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Fuzzy-AHP Application to Country Risk Assessment

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INTRODUCTION

In solving various real-world decision situations, it is necessary to handle uncertainties efficiently and effectively. There may be several reasons for uncertainty in a decision-making situation. Some of the reasons are problem complexity, ill-posed questions, imprecision in computations, ambiguity in data/knowledge representation, problems in input interpretations, and noise (Keller and Tahani 1992). In the past, rule-based expert systems have been used for handling uncertainty in such problems. Generally, the expert systems are based on classical logic and developers need to add special methods for handling uncertainty. Some of the methods used for handling uncertainty in expert systems include heuristic approaches, probability theory, possibility theory, and fuzzy theory.

Fuzzy reasoning and logic offers a more natural way of handling uncertainty. All propositions can be modeled by possibility distributions over appropriate domains. Fuzzy reasoning process is similar to human logical reasoning, and a considerable amount of research work has been performed in this area (Takagi and Hayashi 1991). The author in this paper presents a fuzzy version of analytic hierarchy process (Fuzzy-AHP) to country risk assessment problem. The outline of the paper is as follows. The next section of this paper presents an overview of fuzzy logic and its role in decision-making, which is followed by a brief summary of analytic hierarchy processing (AHP) and fuzzy-AHP. Afterwards, the author presents the country risk analysis problem followed by the application of Fuzzy-AHP to country risk assessment. The paper then outlines the validation process followed by the conclusions.

FUZZY LOGIC AND DECISION MAKING

In general, human mind is not capable of handling a huge mass of numerical information. Instead, its excellence at classification and categorization tasks results from its capability of processing a mixture of symbolic and numeric information (Pedrycz 1991). There are two major tools that are applicable to the design of a classification procedure - traditional artificial intelligence techniques (symbolic computation) and numerical computation. In pattern recognition, symbolic computations generally do not handle any numerical information. When numerical information is available, it is converted to symbolic form. Numerical computation methods that are generally used in science and engineering applications are complementary to artificial intelligence techniques. Although they are efficient and effective, they do not use any interpretation mechanisms for numeric data.

Because of the use of such characteristics as gradual membership, fuzzy sets form links between symbolic and numerical computation. In essence, a fuzzy set represents a collection of objects which is a general symbolic concept. And the grades of membership within the fuzzy set that specify the relationship of objects are numerical in nature. When specifying the degree of membership in a class, there is no requirement that it is to be denoted by a single number. Thus, it offers an ability to describe class membership

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in a linguistic format.

As an example, use of four terms such as high belongingness to the class, moderate belongingness, low belongingness, and no belongingness may be more appropriate in a situation rather than giving one single value. Compared to probability based pattern classification, the fuzzy logic based method does not impose any strict restrictions. In probability based classification, sum of probabilities stating class membership must be equal to one. Fuzzy logic is free of this kind of constraints and, thus, can handle unclear and ambiguous classification situations more easily.

ANALYTIC HIERARCHY PROCESSING (AHP)

One of the commonly used methods for multi attribute decision-making is analytic hierarchy process (AHP), which was developed by Saaty (1980). During last two decades, the analytic hierarchy process has been successfully applied to numerous decision areas. The essence of AHP is in permitting the decision-maker to perform pair-wise comparisons of each of the factors or *criteria* — one-on-one — to derive overall priorities. These pair-wise comparisons may be stated verbally as in "Criterion A is *equally, moderately more, or strongly more important* than criterion B." The adjectives *likely* or *preferable* may be substituted for *important*. These are converted to numerical values (generally in pre-specified range like 1 to 9) in the traditional, non-fuzzy AHP approach.

The AHP method may be used for such decisions as selecting a single course of action from several, for priority setting, and for resource allocation. For the *single decision-event*, AHP's use is based on the following assumptions, that for a significant decision, there are several courses of action (alternatives) available, from which one will be selected based on governing criteria, not all of which will be of equal weight. To use AHP for such an event, the decision-maker first defines the decision to be made. A clear and concise statement of the decision is critical: if not properly done, the process becomes a meaningless exercise.

Once the definition has been clearly established, the next step is to develop the relevant or governing criteria for the decision problem. This could be done in several stages. The first stage is to brainstorm all possible criteria on which to make the decision. If we use the example of selecting a person for a position, some of the criteria would be previous experience, years with the company, people skills, language skills, education, compensation requirements, etc. Often each of the major criteria has sub-criteria, and these must be identified as well. At the second stage a decision-maker should review both the decision statement and the criteria to ensure that both are synchronized. It may be possible to condense or combine some possibly redundant criteria. And at the third stage is to develop the final list of criteria.

Once the criteria have been finalized, each one is compared to each of the others using a numerical rating scheme. This is the pair-wise comparison, and it allows the decision-maker to weight the different criteria. The assumption is that not all criteria will have equal importance, likelihood, or preference with respect to satisfying the goal.

Thus, the AHP approach involves four essential steps (Zahedi, 1986) that can be summarized as follows:

a) Reduce the decision problem into a hierarchy of interrelated decision elements (factors/criteria and alternatives),
b) collect input data by pair-wise comparisons of decision elements,
c) use the eigenvalue method to estimate the relative weights of decision elements, and
d) aggregate the relative weights of decision elements to arrive at a set of ratings for the decision alternatives.

The final two steps of the traditional AHP approach deal with the construction of an MxN matrix, where M is the number of alternatives and N is the number of criteria. In this matrix, an element *aij* represents the relative performance of the *ith* alternative in terms of the *jth* criteria, which is generally given by a range between 1 to 9. The vector $Xi = (ai1, ai2, \ldots, aiN)$ for the *ith* alternative (i=1,2,..,M) is the eigenvector of an NxN reciprocal matrix. The elements in each vector add up to one. Later on, due to some possible inconsistencies, it was suggested that instead of having the relative values sum up to one, each relative value should be divided by the maximum value in the corresponding vector of values.

FUZZY-AHP

The Analytic Hierarchy Process (AHP) is a method for formalizing decision-making where there are a limited number of choices but each has a number of attributes and it is difficult to formalize some of those attributes. So instead of using exact numbers, we can use phrases like "much more important than" to extract the decision makers preferences. Fuzzy logic and values offer a more natural way of dealing with these preferences instead of exact values. Note that the traditional AHP approach is somewhat arbitrary, for example, use of a particular range of values like 1-9 range. And there are a number of "hidden assumptions", such as, if *i* is weakly preferred to *j* and *j* weakly preferred to *k*, then a consistent decision maker must have *i* absolutely preferred to *k*, which may not necessarily be true. Again, the use of fuzzy numbers and linguistic terms (Zadeh, 1965) would be more suitable in such a situation.

Several theoretical results have been presented in literature as to the application of fuzzy theory in analytic hierarchy process (Boender, et al., 1989; Laarhoeven, et al., 1983). The overall Fuzzy AHP approach can be summarized as follows (Triantophyllou et al., 1996):

a) The decision-maker needs to ascertain fuzzy estimates of relative significance of each pair of decision factors. Similarly, the decision-maker needs to decide about each of the pair of alternative solutions based on each criteria. This process will result in a series of matrices.
b) Estimate the fuzzy eigenvector for each matrix. According to Saaty (1980), in original AHP, the right principal eigenvector of the matrix expresses the relative importance of the alternatives and factors. There are several alternative approaches to this step. One such way is to approximate the eigenvector by multiplying all the elements in a row and then taking the *n*th root.
c) The next step is to normalize each vector, by dividing each element by the sum of the entries in the vector.
d) Compute the priority scores of each alternative by multiplying criteria weights by the values in the column of each alternative and summing those values.
e) Finally, rank each of the alternatives and select the best one.

There are several possible ways to represent fuzzy numbers. One special class of fuzzy numbers is triangular fuzzy number, which is relatively easy to model and works well with most applications. The membership function of a triangular fuzzy number is defined as

$$\mu_M(x) = \begin{cases} \dfrac{1}{m-l}x - \dfrac{l}{m-l}, x \in [l,m], \\ \dfrac{1}{m-u}x - \dfrac{u}{m-u}, x \in [m,u], \\ 0 \text{ otherwise} \end{cases}$$

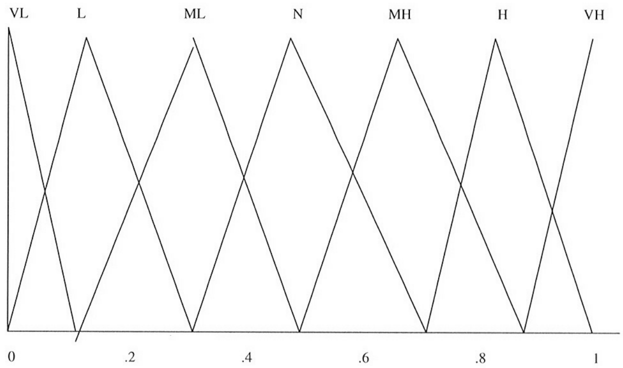
where $l \leq m \leq u$, l and u stand for lower and upper value of the support of M, and m for the modal value. Most of the basic mathematical operations on fuzzy triangular numbers have been defined (Laarhoeven, et al., 1983).

For addition,
$n_1 + n_2 = (n_{1l} + n_{2l}, n_{1m} + n_{2m}, n_{1u} + n_{2u})$

for multiplication,
$n_1 \times n_2 = (n_{1l} \times n_{2l}, n_{1m} \times n_{2m}, n_{1u} \times n_{2u})$
for division,
$1/ n_1 = (1/n_{1u}, 1/n_{1m}, 1/n_{1l})$
where $n_1 = (n_{1l}, n_{1m}, n_{1u})$ and $n_2 = (n_{2l}, n_{2m}, n_{2u})$ are two fuzzy triangular numbers.

The most common implementation of fuzzy sets involves mapping a continuous real variable to a small collection of fuzzy sets representing linguistic labels. Some researchers have suggested using seven fuzzy sets to represent the practical range of a real variable (Kosko 1992). A typical example of such a mapping is given in Fig. 1. For example, somewhat high (SH) equals fuzzy triangular number (.5,.7,.9) and much higher (MH) equals (.9,1,1). There have been a few applications of Fuzzy AHP in decision-making, for example, Kuo et al (1999), developed a decision support system for locating convenience store using Fuzzy AHP. Zhu et al (1999) used Fuzzy AHP in petroleum prospecting decision. In this paper, author applies Fuzzy AHP to country risk assessment.

FIGURE 1
Fuzzy Membership Function for Linguistic Values for Criteria or Alternatives



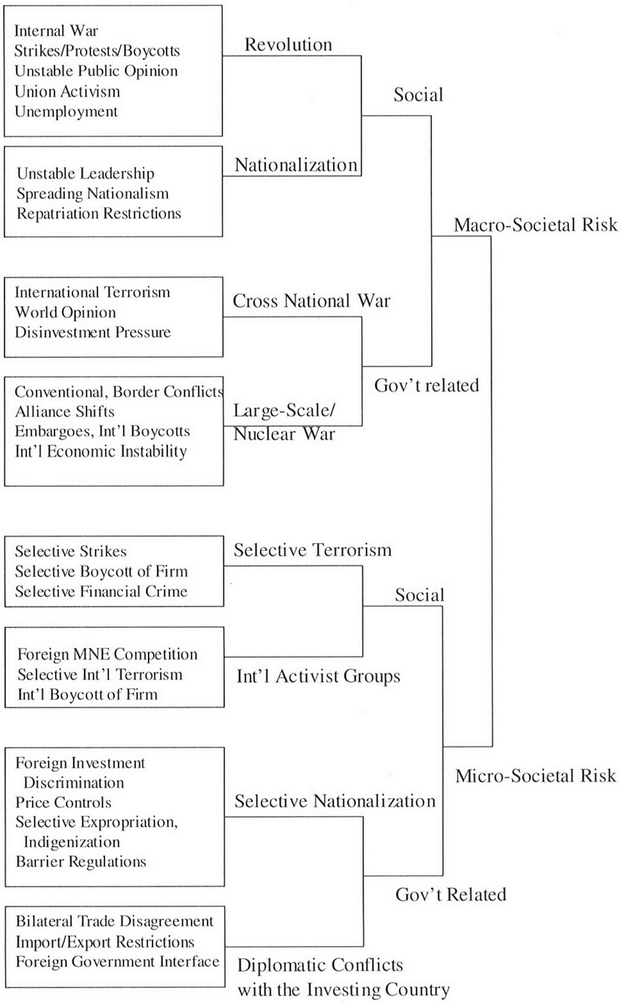
Legend-VL very low, ML-much lower, N-normal, MH-much higher, H-high, VH-very high

COUNTRY RISK ANALYSIS

The aim of country risk assessment models is to obtain a careful evaluation of target countries in order to make appropriate evaluation and decisions regarding whether or not to do business in those countries. Timing of entry in the host country is important for the overall performance of international organizations. There have been a few attempts to model global market entry decision using fuzzy reasoning (Levy et al., 1995). The approach used by Levy requires specific data from the countries to develop the model; therefore the model is dependent on the country under consideration. The approach discussed in this paper differs from that of Levy since it is developed from the knowledge acquired from experts, coupled with a large classification of social and political factors (Fig. 2).

There are several agencies and services that pro-

FIGURE 2
Socio-Political Factors for Country Risk Assessment



vide country risk measurements, such as, Bank of America World Information Services, Institutional Investor, International Country Risk Guide, Standard & Poor's Rating Group and other major financial institutions. Most of these services either survey top bankers and experts or use weighted scoring method to ascertain risk level based on a fixed number of factors and their weights as determined by the agency staff or experts (Erb et al. 1996; Saini et al. 1984). Several researchers have applied statistical approaches, like discriminant analysis, logit analysis, etc.; Saini et al (1984) provide a good review of these techniques. The major problem associated with those approaches is that they depend solely on economic and financial data that sometimes may be unavailable, inaccurate, or outdated. World Bank has increasingly been adding available data as far as financial side of the equation is concerned. However, the information related to social and political issues is a little more difficult to obtain, and therefore, it may be up to the decision-maker to acquire or in some cases use his/her own judgment. Rivoli et al. (1997) have shown that even for debt rescheduling prediction, inclusion of the political variables instead of just economic indicators improves predictive power.

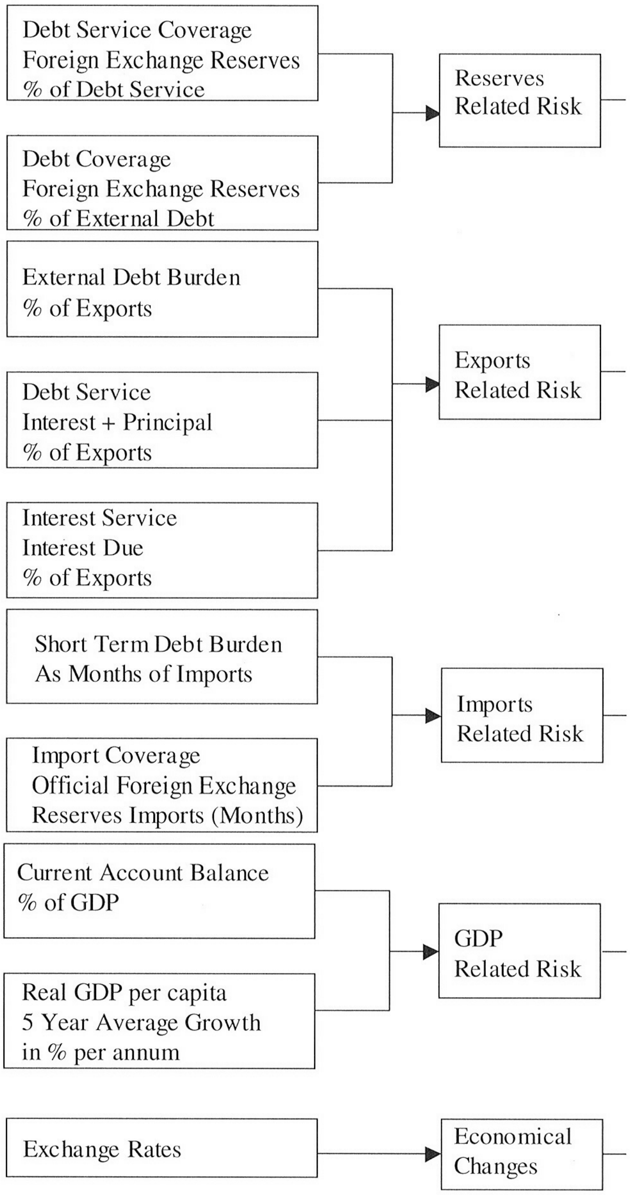
The author in this paper offers a model that can be used by individual managers who would like to determine risk level of a country at a particular time based on the knowledge and data that they may have collected. This model can also be used to compare relative risk level of two or more countries. Additionally, this approach can be used as a teaching tool for students and management trainees as it helps them start thinking about the relevant issues that must be considered in global decision making.

The global risk factors can be broadly defined in three categories, namely, social, political, and economic factors. Economic factors are mostly numeric, but social and political factors are mostly subjective. This, of course, adds to the complexity of the problem. The economic risk assessment component of the model analyzes risk in four major categories: Export-related risk, import-related risk, reserves-related risk and GDP-related risk (Fig. 3). Thus, the model can be utilized in absence of available exact data as long as the user is able to provide some relative fuzzy values for these ratios. Therefore, users can apply the model if they are able to predict the approximate values for various ratios.

Socio-Political assessment is a major category of country risk analysis and prediction. It is a result of thorough consideration of factors that affect and continuously reshape the social environment of a country by emphasizing the causal relationships with the dynamics of political instability. A systems approach looks at two aspects of evaluation attributes: the macro-environment and the micro-environment. The study of the macro-environment focuses on the relationships between societal and governmental characteristics. The former category includes such social dynamical attributes as revolutionary activities, cross-national guerilla wars, boycotts, religious turmoil, international terrorism, etc. The later category comprises of government dynamics, like nationalization/expropriation, interest rates, political corruption, leadership struggles, and nuclear/convention war among others. The study of micro-environment is based on the same attributes but in a qualitative level of focused and target actions. The assessment factors that can be used as evaluation criteria are shown in Fig. 2.

There are some static factors that fluctuate relatively slowly and are affected, generally, by the long-term plans and activities of the country. The changes in these factors impact the economy and social/political situations, mainly, in the long term. Therefore, their influence in short run can be ignored. Some of these factors are exports, imports, GDP, and reserves. On the other hand, dynamic factors fluctuate very fast, are affected by short-term plans and decisions, and usually

FIGURE 3
Economic Factors for Country Risk Assessment



impact the economy of a country quickly and rather dramatically. Some of these factors are strikes, wars, exchange rates, decisions on taxes, etc., as well as social changes. Additionally, debt has become a very important parameter for defining the country risk. Recent history shows that debt has played a major role in triggering unexpected crisis, being responsible for fluctuations in economy as well as in socio/political conditions. Although debt is a relatively static factor, it is different from exports, reserves and other similar factors due to its feedback power. A crisis of confidence in any country translates into pressure on the exchange rates (a dynamic factor) which forces devaluation of the currency. The devaluation would lead to potential debt-servicing difficulties with unhedged foreign currency borrowings, weakening, very quickly, the country's economy and, ultimately, dramatically increasing its sensitivity to dynamic factors. According to Reeb et al. (1998), there is a highly significant positive relationship between globalization and systematic risk, due to foreign exchange risk, political risk, etc. In order to appropriately incorporate this feedback characteristic of debt on the set of static factors, the economic risk assessment model is based on debt-ratio parameters such as external debt as percent of exports, short-term debt as months of imports, reserves as percent of debt service, etc. The main components of this risk assessment model – economic and socio-political - are described below.

The assessment methodology, applied here, consists of a step-by-step approach as follows:

a) Selection of appropriate risk attributes as evaluation criteria.
b) Development of the relative importance of the attributes by means of a systemic study that compares pairs of criteria.
c) Collection or evaluation of data for each evaluation factor. If more than one country is being evaluated to make a choice, there would a pair-wise comparison of the countries at this stage.
d) A choice has to be made at this decision-making stage. The country with the lowest risk level would obviously be the best choice.

A complete review of the factors and assessment methods that are most widely used can be found in Mayer (1985).

RISK ASSESSMENT PROCESS

The risk assessment process can be performed in two steps. First, a socio-political assessment should be performed, followed by an economic assessment. In order to assess the socio-political environment of a country, we should estimate the risks of revolution, nationalization, cross-national war, etc., as well as consider each of the other sub-factors depicted in Fig. 2. The user needs to provide a series of answers relating to these factors by indicating whether existence of one factor as opposed to the other factor is lower, somewhat higher, or much higher etc. The system will ascertain relative significance level for each factor based on the answers given. In the similar manner, the user must rank the economic factors in relative terms. For example, if the significance level of debt service ratio is lower, somewhat higher, or higher, etc. as compared to current account balance.

It is not necessary to use all social-political factors in each decision situation as some of those factors may be irrelevant for a particular country. To illustrate the mechanism of this analysis, we chose a total of eight factors (including four social-political and four economic factors). These factors are Nationalization (C1), Large-scale war (C2), selective terrorism (C3) and diplomatic conflicts with the investing country (C4) on the social-political end. The economic factors used are Reserves related risk (C5), exports-related risk (C6), imports-related risks (C7) and GDP-related risks (C8).

Once the factors used in decision making are determined, the next step is to decide on the relative importance of the eight decision criteria discussed above. Using pair-wise comparisons, the table containing the reciprocal matrix is developed (Table 1). That is, the evaluator determines that C2, C5 and C8 are higher than C1, and C3, C4, and C7, are much higher than C1 and C6 is very high as compared to C1. These linguistic terms are then converted to triangular fuzzy values using Fig. 1. This is shown in the matrix of Table 1, only the values above the diagonal have to be determined by the decision-maker. The values below the diagonal are just the inverses. In a similar fashion, the decision-maker makes a comparison of each alternative country based on each of the criteria separately. When a criteria or alternative is compared to itself, the triangular fuzzy number (1,1,1) is assigned.

The next step is to determine the importance of each factor (i.e., to approximate the eigenvector) resulting from the pair-wise comparison. This vector giving importance of each criterion and can be found by multiplying all of the fuzzy triangular number in a row and taking the *nth* (8th in this case) root of the resulting value (Table 1, last column). Now this vector needs to be normalized, which can be done by dividing each value by the sum of values of the vector. In case of triangular numbers, it is found by dividing lower values by the sum of upper values and vice versa. For modal values, each value is divided by the sum of the entries in its vector. After applying this procedure, the normalized weight vector is obtained (Table 2, Column 2).

The same process as described above is applied to determine normalized vectors for each of the alternatives (countries). First a pair-wise comparison of each alternative with each of the other alternatives is performed based on each of the eight criteria. The decision maker needs to determine, for example, considering criteria C1, how does alternative A1 compares

TABLE 1
Reciprocal judgment matrix for eight decision criteria

(1)	C1 (2)	C2 (3)	C3 (4)	C4 (5)	C5 (6)	C6 (7)	C7 (8)	C8 (9)	Fuzzy Fuzzy Importance (10)
C1	1,1,1	.7,.9,1	.5,.7,.9	.5,.7,.9	.7,.9,1	.9,1,1	.5,.7,.9	.7,.9,1	.67,.84,.96
C2	1,1.11,1.43	1,1,1	.7,.9,1	.1,.3,.5	.3,.5,.7	.7,.9,1	.5,.7,.9	.7,.9,1	.52,.73,.91
C3	1.11,1.43,2	2,3.33,10	1,1,1	.3,.5,.7	.3,.5,.7	.3,.5,.7	.3,.5,.7	.3,.5,.7	.52,.79,1.16
C4	1.11,1.43, 2	1, 1.11, 1.43	1.43,2, 3.33	1,1,1	.3,.5,.7	.3,.5,.7	.3,.5,.7	.3,.5,.7	.58,.82,1.11
C5	1, 1.11, 1.43	1.43,2,3.33	1.43,2,3.33	1,43,2,3.33	1,1,1	.3,.5,.7	.7,.9,1	.7,.9,1	.90,1.17,1.57
C6	1,1,1.11	1,1.11,1.43	1.43,2,3.33	1.43,2,3.33	1.43,2,3.33	1,1,1	.3,.5,.7	.5,.7,.9	.90,1.15,1.57
C7	1.11,1.43,2	1.11,1.43,2	1.43,2,3.33	1.43,2,3.33	1,1.11,1.43	1.43,2,3.33	1,1,1	.7,.9,1	1.12,1.42,1.95
C8	1,1.11,1.43	1,1.11,1.43	1.43,2,3.33	1.43,2,3.33	1,1.11,1.43	1.11,1.43,2	1,1.11,1.43	1,1,1	1.11,1.31,1.76

TABLE 2
Fuzzy Decision Matrix with Priority Scores of each alternative

Criteria (1)	Importance (2)	A1 (3)	A2 (4)	A3 (5)
C1	.16,.26,.42	.22,.29,.37	.24,.33,.46	.3,.37,.5
C2	.13,.23,.40	.18,.26,.34	.25,.37,.56	.28,.37,.51
C3	.13,.25,.51	.16,.25,.35	.24,.37,57	.28,.38,.56
C4	.14,.26,.49	0,.19,.38	.18,.37,.95	.26,.44,.94
C5	.22,.37,.69	.16,.28,.38	.18,.33,.81	.23,.39,.55
C6	.22,.36,.69	.11,.23,.35	.16,.32,.78	.25,.45,.77
C7	.27,.45,.85	.09,.2,.32	.15,.31,.77	.26,.49,.9
C8	.27,.41,.77	.12,.23,.33	.23,.39,.84	.23,.38,.55
	Priority Scores	.195,.618,1.68	.305,.896,.3.566	.395,1.072,3.255

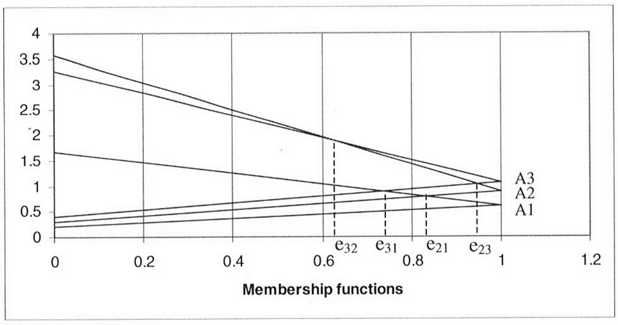
to A2 and A3. This step is followed by determination of approximate eigenvector. The end result is to have a table with all the criteria (along with their weights) and each of the alternatives; this table can be used to determine priority scores for each alternative (Table 2). Since the application involves risk rating, the alternative with least score would be preferred.

Once the priority scores of each of the alternatives are obtained, a ranking of alternatives can be determined using any of the several available ranking procedures. If $\mu_i(x)$ denotes the membership function for a fuzzy number n_i, define

$$e_{ij} = \max_{x \geq y}\left\{\min\left(\mu_i(x), \mu_j(y)\right)\right\} \text{ for all i,j = 1,2,3, ...,m}$$

The fuzzy number n_i outranks n_2 if and only if $e_{ij} = 1$ and $e_{ji} < Q$, where Q is a fixed fraction less than 1 (Buckley, 1988). Using Q = .95, in this example, $e_{12} = e_{13} = 1$ and e_{21} and e_{31} both are less than Q (Fig. 4). Thus, alternative A1 dominates A2 and A3. However, using this ranking method, there is no clear winner between A2 and A3 since both e_{23} and e_{32} are less than 1. However, observing Fig. 4, it can be said that A2 is a better alternative than A3.

FIGURE 4
Membership function of the three alternative countries



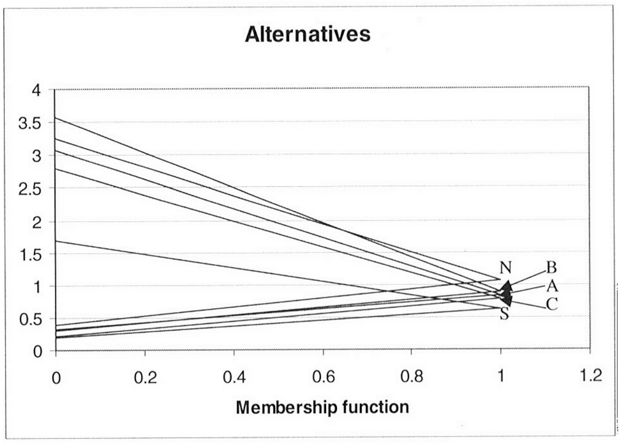
VALIDATION PROCESS

One of the important steps in the design of a decision support tool is validation and verification. In the design of Country Risk Assessment system, validation and verification was given a high priority. At each step of the design, the authors went back and verified the logic used in the step several times. The authors also used a comprehensive approach to validation of this system. It included two major efforts as described below. First of all, the general framework of prediction using socio-political and economic factors was distributed to several faculty members and a review of factors was invited. Based on their reviews certain minor adjustments were made to the factors list.

Secondly, all the necessary data was collected regarding five important countries – Argentina, Brazil, China, Nigeria and Switzerland. All of these countries exhibit different levels of economic stability along with varied social and political history and background which makes them good candidates for the validation of this fuzzy-AHP model. Although the countries differ from each other substantially in social, political and economic terms, they can be evaluated using same factors. The data used for the testing was from 1995-96 along with some expert opinions obtained for the model evaluation purpose.

The above discussed data relating to these countries was then applied on the model to obtain specific assessment. For comparison purposes, the risk levels of these countries were also obtained from International Country Risk Guide (IRCG). Most agencies, including ICRG, use a 0 to 100 risk level which is not directly comparable to the output of the model presented here. In ICRG risk ratings a higher score equates to a lower risk and a lower score means higher risk. However, based on the risk ratings, the relative standing of the countries was identical to the one obtained from IRCG. Fig. 5 displays relative ranking of these five countries obtained from the Fuzzy-AHP model. Switzerland is clearly the country with the least risk. After that China, Argentina and Brazil, although very close, ranked number 2, 3, and 4. Nigeria has the highest risk level in this set of five countries. This corresponds to ICRG composite risk ratings of these countries for the same time frame – Switzerland (89), China (72), Argentina (70), Brazil (62.5) and Nigeria (52.5).

FIGURE 5
Membership functions of the five alternative countries



CONCLUSIONS

In this paper, the authors have developed a fuzzy analytic hierarchy model for risk assessment that was applied successfully to several countries. The model uses various social, political and economic factors, provides a systematic approach, and includes an extensive framework that helps in acquiring relevant social, political and economic data that is essential for the analysis. Additionally, it uses a methodology that provides guidance to information gathering and processing.

The major advantages of the method discussed in this paper are potential evaluation of a vast array of factors from various significant areas of the target country's environment that includes economic, political and social indicators. Another major benefit of the model is its robustness. Since it allows adjustment of weights, it can be applied to very distinct countries. As compared to traditional weighted score approach used by major banks and agencies, this model does not force same set of factor weights on all countries and hence better suited to situation when a decision-maker is evaluating a small set of countries or a particular region of the world.

REFERENCES

Boender, C.G.E., de Graan, J.G., and Lootsma, F. A. (1989) "Multi-Criteria Decision Analysis with Fuzzy Pairwise Comparisons," *Fuzzy Sets and Systems,* Vol. 29,133-143.

Buckley, J.J. (1985) "Ranking Alternatives using Fuzzy Numbers," *Fuzzy Sets and Systems,* Vol. 15, 21-31.

Erb, C.B., Harvey, C.R., and Viskanta, T.E. (1996) "Political Risk, Economic Risk, and Financial Risk," *Financial Analysts Journal,* November-December 1996, Vol. 52(6), 28-46.

Keller, J.M., and Tahani, H. (1992) "Implementation of Conjunctive and Disjunctive Fuzzy Logic Rules With Neural Networks," *International Journal of Approximate Reasoning,* 6, 221-240.

Kosko, B. (1992) *Neural Networks and Fuzzy Systems,* Prentice-Hall.

Kuo, R.J., Chi, S.C., and Kao, S.S. (1999) "A Decision Support System for Locating Convenience Store through Fuzzy AHP," *Computers and Industrial Engineering,* Vol. 37, 323-326.

Laarhoeven, P.J.M., and Pedrycz, W. (1983) "A Fuzzy Extension of Saaty's Priority Theory," *Fuzzy Sets and Systems,* Vol. 11, 229-241.

Levy, J. B., and Yoon, E. (1995) "Modeling Global Market Entry Decision by Fuzzy Logic," *European Journal of Operational Research, 82,* 53-78.

Mayer, E. (1985) International lending: country risk analysis. Reston Financial Services, Reston, Va.

Pedrycz, W. (1991) Fuzzy Logic in Development of Fundamentals of Pattern Recognition *International Journal of Approximate Reasoning, 5,* 251-264.

Reeb, D., Kwok, C., and Baek, Y. (1998) Systematic risk of the Multinational Corporation. *Journal of International Business Studies,* 29(2).

Saini, K., and Bates, P.S. (1984) "A Survey of the Quantitative Approaches to Country Risk Analysis," *Journal of Banking and Finance,* Vol. 8, 341-356.

Saaty, T.L. (1980) *The Analytic Hierarchy Process,* McGraw-Hill.

Takagi, H., and Hayashi, I. (1991) NN-Driven Fuzzy Reasoning. *International Journal of Approximate Reasoning, 5,* 191-212.

Triantophyllou, E., and Lin, C-T. (1996) "Development and Evaluation of Five Fuzzy Multiattribute Decision-Making Methods," *Int'l Journal of Approximate Reasoning,* Vol. 14, 281-310.

Zadeh, L.A. (1965) "Fuzzy Sets," *Information and Control,* Vol. 8, 338-353.

Zahedi, F. (1986) "The Analytic Hierarchy Process-A Survey of the Method and its Applications," *Interfaces,* Vol. 16, 96-108.

Zhu, K-J., Jing, Y., and Chang, D-Y. (1999) "A discussion on Extent Analysis Method and applications of Fuzzy AHP," *European Journal of Operational Research,* Vol. 116, 450-456.