A Neutrosophic Decision Making Method for Evaluation of Efficiency of General Insurance Companies

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A Neutrosophic Decision Making Method for Evaluation of Efficiency of General Insurance Companies

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ABSTRACT This paper proposes an integration of two neutrosophic based multi-criteria decision making methods, namely the neutrosophic data analytical hierarchy process (NDAHP) and the Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) with maximizing deviation method, both based on the single-valued neutrosophic set (SVNS) to evaluate the efficiency of general insurance companies in Malaysia. The level of efficiency of insurance companies is a subjective and vague matter, as the efficiency can be further branched into operational efficiency, investment efficiency, underwriting efficiency, and risk management efficiency, thereby making fuzzy based decision making methods highly appropriate to be used. Our proposed decision making algorithm uses an integrated weighting mechanism takes into consideration both the objective and subjective weights of the data attributes. The objective weighting mechanism handles the actual datasets that were used which consists of crisp values, whereas the subjective weighing mechanism handles the opinions of the experts in the general insurance industry who were surveyed in this study. This makes our proposed method a more holistic approach to evaluate the efficiency of general insurance companies in Malaysia as previous researches in this area are generally based on the actual datasets without consideration of the opinions and evaluations of the industry experts, or vice-versa. Our proposed decision making algorithm is applied on actual datasets of management expenses, net commission, net earned premium and the net investment income for 19 selected general insurance companies in Malaysia over a two year period from 2016 to 2017. The results obtained are then discussed and the possible reasons for the results are analyzed. A comprehensive comparative study of the results obtained via our proposed method and two other commonly used methods are then presented, analyzed and discussed.

Keywords: Single-valued neutrosophic set; Analytic hierarchy process (AHP); Multi-criteria decision making; Neutrosophic data AHP; Neutrosophic decision making; Efficiency of general insurance companies; TOPSIS; Maximizing deviation method

1. INTRODUCTION

General insurance is basically a type of insurance product that protects the insured against losses and damages other than those covered in the category of life insurance, which pays the benefit or sum assured upon death or expiry of the policy. The risk covered in general insurance includes property loss, liability loss or damage caused by a third party as well as accidental death or injury. Generally, products in the category of general insurance are insurances which are related to property and casualty. The general insurance industry in Malaysia is still in the development process compared to other developing countries. According to the official website of the General Insurances Association of Malaysia (PIAM), the number of general insurance companies which have been registered as a member of the Association currently stands at 21. The intense competition has meant that there is a need for the insurance companies to strengthen their position in the market and to operate in the most efficient manner. This is also true in other developing and developed markets, and this has led to an increasing number of researches on the evaluation of the efficiency of financial institutions in the past few years.

Fuzzy set is modified from the classical set theory which was firstly introduced by Lofti A. Zadeh in 1965 [1]. In classical set theory, the way to classify each element in a set was dichotomous, which means the belongingness of an element is either positive or negative in the set. On the contrary, in fuzzy set theory, the set is able to deal with a certain magnitude of membership. The concept of fuzziness generally deals with a degree of truthfulness of values, uncertainty, vagueness and imprecision. The ability of fuzzy sets to model the uncertainty of objects and its ability in capturing the imprecision in defining a sharp criteria of class membership functions has led to the rapid progress in research pertaining to the fuzzy set theory. This phenomenon led to the development of many similar models. The most commonly used ones which are relevant to this research project are the intuitionistic fuzzy set [2] and neutrosophic set [3]. In 1986, Atanassov and Stoeva [2] proposed the concept of intuitionistic fuzzy set (IFS), which was modified from the general fuzzy set model. In Zadeh's fuzzy set theory, the membership function is single-valued and assumes values between zero and one, while the IFS model has the characteristic of having a dual membership function system which comprises of a membership function and a non-membership function. In the real world, it is not always true that the magnitude to which an object does not belong to a set fully complements the magnitude to which an object belongs to the set. Since the IFS model takes a degree of non-membership into account, it has been powerful enough to attract researchers and authors to apply the IFS model in various fields of study.

In 1995, Smarandache introduced a more advanced form of fuzzy sets called neutrosophic sets that is able to handle the fuzziness that exists in real-life situations in a more practical manner compared to Zadeh's fuzzy set model [1] and the IFS model [3]. The neutrosophic set is essentially an extension of the IFS model, albeit a more accurate one. The basis of neutrosophic set is neutrosophic logic that can describe a degree of membership of an indeterminable element that neither belongs nor does not belong, cases which are not taken into consideration in the ordinary fuzzy set model and the IFS model. The distinctive characteristics of neutrosophic set is that it has a unique triple membership structure that describes the degree of truth (T), falsity (F) and indeterminacy (I) for each model. In the neutrosophic model, the values from the three membership functions are not influenced by one another, that is, the sum of the three membership functions do not necessarily need to sum up to 1, and need not necessarily complement to 1. Unlike other fuzzy sets, the interval of the membership function for the original neutrosophic sets is defined to be the non-standard interval of $]^{-}0, 1^{+}[$. Using this non-standard interval, it enables users to distinguish whether the grade of membership of the set is relative or absolute. In the event that the truth is relative, it is represented as 1 and the truth is absolute, it is represented as 1^{+}. Likewise, in the event that the falsehood is relative, it is represented as 0, and in the event that the falsehood is absolute, it is represented as $^{-}0$.

The non-standard interval of $]^{-}0, 1^{+}[$ in which the membership functions of neutrosophic sets are generated makes the application to solve the problems existing in real world exceedingly impractical especially in the areas of engineering and science. This led to the conceptualization of a type of neutrosophic sets called the single-valued neutrosophic sets (SVNSs) [4]. The SVNS model's membership structure is similar to the original model, but all of these membership functions take on values between 0 and 1, similar to the membership function in fuzzy sets and IFSs. This also makes it more compatible with the other fuzzy decision making methods. In this sense, the SVNS model would be more suitable to be used to solve problems that arise in real-life with indeterminate and incomplete information [40-50].

The analytic hierarchy process (AHP) is a technique to handle complex criteria which could be quantifiable or intangible in decision-making. The AHP was first introduced by Thomas L. Saaty in 1980 [5]. The AHP analyses a set of criteria to be assessed and chooses the optimal alternative. The most powerful feature of AHP is that AHP can create a weight of every single criterion in a set according to the decision maker's pairwise comparisons of the criteria. In addition, when making decisions, the AHP considers human experiences and knowledge [6]. However, in the real-world, all of the information is not necessarily quantifiable nor complete. To resolve the problem, the fuzzy analytic hierarchy process (FAHP) was developed by Van Laarhoven and Pedrycz in 1983 [7]. The FAHP is an integration of fuzzy set theory and the AHP method, which is an effective tool to deal with such vagueness that may exist in the decision-making process. As the popularity of AHP grew, it was adapted to other forms of fuzzy sets and this led to the introduction of intuitionistic fuzzy AHP (IFAHP) by Xu and Liao [8], interval-valued fuzzy AHP (IVFAHP) by Mirzaei [9], interval-valued intuitionistic fuzzy AHP (IVIFAHP) by Abdullah and Najib [10], and neutrosophic AHP (NAHP) by Radwan, Senousy and Riad [11]. Some of the recent research development on FAHP, IFAHP and NAHP are expounded below.

Putra et al. [12] proposed a FAHP model to determine the quality of gemstones. This research has created a system which can evaluate the quality of gemstones accurately and effectively, based on the data criteria which consist of the specific gravity, color, hardness, cutting and clarity of the gemstones. Recognizing that medical practitioners may have different opinions during medical procedures, particularly in diagnosis of patients, and that this may lead to different actions and decisions, Somayeh Nazari Moghaddam et al. [13] proposed a diagnosis system based on FAHP and Fuzzy Inference System (FIS). This system was used to evaluate the conditions of patients who were being examined for heart disease. Biswas et al. [14] on the other hand, developed a FAHP based method to determine the apparel item that should be manufactured among a wide range of apparel items to obtain maximum profit, with the aim of helping investors looking to invest in a garment factory in Bangladesh. Basar [15] utilized FAHP to design a strategic decision making method to assess the supplier selection problem in the Turkish construction industry. The proposed model considered three main supplier selection criteria, namely product features, suppliers' features and delivery conditions in the study. The proposed method has shorten and simplified the complicated and generally tangled process of choosing the right construction supplier. Tan et al. [16] has proposed a FAHP approach, as a systematic and simple methodology in the multi- criteria evaluation of alternatives for the harvesting and drying process of microalgae production. Several criteria related to the harvesting and drying methods as well as technology capability, cost and environmental impact of these methods were considered in this study.

Kaur [17] proposed a triangular intuitionistic fuzzy number based approach for vendor selection problem using the AHP method. In this research study, the five criteria that were considered were the cost, quality, cycle time, service and reputation. Lazim Abdullah et al. [18] has ranked the human capital indicators using a hybridization of the AHP and two- sided evaluation using the IFAHP method. In this study, linguistic data were obtained from experts in the area of human capital management via questionnaires. The proposed IFAHP method was used to evaluate the four main indicators of human capital, and subsequently determine the most important criteria in human capital management. Lazim Abdullah et al. [19] also proposed a new IFAHP method that is characterized by a new preference scale of pair- wise comparison matrix measurement. The new preference scale has considered the degree of hesitation of IFS in expressing the conversion of consistency to triangular intuitionistic fuzzy numbers, and the proposed method were applied on three MCDM problems. Burak and Faruk [20] has proposed an integrated multi- criteria decision making method for personnel selection with perfect multiplicative consistent intuitionistic preference relation under an intuitionistic fuzzy environment. Ouyang and Guo [21] have developed an IFAHP method to select the mangrove paradigm which is optimal for municipal wastewater treatment. The entropy weights in this research were entrained by the valid evaluation of 64 experts and representatives via an online survey.

One of the biggest shortcomings of the AHP method is that the computation process is mainly based on experts' opinion, whereby each criteria or data attributes are evaluated by the experts' personal experience and own judgement, in which the issue of subjectivity is a major concern. To address this issue, an extension of the NAHP called the Neutrosophic Data Analytic Hierarchy Process (NDAHP) was introduced by Tey et al. in [22]. The NDAHP method is based on an objective weighting mechanism that is designed to handle actual data sets that consists of crisp values. This framework was used to assess the financial performance of five petrochemical companies listed on the main board of the Kuala Lumpur Stock Exchange (KLSE).

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The maximizing deviation approach was first introduced by Wang [23] with the goal of utilizing this method to quantify the importance of attributes which are completely unknown or only partially known input arguments. This approach involves the magnitude of the membership function of each alternative for each data attribute in the derivation of the weight coefficients. It has been used to determine the objective weightage of data attributes combined with the subjective weightage in an integrated manner to solve a multitude of MADM problems [24].

The technique for order preference by similarity to ideal solution (TOPSIS) was introduced by Hwang and Yoon in 1981 [25]. In this method, there are two artificial hypothesized alternatives which are the positive ideal alternative and the negative ideal alternative. The positive ideal alternative is the alternative that can generate the maximum benefit criteria and the minimum cost criteria, whereas the negative ideal alternative is the alternative that performs on the contrary to the former. In TOPSIS, the optimal alternative should have the shortest distance from the positive ideal alternative and the farthest distance from the negative ideal solution. Bulgurcu [26] proposed a TOPSIS based group decision making method to identify the company with the best green supply chain management among six different tyre companies. Five criteria were considered namely green design, green transformation, green purchasing, green logistics and reverse logistics. Sahin and Yigider [27] has extended the TOPSIS approach to multi- criteria group decision making and applied this method in a supplier selection problem, whereby the importance of the criteria and alternatives were identified by aggregating individual opinions of the decision makers via single-valued neutrosophic weighted averaging (SVNWA) operator. Balioti et al. [28] introduced an integrated model of fuzzy TOPSIS and AHP to select the optimal spillway for a dam in the district of Kilkis in Northern Greece. A modified TOPSIS method called the D-TOPSIS method was introduced by Fei et al. [29] and applied on the selection of candidates in human resource management. This method is based on the concept of D-numbers which has been generalized from the Dempster-Shafer evidence theory to represent uncertain information which can denote fuzzy conditions more effectively. Forgahani et al. [30] applied principal component analysis, TOPSIS and mixed integer linear programming to solve a pharmaceutical supply chain problem, particularly on the selection of the suppliers. Siddique et al. [31] applied fuzzy TOPSIS in ranking the decision criteria of flexible manufacturing system (FMS) with the aim of assisting the management of a company in their decision making process during the implementation of FMS.

Huang and Jiang [32] extended the fuzzy TOPSIS method by introducing a component known as optimism coefficient in solving problems related to investment, with the optimism coefficient used to describe the attitudes of investors towards risk and profit.

The remainder of this paper is organized as follows. In Section 2, we recapitulate some of the fundamental concepts related to SVNSs and some of the recent developments related to SVNS based decision making. In Section 3, we introduce a decision making algorithm that integrates the concepts of converting raw numerical data into fuzzy number using the NDAHP method, followed by the derivation of weightage for each criteria based on the maximizing deviation method, and subsequently the ranking of the alternatives based on the SVNS TOPSIS approach to evaluate the efficiency of 19 general insurance companies in Malaysia over the period of 2016- 2017 based on four selected financial parameters. In Section 4, the results obtained from the proposed decision making algorithm are presented, along with a brief discussion on certain observations. Furthermore, a comparative study that compares and analyzes the results obtained through our proposed method and two other conventionally used decision making methods to evaluate the efficiency of general insurance companies are provided. Concluding remarks are given in Section 5, followed by acknowledgements and the list of references.

2. PRELIMINARIES

In this section, we recapitulate some important concepts pertaining to the theory of SVNSs, and some of the recent developments related to SVNS based decision making.

The formal definition of the classical neutrosophic set introduced by Smarandache [3, 4] in 1998 is outlined as below:

Definition 2.1. Set B is a neutrosophic set drawn from a universal set Y. Then B is as follows

$$B = \{\langle y, T_{\mathrm{B}}(y), I_{\mathrm{B}}(y), F_{\mathrm{B}}(y)\rangle \mid y \in Y\},$$

where $T_{\mathrm{B}}(y)$ is a membership function which describes the degree of truth of element y to set B, $I_{\mathrm{B}}(y)$ is a membership function which describes the level of indeterminacy between truth and false of element y to set B and $F_{\mathrm{B}}(y)$ is a membership function which describes the degree of falsity of element y to set B and T_{B}, I_{B} and F_{B}: $Y \to P(\,]^{-}0, 1^{+}[\,)$, which is the power set of $]^{-}0, 1^{+}[$. The sum of the values assigned by $T_{\mathrm{B}}(y), I_{\mathrm{B}}(y), F_{\mathrm{B}}(y)$ is not restricted, which means the summation of the values is between 0 and 3.

Let B and C be neutrosophic sets defined as given below:

$$B = \{\langle y, T_{\mathrm{B}}(y), I_{\mathrm{B}}(y), F_{\mathrm{B}}(y)\rangle \mid y \in Y\}$$
$$C = \{\langle y, T_{\mathrm{C}}(y), I_{\mathrm{C}}(y), F_{\mathrm{C}}(y)\rangle \mid y \in \mathrm{Y}\}$$

Definition 2.2. [3] For neutrosophic sets B and C, the basic concepts are as below:

(i) B is contained in C, represented by the notation, $B \subseteq C$, if and only if $\inf T_{\mathrm{B}}(y) \leq \inf T_{\mathrm{C}}(y)$, $\sup T_{\mathrm{B}}(y) \leq \sup T_{\mathrm{C}}(y)$, $\inf F_{\mathrm{B}}(y) \leq \inf F_{\mathrm{C}}(y)$ and $\sup F_{\mathrm{B}}(y) \leq \sup F_{\mathrm{C}}(y)$

(ii) B is equivalent to C if $B \subseteq C$ and $B \supseteq C$

Single-valued neutrosophic set (SvNS), a particular case of neutrosophic sets was proposed by Smarandache [3] and Wang et al. [4] to supplement the difficulties in applying the classical neutrosophic sets which have membership functions defined in the non-standardized interval of 0 and 1. The SvNS also has a triple membership structure that consists of a truth membership, indeterminacy membership and falsity membership functions. However, the membership functions in the SvNS model assigns values within the standard interval of $[0,1]$. The SVNS model is one of the most commonly used versions of the neutrosophic set model, and a lot of research related to SVNS based decision making have been done. SvNS based decision making provides a way of adequately handling the ambiguities that often exists in the data of most of the problems encountered in everyday life.

Definition 2.3. [4] Let B be a SvNS defined over a universal set Y, where B is expressed as

$$B = \{\langle y, T_{\mathrm{B}}(y), I_{\mathrm{B}}(y), F_{\mathrm{B}}(y)\rangle \mid y \in Y\}.$$

Here, $T_{\mathrm{B}}(y)$, $I_{\mathrm{B}}(y)$ and $F_{\mathrm{B}}(y)$ are functions that assign the magnitude of truth membership, indeterminacy membership and falsity membership respectively, $T_{\mathrm{B}}(y), I_{\mathrm{B}}(y), F_{\mathrm{B}}(y) \in [0,1]$, and the membership functions must conform to this condition $0 \leq T_{\mathrm{B}}(y) + I_{\mathrm{B}}(y) + F_{\mathrm{B}}(y) \leq 3$. A triplet of the form $(T_{\mathrm{B}}(y), I_{\mathrm{B}}(y), F_{\mathrm{B}}(y))$ is called a single-valued neutrosophic number (SvNN).

Let B and C be SvNSs that are defined as follows:

$$B = \{\langle y, T_B(y), I_B(y), F_B(y)\rangle \mid y \in Y\}$$
$$C = \{\langle y, T_C(y), I_C(y), F_C(y)\rangle \mid y \in \mathrm{Y}\}$$

Definition 2.4. [4] Let B and C be two SvNSs over a universe Y. Some of the basic operations for B and C are as given below:

(i) B is contained in C, if $T_B(y) \leq T_C(y), I_B(y) \geq I_C(y)$, and $F_B(y) \geq F_C(y)$, for all $y \in Y$. This relationship is denoted as $B \subseteq C$.

(ii) B and C are said to be equal if $B \subseteq C$ and $C \subseteq B$.

(iii) $B^c = \Big(y, \big(F_A(y), 1 - I_A(y), T_A(y)\big)\Big)$, for all $y \in Y$.

(iv) $B \cup C = \Big(y, \big(\max\big(T_B(y), T_C(y)\big), \min\big(I_B(y), I_C(y)\big), \min\big(F_B(y), F_C(y)\big)\big)\Big), \forall\, y \in Y$.

(v) $B \cap C = \Big(y, \big(\min\big(T_B(y), T_C(y)\big), \max\big(I_B(y), I_C(y)\big), \max\big(F_B(y), F_C(y)\big)\big)\Big), \forall\, y \in Y$.

Majumdar and Samanta [33] introduced the information measures of distance, similarity and entropy for SVNSs. Here we only present the definition of the distance measures between SVNSs as it is the only component that is relevant to this paper.

Definition 2.5. [33] Let B and C be two SvNSs over a finite universe $Y = \{y_1, y_2, \dots, y_n\}$. The various distance measures between B and C are as given below:

(i) The Hamming distance between B and C are defined as:

$$d_H(B, C) = \sum_{i=1}^{n} \{|T_B(y_i) - T_C(y_i)| + |I_B(y_i) - I_C(y_i)| + |F_B(y_i) - F_C(y_i)|\} \qquad (1)$$

(ii) The normalized Hamming distance between B and C are defined as:

$$d_H^N(B, C) = \frac{1}{3n} \sum_{i=1}^{n} \{|T_B(y_i) - T_C(y_i)| + |I_B(y_i) - I_C(y_i)| + |F_B(y_i) - F_C(y_i)|\} \qquad (2)$$

(iii) The Euclidean distance between B and C are defined as:

$$d_E(B,C) = \sqrt{\sum_{i=1}^{n}\left\{\left(T_B(y_i)-T_C(y_i)\right)^2+\left(I_B(y_i)-I_C(y_i)\right)^2+\left(F_B(y_i)-F_C(y_i)\right)^2\right\}} \quad (3)$$

(iv) The normalized Euclidean distance between B and C are defined as:

$$d_E^N(B,C) = \sqrt{\frac{1}{3n}\sum_{i=1}^{n}\left\{\left(T_B(y_i)-T_C(y_i)\right)^2+\left(I_B(y_i)-I_C(y_i)\right)^2+\left(F_B(y_i)-F_C(y_i)\right)^2\right\}} \quad (4)$$

3. THE PROPOSED MODEL

This section presents the application of the neutrosophic data analytic hierarchy process (NDAHP), the integration of the weightage of each data component both objectively and subjectively using the maximizing deviation method, followed by the evaluation of the performance of the general insurance companies in Malaysia with respect to their efficiency level via the neutrosophic TOPSIS method.

3.1 Description of problem and parameters

In this section, let $G = \{G_1, G_2, G_3, \ldots G_m\}$ be a set of alternatives that represents Malaysia's general insurance companies that are considered in this study, $C = \{C_1, C_2, \ldots, C_n\}$ be the set of criteria or data attributes that are considered in this study, $O = \{O_1, O_2, \ldots, O_n\}$ and $S = \{S_1, S_2, \ldots, S_n\}$ be the set of objective weightage and subjective weights, respectively for each data attribute in the evaluation of each criteria, and let $\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_n\}$ be the set of integrated weights for each attribute.

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3.2 Setting up the hierarchical model of the study

The concept of neutrosophic data analytic hierarchy process (NDAHP) that was introduced by Tey et al. [22] is used to determine the weightage of each data attribute. The overall framework and visualization of model is important to present a proper understanding of the concepts to the decision maker on the problem that is being studied. In this stage, the core focus of the whole model has to be identified. This is followed by the selection of criteria that are relevant to the objective of the model. Each definition of criteria is studied in depth before it is selected in order to reduce the possibility of involving irrelevant criteria in the computation process which might affect the accuracy and completeness of the results obtained and/or increase the computational complexity and computation time of the decision making process.

Out of all the criterion which are made available, the four data attributes which are selected as the criteria for further evaluation are the net earned premium of the general insurance business, the net investment income, the management expenses and the net commission of the company. Evaluation of efficiency of the general insurance industry involves fuzziness as it involves a lot of subjective judgement. From all the criteria that are available from the sources, these data are selected as these figures are able to justify both the underwriting and operational efficiency of a general insurance business. These four criteria are as explained below:

(i) The net earned premium represents the total amount of premium an insurance business collects from the policyholders or the insured at which that portion is considered "earned" when there no claim request has been made since the policy inception date until the date where the figure is extracted.

(ii) The net investment income justifies the return of investment for the portfolio that the general insurance business has invested in after the deduction of the cost of investment which may include costs such as transaction costs and fund management charges.

(iii) The management expenses represents the operational expenses of running a general insurance company. These include expenses such as office rental, staff wages and directors' fee.

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(iv) The net commission represents the amount of expenses incurred during the distribution of the insurance products such as the commission paid to the agencies and general insurance agents, and remuneration.

The NDAHP framework for this study is illustrated in Figure 3.1.

3.3 Source of data

The data for the criteria that has been selected in Section 3.2 is extracted from the annual statistical report published by the Insurance Services Malaysia Berhad (ISM) which is a registered company with the local insurance regulatory body, the Central Bank of Malaysia (BNM). The statistical year books are published by ISM on a yearly basis based on the audited financial performance reports provided by all the insurance and takaful (Islamic insurance) operators in Malaysia. The extraction of financial figures from the annual report from each company is not preferable due to the difference in the financial reporting periods as different companies have different start and end dates for their financial years. Therefore, using data extracted from the annual statistical reports published by ISM ensures that all of the data that we are using are consistent and in compliance with the regulations of the BNM.

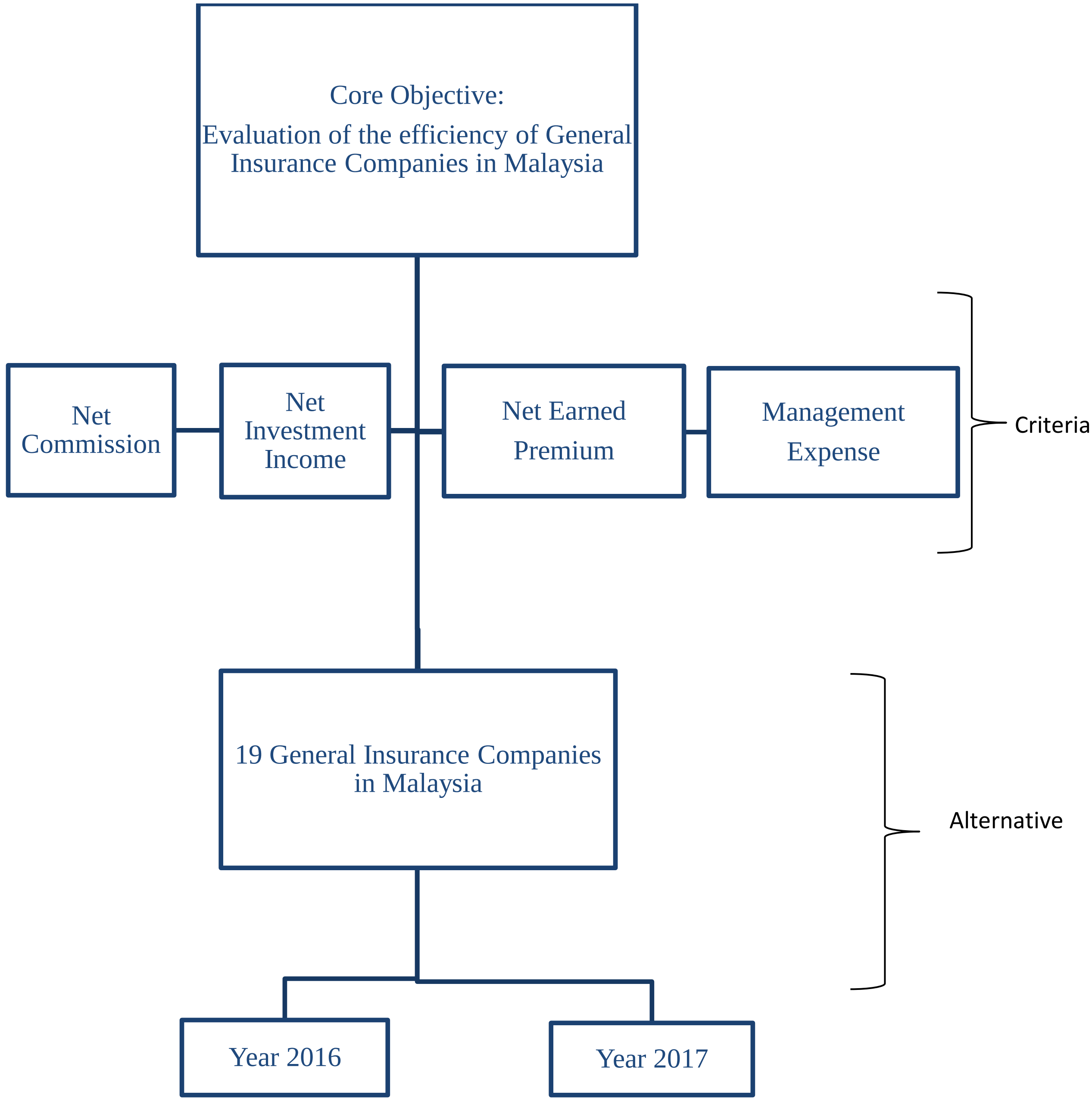

Figure 3.1: The NDAHP framework for this study

3.4 Conversion of crisp data into SvNNs

Before the derivation of weightage for each data attribute, the crisp data obtained from the original source needs to be converted into single-valued neutrosophic numbers (SvNN). In this study, we have used the Vector-Normalization Method (VNM) introduced by Nirmal and Bhatt [34] that is outlined below in Eq. (7) and (8).

The four criteria which have been presented in the previous section can be differentiated into two categories of criteria, namely the beneficial criteria and non-beneficial criteria, respectively. The criteria which can be included in the category of beneficial criteria are those which are relatively better if the value is higher, and the criteria which are better if the value is lower will be grouped into the category of non-beneficial criteria.

In Eq. (5) and (6) below, u_{ij} denotes the crisp numbers for each criterion for each alternative, whereas a_{ij} denotes the fuzzy numbers for each corresponding criteria for each alternative, and $= 1,2, \dots m, j = 1,2, \dots n$.

For beneficial criteria:

$$a_{ij} = \frac{u_{ij}}{\sum_{i=0}^{m} {u_{ij}}^2} \tag{5}$$

For non-beneficial criteria:

$$a_{ij} = 1 - \frac{u_{ij}}{\sum_{i=0}^{m} {u_{ij}}^2} \tag{6}$$

The fuzzy numbers a_{ij} are then converted to SvNNs by applying Eq. (7) and (8), both of which were also introduced by Nirmal and Bhatt [34]:

Beneficial criteria: $(t_{ij}, i_{ij}, f_{ij}) = (a_{ij}, 1 - a_{ij}, 1 - a_{ij})$ (7)

Non-beneficial criteria: $(t_{ij}, i_{ij}, f_{ij}) = (1 - a_{ij}, 1 - a_{ij}, a_{ij})$ (8)

3.5 Attribute weight determination

In the decision-making process, especially in the subject matter dealing with fuzziness, two main types of weight coefficients need to be taken into consideration, namely the objective weight and subjective weight. Objective weight refers to the weightage of the data attribute that is derived through mathematical concepts, and is calculated based on the actual datasets that are used in the study or decision making process. Subjective weights refers to the weightage for each attribute that is assigned by the decision makers based on their expert judgement, preference and individual points of view. In our study, it would not be adequate to use only one type of weight as the evaluation of the efficiency of a company deals with both objective and subjective judgement. Therefore, both the objective weights and subjective weights for each criteria for each attribute will be calculated/obtained, and subsequently used to determine an integrated weight. This is more appropriate in reflecting the level of importance of each data attribute.

The objective weight o_j for each data attribute, j is calculated using Eq. (9) which is based on the modified maximizing deviation method for the SvNS model introduced in [24]:

$$o_j = \frac{\sum_{i=1}^{m}\sum_{k=1}^{m} d(a_{ij}, a_{ij})}{\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} d(a_{ij}, a_{ij})} \tag{9}$$

In Eq. (9), d refers to the normalized Euclidean distance measure given in Eq. (4).

To determine the subjective weight of each data attribute, a short survey was conducted on a group of people with extensive industrial experience in the general insurance industry. The respondents are given a scale of 1-4 to rank the importance of each criterion in the evaluation of the efficiency of general insurance companies'. Here, a score of 1 indicates that a criteria is a least important criteria, whereas a score of 4 indicates that a criteria is a most important criteria. The subjective weight, S for each criterion for each attribute is then computed by using Eq. (10) which is due to [24].

$$s_j = \frac{\sum_{i=0}^{v} K_j}{v} \tag{10}$$

where K_j represents the score given by each respondent and v represents the number of respondents.

The integrated weight, α for each criterion is then calculated by using Eq. (11) which was introduced in [24]:

$$\alpha_j = \frac{o_j s_j}{\sum_{j=1}^{n} o_j s_j} \tag{11}$$

3.6 Identifying the relative ideal solution

In this stage, the relative neutrosophic positive ideal solution (RNPIS) and relative neutrosophic negative ideal solution (RNNIS) are to be determined.

Let the RNPIS and RNNIS be denoted by p^+ and p^- respectively where the derivations are as defined below:

$$p^+ = \left\{\left(\max T_{ij}, \min I_{ij}, \min F_{ij}\right)\middle| j = 1,2 \ldots, n\right\} \tag{12}$$

$$p^- = \left\{\left(\min T_{ij}, \max I_{ij}, \max F_{ij}\right)\middle| j = 1,2 \ldots, n\right\} \tag{13}$$

3.7 Calculating the distance of each alternative and their relative ideal solution

The distance between each element and the RNPIS denoted by ${d_i}^+$, and the distance between each element and the RNNIS denoted by ${d_i}^-$ are then computed using the normalized Euclidean distance formula presented in Eq. (4) of Definition 2.5. In the formula, α_j represents the integrated weight for each criterion.

$${d_i}^+ = \sum_{j=1}^{n} \alpha_j\, d_E^N\left(p_{ij}, p^+\right) \tag{14}$$

$${d_i}^- = \sum_{j=1}^{n} \alpha_j\, d_E^N\left(p_{ij}, p^-\right) \tag{15}$$

3.8 Computing the relative closeness coefficient for each alternative

The optimal alternative can be found by computing the relative closeness coefficient of each alternative denoted by C_i using the formula outlined below which is due to [24].

$$C_i = \frac{{d_i}^-}{max{d_j}^-} - \frac{{d_i}^+}{min{d_j}^+} \tag{16}$$

where $i, j = 1,2, . . , m$.

3.9 Ranking the alternatives based on their closeness coefficient

The general insurance companies are then ranked based on their closeness coefficient. The rule of thumb for this process is the alternative with the maximum or largest closeness coefficient would be the optimal alternative. In the context of our study the optimal alternative is the general insurance company with the highest efficiency among the 19 general insurance companies in Malaysia that were considered in this study.

4. RESULTS

In this section, the level of importance for each data attribute which have been quantified through the integrated weighing mechanism proposed in this study are presented, and followed by the ranking of the efficiency of 19 general insurance companies based on their closeness coefficient. A discussion on the results that are obtained is also included in this section.

4.1 Weightage of the criteria studied in the project

The justification on the level of efficiency of the general insurance businesses is not as easy as extracting the figure directly from the financial reports of the companies. It involves a multitude of complex financial criteria which has to be studied in depth, and the weightage of each criterion will then have to be evaluated based on the objective and subjective weighting methods. For the objective weighting mechanism, the maximizing deviation method was used to objectively evaluate the weightage of the criteria. For the subjective weighting mechanism, a short survey was conducted among professionals in the general insurance industry. The respondents involved in this short survey are all professionals with extensive experience in different areas of the general insurance industry, with 3 of the respondents from general insurance companies and the remaining 2 respondents from actuarial consulting firms. Table 4.1 provides a summary of the objective, subjective and the integrated weights for each criterion from year 2016 to 2017.

Table 4.1: Objective, subjective and integrated weight of each criteria

Criteria	2016			2017		
	Objective weight	Subjective weight	Integrated weight	Objective weight	Subjective weight	Integrated weight
Net Investment Income	0.2656	0.22	0.2374	0.2665	0.22	0.2389
Net Earned Premium	0.2751	0.30	0.3353	0.2740	0.30	0.3350
Management Expense	0.2044	0.34	0.2824	0.2014	0.34	0.2790
Net Commissions	0.2549	0.14	0.1450	0.2580	0.14	0.1472

4.2 Ranking of the general insurance companies based on their level of efficiency

The results of the ranking of the 19 general insurance companies are given in Table 4.2. A rank of 1 indicates that based on the proposed model, the company has the highest level of efficiency compared to the other 18 companies; a rank of 19 indicates that based on the proposed model the company has the lowest level of efficiency compared to the other 18 companies that were studied.

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Table 4.2: Results of the ranking of the 19 general insurance companies using proposed method

Ranking	2016	2017
1	LONPAC	LONPAC
2	P&O	P&O
3	ALLIANZ GENERAL	ALLIANZ GENERAL
4	PROGRESSIVE	TUNE
5	TUNE	PROGRESSIVE
6	MSIG	MPI GENERALI
7	PACIFIC	PACIFIC
8	BERJAYA SOMPO	BERJAYA SOMPO
9	MPI GENERALI	RHB
10	RHB	MSIG
11	ETIQA	TOKIO MARINE
12	GE GENERAL	GE GENERAL
13	QBE	ETIQA
14	AMGENERAL	QBE
15	AXA AFFIN GENERAL	AXA AFFIN GENERAL
16	TOKIO MARINE	AIG
17	ZURICH	AMGENERAL
18	AIG	ZURICH
19	AIA	AIA

4.3 Discussion of results obtained via our proposed method

From Table 4.1, the significant observation is that both the net earned premium and management expenses of a general insurance business have consistently remained as the most important attributes in the evaluation of the level of efficiency of general insurance companies. This information infers that the data figures for these two criteria have material impact on the ranking of the general insurance companies with regards to the level of efficiency.

From Table 4.2, for two consecutive years i.e. from 2016 to 2017, LONPAQ, P&O and ALLIANZ GENERAL have emerged as the top 3 most efficient general insurance companies compared to their peers in the general insurance industry. One of the key reasons for this is because the combined net earned premiums of these general insurance companies' portfolio achieves 23% to 24% out of the whole industry performance. As the net earned premium has been identified as the most important evaluation criteria from our objective and subjective weighting mechanisms,

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the high net earned premium figures of these companies have contributed to the high overall ranking of these 3 companies.

Based on our proposed model, AIA had consistently shown the lowest efficiency for the two observed years. This could possibly be due to their consistently low net earned premium generated and a low net investment income achieved. In the general insurance industry, a low net earned premium can be justified by two main factors, which are due to high claims observed from their underwriting portfolio, or because the business underwritten is relatively smaller compared to the other competitors. Low net investment income could be due the company having invested in less risky investment portfolios which typically yields lower returns, or because the company might have invested a significant amount of funds in the long-term investment tools such as bonds for which the return of investment is not likely to be observed in the short-term period, and therefore the returns are not recognized or captured in their annual financial reports.

Another important observation on the movement in the rankings of the 19 companies is that TOKIO MARINE had risen by 5 places from being ranked at 16 in 2016 to being ranked at 11 in 2017 due to their higher growth of net earned premium which was 2.26% compared to the overall industry growth of 1.6%.

From Table 4.2, we can infer that our proposed fuzzy model yields a consistent output, at which the fluctuation of the ranking of the companies is not considered extremely volatile. There are only a few companies which showed some significant changes in their year to year rankings due to their better performance in the beneficial criteria compared to their peers and the performance of the industry as a whole.

4.4 Comparative studies using the DEA and SFA methods

In existing literature, the evaluation of efficiency of insurance companies is mostly focused on two types of approaches that are methods based on parametric model and non-parametric model. In the parametric model, the most commonly used methods are the Stochastic Frontier Approach (SFA), Distribution Free Approach (DFA) and Thick Frontier Approach (TFA). In our study, we have the model of Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) as a benchmark of comparison.

DEA is a non-parametric method which evaluates the efficiency of objects based on the assumptions of constant returns to scale and variable returns to scale. The DEA method was first introduced by Charnes, Cooper and Rhodes in 1994 [35]. DEA is a non-parametric technique to evaluate productive efficiency with numerous inputs and outputs. DEA generates an efficient frontier which is developed by decision-making units (DMUs) that shows the best performance. This approach has a basic assumption that there is a linear assumption between the observed input combinations on an isoquant [36]. It determines the DMU's relative efficiency that has multiple inputs and outputs [37]. The DEA works by categorizing the actual financial data into two categories, which are output and input, similar to the concept included in our suggested fuzzy model which have differentiated the data into beneficial and non- beneficial components. However, the DEA methodology is completely objective, and the efficiency score can only be derived if the data from the previous year is available. The most important component in the DEA, which is the Malmquist productivity index is evaluated based on a company's performance from the previous year and the changes in the productivity frontier which is different from our suggested fuzzy model that actually evaluates the efficiency of a company based on individual performance and the industry's overall performance, irrespective and independent of the performance of the company in the previous year [38].

The SFA is a parametric method where a functional form is assumed and random factors are introduced to fit in the production function and enable the frontier to shift around the fitted function for companies [39]. One of the key process of this method is the composition of error term. For error term, it is subdivided into one-sided error term which is used to measure the firm-specific inefficiency and two-sided error term which shows the random fluctuations. Here, the two-sided error term is identically and independently distributed among the firms.

As the DEA is a non-parametric method, the risk of imposing the wrong functional form is avoided. SFA requires assumptions about the form of the relationship between the inputs and outputs, and the distribution of the random error and inefficiency terms. Due to the nature of the SFA to incorporate the error term or noise component in the evaluation, the DEA appears to be sensitive to outliers as it is a deterministic approach and assumes no random noise in the data. A more detailed and comprehensive analysis of the comparison of the DEA and SFA methods, and our proposed models will be presented in Section 4.5.

In our study, the computer software which we have used to study the results based on the DEA and SFA model are the DEAP Version 2.1 and FRONTIER Version 4.1. The results of the ranking of the efficiency of the 19 general insurance companies based on the DEA and SFA approaches are presented in the Table 4.3 and Table 4.4, respectively.

Table 4.3: Results of the ranking of the 19 general insurance companies using the DEA approach

Ranking	**2016**	**2017**
1	ETIQA	PACIFIC
2	PACIFIC	TUNE
3	RHB	TOKIO MARINE
4	AXA AFFIN GENERAL	QBE
5	GE GENERAL	MPI GENERALI
6	LONPAC	RHB
7	PROGRESSIVE	AIG
8	MSIG	ALLIANZ GENERAL
9	MPI GENERALI	LONPAC
10	ZURICH	PROGRESSIVE
11	ALLIANZ GENERAL	BERJAYA SOMPO
12	AIG	MSIG
13	QBE	GE GENERAL
14	BERJAYA SOMPO	P&O
15	AMGENERAL	AIA
16	P&O	AXA AFFIN GENERAL
17	TOKIO MARINE	ZURICH
18	TUNE	AMGENERAL
19	AIA	ETIQA

Table 4.4: Results of the ranking of the 19 general insurance companies using the SFA approach

Ranking	2016	2017
1	LONPAC	LONPAC
2	MSIG	MSIG
3	ALLIANZ GENERAL	ALLIANZ GENERAL
4	BERJAYA SOMPO	BERJAYA SOMPO
5	P&O	P&O
6	MPI GENERALI	MPI GENERALI
7	TUNE	TUNE
8	AXA AFFIN GENERAL	AXA AFFIN GENERAL
9	QBE	QBE
10	TOKIO MARINE	TOKIO MARINE
11	RHB	RHB
12	PACIFIC	PACIFIC
13	AMGENERAL	AMGENERAL
14	PROGRESSIVE	PROGRESSIVE
15	GE GENERAL	GE GENERAL
16	AIA	AIA
17	ETIQA	ETIQA
18	ZURICH	ZURICH
19	AIG	AIG

As observed from Table 4.3 and Table 4.4, both the DEA and SFA approaches yield inconsistent results which is due to differences in the methodology that is used in both of these approaches. The DEA approach being a deterministic and non-parametric model does not include an error component in the evaluation. The SFA has an error component which is commonly known as noise included in the assumption of functional form in the evaluation process.

The rankings obtained via the SFA method for the top three most efficient general insurance companies are almost the same with the rankings obtained via our proposed method, whereas the results obtained via the DEA method is very different from the other two methods. The first and third ranked companies according to the SFA method and our method are LONPAC and Allianz General, respectively. This difference in results may be due to several reasons.

Both the DEA and SFA methods do not have any mechanism to incorporate the opinions and inputs of industry experts in the decision making process. Thus, these methods are not able to take the subjective weights into consideration in the decision making process, and hence the results

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obtained is less reliable compared to the results obtained via our proposed method that takes the integrated weights into consideration. Moreover, although the DEA and SFA can assume multiple inputs and outputs in the analysis and decision making process, both of these approaches do not take into consideration the level of importance of each factor or criteria that contributes to the efficiency of the organizations. The failure of the DEA and SFA methods in determining the importance of each criteria in the evaluation of the efficiency of a company means that both of these approaches are entirely based on relative comparison of the criteria, making the results obtained via these methods less reliable compared to the results obtained via our proposed method. However, in the industry, it is pertinent to determine the level of importance of each factor or criteria to enable the company to implement the necessary strategies to improve the overall efficiency of the companies. These prove the reliability and accuracy of the results from our proposed method, and by extension the superiority of our proposed method compared to the DEA and SFA methods in evaluating the efficiency of general insurance companies.

5. CONCLUSION AND REMARKS

The concluding remarks and the significant contributions of this paper are summarized below:

(i) A novel integrated model for the single- valued neutrosophic set (SVNS) model was introduced. The key operations from the NDAHP method was used to convert the raw data which comprised of the net earned premium, net investment income, management expenses and net commissions for 19 selected general insurance companies over the year 2016 to 2017 into single-valued neutrosophic numbers (SVNN). The maximizing deviation method was then applied to quantify the objective weight of the criteria before integrating it with the subjective weight which was derived from the evaluation of five selected experienced professionals from the general insurance industry. The companies are then ranked to determine their level of efficiency via the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

(ii) The key components extracted from the NDAHP method to convert the crisp values in the raw numerical data to SVNNs are able to differentiate between the beneficial criteria and non-beneficial criteria. This key feature has justified that our analytical procedure is indeed objective, and will not be impacted by the differing opinions of different decision makers in which subjectivity and biasness would be a major concern. As the concept of efficiency of a business does involves a certain level of subjectivity, the subjective weighting mechanism was also introduced in our study, and this was integrated with the objective weights obtained using the maximizing deviation method. The integration of the objective and subjective weighting mechanisms, and the integration of methods proposed in this project makes the analysis more comprehensive compared to most of the existing research on the study of efficiency of general insurance companies as our proposed method is able to handle actual datasets that are objective with expert opinions which are subjective and biased in an effective manner. Furthermore, as the concept of efficiency of general insurance companies is in itself a very subjective and vague concept, it is most appropriate to use fuzzy tools and decision making methods to study this concept in a fuzzy environment.

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