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ABSTRACT

While there are a number of finance methods (fundamental analysis, technical analysis, contrarians' theory, risks management, etc) used in stock markets to help make investment decisions, they have different strengths and weakness. It is observed that these different finance methods are not being integrated by existing technologies in a systematic way, thus their performance for identifying investment opportunities is limited. In this research, I propose a systematic method (i.e. an IDSS system) to take advantage of and to optimize existing and newly proposed methods in order to obtain better investment performance, through identification and classification of Positive, Neutral and Negative investment opportunity ranges and related risks. This IDSS system will be mainly based on *Turning Point Model* and Optimized AutoSplit method, which help find hidden investment opportunities and risk variables, particularly a stock's unique trend. The key methodology is to use Decision Tree theory with finance knowledge. The IDSS system will be built on the top of *F-trade platform* which has been already developed by UTS Data Mining team and has a RDP structure, with agent-based distributed expert systems. Initial system evaluation shows that the system successfully identified investment opportunity ranges, outperforming the benchmark index and other systems.

Keywords: DSS, E-commerce, stock markets, RDP, turning point model, AutoSplit

1 BACKGROUND

While stock market is studied to be predictable, it has a number of finance methods with different strengths and weakness to identify investment opportunities. It is necessary to integrate them in a systematic way to take advantage of their strengths, but literature shows that few IT systems have accomplished it. Therefore, I design an Investment Decision Support System (IDSS) to integrate their strength in order to identify investment opportunities and risk factors.

Stock Investment Opportunity Identifiability: Research on the microstructure of security markets has concluded that the intersection of supply and demand curves for stocks determines stock price and accordingly liquidity [1]. For many years, stock investment opportunity identifiability has been studied by both academics and practitioners. It was observed that two competing explanations have been offered for it. Proponents of EMH (e.g. [2]) maintain that such identifiability results from time-varying equilibrium expected returns generated by rational pricing in an efficient market that compensates for the level of risk undertaken. Critics of EMH (e.g. [3]) argue that the identifiability of investment opportunities reflects the psychological factors, social movements, noise trading, and fashions or "fads" of irrational investors in a speculative market.

Necessity of Integrating Distinct Finance Methods: While there are so many finance methods (such as fundamental analysis, technical analysis, contrarians' theory, etc) in capital markets to help identify investment opportunities, they have different characteristics and accordingly, strengths, weakness ([4], [5], [6], etc). For example, fundamental analysis focuses on stock's real value and its long term benefit, while technical analysis focuses on stock's price and volume changes and tries to achieve short-term profit. It is observed that these different methods are not integrated in a systematic way thus their performance for sound decision making are limited [7]. However, there is an increasing need of integration of different methods in stock markets, and it is becoming more and more common for practitioners to use different methods simultaneously to get an optimized result [8].

Current Information Technologies for Identifying Stock Investment Opportunities*:* There are a number of expert systems, knowledge engineering and other technologies to accomplish identification of stock investment opportunities. Many employ technical analysis momentum heuristics, and some use neural networks to learn patterns. Example include: neural networks learning form past price history [9]; neural network using knowledge of real world events [10]; fuzzy expert system combining several sources of information [11] rough sets to extract trading rules from price history [12]; data mining employing signal processing techniques [13]; grey theory and fuzzification [14]; and rules [15] or agents [16] using technical heuristics combined with other sorts of knowledge in an expert system framework. However, these information technologies mainly focus on technical analysis and few considered integrating different finance methods in a systematic way to achieve an optimized performance than any single method does; more importantly, they often ignore or misunderstand importance of expert's domain knowledge and its distribution, therefore, their performance for sound investment decision is limited and they can not well meet the need of identifying investment opportunities for finance industry (i.e. brokerage firms).

Therefore, in this paper, I focus on designing an Investment Decision Support System (IDSS) for integrating both above-mentioned existing methods and proposed new methods in both finance and IT to help identify investment opportunities and risk factors, which can create a better performance than the benchmark index and other systems. In section 2, I will provide a detailed description of Investment Decision System (IDSS) and related methodologies, including *Turning Point Model* and *Optimized AutoSplit Method,* and how to use them to identify investment opportunities and risk. In section 3, I will introduce IDSS implementation and its evaluation. Section 4 is conclusion.

2 INVESTMENT DECISION SUPPORT SYSTEM (IDSS) AND RELATED METHODOLOGIES

2.1 As the kernel of IDSS, *a simplified architecture* was depicted in Figure 1.

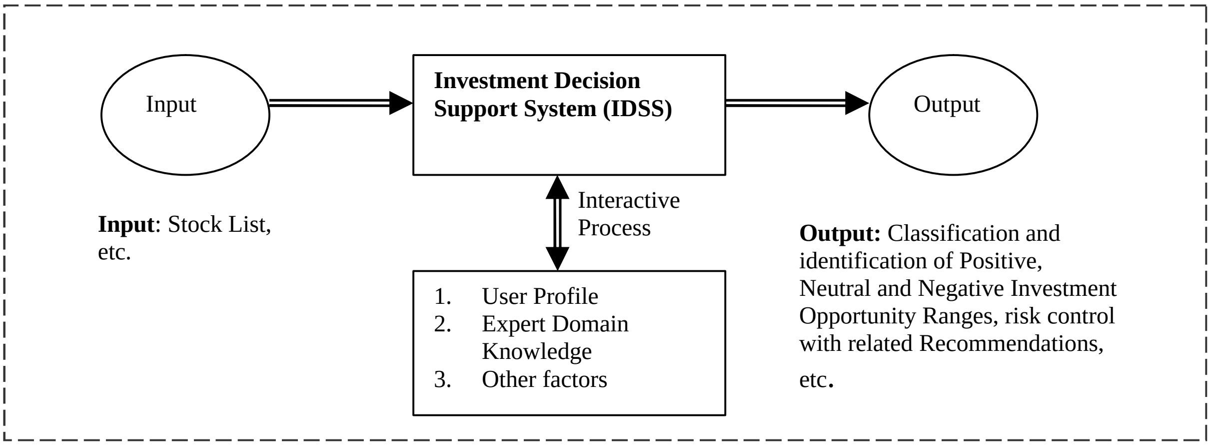

Figure 1: a simplified architecture of IDSS system

2.2 Turning Point Model

As shown in Figure 1, in order to build architecture of IDSS system, it is important to clarify three concepts: *Positive, Neutral and Negative Investment Opportunity Ranges*. This Section provided a brief Introduction of *Turning Point Model* and the three concepts. A basic structure of "*Turning Point Model*" was depicted in Figure 2.

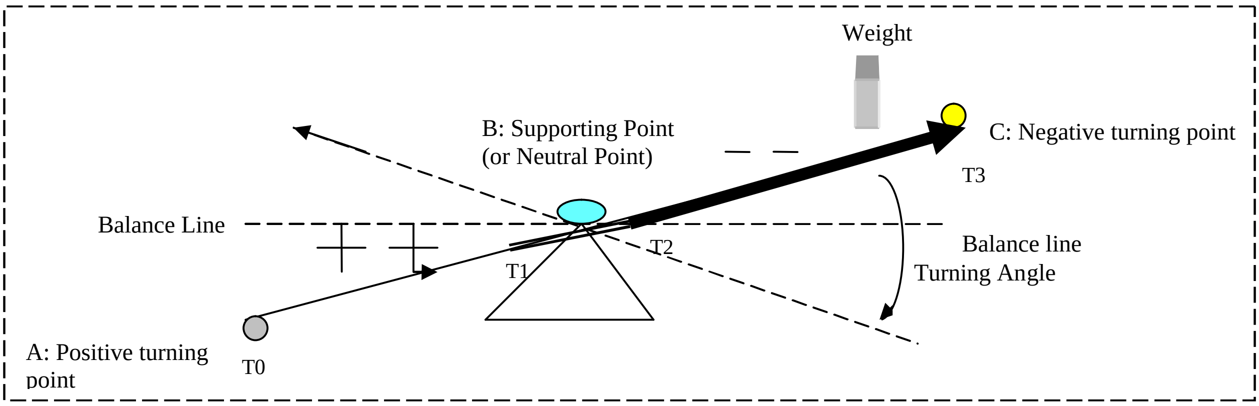

Figure 2: a basic structure of *Turning Point Model*.

From Figure 2, following methods can be derived to help identify investment opportunities and risks:

1) **Supporting Point (or Neutral Point):** This is the fuzzy point of indicating stocks' real value, where the market is rational and its effect is neutral (neither positive nor negative). Note that *Supporting Point* could move within a range when fundamental factors affect stock's real value, represented by Neutral Range **( ).**
2) **Positive Turning Point:** This is the fuzzy point where market undervalues stocks to such an extreme extent that most investors run away and the rest are waiting on sell side of order book, but it starts turning positive because of contrarians' entry and others' subsequent following. The signals include: large (percentage) investors or/and previous large profit-makers start buying, combining with other related signals, such as their

historic behavior and trading patterns in similar situations, fundamental info (such as lowest P/E), how close they are to important fundamental info source, the confidence extent in which they can be followed, and medias' apparent exacerbation of stock's bad side.

3) **Accelerating Speed (++)**: Moving from Positive Turning Point, some leading investors notice contrarians' entry signal and start buying, then more and more investors follows. This trend moves on until it passes supporting point. *Accelerating speed* indicates the change extent of market movement and growth, which becomes faster and faster.
4) **Negative Turning Point:** when above trend moves beyond supporting point, most new investors are becoming over-optimistic about it and rush in. The lever becomes so unbalanced that a *negative turning point* comes. This is the fuzzy point where the stock value is extremely overvalued and most investors already rush in out of mood.
5) **Decreasing Speed (--)**: it indicates that the extent of change of market movement and growth when it is close to *negative turning point*, becomes slower and slower. The speed even decreases to become negative since most possible investors are already in, and investment temperature starts turning cooler from its hottest moment. Therefore, market *Decreasing Speed* and cooing signals need be observed for investment, i.e., large (percentage) investors and/or previous large profit-makers procedurally leave the market and small investors now dominate a high percentage but their growth speed is decreasing even to be negative, and demand decreasing speed and supply increasing speed become equal which make no "momentum" any more.
6) **Relevant Balance:** it indicates the extent of out-of-balance of a point to balance line, and the model assumes that lever will finally bounce back to balance line.
7) **Turning Angle:** when lever is out of balance, it moves up and down and extent is *turning angle*.
8) **Weight ( ):** it indicates the weight of changes of a particular point, including multiplier of changes of volume, price, depth, individual (large) investors' market affectability etc.
9) **Weight Distance Multiplier:** it is a point' distance to *Supporting Point* multiplied by *weight.*
10) **Risk Factors Coefficiency:** the risk extent of a particular point can be identified based on its distance to *positive turning point, negative turning point and supporting point*, multiplied by weight, turning angle, speed, and other factors.

Figure 3 simplified Figure 2 and depicted how to use *Turning Point Model* in IDSS system.

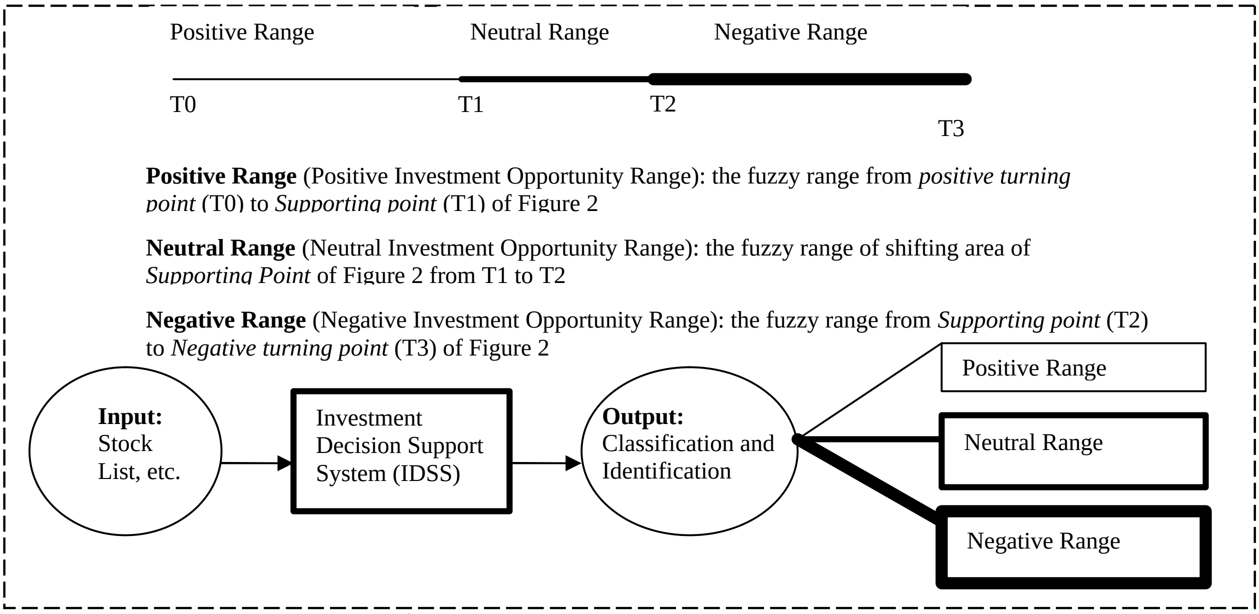

Figure 3: a simplified *Turning Point Model* and its usage in IDSS system

Benefits of using *Turning Point Model* and three concepts in IDSS system include:

- It avoids identifying an exact trading point which is difficult and unnecessary in real stock trading practice and it ignores frequent fluctuations in a short time; instead, IDSS system can use *Turning Point Model* to identify accurate different types of investment opportunity ranges for a mid-term time, which is much easier and suitable for stock trading practice and can create higher profit.
- The model integrates concepts and strengths of Fundamental Analysis, Technical Analysis, Contrarians' theory, etc. Based on it, IDSS can create better output than any single method does.
- The model also proposes new concepts and methods which can help better identify investment opportunities and related risks than most conventional methods do.

2.3 Optimized AutoSplit Methods

In order for IDSS to efficiently identify Positive, Neutral and Negative Investment ranges, I use *Optimized Autosplit Methods* to help identify these hidden investment features and risk variables. Pan et al [17] proposed AutoSplit Method and claimed that it is able to find features which are mutually independent and able to discover non-orthogonal features. However, it is mainly designed for image processing and not suitable for capital markets, thus it has much room for improvement. I proposed optimized AutoSplit methods to help better find investment opportunities and risk factors:

1) Setting Precondition of AutoSplit: AutoSplit method assumes that stock data distribution is not Gaussian (normal) and used a company as an attribute, without any proof. To improve it, I judge if stock data distribution is Gaussian as first step. If it is Gaussian, SVD is more suitable; if not, AutoSplit method is suitable. I use following methods to judge it:
   - Using *Kolmogorov-Smirnov test to test Gaussian distribution*. I used GraphPad InStat software**,** when "P<0.10" (small P values), the population is unlikely to be Gaussian.
   - Using *Shapiro-Wilk normality test or Dgostino-Pearson omnibus test*.
2) Integrating Multi-dimensional methods: in the experiment, AutoSplit only considers price thus data set is one dimensional. While in practice more types of data (i.e. company, price, volume, depth, spread or fundamental factors (P/E, Asset/liability), etc) need to be considered for prediction, the data set should be multi-dimensional. To improve it, I
   - add multiple loops into algorithm to handle multi-dimensions, and
   - Include (price, volume, any other data type) as a data cube.
2) Integrating with streaming methods: AutoSplit method does not consider change among time windows thus it is not quite useful for predicting trend. To improve it, I integrate following window models with it:
   - *Landmark windows*: Aggregates are computed based on the values between a specific time point called the landmark and the present. Similarly, data stream can be divided into a "baseline window" and a "sliding window" and compare two data sets.
   - *Sliding windows*: Aggregates are computed based on the last w values in the data stream. The size of a sliding window w is predefined.
   - *Damped window*. The weights of data decrease exponentially into the past.
3) Reverse AutoSplit: While time is treated as major attributes and controls the order of data in AutoSplit method, reversely I treat time as a common attribute and use other attribute (such as price) to control the order and compare the results to see new patterns (say, what time patterns shows at a particular price range).
4) Improving the experiments: Experiments can be improved in following ways:
   - While it claims h1 and h2 represents the general trend and internet bubble of share price series, it can be proved by including DJIA index and Nastaq index (or IT industry particular index) as an attribute. If the claim is right, DJIA and Nastaq index should have highest
   - To get richer or more interesting experiment results by doing following tasks:
     a. Using intraday trading data as data source rather than weekly closing price;
     b. Using real-time data as data set;
     c. Conducting "auto-split" first within an industry, then across industries;
     d. Findings of hidden variables should relate to domain knowledge;
5) Improving analysis of experiment results: Current AutoSplit focuses on major variables and ignore less significant ones, but less significant variables can have important impact on stock market and investment. I improve analysis of experimental results in following ways:
   - To see if less significant hidden variables disclose more important information;
   - To detect bursts of activities or abrupt changes in real time;
   - To mine outlier or unusual patterns in stream data;
   - To make the number of hidden variables more accurate: AutoSplit assumes that the number of hidden variables is the same as the number of attributes and it also use the *Whitening* step to control the number, thus it may ignore or mix important variables. Therefore, I assess the assumption first to make the number of hidden variables accurate.

Initial experimental results show that above methods are of research value and can play an important role in the success of IDSS, for instance:

- They efficiently identify a stock's unique trends which only belong to the stock itself.
- They more efficiently help find hidden important investment opportunity variables and risk factors for sound investment decisions than conventional methods do.

2.4 a Sample of Investment Decision Support System (IDSS)

Based on the architecture of IDSS system (Figure 1), concepts of *Positive, Neutral and Negative Investment Opportunity Ranges* (Figure 2 and Figure 3) and *Optimized AutoSplit Model*, a sample of *Investment Decision Support System* (of identifying Positive Point and Range) was roughly depicted in Figure 4. Note that this sample shows Decision Tree methodology broadly, but in details and implementation, IDSS uses fuzzy rules rather than Boolean rules.

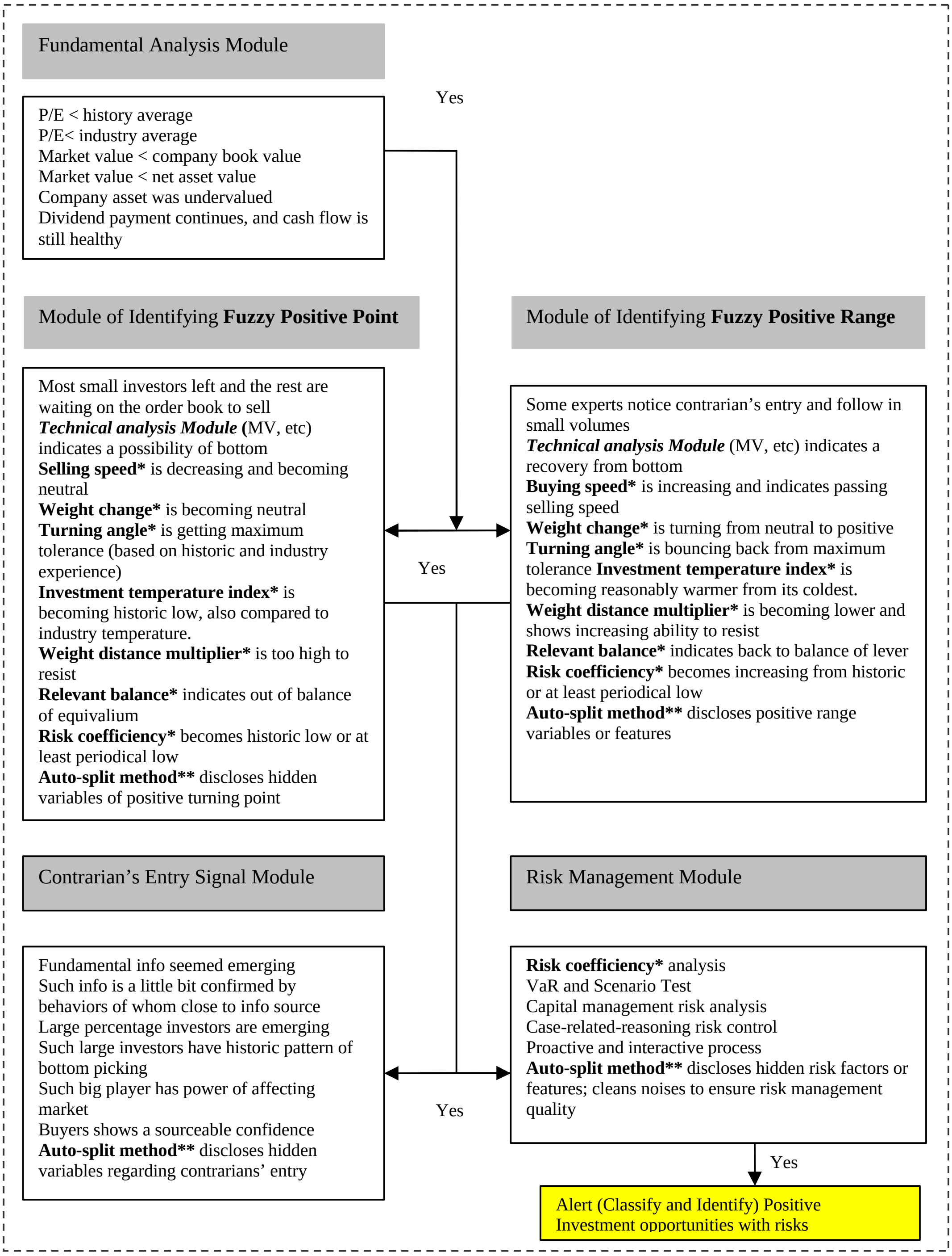

Figure 4: a sample *Investment Decision Support System* for identifying fuzzy ***Positive*** *Investment Opportunity Ranges* with Risk Control. * parts come from *Turning Point* model; ** parts come from *AutoSplit* method.

As shown in Figure 4, IDSS system is constituted by six modules, including Fundamental analysis module, Technical Analysis module, Identifying Fuzzy (Positive or Negative) Turning Point module, Identifying fuzzy (Positive or Negative) Investment Range module, Contrarian's Entry Signal module and Risk Control module. All these six modules are totally implemented on existing Capital Market Cooperative Research Center (CMCRC) project *F-trade platform*, thus they will greatly benefit from strengths of *F-trade platform*. On the other hand, IDSS system extends the functions of *F-trade platform* and makes it more powerful. Their relationship was depicted in Figure 5.

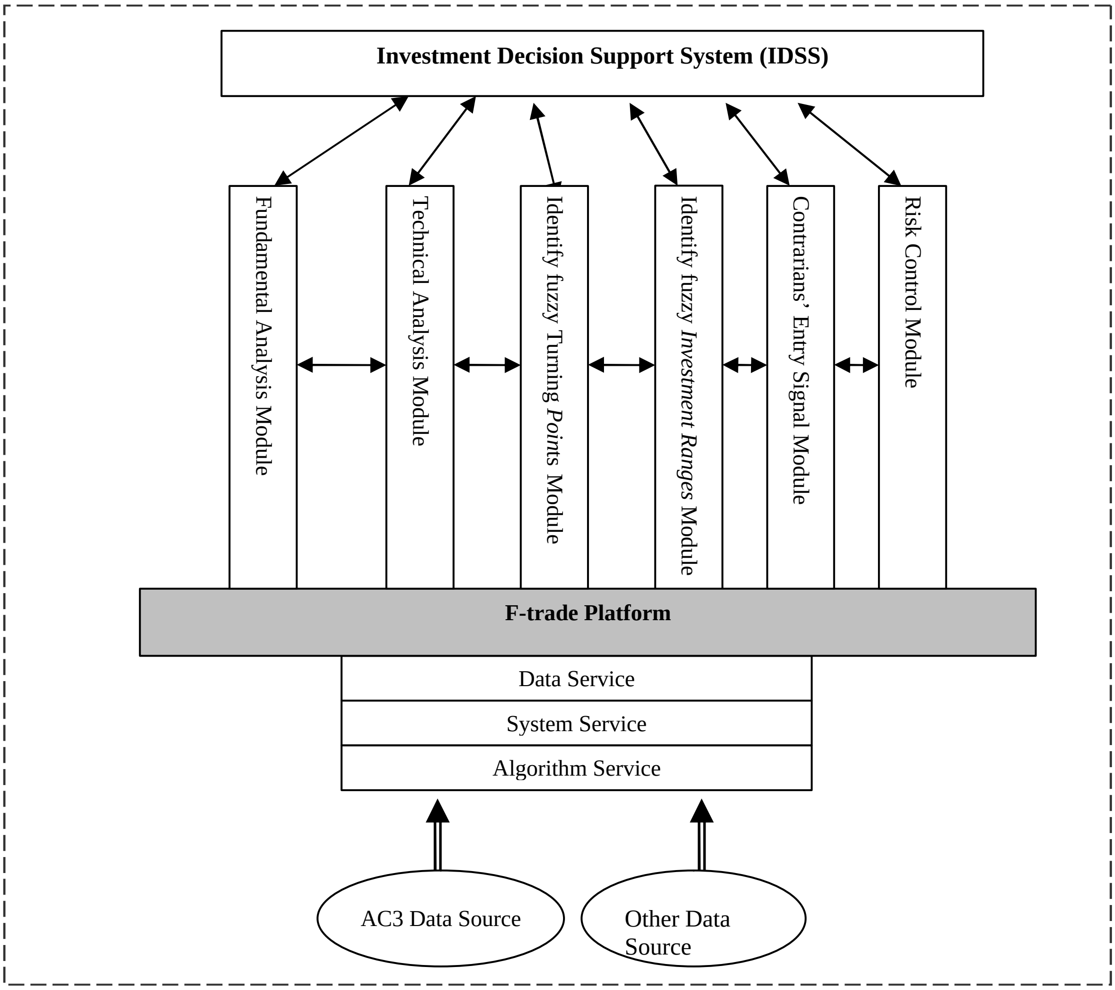

Figure 5: Relationship of IDSS System Modules and CRC project *F-trade platform*

Functionalities of six modules under IDSS system are described in this section:

- *Fundamental analysis module*: This module analyses fundamental factors which determines and affect a stock's real value. As show in Figure 4 & 5, the module may consider financial ratios such as P/E, financial figures such as book value, net asset value, cash flow, dividends payment and so on. It is mainly used to assess if the stock is undervalued or overvalued and the extent.
- *Technical analysis module:* This module uses existing technical analysis methods and algorithms such as Moving Average to evaluate the condition and trend of stock movement.
- *Identifying Fuzzy Turning Point module:* In this module, concepts and methods of *Turning Point Model* will be used to help assess if the stock is at fuzzy Positive Turning Point (in figure 4) or Negative Turning Point. It uses methods of Selling speed, Weight change, Turning angle, Investment temperature index, Weight distance multiplier, etc. Additionally, I adopt *Optimized Auto-split method* to help identify hidden variables and features of fuzzy Turning Point.
- *Identifying Fuzzy Investment Range module:* This module adopts same methods used by above module, but they are used to assess if stock is in fuzzy range, rather than turning points.
- *Contrarians' Entry Signal module:* Contrarians have the power of affecting market thus their entry means a turnaround of market. Not only quantitative methods (i.e. transaction details on orderbook, hidden variables of *Auto-split method*), but experts' experience and judgments work.
- *Risk Control module:* As risk and return are closed related, risk control is closely related to above modules. Not only traditional risk control methods (including VaR, Stress test, capital management, etc), but new methods from *Turning Point model* and *Auto-split method* work.

While IDSS system (top module) depends on above six modules, it has much more important roles. For example, IDSS will decide which of above six modules and other knowledge source will be used, how to use, and how to integrate and optimize the results from individual module to get an ideal output (i.e., classification and identification of *Positive, Neutral and Negative Ranges*). In follow section, I use a RDP model to depict a detailed system structure of IDSS.

Figure 6 used a RDP (Requestor-Dispatcher-Provider) model to depict the structure of IDSS. Simply speaking, once *Requestor* sends users' request to *Dispatcher*, *Dispatcher* will choose appropriate *Provider*, and then *Provider* will look into model base, knowledge base, data base and expert domains to find appropriate solution. On a reverse way, the solution will be passed to users. It includes:

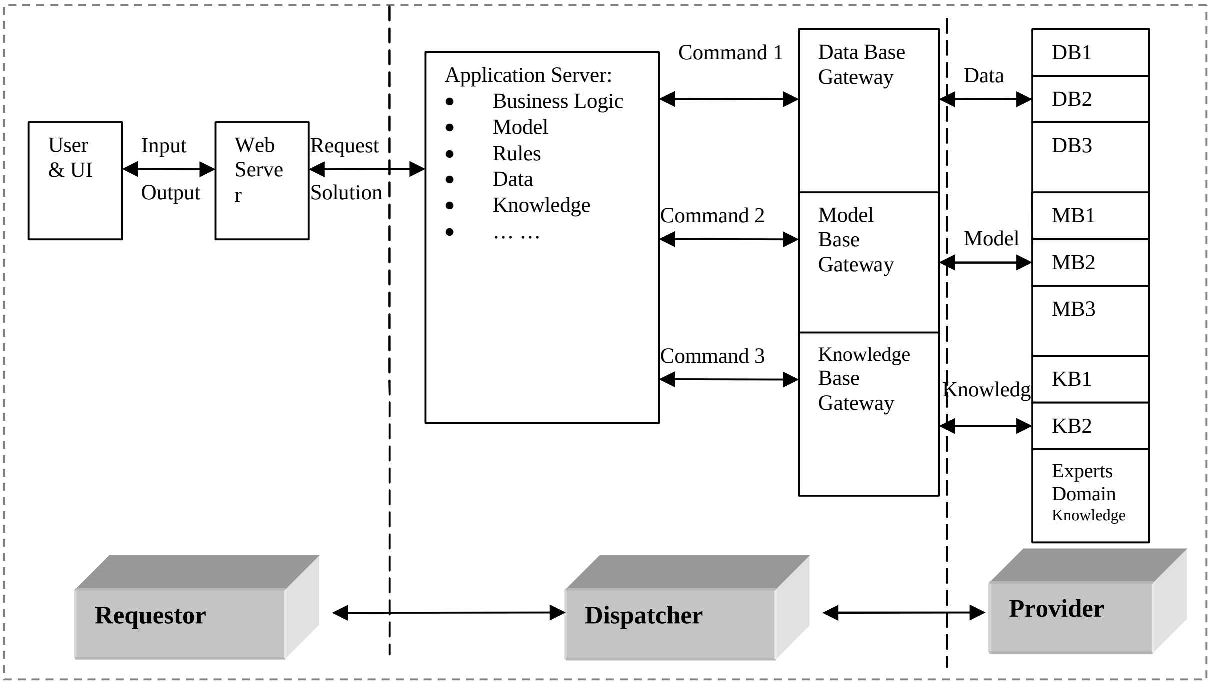

Figure 6: a System Structure of IDSS by Using RDP Model

(1) ***Investment Requestor:*** It contains user interface and web server and covers all aspects of the communications (i.e., input and output, problems and solutions) between a user (i.e., brokers, individual investors) and the IDSS; as a result, it derives much of the power, flexibility, and ease of use of IDSS. For example, it could send users' request of classifying a particular stock (i.e. BHP) at a particular time point (i.e. right now) to following Dispatcher Subsystem. It includes: 1) menu or form interface to issue requests to the DSS; 2) customized visual (or graphical) forms to collect, revise customer/stock/company data. Additionally, the messages (of solution) emitted by the IDSS may consist of graphical presentation of some decisions; textual responses; displays of results via customized visual forms. For example, a classification with parameters (like certainty, weight, coefficients, etc) is depicted with the help of a 3-D graph or chart.

(2) ***Investment Dispatcher:*** Once receiving particular user requests, *investment dispatcher* will process them immediately. It may contain application server and gateways of database, model base and knowledge base. Note that this processing very well requires the *Investment Dispatcher* to draw on *Investment Provider* contents. The processing also changes the knowledge held in the *Investment Provider*. In either event, the *Investment Dispatcher* will issue a response to the user. Basically, the *Investment Dispatcher* has following abilities:

- Knowledge acquisition: for example, an *Investment Dispatcher* acquires knowledge about what a user wants the IDSS to do (i.e. request) or what is happening in the surrounding world (i.e. fundamental information, technical factors, risk information and market reaction, expert's opinion, etc). The *Investment Dispatcher* may draw on *Investment Provider* contents when using its acquisition ability. For example, its interpretation of a request (i.e., classification of positive, neutral or negative ranges of BHP at current time) may be based on previously acquired linguistic knowledge (i.e., *Turning Point or Ranges Models*). On the other hand, Knowledge acquisition ability can cause a change in the *Investment Provider*. For example, new knowledge obtained (i.e., company info, stock info, market info, etc) may be added in, edit or replace existing ones.
- Knowledge selection/derivation: *The Investment Dispatcher* is able to selectively recall or derives knowledge in following *Investment Provider* that forms a solution. For example, to classify BHP at current time, the *Investment dispatcher* may recall or derive knowledge from Experts' domain knowledge (i.e., experience of trading BHP stock), Fundamental knowledge (i.e., BHP company info), technical knowledge (i.e., Stock price and volume history), market reactions (i.e.,

contrarians' entry, market constituent) and so on. Additionally, it gives the ability to create, combine, revise, and delete models, knowledge and datasets in an *Investment Provider*. For example, some false or invalid market info (i.e., proven rumors) is identified useless and could be deleted from *Investment Provider*.

(3) Investment Provider: In response to *investment dispatcher's* command, the *Investment Provider* provides requested knowledge from model base, knowledge base, data base and expert domains (with fuzzy logic), which together will form a solution. It includes following components:

- Model Bases: It contains models and building blocks used to develop applications to run IDSS system. It may contain standard models (e.g. financial models like *DCF* or Risk models like *VaR*) and customized models (i.e. *Turning Point and Ranges Models*). Such models identify relationships among some collection of variables and numbers (i.e., constants). They may relate variables and constants within a series of numberic expressions involved in equations or inequalities, within a graph of nodes and arcs (e.g., a decision tree used in Figure 5 and 6), or via an arrangement of numbers in a data set. In effect, these are alternative ways to characterize a problem which a dispatcher uses to manufacture a solution. For example, using a VaR model to assess risks; using ROI, IRR, NPV, or a Discounted Cash-flow model to assess company value. All these models can be organized into what is called a model case. Note that problems that can be analyzed by the same dispatcher form a model class.
- Knowledge Bases: Knowledge may include descriptive, procedural and reasoning knowledge. For example, *Investment Provider* may contain knowledge about how long to retain historical data about a particular stock, or which inactive stock or invalid information should be discarded from the knowledge base. Additionally, descriptive knowledge will reside in the form of a particular company's data. A quantity of important knowledge comes from six modules discussed above. It may include (fuzzy) "IF-THEN" rules, for instance:

  Rule 1:

  IF: current P/E / history average of P/E < 0.8 AND

  Current P/E / industry average < 0.7 AND

  Market value / company book value <0.8 AND

  Market value / net asset value < 0.7 AND

  Company asset (land, plant, goodwill, etc) was undervalued by 30% AND

  Dividend payment is consistent in last 5 year AND

  Dividend payment is increasing by 10% each year AND

  Cash flow is positive and healthy in last 3 years and future 1 year

  THEN: Fundamental side of the stock is "GOOD" CF=80 (CF: Certainty Factor)
- Data Bases: Data could flow from several sources, i.e. Australian Centre for Advanced Computing & Communications (ac3) and other sources (i.e., announcements from ASX) and the databases formed contain variety of data forms and types. Their gateway provides necessary functions of data access, extraction, capture, integration and management. Particularly, it may be employed to accurately track and selectively recall descriptive knowledge in a relational database about a particular stock/company/market situation that satisfies a particular request or need.
- Expert Domain Knowledge with Fuzzy Logic: *Investment Provider* is also composed of expert (or other intelligent) domain knowledge and it provides the necessary execution and integration of the expert subsystems. It realizes that domain knowledge (or Investment sense) of experts (such as brokers, fund managers or large investors) could play an important role in IDSS execution process and make a real difference to sound investment decisions. For instance, the expert subsystem draws on descriptive and reasoning knowledge to infer advice in response to a user's request for a recommendation. The advice is comparable to that of a human expert. The expert knowledge acquisition process involves obtaining, structuring, and formalizing the knowledge of experts. Additionally, experts' domain knowledge and users' profiles could interactively affect IDSS (see Figure 1). For example, based on a broker's knowledge and experience (or investment sense), he could observe a unique Contrarians' Entry Signal and assess its importance. Then he can interact with IDSS system to manipulate above-discussed six modules to create a better result. On the other hand, results of individual modules could strengthen experts' knowledge base and then improve their interaction. Additionally, results of individual modules can become the basis for experts to decide which module to use or how to integrate them using particular optimization methods.

  Note that often a human expert (i.e. a broker) is confronted with the task of making some sense out of a fuzzy situation, since one or more of the factors involved in the reasoning process is unclear or out of focus, in the sense that it has simultaneously several plausible appearances. For instance, an investment expert who reasons about the macroeconomic outlook (or company/stock outlook) might simultaneously think that the outlook is good (60% certain) or fair (40% certain), each with some degree of certainty. The outlooks might be fuzzy. Therefore, fuzzy logic technology is useful in such fuzzy situation. Fuzzy variable and its own certainty factors become an important part of expert knowledge base.

IDSS may involve cooperation of a few of sub-expert systems which distribute in different sites (i.e. brokerage firms), thus it is necessary to organize them to integrate their intelligence and to achieve a better solution. For instance, stock broker A at *Sydney* can provide particular company info (i.e. BHP), stock broker B at *Melbourne* can provide a macroeconomic knowledge (i.e. energy), stock broker C at *Brisbane* can expertise in BHP stock traders' behaviors, and stock broker D at Caines can observe contrarian's activities. In order for an investor E at *Perth* to make a sound investment decision for BHP stock, it is necessary to integrate intelligence at five different sites. Therefore, I propose an agent-based distributed expert system which supports the sharing, managing, searching and presentation of distributed experts' knowledge. Note that such agent-based distributed expert systems have four kinds of cooperation which are *horizontal* cooperation, *tree* cooperation, *recursive* cooperation, and *hybrid* cooperation [18]. An intelligent agent is an object with its own knowledge and information base. Each intelligent agent acts in parallel with other intelligent agents and cooperates with a selected set of other agents to achieve a common set of goals. Intelligent agents must be able to recognize events, determine the meaning of those events and then take actions on behalf of a user. Figure 7 depicts sample *horizontal* agent-based distributed expert systems, which may integrates usage of Matchmaker and Broker structure in different situations. For instance, if expert systems at Sydney, Melbourne and Perth involve a large volume of communication and communication speed is slow (type1), it is better to use Matchmaker structure, as once match was made, expert systems at Perth can communicate with ones at Sydney and Melbourne directly thus no need of matchmaker's involvement again. On the contrary, in case of expert systems at Brisbane, Caines and Perth, communication is quite fast and volume is small (Type 2), Broker structure is more suitable, as involvement of broker will not slow communication but will increase accuracy. Figure 8 depicts two types of distribution. In type 1, agent 2 of ES Melbourne & agent 3 of ES Sydney advertise their intelligence x (BHP company info) and y (energy sector's macroeconomic info) to Matchmaker (process1a & 1b). Agent 1 of ES Perth needs intelligence of both x and y to make an investment decision, thus it asks matchmaker and the matchmaker answers with agent 2 and agent 3 (process 2 & 3). Once agent 1 of Perth receives the answer, it contacts agent 2 of ES Sydney and agent 3 of ES Melbourne directly and get corresponding intelligence x and y (process 4 & 5). In type 2, agent 1 of ES Perth can not contact agent 4 of Brisbane ES and agent 5 of Caines directly, on the contrary, it need to send request of p (BHP traders' behavior) and q (contrarian's observation) first to broker (process 6), then broker will get answers from agent 4 and 5 (process 7), then broker sends answers to agent 1 (process 8). Note in large distributed expert systems, both Matchmaker and Broker may be adopted, according to distribution difference and characteristics of expert systems.

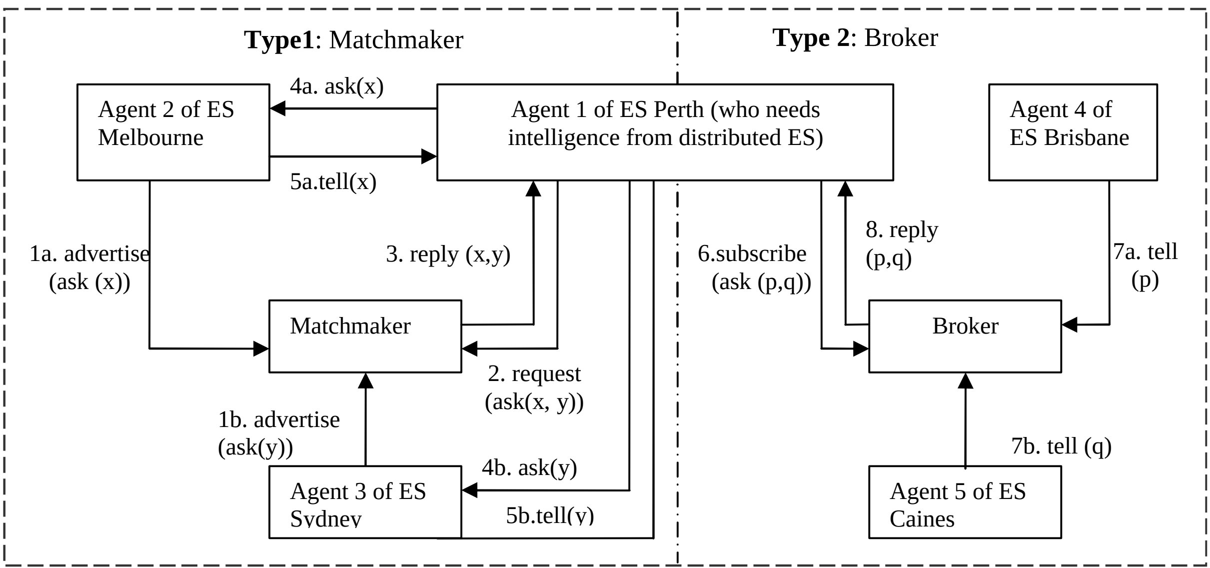

Figure 7: sample agent-based distributed expert systems

3. IDSS SYSTEM IMPLEMENTATION AND EVALUATION

Proposed IDSS is a KB-DSS in essence, thus building it involves the capabilities, functionality and structures of both DSS and ES with the emphasis on the support of DSS. I adopted a KB-DSS methodology proposed by Klein and Methlie [19]. Additionally, Evolutionary Prototyping proposed by Turbon and Aronson [20] was used as an aid. The initial prototype was implemented by mainly using Jess and Java. An industry partner, Tricom (www.tricom.com.au), contributed expert domain knowledge and involved in IDSS implementation.

Based on initial prototype, I got following initial evaluation results:

1) Real transaction results. For instance, IDSS system picks up 10 stocks at an experiment and return is over 20%, which is higher than benchmark (i.e. ASX index) and most fund performance.
2) Experts' feedback. Experts (such as brokers, fund managers or large investors) are users and interact with the system. An industry partner TRICOM (broker) gave positive feedbacks (like ease of use, usefulness or other features) in both experiment and real trading practice.
3) Compared to other stock trading support systems, IDSS shows better performance in experiments, including effectiveness, ease of use, powerfulness of system functions, efficiency, etc.

While further implementation is in progress and more evaluation will be done, I expect a more efficient IDSS to be finalized and more solid experimental results to be obtained by December 2004.

4. CONCLUSIONS

I propose an Investment Decision Support System (IDSS) in order to get better mid-term investment results than conventional methods, through identification and classification of Positive, Neutral and Negative investment opportunity ranges and related risks. This IDSS system takes advantage of and optimizes existing methods and newly proposed methods - *Turning Point Model* (in finance) and *Optimized AutoSplit method* (in IT), which can help better identify investment opportunities and risks features. Initial system evaluation shows that the IDSS system (with proposed methods) can successfully identify and classify investment opportunity ranges and other hidden variables, outperforming the benchmark index and other systems.

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