AN INTERVAL TYPE 2 FUZZY EVIDENTIAL REASONING APPROACH TO PERSONNEL RECRUITMENT

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CERTIFICATION

I hereby declare that the contained report on "An Interval Type 2 fuzzy Evidential Reasoning Approach to Personnel Recruitment" was researched, and the results thoroughly analyzed, under the supervision of the project supervisor and approved having satisfied the partial requirements for the award of Masters of Science in Management Information Systems, Covenant University, Ota.

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DEDICATION

This dissertation is dedicated to my loving parents Mr & Mrs Funso Kehinde Olawoye, for all the love, patience, kindness and support throughout my stay in school.

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I want to thank the Lord Almighty, who gave me the grace and strength to walk this path, pulled me up when I was down, gave me hope when there was no hope and walked with me when I was alone, for without His grace and blessings, this study would not have been possible.

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ABSTRACT

Recruitment process is a procedure of selecting an ideal candidate amongst different applicants who suit the qualifications required by the given institution in the best way. Due to the multi criteria nature of the recruitment process, it involves contradictory, numerous and incommensurable criteria that are based on quantitative and qualitative measurements. Quantitative criteria evaluation are not always dependent on the judgement of the expert, they are expressed in either monetary terms or engineering measurements, meanwhile qualitative criteria evaluation depend on the subjective judgement of the decision maker, human evaluation which is often characterized with subjectivity and uncertainties in decision making. Given the uncertain, ambiguous, and vague nature of recruitment process there is need for an applicable methodology that could resolve various inherent uncertainties of human evaluation during the decision making process. This work thus proposes an interval type 2 fuzzy evidential reasoning

approach to recruitment process. The approach is in three phases; in the first phase in order to capture word uncertainty an interval type 2(IT2) fuzzy set Hao and Mendel Approach (HMA) is proposed to model the qualification requirement for recruitment process. This approach will cater for both intra and inter uncertainty in decision makers' judgments and demonstrates agreements by all subjects (decision makers) for the regular overlap of subject data intervals and the manner in which data intervals are collectively classified into their respective footprint of uncertainty. In the second phase the Interval type 2 fuzzy Analytical hierarchical process was employed as the weighting model to determine the weight of each criterion gotten from the decision makers. In the third phase the interval type 2 fuzzy was hybridized with the ranking evidential reasoning algorithm to evaluate each applicant to determine their final score in order to choose the most ideal candidate for recruitment. The implementation tool for phase two and three is Java programming language. Application of this proposed approach in recruitment process will resolve both intra and inter uncertainty in decision maker's judgement and give room for consistent ranking even in place of incomplete requirement.

CHAPTER ONE

INTRODUCTION

• BACKGROUND INFORMATION

Modern organizations face great challenges due to the increasing competition in the global market, making the future survival of companies depends mainly on the contribution of their personnel to companies; so there is every need to employ qualified personnel that would be of benefit to the company. Recruitment is an act of decision making that cut across the span of every organization. This can be seen as a process of making choices by identifying a decision, gathering information towards choosing optimal decision based on provided decision information under the given environment in midst of multiple alternatives (Dursun and Karsak, 2010). Recruitment problems are extremely complex and multi-dimensional nature. It also involves human judgment, cognitive process, multi and different attributes. Due to the nature of this problem there is a need for an approach that can successfully handles its complexity, multi-dimensional nature and subjectivity in human judgment.

Multi criteria decision making (MCDM) is defined as a field that helps decision makers choose optimal decision in the presence of numerous, incommensurable and contradictory criteria. MCDM problem solving methods have done well in resolving different decision making problems such as sorting problem (Wu and Mendel, 2007), choice selection, ranking problem etc.(Bozdag et al, 2003; Gungor et al; 2009; Can'os et al, 2014). MCDM support both qualitative and quantitative evaluation of alternatives (Mardani et al., 2015). Quantitative criteria evaluation are not always dependent on the judgement of the expert, they are expressed in either monetary terms or engineering measurements, meanwhile qualitative criteria evaluation depend on the subjective judgement of the decision maker(Mulliner et al., 2016).

For assessment, reasoning and decision making, the use of natural language is often employed in order to articulate thinking and also for general expression. The linguistic terms used in the evaluation process could mean different things to different people and much influenced by subjectivity of the decision makers. Due to this, words might not have a clear and well-defined meaning (Mardani et al., 2015). This is responsible for high level of uncertainties in qualitative measurements of criteria and further establishes inconsistency in the preference elicitation process from the decision makers. Despite all these inconsistencies, subjective evaluation of alternatives by the decision makers are still much more required during the decision making process. So many MCDM methods have been proposed and have been gaining their various applicability in literature. Recently, Evidential Reasoning (ER) approach which was developed to solve MCDM problems has started gaining grounds in the MCDM area (Yang and Xu, 2000; Yang, 2001; Yang and Singh, 1994). When compared to alternative MCDM methods, the ER approach has a lot of advantages in its ability to handle what all other MCDM methods cannot handle. For instance, ER uses the extended decision matrix in describing the MCDM problem by providing a distributed assessment of the alternatives to be evaluated through the use of a belief structure(Wang et al., 2006), which in turn provides the decision maker with a more panoramic view about the diversity of the performance of an alternative, this is one of the advantages that the ER method has over other existing MCDM methods.

Due to the fact that the human evaluation is involved recruitment problem, Evidential Reasoning approach cannot accurately deal with the kind of uncertainties it involves. Thus, the inadequacies of Evidential reasoning approach can be handled by introducing the fuzzy logic system concept into the former. Zadeh (1965) proposed the Type 1 fuzzy set concept which captures intra-uncertainty in the decision making process, intra-uncertainty means "the uncertainty a person has about a word", this uncertainty is always associated with the knowledge Engineer who creates the fuzzy expression for every word (qualitative measures) within the interval [0, 1] which then restricted the construction of the type-1 fuzzy sets for each word to only the opinion of the knowledge engineer (Doctor et al., 2016). The major disadvantage of this Type 1 Fuzzy set is that all the decision makers' opinions are not being involved in the decision making processes. Type-1 fuzzy set has been widely applied in literature with the incorporation of MCDM methods to estimate a desirable recommendation for the decision making situations (Rouyendegh and Erkan, 2013; Kabak et al., 2012; Chaghooshia et al., 2016; Kusumawardani and Agintiara, 2015). Despite the uncertainties that are being modelled by type-1 fuzzy set, it cannot accurately reflect the linguistic uncertainties of different decision makers in the decision making process which was earlier mentioned.

However, In order to curb the weakness of type-1 fuzzy set, type 2 fuzzy set was proposed by Mendel (2008). This is to model both intra-uncertainties and inter-uncertainties in the decision making process. Inter-uncertainty on the other hand means the "*uncertainty that captures a group of people's intra-uncertainties about a word*" (Mendel and Liu, 2008), but due to the computational requirements of the type-2 fuzzy, the *interval type-2 fuzzy set* was suggested and has recently started gaining its various applicability in literature. The interval type-2 fuzzy set characterizes its members as type-1 fuzzy set membership grades and can accommodate situations where precisely defined membership function may not be feasible for a fuzzy set. This makes interval type-2 fuzzy suitable for capturing linguistic uncertainties where the same word has different connotations to different people. To this effect, in this study an interval type 2 fuzzy with evidential reasoning approach is proposed to resolve recruitment problems.

1.2 STATEMENT OF THE PROBLEM

Recruitment problem is often characterized by the presence of multiple and conflicting criteria. The decisions that are made when evaluation of a set of criteria performance/importance is required by decision makers can be qualitative in nature. The qualitative assessment is represented using linguistic terms/scores/grades by the decision makers in the evaluation of alternatives in the recruitment process. This is subjective and varies due to the fact that words mean different things to different people. Hence, the degree of uncertainties and imprecision becomes inevitable. Despite the high level of uncertainties involved in subjective evaluation of applicants, the classical MCDM approach represents the words used in assessment by the decision makers as exact numerical values. This is done without consideration of the imprecision, ignorance and uncertainties on the part of the decision makers involved in making recommendations or decision making process. Due to this, the following problems are observed.

- Inconsistent judgments from modelling of the linguistic terms using the type-1 fuzzy that capture only the intra-uncertainties of the decision maker (Erdogan et al., 2014).
- Lack of an elicitation methodology in establishing the footprint of uncertainty to capture the imprecision and high level of uncertainties on the part of the decision makers when ranking alternatives (Wu et al., 2012).
- Rank reversal problem associated with other MCDM methods due to the usage of

comparative matrix for evaluating alternatives in the evaluation process (Xu, 2012).

1.3 AIM AND OBJECTIVES

The aim of this research is to propose an Interval Type 2 Evidential Reasoning Approach to Personnel Recruitment problem.

The aim would be realized from the following objectives.

- To gather recruitment requirements, identify alternatives and formulate the recruitment process into MCDM problem.
- To introduce interval type 2 fuzzy set into the ER approach to recruitment process.
- To evaluate the proposed IT2ER approach.

1.4 RESEARCH METHODOLOGY

In achieving the first objective, requirements were elicited through one-on-one interaction with the human resource department of the academic institution considered. The recruitment problem was then formulated into MCDM problem by identifying the number of alternatives to be evaluated, the number of recruitment requirement to be used as criteria for ranking alternatives.

In achieving the second objective, five major steps are carried out as thus:

Step 1: Online questionnaires were used for collection of data intervals defined by the human resource department of the academic institution. Linguistic terms like {Exactly important, slightly important, fairly important, strongly important and absolutely important} {very poor, poor, average, good, very good, low, very low, average, high, very high} were used. This is needed for polling opinions about the perceptions of people.

Step 2: Interval type 2 Fuzzy numbers were constructed from the data interval collected from step 1 using the interval type 2 fuzzy set through the Hao and Mendel approach which comprises of the data part and the fuzzy set part (Hao and Mendel, 2016).

Step 3: The aggregated FOU is typed reduced by computing the centroid (measure of uncertainty) of the IT2FS using the Enhanced Kernik Mendel (EKM) approach. The result is an interval valued set which is defuzzified by taking the average of the interval's end point.

Step 4: The new interval type 2 fuzzy AHP approach for weight generation was used whereby experts give the importance they attach to each recruitment requirement, the already established type 2 fuzzy parameter for each word described in step 1 gotten from using the Hao and Mendel approach from step 2 is used in representing the decision makers' judgement.

Step 5: Then finally the proposed interval type 2 fuzzy ER approach for ranking of alternatives was incorporated to evaluate and rank the applicants accordingly.

In achieving objective 3, evaluation of the new Interval Type 2 Fuzzy Evidential Reasoning approach was done with the use of Intelligent Decision System (IDS).

1.5 SIGNIFICANCE OF STUDY

- This research work will create an avenue to improve decisions in an environment of uncertainty.
- This study will enhance organizations decision making in selecting the best fit candidate thereby reducing the overall recruitment time cycle, in order to reduce cost.
- This study will help organizations provide objective solutions when the personal sentiments of the decision-maker come into play.

1.6 SCOPE AND LIMITATION OF STUDY

The scope of this study is limited to the evaluation of applicants for recruitment in academic institutions because the recruitment requirements used is restricted to selection of applicants in an academic environment.

1.7 OUTLINE OF THESIS

The rest of the project follows with an extensive review of literature. The system methodology and the formulation of the model are the highlights of chapter Three. The experimental results and the evaluation of the ER Approach are the contents of chapter four. The project is concluded in chapter five where the platforms for future research work are highlighted.

CHAPTER 2

LITERATURE REVIEW

2.1 PERSONNEL RECRUITMENT AS A MCDM PROBLEM

In the global market, modern organizations face high levels of competition. In the wake of increasingly competitive world market the future survival of most companies, depends mostly on the dedication of their personnel to companies. Personnel recruitment is a procedure of selecting an ideal candidate amongst different applicants who suits the qualifications required by the given company in the best way (Dursun and Karsak, 2010). It is one of the levels of the Human Resource Management of an organization. Among the features of the human resource which are identifying, evaluating, hiring, motivating, educating and developing employees to reap organizational targets. Thus, an effective personnel selection method is needed to assist organizations pick the best person among alternatives for a given task.

Personnel recruitment is an extremely complex problem just like every other decision problem because it is characterized by multiple, incommensurable and conflicting criteria. Many studies have been conducted to assist companies resolve the problem of employees selection and so a lot of strategies have been developed, similarly further development of useful methods are nonetheless still being developed. There have also been so many techniques that have been used during the process such as application paperwork, interview and so on. MCDM methods have found applicability in decision making problems whilst these techniques come to a conclusion on the use of subjective judgements of the experts which makes the accuracy of the end result questionable (Zhang and Liu, 2011). MCDM methods are models/methods that analyze decision makers' preferences of criteria concurrently in order to arrive at a decision out of all alternatives concerned (Turskis and Zavadskas, 2010).

The issue of subjectivity can have a negative impact on the quality of the selection process thus leading to a wrong selection if not properly controlled (Daramola et al., 2010). Thus, due to the multi-criteria nature of the problem, MCDM methods incorporated with fuzzy logic has the capability of coping with it (Behera and Sarkar, 2013). The fuzzy set theory has projected by Zadeh is an important tool that incorporates imprecise judgements by allowing the utilization of words when rating alternatives during the selection process due to the fact that the human form of expression is always in words as it is in many decision problems(Zadeh,1965).

Therefore, the use of MCDM method by many academicians and researchers has now become one of the most popular and important techniques for decision making (Aydin et al., 2015).

2.2 MULTICRITERIA DECISION MAKING (MCDM)

Decision making is an inevitable aspect of human existence; it deals with how to make the optimal decision in the midst of multiple alternatives, this can be seen as a process of making choices by identifying a decision, gathering information towards choosing optimal decision based on provided decision information in a given situation. It has brought about improvement in various disciplines which include operations research, management science, computer science, and statistics, in order to help people in making an optimal choice in a given situation (Zardari et al., 2015).

Accordingly, MCDM has found suitability in the fields of decision making by researchers over the years (Muliner et al., 2016; Akdag et al., 2014; Ghorabee, 2016). Multi criteria decision making which is a field which aims to helping decision makers make decisions in the presence of numerous, incommensurable and contradictory criteria when evaluating alternatives (Kumru and Kumru, 2013). Hence, their demonstrations of practicability of solving problems in terms of its classification of criteria needed in evaluating a problem at hand are emphasized.

MCDM methods are models/methods that analyze decision makers' preferences of criteria concurrently in order to arrive at a decision out of all alternatives concerned (Turskis and Zavadskas, 2010), in other words, with the rapid increase of multi criteria decision methods and their subsequent modifications, the goal of MCDM is still to help decision makers make choices, rank alternatives to get best option, description, classification, sorting of alternatives into different categories and in a majority of cases an order of alternatives, from the most preferred to the least preferred option (Mulliner et al., 2016). Several methods have been developed in the past to solve these multi criteria problems, the number of MCDM related publications are steadily increasing also. This development is due to the competence and productivity of researchers and also the discovery of different types of problem in our everyday life. Each of the methods has a unique way of helping decision makers choose among a discrete set of alternatives, which is achieved on the level of impact each alternatives have on a set of criteria and thereby on the overall preference of each decision maker (Triantaphyllou, 2000). In literature, many terms have been used for MCDM and these terms are given as below: Multi-Criteria Decision Analysis (MCDA), Multi-Objective Decision Making (MODM), Multi-Attributes Decision Making (MADM), Multi-Dimensions Decision-Making (MDDM).

Despite the numerous types of MCDM methods available, no single method is considered the most suitable for any decision- making situation (Guitouni and Martel, 1998, Roy, 1985). Thus, the selection of a suitable MCDM method is not known to be a simple task and also a substantial consideration must be given to any choice of method (Mulliner et al., 2016). However, Guitouni and Martel (1998) have developed some guidelines which can still be helpful when confronted with multiple choices of MCDM method.

2.3 HOW TO SELECT AN APPROPRIATE MCDM METHOD

The importance of every MCDM method is to make good recommendations (Figueira et al., 2005; Guitouni and Martel, 1998). However, researchers sometimes use methods that they are conversant with without the knowledge of why it is being used to model that specific problem. The necessary prerequisite for being in the position to choose an MCDM method is to deploy a methodology of how to choose an appropriate MCDM method. According to Guitouni and Martel (1998), this framework can be viewed as shown.

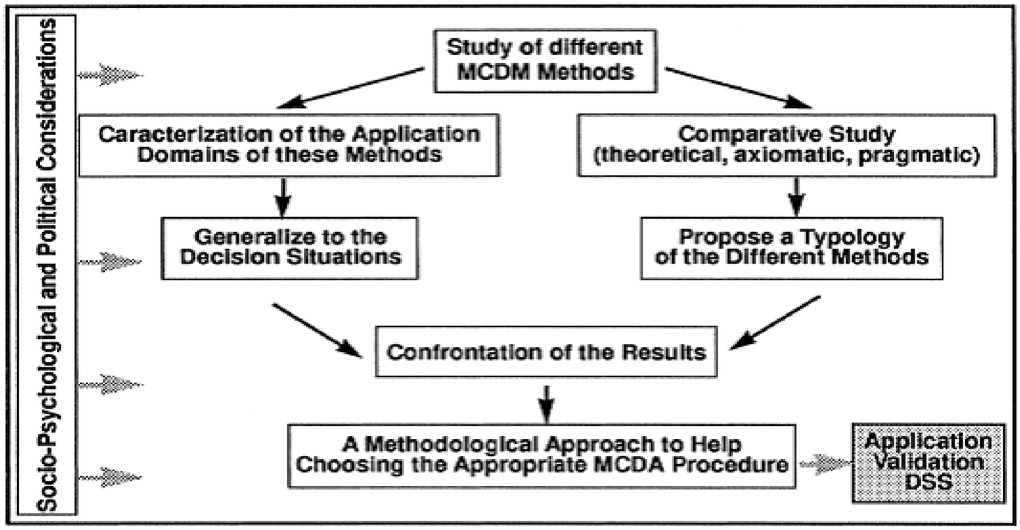


Figure 2.1: Methodology in selecting an appropriate Mcdm Method (Guitouni and Martel, 1998)

The following seven steps show the path in choosing an appropriate MCDM method as described above.

Guideline G1: Identify the decision makers that are involved in the evaluation process. If the situation involves many decision makers (judges), then a group decision making method should be considered.

Guideline G2: Examining the decision maker's suitability in terms of preference modelling for alternatives i.e. the decision maker's way of thinking of how alternatives should be preferred. It could be in terms of pair wise comparisons between alternatives or tradeoffs between criteria in the final aggregation. If the decision maker prefers anyone of them, it should be factored into consideration.

Guideline G3: Identify the type of decision making problem the decision maker is aiming to solve, whether it is a ranking of alternatives or choice problem, the best fit decision making model is then used.

Guideline G4: Selection of the appropriate MADM method that can accommodate or capture the kind of input information and for which it will be easy for the decision maker to put the required information.

Guideline G5: The analyst needs to confirm the aggregation procedure of the decision making situation whether if the decision maker will allow compensatory procedure or a non-compensatory procedure. Then a suitable MADM method can be decided.

Guideline G6: The MADM method should be verified to be able to work for that kind of problem and if not, another MADM should be chosen.

Guideline G7: The MADM method implementation availability to the decision support system being modelled. If the MADM method is not implemented, it is recommended to develop user friendly system for the decision maker.

2.4 CATEGORIES OF DECISION MAKING PROBLEMS

In our everyday life we face a plethora of different decisions. However, these main types of decision have been identified which are based on the following:

- The choice problem: This arises when the ultimate aim is to choose the best alternative/option or lessen to a subset of almost similar good alternatives. For example, a manager selecting the right person for a particular project.

- The sorting problem: Here, the decision making processes involve the ordering or regrouping of options into their respective pre-defined categories. The target is to group options with similar characteristics/behaviours for predictive or descriptive motives, for example, the classification of papers into three different categories such as "reject", "revise" or "accept" by a journal with the aid of reviewers (Wu and Mendel, 2007).

- The ranking problem: This decision making problem arises when options are supposed to be aligned in the order of the best to the least effective by means of scores or 'pair wise comparison of criteria for evaluating the options, for example the ranking of universities based on their quality of service.

- The description problem: This decision making problem exhibits the characteristics involved when options and their consequences are supposed to be described.

- Elimination problem: Bana et al., (2005) proposed the elimination problem, particular branch of the sorting problem.

- Design problem. The aim is to identify and develop a new alternative/action based on the objectives and goals of the decision maker.

2.5 OVERVIEW OF CLASSIFICATION OF MULTI-CRITERIA DECISION MAKING METHODS

According to the literature, MCDM can be broadly classified into two main categories (Multiple Attribute Decision Making (MADM) and Multiple Objective Decision Making (MODM)(Tzeng and Huang, 2013; Zavadskas et al., 2014). MADM problems are distinguished from MODM problems; MADM belongs to a class of methods that solve decision making problems that are discrete in nature (Lu et al., 2007). The problem space is finite and the alternatives that are being evaluated are countable (Mulliner et al., 2015;

Tzeng and Huang, 2013). This approach entails the selection of the best alternative in a ranking order by evaluating the conflicting criteria of the decision makers across all pre-defined alternatives. The MODM approach on the other hand encompasses methods that deal with decision making problems that are non-deterministic in nature, whereby decision space is continuous and alternatives are infinite. This characterizes the effect that alternatives are not pre-determined and MODM methods design alternatives from the conflicting objectives, constraints, objective functions of the decision makers and plans the most optimal solution. The MODM accommodates the consideration for decision makers to have various parameters specific to the decision making problem at a point in time in achieving their goals.

MADM methods have gained applicability in literature and each method has its own functions and characteristics. There are many ways MADM method can be classified; one way is to classify them according to the type of the data they use. Namely, deterministic, stochastic, or fuzzy MADM methods, another way used in literature of classifying MADM methods is according to the number of decision makers involved in the decision process. That is, we can have single decision making MADM methods and group decision making MADM methods, MADM methods are also further classified according to the type of information and the important features of the information.

According to (Liou and Tzeng, 2012), MADM methods can also be categorised into three classes such as the selection or evaluating models (e.g.,Fuzzy Interpretive Structuring Modelling(ISM), Fuzzy Cognitive Map (FCM), Linear Structure Equation Models (LISEM, or called ‘‘SEM’’), Formal Concept Analysis, and Input–Output Analysis), weighting models (Fuzzy Analytical Network Process(ANP), Fuzzy Analytical Hierarchical Process (AHP), Entropy Measure, Neural Network Weighting, and Dynamic Weighting), and normalizing models (additive types: Technique of Order of Preference by Similarity to Ideal Solution(TOPSIS), Simple Additive Weighting(SAW), Elimination et Chroix Traduisant la Realite(ELECTRE), Preference Ranking Organization Method for Enrichment Evaluation(PROMETHEE), and Grey Relation and non-additive types: Fuzzy Integral Neural Network Plus Fuzzy).

According to (Guitouni and Martel, 1998) MADM can also be classified based on operational dimensions of criteria as: Elementary methods, Single synthesizing and Outranking methods as shown in Figure 2.2. However, MADM methods can be further classified into many categories but previous classification are the most used in literature.

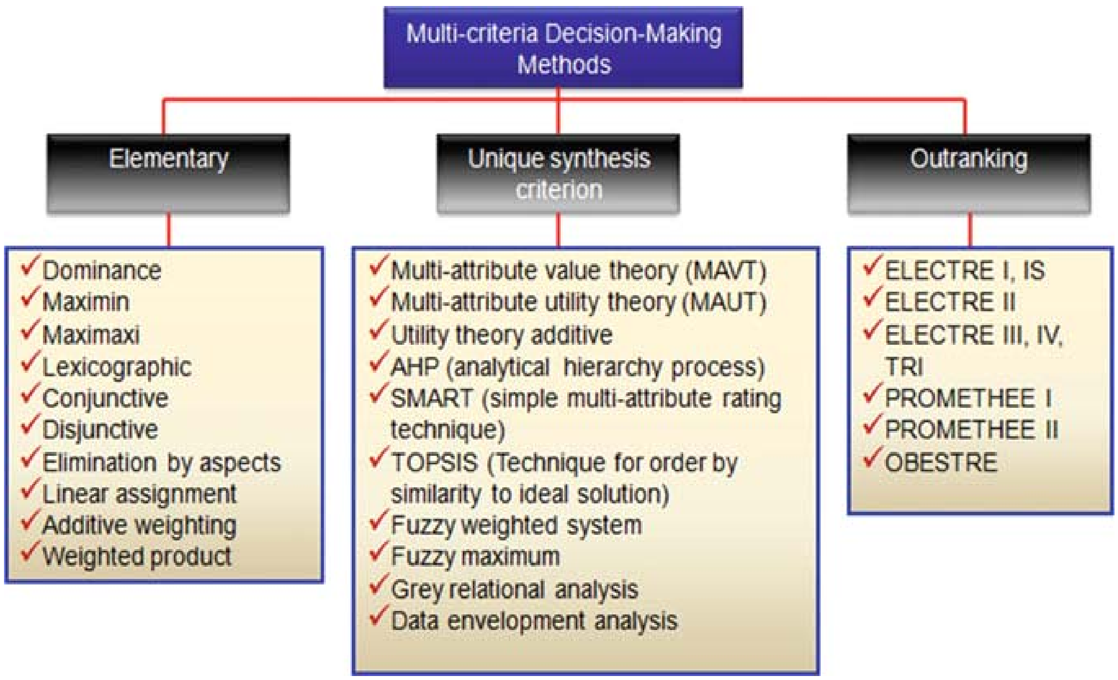


Figure 2.2: Classification of Mcdm Methods (Guitouni and Martel, 1998)

2.6 THE ROLE OF WEIGHTS IN MCDM METHODS

Weight play an important role in every MCDM method, it has been known to help most MCDM methods in their aggregation process in measuring the overall preference of all alternatives involved. Also because of the different types of aggregation rules in literature, MCDM therefore use these weights in different ways.

2.7 CLASSIFICATION OF WEIGHTING METHODS

Different weighting techniques have been developed in literature to help decision makers assign weights to criteria (Pöyhönen and Hämäläinen, 2001; Stewart, 1992). It has been known that the easiest way to assign weights to criteria is by using the ‘equal weights method’ that is distributing weights to criteria equally. This ‘Equal weights method’ has gained applicability in many decision-making problems (Wang et al., 2009).

Weight assignment in MCDM is an important step as the overall result of each alternative depends solely on such weight (Tervonen et al*.,* 2009). It has also been stated that assigning weight is the most difficult task, weight assignment has therefore been classified into three categories (Wang et al., 2009) namely: subjective weighting method, objective weighting method and combination weighting method (subjective weighting method combined with objective weighting method). In subjective weighting methods, determination of criteria weight is often based on the utility preferences of the decision-makers. This method of weight generation gives a broader view and explains the elicitation process more clearly. This makes it the most used for MCDM. They include Simple Multi-Attribute Rating Technique (SMART), AHP, SIMOS and the Delphi method.

Different from subjective weight method, in objective weight method, analysis of initial data is often based on the use of mathematical method. In this type of weight generation method; procedures are unclear and includes methods such as least mean square (LMS), minmax deviation, entropy, TOPSIS and multi-objective optimization. The combinations of subjective and objective weighting methods are a hybrid of methods that include multiplication and additive synthesis. This figure below gives a clear understanding of the classification of the different weighting methods in literature.

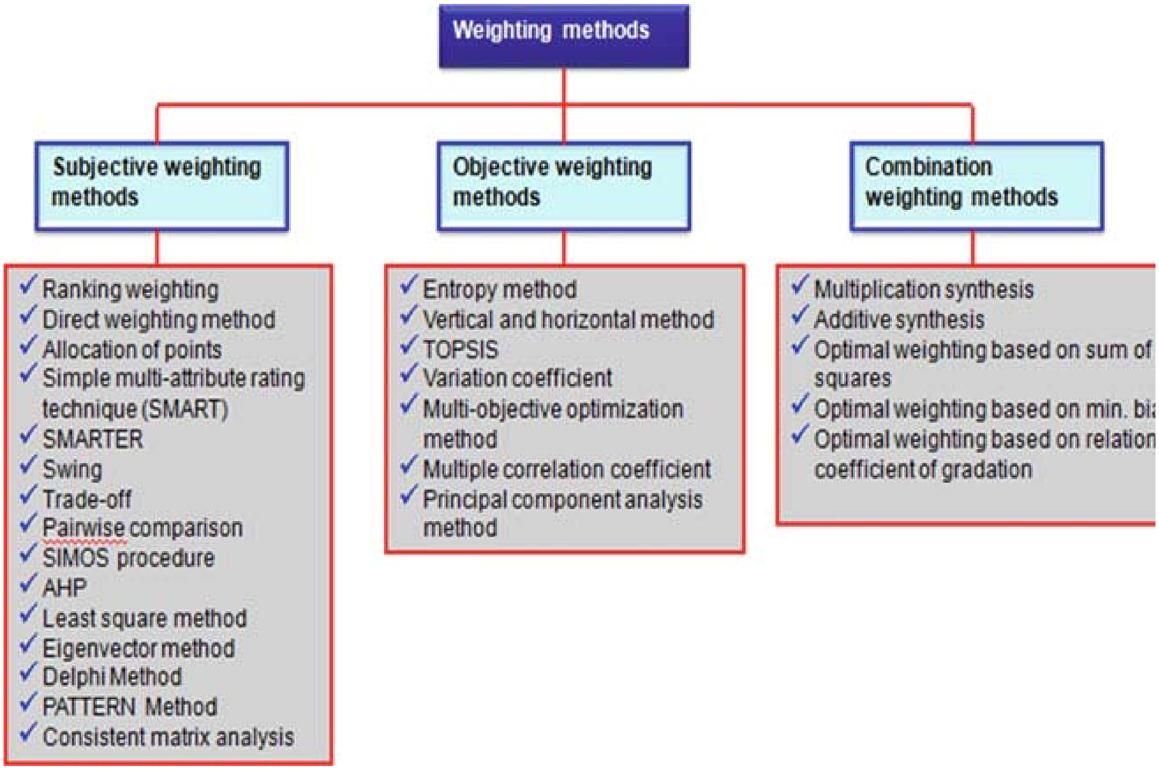


Figure 2.3: Classification of Weighting Methods (Pöyhönen and Hamalainen, 2001)

2.8 POPULAR SUBJECTIVE WEIGHTING METHODS

According to literature, subjective weighting methods are the most popular weighting method used. According to Hobbs (1980) he states that when different weighting methods are used, the result produces different set of criteria weights and also the final results of every multi-criteria decision-making method are sensitive to criteria weights.

Therefore, it is very important to lay emphasis on choosing the best weighting method for solving a multi-criteria decision problem. Here are some of the most popular subjective weighting method

- **DIRECT RATING**

In this weighing technique, the importance of criteria are represented by the use of scoring method which is similar to scales used in Likert-scale questionnaire. In direct rating a decision maker's response are not limited as it is in the fixed point scoring method and this method also gives the opportunity to change the importance of a criterion without altering that of another criterion.

- **RANKING METHOD**

This weighting technique is known as the easiest approach for weight generation. It gives opportunity for criteria to be ranked in order of importance, which is from most important to the least. It uses three main methods in generating criteria:

1. Rank sum,
2. Rank reciprocal and
3. The rank exponent method

In rank sum, the weighted value of each rank position is obtained and normalized by calculating the sum of all the weight. The other method which is the rank reciprocal weights is derived by reciprocating the normalized values gotten from the first method. While in rank exponent method, it requires the decision maker to specify the weight on a scale from most preferred to the least preferred. These three ranking methods are very attractive due to their simplicity.

- **POINT ALLOCATION**

In this weighting method, criteria are weighted directly by the decision maker, which are asked to assign any number as they like to reflect the weight of each criterion. The relative importance of the criteria is determined by the point attached to it. The total of all criterion weights must sum to 100. This method is known to be one of the easiest weighting methods in history because it is easy to normalize. However, the results generated by this method are not very precise. This can serve as a disadvantage in using this method.

- **RATIO WEIGHTING METHOD**

In ratio method, decision makers rank the criteria according to their order of importance. For example the least important criterion is assigned a weight of 10, all others would then be judged as multiples of 10, resulting raw weights are then normalized to sum to one.

- **DELPHI METHOD**

Delphi Method is also one of the most popular methods used in literature. In this weight generation techniques, weights are derived in three stages.

Stage 1: Participants are chosen. Initial data is gathered and participants present their views on the policy.

Stage 2: A list of possible alternatives is compiled and distributed to participants. Ideas are synthesized and a smaller number of possible policy recommendations are compiled.

Stage 3: An amended list of alternatives is distributed. These "policy" ideas are fine-tuned by the participants.

- **PAIRWISE COMPARISON METHOD**

This is known as one of the oldest and the most effective weight generation method used today. It simply involves comparing criterion against every other criterion in pairs. Thereby it requires the decision maker having a deep knowledge about the performance of each criterion which in turn forces the expert to give a rigorous consideration to all elements of a decision problem.

- **ANALYTICAL HIERARCHICAL PROCESS**

AHP was proposed by Saaty in 1980. It decomposes MCDM problems into a hierarchical nature. This solves MCDM problems that are complex in nature and therefore breaks the identified components of the MCDM problem into sub-layers to form a hierarchy of independent components. The complex MCDM components are broken into: the goal of the decision making problem, criteria involved and alternatives. This breakdown is achieved in two stages of the decision process: Firstly, Structuring of the Decision making problem; secondly, elicitation of preference information/weights of criteria through pair wise comparisons (Ishizaka and Nemery, 2013). For priority estimation, a scale for evaluating preferences of decision makers among criteria in estimating the importance of each criterion was proposed by Saaty, 1980. The fundamental scale is within the interval of 1-9. This has been widely applied in the estimation of weights of criteria in decision making problems (Akdag et al., 2014).

However, the AHP has come with some criticisms from researchers (Goodwin and Wright, 2004). There is no concrete approach within the scale to establish the difference between the words on the verbal scale to their respective numbers mapped on the interval defined. No scientific model to establish the verbal scale to their respective numerical scale and as such may not give a realistic estimate to the truth. Another weakness is that the established options can be reversed in the ranking order originally established if another worse alternative is added or removed (Belton and Gear, 1983). It takes no cognizance of the uncertainties or imprecision's that might be associated with the subjective judgements of the decision makers. These weaknesses of AHP are addressed by the fuzzy type-1 incorporation with the AHP to represent uncertainties of the subjective opinion of the expert. Because according to (Bozdag et al., 2006), decision makers usually found interval judgements to be more fitting and pragmatic than fixed judgment values. According to literature, different AHP methods have been proposed and used for weighting. Table 2.1 is a list of different AHP methods incorporated with fuzzy concept.

Table 2.1: Comparisons of different AHP methods

Sources	**Main characteristics of the method**

Van Laarhoven and Pedrycz 1983	Saaty's AHP method was extended through the use of fuzzy numbers which is then used to derive the fuzzy weight and score of each criteria.
Buckley,1985	Saaty's AHP was also extended. This method uses the geometric mean method to derive fuzzy weights of the criteria.
Boender et al.,1989	This method extends the Laarhoven and Pedryz's AHP method which present a more robust approach to priorities been normalized.
Zeng et al.,2007	This method uses the arithmetic averaging method to weigh the criteria.

Most of all these methods have come with some criticism, Buckley's method have no critics due to this it remains one of the most used methods today. Due to the inability of the method to successfully model inter uncertainty in the decision process. Karhaman (2014) extended the Buckley's Type 1 Fuzzy AHP by introducing the interval type 2 fuzzy set into it. The Extended Type 1 Fuzzy AHP is used in this study to generate weight of criteria. The steps of the extension of Buckley's extended Interval Type 2 Fuzzy AHP proposed by Karhaman are given below.

2.8.1 Interval T ype-2 Fuzzy AHP algorithm

In this section, Buckley's Type 2 Fuzzy AHP approach was modified with the interval type 2 fuzzy set. The procedure is explained below.

Step 1: Generation of the interval type 2 fuzzy numbers for each word by an expert

Step 2: Construct a fuzzy pair wise comparison matrix between criteria for each evaluator using the interval type-2 fuzzy UMF and LMF parameters for each word selected.

Step 3: Aggregate the interval type-2 fuzzy UMF and LMF parameters selected by each evaluators' ith and jth pair wise comparison matrix, if there are more than one evaluators.

Such that $A_{11}U + A_{21}U$, $A_{12}U + A_{22}U \ldots A_{11}L+A_{21}L$, $A_{12}L+A_{21}L$, min (H_1 (A_1U), H_1 (A_2U)),min(H_2 (A_1U), H_2 (A_2U)); min (H_1 (A_1L), H_1 (A_2L)),min(H_2 (A_1L), H_2 (A_2L));

Step 4: Defuzzify the aggregated interval type-2 fuzzy pair wise comparison matrix using the DTrit **equation** or DTrat equation due to the condition required of linear additive models as certainty is prerequisite before final results.

Step 5: Normalize the defuzzified comparison matrix using equations to estimate the weight of each criterion.

In the Interval Type 2 Fuzzy algorithm proposed by Kahraman, subjectivity among decision makers wasn't considered, therefore in this study the Hao and Mendel approach for collecting data interval from decision makers would be used and applied to the AHP approach.

2.9 EVIDENTIAL REASONING APPROACH

The main goal of every MCDM method is to help analyze decision makers' preferences of criteria concurrently in order to arrive at a decision. The evidential Reasoning (ER) approach is the latest development in the MCDM area [Yang and Xu, 2000, Yang, 2001; Yang and Singh, 1994]. It is different from the conventional mcdm methods in such a way that it analyzes multiple criteria decision making (MCDM) problems under uncertainties. Traditionally, most MCDM problems are modeled by using decision matrices, including pairwise comparison matrices used in AHP (Saaty, 1988), in which exact numbers without uncertainties lacks the capability of explicitly modeling uncertainties like ignorance. The Evidential Reasoning approach is developed on the basis on Dempster-Shafter evidence theory (Shafer, 1976) and decision theory. It is different from most traditional methods because it employs the use of belief structure (Yang and Xu, 2002a; Yang and Singh, 1994; Zhang et al., 1989) through the use of extended belief decision matrix in describing the MCDM problem (Xu and Yang, 2003). One of the advantages of using the ER approach is that it uses the distributed assessment to evaluate alternatives and the main advantage of using a distributed assessment (Zhang et al., 1989) include that it has the ability to model precise data and therefore capture various degrees of uncertainties such as probabilities and vagueness in subjective judgements.

Dampster-Shafer Evidence Combination rule for criteria aggregation is used in ER approach to combine all assessment for a particular alternative also known as the probability mass. That is, it shows the confidence of how well you know an object, if an object has a worse or bad attribute, then the object must be worse or bad to a certain confidence degree, this is measured by both the degree to which that attribute is important to the object and the degree to which the attribute belongs to the worse or bad category. Accordingly, Evidential Reasoning Approach has found suitability in the fields of decision making by researchers over the years. Hence, their demonstrations of practicability of solving problems that are multi-dimensional in nature in terms of its classification of criteria needed in evaluating a problem at hand are emphasized. In evaluating alternatives, the ER Approach must exercise the following steps.

- Belief structures of the alternatives are generated
- Combined probability masses are calculated
- Combined assessments for each alternatives are aggregated for the combined probability masses
- Expected utility are obtained and then used to rank the alternatives.

2.9.1 DESCRIPTION OF CONCEPTS/TERMS

The following are the description of concepts in the Evidential Reasoning approach.

Grades

Grades are known to be used for assessing the attribute of an alternative. For example, in evaluating the dressing of student required for public speaking, a number of students are available and you need to make a choice according to the way they are dressed. A commonly used set of grades for evaluating could be {Excellent, Good, Average, Poor, Worst}. It should be noted that the number of grades one can use are not restricted and also different grade names can be used for each attribute.

Degrees of Belief or Belief Degrees

This is when the confidence level of an associated attribute is to be obtained. Degrees of belief are always subjective probabilities associated with assessment grade. For example, the communication skill of an applicant could be assessed to be Excellent with 60% of belief degree and Good with 40% of belief degree.

Uncertainties

In ER approach, various uncertainties can be handled which is explained below.

Absence of data.

This is classified to when there is no data available to assess an attribute or an alternative, if this is the case, the total degree of belief for that attribute or alternative would then be zero.

Incomplete description of an attribute

This is the situation where data for assessing an attribute or an alternative is incomplete. For this case, the total sum of degree of belief will be between 0% and 100%.

Random nature of an attribute

In every decision making process, there are always attributes that are not deterministic in nature. These are always referred to as random attributes. For example the fuel consumption of a vehicle which depends on the road and traffic condition, this figure may vary in this aspect. If this is the case it is assessed using a probability distribution which is then transformed into a distributed assessment.

Utility or **Utility Function**

Utility function measures the preference a decision maker associates with the evaluation grade used in the decision making process. It is denoted by a number within a defined range of value. The highest number is always assigned to the most preferred grade while the least value is assigned to the least preferred grade.

2.9.2 ADVANTAGES OF THE EVIDENTIAL REASONING APPROACH

According to literature, ER approach is a more preferred approach to most traditional MCDM methods because it has the ability to handle what other approaches cannot handle.

- While other methods are limited in the number of attributes they can handle in the hierarchy ER model has the capability to handle very large scale MADM problems.
- ER model assesses alternatives and newly added alternatives independently by calculating the absolute ranking score independently, this is the opposite for most methods such as they use the comparison matrix to evaluate each alternative which in turn causes re-evaluation of alternatives when new ones are added into the system.
- ER model produces consistent ranking of alternatives due to the fact that they are assessed independently, this will be a difficult task for other MCDM methods as it may lead to problems like rank reversal of alternatives.
- ER uses the distributed assessment method to evaluate each alternative which provides the decision maker with a holistic view about diversity of performance of each alternative.

2.9.3 THE EVIDENTIAL REASONING APPROACH FOR MCDM PROBLEM

This shows how the evidential reasoning approach is formulated as a MCDM problem

A. Concept of Belief Matrix

Concept of belief structure: A belief structure is used to represent the distributed assessment of an alternative against a criterion using the concept of belief degree.

Table 2.2: Belief Decision Matrix (Xu, 2012)

Alternative	Attribute		
	1……………………………I……………………………………….L		
1 …..	A_{11}	A_{1I}	A_{1L}
m ……	A_{m1}	A_{mI}={ $(H_1,\beta_{l,1})$},….. $(H_N,\beta_{l,N})$}	A_{mL}
M ……	A_{M1}	A_{MI}	A_{ML}

According to (Xu et al., 2001) For example, suppose we have a MCDM problem that has *K* alternatives, O_J (J=1,…, K) assessed on *M* criteria A_i (i=1,…M). Let H = {H_1, . . . , H_N} be a collectively exhaustive and mutually exclusive set of assessment grades where *N* is the number of grades in the set (N= 1,….,R).Then a belief structure can be expressed as

$$S\ (A_1(O_1))= \{(H_1,\beta_{l,1}), \ldots, (H_N,\beta_{1,N})\} \quad 2.1$$

$1 \geq \beta_{l,1} \geq 0$ is a belief degree to which the performance of the alternative is assessed to the grade H_N on criterion *A* and H_N is the set of grades from H_1 to H_N . Aggregating assessments together to generate a combined assessment is as follow.

Generate basic probability masses aggregating assessments to generate a combined assessment, denoted by M_1 (n= 1,..,R)

$$M_{1,1} = \omega_1\ \beta_{1,1}\ (n=1, \ldots, R) \text{ and } M_{H,1} = 1-w_1= 1-w_1 \quad 2.2$$

The ER algorithm is used to aggregate the basic probability masses to generate combined probability masses.

$M_1 = k(M_{1,1}\, M_{1,2}\ldots\ldots\, M_{n,n}+M_{H,1}M_{1,2}\, M_{1,1}+M_{H,2}\ldots\, +M_{n,n}\, M_{H,n})$

$M_H= k(M_{H,1}\, M_{H,2}\ldots\ldots\, M_{H,n})$ 2.3

Where

$K=)^{-1}$ 2.4

The final combined probability masses are independent of the order in which individual assessments are aggregated. The combined degrees of belief β_n (*n*=1, ….m) are generated by:

β_n 2.5

The combined assessment for the alternative can then be represented as follows:

$S\ (O_n) = \{(H_n\ \beta_n\ )$

2.6

An average score for O_n , denoted by u(O_n) , can also be provided as the weighted average of the scores (utilities) of the evaluation grades with the belief degrees as weights.

$H_n)\ \beta_n$ 2.7

where u(H_n) is the utility of the *i*-th evaluation grade *H* . If evaluation grades are assumed to be equidistantly distributed in the utility space.

In incorporating the Evidential Reasoning approach with fuzzy sets, the Fuzzy Multi Criteria Decision Making models (FMCDM) which has been the most widely used Mardani et al., (2015) incorporates the ambiguity in measuring with the aid of linguistic scales used in evaluating the importance of each criterion over another by experts. This gives a more realistic expression of the most suitable alternatives by factoring characteristics like imprecision and ambiguity involved in human decision making processes. For evaluating the preference information by decision makers, extension to the type-1 fuzzy has been proposed. This was as a result of contradiction of type-1 fuzzy in its formulation of establishing ambiguity and imprecision about qualitative measurements used in decision making.

This was observed not to give a close estimate to the truth (Mendel and Wu, 2010). In Mardani et al (2015) with their comparative review observed the extension of variants of interval-valued type-2 fuzzy have not been widely proposed into MCDM problems for decision making. Likewise, in decision making problems, factors like uncertainty or imprecision are inevitable in the platform of decision making. This has brought such variants of interval valued type-2 fuzzy sets like the Hesitancy tye-2 fuzzy set (Torra and Narukawa ,2009) and the intuitionist type-2 fuzzy set (Atanassov, 1986). The result in this study demonstrated that ER compared to other MCDM methods is more efficient. So this study concluded that ER is efficient to use.

2.10 FUZZY LOGIC SYSTEM

Fuzzy set theory was first proposed by Lotfi A. Zadeh, a Professor of Computer Science at the University of California in Berkeley in 1965 (Zadeh, 1965). It has been utilized progressively in intelligent systems, controlling and steering systems, complex modern processes, household and entertainment electronics, expert systems and applications in light of its effortlessness and comparability to human thinking. It is basically concerned with quantifying and reasoning using natural language in which words can have ambiguous meanings, it is the theory of fuzzy sets that align vagueness, and used to describe fuzziness. This can be considered as an augmentation of traditional crisp sets, in which each element must either be in or not in a set. The theory has been applied in many fields, for example, manufacturing, engineering, diagnosis, economics, among others.

As an example, we could think of the age of a person. Let us assume that we want to divide the age into the three categories young, middle and old. Using crisp sets, we could state that, for example, a person below 35 years is young, a person between 35 and 55 years is of middle age and a person over 55 years is old. The problem that arises is even though a person that is 34 years of age is almost the same age as a person of 35 years; the person would be classified significantly lower than the other person. This is called the sharp boundary problem. Fuzzy sets can help overcome this problem by allowing different degrees of membership, not only 1 and 0. Objects can thereby be members of more than one set and therefore give a more realistic view on such data.

Fuzzy logic has widely been applied in different studies because of its unique functionalities, particularly the ability to handle imprecision, decision-making, uncertainty (Wu and Mendel, 2010) etc.

2.10.1 TYPE-1 FUZZY SET OPERATION

Fuzzy sets can generally be viewed as an extension of the classical crisp sets. (Zadeh , 1965).

"*Fuzzy sets are generalized sets which allow for a graded membership of their elements. Usually the real unit interval [0; 1] is chosen as the membership degree structure.*"

Crisp sets are separating between members and non-members of a set by assigning 0 or 1 to each object of the universal set. Fuzzy sets generalize this function by assigning values that fall in a specified range, typically 0 to 1, to the elements. This evolved out of the attempt to build a mathematical model which can show the vague colloquial language. Let X be the universal set. The function is the membership function which characterizes set A.

Formally: where:

(x)=1 $if x is totally in A$;

(x)=0 if x is not in A; (2.8)

0 <(x)<1 if x is partially in A

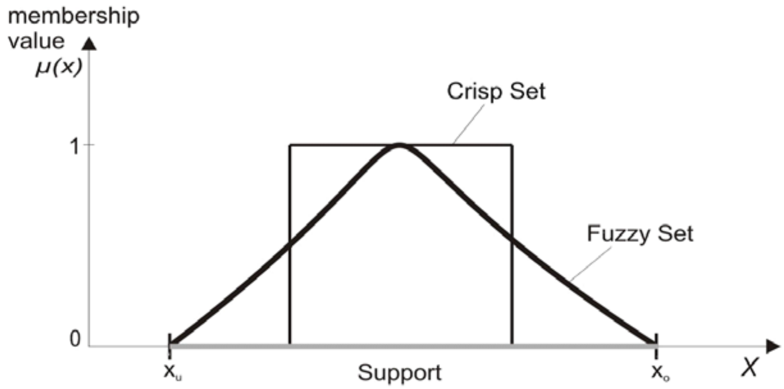


Figure 2.4: Fuzzy set

The Figure 2.4 represents a graph of a crisp set and a fuzzy set. The fuzzy set can look altogether different depending on the chosen membership function. Utilizing this function, it is conceivable to allocate a membership degree to each of the elements in X. Elements of the set could but are not required to be numbers as long as a degree of membership can be deduced from them. It is essential to take note of the fact that membership grades are not probabilities. One critical distinction is that the summation of probabilities on a finite universal set must equivalent 1, while there is no such necessity for membership grades.

2.10.2 LIMITATION OF TYPE-1 FUZZY SET

- Accurate reflection of the linguistic uncertainties of diverse opinions from different domain experts
- Elicitation and construction of data intervals for words used in collecting experts' knowledge and in establishing the FOU to capture the imprecision and high level of uncertainties.

- Change in environmental and operating conditions render type-1 fuzzy sub-optimal.

2.10.3 INTERVAL TYPE-2 FUZZY DEFINITIONS

The general mathematical terms entailed for interval type-2 fuzzy is described thus:

Definition 2.1. An IT2 FS A is characterized by the MF$u_{\tilde{A}}$ (x,u) $where\ x \in X\ and\ u \in J_x$ ⊆[0,1].

$$\tilde{A}=\int_{x\in XU\in}\int_{Jx\subseteq[0.1]}1/(x,u)=\int_{x\in X}[\int_{U\in Jx\subseteq[0.1]}1/u]/x$$

(2.9)

Where x, called the primary variable, has domain X; u $\in$ [0,1], called the secondary variable, has domain $J_{x\subseteq U=[0,1]}$ at each x $\in$ X; Jx, is called the primary membership (or the codomain) of x, and the amplitude of $u\tilde{A}$ (x, u), called a secondary grade of $\tilde{A}$, equals 1 for $\forall x\in X$ and $\forall u \in$ Jx⊆ [0, 1]. The bracketed term is called the secondary MF, or vertical slice, of $\tilde{A}$, and is denoted $\tilde{A}$(x), that is,

$$\mu_{\tilde{A}}(x)=\int_{u\in J_x\subseteq[0,1]} 1/u \qquad (2.10)$$

So that $\tilde{A}$ can also be stated in terms of its vertical slices as

$$\tilde{A}=\int_{x\in X}\mu\tilde{A}(x)/x$$

(2.11)

$$Jx=[\underline{\mu}\lambda(x),\bar{\mu}\lambda(x)]$$

(2.12)

Definition 2.2: Uncertainty about $\tilde{A}$ is conveyed by the union of all its primary memberships, which is called the *footprint of uncertainty* (FOU) of $\tilde{A}$:

$$FOU(\tilde{A})=u_{\forall x\in X}\quad Jx=\{(x,u):u\in J_x\subseteq[0,1]\}$$

(2.13)

the FOU ($\tilde{A}$) can also be stated as:

FOU($\tilde{A}$)=$\cup_{\forall x \epsilon X}[\underline{\mu}_{\tilde{A}}(x),\bar{\mu}_{\tilde{A}}(x)]$

(2.14)

Definition 2.3: The upper membership function (UMF) and lower membership function (LMF) of $\tilde{A}$ are two type-1 MFs that bound the FOU. UMF ($\tilde{A}$) is associated with the upper bound of FOU($\tilde{A}$) and is denoted $u\tilde{A}$ (x),$\forall x\epsilon$ X,and $LMF(\tilde{A})$ is associated with the lower bound of FOU($\tilde{A}$) and is denoted $u\tilde{A}$ (x),$\forall x\epsilon$ X, that is,

UMF($\tilde{A}$)≡$\bar{\mu}_{\lambda}(x)$=$FOU(\tilde{A})\forall x\epsilon X$

(2.15)

$LMF(\tilde{A})$≡$\mu_{\lambda}(x)$=$FOU(\tilde{A})\forall x\epsilon X$

(2.16)

The general property of the interval type-2 fuzzy set is shown in the Figure 2.5

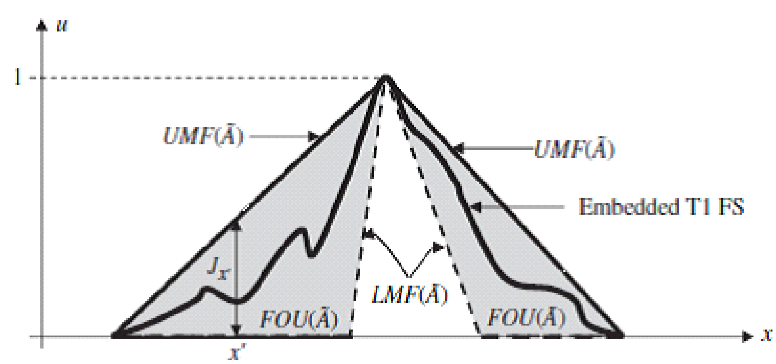


Figure 2.5: Interval type-2 fuzzy sets and associated quantities (Mendel, 2007)

Definition 2.4: **(Wavy-Slice Representation Theorem).** Assume that the primary variable x of an IT2 FS is sampled at N values, $x1 \ldots xN$, and at each of these values its primary memberships ui are sampled at Mi values, $ui1, \ldots, uiMi$. Then $\tilde{A}$ is represented by as:

$$FOU(\tilde{A}) = \bigcup_{j=1}^{nA} A_e^j = \{\mu_{\tilde{A}}(x), \ldots, \mu_{\tilde{A}}(x)\} \equiv [\mu_{\tilde{A}}(x), \mu_{\tilde{A}}(x)] \quad (2.17)$$

2.10.4 INTERVAL TYPE 2 FUZZY SETS

Generally, the IT2 fuzzy set models can be modelled according to (Wu et al., 2012):

1) The person FOU
2) The interval end points approach
3) The Interval Approach
4) Enhanced Interval Approach
5) Hao and Mendel Interval Approach

1) THE PERSON FOU

This is modelled by allowing each subject exhibit/highlight their MF and the FOU for the respective word concerned. These reflect the intra and inter- personal uncertainties of the subject. All subjects FOU are aggregated which will be mathematically modelled to represent the word. This is useful when there is no uncertainty associated with the word, the IT2 can be reduced to a type1 fuzzy set. The usage of statistics in compiling the intervals is not needed so all of the subject information is captured. The drawbacks are: the user/subject has to have a well-established knowledge about fuzzy set, FOU (Footprint of uncertainty) and membership functions. There is no elicitation methodology for drawing upon each person FOUs. Figure 2.6 and 2.7 shows a person FOU for a word “some” and 3 persons FOUs respectively.

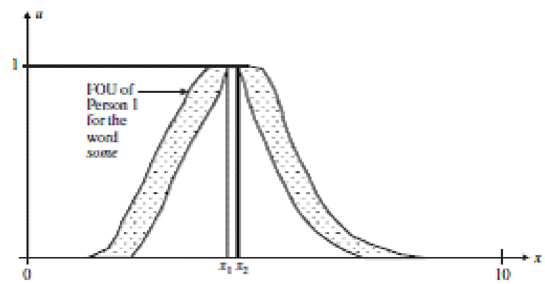


Figure 2.6: A person 1 FOU for a word “some’’ (Mendel, 2007)

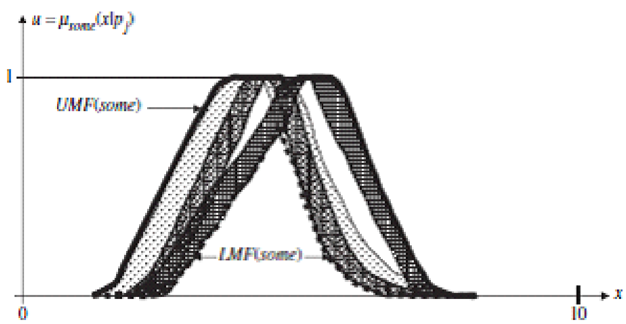


Figure 2.7: Lower and upper Membership functions for 3 person FOUs (Mendel, 2007)

2) THE INTERVAL END POINTS APPROACH

This allows subjects to only state their intervals for each word on a pre-specified scale. This follows statistical calculation of the mean and standard deviation of each end point of the interval of all subjects .i.e. the left and right end points defined by each subject for a word. The results of the statistics are mapped into the pre-specified Fuzzy Set or Membership Function. This gives a more sophisticated approach in generating the FOU for each word. However, it doesn’t allow the results of data from the statistics to dictate the shape of FOU, whether symmetric or non-symmetrical, that should be used. The

MF/FOU must be decided before hand by the user and not necessarily the data dictating the shape of the MF.

3) INTERVAL APPROACH

This encapsulates the strong points of both interval end point approach and person FOU. Firstly, it allows the collection of interval end points from experts. Secondly, the subjects' knowledge about Fuzzy set or MF is not needed. Thirdly, there is a straightforward mapping from data to an FOU. Fourthly, an a priori notion about the shape of the FOU is not needed i.e. whether a shape should be symmetrical or non-symmetrical. Lastly, if there is no uncertainty observed about a word from subjects i.e. if all subjects intervals are the same, then type 2 fuzzy set can be reduced to a type 1. It consists of 2 parts i.e. the data part and the fuzzy part. Figure 2.8 shows the architecture of the data part of the Interval Approach and Figure 2.9 shows the architecture of the fuzzy set part of the Interval Approach.

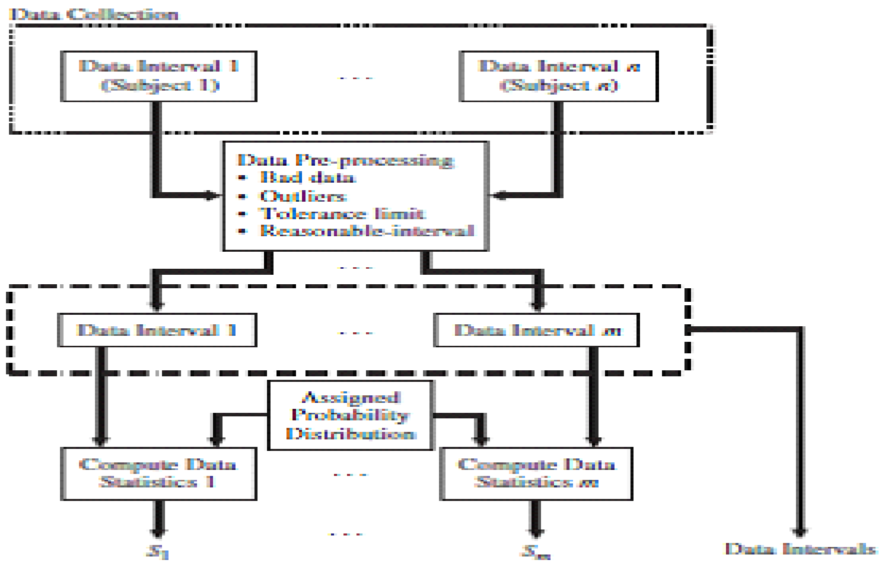


Figure 2.8: Data part of the Interval Approach method (Liu and Mendel, 2008)

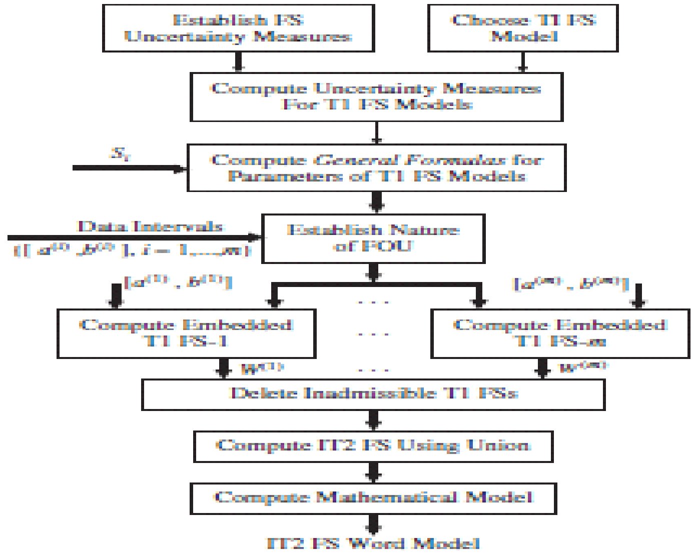


Figure 2.9: Fuzzy Set part of the Interval Approach (Liu and Mendel, 2008)

- **ENHANCED INTERVAL APPROACH**

The Enhanced Interval Approach proposed by Wu et al (2012) addressed the limitations of the Interval Approach. This modified the processes in the data part and other processes in the Fuzzy set part of the interval Approach. It was classified to perform better in its FOU representation of words than the Interval approach. Therefore, the type 2 fuzzy can be modelled to a particular FOU of a word using either one of the following approaches as described above i.e. the Interval end point approach, the Interval Approach and Enhanced Interval Approach. This is possible because each one of the approaches allow the use of statistics and fuzzy in capturing the uncertainties of a particular word.

- **HAO AND MENDEL APPROACH (HM)**

Hao and Mendel approach addresses the limitations of the Enhanced Interval approach. **HM** Approach (HMA) proposed by Hao and Mendel is used to encode words into normal interval type 2 fuzzy sets, this is the first time a normal interval type 2 fuzzy set for a word would be developed. Interval data about a word are collected either from a group of subjects or from one subject. The HMA is divided into two parts just like the previous methods in literature : (1) Data Part, which is the same as the Data Part of the Enhanced Interval Approach (EIA) and (2) Fuzzy Set Part, the fuzzy set part of HM is very much different from the fuzzy set part of the EIA, the most notable difference being that in the HMA , the subjects have a common overlap of data intervals that is interpreted to indicate that they all agree at a point for that overlap, and therefore a membership grade of 1 is assigned to the common overlap. Another notable difference between the fuzzy set part of the HMA and EIA is the simple way data intervals are collectively sorted into a Left-shoulder, Interior or Right-shoulder footprint of uncertainty. It requires fewer probability assumptions about these intervals than the EIA. (Hao and Mendel, 2016).

2.11 APPLICATION OF DECISION MAKING APPROACHES FOR RECRUITMENT PROCESS

Different methods have been considered in literature to solve the recruitment problem. This section discusses several methodologies that have been used in literature for the recruitment problem. Most commonly used methods are the artificial intelligence methods and MCDM methods.

2.11.1 Artificial Intelligence approach for recruitment problem

Hooper et al.,(1998) used an expert system in a personnel selection process. The purpose of this study was to begin the development and testing of an Expert System to screen officer personnel records being considered for Command and General Staff College in US Army. The Artificial Intelligence (AI) computer language “PROLOG” is used to develop a basic rule-based expert system called BOARDEX for officer selection in order to education and training in US Army Command and General Staff College. The considered criteria in this paper for officer selection were: grade, military education level, civilian education level, height, weight, assignment history, and Officer Efficiency Report (OER) evaluations. Huang et al.,(2004) applied Fuzzy Neural Network (FNN) to construct a new model for evaluation of managerial talent and they developed a decision support system in Human Resource Selection System. They used FNN to train the concrete database, on the basis of 191 questionnaires from experts. Additionally, they adopted simple additive weighting (SAW) and FAHP methods to let decision makers for adjusting weighted values and obtain decisive results of each phase‟s scores. FNN is used to construct the human resource selection system of JAVA user interface. They used **"**FuzzyTECH software**"** as a tool for FNN to let the output network model transferred the information to six dimensions and JSP dynamic programming language is used to construct a human resource selection system. The criteria in this paper were: Capability trait, personality trait, motivational trait, conceptual skill, interpersonal skill, and technical skill. Drigas et al.,(2004) developed a hybrid expert system job matching of unemployed at certain offered posts. They applied Neuro-Fuzzy methods for analyzing a corporate database of unemployed and enterprises profile data. Sugeno type Neuro-Fuzzy interface system performed the process of matching on unemployed with an offered job. Six fields (criteria) are used to formulate the query/job opportunity. These six criteria were: Age, Education, Previous Employment (Experience), Additional Education (Training), Foreign Language (English), and Computer Knowledge. Jereb et al.,(2005) proposed a novel approach to decision making in human resource management that this approach integrated a hierarchical MADM techniques with expert systems and it was based on the explicit articulation of qualitative decision knowledge. They used a computer-based on attributes arranged in a form of a tree structure as supporting tools named DEXi, a specialized expert system shell for interactive construction of the knowledge base that was developed in collaboration between Josef Stefan Institute and University of Maribor, to develop and employ qualitative decision models. Rashidi et al.,(2011) proposed a model Neurofuzzy Genetic System to solve a decision making issue in the construction firms for choosing a qualified Project Managers. The important criteria in selection a project manager is identified based on the opinions of experienced construction managers by means of interviews through a fuzzy system which is based on IF-THEN rules. They used a genetic algorithm to determine initial cluster center, along with membership function parameters, and ANN is also used to determine the efficiency grade of deduction parameters. Zavadskas et al.,(2008) considered the application of Grey Relations Methodology to define the utility of alternatives and developed a multi criteria approach of Complex Proportional Assessment of alternatives with grey relations (COPRAS-G) for analysis to project manager selection. They investigated a related literature and interviews of management personnel involved in the project managers selection and they selected most important criteria for a project manager in construction firm. They identified six criteria for the selection of a construction project manager based on the review of literature, and managers" questionnaires. These six criteria were: personal skills, business skills, technical skills, project management skills, quality skills and time of decision making.

2.11.2 Evaluation of recruitment process using MCDM

So many MCDM methods have been developed to solve real world complex decision problems. The aim of every MCDM method is to help make good recommendation by determining the overall preferences among various alternatives. Among the MCDM problems encountered in real life is the recruitment problem and from the multi-criteria perspective, this has attracted the interest of so many researchers, thus researchers have contributed immensely using different MCDM methods in this research area. The fuzzy logic concept has thus been hybridized with so many MCDM method.

Kabak et al., 2012 proposed a fuzzy hybrid multi criteria decision making technique composed of three different MCDM methods for sniper choice as a part of employees selection. Fuzzy ANP, Fuzzy TOPSIS, and Fuzzy ELECTRE techniques were hybridized for sniper choice that allows the usage of the aggregation of both qualitative and quantitative factors. Fuzzy ANP was used to calculate the overall weights of standards, Fuzzy TOPSIS was used to determine the most appropriate candidate, and the top 3 ranked applicants by Fuzzy TOPSIS were taken so as to get the very last ranking procedure through Fuzzy ELECTRE. Afshari et al., (2013) proposed a new linguistic extension of fuzzy measure and fuzzy integral for aggregation of information for evaluation and implemented it for personnel selection under organization group decision making environment wherein feasible dependencies among the criteria had been considered stating the fact that other methods that had been used in literature do not consider the interdependencies of these criteria. In Kumar et al., (2014). The application of MADM methods was examined in choosing the most ideal academic staff in an institution where seven different applicants under seven different criteria were evaluated and assessed. For successful implementation the study utilized the SAW method, WPM method, AHP and TOPSIS for selecting the ideal candidate among various alternatives in an academic institution.

Dondangeh et al., 2014 developed a fuzzy MCDM model for linguistic reasoning under new fuzzy cluster higher cognitive process that new linguistic reasoning for cluster higher cognitive process that has the ability to combine subjective analysis of the decision makers and therefore produce a chance to perform more robust human resource choice procedures. They validated the procedure by employing a case study of Project manager selection in MAPNA firm a massive multi-disciplinary power holding situated in Tehran, capital of Persia. In Saad et al., (2014), the Shannon's entropy concept was used to determine the objective weights and then the preference of each decision maker to obtain subjective weight. They used weighted Hamming distance to identify the distance value between the ideal alternative and the options. Moreover, ranking of alternatives was made based on the general evaluation of the criteria. The method was validated with an illustration of a lecturer selection in an academic institution.

Kabir, 2014. In this paper, extended VIKOR approach was proposed to select the most suitable TQM representative. The VIKOR method in this paper specializes in ranking of the alternatives. It additionally enables generation of solution that might be regularly occurring during the selection process. Unlike the TOPSIS method that determines a solution with the shortest distance from the best solution and the farthest distance from the poor solution, however it does not consider the relative significance of these. The highest ranked alternative by VIKOR is the closest to the suitable solution. However, the best ranked alternative by TOPSIS is the best in terms of the ranking index, which does not mean that it is always the nearest to the ideal solution.

Safari et al., (2014). Proposed the MCDM method, Fuzzy AHP and Fuzzy TOPSIS in solving the human resource problem, first of all the criteria and sub criteria were determined which are influencing the organizational performance based totally on a survey on the literatures and theoretical concepts. The relative weight and ranking of relevant criteria and sub-criteria affecting the organizational performance using Fuzzy AHP were determined. In addition, the final ranking of these criteria have been determined by calculating mean using the Topsis ranking method. In Canos et al., (2014). Soft computing methods were used in solving the personnel selection method. The aggregated fuzzy evaluations of each candidate were obtained from the individual evaluation provided by experts. The candidates were ranked according to the similarity with the ideal alternative. The method was validated with a real world scenario using the "*StaffDesigner*" developed with JAVA and MATLAB languages.Varmazyar et al*.,* 2014. The present work proposes a Fuzzy Analytic Hierarchy Process (FAHP) as one of the most popular multi-criteria decision making techniques. A computer application is developed where it receives the configuration of the employee selection problem, evaluates the candidates and ranks them using the appropriate voting system.

Kusumawardani and Agintiara, (2015) proposed an application of a hybrid method Fuzzy AHP and Fuzzy TOPSIS was used in the selection of a manager using a case study of a telecommunication company in Indonesia; the application also includes assigning its employees to different roles in the company. Fuzzy AHP and F-TOPSIS were used to weigh the relative important of criteria and then get the ranking consecutively. In Liu et al., (2015) VIKOR method was hybridized with interval 2-tuple linguistic variables. This method was proposed to choose appropriate applicants among different applicants in a group decision-making environment. The interval 2-tuple linguistic variable was incorporated to deal with linguistic information involved in the solving of personnel selection problems.

However, from the different research studies reviewed, the fuzzy set engaged in the analysis was basically type 1 fuzzy sets which use precise real numbers to represent fuzziness measures. The effect of this is that, the fuzzy membership functions are model based on an opinion from one individual over a repeated survey which caters for a low level of subjectivity (Intra-expert) (Mendel, 2007). In order to cater for a high level of subjectivity and resolve both intra and inter uncertainties, an extension to the concept of fuzzy sets has been developed. As observed from the different research studies, type-1 fuzzy set is only capable of handling intra-uncertainty. Type-2 fuzzy set can handle both inter- and intra-uncertainties i.e. it can effectively model diverse opinions. Also, type-1 fuzzy set cannot accurately reflect the linguistic uncertainties of diverse opinions from different domain experts. These are very important in any decision-making process and also there is lack of elicitation methodology for establishing all decision makers' overall meaning of each word used as qualitative measurement of criteria in the MCDM process. Therefore, this fusion of the establishment of footprint of uncertainty using the decision makers' data intervals for that particular word to the MCDM process is missing before recommending a decision.

This will foster incoherence in judgements from the decision makers before the MCDM makes its recommendation and also maintain a degree of inaccuracy in the elicitation process when recommending a decision or choosing an alternative. Accordingly, as observed in literature there is lack of effective utilization of interval type 2 fuzzy evidential reasoning to recruitment process. To this effect, the hybridization of interval type 2 fuzzy evidential reasoning approach to recruitment problem is proposed.

CHAPTER THREE

METHODOLOGY

3.1 INTRODUCTION

This section is carried out systematically by first gathering the recruitment criteria needed for the process, identification of alternatives to be evaluated and definition of linguistic terms for criteria preference elicitation and evaluation grades. An interval type 2 fuzzy evidential reasoning approach is proposed and distinctly covered in three major sequential phases and the framework is shown in Figure 3.1. The first phase is Data preprocessing, the second stage is the weighting phase using Interval Type 2 Fuzzy AHP and the final phase is the Ranking phase using the interval type 2 fuzzy evidential reasoning approach. The theoretical background of the evaluation process is explained briefly in this section.

In this research, 14 criteria were considered, three main criteria which were sub-divided into seven, four and three sub criteria consecutively, alternatives to be evaluated, linguistic terms used for criteria preference elicitation and evaluation grades in this study were gotten through one on one interaction with the human resource department of the academic institution used as our case study.

- The data was preprocessed using the interval type 2 fuzzy set: Hao and Mendel approach consisting of the data part and the fuzzy set part. This is achieved in three steps firstly, the data part involves the data interval preprocessing and the fuzzy set part establishes the nature of the FOU as either left, right of interior shoulder and generates the interval type 2 fuzzy values. Secondly, the aggregated FOU is type reduced by computing the centroid (measure of uncertainty) of the IT2FS using the Enhanced Kernik Mendel approach. The result is an interval valued set; lastly, the interval valued set was deffuzified by taking the average of the interval’s two endpoints.

- In the weighting stage, IT2 AHP (Hao and Mendel approach) was employed. The input into this model is the interval type 2 fuzzy numbers generated from the first step mentioned above. Dtrit was the deffuzzification method used to deffuzzify the final output. This method is used for the weight generation of each criterion.

- In the ranking stage, the IT2 Fuzzy evidential reasoning approach was used. The input into this method is the deffuzzified values gotten from the last stage in the preprocessing stage using the EKM algorithm. This method is used in ranking of alternatives in order to pick an ideal candidate for recruitment. The framework of the study work flow is shown in Figure 3.1.

3.2 FORMULATION OF THE RECRUITMENT PROBLEM

This section is divided into three phases: criteria definition phase, identification of alternatives phase, definition of linguistic terms for criteria preference elicitation and evaluation grades phase.

3.2.1 CRITERIA DEFINITION

In this section, we illustrate this approach by using a numerical example, using a prestigious academic institution in Nigeria as a case study; they desire to employ a senior lecturer in the department of computer and information science. During the initial elicitation of criteria, the criteria were gotten from one on one interaction with the human resource department of the institution. The recruitment requirements that was obtained are based on three dimensional concepts which are Academic Factors of the applicants (AF), Individual Factors of the applicants (IF) and Work Factors of the applicants (WF). These all together produced 14 criteria. The Table 3.1 shows their categorization.

IT2 Fuzzy Evidential Reasoning Approach

Expert

Defuzzification

(Dtrit deffuzication method)

Ranking of alternative

(IT2 Evidential Reasoning approach)

Identification of recruitment criteria, alternatives, and Definition of linguistic terms for criteria preference elicitation and Evaluation grades

Utility value for Evaluation grades

IT2 fuzzy set for criteria Preference

IT2 Criterion weight

Defuzzification process

(Average Sum)

Collection of data interval for the linguistic terms defined (Questionnaire method)

Weighting model

Calculation of Weight

(IT2 AHP)

Type Reduction of Fuzzified data interval

(EKM Approach)

Fuzzification of Data Interval collected

(HM Approach)

Ranking model

Figure 3.1: Framework for Interval Type 2 Fuzzy Evidential Reasoning approach for recruitment process

Table 3.1 Criteria definition

S/N	Sub-Criteria	Main Criteria
1	AF1: Qualification	Academic Factors of the applicants (AF)
2	AF2: Class of Degree	
3	AF3: Relevance of Degree	
4	AF4: Corporate Registration	
5	AF5: Teaching Experience	
6	AF6:Administrative Experience	
7	AF7: Publication	
8	IF1: Communication Ability	Individual Factors of the applicants (IF)
9	IF2: Presentation Ability	
10	IF3:Quick-Wittedness	
11	IF4: Job Knowledge	
12	WF1: Emotional stability	Work Factors of the applicants (WF)
13	WF2: Self Confidence	
14	WF3: Dressing	

3.2.2 IDENTIFICATION OF ALTERNATIVES

In recruitment process, identification of alternatives is a major process; these are the sets of candidates that apply for a particular job position with the hope of getting selected if they meet the required job requirements. Therefore, in this study ten alternatives were identified and interviewed for an academic position in a reputable institution.

3.2.3 DEFINITION OF LINGUISTIC TERMS FOR CRITERIA PREFERENCE ELICITATION AND EVALUATION GRADES

In this work, linguistic terms (words) were defined for eliciting the importance of each criterion and also the alternative performance with respect to each criterion. These words were defined by the decision makers of the academic institution and are used in approximate reasoning by decision makers for eliciting all the criteria in Table 3.2.

Table 3.2 Linguistic terms for criteria preference

Linguistic terms
Exactly equal
Slightly important
Fairly important
Strongly important
Extremely important

The following linguistic terms in Table 3.3 were also defined as the evaluation grade for evaluating each alternative.

Table 3.3: Linguistic terms for alternatives performance

Main criteria	Sub-criteria	Evaluation grades
ACADEMIC FACTORS	QUALIFICATION	Very low,low,average,high,very high
	CLASS OF DEGREE	Very low,low,average,high,very high
	RELEVANCE OF DEGREE	very poor, poor, average,good,very good
	CORP REGISTRATION	Very low,low,average,high,very high
	TEACHING EXP	very poor, poor, average,good,very good

ACADEMIC FACTORS	QUALIFICATION	Very low,low,average,high,very high
	CLASS OF DEGREE	Very low,low,average,high,very high
	RELEVANCE OF DEGREE	very poor, poor, average,good,very good
	CORP REGISTRATION	Very low,low,average,high,very high
	TEACHING EXP	very poor, poor, average,good,very good
	ADMIN EXP	very poor, poor, average,good,very good
	PUBLICATION	Very low,low,average,high,very high
INDIVIDUAL FACTORS	COMMUNICATION ABILITY	very poor, poor, average,good,very good
	PRESENTATION ABILITY	very poor, poor, average,good,very good
	QUICK WITTEDNESS	very poor, poor, average,good,very good
	JOB KNOWLEDGE	very poor, poor, average,good,very good
WORK FACTORS	EMOTIONAL STABILITY	very poor, poor, average,good,very good
	SELF CONFIDENCE	very poor, poor, average,good,very good
	DRESSING	very poor, poor, average,good,very good

Subsequently, the data intervals for each word defined above were collected from the decision makers using an online questionnaire.

3.3 COLLECTION OF DATA INTERVAL

This process follows the establishment of the linguistic terms used in the preference elicitation and evaluation of alternatives. Online questionnaire was used to gather the opinion of the decision makers. 37 decision makers were involved in the process. The words described in Table 3.2 and Table 3.3 were used. In order to ascertain the sufficiency of the linguistic terms defined by the decision makers, Jaccard similarity measure was used. Decision makers were required to describe an interval or range using this statement.

Below are a number of words that describe an interval or a "range" that falls somewhere between 0 and 10. For each word, please tell us where this range would start and where it would end. The Figure 3.2 show samples of how the data intervals were gathered. After collection of all interval end points data for all words from all subjects, this follows:

This part shows the linguistic grades used for the evaluation of each alternative. Kindly give us your range of value.

for example "In my own opinion, when I say an applicant's teaching experience is (very poor, poor, average, good, very good), the data interval(from 1-10) that I attach to this is between ………… To ……………".

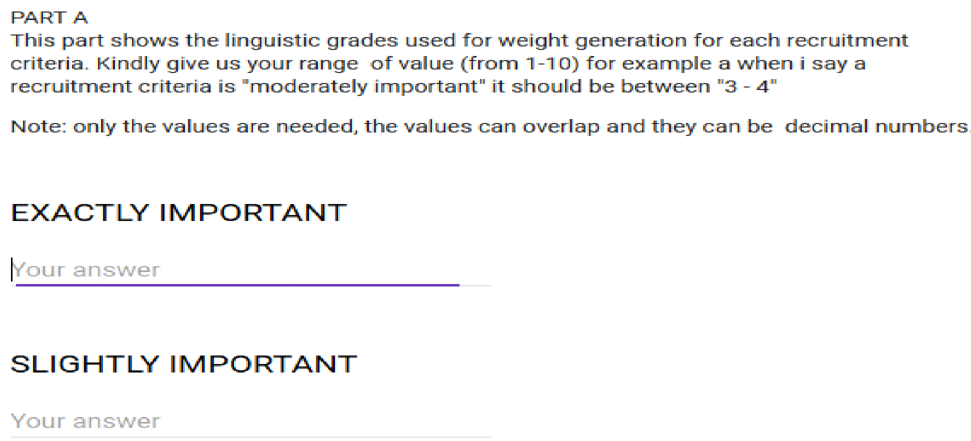
NOTE: only the values are needed, the values can overlap and they can be decimal numbers.

Very poor

Your answer

Poor

Your answer



PART A
This part shows the linguistic grades used for weight generation for each recruitment criteria. Kindly give us your range of value (from 1-10) for example a when i say a recruitment criteria is "moderately important" it should be between "3 - 4"

Note: only the values are needed, the values can overlap and they can be decimal numbers.

EXACTLY IMPORTANT

Your answer

SLIGHTLY IMPORTANT

Your answer

Figure 3.2: Decision maker’s data interval questionnaire

3.4 INTERVAL TYPE 2 FUZZIFICATION

The interval type 2 fuzzification process was carried out using the Hao and Mendel approach. HMA was proposed by Hao and Mendel is used to encode words into normal interval type 2 fuzzy sets, this is the first time a normal interval type 2 fuzzy set for a word would be developed. Interval data about a word are collected either from a group of subjects or from one subject. The HMA is divided into two parts just like the previous methods in literature : (1) Data Part, which is the same as the Data Part of the Enhanced Interval Approach (EIA) and (2) Fuzzy Set Part, the fuzzy set part of HM is very much different from the fuzzy set part of the EIA, the most notable difference being that in the HMA , the subjects have a common overlap of data intervals that is interpreted to indicate that they all agree at a point for that overlap, and therefore a membership grade of 1 is assigned to the common overlap. Another notable difference between the fuzzy set part of the HMA and EIA is the simple way data intervals are collectively sorted into a Left-shoulder, Interior or Right-shoulder footprint of uncertainty. It requires fewer probability assumptions about these intervals than the EIA. (Hao and Mendel, 2016).The data part in the Hao and Mendel Approach uses these processes in 4 stages to remove unwanted data intervals that might have been gotten from decision makers:

i) Bad data processing: Interval end points for a particular word are collected from people/subjects using a questionnaire polling method.

Only intervals that satisfy:

$0 \leq a^{(i)} < b^{(i)} \leq 10$ and $b^{(i)} - a^{(i)} < 10$ are accepted; others are rejected. (3.1)

This step reduces n interval endpoints to n' interval endpoints.

ii) Outlier processing: Box and Whiskers tests are carried out on the remaining n' interval endpoints starting from $a^{(i)}$ and $b^{(i)}$ and then on $L^{(i)} = b^{(i)} - a^{(i)}$;i.e., first, $Q_a(0.25)$,$Q_a(0.75)$, IQR_a, $Q_b(0.25)$,$Q_b(0.75)$ and IQR_b are computed based on the remaining data intervals. Then, only intervals satisfying the following are kept.

$$^{(t)} \in [(.25) -1.5IQR_a,(.75)+1.5IQR_a] \quad (3.2)$$

$$^{(t)} \in [(.25) -1.5IQR_b,(.75) +1.5IQR_b] \quad (3.3)$$

This step reduces the n' interval endpoints to n'' interval endpoints.

Consequently, Q_L (0.25), Q_L (0.75), and IQR_L are computed based on the remaining n intervals, and only intervals satisfying the following are kept:

$$^{(i)} \in [(.25)-1.5IQR_L,Q_L(.75)+1.5IQR_L] \quad (3.4)$$

This step reduces the n'' interval endpoints to m' interval endpoints.

iii) Tolerance Limit Processing: This is performed on $a^{(i)}$ and $b^{(i)}$ firstly and then on

$L^{(i)} = b^{(i)} - a^{(i)}$. Consequently, only intervals satisfying the following are kept:

$^{(i)} \in [m_a - k\sigma_a, + k\sigma_a$ (3.5)

$^{(i)} \in [m_b - k\sigma_b, + k\sigma_b$ (3.6)

where k is determined such that one can assert with 95% confidence that the given limits contain at least 95% of the subject data intervals. This thereby reduces the m′ interval endpoints to m^+ interval endpoints. m_L and σ_L are then computed on the remaining m+ intervals, and only intervals satisfying the following are kept:

$^{(i)} \in [m_L - k'\sigma_L, + k'\sigma_L$ (3.7)

where $k' = \min(k_1, k_2, k_3)$ (3.8)

in which k_1 is determined such that one can assert with 95% confidence that

$[m_L - k_1\sigma_L, m_L + k_1\sigma_L]$ contains at least 95% of $L^{(i)}$, and

$k_2 = m_L/\sigma_L$ (3.9)

$k_3 = (10 - m_L)/\sigma_L$ (3.10)

Equation (3.7) makes sure $m_L - k'\sigma_L \geq 0$, and (3.8) ensures that $m_L + k'\sigma_L \leq 10$ so that intervals with too small or too large $L(i)$ can be removed. This step reduces m^+ interval endpoints to m″ interval endpoints.

iv) Reasonable- interval processing: To do this, one finds one of the values

$\xi * =$

(3.11)

such that $m_a \leq \xi * \leq m_b$.

(3.12)

where m_a and m_b are the mean values of the left and right endpoints of the surviving m″ intervals. In EIA, only the intervals [$a^{(i)}$, $b^{(i)}$] are kept such that:

$$2m_a - \xi^* \leq {}^{(i)} < \xi^* < {}^{(i)} \leq 2m_b - \xi^* \quad (3.13)$$

where ξ∗ is again computed by (3.11). This reduces the m″ intervals to m interval endpoints. Figure 3.3 shows an example of a reasonable interval

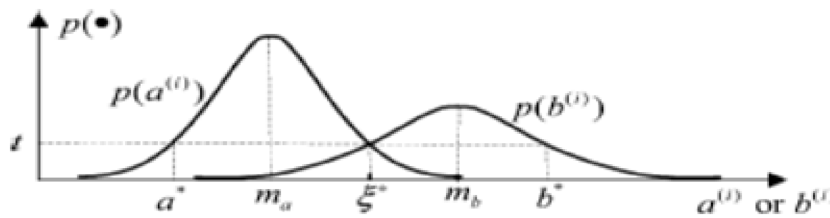


Figure 3.3: Reasonable Interval (Wu et al., 2012)

The reasonable intervals must have $a^* < a^{(i)} < \xi^* < b^{(i)} < b^*$.

Lastly, a uniform distribution is assigned to each of the remaining m intervals [$a^{(i)}$, $b^{(i)}$], and its mean and standard deviation are computed as follows:

(3.14)

(3.15)

At the end of the Data Part, the original *n* data intervals have been reduced to a set of *m* data intervals where $m \leq n$.

The fuzzy set part of the HM Approach (HMA) is as follows in four steps:

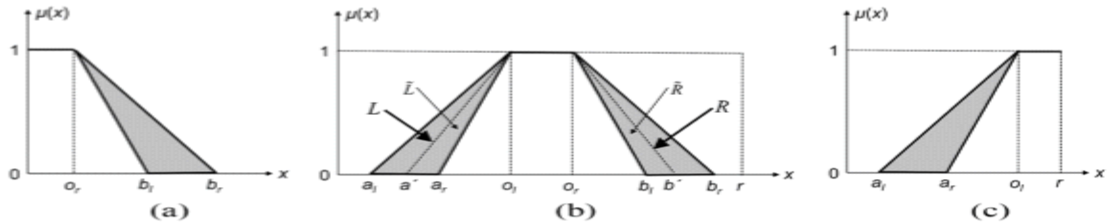


Figure. 3.4: Three kinds of FOUs and their parameters: (a) Left-shoulder FOU, (b) Interior FOU, and (c) Right-shoulder FOU (r = 10).

- Establish the nature of the FOU as either a Left- or Right shoulder or an Interior FOU (see Fig. 3.3). This is done by first computing one-sided tolerance intervals for the end-points , namely $\underline{a}$ = $_l$ − k(m)$_l$ for and =$_r$ +k(m)$_r$ for ,where $_l$ and $_l$ are the sample mean and standard deviation of , $_r$, and $_r$ are the sample mean and standard deviation of , k(m) is a one-sided tolerance factor that is a function of m, so that one can assert with 95% confidence that the given limits contain at least 95% of the endpoints. Then, a word is classified as follows:

  when $\underline{a}$ ≤ 0, *W → Left-shoulder FOU; when* b ≥ 10, *W → Right-shoulder FOU; otherwise, W → Interior FOU.*

- Compute the overlap [o_l, o_r] of the *m* intervals. For a Left- shoulder FOU, [o_l, o_r] = ; for an Interior FOU, [o_l, o_r] = ; and, for a Right-shoulder FOU, [o_l, o_r] = .

- Remove the overlap [o_l, o_r] from each of the original *m* intervals, . For a Left-shoulder FOU, this leaves a new set of smaller intervals, ; for a Right-shoulder FOU, this leaves a new set of smaller intervals, ; and, for an Interior FOU, this leaves two new sets of smaller intervals, and .

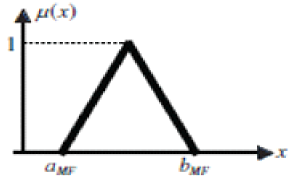
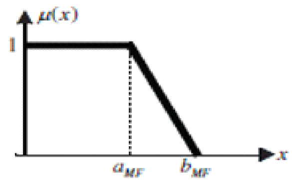
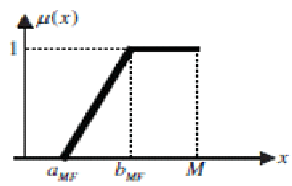
- Map the set(s) of smaller intervals into the two parameters that define the respective FOU. For a Left- or Right-shoulder FOU, there are exactly two such parameters, b_l

and b_r, or a_l and a_r; but, for an Interior FOU, there are four such parameters a_l, a_r, b_l, and b_r. For the Interior FOU, are mapped into a_l and a_r, and are mapped into b_l and b_r. The mappings are done so that two measures of uncertainty about the *m* smaller length data intervals are mapped into two comparable measures of uncertainty about the FOU.

Table 3.4: Transformations of the uniformly distributed data interval $[a^{(i)}, b^{(i)}]$ to the parameters and of a T1 FS.

MF	Transformations
Symmetric triangle (interior MF)	$a_{MF}^{(i)} = \frac{1}{2}[(a^{(i)} + b^{(i)}) - \sqrt{2}(b^{(i)} - a^{(i)})]$ $b_{MF}^{(i)} = \frac{1}{2}[(a^{(i)} + b^{(i)}) + \sqrt{2}(b^{(i)} - a^{(i)})]$
Left-shoulder	$a_{MF}^{(i)} = \dfrac{(a^{(i)} + b^{(i)})}{2} - \dfrac{(b^{(i)} - a^{(i)})}{\sqrt{6}}$ $b_{MF}^{(i)} = \dfrac{(a^{(i)} + b^{(i)})}{2} + \dfrac{\sqrt{6}(b^{(i)} - a^{(i)})}{3}$
Right-shoulder	$a_{MF}^{(i)} = M - \dfrac{(a'^{(i)} + b'^{(i)})}{2} - \dfrac{\sqrt{6}(b'^{(i)} - a'^{(i)})}{3}$ $b_{MF}^{(i)} = M - \dfrac{(a'^{(i)} + b'^{(i)})}{2} + \dfrac{(b'^{(i)} - a'^{(i)})}{\sqrt{6}}$ $a'^{(i)} = M - b^{(i)}$ $b'^{(i)} = M - a^{(i)}$

Table3.5: Mean and Standard Deviation for Interior and Shoulder T1 MF

Name	MF	Mean (m_{MF}) and standard deviation (σ_{MF})
Symmetric triangle (interior MF)		$m_{MF} = (a_{MF} + b_{MF}) / 2$ $\sigma_{MF} = (b_{MF} - a_{MF}) / 2\sqrt{6}$
Left-shoulder		$m_{MF} = (2a_{MF} + b_{MF}) / 3$ $\sigma_{MF} = \left[\frac{1}{6}\left[(a_{MF} + b_{MF})^2 + 2a_{MF}^2\right] - m_{MF}^2\right]^{1/2}$
Right-shoulder		$m_{MF} = (2a_{MF} + b_{MF}) / 3$ $\sigma_{MF} = \left[\frac{1}{6}\left[(a'_{MF} + b'_{MF})^2 + 2a'^2_{MF}\right] - m'^2_{MF}\right]^{1/2}$ $a'_{MF} = M - b_{MF}$ $b'_{MF} = M - a_{MF}$ $m'_{MF} = M - m_{MF}$

3.5 JACCARD SIMILARITY MEASURE

It was observed that there is a limit to the capacity one can process information on simultaneously interacting elements. So, when we provide people with a vocabulary of words from which they have to make a choice, they sometimes find it difficult, so due to this vocabulary of words are then reduced. In order to accomplish this, the Jaccard Similarity Measure is used in order to gather enough dissimilar words. A new similarity measure for Interval Type 2 Fuzzy sets was proposed in Wu and Mendel (2009).It uses average cardinality and applied to

Ã,= = 3.16

Note that each integral is an area is an area under the minimum of and . Closed form solutions cannot always be found for these integrals, so the following discrete version of equation is used in calculations.

Ã,= 3.17

The Jaccard Similarity Measure, Ã,) satisfies reflexivity, symmetry, transitivity and overlapping.

3.6 TYPE REDUCTION AND DEFUZZIFICATION

The aggregated FOU can be type reduced by computing the centroid of the IT2 FS. The result is an interval valued set, which is defuzzified by taking the average of the interval's two endpoints.

The centroid of an IT2 FS provides a measure of the uncertainty of such a FS, the centroid of IT2 FS $\tilde{A}$, $C_{\tilde{A}}(x)$, is defined as follows:

Definition 3.1: The centroid $C_{\tilde{A}}(x)$ of an IT2 FS $\tilde{A}$ is the union of the centroids of all its embedded T1 FSs, $c(A_e)$, that is, ≡

$C_{\tilde{A}}(x)$ = (3.18)

Where,

$C_l(\tilde{A})$ = (3.19)

$C_r(\tilde{A})$ = (3.20)

Karnik and Mendel (2001) have developed iterative algorithms - now known as KM Algorithms - for computing c_l and c_r which has the following structure:

(3.21)

(3.22)

The Enhanced KM algorithms [Wu and Mendel (2007; 2009)] start with the KM algorithms and modify them in three ways:

1) A better initialization is used to reduce the number of iterations.

2) The termination condition of the iterations is changed to remove an unnecessary iteration.

3) A subtle computing technique is used to reduce the computational cost of each of the algorithm's iterations.

The EKM algorithms are summarized below. The better initializations are shown in Step 1 of Table 3.8, and both were obtained from extensive simulations (Wu and Mendel, 2009). Extensive simulations have shown that on average the EKM algorithms can save about two iterations, which corresponds to a more than 39% reduction in computation time.

The EKM algorithm for computing is:

- Sort (i = 1,2,….., *N*) in increasing order and call the sorted by the same name, but now Match the weights with their respective and renumber them so that their index corresponds to the renumbered

- Set k = [N/2.4] (the nearest integer to N/2.4), and compute

  a =

  b =

  and, y = a/b

- Find k' such that
- Check if k' = k. If yes, stop, set y_l = y and call k L. If no, continue.
- Compute s = sign(k' - k), and

  a' = a + s

  b' = b + s

  y' = a'/b'

- Set y = y', a = a', b = b' and k = k'. Go to Step 3.

The EKM algorithm for computing y_r is:

- Sort (i = 1,2,….., N) in increasing order and call the sorted by the same name, but now Match the weights with their respective and renumber them so that their index corresponds to the renumbered
- Set k = [N/1.7] (the nearest integer to N/1.7), and compute

  a =

  b =

  and, y = a/b

- Find k' such that
- Check if k' = k. If yes, stop, set y_r = y and call k R. If no, continue.

- Compute s = sign(k' - k), and

  a' = a - s

  b' = b - s

  y' = a'/b'

- Set y = y', a = a', b = b' and k = k'. Go to Step 3.

  EKM algorithms for computing the centroid end-points of an IT2 FS, $\tilde{A}$ ([a]Note that x_1 x_2 . . . x_N.)

3.7 WEIGHTING MODEL

In order to determine the order of importance of each criterion, the weighting MCDM model: Interval type 2 fuzzy AHP (an extended Buckley's type 1 fuzzy AHP) proposed by Karhaman was employed. This was employed due to its suitability for MADM structured problems in estimating the importance of each criterion. The Java programming language was utilized in the implementation process.

3.7.1 INTERVAL TYPE-2 FUZZY AHP

It is utilised due to demonstrated suitability for MADM structured problems in estimating the importance of each criterion. This fusion of interval type 2 Fuzzy set concept and AHP captures the intra and inter uncertainties of the decision makers before making recommendations on criteria importance. The input into this weighting model is the interval type 2 fuzzy numbers generated from the fuzzification process. The Experts considered in this study are people in the university recruitment unit. AHP was employed because the relationship between the criteria is non-dependent and has no feedbacks. In this research work, this fundamental scale was adopted.

Table 3.6 fundamental scale for weighting of criteria adopted in this research work.

Degree of importance	Definition

1	Equally important
3	Slightly important
5	Fairly important
7	Strongly important
9	Extremely important

The pairwise comparison is then achieved as follows:

If criterion A is equally important to criterion B, enter E;
If criterion A is slightly important than criterion B; enter SI;
If criterion A is fairly important than criterion B; enter FI;
If criterion A is strongly more important than criterion B; enter SM;
If criterion A is extremely more important than criterion B; enter EM

3.7.2 INTERVAL TYPE-2 FUZZY AHP ALGORITHM

Step 1: Get interval end data points for all the words used in eliciting criteria importance from the decision makers.

Step 2: Translate the interval end points data from all subjects for each word to their respective UMF and LMF parameters using the Hao and Mendel Approach.

Step 3: Construct a fuzzy pair wise comparison matrix between criteria for each evaluator using the type-2 fuzzy UMF and LMF parameters for each word selected.

Step 4: Aggregate the type-2 fuzzy UMF and LMF parameters selected by each evaluators' ith and jth pair wise comparison matrix, if there are more than one evaluators.

Such that $A_{11}U + A_{21}U$, $A_{12}U + A_{22}U \ldots A_{11}L + A_{21}L$, $A_{12}L + A_{21}L$, min (H_1 (A_1U), H_1 (A_2U),min(H_2 (A_1U), H_2 (A_2U)); min (H_1 (A_1L), H_1 (A_2L),min(H_2 (A_1L), H_2 (A_2L));

Step 5: Defuzzify the aggregated type-2 fuzzy pair wise comparison matrix using the DTrit **equation** or DTrat equation due to the condition required of linear additive models as certainty is prerequisite before final results.

Step 6: Normalize the defuzzified comparison matrix using equations to estimate the weight of each criterion.

where ri is the summation of the row values and pi is the normalization of the sum

wj= weight of the jth criterion.

3.7.3 Arithmetic operations of Interval Type 2 Fuzzy Set

The upper membership function and the lower membership function of an interval type-2 fuzzy set are type-1 membership functions, respectively**.**

H_1, H_1 (3.21)

$where\ and\ are\ type$

$-1\ fuzzy\ sets,$

$are\ the\ reference\ points\ of\ the\ interval\ type$

-2 ; $denotes\ the\ membership\ value\ of\ the\ element\ in\ the\ upper\ trapezoial$ membership function.

;$1 \leq j \leq 2, H_j()$ denotes the membership value of the element in the lower trapezoidal membership function ;$1 \leq j \leq 2, H_j()$

$H_i() \epsilon$ [0,1], $H_2() \epsilon$ [0,1], $H_1() \epsilon$ [0,1], $H_2() \epsilon$ [0,1]$and\ 1 \leq i \leq n.$

The addition operation between two trapezoidal interval type-2 fuzzy sets is defined in Chen and Lee(2010) as follows:

H_1,

H_1 (3.22)

H_1,

H_1 (3.23a)

$\oplus = \oplus$ H_1,H_2 ,

H_1H_2 (3.23b)

The subtraction operation between the trapezoidal interval type-2 fuzzy sets is defined in (Chen et al., 2010) as follows:

$\ominus$ $\ominus$

H_1,H_2 ,

H_1,H_2 (3.24)

The multiplication operation between the trapezoidal interval type-2 fuzzy sets is defined in (Chen et al., 2010) as follows:

$\otimes$ $\otimes$

H_1,H_2H_1,H_2 (3.25)

3.7.4 DEFFUZIFICATION OF THE TYPE-2 FUZZY SETS:

The defuzzification of triangular type-2 fuzzy sets (DTriT) proposed by Kahraman et al., (2014) is as follow:

(3.26)

where α is the maximum membership degree of the lower membership function of the considered type-2 fuzzy set; u_U is the largest possible value of the upper membership function; lU is the least possible value of the upper membership function; m_U is the most possible value of the upper membership function; u_L is the largest possible value of the lower membership function; l_L is the least possible value of the lower membership function; mL is the most possible value of the lower membership function.

Additionally, the defuzzification of trapezoidal type-2 fuzzy sets (DTraT) proposed by Kahraman et al., (2014) was employed in this work as follows:

(3.27)

where α and β are the maximum membership degrees of the lower membership function of the considered type-2 fuzzy set; u_U is the largest possible value of the upper membership function; l_U is the least possible value of the upper membership function; m_{1U} and m_{2U} are the second and third parameters of the upper membership function; u_L is the largest possible value of the lower membership function; l_L is the least possible value of the lower membership function; m_{1L} and m_{2L} are the second and third parameters of the lower membership function, respectively.

3.8 RANKING OF ALTERNATIVES

The interval type 2 fuzzy evidential reasoning approach is used in ranking the alternatives. The deffuzified weight for each recruitment requirement generated from using interval type 2 fuzzy Ahp, deffuzified values of the utility functions and evaluation grades using the EKM algorithm are the inputs into this model. Each alternative are assessed independently using belief degrees. Thus, this theory is more appropriate for this work because the recruitment problem is a ranking problem that deals with choosing the best alternative. To this effect, the interval type 2 ER approach is proposed to rank the applicants according to their performances.

3.8.1 PROPOSED INTERVAL TYPE 2 FUZZY EVIDENTIAL REASONING

The evidential Reasoning approach is developed on the basis on Dempster-Shafter evidence theory (Shafer, 1976) and decision theory. It is different from most traditional methods because it employs the use of belief structure (Yang and Xu, 2002a; Yang and Singh, 1994; Zhang et al., 1989) through the use of extended belief decision matrix in describing the MCDM problem (Xu and Yang, 2003). The best alternative is selected using the following steps.

Step 1: Formulation of the problem into a MCDM problem, firstly by identifying the goal, criteria and the alternatives.

Alternatives(job seekers)= O_j (j=1, 2 ……….10)

criteria = A_i (i=1, 2 ………..14)

Evaluation grades H_n= (H_1,H_2……H_5) , n = 1……..m

Step 2: Get interval end data points for all the evaluation grades used in evaluating alternatives from the decision makers.

Step 3: Translate the interval end points data from all subjects for each word to their respective UMF and LMF parameters using the Hao and Mendel Approach.

Step 4: Defuzzify the type-2 fuzzistics numbers using the EKM Algorithm due to the condition required of linear additive models as certainty is prerequisite before final results.

Step 5: Analyzing the decision problem by obtaining the belief structure of each alternative in respect of each criterion.

$$S(A_i(O_j))=\{(\beta_{1,1}, H_1), (\beta_{2,1},H_2), (\beta_{3,1},H_3)\ldots(\beta_{n,1},H_n)\}. \quad (3.28)$$

Step 6: Calculate the combined probability masses of all the assessments for each alternative.

$$M_{n,1} = \omega_1 \beta_{n,1} \ (n=1, \ldots, m) \text{ and } M_{H,1} = 1-w_1= 1-w_1 \quad (3.29)$$

Step 7: Calculate aggregation of assessments for the combined probability masses(ER Algorithm).

$$Mn = k(M_{n,1} M_{n,2} \ldots\ldots M_{n,n}+M_{H,1}M_{n,1+} M_{n,2}+M_{H,2} \ldots\ldots M_{n,n}+M_{H,n})$$

(n= 1………m)

$$M_H= k(M_{H,1} M_{H,2} \ldots\ldots M_{H,n}) \quad (3.30)$$

$$\text{Where } K =)^{-1} \quad (3.31)$$

Step 8: Calculate expected utility for the alternatives.

(3.32)

Combined assessments for each alternative for ranking.$S(O_1)=\{H_1, \beta_1), (H_2, \beta_2), (H_3, \beta_3) \ldots. (H_n, \beta_n)\}$ An average score for O_n , denoted by $u(O_n)$, can also be provided as the weighted average of the scores (utilities) of the evaluation grades with the belief degrees as weights, or where u(H_n) is the utility of the *i*-th evaluation grade *H* . If evaluation grades are assumed to be equidistantly distributed in the utility space.

$$H_n)\ \beta_n \qquad (n= 1.....m) \tag{3.23}$$

CHAPTER FOUR

IMPLEMENTATION RESULTS AND DISCUSSION

4.1 INTRODUCTION

This chapter discusses the implementation process of the proposed Interval type-2 fuzzy Evidential Reasoning approach. It is then validated as follows and applied to recruitment process. Firstly, recruitment criteria, alternatives, linguistic terms used for criteria preference elicitation and alternatives performance were gathered through one on one interaction with the decision maker. The criteria gathered consist of three main criteria which were subdivided into seven, four and three sub criteria consecutively. The next phase which is the data preprocessing stage using the interval type 2 fuzzy approach: HM approach to model the inevitability of uncertainties of the decision makers that gave their respective ranges on each of the linguistic terms used for criteria elicitation and evaluation of alternatives. The next phase is the use of interval type 2 fuzzy Ahp to generate the weight for each recruitment criterion and the lastly the interval type 2 fuzzy ER was utilized to rank alternatives according to their performance. MATLAB tool box was used to implement the HM interval type 2 fuzzy approach and Java programming language for implementing the interval type 2 fuzzy Ahp and the interval type 2 fuzzy ER.

- **CRITERIA DEFINITION**

Recruitment requirements were acquired from the human resource department of the academic institution used as case study. The recruitment requirements that were obtained are based on 3 dimensional concepts which are Academic Factors of the applicants (AF), Individual Factors of the applicants (IF) and Work Factors of the applicants (WF). These all together produced 14 criteria. The Table 4.1 shows their categorization.

Table 4.1: Criteria Definition

S/No	Criteria
1	AF1: Qualification
2	AF2: Class of Degree
3	AF3: Relevance of Degree
4	AF4: Corporate Registration
5	AF5: Teaching Experience
6	AF6: Administrative Experience
7	AF7: Publication
8	IF1: Communication Ability
9	IF2: Presentation Ability
10	IF3:Quick-Wittedness
11	IF4: Job Knowledge
12	WF1: Emotional stability
13	WF2: Self Confidence
14	WF3: Dressing

4.3 COLLECTION OF DATA INTERVAL.

The decision makers defined data intervals for each linguistic word defined. The screenshots of the data intervals described by the decision makers are shown in Figures 4.1, 4.2 and 4.3

Very low		low		average		high		very high	
1	2	2	3	3	6	7	8	9	10
1	2	2	4	4	6	6	8	8	10
0	3	4	5	6	7	8	8.5	8.6	10
								7	7
1	2	2	4	5	6	7	8	9	10
0	2	3	4	5	5	7	7	8	10
1	2	2	4	3	5	4	8	8	10
1	2	1	4	3	6	5	7	6	10
0	2	2.1	3.5	3	5	5.1	7.5	7.6	10
1	2	2	3	3	4	5	7	7	10
0	2	2	3	3	3-4	5	7	7.5	10
1	1.4	2	3.4	4	6	7	8	9	10
1	3	3	5	5	7	7.5	8.6	8	10
1	2	2	4	4	6	6	8	8	10
0	2.5	2.6	4	5	7	8	9.5	9.6	10
								7	7
1	2	2	4	4	6	6	8	8	10
0	2	3	4	5	5	6	7	8	10
1	2	2	3	4	5	5	7	5	10
1	2	2	4	6	8	6	9	9	10
0	2	2.1	3.5	3.6	5	5.1	7.5	7.6	10
1	2	1	4	5	5	4	5	9	10
0	2	2	3.5	4	5	5.5	7	7	10
1	1	3	3	5	5	4	4	8	10

Figure 4.1 Data intervals for the linguistic words

Exactly equal		slightly important		fairly important		very strongly important		Absolutely important	
4	5	4	5	5	7	7	7.5	8	10
5	6	3	5	5	7	7	9	8	10
4.4	6.6	2	4	5	6	7	8	9	10
4	7	3	5	4	7	7	8.5	7	10
3	4	3	3.2	4	5	5	7	8	10
4	5.5	4	4.4	4	7	8	9	9	10
4	5.5	5	6	5	7	7	8	8	10
6	7	3.5	5.4	5.5	7.4	7.5	8.5	8.6	10
3	4	0	2	1	3	3	5	6	10
5	6	3	4	4.5	5.5	6.5	7.5	8	10
7	9	0	1	1	2	3	6	7	10
4	5	1	1.5	2	3	4	6	6	7
6	7	1.1	2	2.4	4	3	6	4	9
3	5.5	1	2	3	4	5	7	8	9
5.6	7.7	2	5	4	6	4	8	7	9
4	5	1	4	1	3	3		5	6.6

Figure 4.2 Data intervals for the linguistic words

Very poor		poor		average		good		very good	
1	3	3	5	5	7	7.5	8.6	8	10
1	2	2	4	4	6	6	8	8	10
0	2.5	2.6	4	5	7	8	9.5	9.6	10
								7	7
1	2	2	4	4	6	6	8	8	10
0	2	3	4	5	5	6	7	8	10
1	2	2	3	4	5	5	7	5	10
1	2	2	4	6	8	6	9	9	10
0	2	2.1	3.5	3.6	5	5.1	7.5	7.6	10
1	2	1	4	5	5	4	5	9	10
0	2	2	3.5	4	5	5.5	7	7	10
1	1	3	3	5	5	4	4	8	10
1	2	2	3	3	6	7	8	9	10
1	2	2	4	4	6	6	8	8	10
0	3	4	5	6	7	8	8.5	8.6	10
								7	7
1	2	2	4	5	6	7	8	9	10
0	2	3	4	5	5	7	7	8	10
1	2	2	4	3	5	4	8	8	10
1	2	1	4	3	6	5	7	6	10
0	2	2.1	3.5	3	5	5.1	7.5	7.6	10
1	2	2	3	3	4	5	7	7	10
0	2	2	3	3	3-4	5	7	7.5	10
1	1.4	2	3.4	4	6	7	8	9	10

Figure 4.3 Screenshot of some of the data intervals described by decision makers for some of the words

As depicted in Figure 4.1, the first decision maker defined the interval of [1, 2] for the word: very low; for low, an interval of [2, 3], Meanwhile, the second decision maker defined the interval [1, 2] for the same word: very low; for low, an interval of [2, 4].Also the third decision maker defined the interval [0,3] for the same word: very low; for low, an interval of [4, 5]. This culminated to a total of 37 decision makers to determine the intervals of what each word means to them but due to some inconsistencies and missing data in the part of the decision maker, some data were discarded. As shown in Figure 4.1, there are different interpretations of the same word to the different decision makers examined as seen in the disparity in data intervals.

4.4 INTERVAL TYPE 2 FUZZY FUZZIFICATION

Using the Hao and Mendel algorithm which consist of the data part and fuzzy set part, the data Intervals obtained from the decision makers are the input into this algorithm. These data intervals are preprocessed and is shown in Table 4.2. The last column for each row shows the number of credible intervals remaining used finally in constructing the foot print of uncertainty for that word.

Each column represents each step in the Hao and Mendel Approach for constructing the FOU and this depicts the remaining number of decision makers' credible data intervals that satisfies the criteria for that step. The steps as represented by each column are: Bad Data processing, Outlier processing, Tolerance limit processing, Reasonable Interval Processing, Fuzzy set Modelling, Fuzzy set uncertainty measures, Embedded T1 Fuzzy set Condition, Interval type 2 Fuzzy Set model.
On the other hand, each row represents the word used in eliciting criteria importance and alternative performance. Row 1-5 represents the word used in eliciting the alternative performance from the decision makers. These words are: {very poor, poor, average, good, very good} Row 6-10 also for eliciting the criterion importance from the decision makers. The following words are: **{**Exactly equal, slightly important, fairly important, Strongly important, absolutely important}. Row 11-15 is also for eliciting the alternative performance from the decision makers. The following words are: **{**very low, low, average, high, very high**}.** After applying the Hao and Mendel algorithm to the data intervals collected by 37 decision makers about each word, due to some inconsistencies and missing data in the part of the decision maker, some data were discarded.

The last column for each row shows the number of credible data intervals remaining used in finally constructing the footprint of uncertainty for that word. This established the maxim that "each word now means similar things to different people (decision makers)" from the initial maxim of "words mean different things to different people".

Table 4.2 Each Words' Remaining Data Intervals for Each Step In the Hao and Mendel Interval Approach.

	Preprocessing (Data part)				Fuzzy set part
	Stage 1 Stage 4	Stage 2		Stage 3	
Word	n'	m'	m"	m	m*
Very poor	36	32	23	23	16
Poor	36	32	23	23	20
Average	36	28	26	26	18
Good	36	28	26	25	7
Very good	36	32	26	24	24
Exactly equal	34	32	33	31	7
Slightly important	34	32	31	31	5
Fairly important	34	33	33	33	7
Strongly important	34	31	31	29	4
Absolutely important	34	32	32	31	5
Very low	34	28	21	21	14
Low	34	29	17	17	15
Average	34	27	25	25	12
High	34	28	25	24	16
Very high	34	32	28	26	26

The type-2 fuzzy set derived for each word after the processing above are shown in the Figures 4.4, 4.5 and 4.6. Each word is plotted and depicted by their type-2 fuzzy set depicting the respective uncertainties (Footprint of Uncertainty) with that word associated with the decision makers involved. For the word: ***very poor***, most decision makers did not have opposing description of what it means to them in evaluation process. So, the type-2 fuzzy set was reduced to the type-1 fuzzy set.

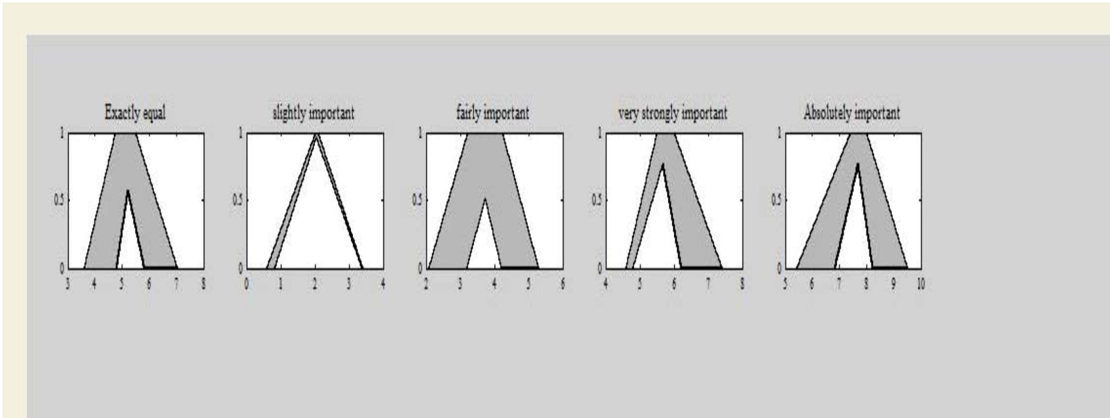


Figure 4.4: Plotting of the Fuzzy Sets for each Word Used in Eliciting Criteria

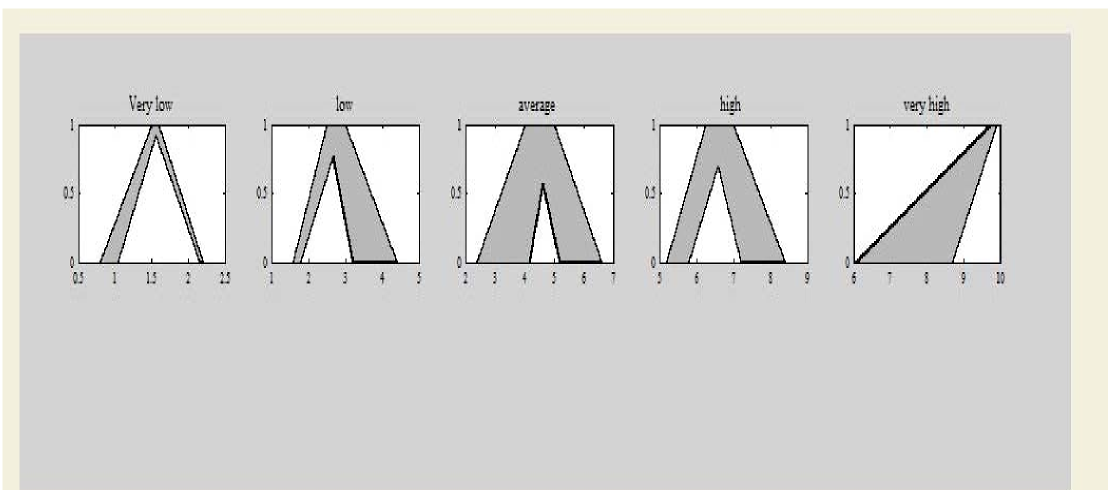


Figure 4.5: Plotting of the Fuzzy Sets for each Word Used in Eliciting alternative performance.

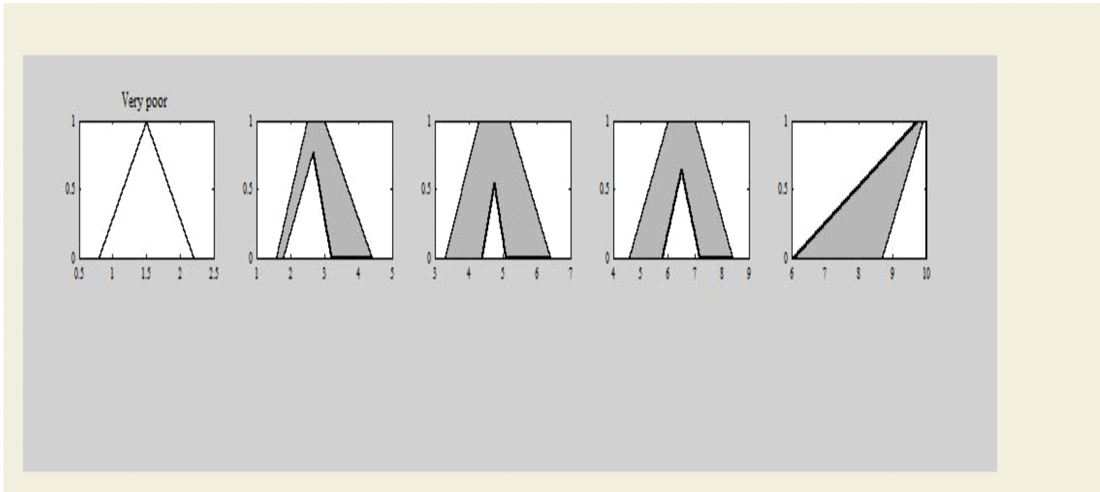


Figure 4.6 Plotting of the Fuzzy Sets for each Word Used in Eliciting alternative performance.

The Upper Membership Function (UMF) and Lower Membership Function (LMF) parameters for each word obtained are represented in Table 4.3. The values obtained after the type reduction process using the EKM algorithm is also represented in the Table 4.3. Lastly deffuzified values of this interval valued numbers gotten from the EKM algorithm for each word is represented at the last column of each row.

Table 4.3 Linguistic Labels for the AHPs Qualitative Measurement of Criteria Importance (Weights) and their Corresponding interval type 2 fuzzy Numbers using HM approach.

Word	UMF	LMF	Centroid	Mean of Centroid
Very poor	(0.79,1.50,1.50,2.21;1,1)	(0.79,1.50,1.50,2.21;1,1)	(1.50,1.50)	1.50
Poor	(1.59,2.50,3.00,4.41;1,1)	(1.79,2.67,2.67,3.21;0.76,0.76)	(2.43,3.08)	2.75
Average	(3.31,4.30,5.20,6.41;1,1)	(4.40,4.75,4.75,5.10;0.55,0.55)	(4.18,5.43)	4.80
Good	(4.59,6.00,7.00,8.41;1,1)	(5.79,6.50,6.50,7.21;0.65,0.65)	(5.91,7.09)	6.50
Very good	(6.05, 9.72, 10,10;1,1)	(8.68,9.91,10,10;1,1)	(8.53,9.55)	9.04
Very low	(0.70,1.50,1.60,2.21;1,1)	(1.03,1.56,1.56,2.17;0.91,0.91)	(1.49,1.61)	1.55
Low	(1.59,2.50,3.00,4.41;1,1)	(1.79,2.67,2.67,3.21;0.76,0.76)	(2.53,3.08)	2.75
Average	(2.38,4.00,5.00,6.62;1,1)	(4.17,4.61,4.61,5.21;0.57,0.57)	(3.76,5.36)	4.56
High	(5.19,6.25,7.00,8.41;1,1)	(5.79,6.57,6.57,7.21;0.70,0.70)	(6.21,7.08)	6.65
Very high	(6.05, 9.72, 10, 10; 1,1)	(8.68, 9.91, 10, 10; 1,1)	(8.53,9.55)	9.04
EI	(3.59,4.75,5.50,7.06;1,1)	(4.79,5.20,5.20,5.81;0.58,0.58)	(1.49,1.61)	1.55
SI	(0.59,2.00,2.10,3.41;1,1)	(0.83,2.05,2.05,3.37;0.96,0.96)	(1.99,2.11)	2.05
FI	(2.07,3.20,4.25,5.31;1,1)	(3.19,3.74,3.74,4.21;0.52,0.52)	(3.10,4.31)	3.71
SM	(4.59,5.50,6.00,7.41;1,1)	(4.79,5.67,5.67,6.21;0.76,0.76)	(5.43,6.08)	5.75
AI	(5.42,7.40,8.00,9.50;1,1)	(6.81,7.67,7.67,8.21;0.76,0.76)	(6.97,8.12)	7.54

4.4.1 SIMILARITY MATRIX

It was observed that there is a limit to the capacity one can process information on simultaneously interacting elements. So, when we provide people with a vocabulary of words from which they have to make a choice, they sometimes find it difficult, so due to this vocabulary of words are then reduced. In order to accomplish this, the Jaccard Similarity Measure is used in order to gather enough dissimilar words. The Tables 4.4, 4.5, 4.6 summarizes the Similarity Matrix for each word defined in this study in relative to others. From the result, The Jaccard Similarity gives reasonable result because it can be observed that the similarity decreases monotonically as two words get further away from each other. This ascertains the sufficiency of the linguistic word defined by the expert.

Table 4.4: similarity matrix for the first set of vocabularies

Word	Very poor	Poor	Average	Good	Very good

Very poor	1.00	0.05	0	0	0
Poor	0.05	1.00	0.06	0	0.00
Average	0	0.06	1.00	0.14	0
Good	0	0	0.14	1.00	0.11
Very good	0	0	0.00	0.11	1.00

Table 4.5: similarity matrix for the second set of vocabularies

Word	Very low	low	Average	High	Very high
Very low	1.00	0.05	0	0	0
low	0.05	1.00	0.15	0	0
Average	0	0.15	1.00	0.06	0.01
High	0	0	0.06	1.00	0.12
Very High	0	0	0.01	0.12	1.00

Table 4.6: similarity matrix for the third set of vocabularies

Word	EQ	SI	FI	SI	AI
Exactly equal	1.00	0.05	0	0	0
Slightly important	0.06	1.00	0.06	0	0
Fairly important	0	0.06	1.00	0.03	0
Strongly important	0	0	0.03	1.00	0.13
Absolutely important	0	0	0	0.13	1.00

In order to accomplish the fact that the vocabularies used are sufficiently dissimilar words, our approach was to set a similarity threshold at 0.6, meaning that words that have similarity greater than 0.6 are considered too similar and needs to be eliminated, our approach for each word was to start from the left column of each similarity matrix and remove all the words to which it is similar to degree greater than 0.6. It was therefore observed that there are no words in the similarity matrix that has similarity greater than

0.6, therefore no word was eliminated.

4.5 INTERVAL TYPE-2 FUZZY AHP FOR DERIVING THE WEIGHTS OF CRITERIA

The interval ***Type-2 fuzzy AHP*** which now captures the intra-uncertainties and inter uncertainties of decision makers before making its recommendation is also employed in estimating the order of importance of each in the recruitment process. The establishment of the weight of each criterion using the interval type-2 Fuzzy AHP approach as shown using the interface below: for an illustrative example, we aim at selecting the most appropriate candidate to fill the position of an assistant lecturer in a reputable institution in Nigeria. Ten applicants were evaluated for the new position, the criteria defined earlier were chosen to evaluate each alternative; the first main criterion, second main criterion and third main criterion are sub divided into seven, four and three criteria respectively. The number of criteria to be compared is entered and received. The weight for each criterion in the first, second, third and fourth hierarchy is shown below. The Tables 4.7 to 4.10 show the data used for the weight generation of each criterion.

Exactly equal = EE, Absolutely important= AI, strongly important= SM, Fairly important = FI, Slightly important = SI.

Table 4.7 comparison of the main criteria

	Academic factor	Individual factor	Work factor
Academic factor	Exactly equal	Absolutely important	Absolutely important
Individual factor	1/absolutely important	Exactly equal	1/strongly important
Work factor	1/absolutely important	Strongly important	Exactly equal

Table 4.8 comparison of the first set of sub criteria

	AF1	AF2	AF3	AF4	AF5	AF6	AF7
AF1	EE	FI	FI	1/SM	1/FI	AI	1/AI
AF2	1/FI	EE	1/FI	FI	1/FI	SI	1/AI
AF3	1/FI	FI	EE	FI	1/SM	SI	1/AI
AF4	SM	1/FI	1/FI	EE	SI	SI	1/FI
AF5	FI	FI	SM	1/SM	EE	SI	1/FI
AF6	1/AI	1/SI	1/SI	1/SI	1/SI	EE	1/SM
AF7	AI	AI	AI	FI	FI	SM	EE

Table 4.9 comparison of the second set of sub-criteria

	Communication ability	Presentation ability	Quick wittedness	Job knowledge
Communication	EE	SI	1/SM	SI
Presentation	1/SI	EE	SM	1/SM
Quick wittedness	SM	1/SM	EE	1/FI
Job knowledge	1/SI	SM	FI	EE

Table 4.10 comparison of the third set of sub criteria

	Emotional stability	Self confidence	dressing
Emotional stability	EE	1/SM	1/SM
Self confidence	SM	EE	1/SI
dressing	SM	SI	EE

The Figures 4.7 to 4.10 shows the implementation result for weight generation of each of the criterion.

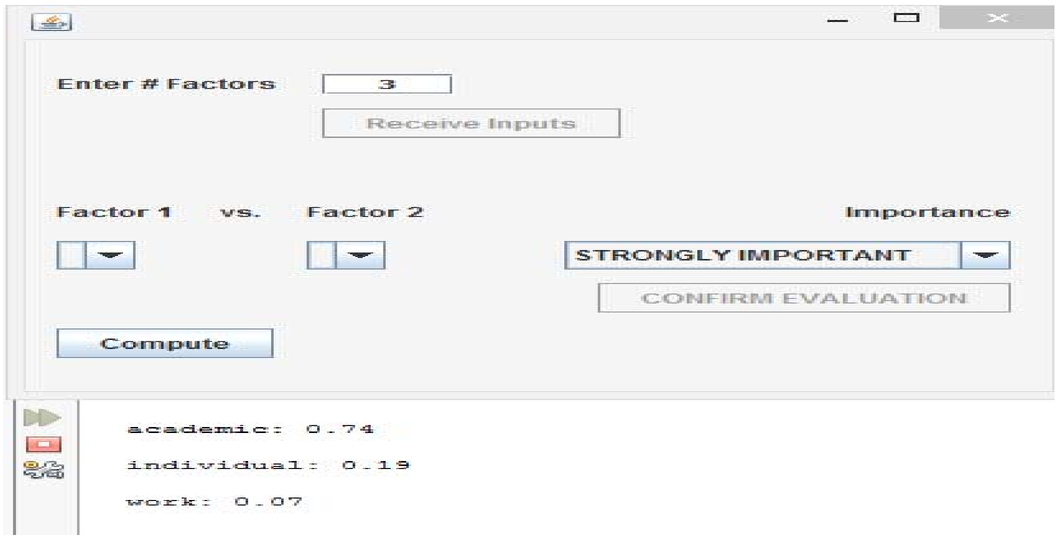


Figure 4.7 First main criteria weight generation

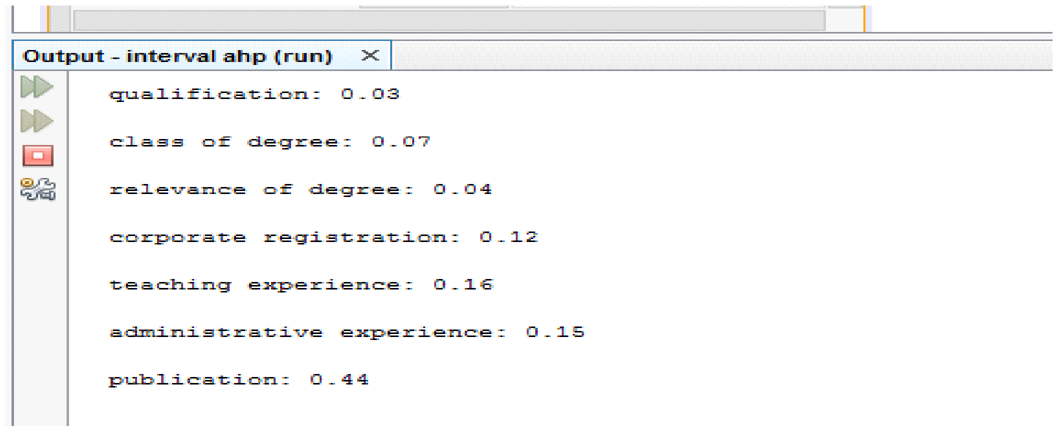


Figure 4.8 first sub criteria weight generation

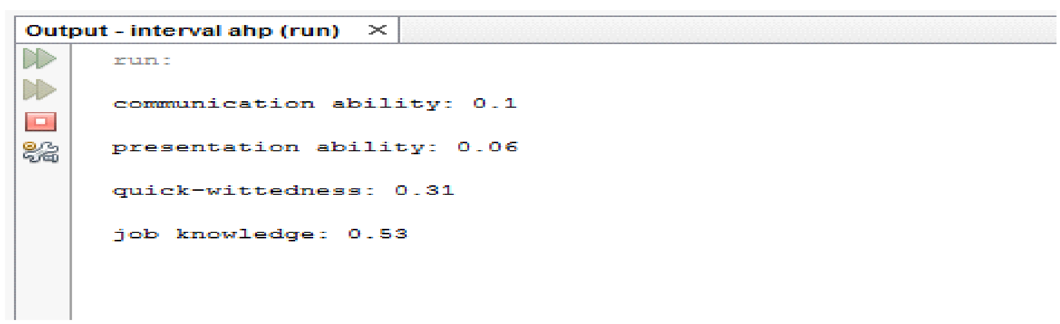


Figure 4.9 second sub criteria weight generation

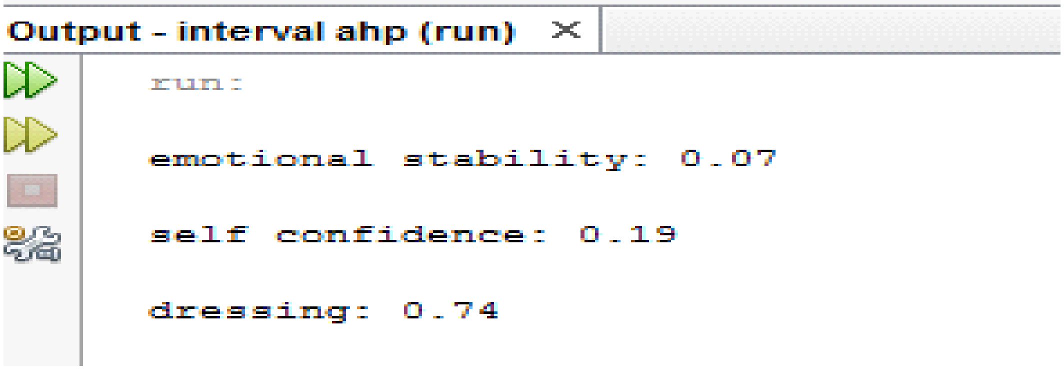


Figure 4.10: third sub criteria weight generation

In this Figure 4.7, Academic was considered the most important requirement and Work is considered as the least important requirement. In Figure 4.8 Publication is considered the most important requirement while qualification is considered the least important criterion. In Figure 4.9 Job knowledge is considered the most important requirement while communication is considered the least important requirement. Figure 4.10 shows that dressing is the most important requirement while emotional stability is considered the least important requirement.

4.6 INTERVAL TYPE-2 FUZZY EVIDENTIAL REASONING RESULT IN THE EVALUATION OF THE APPLICANTS

Using the weight of the criteria generated with interval type 2 fuzzy Ahp algorithm and the utility function of each deffuzzified evaluation grade gotten using the EKM algorithm which is shown in Table 4.11 extracted from Table 4.3, the score of each applicant is gotten by firstly choosing the academic position applicants are being recruited for, the numbers of applicants to be evaluated is also chosen. The system has been designed to intelligently know the minimum requirements considered for each academic position which has been given previously by the academic institution, such that when an academic position is chosen, the applicants who doesn't meet up with the minimum requirement considered would be automatically given a low mark. One other advantage of using this system is shown in this section where the addition of one or more alternatives do not cause a rank reversal because of the fact that alternatives are evaluated independently unlike other MCDM methods that uses the comparison matrix where alternatives are compared in such a way that when a new alternative is added, the computation needs to be restarted. The utility function of each deffuzzified evaluation grade gotten using the EKM algorithm is shown in Table 4.11 which was extracted from Table 4.3.

Table 4.11 Linguistic Labels for the Utility functions using EKM approach

Linguistic Labels	Defuzzified Interval type 2 fuzzy numbers
Very poor/very low	1.55
Poor/low	2.75
average	4.56
Good/high	6.65
Very good/ very high	9.04

The Table 4.12 shows the data used for evaluation of alternatives; the data was extracted from the curriculum vitae of the department of computer science of the university used as case study.

Applica nts	AF1	AF 2	AF 3	AF4	AF 5	AF6	AF7	IF1	IF2	IF3	IF4	WF1

1	2:1	0	2	Msc	2	Very good(1)	Very good(0.5) good (0.5)	Very good(0.8) good(0.2)	Very good(0.33) good(0.45)	Very good(0.25) good(0.11) Average(0.2)	Very good (1)	Very good (1)
2	First class	1	2	Msc	3	Very good (1)	Good(0.8) Average (0.2)	Good(0.40) average (0.20) poor(0.20)	Average (1)	Very good(0.45) good(0.20) Average(0.2)	Average(0.2) Poor (0.35) Very poor (0.25)	Good 0.55) very good .45)

3	First class	6	9	Msc	2	Very good (1)	Very good(0.85) good(0.1) average (0.1)	Very good(0.75) good(0.15)	Very good(0.45) good(0.60)	Poor(0.85) Very poor(0.15)	Very good (0.5) good (0.35) Average(0.2)	Very good .25) good (0.35 Aver e(0.2
4	2:1	0	8	Msc	32	Very good (1)	Poor(0.25)Very poor(0.25)	Average (1)	Poor(0.15) Very poor(0.25)	Very good (1)	Very good (0.75) good (0.25)	Very good .5) good .5)
5	First class	0	5	Msc	10	Very good (1)	Average (1)	Poor(0.35)Very poor(0.45)	Very good(0.45) good(0.25)	Very good (1)	Poor (0.85) Very poor (0.15)	Very good .25) good .11) Aver e(0.2

6	First class	5	9	Msc	19	Very good (1)	Good(0.75)very good(0.25)	Good(1)	Poor(0.55) Very poor(0.45) good(0.10)	Very good (1)	Poor (0.15) Very poor (0.35) good (0.10)	Good 0.55) very good .45)
7	2:1	0	8	Msc	6	Very good (1)	Very poor(1)	Good(0.55) very good(0.45)	Very good(0.65) good(0.10)	Very good(0.25) good(0.11) Average(0.2)	Very poor (1)	Poor 45) Very poor 15) Aver e(0.2

8	2:1	1	5	Phd	20	Very good (1)	Very good(0.5) good(0.5)	Very poor(1)	Poor(0.25) Very poor(0.15) good(0.10)	Very good (1)	Good(0.32) very good (0.45)	Good 0.22) very good .15)
9	2:1	0	6	Phd	22	Very good (1)	Average (1)	Average(1)	Good(0.22) very good(0.15)	Very good (1)	Very good (1)	Very good .15) good .70)
10	First class	2	8	Phd	17	Very good (1)	Very poor(1)	Very good(0.35) good(0.45)	Very good(0.5) good(0.5)	Very good(0.15) good(0.25)	Good(0.22) very good (0.15)	poor 3) Aver e(0.2 Very good .15) good .25)

Table 4.12 Recruitment data for evaluation of applicants

Figure 4.11 shows the evaluation of the five alternatives using the data in Table 4.12.

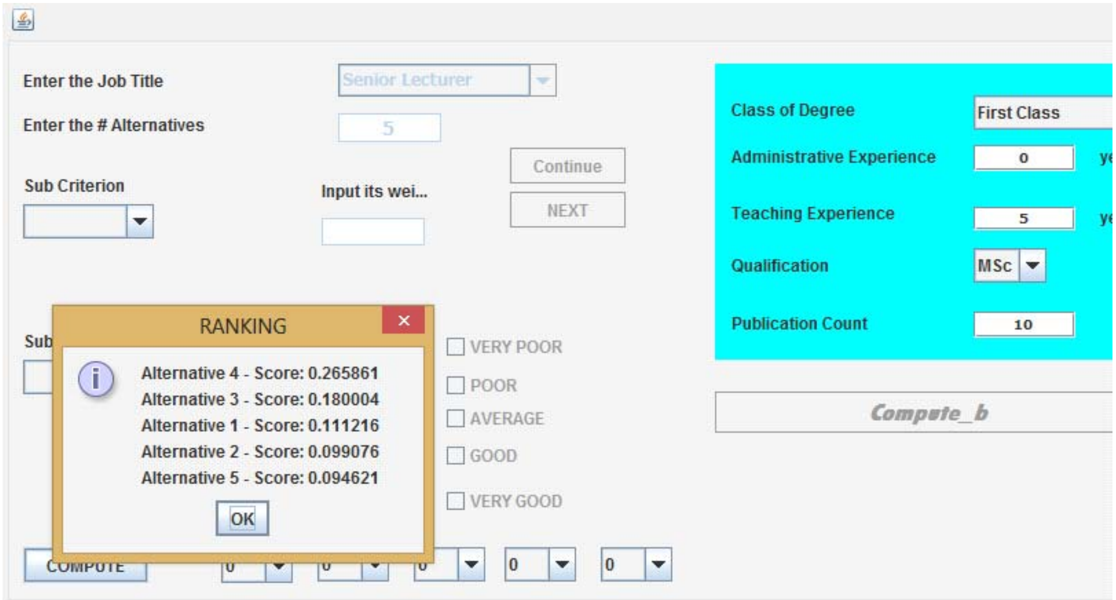


Figure 4.11 First ranking result

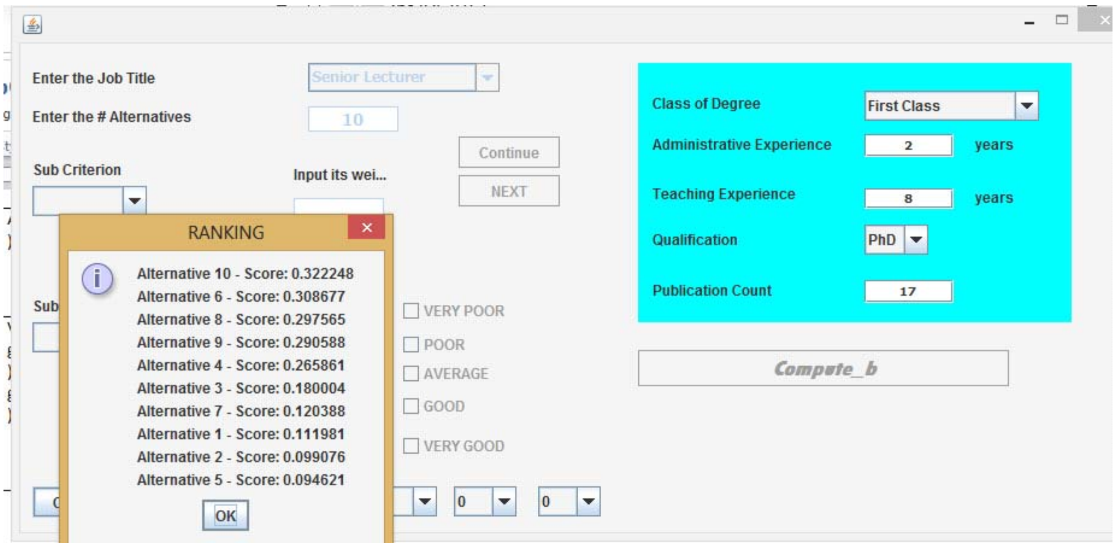


Figure 4.12 Second ranking result

From the Figure 4.11, five alternatives were initially evaluated with the data in Table 4.11, and as we have said earlier that one advantage of the ER model is its ability to continuously add alternatives for evaluation and its independent way of assessing these alternatives, in Figure 4.12 five more alternatives were added into the model for continuous evaluation. This is fact did not change the ranking score of the previously ranked alternatives. In the Table 4.13 the first three best alternatives were then chosen for recruitment. For Applicants: Ten Applicants were considered. The evaluation of the applicants was based on 14 criteria defined earlier. Results of the overall ranking were provided in Table 4.13.

Table 4.13 Interval Type 2 Fuzzy Evidential Reasoning ranking result

METHOD	Best ranked alternative	Second best alternative	Third best alternative

Interval type 2 ER	Alternative 10 (0.3222)	Alternative 6 (0.3086)	Alternative 8 (0.297)

4.7 SYSTEM EVALUATION

In this work, an interval type 2 evidential reasoning approach to personnel recruitment was proposed. The existing multi criteria decision assessor known as intelligent decision system known (IDS) incorporated with AHP and Evidential reasoning was used in this study for system evaluation. The existing system uses classical AHP for weight generation and the classical ER for ranking. A comparison of the proposed IT2FER and classical ER using IDS using the same data was carried out. A representation of the result obtained is shown in Figure 4.13.

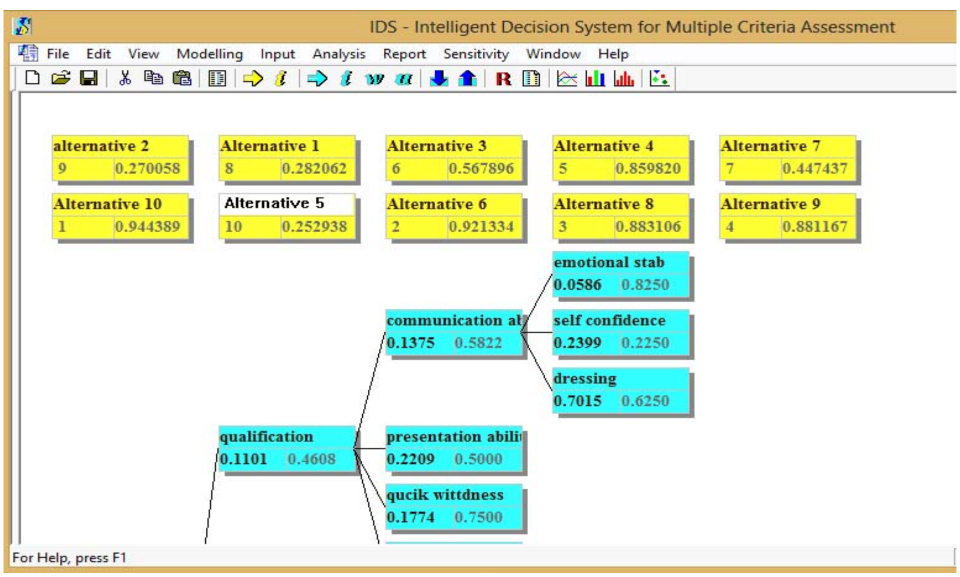


Figure 4.13 snapshot of the result using IDS

4.7.1 OBSERVATION ABOUT THE TWO APPROACHES'S RESULT

- The proposed approach is more intuitive because it corresponds more to human perception of the domain as it reflects and handles uncertainties of diverse opinions from different domain experts which is very important in any decision making process.
- The expression of linguistic terms is also very crucial in order to make result from the system understandable to non-experts.

CHAPTER FIVE

SUMMARY, CONCLUSION AND FUTURE WORK

5.1 SUMMARY

This dissertation has been able to come up with an interval type 2 fuzzy evidential reasoning approach that is able to help academic institutions determine that best candidate for any academic position they wish to recruit applicants for in the face of uncertainty and vague nature of the recruitment process.

This research work has shown that human judgements which are usually characterized by approximate reasoning rather than precise judgements can be misleading and incoherent. To this effect, the modeling of words to accommodate approximate reasoning in order to make right recommendations was established in this study.

In achieving this, a set of criteria were elicited from decision makers which was used for the evaluation of the alternatives, firstly qualitative measurements using words like exactly equal, slightly important, fairly important, strongly important and absolutely important were used to elicit the importance of each criterion from decision makers in order to generate the weight. This followed another set of linguistic terms for evaluating alternatives. These words were modelled using the interval type 2 fuzzy theory due to approximate reasoning entailed in human judgements. It made an attempt of developing a system that helps recruiters determine the most ideal person for recruitment.

5.2 CONCLUSION

In this present age of competitive market, modern organizations face great challenges due to the increasing competition in the global market, making the future survival of companies depends mainly on the contribution of their personnel to companies. Personnel recruitment problem has thus been an area of interest to researchers. During recruitment, decision makers are often uncertain when assigning evaluation score in crisp value.

Therefore, this research work has been able to come up with an interval type 2 fuzzy evidential reasoning approaches for solving recruitment problem. A recruitment system using the Evidential reasoning approach with the fuzzy set theory was designed to select the most adequate person. The model can intelligently select the most adequate person for the academic vacancies. AHP was employed as the weighting model while Evidential Reasoning was used as the ranking model. The proposed model is then used in recruiting applicants in an academic institution in Nigeria.

5.3 FUTURE WORK

Thus, for future improvements on this research, the following recommendations are made:

- Another elicitation methodology can be proposed in establishing the parameters of the interval type-2 fuzzy sets, construction of the FOU of linguistic terms/words defined and incorporated with the AHP algorithm.
- The existing elicitation methodologies for establishing the parameters of the interval type-2 fuzzy sets can be used in solving the same MCDM problem and then a comparison done in order to know the differences and also how one method is addressing the limitation of other.
- Also, web based and mobile application can be applied.

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APPENDIX

SURVEY QUESTIONNAIRE FOR RECRUITMENT PROCESS STUDY

DEAR RESPONDENTS,

The purpose of this study is to examine decision maker's belief on the need to recruit the best candidate from a pool of applicants in an organization. This study is being conducted in selected universities considering the fact that the scope of the study is limited to the selection of personnel in an academic environment. This questionnaire asks about the various recruitment requirements used in this institution and also the importance each expert attaches to each attribute and also the data intervals considered for each evaluation grade.

You will be required to fill out the various sections of the questionnaire to aid in the eventual results that will be obtained. The data collected from this study would be used solely for the purpose of this research and for no other purpose. Furthermore, anonymity of respondents is strictly maintained. We would appreciate if you spare some time out of your busy schedule to complete this questionnaire.

An interest in participation and sensitivity towards the subject is of utmost importance in the filling of this questionnaire.

PART 1: BIODATA

Please circle the most appropriate response.

- Gender: (a) Male (b) Female
- Job Title:
- Type of School you work in (a) Government (b) Religious Private (c) NGO

Private (d) other private.

- Age (a) 18-30 (b) 31-50 (c) 51-65 (d) 66 and above

PART 2: BODY

Specific instructions

Assuming an institution wants to recruit set of academic staff, set of applicants have applied to the institution denoted by A_n (A_1, A_2……..A_N), with some set of recruitment requirements denoted by C_n (C_1, C_2……C_N) which have been chosen to judge the set of alternatives. The institution's goal is to decide which applicant to choose. Additionally each judge (decision maker) does not necessarily consider each requirement to be equally important, so a weight must be assigned to each of them. The following linguistic ratings are then going to be used to assess the recruitment requirement.

1	2	3	4	5
Equally important	slightly important	fairly important	strongly important	Absolutely important

EVALUATION GRADE	VALUES
Very poor	
Poor	
Fair	
Good	
Very good	
Very low	
low	

average	
High	

COLLECTION OF WORD INTERVALS

Below are labels that describe an interval or range that falls somewhere between 0 and 10, for each label, please tell us where this range would start and where it would end, in order words, please tell us how much of the distance from 0 to 10 this range would cover. For example the range for “extremely important” might start from 8 and stop at 10. It is therefore important to note that not all ranges are the same and ranges are allowed to overlap.

PART A
This part shows the linguistic grades used for weight generation for each recruitment criteria. Kindly give us your range of value (from 1-10) for example a when i say a recruitment criteria is "moderately important" it should be between "3 - 4"

Note: only the values are needed, the values can overlap and they can be decimal numbers.

EXACTLY IMPORTANT

Your answer

SLIGHTLY IMPORTANT

Your answer

This part shows the linguistic grades used for the evaluation of each alternative. Kindly give us your range of value.

for example "In my own opinion, when I say an applicant's teaching experience is (very poor, poor, average, good, very good), the data interval(from 1-10) that I attach to this is between ………… To …………..".

NOTE: only the values are needed, the values can overlap and they can be decimal numbers.

Very poor

Your answer

Poor

Your answer

These values were given by the decision makers for each word described.

Very low		low		average		high		very high	
1	2	2	3	3	6	7	8	9	10
1	2	2	4	4	6	6	8	8	10
0	3	4	5	6	7	8	8.5	8.6	10
								7	7
1	2	2	4	5	6	7	8	9	10
0	2	3	4	5	5	7	7	8	10
1	2	2	4	3	5	4	8	8	10
1	2	1	4	3	6	5	7	6	10
0	2	2.1	3.5	3	5	5.1	7.5	7.6	10
1	2	2	3	3	4	5	7	7	10
0	2	2	3	3	3-4	5	7	7.5	10
1	1.4	2	3.4	4	6	7	8	9	10
1	3	3	5	5	7	7.5	8.6	8	10
1	2	2	4	4	6	6	8	8	10
0	2.5	2.6	4	5	7	8	9.5	9.6	10
								7	7
1	2	2	4	4	6	6	8	8	10
0	2	3	4	5	5	6	7	8	10
1	2	2	3	4	5	5	7	5	10
1	2	2	4	6	8	6	9	9	10
0	2	2.1	3.5	3.6	5	5.1	7.5	7.6	10
1	2	1	4	5	5	4	5	9	10
0	2	2	3.5	4	5	5.5	7	7	10
1	1	3	3	5	5	4	4	8	10

Exactly equal		slightly important		fairly important		very strongly important		Absolutely important	
4	5	4	5	5	7	7	7.5	8	10
5	6	3	5	5	7	7	9	8	10
4.4	6.6	2	4	5	6	7	8	9	10
4	7	3	5	4	7	7	8.5	7	10
3	4	3	3.2	4	5	5	7	8	10
4	5.5	4	4.4	4	7	8	9	9	10
4	5.5	5	6	5	7	7	8	8	10
6	7	3.5	5.4	5.5	7.4	7.5	8.5	8.6	10
3	4	0	2	1	3	3	5	6	10
5	6	3	4	4.5	5.5	6.5	7.5	8	10
7	9	0	1	1	2	3	6	7	10
4	5	1	1.5	2	3	4	6	6	7
6	7	1.1	2	2.4	4	3	6	4	9
3	5.5	1	2	3	4	5	7	8	9
5.6	7.7	2	5	4	6	4	8	7	9
4	5	1	4	1	3	3		5	6.6

Very poor		poor		average		good		very good	
1	3	3	5	5	7	7.5	8.6	8	10
1	2	2	4	4	6	6	8	8	10
0	2.5	2.6	4	5	7	8	9.5	9.6	10
								7	7
1	2	2	4	4	6	6	8	8	10
0	2	3	4	5	5	6	7	8	10
1	2	2	3	4	5	5	7	5	10
1	2	2	4	6	8	6	9	9	10
0	2	2.1	3.5	3.6	5	5.1	7.5	7.6	10
1	2	1	4	5	5	4	5	9	10
0	2	2	3.5	4	5	5.5	7	7	10
1	1	3	3	5	5	4	4	8	10
1	2	2	3	3	6	7	8	9	10
1	2	2	4	4	6	6	8	8	10
0	3	4	5	6	7	8	8.5	8.6	10
								7	7
1	2	2	4	5	6	7	8	9	10
0	2	3	4	5	5	7	7	8	10
1	2	2	4	3	5	4	8	8	10
1	2	1	4	3	6	5	7	6	10
0	2	2.1	3.5	3	5	5.1	7.5	7.6	10
1	2	2	3	3	4	5	7	7	10
0	2	2	3	3	3-4	5	7	7.5	10
1	1.4	2	3.4	4	6	7	8	9	10

AN INTERVAL TYPE 2 FUZZY EVIDENTIAL REASONING APPROACH TO PERSONNEL RECRUITMENT

BY

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IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTER OF SCIENCE DEGREE IN MANAGEMENT INFORMATION SYSTEMS

JUNE, 2017

CERTIFICATION

I hereby declare that the contained report on “An Interval Type 2 fuzzy Evidential Reasoning Approach to Personnel Recruitment” was researched, and the results thoroughly analyzed, under the supervision of the project supervisor and approved having satisfied the partial requirements for the award of Masters of Science in Management Information Systems, Covenant University, Ota.

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DEDICATION

This dissertation is dedicated to my loving parents Mr & Mrs Funso Kehinde Olawoye, for all the love, patience, kindness and support throughout my stay in school.

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ABSTRACT

Recruitment process is a procedure of selecting an ideal candidate amongst different applicants who suit the qualifications required by the given institution in the best way. Due to the multi criteria nature of the recruitment process, it involves contradictory, numerous and incommensurable criteria that are based on quantitative and qualitative measurements. Quantitative criteria evaluation are not always dependent on the judgement of the expert, they are expressed in either monetary terms or engineering measurements, meanwhile qualitative criteria evaluation depend on the subjective judgement of the decision maker, human evaluation which is often characterized with subjectivity and uncertainties in decision making. Given the uncertain, ambiguous, and vague nature of recruitment process there is need for an applicable methodology that could resolve various inherent uncertainties of human evaluation during the decision making process. This work thus proposes an interval type 2 fuzzy evidential reasoning