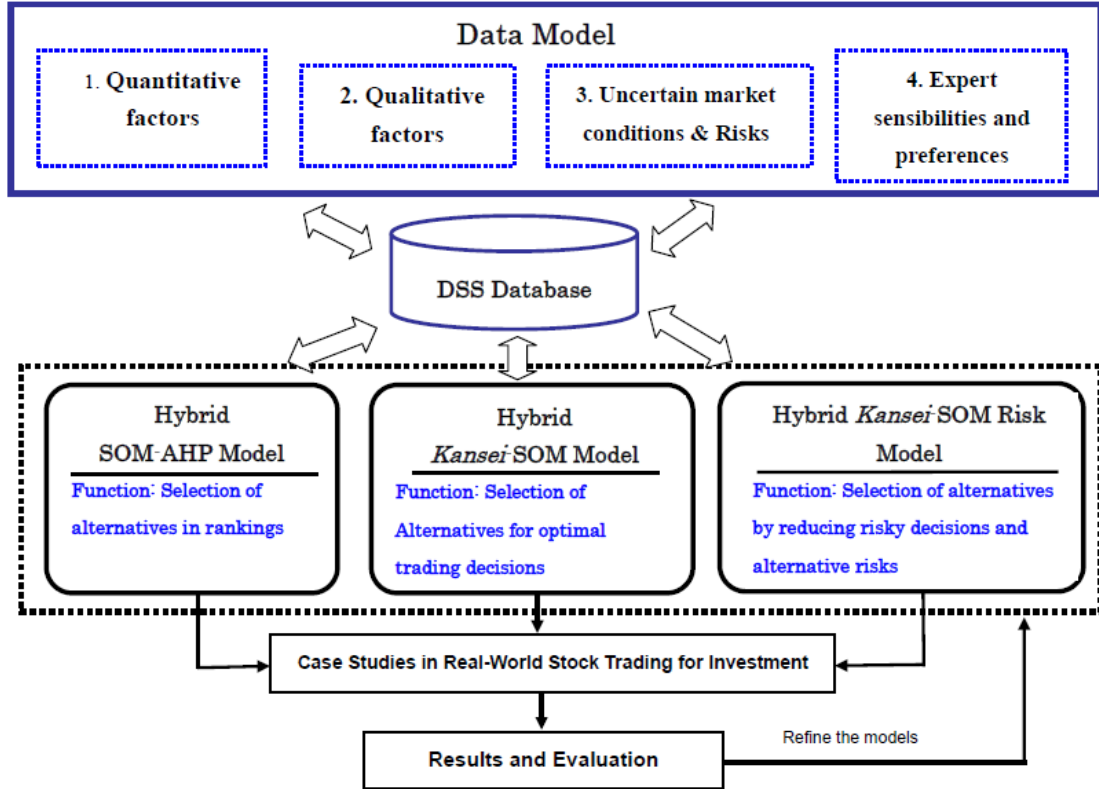


Figure 3.1: Framework for selection of alternatives in stock trading

by decision makers. Most processes of data sets and fuzzy rules are executed in the DSS database.

This framework using Hybrid Intelligent DSS includes three proposed models (Hybrid SOM-AHP, Hybrid *Kansei*-SOM, Hybrid *Kansei*-risk SOM) for the selection of multiple alternatives under uncertainty in the domain of stock trading. This framework which uses qualitative and quantitative attributes of alternatives, together with expert sensibilities under uncertain market conditions, aims to find out a short list of appropriate alternatives (companies, company groups, and stocks) for investment in stock trading.

In terms of stock selection in real-world trading, the features in this framework includes addressing these issues as follows:

- (1) To enhance capability for investment returns of the proposed framework, this

uses uncertain values consisting of quantitative and qualitative factors to evaluate companies for investment.

(2) To select appropriate companies in trading decisions, the quantification of expert sensibilities and impressions about stock trading in market conditions allows the proposed model to determine the potential companies (superior stocks) at the right time for stock trading.

To confirm these model's performance, we have selected Vietnam and US stock markets, representing economically developing and developed countries. The proposed framework has been tested and performed well in simulated trading and real-world stock trading on the HOSE, HNX (Vietnam), NYSE and NASDAQ (US) stock markets through case studies.

### 3.2.2 Formulation and Conceptual Terms

This section explains how we can define conceptual terms, qualitative factors, quantitative factors, *Kansei* evaluation, and constructing matrices for stock trading.

Suppose there is a group of  $n$  experts in a making decision for stock investment portfolio. Let  $E = \{e_1, e_2, \dots, e_n\}$  be a set of experts, where  $n$  is the number of experts. Experts may have different degrees of knowledge and each of these experts indicates preferences. A set of  $X^S = \{x_1^S, x_2^S, \dots, x_k^S\}$  is a set of  $k$  alternatives in an environment  $S$ . Let  $\mu_i(x_j^S)$  be the interval membership degree of expert  $e_i$ , in which the expert  $e_i$  prefers alternative  $x_j^S$ . We consider  $\mu_i(x_j^S) \in [0, 1] \forall i, j$  as representing membership values. To construct a factor structure in evaluation of alternatives, both quantitative and qualitative data need to be either normalized or evaluated in interval membership values  $[0, 1]$ .

Let  $B^S = \{B_1^S, B_2^S, \dots, B_h^S\}$  be a set of group companies, where  $h$  is the numbers of group companies in stock market  $S$ . Let  $C^S = \{C_1^S, C_2^S, \dots, C_n^S\}$  be a set of companies in stock market  $S$ , where  $n$  is the numbers of companies in stock market  $S$ .  $C_i^S \in B_j^S$  and  $C_i^S$  represents by the  $i$ -th company belonging to the  $j$ -th company group in the same industry.

Let  $G^S = \{g_1^S, g_2^S, \dots, g_m^S\}$  be a set of company factors in stock market  $S$ , where

$m$  is the number of company factors. Factor  $g_j^S$  is evaluated by expert preference so that each factor has a different factor degree, based on the time under uncertainty.

Let  $B^R = \{B_1^R, B_2^R, \dots, B_p^R\}$  be a set of potential group companies for investment, where  $p$  is the numbers of potential group companies in system result  $R$ . Let  $G^R = \{G_1^R, G_2^R, \dots, G_k^R\}$  be a set of risk group companies for risky investment, where  $k$  is the numbers of risky group companies in system result  $R$ .

### 3.2.3 Data Sets for Matrices Construction

The purpose of *Kansei* stock matrix construction is used to quantify *Kansei*, stock-market data sets, together with expert preferences for evaluation of companies, representing in fuzzy weight values  $[0,1]$ . There are three matrices which have been constructed for the framework.

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 [77] to normalize quantitative factors, supported for experts to evaluate a company.

Let  $B^S = \{B_1^S, B_2^S, \dots, B_h^S\}$  be a set of group companies in stock market  $S$ , where  $h$  is the numbers of group companies. Let  $C^S = \{C_1^S, C_2^S, \dots, C_n^S\}$  be a set of companies in stock market  $S$ , where  $n$  is the numbers of companies in stock market  $S$ .  $C_i^S \in B_j^S$  and  $C_i^S$  represents by the  $i$ -th company belonging to the  $j$ -th company group in the same industry.

Let  $f^S = \{f_1^S, f_2^S, \dots, f_l^S\}$  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 preference so that each factor has a different significant factor degree.

Let  $B^R = \{B_1^R, B_2^R, \dots, B_p^R\}$  be a set of potential group companies for investment, where  $p$  is the numbers of potential group companies in system result  $R$ . Let  $G^R = \{G_1^R, G_2^R, \dots, G_k^R\}$  be a set of risk group companies for risky investment, where  $k$  is the numbers of risky group companies in system result  $R$ .

$\{K_{n \times m}^S | (i = 1, \dots, n, j = 1, \dots, m)\}$  is a *Kansei* matrix construction, where  $n$  and

$m$  is the number of companies and *Kansei* words respectively.

$\{Q_{n \times g}^S | (i = 1, \dots, n, j = 1, \dots, g)\}$  is a Quantitative-qualitative matrix of stock market  $S$ , where  $n$  is the number of companies and  $g$  is the number of quantitative and qualitative factors. A Quantitative-qualitative stock matrix  $Q_{n \times p}^S$  is constructed, representing in membership weight values  $[0,1]$  for the results of qualitative and quantitative factor quantification of company assessments.

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

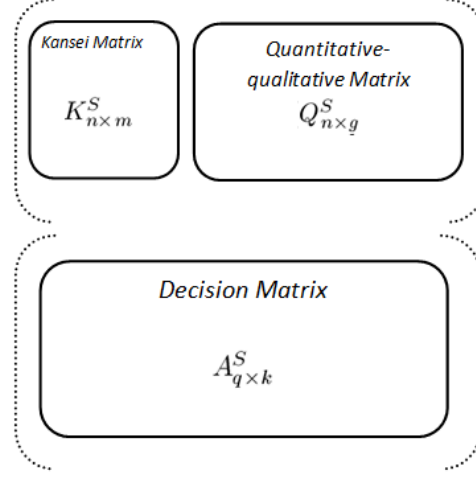
$\{p_t^S (t = 1, \dots, c)\}$  is a set of stock trading strategies and Decision matrix  $\{A_{q \times k}^S | (i = 1, \dots, q, j = 1, \dots, k)\}$  represents expert decisions about stock trading in stock market  $S$ .

An expert provides his/her preference  $\beta_i^S$ . Further more, an expert may evaluate stocks in terms of investment risks based on his/her preference  $\gamma_i^S$ . Both  $\beta_i^S$  and  $\gamma_i^S$  can be defined in a five-point scale (0: *oppose*, 0.25: *almost oppose*, 0.5: *have no preference*, 0.75: *almost agree*, 1: *agree*). An expert decision matrix  $A_{q \times k}^S$  is constructed and risk decision matrix  $R_{q \times v}^S$  is the similar the decision matrix manner.

A *Kansei* stock matrix  $M_{n \times p}^S$  is constructed by joining *Kansei* matrix  $K_{n \times m}^S$  and Quantitative-qualitative matrix  $Q_{n \times g}^S$  with the Decision matrix  $A_{q \times k}^S$ , where  $n$  is the number of companies,  $k=m+g$  is the total number of dimensions (*Kansei* words, quantitative and qualitative factors) and  $p=t+n$  is the total number of dimensions (companies and experts). The constructed matrices are shown in shown in Figure 3.2.

### 3.2.4 Qualitative Factor Evaluation Using Fuzzy Reasoning

To evaluate a company based on qualitative stock-market factors, qualitative factor weights representing in fuzzy reasoning are evaluated by expert preferences using fuzzy expression and fuzzy inference [34, 36].

Figure 3.2: Construction of *Kansei* stock matrix

*a. Fuzzy Expressions*

Let  $f^S = \{f_1^S, f_2^S, \dots, f_l^S\}$  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 preference so that each factor has a different significant factor degree. Let  $I^{CS} = \{I_1^{CS}, I_2^{CS}, \dots, I_l^{CS}\}$  be a set of factor weight states of a company. Let  $R^{f_j} = \{R_1^{f_j}, R_2^{f_j}, \dots, R_m^{f_j}\}$  be a set of fuzzy rules, where  $m$  is the number of fuzzy rules. These fuzzy rules represent by the stock market environment of the  $j$ -th factor  $f_j^S$  affected by  $R_i^{f_j}$  to evaluate a company based on expert preferences. Rule  $R_i^{f_j}$  represents by the form as follows:

$R_i^{f_j}$ : **IF**  $\langle$  Market fuzzy conditions  $\rangle$   
**THEN** Update weights in  $I_j^{CS}$  of the DSS database

where

$m$  is the number of fuzzy rules. Market fuzzy conditions given by decision makers are commonly used in stock markets as shown in Table 6.1 in Chapter 6.

The values  $R_i^0$  and  $R_i^{f_j}$  are defined by  $\mu_{R_i}^0$  and  $\mu_{R_i}^{f_j}$  fuzzy membership values respectively that represent by as follows:

- $R_i^0$  has  $\mu_{R_i}^0 \in [0,1]$  given by significant factors of a company in stock market  $S$  with severity  $\mu_{R_i}^0$  as follows:

$\mu_{R_i}^0 = 1$  means  $R_i^0$  having significant factors.

$\mu_{R_i}^0 = 0$  means  $R_i^0$  that do not satisfy significant factors.

$0 < \mu_{R_i}^0 < 1$  means  $R_i^0$  having significant factors of a company with severity  $\mu_{R_i}^0$ .

- $\mu_{R_i}^{f_j} \in [0,1]$  has significant factors in fuzzy membership values, which are evaluated by expert preferences using fuzzy membership values of the rule  $R_i^{f_j}$  in stock market  $S$  as expressed by Eq.(3.1).

$$\sum_{i=1}^m \mu_{R_i}^{f_j} \quad (3.1)$$

where  $m$  is the number of fuzzy rules assigned by expert preferences and the fuzzy membership values are defined in Table 3.1.

Table 3.1: Expert scale representing by fuzzy weights

| ID No | $\mu_{R_i}^{f_j}$ | 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  $0 < \mu_{R_i}^{f_j} < 1$  means fuzzy membership values evaluated by expert preferences of  $R_i^{f_j}$  updated its status in  $I_j^S$  with severity  $\mu_{R_i}^{f_j}$  fuzzy membership values.

#### b. Fuzzy Inference Process

In the inference process, fuzzy rules represent by the stock market environment of the factor  $f_j$  affected by  $R_i^{f_j}$  ( $i = 1, \dots, m$ ) to evaluate company  $C_i^S$  based on expert preferences. The weight  $w_{C_i^S}^j$  is expressed by Eq.(3.2).

$$w_{C_i^S}^j = \mu_{R_i}^0 \otimes \mu_{R_i}^{f_j} \quad (3.2)$$

where  $\otimes$  is a *t-norm* operator,  $a \otimes b = a \times b$  as an execution in the DSS database.

Hence,  $I_j^{C_i^S} = w_{C_i^S}^j$  is the fuzzy membership value of factor  $f_j^S$ , used to evaluate company  $C_i^S$ .

### 3.2.5 Quantitative Factor for Data Normalization

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.(3.3).

$$k_j = \frac{1}{1 + \exp \frac{(-D_j - a)}{b}} \quad (3.3)$$

where  $k_j$  ( $j = 1, \dots, l$ ) is the normalized value of quantitative factors of a company;  $D_j$  ( $j = 1, \dots, l$ ) 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 other words, experts adjust these parameters of the Sigmoid function based on the normalization of the Sigmoid function line.

For example of stock market conditions, we use logical rule expressions and inference that are combined with common preferences among group members, under uncertain values in dynamic market environment. In other words, Common Sense Human Reasoning can be presented as an integration of fuzzy rules, quantitative knowledge and reasoning evidence. Linguistic expressions are used to represent rules for expert decision situations. To quantify the Common Sense Human Reasoning [2, 77] of expert  $e_i$  in stock-market dynamics, we use the following logical rules as an example:

**Rule 1:** **IF** Inflation is high **AND** industrial product exports are low **THEN** Stock prices of groups of export companies will decrease.

**Rule 2:** **IF** CPI (consumer price index) is low **THEN** stock prices of product and food companies may rise quickly.

**Rule 3:** **IF** oil and gas prices on the global market are low **AND** transportation

costs are acceptable **THEN** stock prices of transportation companies rise quickly.

These rules represent market conditions, which are influenced to stock-market factors of companies or group companies, assigned by decision makers. These weights of stock-market factors are updated in the *Kansei* stock matrix, expressed by Eq.(3.2) for each company under the market condition. Figure 3.3 shows updated weights in the *Kansei* stock matrix.

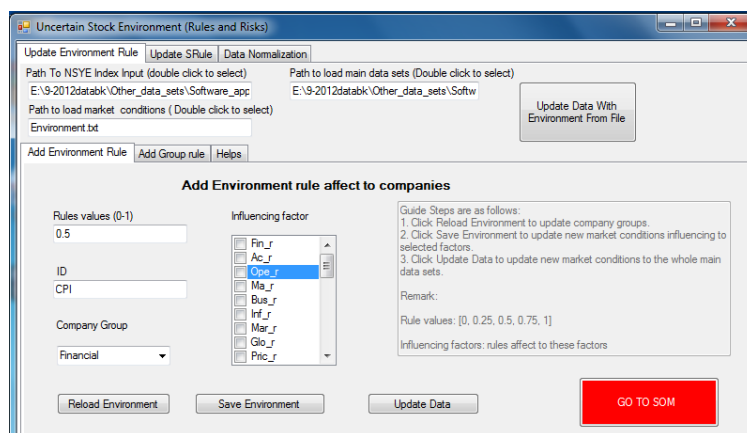


Figure 3.3: Updated weights in the *Kansei* stock matrix

### 3.3 Steps of the Framework for Selection of Alternatives in Stock Trading

The proposed framework is shown in Figure 3.1 for the selection of stock in trading decisions. This framework uses uncertain values of quantitative and qualitative factors, together with the quantification of expert sensibilities and preferences in uncertain environments. These weights can be transformed through for the framework, represented in interval values  $[0,1]$ . These data sets, including *Kansei* and stock-market data sets, are updated in the DSS database. Steps of the framework for selection of alternatives in stock trading are as follows:

**Step 1. Hybrid SOM-AHP Model form ranking a short list of companies for investment**



The first model, called the Hybrid SOM-AHP model, is a Self-Organizing Map (SOM) integrated with Analytic Hierarchy Process (AHP). This model using an individual expert aims to select short-list investment alternatives in rankings for stock trading. Stock market factors including qualitative and quantitative factors are structured in the hierarchical model. Additionally, these factors are also placed in Quantitative-qualitative matrix  $Q_{n \times g}^S$ .

**Step 1.1 Alternative attribute distance definition** To calculate differences among *Kansei* stock attributes of companies, the *Kansei* stock distance  $d_{C_i \rightarrow C_j}^S$  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.(3.4).

$$d_{C_i \rightarrow C_j}^S = \| D_{C_i}^S - D_{C_j}^S \| \quad (3.4)$$

**Step 1.2 Finding appropriate companies for investment by SOM training** . A stock matrix  $Q_{n \times g}^S$  is visualised by SOM to find similar features of stocks in terms of high financial weights, considered by an expert. These group results in a SOM map are shown in a short list of companies for investment.

**Step 1.3 Evaluating short-list companies for investment using Analytic Hierarchy Process (AHP)**. To rank the alternatives in the short-list companies, these alternatives are used in AHP model to evaluate the companies for investment by checking consistency ratios (CR), where RI is the random index and CI is the consistency index. Decision makers input data sets in the judgment matrix if CR is less than 0.1. The AHP results are appropriate companies in short-list rankings for investment.

**Step 2 Hybrid *Kansei*-SOM model for selection of companies matching with trading strategies**

**Step 2.1 Expert preference distance definition**

Expert preference distance  $d_{e_i \rightarrow e_j}^S$  between two vectors  $D_{e_i}^S$  and  $D_{e_j}^S$  represents by expert preferences, as defined by Euclidean distance given by Eq.(3.5).

$$d_{e_i \rightarrow e_j}^S = \| D_{e_i}^S - D_{e_j}^S \| \quad (3.5)$$

**Step 2.2. Visualizing *Kansei* stock matrix by SOM.** The *Kansei* stock matrix  $M_{n \times p}^S$  is visualized by SOM in order to find the similar attributes of companies by aggregating expert preferences, matching with appropriate trading strategies.

**Step 2.3. Calculating *Kansei* stock weights by identifying distances between expert and the average of expert group.** The distance between expert and the average of expert group  $x_{ij}^t$  at iteration  $t$  of each group is expressed by Eq.(3.6).

$$x_{ij}^t = \frac{1}{K} \sum_{\xi=1}^K w_{\xi j}^t - v_{ij}^t \quad (3.6)$$

where

$x_{ij}^t$  represents a member of Expert decision matrix.

$w_{\xi j}^t$  represents the *Kansei* stock weight of the  $\xi$ -th expert preference for the  $j$ -th *Kansei* word, or quantitative and qualitative factor, in order to calculate the distances between expert preference and other member preference within his/her group.

$v_{ij}^t$  represents the *Kansei* stock weight of the  $i$ -th expert preference for the  $j$ -th *Kansei* word, or quantitative and qualitative factor, which is a member of both the *Kansei* stock matrix and expert decision matrix.

$K$  is the number of experts in the group; ( $j = 1, \dots, p$ ) and  $p$  is the number of *Kansei* words, or quantitative and qualitative factors.

**Step 2.4 Updating *Kansei* stock weights of an expert decision matrix.**

An expert decision matrix  $A_{q \times k}^S$  is updated by its weights given by Eq.(3.7). After that, the expert decision matrix  $A_{q \times k}^S$  is joined with *Kansei* stock matrix  $M_{n \times p}^S$  and its weights are updated to  $M_{n \times p}^S$ .

$$v_{ij}^{t+1} = v_{ij}^t + v_{ij}^t x_{ij}^t \quad (3.7)$$

where  $K$  is the number of experts in each group. To select trading strategies  $(p_1^S, p_2^S, \dots, p_c^S)$ ,  $K \in [1, \dots, c]$  is the number of experts in each group, representing in its trading strategy.

To aggregate multiple expert trading decisions, the similar steps are repeated

between Step 2.2 and Step 2.4 until  $c$  expert groups are updating weights to the expert decision matrix completely in training process.

**Step 3. Hybrid *Kansei* SOM risk model for selection of companies under risk**

**Step 3.1 Alternative risk attribute distance definition** To calculate differences among *Kansei* risk attributes of companies, the *Kansei* risk distance  $d_{C_i \rightarrow C_j}^R$  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.(3.8).

$$d_{C_i \rightarrow C_j}^R = \| D_{C_i}^R - D_{C_j}^R \| \quad (3.8)$$

**Step 3.2. Visualizing *Kansei* risk matrix by SOM.** The *Kansei* risk matrix  $Q_{n \times p}^S$  is visualized by SOM in order to find the similar attributes of companies by aggregating expert preferences in terms of investment risks.

To eliminate risky stocks, we apply similar steps to calculate *Kansei* risk weight among expert preferences, as given by Eq.(3.6) from Step 2.3 to 2.4. These alternatives are clustered in groups, occurred by risky decisions.

**Step 3.3 Comparison of the results by SOM visualization.** After the *Kansei* stock and *Kansei* risk matrices are visualized by SOM, these SOM results showed on a map. Assume that  $B_i^R$  and  $\Gamma_i^R$  are appropriate company groups in SOM results of *Kansei* stock matrix and *Kansei* risk matrix, respectively visualized by SOM. The final result on a map of the proposed system is determined by the following conditions.

**IF**  $C_j^S \subseteq B_i^R$  AND  $C_j^S \notin \Gamma_i^R$  **THEN**  
 $C_j^S$  is a potential company (superior stock) for investment  
**ELSE**  $C_j^S$  is not a candidate.

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 stocks, matching with appropriate trading strategies and eliminating risky stocks.

### 3.4 Data Collection in Experiments

Experiments of the models (Hybrid SOM-AHP, Hybrid *Kansei*-SOM, Hybrid *Kansei*-SOM Risk) have been conducted by experts objectively on the Vietnam and US stock markets, representing economically developing and developed countries. To validate the performance of this framework, these models have been tested and performed well in real-world stock trading by experiments in case studies on the HOSE, HNX (Vietnam) and NYSE and NASDAQ (USA) stock markets. In case studies of stock market investments, we have investigated how these models perform with respect to various market conditions. In this study, the processes of data collection for experiments is shown in Figure 3.4.

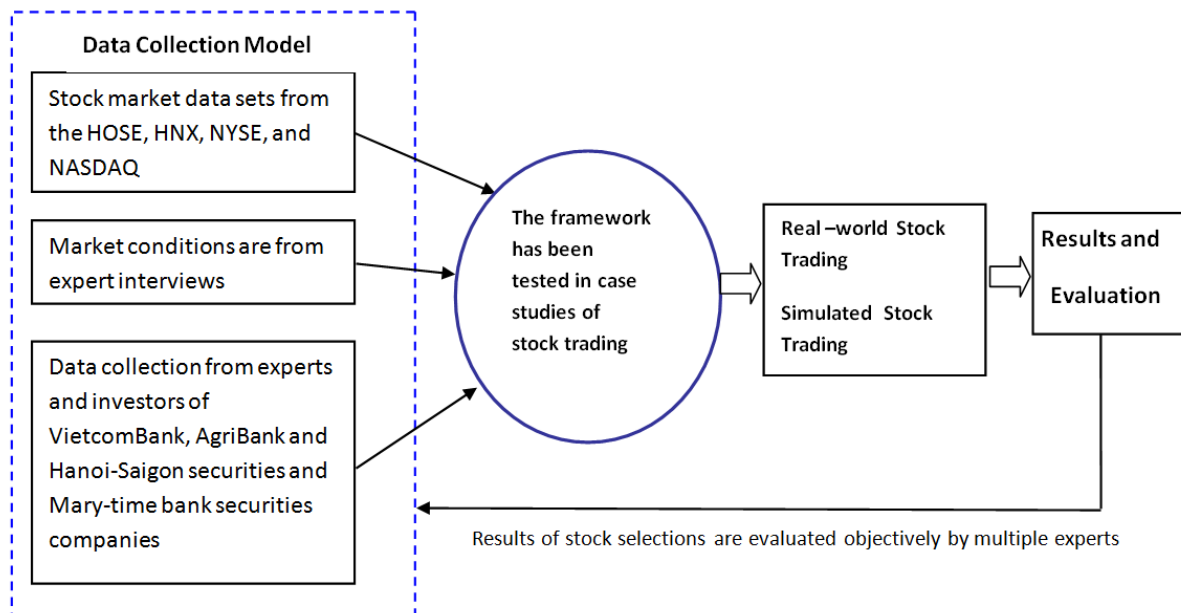


Figure 3.4: Process of data collection in experiments

In case studies for stock selection in stock trading of this framework, the experiments in real-world stock trading of these models have been conducted by users in evaluation objectively and the author in evaluation subjectively. In this study, the data collection for on-line by Internet and off-line has been done by surveys and interviews to international financial, securities companies in Hanoi, Vietnam and Ritsumeikan University in Japan from the period of April 2009 to June 2013, as follows:

- **From June to August 2009:** The author went directly to stock market exchange trading centers to work closely with 5 experts and 15 investors at Vietcombank securities company in Hanoi, Vietnam for data collection on the HOSE, HNX (Vietnam) stock markets from the period of June to August 2009.
- **From January to March 2010:** The author went to Hanoi, Vietnam for data collection from 12 experts and 20 investors from stock market exchange trading centers of Vietcombank securities, Agribank Securities, and Saigon-Hanoi securities companies on the HOSE, HNX (Vietnam) and NYSE, NASDAQ (USA) stock markets from the period of January to March 2010.
- **From March to September 2011:** Data collection was participated with 12 experts and 15 investors at Vietcombank securities, Agribank Securities, Saigon-Hanoi securities and other international financial companies in Hanoi, Vietnam for data collection on the HOSE, HNX (Vietnam) and NYSE, NASDAQ (USA) stock markets from the two periods of January to March 2011 and September to October 2011, respectively.
- **From January 2012 to June 2013:** There are 8 experts from Graduate School of Economics, Ritsumeikan University and 5 experts with investors at Maritime bank, Vietcombank securities, Agribank Securities and Saigon-Hanoi securities, participated for data collection in objective evaluation of proposed models on the HOSE, HNX (Vietnam) and NYSE, NASDAQ (USA) stock markets from the two periods of January to October 2012 and October 2012 to June 2013.

Experiments of the proposed models in this framework have been conducted by experts through case studies in daily real-world stock trading on the HOSE, HNX, NYSE and NASDAQ stock markets. There was a group of three to five investors and experts participating in each trading period for making the surveys of data connection during the experiments, as listed in Appendix C. The surveys and experts/investor used in the experiments are described in detail of Appendices A and B. In the Internet online and off-line data connection, survey forms are used to collect investors/experts and surveys in the experiments using a five-point scale definition (0: *oppose*, 0.25: *almost oppose*, 0.5: *have no preference*, 0.75: *almost agree*, 1: *agree*) are defined in Table 3.1. Interviews for experts are considered in market conditions that use fuzzy rules present these conditions in the framework.

After collecting stock market and *Kansei* data sets from experts and investors, users have conducted the experiments of these models (Hybrid SOM-AHP, Hybrid *Kansei*-SOM, Hybrid *Kansei*-SOM Risk). The guide for users in experiments are described in Appendix E and alternative selection are used actual trading investment and virtual trading systems, as shown in Figures C.5 and C.7 of Appendix C. In experiments, evaluation methods by subjectively and objectively decision makers applied to asset these models' performance. The results of stock selections in experiments have been evaluated by the users subjectively. Feedbacks from expert and investors are good for improvement of these models' performance.

### 3.5 Methods of Evaluation

In the evaluation of the framework, we have investigated how the models (Hybrid SOM-AHP, Hybrid *Kansei*-SOM, Hybrid *Kansei*-SOM Risk) perform with respect to various market conditions. In this study, the processes of data collection for experiments is shown in Figure 3.5.

These proposed models have been tested in real-world stock trading with multiple expert preferences objectively who are currently working at securities, financial, economics companies, and Ritsumeikan university from various nationalities. In the

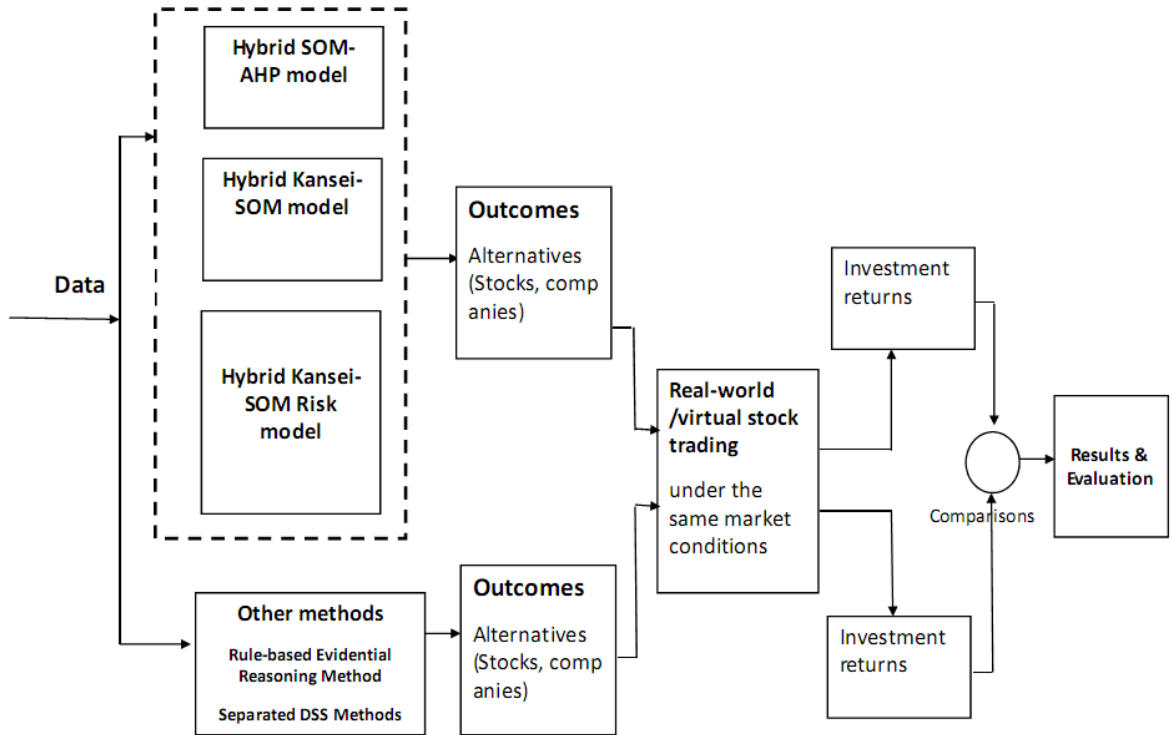


Figure 3.5: Models in evaluation

experiments, we have also conducted tests and experiments in comparisons with separated DSS methods and the latest stock trading system. To validate these models' performance, there are two basic methods in evaluation of real-world stock trading such as subjective and objective evaluations [42, 43, 60]. In particular, subjective evaluation is used to validate these model's performance by decision makers subjectively. The investors and experts participated in data collection and user runs models and trading experiments subjectively from the years of 2009, 2010, and 2011.

For further testing, objective evaluation is defined as a technique, which is consistent and reliable from the influence of the evaluators. In objective evaluation, individual experts conducted and tested these models through experiments in real stock trading from the period of January 2012 to June 2013. The experiments were performed by separately individual decision makers and these decisions. These user trading results were calculated profitability average from directly their virtual trading

systems. Average trading results of all the users were calculated, in order to evaluate the proposed model objectively.

Note that experts participated in experiments have collected data from the period of January 2012 to June 2013, as shown in Table A.1 and A.2. Evaluation of the Hybrid SOM-AHP model, Hybrid *Kansei*-SOM and Hybrid *Kansei*-SOM Risk) models are described in details of Chapters 4, 5 and 6. In comparisons with other models in experiments, decision makers were used for SOM model [79]. The software is widely used in testing SOM experiments.

### **3.6 Conclusion**

This chapter discussed the framework using Hybrid Intelligent DSS for selection of alternatives in stock market investments. Mechanisms of this framework and data collection methods in experiments have described in this chapter. There are some conceptual terms and definition, evaluation methods represented in common formulations in stock market investments. Experimental results and evaluations are discussed in the following Chapters 4, 5, and 6.



# Chapter 4

## Case Studies using Hybrid SOM-AHP Model in Stock Trading

### 4.1 Introduction

This chapter presents case studies using Hybrid SOM-AHP model. The model is integrated by Self-Organizing Map (SOM) and Analytic Hierarchy Process (AHP) to analyze both quantitative and qualitative factors from stock markets. This model aims to select short-list investment alternatives in rankings for stock trading. Firstly, these factors are placed in a stock matrix which is visualized by SOM in order to select appropriate alternatives (stocks, companies, and company groups) for investment on stock markets. Secondly, based on financial factor weights in fuzzy decision making and SOM results, potential alternatives are considered for investment. Finally, the AHP is applied to select the alternatives in rankings for investment. This model has been tested in both in simulated stock trading and real-world stock trading.

## 4.2 Case Studies

### 4.2.1 Application of Hybrid SOM-AHP Model in Case Studies of Stock Trading

Mechanisms of Hybrid SOM-AHP model are from Steps 1.1 to 1.3, as described in Section 3.3 of Chapter 3. Experiments of the proposed model conducted by expert in financial and economy at Ritsumeikan University on the HOSE and HNX stock markets from June to October 2012, carried out by users with data collection in surveys of experts from Agri-Bank and Vietcombank securities companies within four stages in this system:

- (1) Real-world stock data sets obtained from a stock market are evaluated by expert in order to construct a stock matrix.
- (2) The quantitative-qualitative matrix is visualized by SOM training and screens out the company groups from among hundreds of companies for investment.
- (3) The potential companies (superior stocks) are identified based on financial factor weights in decision making results.
- (4) AHP is applied to select the companies in rankings for investment.
- (5) Appropriate actions (buying, selling, and holding) are determined by expert decisions, based on market conditions.

### 4.2.2 Experimental Results

In the experiments, the proposed model was tested by decision maker, collected data from 5 experts and 15 investors, through case studies in daily real-world stock trading on the HOSE and HNX stock markets from the period of April 2009 to March 2011. To get data sets from experts and investors, there was a group of three to five investors and experts participating in each trading period for making the surveys of data connection during the experiments, as described in Appendices B and C. The proposed model has tested and performed well in daily real-world stock trading for investment on the HOSE and HNX stock markets.

Here is one of the experiments on the HOSE and HNX stock markets from April to

October 2009, carried out by the user with data collection in surveys of experts from Agri-Bank and Vietcombank securities companies within four stages in this system:

- (1) Real-world stock data sets obtained from a stock market are evaluated by experts in order to construct a stock matrix.
- (2) The stock matrix is visualized by SOM training and screens out the company groups from among hundreds of companies for investment.
- (3) The potential companies (superior stocks) are identified based on financial factor weights in decision making results.
- (4) AHP is applied to select the companies in rankings for investment.
- (5) Appropriate actions (buying, selling, and holding) are determined by author and expert decisions, based on market conditions. The experiments through case studies are applied to real-world stock trading.

In SOM training, SOM uses Gaussian neighborhood function with an adaptive variance and learning rate. We set training parameters in SOM training (SOM Sizes = 20, Sigma Max = 10, Sigma min = 2 and Iteration set = 40) in data sets. The learning rates are stored in the graph in the system interface from 0.04 to 0.02. After the training, SOM result was visualized in three groups of companies. In the simulation result, the map result is shown the distance among appropriate companies in Figure 4.1.

In simulations, the map result showed the distance among the appropriate companies. As observed the summary estimations from current financial markets results demonstrate that SSI and DPM companies had the highest average weights in terms of P/E (*price-to-earnings*), EPS (*earnings per share*) and ROE (*return on equity*) ratio in percents.

Figure 4.2 illustrates that the SOM map result showed the appropriate companies (SSI, DPM, VTO, and DMC). Attributes of companies are placed in vectors. These vector distances are represented by stock distances, as defined by Eq.(3.4). The stock distance from SSI to the other companies is shown in contents of SSI vector is similarly closed to the other companies DPM, VTO, and DMC. Decision maker who is the user selected the closest SSI and DPM companies by reducing the maximum distance of the companies and eliminating those that have a great distance. The result of AHP

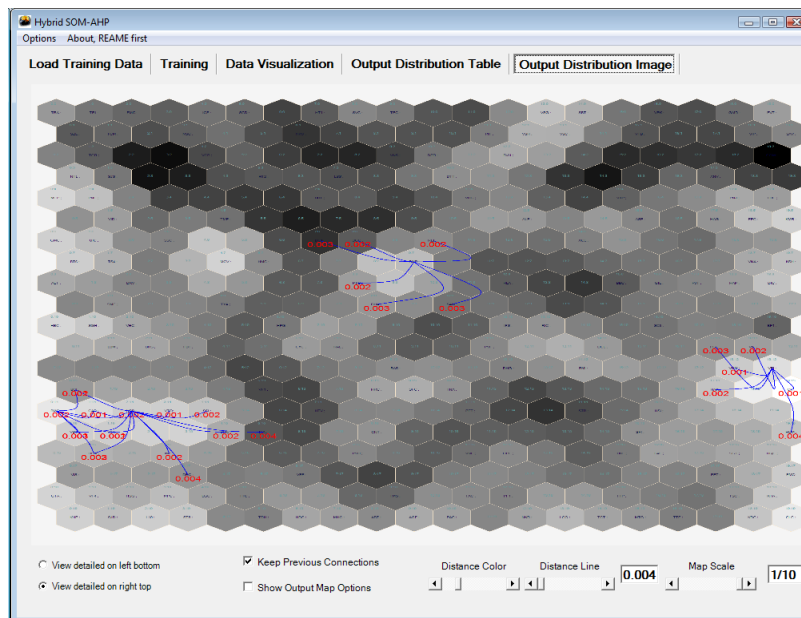


Figure 4.1: The screen of SOM result

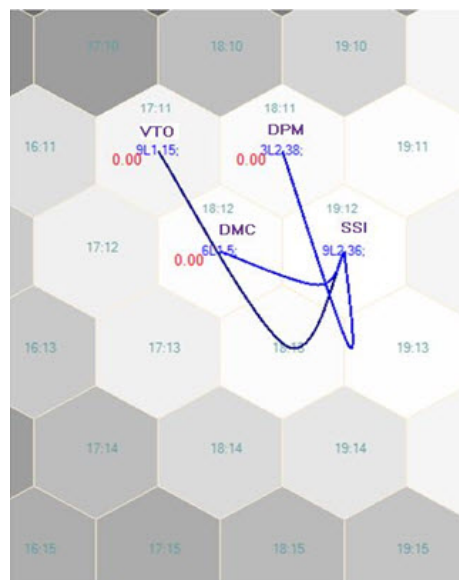


Figure 4.2: The screen of SOM result in detail

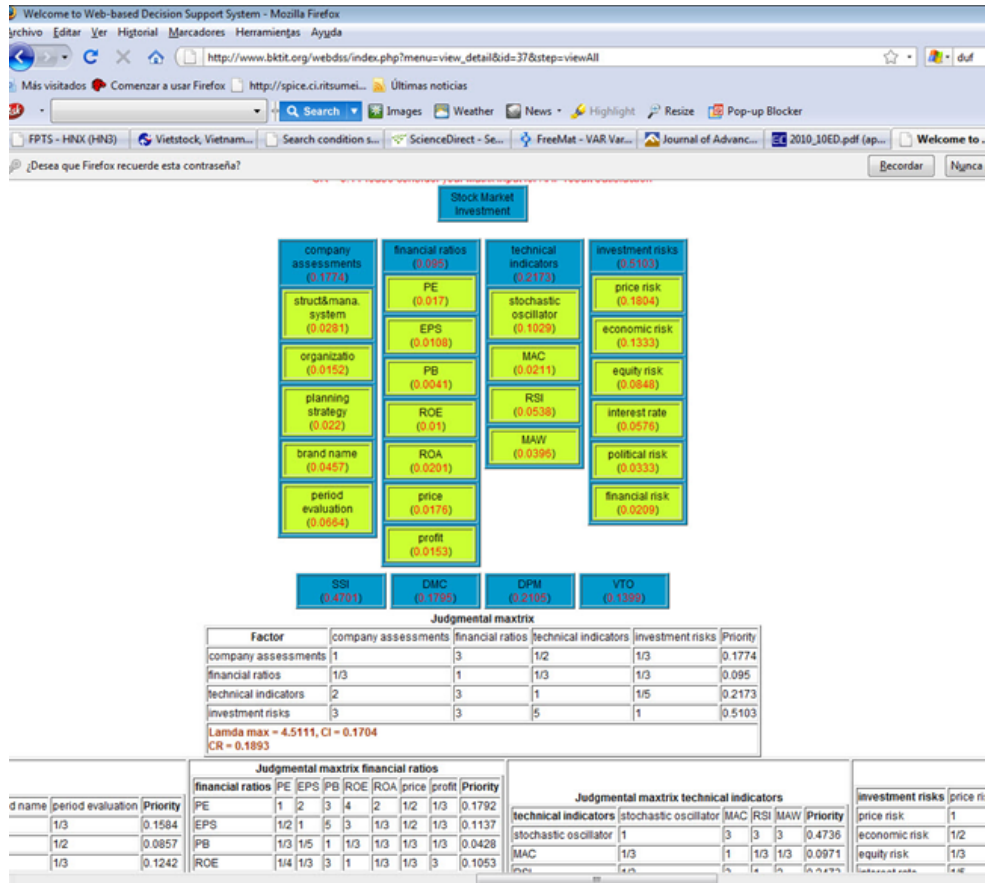


Figure 4.3: The screen of Web-based DSS result

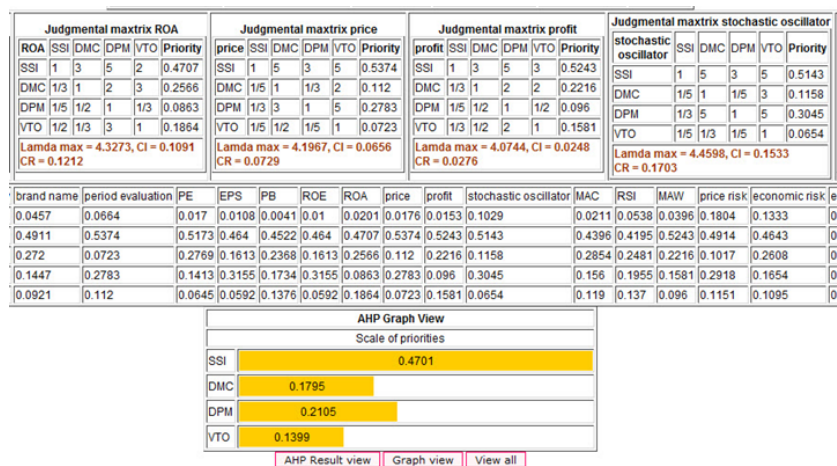


Figure 4.4: The AHP result

showed the most appropriate companies by rankings in a short list (SSI=0.4701, DMC=0.2105, DPM=0.1795, VTO=0.1399), as shown in Figures 4.3 and 4.4.

It is indicated that SSI company (rating weights 0.4701) and DMC (rating weights DMC=0.2105) are the first choice and second choice respectively for investment. Because of the highest rating weights, SSI and DMC were selected for trading decisions. There are two companies given lower rating weights (DPM=0.1795 and VTO=0.1399), the third and the fourth choices for investment. The ranked companies (superior stocks) were applied in real-world stock trading on the HOSE from the period of April to October 2009. The profits of the stocks are estimated within two months at SSI (25%), DPM (20%), DMC (12%) and VTO (10%) when calculated for investment returns.

To evaluate the capability of the proposed system by making profits, we have estimated the average profits that would be applied by trading stocks from the period of April 2009 to December 2010. Stock market investment outcomes of 25 stocks including these shares was accounted for calculating investment returns in various stock market conditions. In terms of winning stocks (successful investment companies), the investment system is estimated only at 70% in overall downward trend for stock index prices. However, it reached at 85% in overall upward trend for stock index prices. The profit average percent was estimated from 7-8% with high risks (30-32% unsuccessful investment companies).

For further experiments in objective evaluation, the average profits (7-8% ) are calculated by all of the experts in simulated trading results on the HOSE and HNX from the period of January to June 2012 and real-world stock trading on the NYSE and NASDAQ from the period of May to October 2012, as shown in Figure 4.5.

Stock market investment outcomes of 15 stocks evaluated by 5 experts objectively from Ritsumeikan University, Vietinbank and Maritime-bank securities were accounted for calculating investment returns in various stock market conditions. In terms of winning stocks (successful investment companies), the investment system is estimated only at 68-70% in an overall evaluation. The profit average percent was estimated from 7-8% with high risks (30-32% unsuccessful investment companies).

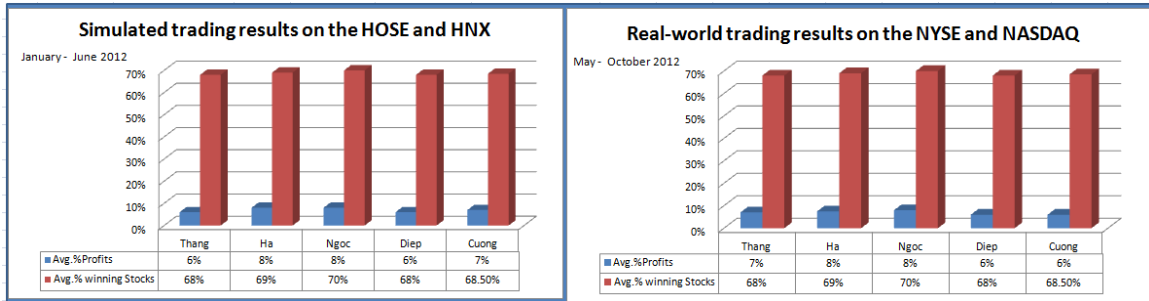


Figure 4.5: Trading results of experts on the US and Vietnam stock markets

### 4.3 Evaluation of Hybrid SOM-AHP Model

Regarding the expert feedbacks and experiments results, the Hybrid SOM-AHP model provides strong points that it shows grouping companies with potential financial indicators. The AHP model as an hierarchical model is used to analyze qualitative and quantitative factors when experts consider a stock selection in rankings for investment. Additionally, The model using Web-based DSS provides a friendly user interface for decision makers through the web development environment to show results online so investors and experts can access from any time and any where. In addition, the system using decision making has basic function applied to support in stock market investment in real-time. The advantages of the proposed model are as follows:

- Decision maker can easily create a new AHP model as well as a variety of models in a case study of stock market investment.
- The Web-based DSS provides a full solution for decision maker to create a new model among of various stock market factors with different purposes.
- Administration as a decision maker can manage all online user accounts via Web-based DSS and control all DSS results granting access levels.
- System authorization has a good security on Web application since decision maker can change password online and access resources under the permission of decision maker.

- Web-base DSS application is not only to focus on whole function of the system but also to extend knowledge in order to apply overall application model in the case study of stock market.

To extend the AHP model using Group Decision Making (GDM), Fuzzy AHP can be solved as decision problems with the selection of alternatives under risk and uncertainty, using GDM to obtain dynamic decision solutions, taking into account decision maker's preferences. In addition, GDM is not static over time so that it can address dynamic decision situations in which the set of solution alternatives could change throughout the decision making process. In practice, experimental results shows that Fuzzy AHP using GDM performs better than AHP model in various market conditions [30]. The step 5 can be replaced by evaluating a short list of companies for investment using Fuzzy AHP as follows:

In fuzzy AHP model, experts evaluate all the companies (alternatives) to find a short list of the companies by rankings. GDM is a solution to aggregate experts' decision. The degree of knowledge, experience and relevancy is not equal among experts' opinions. To evaluate the uncertain information on criteria, triangular fuzzy numbers are used in GDM processes with linguistic terms. Triangular fuzzy numbers are defined by the numbers, expressed as  $(l, m, u)$ . Fuzzy AHP scale in triangular fuzzy numbers are defined as shown in Table 4.1.

Table 4.1: Triangular fuzzy conversion scale

| <b>Linguistic scale for importance</b> | <b>Triangular fuzzy scale</b> | <b>Triangular fuzzy reciprocal scale</b> |
|--|-------------------------------|--|
| Equal                                  | $(1,1,1)$                     | $(1,1,1)$                                |
| Moderate                               | $(2/3,1,3/2)$                 | $(2/3,1,3/2)$                            |
| Strong                                 | $(1,3/2,2)$                   | $(1/2,2/3,1)$                            |
| Very strong                            | $(3/2,2,5/2)$                 | $(2/5,1/2,2/3)$                          |
| Extremely strong                       | $(5/2,3,7/2)$                 | $(2/7,1/3,2/5)$                          |

The Fuzzy AHP model in stock market investment is described as follows:



a. State the problems in the hierarchy structure and analyze factors in order to evaluate the most appropriate companies in rankings for investment.

b. Input values and establish fuzzy judgment matrices by the experts. The input data from qualitative factors is expressed by Eq.(4.1).

$$\tilde{A} = [\tilde{a}_{ij}] \quad (i, j = 1, \dots, n) \quad (4.1)$$

In order to get quantitative factor weights from the real-time stock market, a Sigmoid function is applied to the system, which is represented by the nonlinear evaluation given by Eq.(4.2).

$$k_j = \frac{1}{1 + \exp \frac{(-R-a)}{b}} \quad (4.2)$$

where  $k_j$  is the normalized index value of quantitative factor  $g_i^S$ ,  $R$  is a real data in stock market  $S$ ,  $a$  and  $b$  are constants assigned in values depending on data sets.

For calculated quantitative factor weights given by Eq.(4.2), the scale of company  $C_i^S$  is compared with company  $C_j^S$  as expressed by Eq.(4.3).

$$a_{pq} = \frac{k_t^{C_i^S}}{k_t^{C_j^S}} \quad (4.3)$$

where  $a_{pq}$  is represented by fuzzy weights for each iteration  $t$ , which are rated by the triangular fuzzy conversion scale in pairwise comparison represented by fuzzy weights updated in a matrix  $\tilde{a}_{ij}$ . The geometric mean of each row is represented as follows:

$$\tilde{a}_{ij} = \{l_{ij}, m_{ij}, u_{ij}\} \quad \text{and} \quad \tilde{x}_i = \{x_1, x_2, \dots, x_m\}$$

Fuzzy positive reciprocal matrix  $\tilde{A}$  and its eigenvalue  $\tilde{\lambda}$  that satisfies

$$\tilde{A}\tilde{x} = [\tilde{\lambda}\tilde{x}] \quad (4.4)$$

c. Check consistency ratios (CR) is given by

$$CR = \frac{CI}{RI} \quad (4.5)$$

where  $RI$  is the random index and  $CI$  is the consistency index. Experts input data sets in the fuzzy judgment matrix if  $CR$  is less than 0.1.

d. Calculate and synthesize the evaluation results. To apply the same steps until the sum of overall criteria is calculated for all the weights of each alternative. In the result of alternatives, a transforming non-fuzzy form for alternative rankings is the final step. The Best Non-fuzzy Performance (BNP) values method is used to rank the alternatives as calculated by

$$BNP_i = l_i + \frac{((u_i - l_i) + (m_i - l_i))}{3} \quad (4.6)$$

### 4.3.1 Limitations of Hybrid SOM-AHP Model

The Web-based DSS using SOM-AHP model has several limitations as follows:

- When stock data sets visualised by SOM training, there are many features of similar stocks which made decision makers confuse to select which grouping companies for investment.
- The model has limited functions when dealing with market conditions, affected directly to stock prices of companies on the stock markets.
- When selling stocks, the model has no ways to show the right time to sell these stocks.
- The model not allows group decision making or collaborative decision making techniques since an individual decision maker may decide wrong decisions in terms of stock selection and trading actions.
- Uncertain conditions and expert sensibilities are not concerned concurrently with the proposed model, that affects to the proposed system performance.

## 4.4 Conclusion

In this chapter, the SOM-AHP model was implemented on Web-based DSS application, showing this model for quantified qualitative and quantitative information for selection of companies in rankings for investment. The Web-based DSS application allows individuals to access any time and any where, using decision making for investment online, however, some limitations of this approach have been addressed all the problems, as discussed in Chapters 5 and 6.



## Chapter 5

# Case Studies using Hybrid *Kansei*-SOM Model in Stock Trading

### 5.1 Introduction

This chapter presents a Hybrid *Kansei*-SOM model, using *Kansei* evaluation integrated with Self-Organizing Map (SOM) for stock market investment strategies. The proposed model, using a group Decision Support System (DSS) aims to aggregate experts' preferences and sensibilities with the selection of the most suitable stocks, matching with investing strategies to achieve investment returns by dealing with complex situations in stock market dynamics. To evaluate companies for investment, the fuzzy evaluation model of stock market investment is applied using fuzzy rules on stock market dynamics to represent stock market factors in fuzzy weights and *Kansei* weights for *Kansei* stock matrix construction. The matrix is visualized by SOM, together with aggregating expert preferences in order to select potential companies that match appropriate stock market investment strategies. The proposed model has been tested and performed well in daily stock trading on the HOSE, HNX (Vietnam), NYSE and NASDAQ (US) stock markets to validate the method in various stock markets. Experiments in real-world stock trading have been conducted by the

users. In experiments, this model has been tested in both in simulated stock trading and real-world stock trading.

## 5.2 Case Studies

### 5.2.1 Application of Hybrid *Kansei*-SOM Model in Case Studies of Real-world Stock Trading

Mechanisms of Hybrid *Kansei*-SOM model is from Steps 2.1 to 2.3, as described in Section 3.3 of Chapter 3. Here is one of the experiments on the NYSE and NASDAQ stock markets in the year of 2012, carried out by investors and experts from Agri-Bank and Hanoi-Saigon securities' companies within four stages in this system:

(1) Real-world stock data sets obtained from a stock market are evaluated by experts' preferences in order to construct a *Kansei* stock matrix.

(2) The *Kansei* stock matrix is visualized by SOM training and screens out the potential companies (superior stocks) from among hundreds of companies for investment.

(3) The potential companies (superior stocks) are matched with appropriate trading strategies for investment.

(4) Appropriate actions (buying, selling, and holding) are determined by expert preferences, based on *Kansei* evaluation in market conditions.

The experiments through case studies are applied to real-world stock trading using the Group Decision Support System (GDSS) for investment.

### 5.2.2 Data Collection in Experiments

In the experiments, the proposed model has been tested by individual experts and the author. The experiments for data collection were carried out by the total numbers of 12 experts and 20 investors at stock market exchange trading centers of Vietcombank securities, Agribank Securities, and Saigon-Hanoi securities companies from the period of April 2009 to October 2011, as shown in detail of Appendix A. When tested

the proposed model and performed stock trading by multiple experts, the experimental results from the period of May to October 2012 are also achieved through expert stock trading experiments in real-world stock trading. The proposed model using Group Decision Support System (GDSS) is applied to collect data sets from experts in two methods (Online Internet and Off-line) in real-world stock trading on the HOSE, HNX, NYSE and NASDAQ stock markets. There was a group of three to five investors and experts participating in each trading period for making the surveys of data connection during the experiments, as listed in Appendix C. In off-line data collection, when working at the stock market exchange trading centers of the financial securities companies in Hanoi, the author have worked closely with experts and investors for their assistants directly in daily real-world stock trading. In the Internet online and off-line data connection, survey forms are used to collect investors/experts and surveys in the experiments, as shown in detail of Appendix B. A *Kansei* word and stock market factor in evaluation of a company is defined in a five-point scale definition, as shown in Table 5.1.

Table 5.1: Expert scale definition

| ID No | Value | Expert scale   |
|-------|-------|----------------|
| 1     | 1     | strongly agree |
| 2     | 0.75  | agree          |
| 3     | 0.5   | almost agree   |
| 4     | 0.25  | almost oppose  |
| 5     | 0     | oppose         |

### 5.2.3 Experimental Results by Optimizing Trading Strategies

In order to demonstrate how the system can accommodate stock market conditions, we have conducted through case studies in daily stock trading on the HOSE and HNX (Vietnam) from the period of April 2009 to December 2009. Furthermore, the proposed approach has been tested and performed on the HOSE, HNX (Vietnam)

and NYSE, NASDAQ (US) stock markets using a virtual trading system in real-world stock trading from the period of February to July 2010. There were several groups of three to five members each participating in the survey for a total of 15 investors and 5 experts [75].

The proposed system was tested with 165 companies from a total of 600 companies on the HOSE and HNX stock markets and three experts with 10 investors for stock trading. Here is one of the experiments on the HOSE and HNX stock markets in the year of 2009, carried out by investors and experts from Agri-Bank and Hanoi-Saigon securities' companies within four stages in this system:

(1) Real-world stock data sets obtained from a stock market are evaluated by experts' preferences in order to construct a *Kansei* stock matrix.

(2) The *Kansei* stock matrix is visualized by SOM training and screens out the potential companies (superior stocks) from among hundreds of companies for investment.

(3) The potential companies (superior stocks) are matched with appropriate stock market investment companies at the right trading time for investment.

(4) Appropriate actions (buying, selling, and holding) are determined by expert preferences, based on *Kansei* evaluation in market conditions.

The experiments through case studies are applied to real-world stock trading using the Group Decision Support System (GDSS) for investment. Note that experts can select market conditions which represent by rules to update weights in the *Kansei* stock matrix when running the *Kansei* SOM application.

To begin this experiment, decision maker who is the user loaded *Kansei* data sets for running the system. The *Kansei* stock matrix was constructed in 37 dimensions (*Kansei* words, quantitative and qualitative factors) for 166 companies. In the system, *Kansei* SOM application uses a Gaussian neighborhood function with an adaptive variance and learning rate. The parameters are set in the *Kansei* SOM application (SOM sizes = 20 x 20, Sigma max = 10, Sigma min = 2, Iteration set = 40 and learning rates from 0.04 to 0.01). In the proposed system, experts can determine their preferences for either a selection of identified investing strategies or adaptive investing strategies. Regarding the expert preferences in the system, the experts were divided



into three groups based on stock market investment strategies such as short-term, mixed-term and long-term trading strategies. Group 1 (experts 1, 2, 3, 4 and 5) focused on a long-term stock market investment strategy by applying value investing. Group 2 (experts 6, 7 and 8) determined short-term stock market investment strategy using technical investing. Group 3 (experts 9, 10, 11 and 12) selected mixed stock market investment strategies such as using value investing, growth investing and technical investing. In the system process, the *Kansei* stock matrix was visualized by SOM training from Step 1 to Step 5 in Section 5.2.3. The final result on the map showed three main groups of companies, as depicted in Figure 5.1.

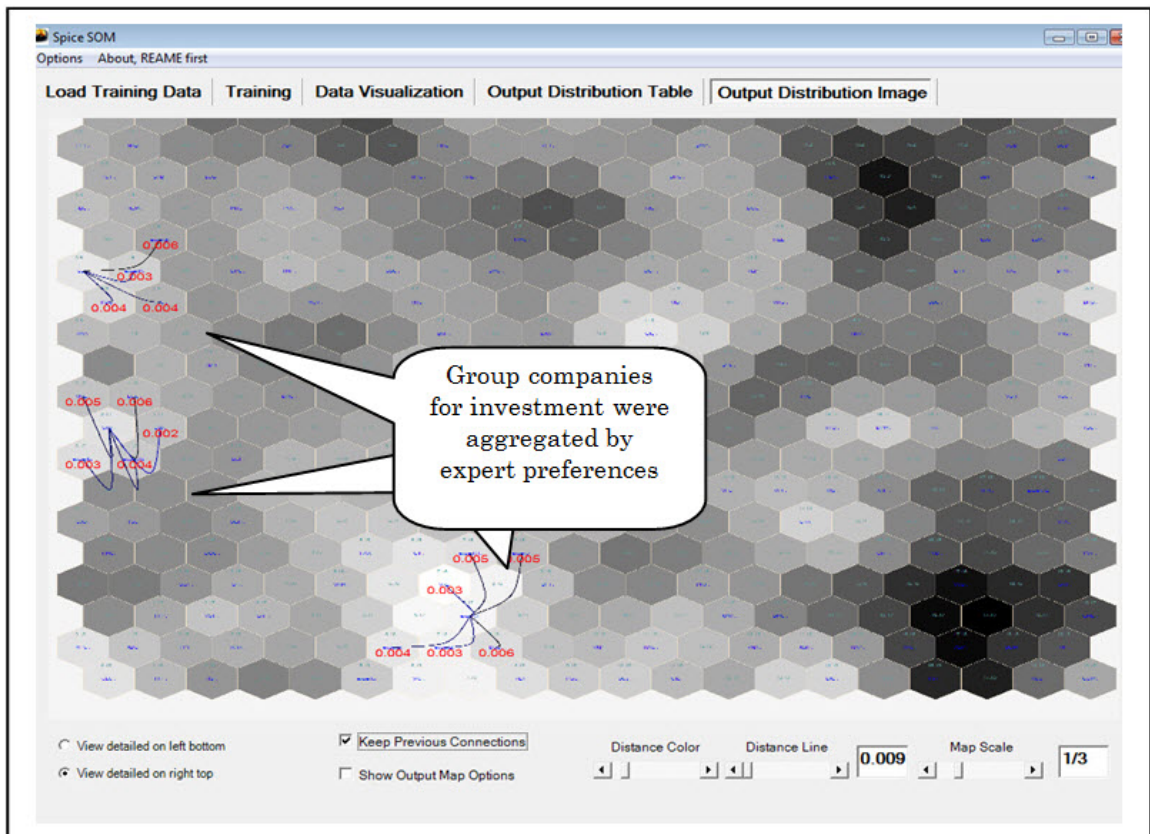


Figure 5.1: The map result of the proposed model

In simulations, the map result showed the *Kansei* stock distance of potential companies among the expert preferences. Attributes of companies and experts are placed in vectors. These vector distances are represented by *Kansei* stock distances,

as is defined by Eq.(3.4). As shown in Figure 5.1, decision maker selected these companies, matched with appropriate stock market investment strategies by reducing the maximum *Kansei* stock distance of the companies and eliminating those that have a great distance. Figure 5.2 illustrates potential companies, aggregated by expert preferences on the map.

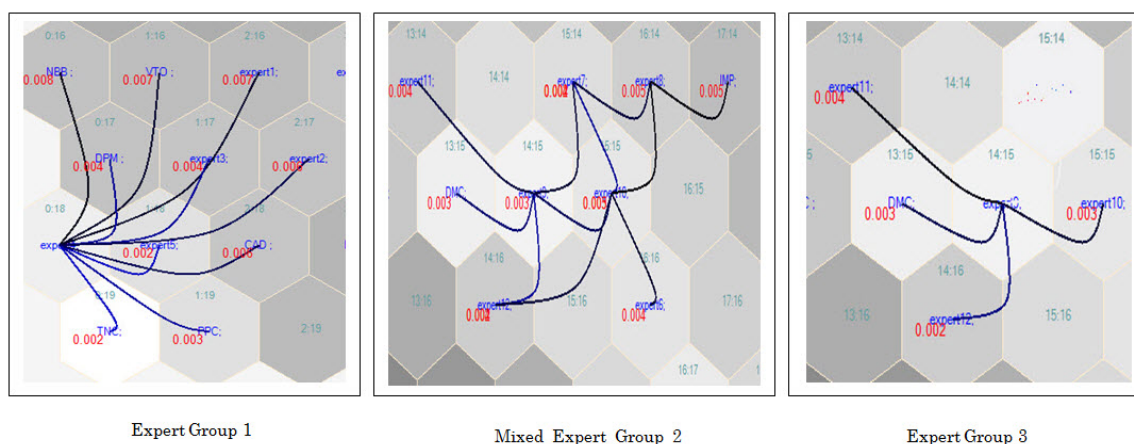


Figure 5.2: The results of companies for investment evaluated by experts

In the final results on the map, the experts of Group 1 are concerned with *Kansei* stock distance among companies (VTO, DPM, CAD, PPC, TNC, NBB). These companies are using long-term stock market investment strategies. The experts of Group 2 closely focused on DMC and IMP companies with a short-term stock market investment strategy. However, the experts of Group 3 only preferred the closest DMC as a mixed stock market investment strategy. In addition, DMC was the priority investment among companies selected by both Group 2 and Group 3 for these investment strategies.

Based on the results of the proposed system, we have conducted experiments with all of the companies, matched with investment strategies in daily stock trading on the HOSE and HNX from the period of April 2009 to September 2009. Figure 5.3 illustrates in actual trading signals of group experts for stock trading.

As observed from Figure 5.3, the experimental results show all of the stocks for trading, represented by buying and selling investment signals of these stocks in the

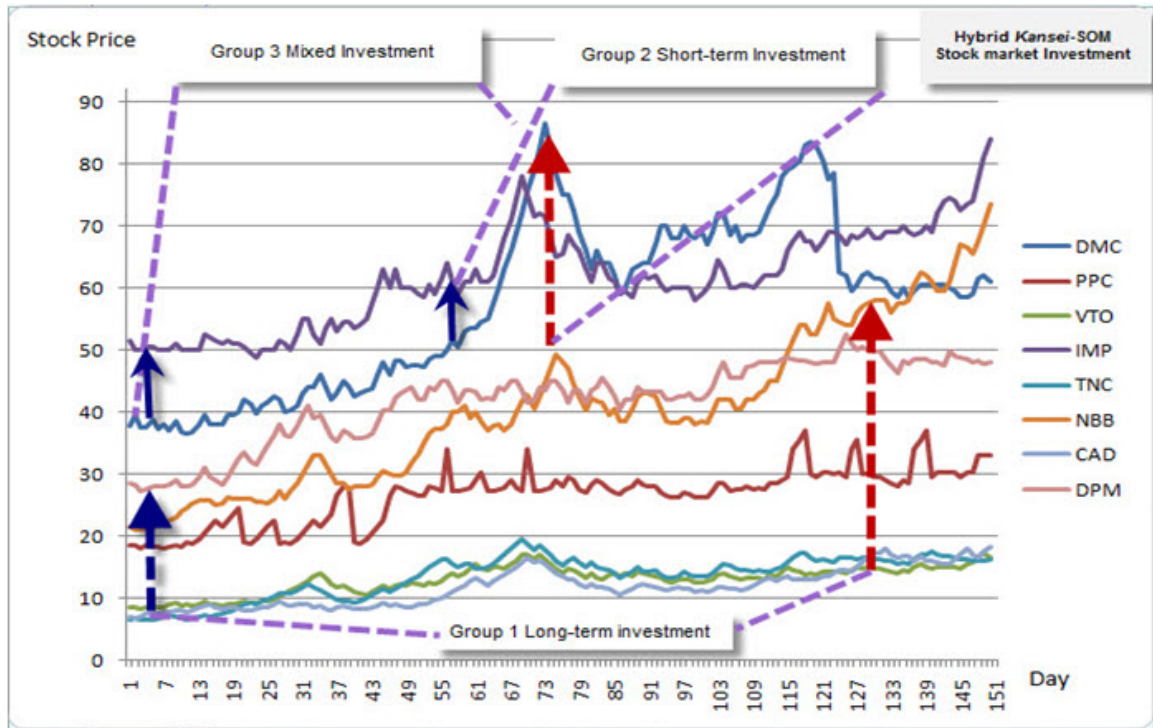


Figure 5.3: Stock trading using expert groups

period. Using *Kansei* evaluation based on the expert's sensibilities about stock trading in the stock market conditions, we carried out buying and selling stocks. For example, DMC was the priority investment using mixed stock market investment strategy (buying price: 39.000 VND in the day 7, selling price: 83.000 VND in 2,5 months) for 151 days in the period. Figure 5.4 demonstrates all investment companies that have been successfully achieved profitable investment returns for five months in the whole stocks trading for the period. When calculated for investment returns, the average profits of Group 1, using a long-term stock market investment strategy, were only 24%. However, the highest average profits of Group 2, using a short-term stock market investment strategy reach 48%. The average profits of Group 3, using a mixed stock market investment strategy were about 28%.

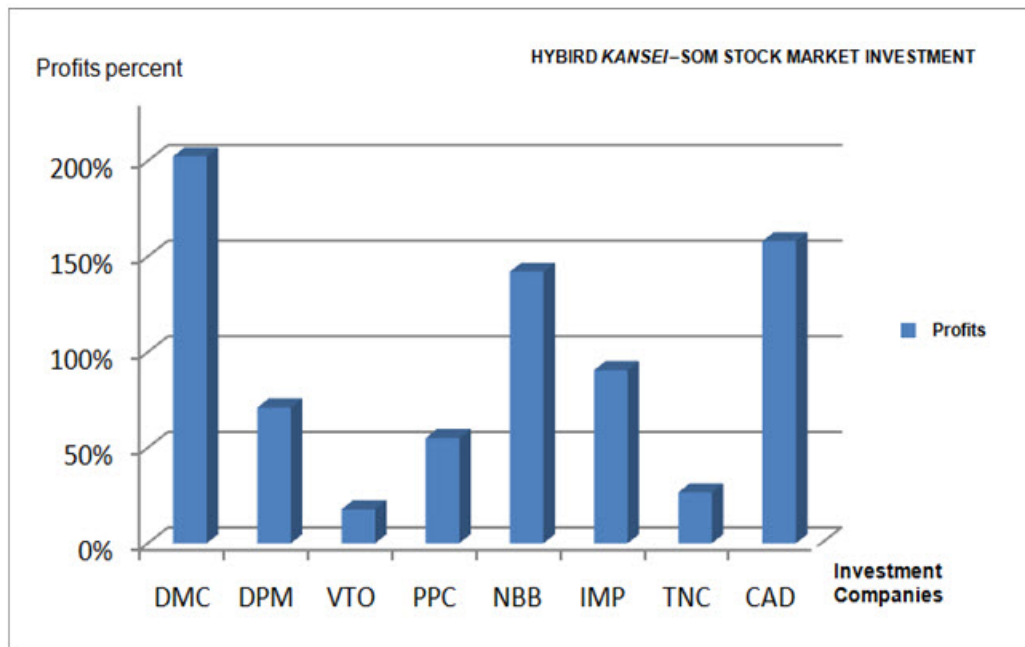


Figure 5.4: The estimation of profits

#### 5.2.4 Experimental Results by Dealing with Various Stock Markets

To evaluate capability for investment returns of the proposed system, we have calculated the average profits that would be made by trading stocks. Stock market investment outcomes must be accounted for when calculating investment returns in various stock market conditions. The proposed system has performed well in daily real-world stock trading for investment on the HOSE and HNX (Vietnam), NYSE, and NASDAQ (US) stock markets, as shown in the experimental results in Table 5.2.

Table 5.2: Experimental results on the HOSE, HNX, NYSE, and NASDAQ

| Stock Market Investment Strategies | The HOSE and HNX |   | The NYSE and NASDAQ |   |
|------------------------------------|------------------|---|---------------------|---|
|                                    | Avg.% Profits    | No. of winning stocks / No. of total stocks for investment (Avg.% winning stocks) | Avg.% Profits       | No. of winning stocks / No. of total stocks for investment (Avg.% winning stocks) |
| Short-term investment              | 28%              | From April to June 2009: 10 /12 (83%)   | 11%                 | From March 2010 to June 2010: 9/10 (90%)  |
| Mixed investment                   | 27%              | From April to September 2009: 12/13 (92%)   | 10%                 | From April 2010 to July 2010: 8/9 (88%)   |
| Long-term investment               | 26%              | From April 2009 to July 2010: 10/10 (100%)  | 12%                 | From February 2010 to July 2010: 8/8 (100%)                                       |
| Avg. Total                         | 26%-28%          | Avg. winning stocks:(91%)   | 10%-12%             | Avg. winning stocks: (92%)  |

The experimental results for stock trading for the period from 2009 to 2011 show that percentages of winning stocks (successful investment companies) in the proposed approach are between 91% and 92% for real-world stock trading on Vietnam and US stock markets. Furthermore, the results consistently show that the proposed model using GDSS yielded successful profits, from 26% to 28% in normal and up trending markets on the HOSE and HNX, and from 10% to 12% in normal markets on the NYSE and NASDAQ.

In further testing experiments of the proposed model under the same data sets and market conditions, each user from Ritsumeikan University, Maritime bank, Vietcombank and international securities companies has tested directly the proposed

model with his/her virtual trading system. Their user trading results were calculated by individual experts from the period of May to October 2012 in real-world stock trading, as shown in Figure 5.5.

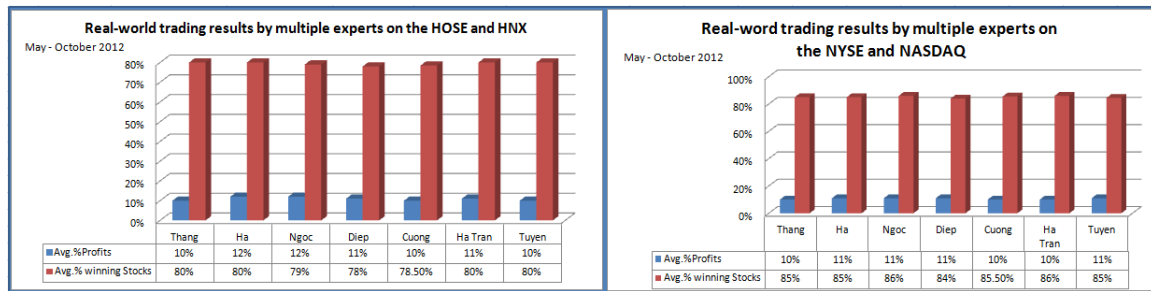


Figure 5.5: Experimental results done by experts in real-world trading

In experimental results, it is indicated that the proposed model performs well in real-world stock trading done by experts in objective evaluation to deal with complex situations of dynamic stock market environments. The results show that the proposed model yield profits, from 10% to 12% in mostly downtrend markets on the HOSE and HNX, and from 11% to 12% in normal markets on the NYSE and NASDAQ.

## 5.3 Evaluation of Hybrid *Kansei*-SOM Model

### 5.3.1 Advantages of the Model

In terms of stock market investments, the advantages in this study includes addressing these issues as follows:

- To enhance capability for investment returns of the proposed model, a framework of this model uses uncertain values consisting of quantitative and qualitative factors to evaluate companies for investment.
- To select appropriate companies in trading decisions, the quantification of expert sensibilities and impressions about stock trading in market conditions allows the proposed model to determine the potential companies (superior stocks) at the right time for stock trading.

- To improve the effectiveness of a stock trading system, the proposed model aggregates experts' preferences for the selection of the most suitable stocks matching with stock market investment strategies by dealing with complex trading situations in stock market dynamics.

Regarding the overall investment outcome and performance of the proposed approach, it is consistently demonstrated that this approach has performed better than its individual DSS methods and these results validated the effectiveness of this approach in various stock market conditions.

### 5.3.2 Limitations of the Model

In dynamic stock market investments, the proposed model should have a function to automatically recommend adaptive stock trading strategies to deal with complex situations with risks on dynamic stock market environments. To solve the problem, a new model will be integrated by *Kansei* Evaluation and SOM using updated *Kansei* stock distance weights with clustering and negotiating expert preferences that will improve the effectiveness of dynamic stock trading investment systems.

The proposed model does not allow to select risky stocks as well as risky trading decisions so a good system can deal with complex situations under uncertainty and risk.

## 5.4 Conclusion

This chapter has presented the Hybrid *Kansei*-SOM model which is a new method for stock market investment strategies in order to enhance investment capability and the effectiveness of the stock trading investment system. This model using *Kansei* evaluation is to quantify experts' sensibilities and preferences about stock trading with uncertain values in various stock market conditions, selecting companies that match appropriate stock market investment strategies for investment. Experiments using real-world stock trading from Vietnam and United States stock markets indicate that

the proposed approach obtains good investment results in term of profitability, successful investment companies, and investment performance. In dynamic stock market environments, experimental results also demonstrate that the proposed approach is able to provide more accurate investment forecasting of the most suitable stocks, matching with stock market investment strategies at the right time for trading to yield higher profits.



# Chapter 6

## Case Studies using Hybrid Kansei-SOM Risk Model in Stock Trading

### 6.1 Introduction

This chapter presents a new stock trading model combined with Risk Management and *Kansei* evaluation integrated with a Self-Organizing Map for improvement of a stock trading system. The experimental results also show that the proposed model performs better than other current methods to deal with various market conditions. Compared with Rule-based Evidential Reasoning (RER) method under the same market conditions, experimental results show profits and winning stocks of this model, higher than those of RER method about 4%-5% and 12%, respectively.

## 6.2 Case Studies

### 6.2.1 Application of Hybrid *Kansei* SOM Risk Model by Aggregating Expert Decisions and Reducing Risky Decisions

Mechanisms of Hybrid SOM-AHP model are from Steps 3.1 to 3.3, as described in Section 3.3 of Chapter 3. A Hybrid *Kansei* SOM risk model which is an extendable model of risk management, based on the Hybrid *Kansei* SOM model. Risk management is used to apply in the Hybrid *Kansei* SOM model, aiming to reduce risky decisions and stock risks. The proposed model aims to reduce risky decisions and alternative risks under uncertainty. *Kansei* evaluation and fuzzy evaluation models are applied to quantify trader sensibilities about stock trading, market conditions, and stock market factors with uncertain risks. In *Kansei* evaluation, group sensibilities of traders are quantified that represent in fuzzy weights. *Kansei* and stock-market data sets are visualized by SOM, together with aggregate expert preferences in order to find potential companies, matching with trading strategies at the right time and eliminating risky stocks. The proposed model has been tested and performed well in daily stock trading on the HOSE, HNX (Vietnam), NYSE and NASDAQ (US) stock markets. The experiments through case studies show that the new approach applying *Kansei* evaluation enhances the capability of investment returns and reduce losses.

In the experiments, the proposed model has been tested using data collection from a total numbers of 15 experts and 20 investors at stock market exchange trading centers of Vietcombank securities, Agribank Securities, Saigon-Hanoi securities, and international securities companies from the period of April 2009 to October 2011. The proposed model using either decision making or group decision making is applied to collect data sets from experts in two methods (Online Internet and Off-line) in real-world stock trading on the HOSE, HNX, NYSE and NASDAQ stock markets. There was a single decision maker or a group of three to five investors and experts participating in each trading period for making the surveys of data connection during the experiments, as shown in Appendices A and C. In off-line data collection, when

working at the stock market exchange trading centers of the financial securities companies in Hanoi, the author have worked closely with experts and investors for their assistants directly in daily real-world stock trading. In the Internet online and off-line data connection, survey forms are used to collect investors/experts and surveys in the experiments, as described in Appendix B. These data collection method of this model is the same as that of Hybrid *Kansei*-SOM model. In addition, this model provides common fuzzy rules to represent market conditions under uncertain environments.

In human reasoning, linguistic expressions represent rules for expert decision situations. To quantify the Common Sense Human Reasoning of expert  $e_i$  in dynamic market environments, we use the following logical rules as **Rule  $i$**  can be presented as follows:

**IF**    *Condition 1* AND...AND *Condition m*  
**THEN**    *Actions*

Market conditions are collected by experts and updated news via financial Web sites. There are about 16 frequently common conditions, as defined in Table D.1.

### 6.2.2 Experimental results

In order to demonstrate how the system can perform on various market conditions, we have conducted case studies in daily stock trading on the HOSE (Vietnam) from the period of June 2009 to October 2010 and the NYSE and NASDAQ (US) stock markets from the period of April to October 2010. There was a group of three to five members participating in each survey for a total of 15 investors and experts making the surveys of data connection during the experiments. After collecting data sets from experts and investors, users have conducted experiments to test the proposed model. In the proposed model, *Kansei*-stock SOM application uses a Gaussian neighborhood function with an adaptive variance and learning rate. In SOM training, the parameters are set in the *Kansei* SOM application (SOM sizes = 20 x 20, Sigma max = 10, Sigma min = 2, Iteration set = 40 and learning rates from 0.04 to 0.01). The steps of process in the *Kansei*-stock SOM application are as follows:

- (1) Screening out companies with significant financial factor standards evaluated

Table 6.1: List of common market conditions

| ID No | Market Conditions                   | Stock Markets               |
|-------|-------------------------------------|-----------------------------|
| 1     | CPI (Consumer Price Index)          | HNX, HOSE, NYSE, and NASDAQ |
| 2     | Government Policy                   | HNX, HOSE, NYSE, and NASDAQ |
| 3     | Bank Interests                      | HNX, HOSE, NYSE, and NASDAQ |
| 4     | Inflation Rates                     | HNX, HOSE, NYSE, and NASDAQ |
| 5     | Macro Economics                     | HNX, HOSE, NYSE, and NASDAQ |
| 6     | Micro Economics                     | HNX, HOSE, NYSE, and NASDAQ |
| 7     | Financial Events                    | HNX, HOSE, NYSE, and NASDAQ |
| 8     | Energy Prices (oil, gas,...etc)     | HNX, HOSE, NYSE, and NASDAQ |
| 9     | Global Stock Markets                | HNX, HOSE, NYSE, and NASDAQ |
| 10    | Disasters (flood, earthquake,..etc) | HNX, HOSE, NYSE, and NASDAQ |
| 11    | FDI funding                         | HNX, HOSE, NYSE, and NASDAQ |
| 12    | GDP (Gross domestic product)        | HNX, HOSE, NYSE, and NASDAQ |
| 13    | World economics                     | HNX, HOSE, NYSE, and NASDAQ |
| 14    | Politics                            | HNX, HOSE, NYSE, and NASDAQ |
| 15    | Consumer Confidence Index           | NYSE and NASDAQ             |
| 16    | Investor Confidence Index           | NYSE and NASDAQ             |

by experts in 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. Experts can set rules for market conditions to update weights in the *Kansei* stock matrix.

(3) The *Kansei* stock and *Kansei* risk matrices are visualized by SOM to screen out the superior and risky stocks from among hundreds of stocks for investment.

(4) The potential companies (superior stocks) are matched with appropriate stock market investment companies at the right trading time for investment.

(5) Appropriate actions (buying, selling, and holding) are determined by expert preferences, based on *Kansei* evaluation and market conditions.

Note that attributes of companies and experts are placed in vectors. These vector distances are represented by either *Kansei* stock distance or *Kansei* risk stock distance, as described in Section 3.3 in Chapter 3.

### 6.2.3 Case Study of Company Selection under Uncertainty and Risk by Aggregating Expert Decisions

The proposed system was tested on over 3000 companies on the NYSE stock markets and 5 users for stock trading for the period from May to October 2010 as listed in Appendix A. The experiment was carried out by investors and experts from VietcomBank and international securities companies. To begin this experiment, decision maker loaded data sets and determined appropriate companies for investment. Table 2.1 shows pairs of *Kansei* words used in the *Kansei* stock matrix that represents in 37 dimensions (*Kansei* words, quantitative and qualitative factors) for evaluation of 165 companies. To evaluate companies in terms of investment risks, Table 2.2 shows pairs of *Kansei* words used in the *Kansei* risk matrix that represents 28 dimensions (*Kansei* words and stock-market risk factors) for evaluation of 165 companies. First, the proposed system screens out 165 companies that satisfy expert requirements such as P/E (price-to-earnings) ratio, EPS (earnings per share). Second, *Kansei* data sets and company attributes of the companies were input to this system. In the SOM training process, the system screened out two groups of companies on the map as shown in Figure 6.1.

After the training process, the final result showed the *Kansei* stock distances among the appropriate companies in a group on the map. The decision maker selected the closest companies by reducing the maximum *Kansei* stock distance of the companies and eliminating those that have a distance greater than the selected threshold. Figure 6.2(a) illustrates that the SOM map result showed the selected companies (EC, YGE, XVG, and IBM) for investment.

As observed from the map of Figure 6.2(b), the final result showed the closest risky stocks based on *Kansei* risk distances, selected by expert preferences. The system recommends the companies (EM, CXW, ELN, FIS, BA and IBM) were eliminated from a list of investment companies. Compared with the list for investment, the superior stocks (EC, YGE, and XVG) were selected for stock trading. These stocks were invested from the period of June to August 2010 using a virtual stock trading system. To determine trading actions (selling or holding), expert sensibilities were

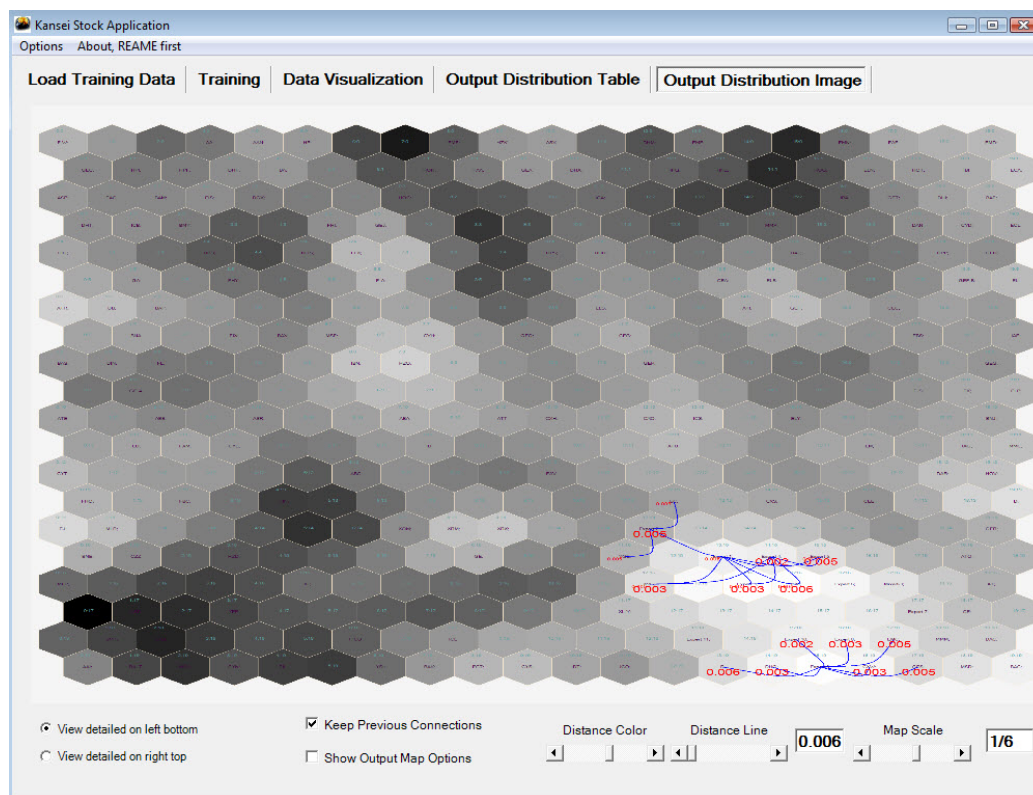
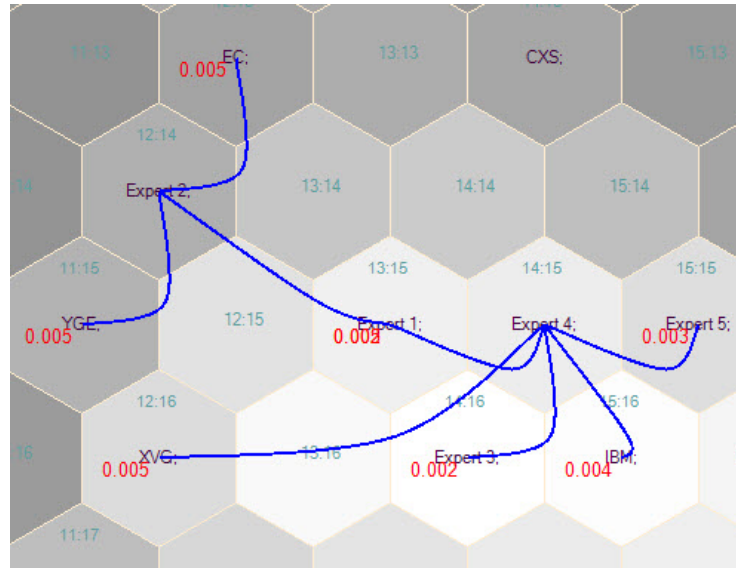


Figure 6.1: The overview of a map result

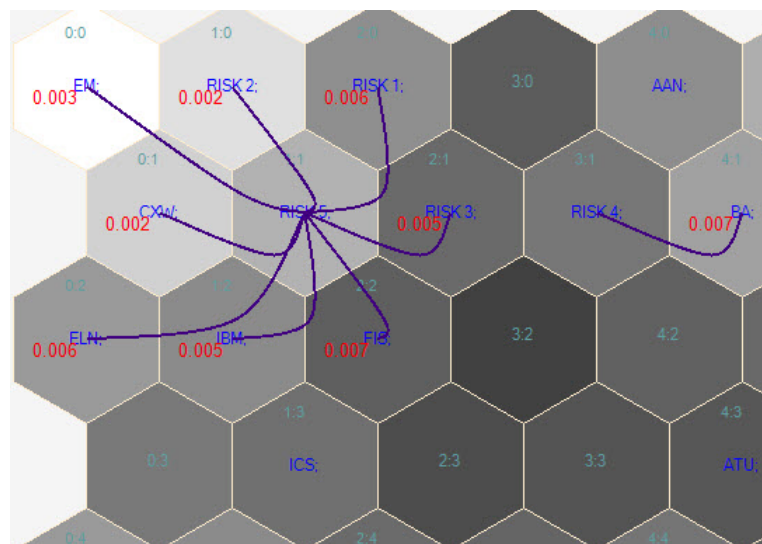
quantified by *Kansei* evaluation in stock trading for the period. The profits of these stocks were estimated at 10%, 9%, and 15% for EC, EGE, and XVG respectively when calculated for investment returns.

#### 6.2.4 Case Study of Company Selection by Matching with Trading Strategies and Risks by Aggregating Expert Decisions

Further experiments were carried out by the author, investors and experts from Vi-etcomBank and international securities companies on the NYSE and NASDAQ from the period of June to October 2010. The proposed system was tested with 165 companies with high PE and profit margin standards from thousands of companies on the NYSE and NASDAQ, and 12 experts for stock trading. In the proposed system,



(a) The map result of appropriate companies (superior stocks)



(b) The map result of risky stocks

Figure 6.2: The final SOM results on a map

experts can determine their preferences for dynamic investment with the selection of trading strategies. An expert can select one or many trading strategies. Regarding the expert preferences, Experts 1, 2, 3, 4, and 5 selected a short-term trading strategy. Experts 2, 6, 7, 8, and 10 selected a mixed trading strategy. Furthermore, Expert 2 and 10 selected both short-term and mixed trading strategies. The other Experts 9, 11 and 12, selected only a long-term trading strategy for investment. After SOM training, the map showed three main groups of companies, as shown in Figure 6.3.

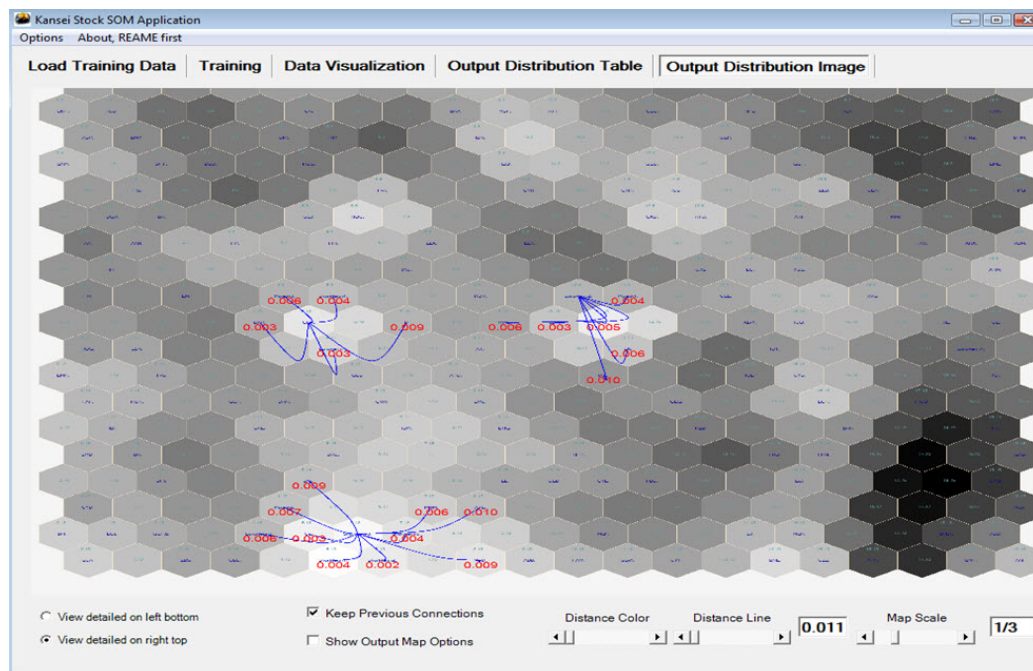
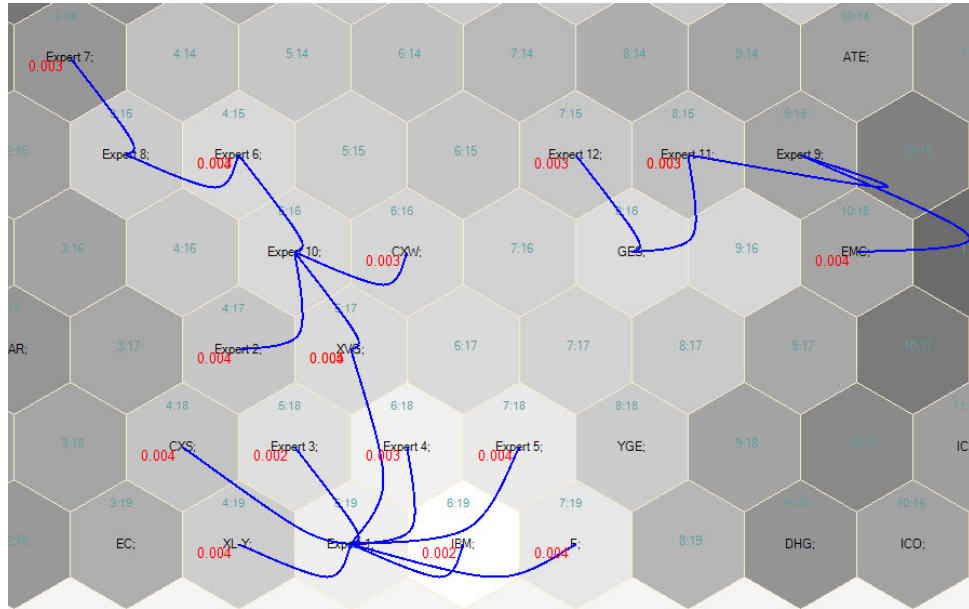


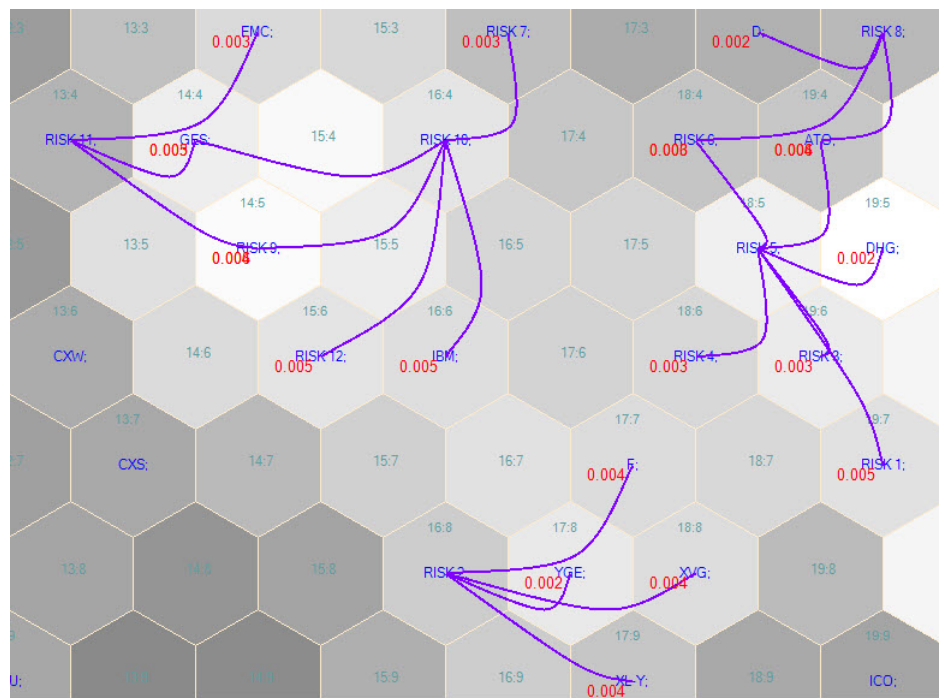
Figure 6.3: The overview of a map result

In the system, the decision maker selected these companies, matched with appropriate stock trading strategies by reducing the maximum *Kansei* stock distance of the companies and eliminating those that have the greatest distance. After the SOM training, the final result on the map showed *Kansei* stock distances among companies matched with trading strategies, as shown in Figure 6.4(a). The short-term trading strategy determined by expert preferences was concerned with the companies (IBM, F, CXS, XLY) for investment. Experts closely focused on the GES and EMC stock symbols with the long-term stock trading strategy. Both CXW and XVG stock





(a) The map result of companies (superior stocks) matching with trading strategies



(b) The map result of risky stocks

Figure 6.4: The final SOM results based on risky and trading decisions on the map

symbols were included in mixed and long-term trading strategies.

For further training process, the *Kansei* risk matrix was also visualized by SOM. The final result on the map showed *Kansei* risk distances between companies and risky investment decisions, as shown in Figure 6.4(b). Regarding the risky investment expert decisions, stock symbols XLY, YGE, F, DHG, ATO, D, IBM, EMC and GES were not selected in the short list for investment because of investment risk warnings. In the final trading decisions, the decision maker selected the stock symbols (CXS, CXW, XVG) for a real-world stock trading from the period of June to October 2010, using a virtual trading system. To determine trading actions (selling/buying) for these stocks, *Kansei* evaluation using expert's sensibilities about stock trading with the market conditions assists experts to make trading decisions. The profits of the stocks are estimated at 11% for CXS (*short-term trading strategy*), 12% for CXW (*long-term trading strategy*), and 8% for XVG (*long-term trading strategy*) when calculated for investment returns.

### 6.3 Evaluation of Hybrid Kansei-SOM Risk Model

In the experiments, we have conducted experiments through case studies in daily real-world stock trading on the HOSE, HNX (Vietnam) stock markets from the period of June 2009 to August 2010 and the NYSE and NASDAQ (US) stock markets from the period of April to August 2010. There was a group of three to five members participating in each survey for a total of 15 investors and experts making the surveys of data connection during the experiments. We selected Vietnam and US stock markets, representing economically developing and developed countries, to perform the proposed model using real-world daily stock trading. In order to establish a performance study, we have investigated how the system performs with respect to various market conditions. There are primary evaluation methods of performance in this study as follows:

- (1) Stock assessment performance in stock trading measured by the proportion of winning stocks (successful investment companies) and losing stocks (failed investment companies).

(2) Overall investment outcome performance in making profits calculated from real-world stock trading by the proposed system.

Investment outcome performance of the proposed model was calculated by profitability average through case studies in daily real-world stock trading on the HOSE, HNX from the period of June 2009 to October 2010 and the NYSE and NASDAQ from the period of March to October 2010. Regarding the profits of the models, the results indicate that the proposed model yielded higher profits, 12-15%, respectively on the HOSE and HNX. For further testing on the NYSE and NASDAQ, the experimental results show profits of the proposed model from 11% to 14 %.

In further evaluation, Figure 6.5 shows the experimental results of the proposed model, representing winning trades (87-92.5%) and average profitability percentages (18-22%) from the period of June 2009 to May 2010 in the HOSE and HNX.

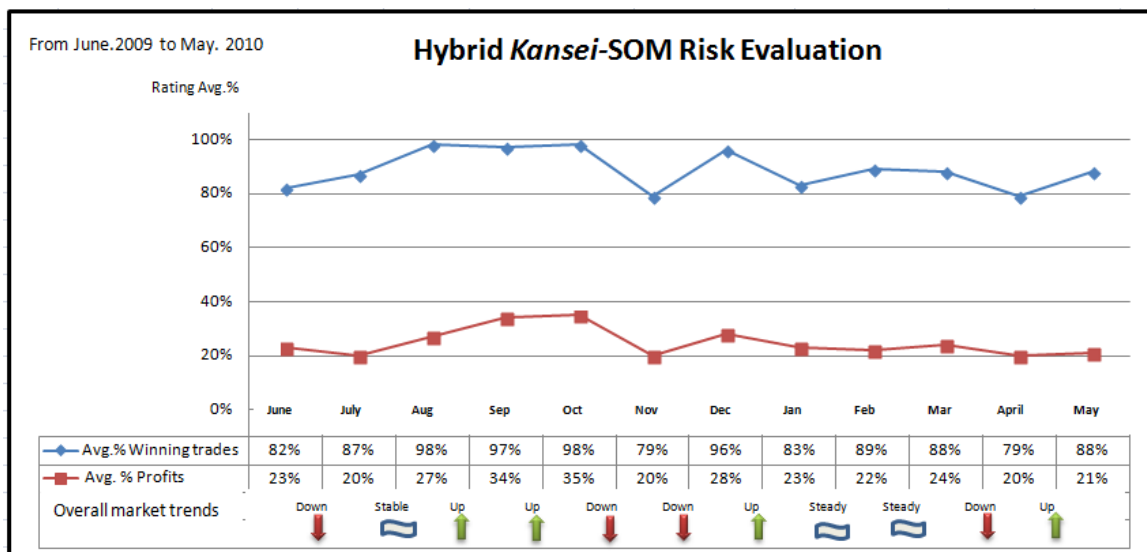


Figure 6.5: Experimental results on the HOSE and HNX

Experimental results of the proposed model was tested using real-world data sets for stock trading from the period of June 2009 to December 2010, showing that an average percent profits are between 12-15% with 87-92.5% winning trades to deal with various market conditions such as downward, upward and steady trends of overall market prices. In downward and steady trends of overall stock prices, the proposed

model shows consistently acceptable investment outcome performance in terms of profits and winning trades. As shown in Figure 6.5, these results through case studies indicate that proposed model is highly qualified as a stock trading system to evaluate companies, select potential companies (superior stocks) and eliminate risky stocks at the right trading time for investment.

In the experiments, there are 9 users from Ritsumeikan University, Maritime bank, Vietinbank, Vietcombank, and other financial-securities companies conducted in the experiments and interviews for identifying market conditions. Average winning stocks in real-world trading result done by these experts objectively on the NYSE and NASDAQ are shown in Figure 6.6.

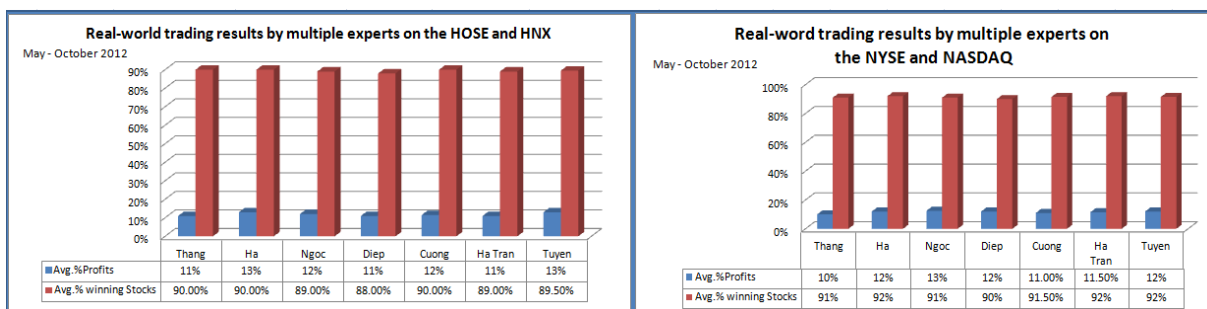


Figure 6.6: Profits and Winning stocks in trading results by multiple experts

### 6.3.1 Advantages of the Model

The unique features of the proposed model are presented as follows:

- In order to improve the effectiveness of a stock trading system, the first issue is to quantify experts' sensibilities about trading stocks, together with aggregation of expert preferences for stock trading, dealing with complex situations in various market conditions.
- All quantitative and qualitative factors with uncertainty in dynamic market conditions, consisting of risks and company assessments are considered through the system based on expert preferences.

- When applying risk management, the Hybrid-*Kansei* SOM model performance has enhanced for the the improvement of the performance and reduce risky trading decisions. In terms of risk management and uncertainty, we can extend the proposed model by positive and negative decisions from experts, represented by Common Sense Human Reasoning.

Common Sense Human Reasoning [77] can be presented as an integration of fuzzy rules, quantitative knowledge and reasoning evidence. Linguistic expressions can be used to represent rules for expert decision situations. To quantify the Common Sense Human Reasoning of expert  $e_i$  in dynamic market environments, we use the following logical rules as **Rule  $i$**  can be presented as follows:

**IF** *Condition 1* AND...AND *Condition  $m$*   
**THEN** *Actions*

Note that expert decision status is represented in a five step scale {invest++, invest+, neutral, risk-, risk- -}

The step 4.2 of the proposed model in this chapter can be replaced by the following steps:

**Step 4.2. Visualizing and updating weights by SOM.**

To evaluate company  $C_j^S$  in terms of investment company assessment and investment risks,  $M_{n \times p}^S$  is visualized by SOM.

**Sub Step 4.2.1. Aggregating decision makers' positive decisions under uncertain conditions.**

**Rule  $l$ :** **IF** *Conditions A* AND *Other conditions* **THEN** Positive decisions with an aggregation of affected factors' weights, together with decision maker preferences, as expressed by Eq.(6.1).

$$v_{ij}^{t+1} = v_{ij}^t + v_{ij}^t x_{ij}^t \quad (6.1)$$

**Sub Step 4.2.2. Aggregating decision makers' negative decisions under uncertain conditions.**

**Rule  $f$ :** **IF** *Market Conditions B* AND *Other conditions* **THEN** Negative decisions and risks with these distribution or aggregation of affected factors' weights,

together with decision preferences as expressed by Eq.(6.2).

$$v_{ij}^{t+1} = v_{ij}^t + v_{ij}^t x_{ij}^t \quad (6.2)$$

where

$v_{ij}^0 = \beta_j^S$ ,  $\beta_j^S$  is a set of decision maker preferences as defined in a five-point scale (0: *oppose*, 0.25: *almost oppose*, 0.5: *have no preference*, 0.75: *almost agree*, 1: *agree*) in the expert decision matrix.

$v_{ij}^0 = \gamma_j^S$ ,  $\gamma_j^S$  is a set of decision maker preferences as defined in a five-point scale (0: *oppose*, 0.25: *almost oppose*, 0.5: *have no preference*, 0.75: *almost agree*, 1: *agree*) in the risk decision matrix.

$t$  is the number of iteration, assigned and  $K$  is the number of uncertainties and risks in market conditions, evaluated by aggregating decision maker preferences.

An uncertainty decision matrix  $A_{n \times p}^S$  is updated by its weights given by Eq.(6.1) or Eq.(6.2). After that, the uncertainty decision matrix  $A_{n \times p}^S$  is joined with the group expert decision matrix  $M_{n \times p}^S$  and its weights are updated to  $M_{n \times p}^S$ .

Uncertain conditions and investment risks are evaluated by experts represent in positive decisions or negative decisions in the subset list with a degree {invest++, invest+, neutral, risk-, risk- -}. After marking decisions' status in system, we aggregate multiple uncertainties and risks on the market conditions. These weights are continuously updated by SOM training from Step 3 to Step 4 of the proposed model until the group expert decision matrix is completely training process.

For example, to represent Sense Human Reasoning of Expert 1,2, and 3 in dynamic market environments, we have applied to the logical rules as illustrations of an application as follows:

**Rule 1** (assigned by Experts 1 and 3): **IF** Oil and Gas prices are high **AND** exports of automation cars and electronic products are low **THEN** Stock prices of groups of automobile and electronic companies will be decreased. In the system, expert 1 and 3 were given with their negative decision status *risk 1-* and *risk 3-*, respectively.



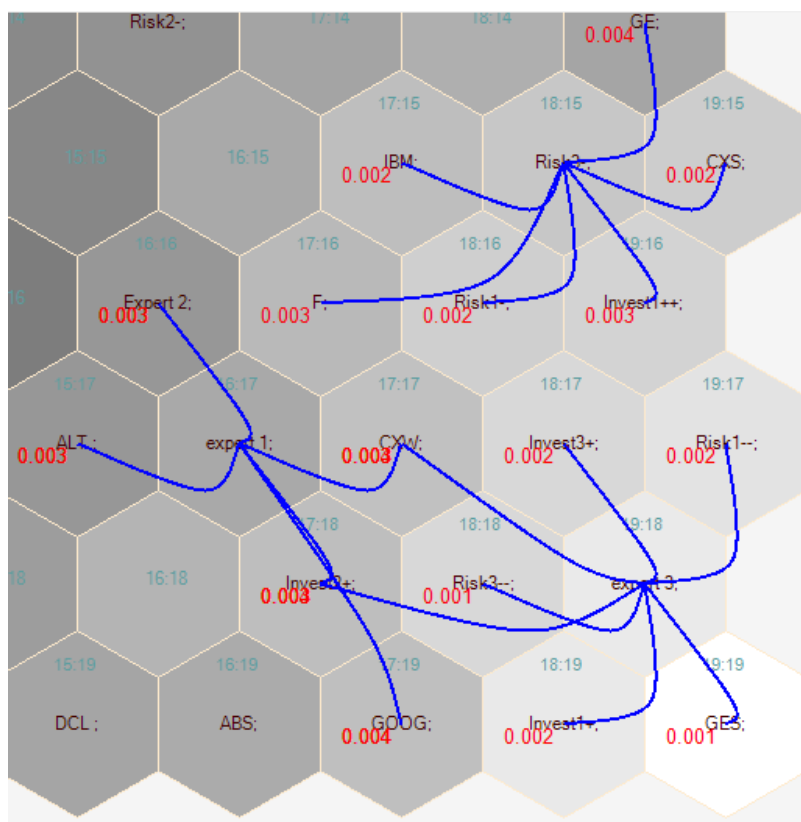


Figure 6.8: Expert reasoning and preference for selection of companies

In the final trading decisions, the decision maker selected the stock symbols (GOOG, CXW, ALT, GES) for a real-world stock trading from the period of September 2010 to March 2011, using a virtual trading system because of strongly positive decisions. To determine trading actions (selling/buying) for these stocks, *Kansei* evaluation using expert's sensibilities about stock trading with the market conditions assists experts to make trading decisions. As selling these stocks, we determined by *Kansei* evaluation and market conditions in terms of expert preferences. The profits of the stocks are estimated at 9% for GOOG , 10% for CXW , 6% for ALT , and 7% for GES when calculated for investment returns. In discussions for further experimental results, we have performed further experiments to visualize company groups under uncertainty and risk. Experimental results show that Rules assigned by experts mostly affect company groups and the companies having with similar features.



## 6.4 Conclusion

This chapter has presented a new method for improvement of stock trading systems by dealing with complex situations in dynamic market environments, such as downward, upward, steady market trends, and other uncertain conditions. The model using GDM focuses on applying *Kansei* evaluation and risk management, integrated with SOM model to enhance investment capability of trading systems, reduce risky stocks and obtain the greatest investment returns. Experimental results demonstrate that the proposed model is able to provide more accurate stock selection, matched with trading strategies at the right trading time and yield higher profits than other current methods. Furthermore, the study results have confirmed that overall performance evaluation of the proposed model is much better than that of the RER method as compared by performance in terms of investment outcome and winning trades. In particular, these results also showed the potential of the proposed system as an efficient stock trading decision with complex situations on various stock markets.



# Chapter 7

## Conclusions and Future Work

### 7.1 Result and Discussions in Three Models

In order to evaluate the effectiveness of the proposed models for stock trading, a proposed model investment performance in winning stocks is calculated from the average of ratings between profits and losses for the successful investment companies based on trading signals on the stock markets. To evaluate the capability of the proposed system by making profits on the HOSE, HNX, NYSE and NASDAQ, we have calculated the average profits that would be applied by trading stocks from the period of March 2012 to April 2013. Experimental results were calculated by users in real-world stock trading. These proposed models have been tested in real-world stock trading with multiple expert preferences objectively who are currently working at Vietinbank and Maritime-bank securities, and Graduate School of Economics, Ritsumeikan university from various nationalities. In the three trading models, the experimental results also demonstrated that the proposed models are able to provide accurate stock selection at the right time for trading to yield higher profits.

In the experiments, we have also conducted tests and experiments in comparisons with separated DSS methods and the latest stock trading system. In the experiments, decision makers use SPICE SOM [79] which is SOM model for testing data sets when compared with the other models. In result discussions, these models using Hybrid Intelligent DSS are used to select appropriate alternatives at the right trading

time for investment. The first model, called the Hybrid SOM-AHP model, is a Self-Organizing Map (SOM) integrated with Analytic Hierarchy Process (AHP). This model aims to select short-list investment alternatives in rankings for stock trading. In experimental results, quantitative and qualitative stock-market factors are visualized by SOM, in order to find grouping companies for investment. Based on the high financial weight results of decision making in appropriate grouping companies, AHP was used to select the best alternatives in rankings for investment. The investment system is estimated only at 68-70% in an overall evaluation. The profit average percent was estimated from 7-8% with high risks (30-32% unsuccessful investment companies). In comparison of Hybrid SOM-AHP model and SOM model [79] for simulated results, the results of real-world stock trading and simulated stock trading show proportion of successful investment companies of the Hybrid SOM-AHP model and SOM model were from 68% to 70%, and from 53% to 58%, respectively on the NYSE and NASDAQ, from the period of March 2012 to May 2013. Experimental results show that the model has limited functions when dealing with market dynamics, affected directly to stock prices of companies on the stock markets.

In various market dynamics, trading results were calculated from users, performed in real-world stock trading on the HOSE, HNX, NYSE and NASDAQ. The second model, called the Hybrid *Kansei*-SOM model, is integrated by SOM with *Kansei* evaluation for optimized trading decisions and selected alternatives with trading strategies. This model was used to quantify qualitative and quantitative attributes of alternatives, together with expert preferences and sensibilities under uncertain market dynamics for selection of alternatives at the right time in stock trading. In terms of winning stocks (successful investment companies), average investment performance of the proposed model was calculated at about 88% with 10% profits, using a Mixed investment strategy on the NYSE and NASDAQ. Furthermore, it reached 91% with 12% profits and 92% with 11% profits using Short-term investment and Long-term investment strategies, respectively. The experimental results consistently showed that the proposed approach using GDSS yielded successful investment companies, from 10% to 12% in terms of profits. In addition, average profits in expert trading results on the HOSE and HNX were estimated higher than 5% trading profits on the NYSE

and NASDAQ. Regarding the experimental results of user feedbacks, short-term investment was appropriate trading strategy on the HOSE and HNX.

In the third model, Hybrid *Kansei*-SOM Risk model aims to reduce risky decisions and alternative risks under uncertain conditions. Risk management, including investment risk factors and *Kansei*-risk words was used to identify stock risks and reduce risky trading decisions. The results showed proportions of winning stocks in the model which are the highest (94 %) with 15 % profits on the the HOSE, HNX and (96%) with 11 % profits on the NYSE, and NASDAQ. Compared to Hybrid *Kansei*-SOM model performance, the Hybrid *Kansei*-SOM Risk model performance was reduced risky stocks from 3% to 5% better than Hybrid *Kansei*-SOM model performance. It is evident that winning trades and losses of the proposed model were better than those of Hybrid *Kansei*-SOM model.

## 7.2 Evaluation of Proposed Models

### 7.2.1 Investment Outcome Performance by Comparison of the Models

Investment outcome performance of Hybrid *Kansei*-SOM Risk (HKSR) model was calculated by profitability average through case studies in daily real-world stock trading on the HOSE, HNX from the period of June 2009 to October 2010 and the NYSE and NASDAQ from the period of March to October 2010. Regarding the profits of the approaches, the results indicate that the HKSR and RER yielded higher profits, 12-15% and 8-10%, respectively on the HOSE and HNX. For further testing on the NYSE and NASDAQ, the experimental results show profits of the proposed approach and RER are from 11% to 14 % and from 5% to 8 %, respectively. Compared to the RER performance, HKSR has the highest investment outcome performance. These experimental results indicates that the HKSR provides a better investment performance than that of the RER.

To confirm this study by comparing the approaches for calculating investment outcome performance, the proposed models have been tested and performed well in

daily stock trading on the NYSE and NASDAQ. In these tests, similar stocks were selected from similar data sets under the same conditions. We conducted the HKSR and RER approaches using with the virtual trading system investment on the NYSE and NASDAQ from the period of April 2010 to October 2010. As observed from Table 7.1, the average investment outcome performance by making profits of the HKSR (proposed approach) and RER are 11.4% and 7% respectively. In terms of profitability percent, the HKSR provides a better investment outcome performance than that of the RER.

Table 7.1: Comparison between HKSR and RER by investment outcome performance using the same stocks

| Stock Symbol  | Models               |                     | Trading Time |                |
|---------------|----------------------|---------------------|--------------|----------------|
|               | HKSR (Avg.% Profits) | RER (Avg.% Profits) | Buying time  | Selling time   |
| HD            | 11%                  | 8%                  | May 2010     | August 2010    |
| DEL           | 15%                  | 9%                  | April 2010   | July 2010      |
| MMM           | 14%                  | 10%                 | June 2010    | August 2010    |
| IBM           | 12%                  | 8%                  | June 2010    | September 2010 |
| GE            | 15%                  | 10%                 | April 2010   | October 2010   |
| DIS           | 15%                  | 9%                  | July 2010    | September 2010 |
| GOOG          | 12%                  | 8%                  | June 2010    | October 2010   |
| F             | 14%                  | 10%                 | May 2010     | September 2010 |
| BAC           | -5%                  | -9%                 | June 2010    | October 2010   |
| Avg.% Profits | <b>11.4%</b>         | <b>7%</b>           |              |                |

### **7.2.2 Investment Outcome Performance by Comparison of the Models Under the Same Conditions**

Recently, the new approach using Rule-based Evidential Reasoning approach (RER) [68] 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. Although this approach has been recently shown in an expert stock trading system based on evidential reasoning, the limitation of this approach is that it selects superior stocks at the suitable trading time mostly based on historical data, technical analysis indicators, and trading rules. In particular, we have employed and tested this approach using Wealth-lab Developer 5 software in daily stock trading with various stock market conditions. The experimental results show that the success of a trading system performance relies on overall up-trending signals of stock indices and technical indicators.

For investment companies using virtual trading system, we have employed HKSR and RER models in the case studies on the NYSE and NASDAQ. The proposed model results show and 9-11% profits with 84-87% successful investment companies to deal with various uncertain conditions of overall market prices for the period of April 2010 to March 2011. Figure 7.1 shows experimental results of successful investment companies and compares with RER and Self-Organizing Map (SOM) models which were tested by using real-world data sets under the same conditions for investment on the NYSE and NASDAQ.

As observed from Figure 7.1, compared to RER and SOM approaches, HKSR model has the highest successful investment companies. It indicates that HKSR performs a better successful investment companies than those of RER and SOM.

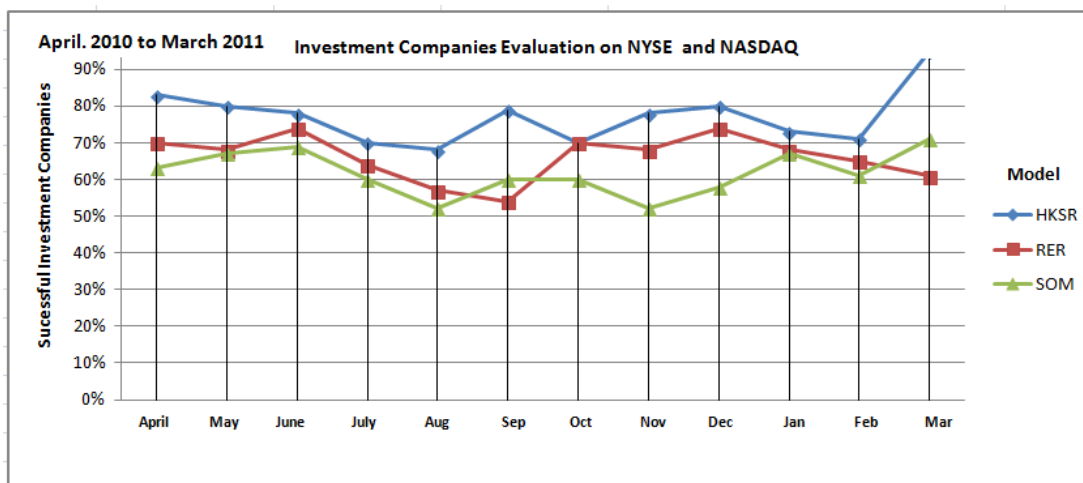


Figure 7.1: Average percents of successful investment companies for trading

### 7.2.3 Evaluation by Comparison of Hybrid *Kansei*-SOM model, Hybrid *Kansei* SOM Risk model and the Latest Method in Stock Trading

In the experiments, the Hybrid *Kansei*-SOM model (HKS), Hybrid *Kansei* SOM Risk model (HKSR), and Rule-based Evidential Reasoning model (RER) [68] have been tested in real-world stock trading under the same market conditions and data sets. To evaluate capability for investment returns of these models, there are seven users running in experiments for these trading results objectively under the same market conditions and data sets, as calculated in the average profits that would be made by these trading stocks. Stock market investment outcomes must be accounted for when calculating investment returns in various stock market conditions. The proposed models have been performed well in daily real-world stock trading for investment on the HOSE and HNX (Vietnam), NYSE, and NASDAQ (US) stock markets, as shown in the experimental results in Table 7.2.

As observed from Table 7.2, the percentages of profits in the HKS, HKSR, and RER are 10-12%, 11-13%, and 6.5-7.5% respectively, as calculated by seven experts performed objectively on the NYSE and NASDAQ. On the HOSE, HNX, NYSE and NASDAQ, the average profit percents of the HKS, HKSR are higher than RER about



Table 7.2: Experimental results on the HOSE, HNX, NYSE, and NASDAQ

| Models | The HOSE and HNX |                               | The NYSE and NASDAQ |                               |
|--------|------------------|-------------------------------|---------------------|-------------------------------|
|        | Avg.% Prof-its   | Avg.% winning stocks          | Avg.% Prof-its      | Avg.% winning stocks          |
| HKS    | 10-12%           | From May to October 2012: 80% | 10-11%              | May to October 2012: 85%      |
| HKSR   | 11-13%           | From May to October 2012: 90% | 10-12.5%            | From May to October 2012: 91% |
| RER    | 7-8%             | From May to October 2012: 70% | 6.5-7.5%            | From May to October 2012: 75% |

3-4%. Compared with HKS and RER, the HKSR model has the highest investment performance (11-13%) with winning stocks (successful investment companies 91%). It indicates that the HKSR provides higher than those of HKS and RER.

### 7.3 Objective Evaluations by Comparison of the Models

In objective evaluation, it is defined as a technique, which is consistent and reliable from the influence of the evaluators. In objective evaluation, individual users conducted and tested these models through experiments in real stock trading from the period of January 2012 to June 2013. The experiments were performed by separately individual users and these decisions. These user trading results were calculated profitability average from directly their virtual trading systems. Average trading results of all the users were calculated, in order to evaluate the proposed model objectively. In case studies of selection for stock trading, we have investigated how these models perform with respect to various market conditions. The Hybrid *Kansei*-SOM model (HKS), Hybrid *Kansei* SOM Risk model (HKSR), and Rule-based Evidential Reasoning model (RER) have been tested in real-world stock trading under the same

market conditions and data sets. To evaluate capability for investment returns of the proposed models, there are seven experts from May to October 2012 and three experts from October 2012 to April 2013, running in experiments for these trading results objectively under the same market conditions and data sets, as calculated in the average profits that would be made by these trading stocks. Stock market investment outcomes must be accounted for when calculating investment returns in various stock market conditions. The proposed models have been performed well in daily real-world stock trading for investment on the HOSE and HNX (Vietnam), NYSE, and NASDAQ (US) stock markets, as shown in the experimental results in Table 7.3.

Table 7.3: Experimental results on the HOSE, HNX, NYSE, and NASDAQ

| Models | The HOSE and HNX |                                      | The NYSE and NASDAQ |  |
|--------|------------------|--------------------------------------|---------------------|--|
|        | Avg.% Profits    | Avg.% winning stocks                 | Avg.% Profits       | Avg.% winning stocks                   |
| HKS    | 11-12%           | From October 2012 to April 2013: 81% | 10.5-11 %           | From October 2012 to April 2013: 84.5% |
| HKSR   | 12-13%           | From October 2012 to April 2013: 91% | 10-12%              | From October 2012 to April 2013: 92%   |
| RER    | 7-9%             | From October 2012 to April 2013: 70% | 6-7.5%              | From October 2012 to April 2013: 75%   |

As observed from Table 7.3, the percentages of profits in the HKS, HKSR, and RER are 10-12%, 11-13%, and 6.5-7.5% respectively, as calculated by seven users performed objectively on the NYSE and NASDAQ. On the HOSE, HNX, NYSE and NASDAQ, the average profit percents of HKS, HKSR are higher than that of RER about 3-4%. Compared with HKS and RER, the HKSR model has the highest profits (11-13%) with winning stocks (successful investment companies 91%). It indicates that the HKSR provides a better profit percentage than those of the HKS and RER.

In further experiments, there are 12 users and experts from Ritsumeikan University, Maritime bank, Vietinbank, Vietcombank, and other financial-securities companies conducted in the experiments and interviews for identifying market conditions. Average winning stocks in real-world trading result done by these experts objectively

on the NYSE and NASDAQ from May to October 2012 are shown in Figure 7.2.

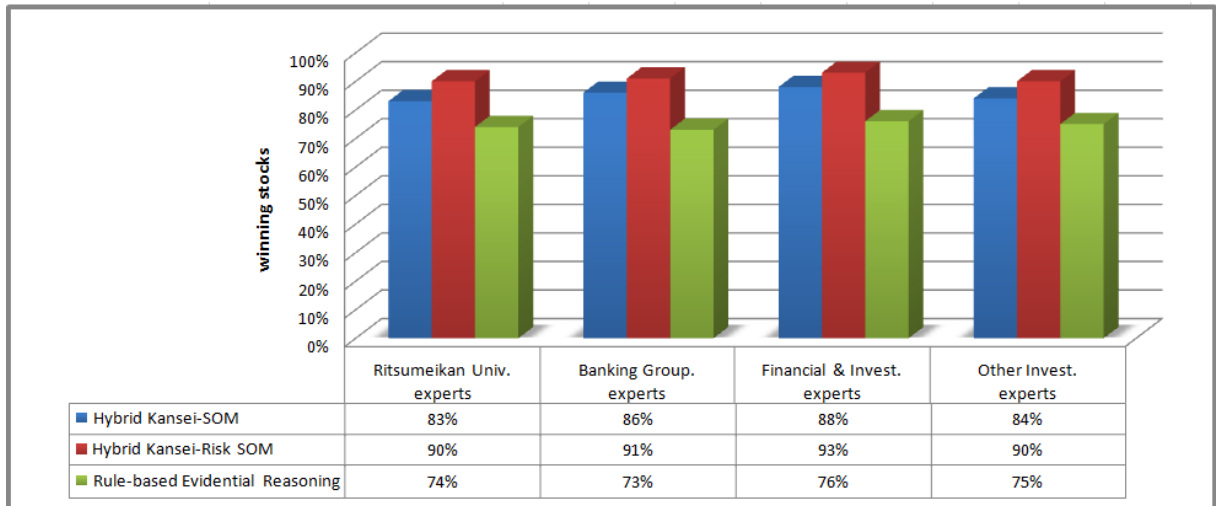


Figure 7.2: Winning stocks in trading results by multiple experts

The experimental results show that percentages of winning stocks in the proposed approach are mostly evaluated by four users in a group for real-world stock trading on US stock markets. The results consistently show that the HKS and HKSR models using yielded successful profits with winning stocks (85-91%), was higher than that of RER on the NYSE and NASDAQ.

In further experiments, the experimental data consists of 6 months for simulated trading stocks based on real-time data sets obtained from Yahoo Inc Stock Prices and Market Watch Online on the NYSE and NASDAQ from the period of January to June 2012. When investing in similar stocks, the users carried out simulated stock trading objectively and showed average winning stocks of these models through experimental simulated trading results as summarized in Table 7.4.

In terms of winning stocks (successful investment companies), average successful investment companies of the HKSR has been calculated at 92.5% with the highest selected stocks in making profits, done by seven experts in simulated trading results with the same market conditions and data sets. Additionally, it reached 81.4% and 72% winning stocks applied by HKS and RER, respectively. The experimental results consistently show that HKSR and HKS yielded successful investment companies,

Table 7.4: Evaluation of simulated stock trading results

| Models  | HKS          |                            | HKSR         |                            | RER        |                            |
|---|--------------|----------------------------|--------------|----------------------------|------------|----------------------------|
|   | Expert       | Avg.%<br>winning<br>stocks | Expert       | Avg.%<br>winning<br>stocks | Expert     | Avg.%<br>winning<br>stocks |
|   | BAYU         | 7/9 (77%)                  | BAYU         | 8/9 (85%)                  |            |                            |
|   | DANNIAR      | 8/10 (80%)                 | DANNIAR      | 9/10 (90%)                 |            |                            |
|   | LINH         | 5/6 (83%)                  | LINH         | 6/6 (100%)                 |            |                            |
|   | MAFUT        | 8/10 (80%)                 | MAFUT        | 9/10 (90%)                 |            |                            |
|   | MURAT        | 6/7 (86%)                  | MURAT        | 7/7 (100%)                 |            |                            |
|   | TUYEN        | 8/10 (80%)                 | TUYEN        | 9/10 (90%)                 |            |                            |
|   | CUONG        | 6/7 (86%)                  | CUONG        | 7/7 (100%)                 |            |                            |
|   | DIEP         | 8/10 (80%)                 | DIEP         | 9/10 (90%)                 |            |                            |
|   | NG. HA       | 9/11 (81%)                 | NG. HA       | 10/11 (91%)                |            |                            |
|   | NGOC         | 10/12 (83%)                | NGOC         | 10/12 (92%)                |            |                            |
|   | THANG        | 8/10 (80%)                 | THANG        | 9/10 (90%)                 |            |                            |
| Avg.%<br>Win-<br>ning<br>stocks<br>in total         | <b>81.4%</b> |                            | <b>92.5%</b> |                            | <b>72%</b> |                            |
| Avg.%<br>Failed<br>stocks<br>for<br>invest-<br>ment | <b>18.6%</b> |                            | <b>7.5%</b>  |                            | <b>28%</b> |                            |

was higher than that of RER. In further testing experiments of HKSR and HKS, the estimation results are also achieved through expert feedbacks and experiments show that the proposed models perform well in real-world stock trading to deal with complex situations of dynamic stock market environments.

## 7.4 Conclusion

This dissertation presented a novel approach using Hybrid Intelligent DSS, which uses to quantify alternatives' attributes, together with expert preferences and sensibilities to predict optimal solutions in the selection of multiple alternatives (companies, stocks, and company groups) and reduce risky decisions in the domain of stock trading. In practice for the domain of stock selection in stock trading, Hybrid Intelligent DSS using *Kansei* Evaluation to select alternatives under uncertainty and risk in stock trading. These models in this study using Hybrid Intelligent DSS techniques are to select appropriate alternatives under uncertainty and risk for optimal solutions in dynamic environments such as stock trading, financial portfolio investment, and investment companies.

In experimental results, HKSR and HKS have been validated in stock investment systems by dealing with complex situations in dynamic market environments, such as downward, upward, steady market trends, and other uncertain conditions. In objective evaluation, the experimental results in the proposed models show average winning stocks (successful investment companies) for all of the users in stock trading are the same as those of subjective evaluation. There are a bit different from trading results of experts in trading stock on the HOSE, HNX and NYSE, NASDAQ. These experimental results of the approaches in this study using Hybrid intelligent DSS enhances investment capability of trading systems, reduces investment risky stocks, and obtains the investment returns. Furthermore, experimental results demonstrate that the HKSR is able to provide more accurate stock selection, matched with trading strategies at the right trading time and yield higher profits than Rule-based Evidential Reasoning method (RER) [68].

It is concluded that the originality of this study is to provide full solutions for

complex situations in selection of alternatives under uncertainty and risk. These approaches using Hybrid Intelligent DSS, presented in this dissertation have been tested and validated in real-world problems for stock trading.

## 7.5 Future Work

For further study, the primary feature of Hybrid Intelligent DSS models should be performed in a dynamic model integration which consists of combining existing DSS models, adapted to new situations of uncertain environments. The models can support complex problems using decision making and group decision making processes in various application domains. The features of the future study are presented as follows:

1. Selection of integrated DSS models, adaptive with complex situations of dynamic environments.
2. All quantitative and qualitative factors with uncertainty and risk, intangible-information events and uncertain consequences in real time data sets.
3. Collaborative uncertain information consequences together with expert preferences in terms of selection and prediction.

We believe that an extended framework using Hybrid Intelligent DSS in this study can be applied to the domains of financial investment, investment risk forecasting, and risk management in the future research.

# Appendix A

## Experts and Investors in Data Collection

In subjective evaluation of trading experiments, the experiments for data collection were collected from experts and investors of Vietcombank securities, Agribank Securities, Saigon-Hanoi Securities and international securities companies in Hanoi, Vietnam from the period of April 2009 to December 2011, as shown in Table A.1.

Note that the experts and investors in the table are explained as follows:

- Experts 1-12 labeled experts 1-12 in SOM results represent by experts from whom data sets were collected in experiments.
- Expert N/A means some experts provide market conditions and assist in data collection.
- Expert 3\* represents the head of a group team to collect data sets from experts and investors at Saigon-Hanoi and ArgiBank securities companies. The author also collected data sets directly from investors and experts and Expert 3\* within a period of three years.
- Investor N/A means an anonymous investor participating in data collection at Stock Market Exchange Centers in Vietcombank, Saigon-Hanoi, International and ArgiBank securities companies.

Table A.1: Expert and investors for data collection from April 2009 to December 2011

| No | Expert ID     | Expert Name      | Org. and Stock Markets        | Disciplines   |
|----|---------------|------------------|-------------------------------|---|
| 1  | Expert 1      | Hai Ha Nguyen    | HOSE, HNX, NYSE, and NASDAQ   | IT<br>Financial<br>Economics<br>IT Financial<br>Financial<br>Securities<br>IT Financial<br>Economics<br>Economics<br>Management<br>Financial<br>Economics |
| 2  | Expert 2      | Ha T. Nguyen     | HOSE, HNX, NYSE, and NASDAQ   |   |
| 3  | Expert 3*     | Ngoc H. Nguyen   | HOSE, HNX, NYSE, and NASDAQ   |   |
| 4  | Expert 4      | Thang P. Manh    | HOSE, HNX, NYSE, and NASDAQ   |   |
| 5  | Expert 5      | Nghi L. Quang    | HOSE, HNX, NYSE, and NASDAQ   |   |
| 6  | Expert 6      | Lan V. Vo        | HOSE, HNX, NYSE, and NASDAQ   |   |
| 7  | Expert 7      | Tung T. Nguyen   | HOSE, HNX, NYSE, and NASDAQ   |   |
| 8  | Expert 8      | Cuong M. Nguyen  | HOSE, HNX, NYSE, and NASDAQ   |   |
| 9  | Expert 9      | Hanh T. Pham     | HOSE, HNX, NYSE, and NASDAQ   |   |
| 10 | Expert 10     | Thinh T. Nguyen  | HOSE, HNX, NYSE, and NASDAQ   |   |
| 11 | Expert 11     | Hai H. Nguyen    | HOSE, HNX, NYSE, and NASDAQ   |   |
| 12 | Expert 12     | Lam H. Nguyen    | HOSE, HNX, NYSE, and NASDAQ   |   |
|    | Other experts |                  |                               | Financial<br>Commercial<br>Economics  |
| 13 | Expert N/A    | Hao T. Quach     | HOSE and HNX                  |   |
| 14 | Expert N/A    | Thuong T. Nguyen | HOSE and HNX                  |   |
| 15 | Expert N/A    | Hong N. Nguyen   | HOSE and HNX                  |   |
|    | Investors     |                  |                               | Investor<br>Investor  |
| 16 | Investor N/A  | 20 Investors     | VietCombank and ArgiBank      |   |
| 17 | Investor N/A  | 15 Investors     | Saigon-HN and Int. securities |   |

- Experts have expertise in specific disciplines such as financial, economics, securities, management, and commercial investment, who have been working at international/local securities, banks and financial companies in Hanoi, Vietnam. Their surveys were used for evaluation of companies matched with their specific majors.
- Investors have experiences in daily real-world stock trading, who have also different backgrounds and disciplines. Their surveys were used for evaluation of general companies.



In further objective evaluation in trading experiments, all of the experts have conducted experiments for data collection from experts of Graduate School of Economics, Ritsumeikan University, Vietcombank, Maritimebanks securities, Agribank Securities, Saigon-Hanoi Securities and international securities companies in Hanoi, Vietnam from the period of January 2012 to June 2013, as shown in Table A.2.

Table A.2: Expert and investors for data collection from January 2012 to June 2013

| No | Expert ID  | Expert Name    | Nationality or Org. | Disciplines       |
|----|------------|----------------|---------------------|-------------------|
| 1  | Expert 1   | BayU           | Indonesia           | Msc. in Economics |
| 2  | Expert 2   | Danniar        | Uzbekistan          | Msc. in Economics |
| 3  | Expert 3   | Mafut          | Uzbekistan          | Msc. in Economics |
| 4  | Expert 4   | Thang P.Manh   | Vietnam             | IT Financial      |
| 5  | Expert 5   | Nghi L.Quang   | Vietnam             | Financial         |
| 6  | Expert 6   | Murat          | Russian-Uzbekistan  | Msc. in Economics |
| 7  | Expert 7   | Tung T. Nguyen | Vietnam             | IT Financial      |
| 8  | Expert 8   | Diep Nguyen    | Study in Japan      | Msc. in Economics |
| 9  | Expert 9   | Cuong Nguyen   | Internship in Japan | Securities        |
| 10 | Expert 10* | Ha Nguyen      | Vietnam             | Financial         |
| 11 | Expert 11  | Tuyen Nguyen   | Study in Japan      | Msc. in Economics |
| 12 | Expert 12  | Ha T. Thanh    | Study in Japan      | Msc. in Economics |
| 13 | Expert 13  | Hong N. Nguyen | Vietnam             | Economics         |
| 14 | Investors  | Some investors | Vietnam             | N/A               |



# Appendix B

## Sample Forms for Data Collection

The author has made four visits within a period of three years (April 2009- October 2011) to Stock Exchange Trading Centers of Securities Companies in Hanoi, Vietnam, as follows:

- Vietcombank Securities Company (VCBS): Website <http://www.vcbs.com.vn/en/>, Floor 12th, Vietcombank Tower, 198 Tran Quang Khai Street, Hoan Kiem District, Ha Noi.
- Saigon Hanoi Securities Company (SHS): Website <http://www.shs.com.vn>, Floor 1-5, No 9 Dao Duy Anh, Dong Da, Ha Noi.
- Agribank Securities (AGR) Company: Website <http://agriseco.com.vn>, 5th Floor, ARTEX Building, 172 Ngoc Khanh, Ba Dinh District, Hanoi.
- International Securities companies are placed in Hanoi, Vietnam.

In this study, the author provided Web-based application and paper-based form for surveys.

A sample of AHP form is used for making a survey in data collection, as shown in Figure B.1.

This form is used for 3  
 Alternatives in evaluation  
 Expert No:  
 Portfolio date:

### Alternative AHP Evaluation

**Question: Consider from each factor, which stock is the best for investment?**

Assume that your task is to determine the relative importance of alternative evaluation according to each factor. Use the matrix below to compare the importance of these scenarios. Please stick the best one among choices.

Your Stocks in the Investment Portfolio:  
 COS:  
 COS:  
 EDUF:

**LV1- Company Assessment**

- LV11- Structure and managing system:

| Scenario | Comparison Scale          | Scenario |
|----------|---------------------------|----------|
| COS      | 7 6 5 4 3 2 1 2 3 4 5 6 7 | EDUF     |
| COS      | 7 6 5 4 3 2 1 2 3 4 5 6 7 | COT      |
| EDUF     | 7 6 5 4 3 2 1 2 3 4 5 6 7 | COT      |

**LV12 – Organization:**

| Scenario | Comparison Scale          | Scenario |
|----------|---------------------------|----------|
| COS      | 7 6 5 4 3 2 1 2 3 4 5 6 7 | EDUF     |
| COS      | 7 6 5 4 3 2 1 2 3 4 5 6 7 | COT      |
| EDUF     | 7 6 5 4 3 2 1 2 3 4 5 6 7 | COT      |

**LV13 - Planning Strategy:**

| Scenario | Comparison Scale          | Scenario |
|----------|---------------------------|----------|
| COS      | 7 6 5 4 3 2 1 2 3 4 5 6 7 | EDUF     |
| COS      | 7 6 5 4 3 2 1 2 3 4 5 6 7 | COT      |
| EDUF     | 7 6 5 4 3 2 1 2 3 4 5 6 7 | COT      |

3

Figure B.1: AHP form for data collection

A sample of *Kansei* Evaluation and factor assessment form is used for making a survey in data collection, as shown in Figure B.2.

**Kansei Evaluation and Factor Assessment Form**

Symbol:

Expert ID name:

Please circle the best one in order rankings of 5->1 in a current market. Each factor marks your two answers for *Kansei* and Factor Assessment.

**Question: Consider from each factor, which company is for the best investment?**

**LV1- Company Assessment**

| Negative. Adj | Assessment Factors  | Positive. Adj |
|---------------|---|---------------|
| Not good      | <b>Structure and managing system</b><br><input type="radio"/> 1 <input type="radio"/> 2 <input type="radio"/> 3 <input type="radio"/> 4 <input type="radio"/> 5<br><br>strongly agree    agree    almost agree    almost oppose    oppose | Good          |
|               | <b>Organization:</b><br><input type="radio"/> 1 <input type="radio"/> 2 <input type="radio"/> 3 <input type="radio"/> 4 <input type="radio"/> 5<br><br>strongly agree    agree    almost agree    almost oppose    oppose                 |               |
| Unpleasant    | <b>Brand name:</b><br><input type="radio"/> 1 <input type="radio"/> 2 <input type="radio"/> 3 <input type="radio"/> 4 <input type="radio"/> 5<br><br>strongly agree    agree    almost agree    almost oppose    oppose                   | Pleasant      |
| Not famous    | <b>Planning Strategy:</b><br><input type="radio"/> 1 <input type="radio"/> 2 <input type="radio"/> 3 <input type="radio"/> 4 <input type="radio"/> 5<br><br>strongly agree    agree    almost agree    almost oppose    oppose            | Famous        |
| Local         |   | Global        |

1

Figure B.2: A sample of *Kansei* Evaluation and factor assessment form

In experiments, experts have a variety of expertise and knowledge so they evaluate companies based on their experiences. When they evaluate the same company, an average score is calculated based on scale definition. Experts and investors evaluated companies based on stock market and *Kansei* data sets. *Kansei* stock matrix and

stock matrix are constructed as shown in Figures B.3 and B.4, respectively. Experts and investors can put data sets directly to an excel file, as shown in Figure B.3.

The screenshot shows an Excel spreadsheet with a grid of data. The columns are labeled with letters from K0 to AC2, and the rows are numbered 1 to 32. The data is organized into a matrix where each cell contains a numerical value, often 0.25 or 0.5, representing the relationships between different stocks in the matrix.

Figure B.3: Data sets for an example of a *Kansei* stock matrix

The screenshot shows a Notepad window with a list of stock tickers and their corresponding numerical values for various financial metrics. The data is organized into a table with columns for the ticker name and several numerical values.

| brname | eval | SO   | MAC  | MAD  | RSI  | MAW  | price_r | eco_ri | equ_r | inte_r | po_r | fin_r | LABEL |
|--------|------|------|------|------|------|------|---------|--------|-------|--------|------|-------|-------|
| 0.25   | 0.25 | 0.25 | 0.5  | 0.25 | 0.25 | 1    | 0.25    | 0.25   | 0.5   | 0.5    | 0.25 | 0.25  | ABT   |
| 0.25   | 0.25 | 0.25 | 0.75 | 0.5  | 0.5  | 0.75 | 0.25    | 0.25   | 0.25  | 0.25   | 1    | 0.25  | ACL   |
| 0.25   | 0.5  | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25    | 0.5    | 0.25  | 0.5    | 0.25 | 0.25  | AGF   |
| 0.25   | 0.5  | 0.25 | 0.5  | 0.5  | 0.5  | 0.5  | 0.25    | 0.5    | 0.25  | 0.5    | 0.5  | 0.25  | ALP   |
| 0.25   | 0.5  | 0.25 | 0.5  | 0.75 | 0.25 | 0.25 | 0.25    | 0.25   | 0.25  | 0.25   | 0.25 | 0.25  | ALT   |
| 0.25   | 0.25 | 0.5  | 0.5  | 0.25 | 0.5  | 0.5  | 0.5     | 0.5    | 0.75  | 0.5    | 0.25 | 0.25  | ANV   |
| 0.25   | 0.25 | 0.75 | 0.5  | 0.25 | 0.75 | 0.5  | 0.25    | 0.25   | 0.5   | 0.25   | 1    | 0.25  | ASP   |
| 0.75   | 0.25 | 0.25 | 0.25 | 0.5  | 0.25 | 0.5  | 0.5     | 0.5    | 0.25  | 0.75   | 0.25 | 0.75  | BAS   |
| 0.25   | 0.25 | 0.5  | 0.5  | 0.25 | 0.5  | 0.5  | 0.75    | 0.25   | 0.5   | 0.75   | 0.25 | 0.25  | BBC   |
| 0.5    | 0.25 | 0.5  | 0.75 | 1    | 0.5  | 0.25 | 0.25    | 1      | 0.25  | 0.75   | 0.25 | 0.5   | BBT   |
| 0.25   | 0.5  | 0.5  | 0.25 | 0.25 | 0.5  | 0.5  | 0.5     | 0.25   | 0.25  | 0.25   | 0.25 | 0.25  | BCI   |
| 0.25   | 0.5  | 0.25 | 0.5  | 0.25 | 0.25 | 0.25 | 0.5     | 0.25   | 0.5   | 0.25   | 0.25 | 0.25  | BF1   |
| 0.25   | 0.25 | 0.5  | 0.5  | 0.5  | 0.5  | 0.25 | 0.5     | 0.5    | 0.25  | 0.5    | 0.25 | 0.25  | BHS   |
| 0.25   | 0.25 | 0.25 | 0.5  | 0.25 | 0.25 | 0.25 | 0.25    | 0.25   | 0.5   | 0.25   | 0.25 | 0.25  | BMC   |
| 0.75   | 0.5  | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25    | 0.5    | 0.25  | 0.25   | 0.25 | 0.75  | BMI   |
| 0.75   | 0.25 | 0.5  | 0.5  | 0.5  | 0.25 | 0.25 | 0.25    | 0.5    | 0.5   | 0.5    | 0.25 | 0.75  | BMP   |
| 0.25   | 0.25 | 0.25 | 0.25 | 0.5  | 0.25 | 0.25 | 0.25    | 0.5    | 0.25  | 0.5    | 0.25 | 0.25  | BT6   |
| 0.25   | 0.25 | 0.5  | 0.25 | 0.5  | 0.75 | 0.5  | 0.25    | 0.5    | 0.25  | 0.5    | 0.25 | 0.25  | BVH   |
| 0.25   | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.25    | 0.25   | 0.25  | 0.25   | 0.25 | 0.25  | CAD   |
| 0.25   | 0.75 | 0.5  | 0.25 | 0.25 | 0.25 | 0.25 | 0.75    | 0.25   | 0.25  | 0.25   | 0.25 | 0.25  | CII   |
| 0.5    | 0.5  | 0.75 | 0.75 | 0.25 | 0.25 | 0.5  | 0.5     | 0.25   | 0.25  | 0.25   | 0.25 | 0.5   | CLC   |
| 0.75   | 0.25 | 0.25 | 0.25 | 0.25 | 0.25 | 0.5  | 0.5     | 0.25   | 0.25  | 0.5    | 0.25 | 0.5   | CNT   |
| 0.5    | 0.5  | 0.5  | 0.25 | 0.25 | 0.25 | 0.25 | 0.5     | 0.5    | 0.25  | 1      | 0.25 | 1     | COM   |
| 0.75   | 0.25 | 0.5  | 0.25 | 0.5  | 0.75 | 0.25 | 0.25    | 0.5    | 0.25  | 0.5    | 0.25 | 0.75  | CYC   |
| 0.75   | 0.25 | 0.5  | 0.25 | 0.5  | 0.25 | 0.25 | 0.25    | 0.5    | 0.5   | 0.5    | 0.5  | 0.75  | DCC   |
| 0.75   | 0.5  | 0.25 | 0.5  | 0.25 | 0.25 | 0.25 | 0.5     | 0.25   | 0.25  | 0.25   | 0.25 | 0.75  | DCL   |
| 0.5    | 0.25 | 0.5  | 0.25 | 0.5  | 0.25 | 0.25 | 0.25    | 0.5    | 0.25  | 0.5    | 0.25 | 0.5   | DCT   |
| 0.25   | 0.25 | 0.5  | 0.25 | 0.5  | 0.25 | 0.5  | 0.25    | 0.25   | 0.5   | 0.25   | 0.5  | 0.25  | DMC   |

Figure B.4: Data sets for an example of a stock matrix

# Appendix C

## Experts Participating in Data Collection and Stock Selection

In this study, the number of a stock selection and experts/investors participating in trading on the HNX and HOSE in 2009, as shown in Figure C.1.

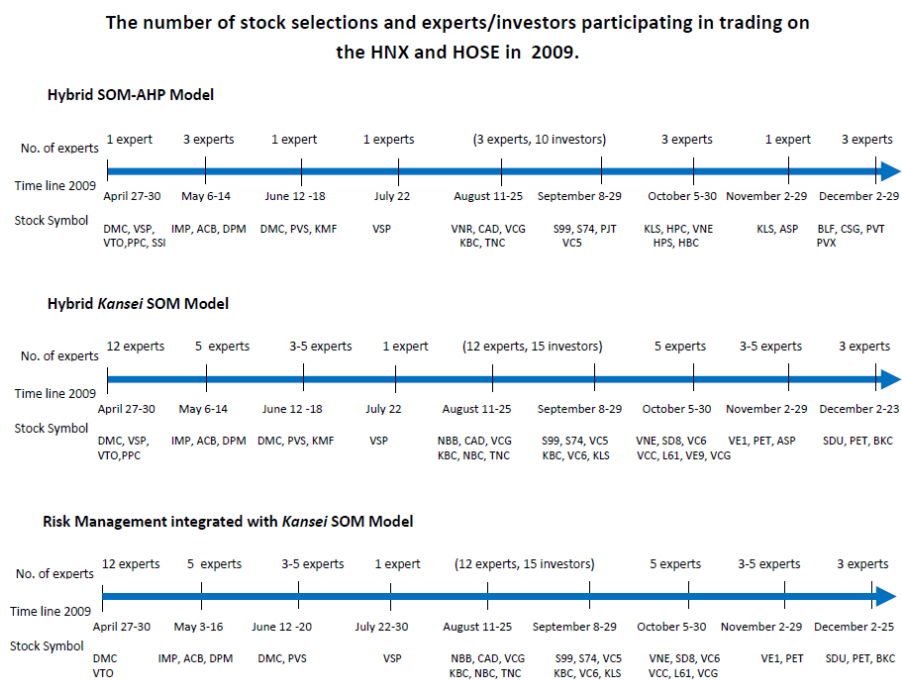


Figure C.1: The number of experts and investors for stock trading in 2009

The number of a stock selection and experts/investors participating in trading on the HNX and HOSE in 2010, as shown in Figure C.2.

**The number of stock selections and experts/investors participating in trading on the HNX and HOSE in 2010.**

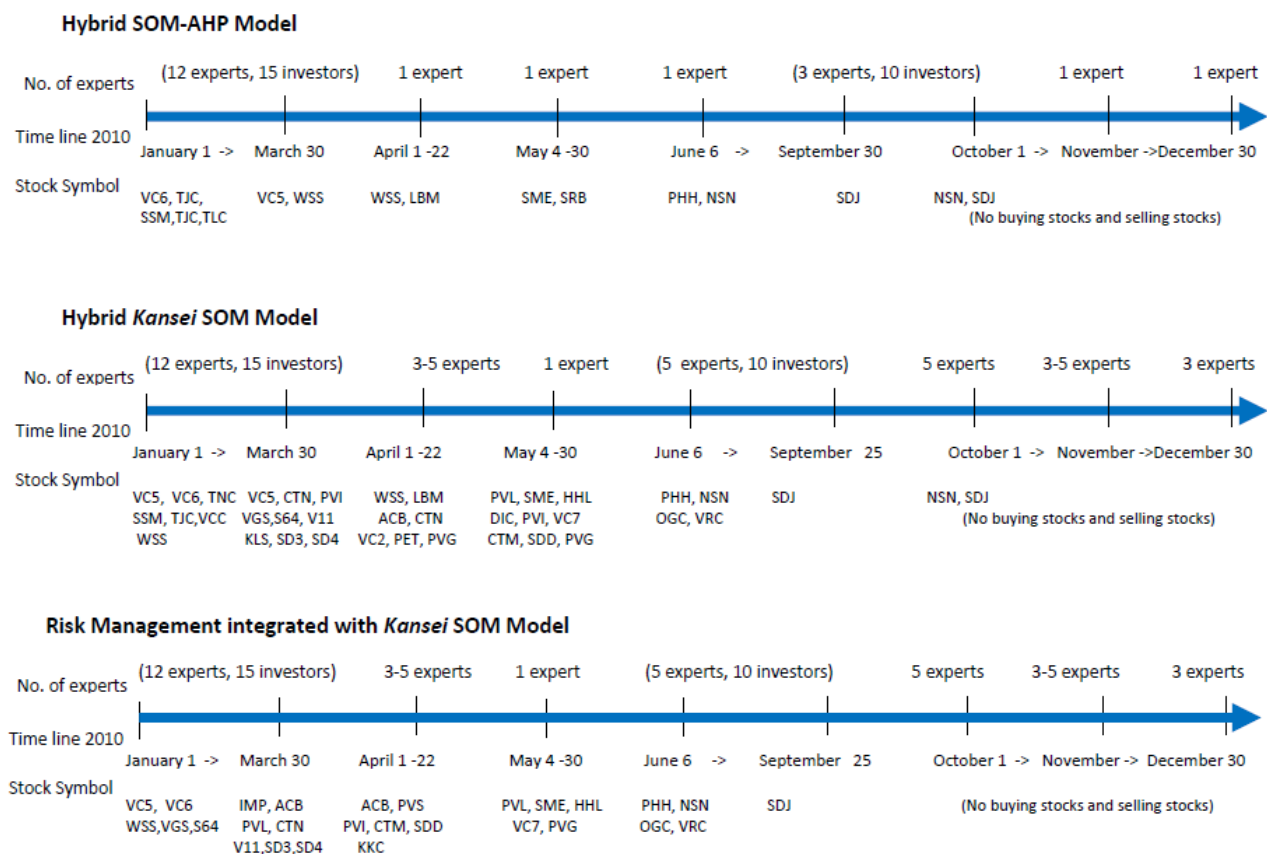


Figure C.2: The number of experts and investors for stock trading in 2010



The number of a stock selection and experts/investors participating in trading on the HNX and HOSE for the period of January 2011 to March 2012, as shown in Figure C.3.

**The number of stock selections and experts/investors participating in trading on the HNX and HOSE from January 2011 to March 2012**

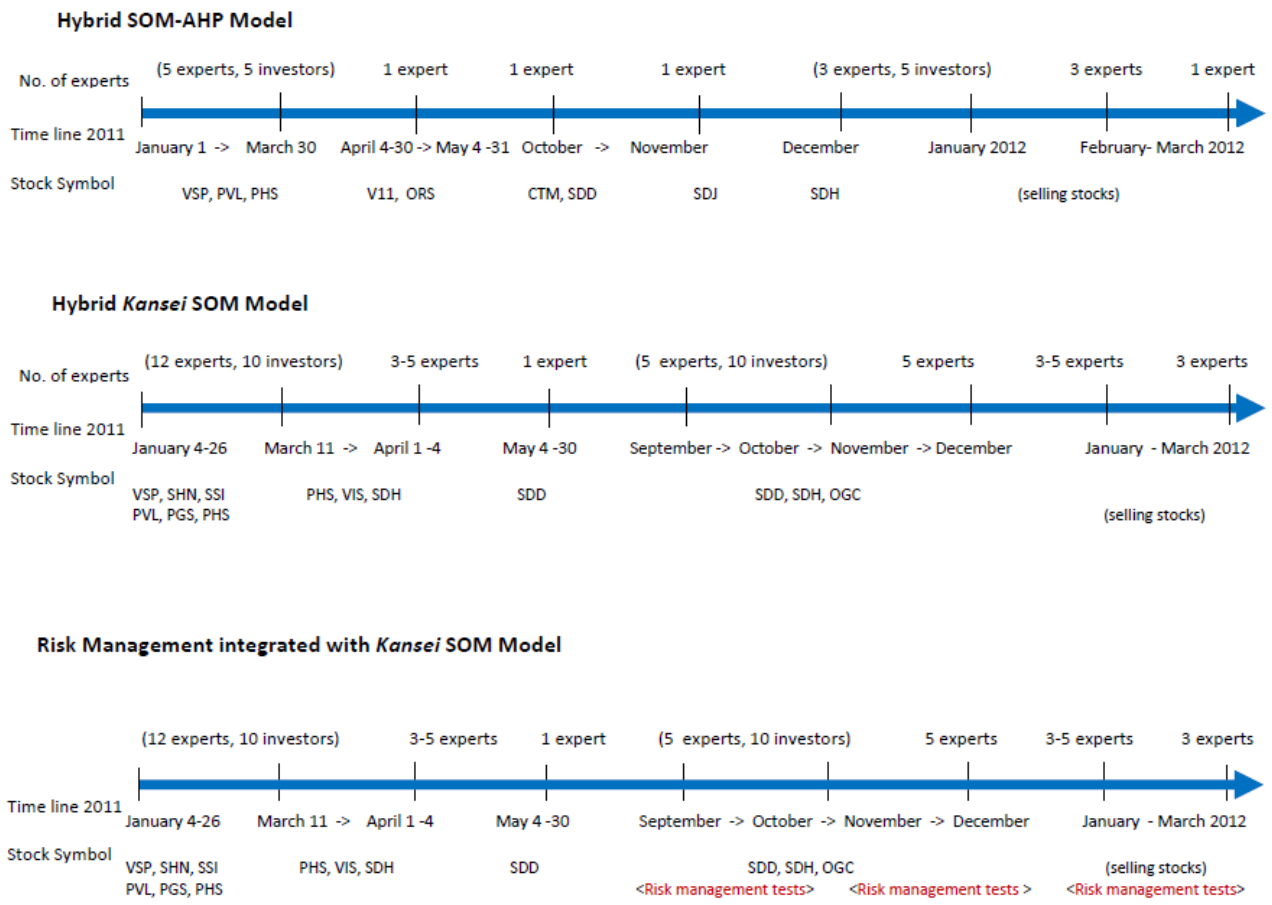


Figure C.3: The number of experts and investors for stock trading in 2011

The number of a stock selection and experts/investors participating in trading on the NYSE and NASDAD for the period of February 2010 to March 2012, as shown in Figure C.4.

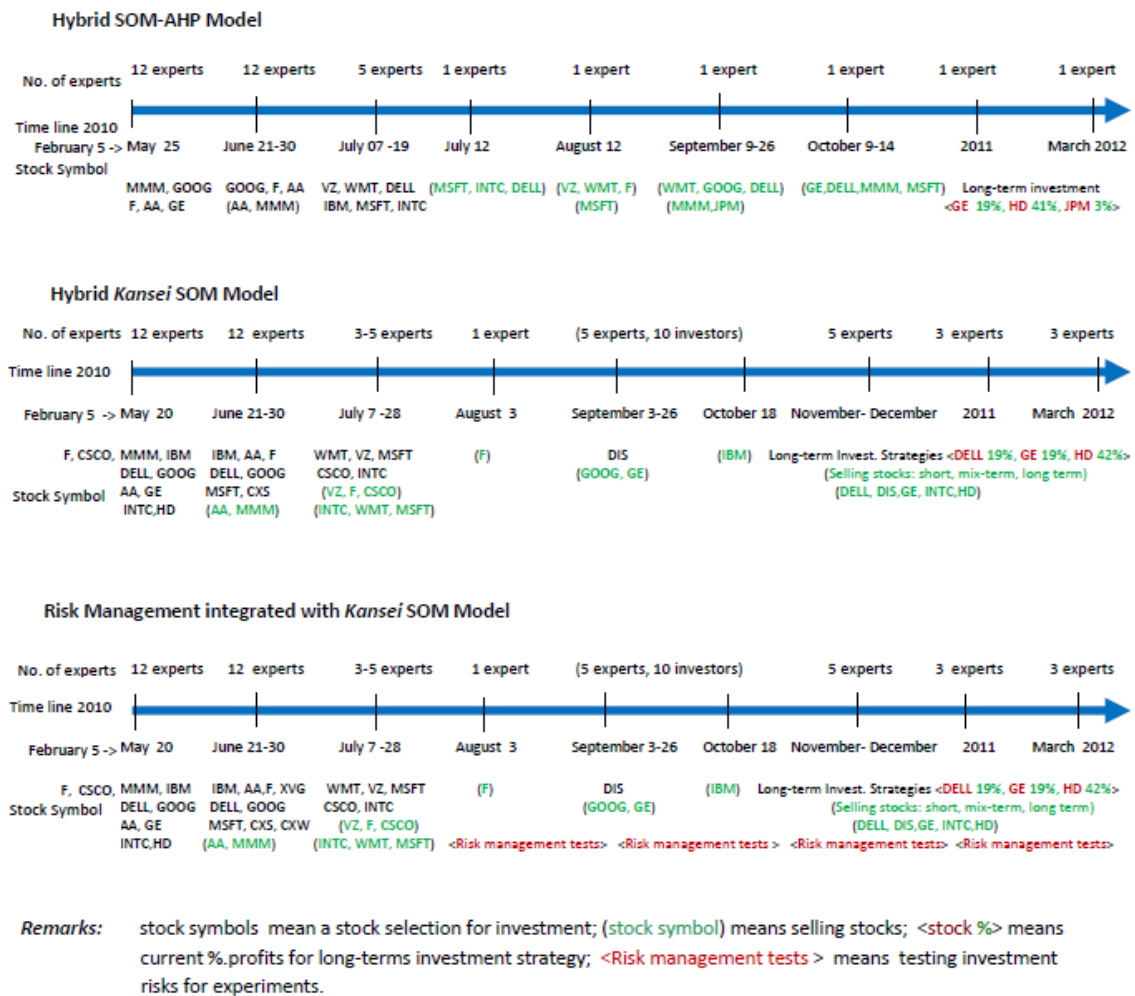


Figure C.4: Experts/investors participating for stock trading on the NYSE and NASDAD

After having results of the stock selection from the proposed models, the author selected stocks for trading of a real investment system called VCBS trading (<https://trading.vcbs.com.vn/>) and virtual investment portal system called Cafef Portal (<http://cafef.vn>) for the HNX and HOSE. The virtual trading system called the Marketwork portal (<http://www.howthemarketworks.com/trading/>) was used for stock trading on the NYSE and NASDAQ. Screens of these systems are used in stock trading, as shown in Figures C.5, C.6, and C.7.

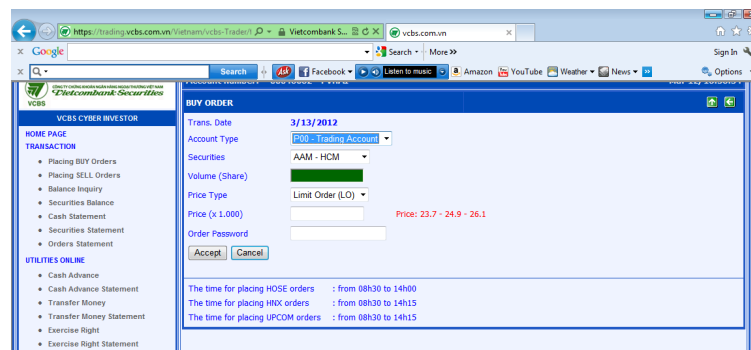


Figure C.5: The screen of the real VCBS trading investment system

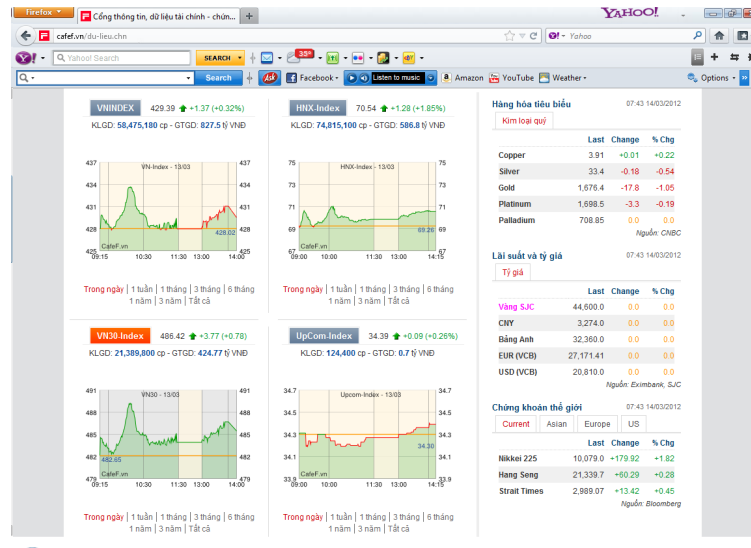


Figure C.6: The screen of a virtual Cafef portal system

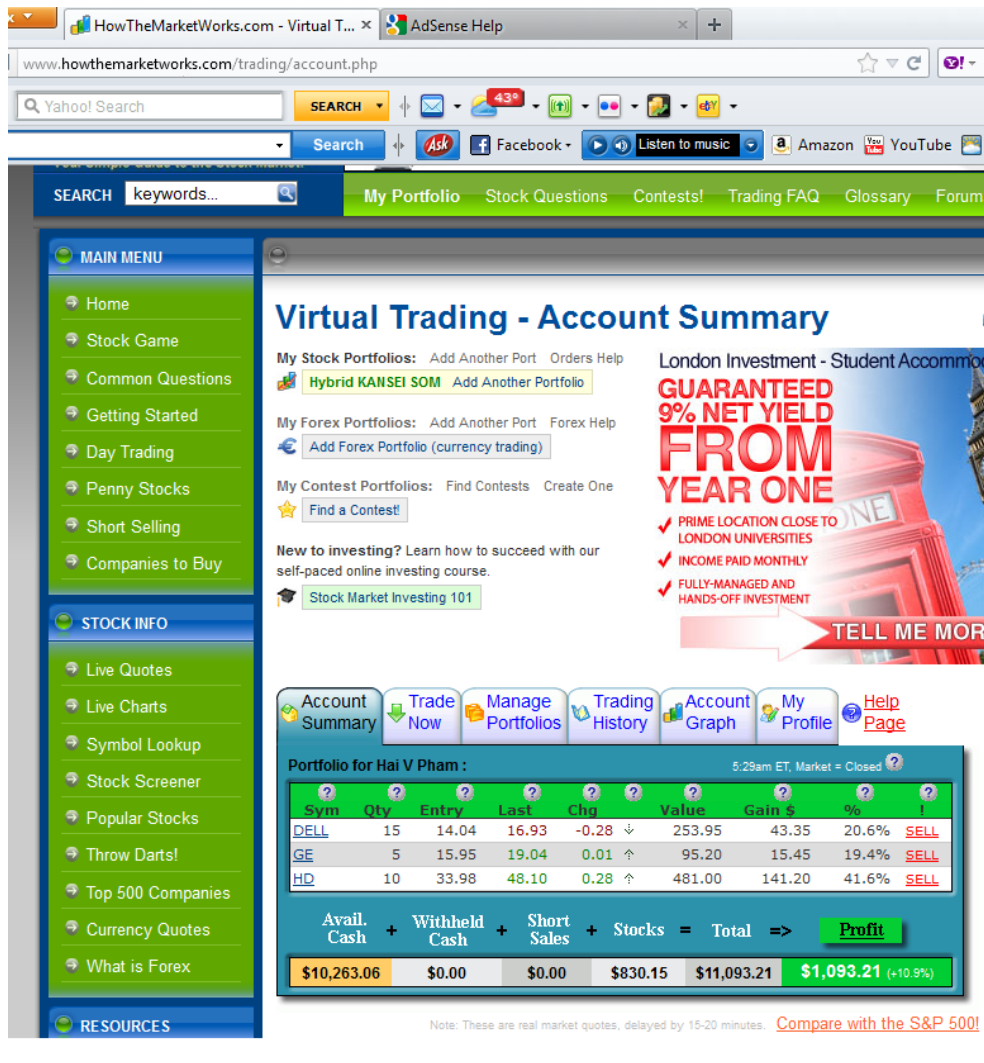


Figure C.7: The screen of the virtual Marketwork trading system

## Appendix D

# List of Rules in the Periods of Stock Trading

Market conditions are represented by Rules, collected from experts in survey and interview methods. There are from 5 to 10 rules which have been used in each trading period for a total number of 16 frequently common rules, as defined in Table D.1.

Table D.1: List of common rules in stock trading

| No. | Rules  | Membership Weight     |
|-----|--|-----------------------|
| 1   | Rule 1: IF < Consumer Price Index > THEN                 | 0, 0.25, 0.5, 0.75, 1 |
| 2   | Rule 2: IF <Government Policy > THEN                     | 0, 0.25, 0.5, 0.75, 1 |
| 3   | Rule 3: IF <Bank Interests > THEN                        | 0, 0.25, 0.5, 0.75, 1 |
| 4   | Rule 4: IF <Inflation Rates > THEN                       | 0, 0.25, 0.5, 0.75, 1 |
| 5   | Rule 5: IF <Macro Economics > THEN                       | 0, 0.25, 0.5, 0.75, 1 |
| 6   | Rule 6: IF <Micro Economics > THEN                       | 0, 0.25, 0.5, 0.75, 1 |
| 7   | Rule 7: IF <Financial Events > THEN                      | 0, 0.25, 0.5, 0.75, 1 |
| 8   | Rule 8: IF < Energy Prices (oil, gas,...etc) > THEN      | 0, 0.25, 0.5, 0.75, 1 |
| 9   | Rule 9: IF < Global Stock Markets > THEN                 | 0, 0.25, 0.5, 0.75, 1 |
| 10  | Rule 10: IF < Disasters (flood, earthquake,..etc) > THEN | 0, 0.25, 0.5, 0.75, 1 |
| 11  | Rule 11: IF < Foreign Development Inter. funding > THEN  | 0, 0.25, 0.5, 0.75, 1 |
| 12  | Rule 12: IF < GDP (Gross domestic product) > THEN        | 0, 0.25, 0.5, 0.75, 1 |
| 13  | Rule 13: IF < World economics > THEN                     | 0, 0.25, 0.5, 0.75, 1 |
| 14  | Rule 14: IF < Politics > THEN                            | 0, 0.25, 0.5, 0.75, 1 |
| 15  | Rule 15: IF < Consumer Confidence Index > THEN           | 0, 0.25, 0.5, 0.75, 1 |
| 16  | Rule 16: IF < Investor Confidence Index > THEN           | 0, 0.25, 0.5, 0.75, 1 |

# Appendix E

## Guide for users to describe experiments in Hybrid Intelligent DSS applications

Guide experiments show users how to use Hybrid Intelligent DSS applications (Hybrid SOM-AHP, Hybrid *Kansei* SOM, Hybrid *Kansei* SOM Risk models). Data sets are collected by experts and investors in an excel file with csv extension or text file with text extension. Users can use the data sets to load in the applications. In experiments, these models are performed by users in individuals in the following:

### E.1 Hybrid SOM-AHP Model

- Step 1. Check data sets (Stock matrix) to SOM model in order to visualize companies on stock markets, as shown an example in Figure E.1.
- Step 2. Load data sets (Stock matrix) to a SOM model for visualizing data, as shown an example in Figure E.2.
- Step 3. Run SOM model to train data sets of stock matrix, as shown in Figure E.3. Note that user can set parameters when training data sets.

Figure E.1: Stock matrix for Hybrid AHP model

Figure E.2: A loading Stock matrix to SOM model



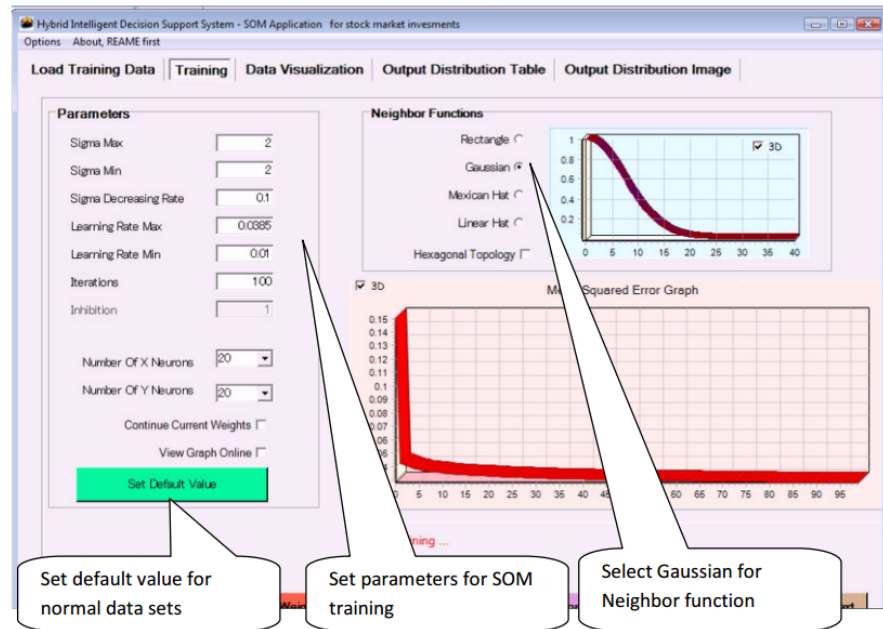


Figure E.3: Training Stock matrix by SOM

- Step 4. View a result on a map done by user. After the training, SOM result was visualized in three groups of companies. In the simulation result, the map result is shown the distance among appropriate companies in Figure E.4.

In simulations, the map result showed the distance among the appropriate companies. As observed the summary estimations from current financial markets results demonstrate that SSI and DPM companies had the highest average weights in terms of P/E (*price-to-earnings*), EPS (*earnings per share*) and ROE (*return on equity*) ratio in percents.

Figure E.5 illustrates that the SOM map result showed the appropriate companies (SSI, DPM, VTO, and DMC). The stock distance from SSI to the other companies is shown in contents of SSI vector which is similarly closed to the other companies DPM, VTO, and DMC.

- Step 5. Select the companies in rankings by AHP model. User can select companies in rankings for a short list (SSI=0.4701, DMC=0.2105, DPM=0.1795, VTO=0.1399), as shown in Figures E.6 and E.7.

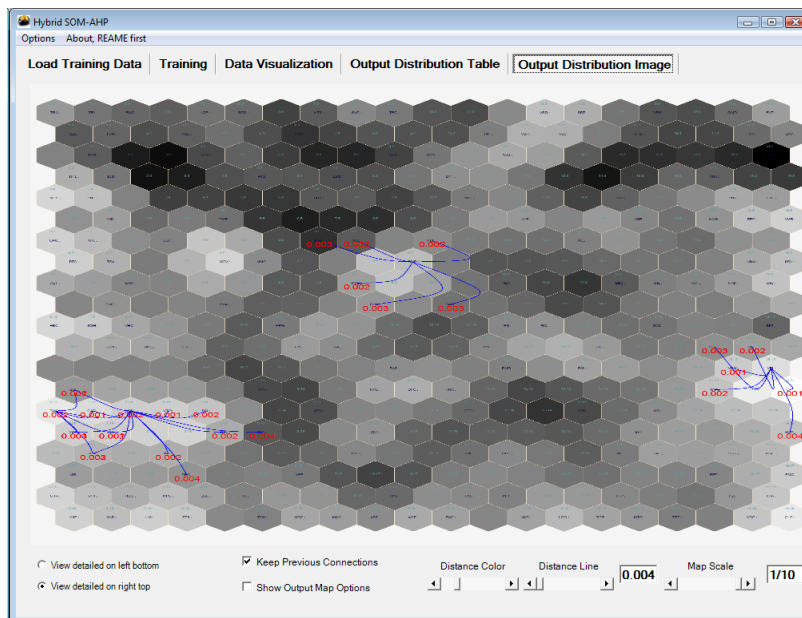


Figure E.4: The screen of SOM result

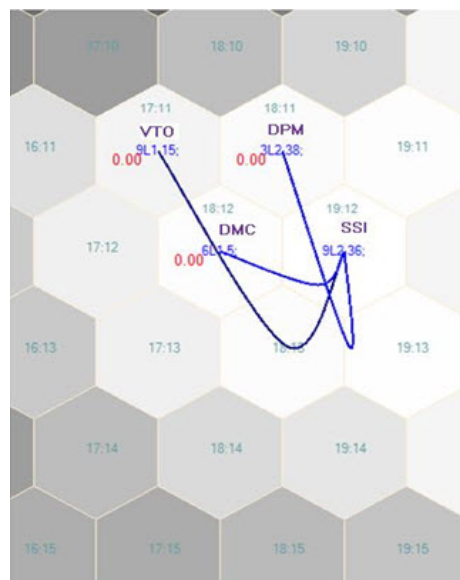


Figure E.5: The screen of SOM result in detail

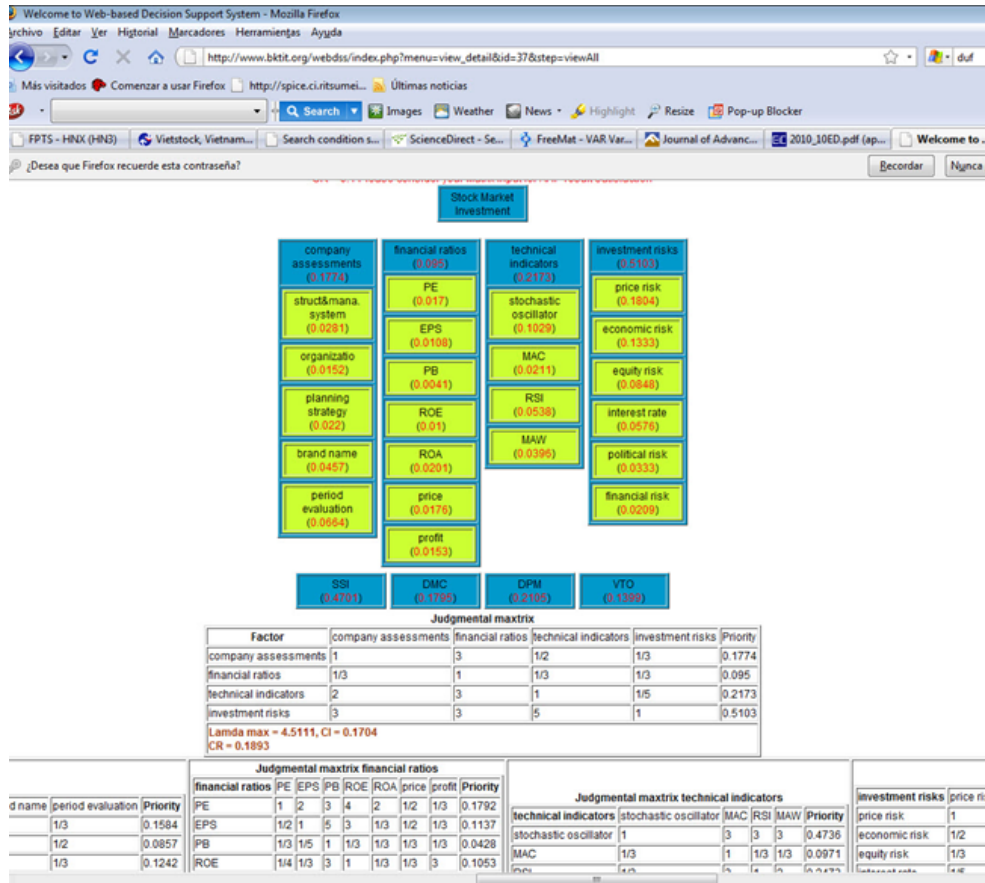


Figure E.6: The screen of Web-based DSS result

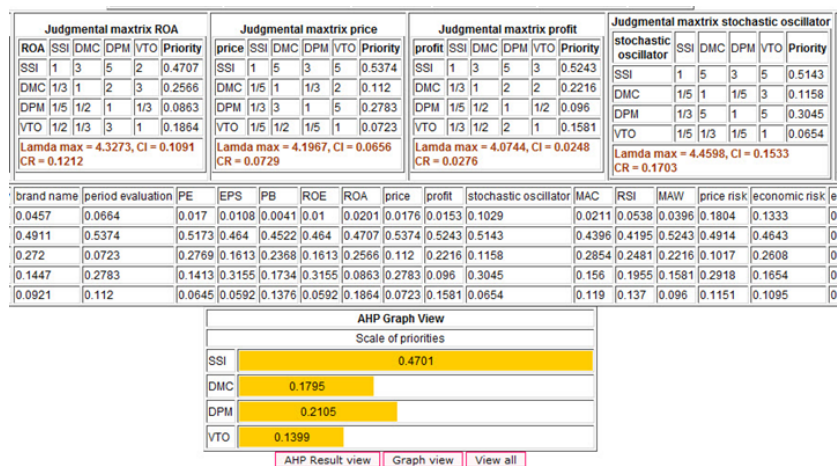


Figure E.7: The AHP result

- Step 6. Put selected companies in virtual or real trading stock system. These stocks can be select for a portfolio for investment based on the user decision. These selected companies are done by the user for real-word stock trading or virtual stock trading, as shown in Figures C.5, C.6, and C.7.

## E.2 Hybrid *Kansei*-SOM Model

- Step 1. Prepare data sets obtained from a stock market in order to construct a *Kansei* stock matrix, as shown in Figure E.8.

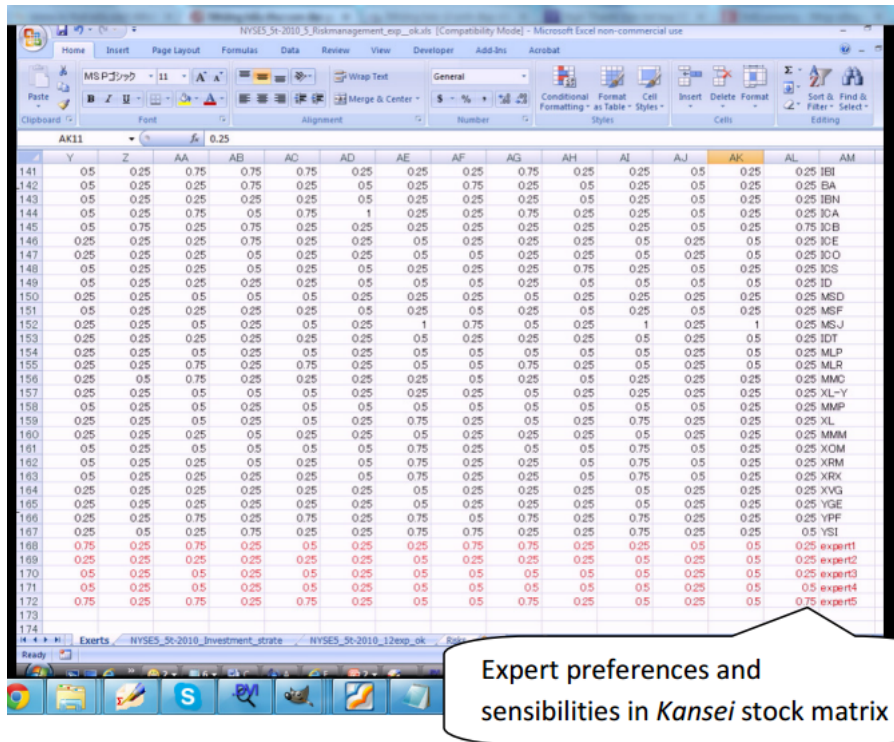


Figure E.8: *Kansei* stock matrix for updating weights

- Step 2. Identify market conditions by an individual user in order to construct a *Kansei* stock matrix, as shown example of Mr. Mafut who is graduate student at Graduate School of Economics, Ritsumeikan University considered his market conditions as shown in Figure E.9.

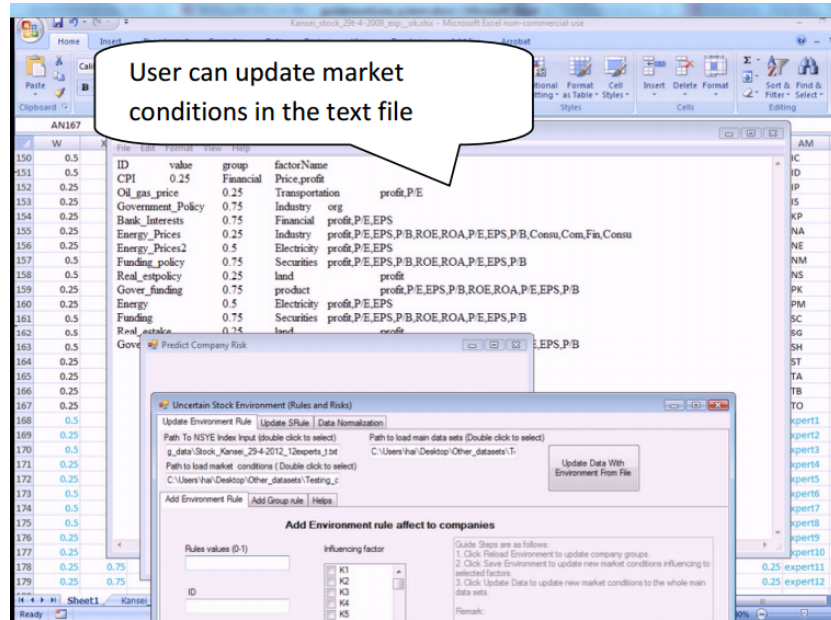


Figure E.9: Identified market conditions represent by rules

In the same data sets for an experiment, Mr. Cuong who works in Vietinbank identifies market conditions, as shown in Figure E.10 represented by rules with action differences from Mafut's rules. Note that each user can consider market conditions based on his/her experiences.

User can update market conditions to *Kansei* stock matrix. Values of attributes in this matrix has been changed which is influenced by the market conditions. The new updated matrix is used to load SOM for visualization with updated clustering expert preferences and sensibilities.

- Step 3. Set dimension 37 factors and the number of companies in the *Kansei* stock matrix for its visualization. The new updated matrix with clustering expert preferences is visualized by SOM, as shown in Figures E.11 and E.12.
- Step 4. Show results of clustering experts for company selection as described in Figure E.13. Mr Mafut who use the system can select company MLP below. As doing the same experiment, Mr Cuong who identifies the market conditions can select companies (MLP, CYT, CZZ) on a map as shown in Figure E.14

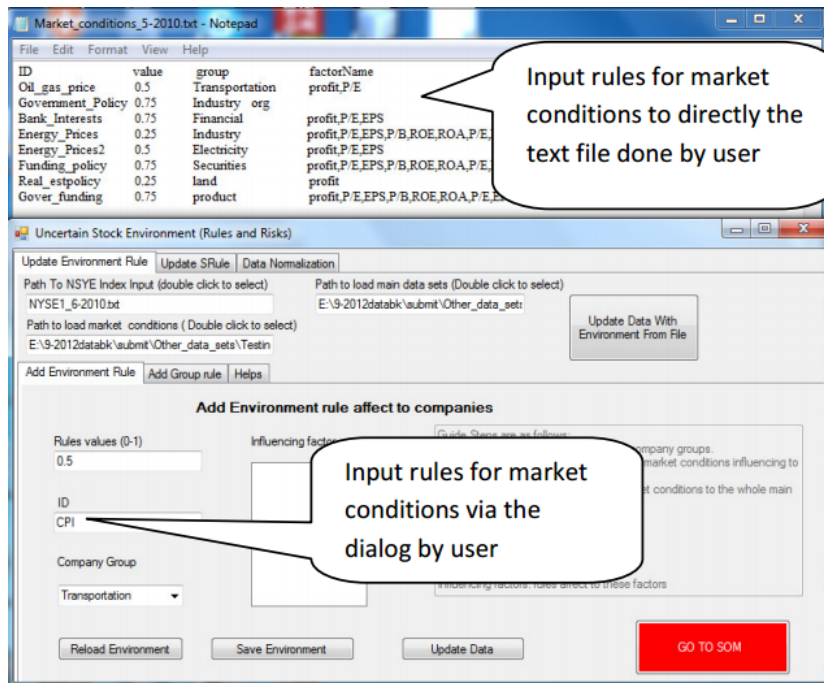


Figure E.10: The other identified market conditions represent by rules

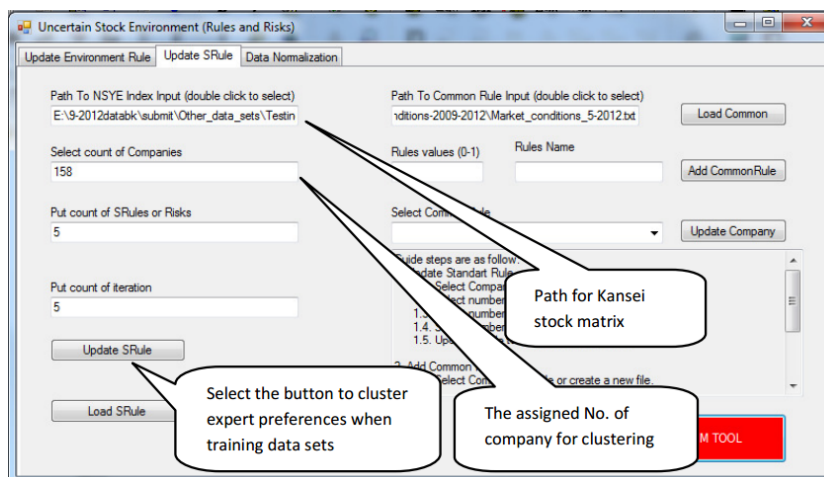


Figure E.11: The updated weights for clustering expert preferences and sensibilities

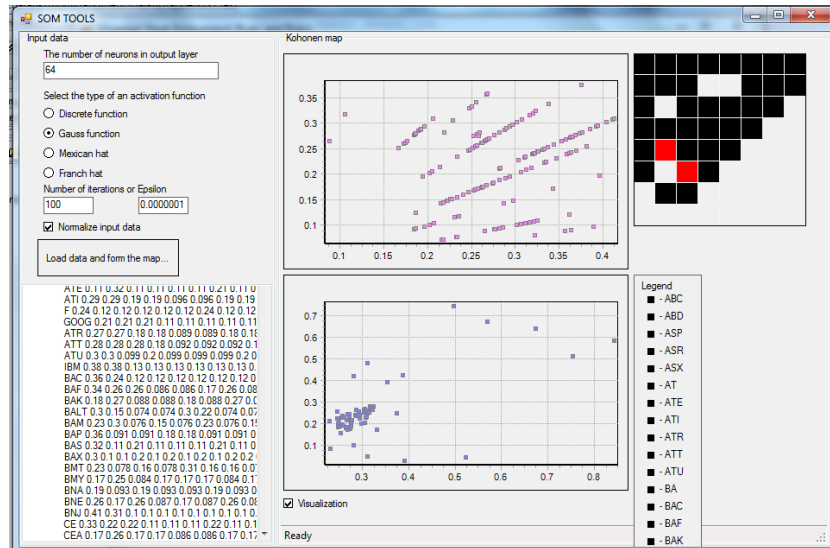


Figure E.12: The SOM training for visualization

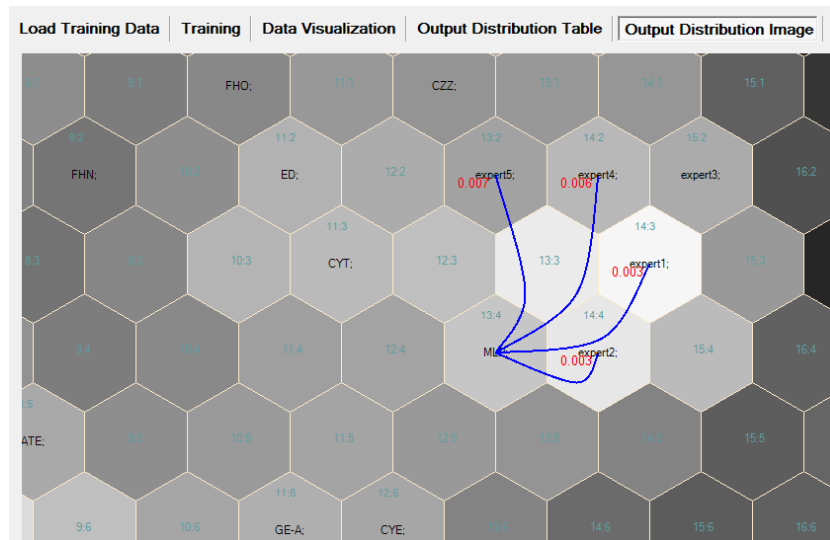


Figure E.13: The result on a map selected by user (Mr Mafut)

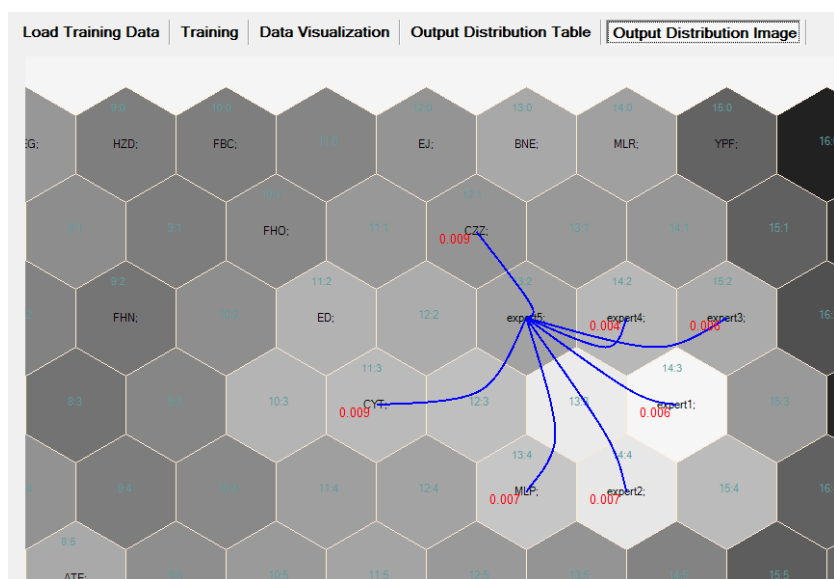


Figure E.14: The result on a map selected by user (Mr Cuong)

Note that identified market conditions have been influenced their results among users who make decisions in the system. On the other hand, user can decide his decisions to select which potential companies for investment.

- Step 5. Select appropriate companies (superior stocks) matched with investment strategies at the right trading time for investment and put these companies in virtual or real-world stock trading.

When clustering expert preferences and sensibilities, user can decide appropriate companies matching with investment strategy based on the results on a map.

### E.3 Hybrid *Kansei*-SOM Risk Model

An experiment of A Hybrid *Kansei*-SOM Risk Model is the same step of that of the Hybrid *Kansei*-SOM Model from Step 1 to 5 of Section E.2 in Appendix E. These results show selected companies for investment done by user. On the other hand, user can reduce risky decisions and company risks by quantifying uncertain risks from Steps 6 to 7 as described in the Hybrid *Kansei*-SOM Risk Model as follows:



- Step 6. Aggregate uncertain risks and visualize a *Kansei* risk matrix by SOM as shown in Figures E.15 and E.16.

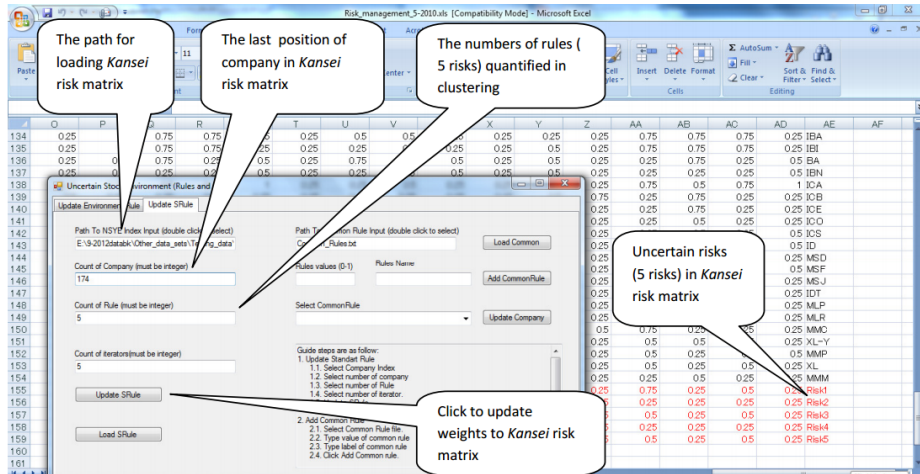


Figure E.15: *Kansei* risk matrix for updating uncertain risk weights

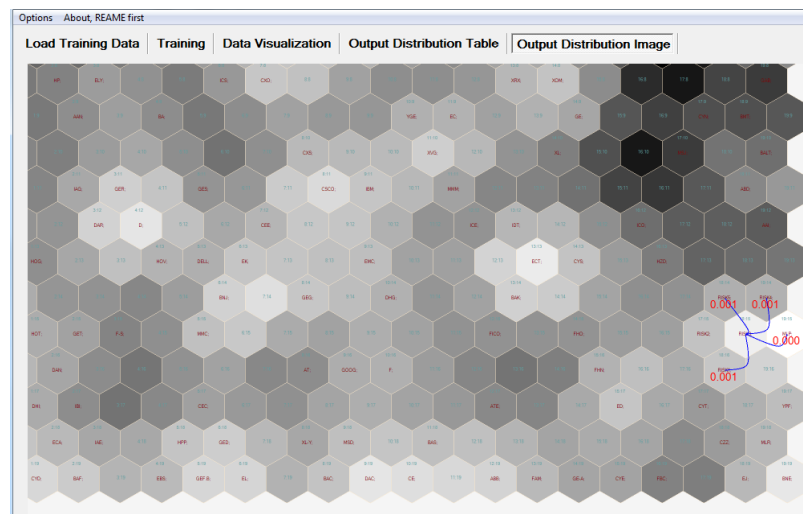


Figure E.16: The result on a map

- Step 7. Compare results on the maps to reduce company risks as shown in Figure E.17.

User can select companies CYT and CZZ, but it is not selected to MLP occurred by risks. Note that each user can interact with the Hybrid Intelligent DSS so

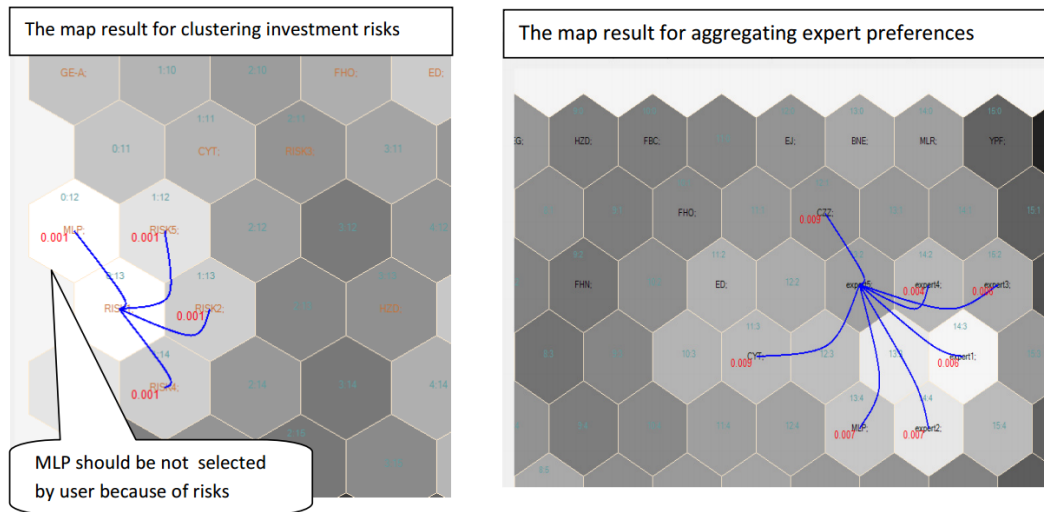


Figure E.17: Results on risk map and clustering expert preference map that the output of its experiment in individuals based on his/her decisions.

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# List of Publications

## Journal Papers

- [1] Hai V. Pham, Khang D. Tran and Kamei K., Applications using Hybrid Intelligent Decision Support Systems for Selection of Alternatives Under Uncertainty and Risk, *International Journal of Innovative Computing, Information and Control* (Paper in Press, Published in 2014).
- [2] Hai V. Pham, Thang C., Cooper E. W. and Kamei K., Hybrid Kansei-SOM Model using Risk Management and Company Assessment for Stock Trading, *Information Sciences*, Elsevier, Vol. 256, pp. 8-24, January 2014.
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## International Conferences

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