NON-DETERMINISTIC APPROACHES FOR STOCK MARKET PREDICTIONS: A CASE STUDY

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Abstract - A stock market prediction is a critical issue for investors and market expert alike. In this paper, we acquire experts' opinions and try to find the best possible scenarios for investors. As it is known that experts' opinions and beliefs are subject to prediction and hence inexact reasoning. Two approaches are used to determine a consensus among experts. The first approach is via the use of the theory of belief (Dempester's Rule of Combination), and the second approach is via the use of the Fuzzy Fusion Formula that is able to integrate (fuse) expert's opinions. The outcome of belief combination is favorable guidelines for investors and decision-makers dealing with a fluctuating stock market. The experimental results of both approaches are evaluated and compared.

I. INTRODUCTION

The Science of stock market prediction is inexact and may be uncertain. Therefore, this issue should be treated through no-deterministic approaches. In the literature, several of these approaches are examined such as the Bayes theory, the theory of belief, and the fuzzy logic theory. The performance of these approaches vary according to the given data. Stock market experts rely on several indicators in their analysis of the market. There are two distinct sets of skills commonly known as fundamental and technical analyses. They are essential for any decision-maker in the stock market. Fundamental skills deal with the history of a company stocks. That is, the number of positive and negative signs over an adequate period of time influence the expert's opinion. Technical analysis deals with the frequency of the trends that likely to occur over and over again. This includes the behavior of the company's stocks chart over a period of time. In both types of analyses, two experts were asked to provide their opinions (beliefs) and then we try to get a final consensus for decision-makers and investors. Unlike the Bayesian theory, the theory of belief does not allowa priori knowledge to dominate the outcome of evidence combination. However, the use of theory of belief through the orthogonal sum yield an overestimated belief. In addition, the outcome of the combined belief is sensitive to the numerical values of given inputs [1],[2]. Many approaches exist in the theory of fuzzy sets theory. Despite the flexibility that we observe in the use of fuzzy sets theory, the combination of contradictory beliefs are not often satisfactory.In this article, we present two approaches for belief combination. First, we use the theory of belief (Dempester;s rule of combination) to combine beliefs. In the second approach, the use of a fuzzy fusion formula for the same purpose is presented. The experimental results are evaluated and compared. The evaluation and the comparison are based on robustness and consistency of outcome when different data are used for analysis.

II. THE THEORY OF EVIDENCE

In this method, evidential reasoning is based on the Dempester-Shafer of belief functions, which is considered to be more general than similar techniques found in probability theory [3]. Dempester's rule of combination can combine two or more belief functions that are given from different knowledge sources. The combination of beliefs is based on computing the orthogonal sum of those belief functions. Belief functions are expressed in terms of their basic probability numbers. Let Bel_1 and Bel_2 be the belief functions over a universe of discourse Ω, and denote Bel_1's and Bel_2' s focal elements by $A_1, A_2, \dots, A_k$ and $B_1, B_2, \dots, B_l$, respectively. As a result, the basic probability numbers suggested by Bel_1 and Bel_2 are $m_1(A_1)$, $m_1(A_2)$, …, $m_1(A_k)$ and $m_2(B_1)$, $m_2(B_2)$, …, $m_2(B_l)$,respectively. A geometric representation of both functions can be found in [3]. The orthogonal sum of two belief functions committed to $A_i \cap B_j$ can be determined by computing the probability mass of measure $m_1(A_i)$ and $m_2(B_j)$ committed to $A_i \cap B_j$. The orthogonal sum is computed as

$$m(A) = \frac{\sum_{\substack{i,j \\ A_i \cap B_j = A}} m_1(A_i) m_2(B_j)}{1 - \sum_{\substack{i,j \\ A_i \cap B_i = \emptyset}} m_1(A_i) m_2(B_j)}. \quad (1)$$

Detailed derivation of (1) can be found in [3]. Several belief functions then can be computed iteratively in a pairwise procedure. In other words, the belief function generated by combining two belief functions can be a candidate to be combined with a third belief function. A special Case of Dempester's is called Bernoulli's Rule of Combination. Bernoulli assumes that two belief functions $S_1(A)$ and $S_2(A)$ support an event A in Ω, respectively, where $S_1(A)$ and $S_2(A)$ are the degrees of support to A. Bernoulli's rule of belief

combination yields the combined belief to be greater than any individual support given by a single belief function. Bernoulli proposed the following formula which is a special case of Dempester's rule of combination:

$$S(A) = 1 - (1 - S_1)(1 - S_2) \quad (2)$$

That is, substituting $m_1 = S_1$ and $m_2 = S_2$ into (1), we have $m(A) = \frac{1-m_1(\Omega).m_2(\Omega)}{1-0}$.

Since there is no belief committed to the empty set, then $S(A) = 1 - (1 - S_1)(1 - S_2)$ is as given in (2), where $m_1(A) = S_1$ and $m_2(A) = S_2$.

III. THE FUZZY LOGIC FORMULA

The development of this formula is based on computing the degree of certainty (belief) committed to the same proposition $\Theta \in \Omega$. Let $m_1, m_2, \dots, m_i$ be the belief values supporting a proposition, where $0 \leq m_i \leq 1$, for $i = 1, 2, \dots, n$. Because the belief values are defined within the interval $[0,1]$, the identity of the belief region, e, is equal to 0.5. If $m_i = e, m_i$ is considered maximally fuzzy and has zero degree of certainty. Then, m_i is said to be more certain than m_j if and only if for $i \neq j$ and $i, j = 1, 2, \dots, n$,

$$|m_i| > |m_j| \quad (3)$$

The combined deviation of $m_1, m_2, \dots, m_i$ from the maximally fuzzy value can be computed by the use of the average Minkowski Distance as follows:

$$D = [\frac{1}{n}\sum_{i=1}^{n}(m_i - e)^{\alpha}]^{\frac{1}{\alpha}}, \quad (4)$$

where α is odd integer number; that is, $\alpha = 1, 3, 5, \dots, \infty$, which is a normalization factor that is able to preserve the degree of belief associated with each m_i. From (4), the combined belief can be computed as the sum of the combined deviation from the identity and the maximally fuzzy point; that is,

$$m = e + [\frac{1}{n}\sum_{i=1}^{n}(m_i - e)^{\alpha}]^{\frac{1}{\alpha}}, \quad (5)$$

where the parameter α determines the weight of each belief. Now, we can see that if

A. $\alpha = 1$: The combined belief is simply the arithmetic mean of all given beliefs.
B. $\alpha = 3$: The fuzzy assessment that has higher degree of certainty will have higher influence on the outcome of the combined belief.
C. $\alpha \to \infty$: The combined belief is given by a hard combination operator $\lim_{\alpha\to\infty} m(m_1, m_2, \dots, m_n) = \max(m_1, m_2, \dots, m_n)$. A complete mathematical derivation can be found in [4].

Therefore, if $\alpha = 1$, the formula is very soft and indicates a perfect compromise among all given beliefs. On the other hand, if $\alpha \to \infty$, the operator is very hard, because it selects the highest degree of certainty regardless of other assessments.

IV. AN OPINION MODEL FOR STOCK MARCKET PREDICTIONS

Stock market dynamics are influenced by several factors. One of the most important factor is that experts and investors rely on hypotheses that relate a range of past information to model their opinions. In other words, the goal is to determine the future of assets for a possible investment. Two experts, A and B, were interviewed by a decision maker C. The interviews were separate and the experts are not influenced by each other.It is logical that experts rely on the history of the stocks over a reasonable period of time. That is, they consider the numbers of positive and negative signs over a long period of time. In addition, they look into other factors that may influence their judgment.

A. Modeling the expert opinion through a dialogue between C and A.

C is speaking to A: I learnt that you have several years of experience in the analysis of the stock market.

A: Yes, it is true. I have many clients who continuously seek my advice.

C: what is the highest support you give me to invest in a company?

A: According to the company's portfolio, if the company has good reputation over years of performance I strongly support the investment. My support is $1 \in [0,1]$.

C: If the company has a large number of positive signs as compared to a small number of negative signs, would you advise me to invest in it?

A: Definitely, my support to this investment is $0.9 \in [0,1]$.

C: What if the unemployment rate goes up, what is your opinion about investment?

A: Unemployment rate has a little impact on a successful company with good reputation. I still have strong support in its stock. My support is $0.9 \in [0,1]$.

C:Do you think an increase in the inflation rate and a slight increase in unemployment rate change your previous belief?

A: I have to agree that I would have less support than previous opinions. I would say this time my belief is $0.8 \in [0,1]$.

C: If the financial liquidity in a company is mildly contracted, would that change your opinion?

A: Yes, I will be less encouraged to invest in the company. My support in this case would be $0.7 \in [0,1]$.

C: If stocks in a company are hot, how much support would you give to your client?

A: This could be a bubble. I would not encourage my client to invest in it. My support would be $0.4 \in [0,1]$.

C: If the earnings ratio (price to earning) is modest, would you invest in the company?

C: I will be cautious to invest in it. My support will not exceed $0.2 \in [0,1]$.

B. Modeling the expert opinion through a dialogue between C and B.

The decision maker C repeats the same questions to expert B. Table I shows the opinions of the two experts where it is noticed that the experts are in a relative agreement. In addition, the combined support using Dempester's Rule of combination (DR) and the Fuzzy Logic Formula (FLF) are shown in the table.

The decision maker interviews are carried out to two other experts but they were in a relative disagreement as it is noticed in Table II. Their beliefs are combined using the same methods we used in the first table.

Table I: The opinions of two experts regarding 12 companies combined using DR and the FLF (experts are in a relative agreement.)

Companies	Expert A	Expert B	Combined Using DR	Combined using FLF
1	0.1	0.15	0.24	0.12
2	0.15	0.17	0.29	0.16
3	0.25	0.2	0.40	0.22
4	0.4	0.45	0.67	0.42
5	0.45	0.5	0.73	0.47
6	0.5	0.48	0.74	0.49
7	0.6	0.65	0.86	0.63
8	0.68	0.72	0.91	0.70
9	0.7	0.75	0.93	0.73
10	0.8	0.85	0.97	0.83
11	0.9	0.95	1	0.93
12	1	0.95	1	0.98

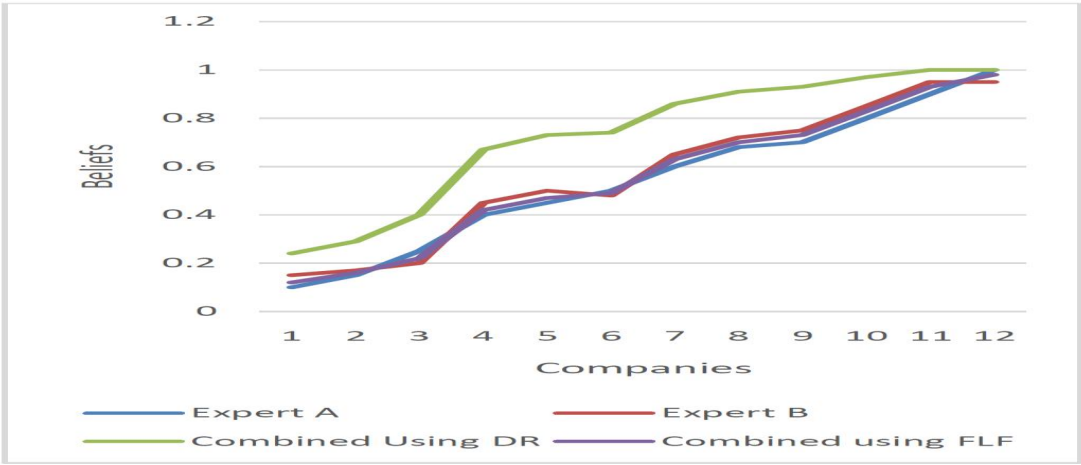

Fig. 1: A graph showing experts' opinions and the combined belief as it is in Table I.

Table II: The opinions of two experts regarding 12 companies combined using DR and the FLF(experts are in a relative disagreement.)

Companies	Expert A	Expert B	Combined Using DR	Combined using FLF
1	0.1	0.3	0.37	0.17
2	0.4	0.2	0.52	0.25
3	0.5	0.2	0.6	0.26
4	0.4	0.45	0.67	0.42
5	0.7	0.5	0.85	0.66
6	0.65	0.4	0.79	0.61
7	0.4	0.6	0.76	0.5
8	0.8	0.6	0.92	0.74
9	0.6	0.75	0.9	0.7
10	0.9	0.7	0.97	0.83
11	0.9	0.65	0.96	0.82
12	1	0.8	1	0.92

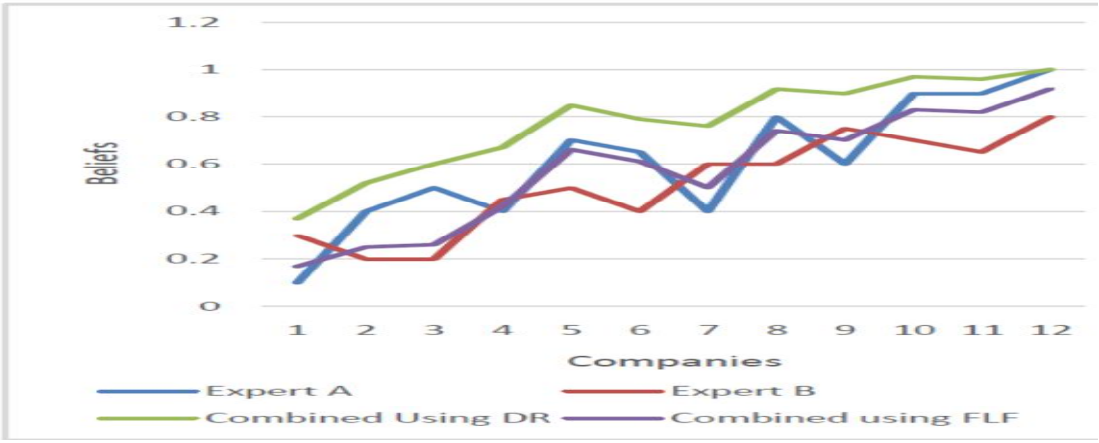

Fig. 2: A graph showing experts' opinions and the combined belief as it is in Table II.

V. DISCUSSIONS

Glancing through Table I and Table II and their corresponding graphs in Fig. 1 and in Fig. 2, we observe thatDRC yields a combined belief that is greater than any given belief. In other words, if we consult several experts, the combined belief goes up in a cumulative fashion. However, the decision maker expects that the combined belief should have a consensus among a panel of experts. Unlike the DRC, the FLF has two main advantages: The first advantage is that it tests a given belief according to the degree of certainty. That means, it gives more weight for a given belief which is away from the maximally fuzzy point. The second advantage is that the FLF takes into consideration all given belief regardless of the degree of certainty. Furthermore, the FLF is robust which means a small change in a given belief will only cause a small change in the combined belief.

There are several methods which are available in the literature that deal with belief combination. Namely, the Linear Opinion Pool, the Independent Opinion Pool, the Harmonic Opinion Pool, the Super Bayesian Approach, and the Possibility Theory. Our approach through the FLF has more logical combination for experts' judgments [4],[5].

SUMMARY AND CONCLUSIONS

In this paper, we have applied two different approaches of belief combination. Stock market prediction were used as a case study for the implementation of the two methods. From the graphs, we see that the DRC yields an overestimated result. It is simply leads to a commutative combination. On the other hand, the FLF yields a true consensus among opinions of experts.

This approach of belief combination can be extended to many other case studies that needs such an inexact reasoning of inexact combination.

REFERENCES

[1] M. A. Abidi and R. C. Gonzalez,"Data Fusion in Robotics and Machine Intelligence," Boston, MA: Academic Press, 1992.

[2] D. Dubios and H. Prade,"Possibility Theory,"New York, NY: Plenum Press, 1988.

[3] G. Shafer,"A Mathematical Theory of Evidence," NJ: Princeton University Press, 1976.

[4] M. Abdulghafour,"Data Fusion through Fuzzy Reasoning Applied to Feature Extraction from Multi-Sensory Images," PhD thesis, The University of Tennessee, Knoxville, TN, 1992.

[5] M. A. Abidi, M. Abdulghafour, and T. Chandra,"Fusion of Visual and Range Features Using Fuzzy Logic," Control Engineering Practice, Vol. 2, No. 5, pp. 833-847, October 1994.

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