DEVELOPMENT OF MULTI-PERSON MULTI-ATTRIBUTE MATCHMAKING DECISION SYSTEM

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(21452700)

Submitted in fulfilment of the requirements for the

MASTERS DEGREE IN INFORMATION AND COMMUNICATION TECHNOLOGY

in the

DEPARTMENT OF INFORMATION TECHNOLOGY

FACULTY OF ACCOUNTING AND INFORMATICS

DURBAN UNIVERSITY OF TECHNOLOGY

JULY 2017

DECLARATION

I, Uko, Edidiong Idungima, declare that the contents of this dissertation represent my own unaided work, and that the dissertation has not previously been submitted for academic examination towards any qualification. Furthermore, it represents my own opinions, ideas and not necessarily those of the Durban University of Technology. I further declare that all the sources cited or quoted are indicated and acknowledged by means of a comprehensive list of references.

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DEDICATION

This dissertation is dedicated to my family without whom this academic goal would not be fulfilled.

Special dedication to my mom, a strong-willed and gentle woman, whose backing and motivation saw me through this journey.

ACKNOWLEDGEMENTS

I thank God for the strength, tenacity and grace He gave me and for His power that kept me going every day throughout the duration of the programme. He is great indeed.

I am very thankful to everyone who has supported me towards the effective and timely completion of this project. I am specifically grateful to my supervisor, Prof. Olugbara, O.O. and co-supervisor, Prof. Joshi, Manish of North Maharashtra University, Jalgaon MS, India for their moral support, mentorship and guidance in the course of this work.

I would like to also thank my parents Dr. Roy and Prof. Ini Uko, and siblings for their immense support and encouragement. My utmost appreciation goes to my wonderful mate and partner, Robert Umoh, for his patience, understanding and assistance. Special thanks to Mr. Otu and Mrs. Emem Anwana, who despite their busy schedules ensured I was always comfortable and on track.

My appreciation also goes to all my colleagues for their assistance in every way.

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ABSTRACT

This dissertation reports on the development of an algorithm based on an existing matchmaking method to solve diverse decision problems in a multi-person environment. The capacity to effectively achieve a lucrative and accurate decision making is a critical aspect of resource management. But the accuracy of a decision making process can be highly compromised because of the high subjectivity and multiple conflicting attributes that are present in human judgement. multi-person decision making is an effective approach for achieving a lucrative and accurate decision making process. The multi-person decision process has proven to be tedious mainly because the existing multi-person decision making methods are extensions of single decision making methods. This imposes additional computational resources, especially for a large number of decision makers because they aggregate the preferences of several decision makers into a unified format.

This work therefore seeks to improve the multi-person decision making process using a matchmaking approach. In doing so, the Hunt ForTune matchmaking algorithm was investigated and improved for this purpose. Thus, the preferences of decision makers for each attribute are collected as an attribute description vector. The attribute, its description vector, flexibility and priority vector are compactly represented as a 4-tuple profile. The improved Hunt ForTune matchmaking algorithm is applied to different sets of multi-person decision problems and offered as an effective way of enhancing decision accuracy. The improved matchmaking decision algorithm is compared with a novel mathematical technique of Hausdorff distance. Results generally show that multi-person matchmaking algorithm is suitable and efficient for diverse decision making in the presence of multiple decision makers. The practical implication of the proposed multi-person matchmaking algorithm for decision making is that it provides a less complicated way to capture and represent the preferences of multiple decision makers irrespective of decision domain. The originality of the work reported in this dissertation is built on a matchmaking algorithm by introducing effective profile representation using vector analysis approach to capture the preferences of multiple decision makers and similarity metrics to provide an efficient and robust way to accurately perform a multi-person decision process.

CHAPTER 1

INTRODUCTION

1.0 Background Information

In many real-life decision situations, decision makers (DMs) are often faced with a problem of choosing the best alternative from a given set of alternatives among the conflicting tangible and intangible criteria (Mousavi, *et al.*, 2013). According to Cambridge English dictionary and Oxford dictionary, a decision maker is one who makes important decisions on things, especially at a high level in an organization. Making a decision implies that there are a wide number of alternatives to be considered with different and often conflicting criteria. In such cases, only the alternatives that best fits with the goals and objectives of the decision making process should be identified and chosen (Cardinal, *et al.*, 2011). In order to achieve this, different procedures are used for classifying an alternative as fitting that makes the process of choosing an alternative a tedious and time-consuming assignment (Jahan and Edwards, 2013; Gastwirth, 2015).

Decision making is the process of choosing suitable alternatives from a pool of competing alternatives in order to select the best alternative (Johnson and Kruse, 2009; Nourianfar and Montazer, 2013). Decision making is a key management instrument and one of the major problems faced by the any organization as it has an important impact on the reputation of that organization (Eisenkopf, 2009). Thus making the question of which alternative should be chosen pertinent in the resource management of an organization (Gavade, 2014). But the accuracy of a decision making process can be highly compromised because of the high subjectivity and multiple conflicting attributes that are present in human judgement. As a result of this, decisions are carried out in a group environment in order to cancel out the biases and special interests of individuals (Bonito and Sanders, 2011).

Most organizations around the world have conventionally established specific criteria aimed at choosing the best alternatives possible and these criteria vary according to the number of quantitative and qualitative factors (Ozfirat, *et al.*, 2014; Zheng, *et al.*, 2011). The typical quantitative factors used for selection in most organizations are standardized tests and written tests while the qualitative factors used include interviews, recommendations (Hardigan, *et al.*, 2001; Chen and Voyles, 2013). However, different authors have pointed out that the major need for proper decision making in any organization is to increase the quality of human and material resources by attracting the appropriate talents, increase the probability of organizational success and provide the best possible resources and services (Ozfirat, *et al.,* 2014; Saputroa, *et al.,* 2015). The decision making process is generally based on the decision maker's (administrators, personnel, managers) perspective, therefore, it is important to have up to date information that meet the requirements of the decision maker (Eisenkopf, 2009). This of course requires that the decision maker specifies his needs and the information will be made readily available. In order for a decision maker to avoid getting irrelevant or unnecessary information, a demand profile has to be defined and every piece of information made accessible to the decision maker will be associated with a supply profile which will in turn aid in eliminating wrong decision making and time wastage (Asif and Krogstie, 2011; Joshi, *et al.,* 2010).

There are several problems that decision makers in the various organizations face, which include selection of quality personnel, selection of an organization that offers the best long-term factors and incentives, prioritization of government policies, availability of quality resources, amongst others and these greatly influences their final choices (Olugbara, *et al.,* 2015; Metcalf, *et al.,* 2005; Lee, *et al.,* 2012; Abebe, 2012; Gulcan, 2008; Rouyendegh and Erkan, 2013). The decision making process can either have a positive or a negative impact on the choices made because the selection of an alternative in any organization can either lead to the satisfaction of different demands or a massive failure occurrence (Eisenkopf, 2009; Jahan and Edwards, 2013). Therefore, researchers have poised that decision making should be carefully done so as to avoid wrong or inappropriate choices as this may limit the ability to select the best set of alternatives which will in turn decrease the value and quality of the resources and outcome of the organization (Ismail, *et al.,* 2010).

The improper decision making process can obviously contribute to the shortlisting of an incompetent alternative which will further lead to a great negative impact on the performance of the organization. Improper alternative shortlisting is generally viewed as a result of various types of gaps, which refer to experiences, skills and competencies that may be of qualitative or quantitative nature (Yaseen, 2015). Incompetent alternative shortlisting is a global concern that has received a lot of attention from various scholars, policy makers and government bodies (Gusdorf, 2008; Public Service Commission, 2015; Yaseen, 2015; Metcalf, *et al.,* 2005; Abebe, 2012; Gulcan, 2008; Johnson and Kruse, 2009; Wale, 2010). Incompetent alternative shortlisting is a major cause of damage on the reputation of an organization (Ismail, *et al.*, 2010). It can further lead to detrimental results at organizational, educational and economic levels, poor or instable service delivery qualities which will negatively affect organizational performance, impede economic growth and innovative capabilities (Metcalf, *et al.*, 2005; Public Service Commission, 2015; Yaseen, 2015). One way to approach incompetent alternative shortlisting is through assigning decision making to groups rather than individuals. Through multi-person decision making, more knowledge and expertise are available to solve the problem, the final decision is better understood and accepted by all group members and ensuring some measure of communal representativeness in the results derived from the group's effort thus eliminating the possibility of incompetent alternative shortlisting (Lunenburg, 2011; Bonito and Sanders, 2011).

The various application areas where decision making becomes critical are supply chain coordination, government organizations, educational institutions, electronic marketplaces (e-Marketplace), material handling equipment (MHE) selection (Gholipour, *et al.*, 2014; Salam, 2011; Singh and Benyoucef, 2013; Enyinda and Bell-Hanyes, 2010; Alpar, 2010; Noia, *et al.*, 2003; Veit, *et al.*, 2001; Saputroa, *et al.*, 2015; Lashgari, *et al.*, 2012). To make a decision process effective and efficient, an automated system such as the one being proposed in this study is imperative (Veit, *et al.*, 2001; Saputroa, *et al.*, 2015).

In this study, the researcher looks at the possibility of effectively and efficiently solving multi-person decision process in various aspects of decision making. In doing so, the decision process is considered as a matchmaking problem by matching an alternative profile with an ideal profile, where a matchmaking algorithm can be considered as a practical solution (Joshi, *et al.*, 2009). A matchmaking algorithm for the selection process is needed in order to facilitate the selection of alternatives by effectively capturing the different types of constraints as well as different data types. The proposed method will ensure that all the preferences of decision makers are adequately captured and stored in the ideal profile and used in the decision process thereby only the most competent alternatives are suitably selected and shortlisted.

1.1 Problem Statement and Research Questions

Pertinent information plays a vital part in any decision making process as this will enable decision makers irrespective of the domain, to make good decisions and also assist in their daily activities. The possibility of achieving tremendous success, the quality of its services and growth in any institution is directly dependent on the quality and performance of the alternatives selected during a decision making process (Public Service Commission, 2015). As a result of this, a variety of methods are used by different organizations to choose the alternatives that best meet the norms or requirements specified by the decision makers (Hardigan, *et al.*, 2001; Yaseen, 2015). Although these methods are designed to aid in the decision process by choosing promising alternatives out of a pool of competing alternatives (Shannon and McKinney, 2011; Abebe, 2012), it was found that they are not the best predictors of success and quality delivery (Yaseen, 2015).

Asides from filling vacancies, one major aim of a decision making process in any domain is to select quality alternatives who are well prepared, effective and innovative and will help in increasing the reputation of the organization. But there are some specific shortcomings during a decision making process which include the required and mandatory skills, competencies, knowledge and experiences of alternatives that vie for certain positions that are not thoroughly considered (Veit, *et al.*, 2001; Public Service Commission, 2015). The neglect of such shortcomings can be as a result of inexperienced decision makers, lack of a reliable automated system in place to ensure compliance with the required decision criteria, poorly determined and inconsistently applied criteria (Noia, *et al.*, 2003; Saputroa, *et al.*, 2015).

The major problem of decision making in any organization is to find an automated method that can conveniently capture all constraint types and criteria as well as support multi-person decision making to effectively solve any form of decision problem and provide a better way of selecting competent alternatives. As a result of this, the overall research question will be dealt with in the present study:

i. How can an effective multi-person decision making process be achieved to reduce incompetent alternative shortlisting?

In order to effectively address the overall research question, the following research sub-problems are addressed:

a. What effective matchmaking algorithm can be developed to conveniently capture diverse data types and effectively represent decision criteria?
b. How can the developed matchmaking algorithm be conveniently implemented to aid in a multi-person decision environment?
c. Can the matchmaking algorithm that supports multi-person decision making be used to minimize incompetent alternative shortlisting?

1.2 Purpose of the Study

The purpose of this study is to delve into the various decision making methods being implemented in practice today for different decision purposes and introduce an improved matchmaking approach that supports multi-person decision making. Furthermore, the study is also aimed at determining the most appropriate matchmaking approach for an alternative selection in any organization. It is aimed through this research to develop a matchmaking system that will enhance multi-person decision making to support precision with alternative shortlisting.

In order to achieve this aim, the following objectives have been set:

a) To compare the effectiveness of two state-of-the-art matchmaking systems in literature for solving decision problems;
b) To develop and implement a matchmaking approach to solve different multi-person decision problems that are frequently encountered by decision makers;
c) To evaluate and validate the multi-person matchmaking algorithm for various decision problems using a novel matching theoretical mathematical technique.

1.3 Significance of the Study

The findings and results of the current study may probably benefit any form of organization globally since the approach is more pragmatic for solving diverse forms of decision problems. This study can also serve as a learning tool for individuals, governmental bodies and policy makers as the reputation of an economy, organization or firm irrespective of size and nature of the job depends solely on the selection of competent, reliable and efficient alternatives.

Consequently, the result may potentially lead to an improvement in organizations that are faced with poor decision making processes which will further lead to an increase in economic growth. Matchmaking has worked well in the e-Commerce and a decision making process can be modelled as a matchmaking problem, it should not be a plight for decision making in other forms of organizations.

1.4 Design Method

To address this study's research question, a multi-person matchmaking algorithm will be proposed to compute the similarities between an alternative profile and the ideal profile. The algorithm applied consists of step-by-step procedures for performing profile similarity calculations. The success of the matchmaking system will depend on how efficiently both the ideal and alternative profiles are modelled (Joshi *et al.,* 2010). The proposed algorithm based on multi-person matchmaking accumulates alternatives' competences with the reference's requirements for the position, based on their defined constraints. It matches alternatives' competence profiles with the reference requirement profile and recommends competent alternatives to the institution.

One major setback found in the current matchmaking algorithm presently in use is that it does not accommodate multi-person decision making. In the current study, the aim is to develop a multi-person matchmaking algorithm which supports group decision making for any decision purpose.

The methodology applied in the present study is based on the effective knowledge representation management and efficient multi-person matchmaking algorithm to match an alternative competence profile with a reference requirement profile. Two new concepts of similarity metrics and vector constraint representation were introduced to enable the researcher to effectively formulate and capture multiple decision makers' preferences as well as in the determination of similarity values. Firstly, the alternative competence was captured in the alternative profile. Secondly, fixed ideal profiles will be formulated based on the decision makers' requirements. In this regard, the model of Joshi et al. (2009) knowledge representation and matching algorithm was helpful.

1.5 Synopsis

The rest of this dissertation can be summarized as follows. In Chapter 2, the literature review the following key subjects are described:

a. Decision making practices in various organizations, focusing on multi-person decision making formulation;
b. Automated methods for decision making;
c. Various application areas of decision making and comparison of two state-of-the-art matchmaking algorithms.

In Chapter 3, the methodological approach is discussed that was followed to accomplish the research objectives. An explanation and description of the algorithm, experimental illustrations, implementations as well as limitations are reported. Additionally, a novel matching theoretical mathematical technique is introduced into the matchmaking approach. In Chapter 4, the results depicting experiments performed to realize the research objectives are presented and discussed. Finally, in Chapter 5, study observations, recommendations, summary of the results of the study, followed by suggestions for possible future research and a conclusion.

1.6 Summary of Chapter 1

In this section (Chapter 1), the field of the research is unveiled. Matchmaking algorithms have been used in various fields to match profiles, for example X and Y. For example, Joshi et al. (2010) applied matchmaking within the real estate market– matching buyers and sellers – based on similarities defined by both parties. In the current study, a multi-person matchmaking algorithm was developed to conveniently capture the preferences of decision makers in a group environment and effectively match alternative profiles with ideal profiles. This multi-person multi-attribute decision approach is yet to be introduced to matchmaking for the selection of alternatives; thus making the current study viable and novel.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

In this chapter, a literature appraisal is provided that will unveil the research capacity that has been done regarding various multi-person decision methods that has been implemented by a range of organizations to choose the best alternative. Some limitations were observed in the literature that supports arguments for necessitating the present research. The emphasis is mostly placed on the aspect of decision making, manual decision making practices, matchmaking and decision making techniques, the incorporation of multi-person decision making in decision processes, multi-person decision methods and the intricate problems associated with multi-person multi-attribute decision process.

The literature search furthermore focused on e-documents – obtained from the Emerald Database (http://www.emeraldinsight.com/products/journals/index.htm), Association for Computing Machinery (ACM) Digital Library (http://portal.acm.org), Springer LNCS (http://springer.com/lncs), IEEE Explore (http://ieeexplore.ieee.org) Google Scholar (http://scholar.google.co.za) – such as student selection journals, textbooks, conferences‟ proceedings and documents by various governmental and non-governmental institutions, academics and researchers. The literature exploration was limited to literature in English and restricted to publications between 2000 and 2017 – in order to incorporate only recent decision making methods and multi-person decision making methods.

Key words used were decision making, decision making techniques, multi-attribute decision making, multi-person decision making techniques, matchmaking algorithms, decision criteria, manual decision making, vector representation and computation. Throughout the literature search, it was noticed that a plethora of literature exists for all sorts and categories of multi-person decision making, particularly in the industrial and educational sector. However, care was taken throughout the literature review phase that this over-representation did not deter or shift the focus from the present study's objectives which is to solve diverse problems of multi-person decision making frequently encountered by decision makers irrespective of the application domain.

2.1 Decision Making

Decision making is one of the most important activities as well as one of the major problems any type of organization faces on a daily basis, which usually involves multiple attributes that should be evaluated simultaneously (Zolfani and Antucheviciene, 2012; Lunenburg, 2011; Ozfirat, *et al.*, 2014). As earlier mentioned, decision making is the process of selecting the best alternative from a pool of competing alternatives in order to achieve specific predefined goal (Cardinal, *et al.*, 2011; Nourianfar and Montazer, 2013; Jahan and Edwards, 2013; Johnson and Kruse, 2009; Gastwirth, 2015). Decision makers in various organizations are faced with different kinds of decision problems such as personnel selection and management, ways of improving organizational achievements, amongst others (Gulcan, 2008; Abebe, 2012). Decision makers in organizations are constantly encountering the challenge of successfully carrying out a transparent and objective selection process that delivers correct, justifiable outcomes of choosing the best alternative among the conflicting cognitive and non-cognitive criteria (Mousavi, *et al.*, 2013; Janic and Reggiani, 2002; Walton, 2015). The complexity of the task of selection and the quality of the decision process is often affected by the choice of the selection process and the technique employed (Joshi, *et al.*, 2012).

Decision making is affected by three sets of factors –decision features, situational factors, and individual differences (Appelt, *et al.*, 2011). As a result, recent research efforts have progressively been focused mainly on simplifying the decision making process of selecting suitable alternatives (Olugbara, *et al.*, 2015). Since decision processes are typically very competitive with more alternatives than available spaces, a multifactorial approach has been adopted by many researchers, citing the need to assess both cognitive and non-cognitive criteria to better choose alternatives that will not only succeed professionally, but will also minimize attrition by choosing well-suited and motivated alternatives (Salvatori, 2001; Timer and Clauson, 2011).

Therefore, different methods have been proposed to support decision making – by applying advanced technological techniques – which has been divided in this study into the conventional decision methods and matchmaking methods. The conventional decision making methods such as AHP, TOPSIS, Fuzzy Inference system, ELECTRE have been criticized for not clearly showing how potential alternatives are searched and found, making rough assumptions due to inability to handle the uncertainty of the data, ineffectiveness to tackle large large date sets and irregularities in ranking alternatives (Saputroa, *et al.*, 2015; Aruldoss, *et al.*, 2013; Mohtar, *et al.*, 2011; Lopez and Carlos, 2005; Alexander, 2012). The matchmaking methods were developed as a remedy in preventing these limitations during decision making (Veit, *et al.*, 2001; Bhavsar, *et al.*, 2004; Kester, *et al.*, 2007; Noia, *et al.*, 2003; Joshi, *et al.*, 2009; Al Rabea and Al Fraihat, 2012). There has been a tremendous increase in research works, analytical and statistical surveys emphasizing on the problems associated with decision making. Some of the instances of decision problems commonly faced in various organizations include the following:

a) Selection of material handling equipment and general equipment used in industrial area;
b) Allocation of learning resources for learners;
c) Selection of applicants into appropriate programmes;
d) Assignment of projects to suitable contractors;
e) Appointment of personnel into job positions;
f) Selection of suitable contractors for resource procurement;
g) Selecting an appropriate supplier in a manufacturing organization.

A large variety of questions have been observed in the present adopted decision making practices. Relevant information has been acquired by researchers which have highlighted the above points as some of the critical issues faced in various organizations during any decision process (Shahroudi and Tonekaboni, 2012; Afshari, *et al.*, 2011). It has been argued that the way to achieve a success during a decision process is to identify alternatives with the highest merits, best set of skills, qualifications and competencies that are directly related to the position they want to take up. But this is not always right since in real world situations it is rarely the case that alternatives match all the required criteria for that particular decision process. The researcher has observed that as organizations are constantly competing to attract the best talents from around the globe, it is therefore crucial to employ decision making practices and strategies that will eliminate any form of failure but rather increase and positively affect the productivity of organizational outcomes. Furthermore, the end results of a decision process can either have a negative or positive impact on the reputation of the organization and economy as a whole.

The basic aim of a decision process is to choose alternatives who meet the related criteria, are self-motivated and directed or inclined towards success, consistent, efficient towards goals, system and organization, contribute well and are quick learners directed towards self-development (Yaseen, 2015). As various organizations are experiencing unprecedented growth and demand for their services and are also being greatly scrutinized with higher standards by regulatory and governing bodies, it is crucial for any success-oriented organization to utilize decision making practices that will not only assess potential talents but also choose quality talents that will aid in providing the best possible resources and services. Therefore, matching alternative's competence and the requirements of an organization remain an imperative task.

2.2 Manual Decision Making Practices

Most organizations aim at choosing alternatives that satisfy some specific requirements at a collective level and these requirements vary according to the number of quantitative and qualitative factors (Zheng, *et al.*, 2011; Ozfirat, *et al.*, 2014). These quantitative and qualitative factors include: recommendations, grade points, entrance examinations or aptitude tests, and statistical procedures such as essay writing, standardized tests, interview assessments, and many more. The use of so many different measures indicates a desire by decision makers to choose the best alternatives among a large selection pool. However, not all quantitative and qualitative variables have demonstrated the same level of criterion-related evidence of validity (Hardigan, *et al.*, 2001). In the following section some of these manual methods are discussed.

2.2.1 Recommendations or References

Despite the varying titles attributed to an alternative written work, the use of personal statements has become a common tool for assessing non-cognitive qualities. One widely used method in decision making is the reference report or a letter of recommendation, simply known as the reference, whereby a referee (e.g., former employer, teacher or colleague) provides a description and usually, but not always, a statement in support of an alternative (Chamorro-Premuzic and Furnham, 2010). Despite controversy regarding the assessment of personal qualities, it is recognized that academic proficiency does not necessarily translate into success nor are personal characteristics such as integrity easily taught, making the assessment an important yet difficult task (Timer and Clauson, 2011). Recommendations or references may include motivation for, or prior experience in, the chosen field, methods of problem solving or dealing with interpersonal conflict. Written references have some drawbacks; for instance, if someone wants to get rid of an alternative, they certainly won't give a poor reference under those circumstances. Poor references could also turn out to be libellous, although one of the main problems is that people just don't know what information is needed (Shell liveWire, 2015).

2.2.2 Aptitude Tests

Aptitude tests (entrance examinations or written tests) have a long history of use as a decision making tool whereby alternatives are selected based on their performance in the aptitude tests as well as grade point average (GPA) (Chen and Voyles, 2013; Lunenburg, 2011). This particular tool is mostly used in learning environments. The mechanism provides a combination of scores for both academic and non-academic areas. The initial phase of the decision making process involves judgments made as to whether an alternative is shortlisted for interview and usually these are based on academic qualifications (Taylor, *et al.,* 2014).

However, it has been widely argued by different authors that decision criteria and decision making processes must include an integration of several types of tests, such as academic and social skills, as well as a combination of interviews at tertiary level (Gallagher *et al.*, 2001; Joshi, *et al.,* 2012). These aptitude tests may cover a range of areas including: general intelligence, verbal ability, numerical ability, spatial ability, technical knowledge, clerical ability, mechanical ability, sensory and motor abilities.

For instance, in the USA, the aptitude tests that are used in the nursing profession, is the Nurse Entrance Examination (NEE). The NEE was developed by an organization named Educational Resources, Inc. (ERI). The objective was to apply this examination as an instrument for selecting students, specifically in medical courses (Gallagher *et al.,* 2001). Although it is often assumed that students with high scores on the aptitude test will perform well at universities. But this is not always the case because the selection model does not consider the specific knowledge and skills required for the programme that a student had indicated an interest (Joshi, et al. 2012).

2.2.3 Other Standardized Tests

There are several other aptitude tests available that measure specific psychological attributes or mental abilities and purport to predict performance of an alternative (Salvatory, 2001). A standardized test is any examination that's administered, scored and interpreted in a consistent, predetermined and standard manner (National Council of Teachers of English, 2014). Properly designed tests are reliable and valid in predicting an alternative's success in the decision making process. To equitably compare the performance of several alternatives, the processes used for testing those alternatives must be as identical as possible. The content of the test, the instructions and the time allowed must be the same for all (Gusdorf, 2008).

Standardized testing helps cut down on the number of alternatives by eliminating those that are incompetent and lack the required skills in that field. These tests are often used for high-stakes purposes such as determining which students will pass or graduate, which teachers are fired or given raises, and which schools are reorganized or given more funding. The effects of these standardized tests on student learning include changing the nature of teaching, narrowing the curriculum, and limiting student learning.

For instance, a study was conducted by (Chestnut and Phillips, 2000) to determine the current admission practices used by colleges of pharmacy and discovered that most pharmacy schools use a standardized test called PCAT (Pharmacy College Admission Test) as one of their decision criteria to admit students into the college of pharmacy. Also, some nursing schools use a 70% score on the Nursing Entrance Test (NET) as a benchmark for admitting aspiring nursing students into diploma programmes. Although these standardized tests enable alternatives with good potentials to be chosen, it only evaluates the alternative performance based on a particular day and individual performance and does not take into account external factors or overall performance of the alternative.

2.2.4 Interviews

Although the interview is the most popular form of decision making, it is also the least useful in predicting the overall performance of the alternative. At one time, interviews with were almost consistently ranked as the most important of all decision making tools (Timer and Clauson, 2011). Whether it comes at the beginning or the end of the decision making process, whether there are one or many interviewers at a time and whether it lasts a few minutes or several hours, the decision making interview is thought as a crucial and central part of the process whereby the interviewer and interviewee can get a good sense or feels about each other (Chamorro-Premuzic and Furnham, 2010).

For instance, in the UK, face to face interviews are a requirement for entry into nursing programmes (Rodgers, *et al.,* 2013). The popularity and widespread of interviews has given rise to a huge industry in interview training. It has also generated a number of books for both interviewers and interviewees where interviewers are taught how to ask difficult questions that get to the heart of the interviewee and interviewees are taught how to give evasive answers to those really tricky questions (Chamorro-Premuzic and Furnham, 2010). As a result, some organizations have argued that the data showing the extremely poor reliability and validity of interviews effectively means that they often hinder rather than help effective decision making (Chamorro-Premuzic and Furnham, 2010) which the reliability of interviews is debatable, particularly in relation to the consistency of decision making because there is no clear right or wrong answer in many cases as most interviews are ubiquitous (Gusdorf, 2008; Rodgers, *et al.,* 2013). The results are subject to interpretation by the interviewer and thus can have a huge potential for error, depending on the questions asked, the answers given and the interviewer's own personal bias (Gusdorf, 2008). According to Yaseen, (2015), the problems with interviews include, but are no limited to:

a. Lack of training by the interviewers;
b. Unstructured interview;
c. Disagreement on questions to be asked;
d. Disagreement on topics to cover;
e. Different perspectives;
f. No valid weight system given to the answers;
g. Risk of asking illegal questions.

In summary, interviews are the most popular method of assessing, and gaining information about, an individual. If this process is handled properly, they can be extremely useful and beneficial but if it is handled badly, they can be a nightmare for all concerned.

2.2.5 Grade Points Average (GPA)

Grade point average is mostly used in learning environments. This is typically regarded as a measure of one's academic achievement (Imose and Barber, 2015). For instance in nursing schools, applicants prenursing grade points are evaluated for admission, although Rodgers, *et al.*, (2013), poised that the only reliable predictor of success in nursing, medicine and allied health profession selection process is Grade Point Average, the evaluation of such grades in determining admission into nursing programs is highly questionnable due to the problems associated with grade inflation and different grading systems which makes the use of grade point as a selection tool controversial (Chen and Voyles, 2013).

A recent study carried out by (Imose and Barber, 2015) shows that the use of minimum GPA cut scores becomes more prevalent as the number of alternatives increases, thus enabling decision makers to differentiate quickly between alternatives during the decision making processes. Although the use of GPA is promising, there are some cons on the use of GPAs in decision making, such as comparability across alternatives, thereby resulting in wrong decision making as all GPAs are not rated equally, misrepresentation or faking of GPAs by alternatives is also a primary point of contention.

2.3 Matchmaking and Decision making Techniques

Decision making is becoming an important activity in the ultra-modern world, despite being invaded with various updated technology advancements assisted decision tools (Abdullah, 2013). Multi-Attribute Decision Making is the most well-known branch of decision making that deals with decision problems under the presence of a number of decision criteria (Rao, 2012). The scientific methods for decision making is divided in this study into three main approaches based on the way alternatives are manipulated namely machine learning, multi-attribute decision analysis and matchmaking system (Olugbara, *et al.*, 2015; Joshi, *et al.*, 2012). The following subsections describe the above main approaches with diverse strategies or methods that are used for various forms of decision making.

2.3.1 Machine Learning

Machine learning is the process of estimating unknown dependencies or structures in a system using a limited number of observations (Miskovic, 2014). Olugbara, et al. (2015), pointed out that this system operates on a series of observed data samples by learning to perform a given task from the data samples. Some methods classified under this approach have been applied in solving various decision problems.

The evolutionary algorithm was used for the assignment of students to courses high on his preference list as much as possible whereby assignment of students to courses was formulated as an instance of the generalized assignment problem (Shannon and McKinney, 2011). Another method used was the artificial neural networks, which was used for the placement of students in universities, i.e student admission (Wabwoba and Mwakondo, 2011) and also for the job assignment problem of the US Navy (Kelemen, *et al.,* 2002).

However, the efficiency and effectiveness of these methods have been questioned because of their inability to adequately handle the uncertainty and imprecision of the decision making process, the level of irregular assumption acquired. That is, different results were obtained each time the process is run, the utilization of complex knowledge representation models and high computational time complexity, thereby often imposing a high cognitive effort on the decision makers (Mohtar *et al.,* 2011; Lopez and Carlos, 2005). In summary, selection of alternatives based on prediction is not the best as there are some inconsistencies in the outcome of the decision process.

2.3.2 Multi-Attribute Decision Analysis

One of the promising decision making tools that was conceptualized in the early seventies is multi attribute decision analysis, which is the process of making decisions in the presence of multiple, but usually conflicting criteria (Aruldoss, *et al.,* 2013; Abdullah, 2013; Gavade, 2014). According to Olugbara, et al. (2015), multi-attribute decision analysis are optimization methods that make use of decision matrices to provide a systematic way for evaluating, or ranking, a set of alternatives, relative to a set of decision criteria. Multi-attribute decision analysis has also been proposed as an alternative approach for solving various decision problems. Examples of multi-attribute decision analysis are analytic hierarchical process (AHP), preference ranking organization method for enrichment of evaluations (PROMETHEE), elimination et choix traduisant la realité (ELECTRE), and technique for order preference by the similarity to ideal solution (TOPSIS) (Kolios, *et al.,* 2016). These methods have been successfully applied to a wide range of decision problems in various application domains such as chain supplier selection, personnel selection, material handling equipment selection, amongst others (Gholipour, *et al.,* 2014; Bali, *et al.,* 2013; Mammadova and Jabrayilova, 2014; Shahroudi and Tonekaboni, 2012; Gavade, 2014; Velasquez and Hester, 2013; Zolfani and Antucheviciene, 2012).

Although, the multi-attribute decision analysis was proposed to aid in decision making where choosing the best alternative is highly complex and includes multiple criteria, this approach has some major limitations such as time complexity when handling large and complex profiles, lack of domain independence and comparison of alternatives with each other which limits scalability, pairwise comparison of different alternatives for different criterion thereby resulting in irregularities in ranking the best alternatives (Lopez and Carlos, 2005; Aruldoss, et al. 2013; Olugbara, *et al.,* 2015).

2.3.3 Matchmaking System

Matchmaking is the process of optimally pairing up alternatives from two groups for possible matches between the groups (Joshi, *et al.,* 2010; Noia, *et al.,* 2003). The matchmaking approach was first proposed with the objective to assist in e-commerce by searching the space of possible matches between demand and supply and finding a match between the trading intentions of the market participants (Joshi, *et al.,* 2009; Noia, *et al.,* 2003). The process of choosing an alternative can be considered as matchmaking between the reference requisites profile and an alternative's competence profile. The matchmaking approach solves a decision problem as a matchmaking task by calculating the similarity score between the alternatives' profile and the reference profile (Olugbara, *et al.,* 2015). This approach has been proposed by different authors to aid in various forms of decision making (Joshi, *et al.,* 2012; Noia, *et al.,* 2003; Kester, *et al.,* 2007).

Over the years, different approaches have been implemented in the development of matchmaking systems. GRAPPA (Generic Request Architecture for Passive Provider Agent) was proposed by Veit, et al. (2001) as a matchmaking system that accept a set of offers and requests, as input – and a distance function to compute the distance similarity of various sets of profiles – where the distance similarity value is between 0 and 1. The system then returns a list of the best possible matches in a ranked format. Moreover, a weighted tree similarity algorithm was proposed as a matchmaking system that represents the attributes as node-labelled, arc-labelled and arc-weighted trees for matching agents in e-business environments. When two profiles are matched, the system displays a list of matches and discards mismatches (Bhavsar, *et al.,* 2004).

Furthermore, Kester, *et al.,* (2007) developed a matchmaking system to respond to a learner's request by matching profiles of other learners who wish to share knowledge, by determining their content competence, sharing competence, eligibility and availability. The learning contents are organized in courses and user profiles (which consists of completed courses, current courses, activities, calendar and other information) and are stored in the database system. When a learner inputs a query to the system using the request module interface and the query data is stored in the database, a Latent Semantic Analyser (LSA) maps the content question of the available documents in the database to generate a list of all suitable matching resources, that is other learners who are content competent, sharing competent and eligible, available.

However, using a case study of an apartment-rental, Noia, et al. (2003) proposed semantics-based matchmaking algorithms that utilize a description logic-based neoclassic – which categorizes matches into potential and partial – and ensures that it ranks matching profiles within categories. In this regard, Ragone, et al. (2007) implemented a matchmaking system – Vague knowledge bases for matchmaking in P2P e-marketplaces that used a hybrid combination of descriptive languages, Fuzzy Rules, and Utility theory to find the most promising alternatives in a P2P e-marketplace. The alternatives were chosen by computing the similarity between two profiles (P1 and P2) and returning the top-matching profiles based on the similarity scores. This system combined both the logical representation of attributes for both profiles and the similarity scores in order to select the best alternatives. Joshi, et al. (2009) proposed a matchmaking system Hunt ForTune for e-marketing, where all alternatives submit their profiles, and in turn these profiles are captured using a set of nodes and are represented as a quadruple of constraints. The ranking of alternatives is determined by the tuning the importance (weights) of the constraints by the participants.

The matchmaking approach has some prominent advantages which include scalability and ability to capture all types of criteria which means that no information is lost, domain independence and novelty, does not compare profiles in the same category with each other, that is, it does not compare alternatives with each other (Noia, *et al.,* 2003; Kester, *et al.,* 2007; Olugbara, *et al.,* 2015; Joshi, et al. 2010). But one outstanding limitation is that it has not been applied to address multi-person decision problem which is fast becoming a great cause of concern as it is an approach employed in all organizations during any decision process. According to Ozfirat, et al. (2014), an effective decision system that solves various forms of decision problems can ensure decreased costs and effective use of the organization's resources and services. In the proposed study, a multi-person decision system is proposed based on a matchmaking algorithm which will support various forms of decision making thereby enhance the selection of the best alternative.

2.3.3.1 Comparison of two Matchmaking Systems

In the current study, one objective is to compare the effectiveness of two state-of-the-art matchmaking systems for solving decision problems. In order to achieve this objective, firstly the features or characteristics of a successful matchmaking system will be explored. The reason being that the chosen matchmaking system for this study should completely possess the required features of a successful matchmaking system. Then the two matchmaking systems which possess most or all of these characteristics will be briefly discussed and compared based on their complexity analysis and experimental designs.

According to Bhavsar, et al. (2004) and Kester, et al. (2007), a successful matchmaking system should possess specific features such as scalable algorithm, ability to capture various types of constraints, domain independence, capability to handle complex profiles and categorization of matchmaking results, amongst others. From research, two matchmaking systems outstandingly possessed most of these features. These matchmaking systems are the Vague Knowledge Bases for Matchmaking in P2P EMarketplaces proposed by Ragone, et al. (2007) and the Hunt ForTune matchmaking system proposed by Joshi, et al. (2010).

a. **Vague Knowledge Bases for Matchmaking in P2P EMarketplaces** (Ragone, *et al.*, 2007), uses a Hybrid Combination of Description Languages, Fuzzy Rules, and Utility theory to find the most promising alternatives in a P2P e-marketplace. These alternatives are generated with respect to the preferences of the profiles compared. This matchmaking system computes two profiles, P1 and P2, and returns only the top matches, rather than all matches. The results were classified by returning top matching profiles based on the similarity score.
b. **Hunt ForTune matchmaking system** (Joshi, et al. 2010), two profiles, P1 and P2, are captured using a set of nodes and are represented by a quadruple of constraints. This matchmaking system calculates the similarity values between the two profiles and locates the closest matches. These matching profiles are classified among categories and ranked within the categories (Joshi, et al. 2010).

Table 2.1: Comparison of Two State-of-the-Art Matchmaking Systems.

Characteristics	**Vague Knowledge Bases for Matchmaking in P2P EMarketplaces** (Ragone, *et al.*, 2007).	**Hunt ForTune matchmaking system** (Joshi, et al. 2010).
Complexity Analysis	The computational time taken to generate the top matching results with a larger number of profiles is long due to the complexity of the algorithm and its vague knowledge base.	This approach can generate results in a satisfactory amount of time, even for a large number of profiles due to the simplicity and computational scalability of the algorithm.
Experimental Design	Computes two profiles, P1 and P2, then returns a top-matching profile based on similarity scores.	Calculates the similarity values between the two profiles and locates the closest matches between the two profiles.

In addition to these special features, the matchmaking system – Hunt ForTune – used in this study supports other features such as domain dependency, capability to handle complex profiles and preferential constraints which facilitates participants to indicate the relative importance among constraints, thereby customizing the results of the matchmaking process to suit their needs which makes it unique (Joshi, *et al.,* 2010; Joshi, *et al.,* 2009; Olugbara, *et al.,* 2015).

2.4 Multi-Person Decision Making

Decision making problems nowadays are increasingly involving interactivity that requires collective effort and detailed information shared by a group of people working together (Khasawneh and Abu-Shanab, 2013). multi-person decision making refers to a situation or a participatory process in which a group of people acting collectively, are jointly responsible for the identification of alternatives, evaluation of these alternatives, and selection of the most appropriate one (Kwok, *et al.,* 2002; Mount Holyoke, 2011). In recent times, the study of multi-person decision making is becoming more and more important in that many decisions take place in environments involving teams, committees, councils and any other type of groups: faculty in an academic department might select a job candidate to hire, a committee of company executives might develop a plan for promoting a new product, and a community board might decide how to allocate usage of the town green (Patalano and LeClair, 2011; Lunenburg, 2010).

Multi-person decision making is becoming pervasive in human affairs all over the world (Bonito and Sanders, 2011). The benefits of assigning such responsibilities to groups rather than individuals include canceling out the biases and special interests of individuals, more knowledge and expertise is available to solve the problem, the final decision is better understood and accepted by all group members and ensuring that some measure of communal representativeness in the results derived from the group's effort (Lunenburg, 2011; Bonito and Sanders, 2011). The nature and composition of groups, their size, demographic makeup, structure, goal and the process used to arrive at decisions all affect the functioning and effectiveness of decision making groups (Mount Holyoke, 2011). Committees who are responsible for selecting alternatives face an important but difficult task due to the fact that the decision process is either simple and made individually or complex and needs collective effort and intensive information (Khasawneh and Abu-Shanab, 2013).

There are different degrees of multi-person decision making: (i) consultative decision making, in which the leader consults with group members before making a decision, (ii) consensus decision making, in which the leader shares the problem with group members and together they generate and evaluate alternatives and attempt to reach agreement on a solution to the problem, and (iii) democratic decision making, in which the problem is given to the group, and group members are empowered to make the decision (Lunenburg, 2011).

Although there are many factors that affect the effectiveness and functioning of a multi-person decision making (Eliaz, *et al.*, 2007; Hashim, *et al.*, 2010), a considerable amount of research has indicated that decision making in groups are superior to individual, majority vote, and leader decisions in various ways such as increasing the confidence of indecisive individuals, ability to select a greater number of outstanding alternatives thereby reaching a superior problem solution, more suggested approaches to solve the problem (Mount Holyoke, 2011; Patalano and LeClair, 2011; Blinder and Morgan, 2005; Lunenburg, 2011). Nevertheless, there are still prominent challenges experienced during a multi-person decision making such as pressures to conform, the tendency to be dominated by one member, conflicting secondary goals and undesirable consequences, cloud responsibility, and time consuming (Kocher and Sutter, 2007; Patalano and LeClair, 2011; Lunenburg, 2010; Charness and Sutter, 2012) which makes it is very important for all types of organizations to improve their multi-person decision processes and activities through the use of several methods and technologies that will make such processes more efficient and effective (Khasawneh and Abu-Shanab, 2013; Kwok, *et al.*, 2002).

As certain groups, teams and committees are constantly making complex decisions to arrive at optimal solutions that can be implemented within organizations and as a result, multi-person decision making is drawing a lot more attention (Singh and Benyoucef, 2013). multi-person decision making has also been well-documented as generally leading to increases in decision confidence in both intellectual tasks and judgment tasks (Patalano and LeClair, 2011). The analysis presented below offers an effective structure for choosing an appropriate course of action for a particular multi-person decision task (Lu, *et al.*, 2007).

Step 1: Define the decision problem

Step 2: Determine Requirements

Step 3: Establish the objectives and goals of the decision process

Step 4: Generate Alternatives

Step 5: Determine Criteria

Step 6: Employ a multi-person decision making method

Step 7: Evaluate alternatives and select the best one

Step 8: Validate solutions based on criteria

Step 9: Implement the solution.

2.5 Multi-Person Decision Methods

As earlier mentioned, most decisions in organizations nowadays are made by groups, teams or committees therefore it is important for all types of organizations to improve their multi-person decision making process and activities through the use of several simple, understandable, and easily applicable methods and technologies that will make the decision making process more efficient and effective, thereby reducing the possibility of making wrong decision that can lead to detrimental consequences (Khasawneh and Abu-Shanab, 2013; Abdullah, 2013; Lunenburg, 2010). Decision making methods generally refer to decision aid tools or sets of techniques that facilitate decision makers in complex decision situations, often involving criteria arising from social, environmental and economic factors, with the aim of providing an overall ranking of alternatives, from the most preferred to the least preferred alternative (Dincer, 2011; Chen, *et al.*, 2009).

The major components of a successful decision making method include decision alternative formulation and evaluation, decision criteria, criteria weight estimation and a reliable distance metric as these components work together to ascertain the selection of the best alternative as these components work together to ascertain the impact of criteria weights on ranking alternatives (Yu and Lai, 2011). Decision making methods have been in use for several decades as new models are being developed and old ones are being improved upon. Their role in different application areas cannot be emphasized as these methods provide a systematic way to help decision makers in selecting the most desirable and satisfactory alternative in uncertain situations (Olugbara and Nepal, 2012; Velasquez and Hester, 2013). When more than one decision maker is involved in a multi-attribute decision making problem, timing becomes an important issue. If the problem is large, collecting data from decision makers, organizing, analysing, synthesizing, and finally reaching a conclusion becomes a tremendous effort (Ozer and Lane, 2010). As a result, the use of technology is highly imperative to aid reduce the time that is spent on these issues (Veit, *et al.*, 2001; Saputroa, *et al.*, 2015).

Although researchers have developed different decision methods to support multi-person decision making (Shih, *et al.*, 2007; Kim and Ye, 2012; Kwok, *et al.*, 2002; Olugbara and Nepal, 2012; Bali, *et al.*, 2013; Jassbi, *et al.*, 2014; Rao, *et al.*, 2016), matchmaking methods have not yet been extended to support group decision making. In addition, matchmaking has been connected to multi-attribute decision making (Noia, *et al.*, 2003) this advantage will accommodate a decision making activity where finding a desirable solution among competing alternatives is carried out by multiple decision makers. multi-person decision making methods can be divided into three categories: Structuring, Ordering and ranking and, Structuring and measuring (Peniwati, 2007; Cunha and Morais, 2017). The focus of this study is on the Structuring and measuring category by reason of selection of competent alternatives by measuring their similarity or performance scores. The following subsections describe the diverse methods that are used for decision making in a multi-person environment.

2.5.1 Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS)

Hwang and Yoon (1981) suggested the TOPSIS method for multi-attribute decision problems. The TOPSIS method is used to determine the best alternative from the concepts of the compromise solution. The best compromise solution should have the shortest distance from the ideal solution and the farthest distance from the negative ideal solution. TOPSIS has been extended by various researchers to a multi-person decision environment.

Shih, et al. (2007) presented Group TOPSIS for selecting a manager in a local chemical company. They classified their method as an integrated procedure as they aggregated the preference of individual decision makers in the TOPSIS process to achieve a decision. Biswas, et al. (2016) proposed a new approach for multi-attribute group decision-making problems by extending TOPSIS to the single-valued Neutrosophic environment. They used the single-valued neutrosophic set-based weighted average to aggregate all the individual decision maker's opinion into one common opinion for rating the importance of criteria and alternatives.

Huang and Li (2012) proposed a TOPSIS group decision aggregation model which consisted of three stages – calculation of weight differences as the degrees of preferences among different alternatives for each decision maker, deriving of alternative priorities with the highest one being denoted as the degree to which a decision maker wants his most favorite alternative to be chosen and group ideal solutions approach in TOPSIS is used for the aggregation of similarities obtained from different decision makers. Singh and Benyoucef (2013) proposed a fuzzy TOPSIS based methodology to improve the coordination in decentralized supply chains and address the imprecision in the formulation of preference values by the decision makers.

2.5.2 Analytic Hierarchy Process and Analytic Network Process (AHP and ANP)

AHP, proposed by Saaty (1980) is one of the most widely used MADM methods. Likewise, ANP proposed by Saaty (1996) is a decision making technique that is suitable for time, where there is a dependency between the criteria. Both methods have been extended and applied in the multi-person decision environment. ANP is a more general form of the AHP, and the AHP is a special case of the ANP (Afshari, *et al.,* 2011). Therefore, this study will analyse and describe the various variants of both the AHP and ANP methods in this subsection.

Mu, et al. (2009), based on the concept of AHP, suggested e-Portfolio selection model in a multi-person decision making with a case study. Levy and Taji (2007) presented group analytic network process (GANP) approach that supports hazards planning and emergency management under incomplete information. They put forth a GANP multi-attribute Decision Support System (DSS) that used quadratic mathematical programming and interval preference information. Shih, et al. (2005) combined group decision making (GDM) with AHP. They presented a group decision support system (GDSS) under a computerized environment for group decision making in the personnel selection process of human resource. Kaboli, et al. (2008) proposed a new mathematical model is proposed with the aid of the fuzzy analytic hierarchy process (FAHP) to make the plant location decision. They used their model to select the optimal plant location that is the most preferable for both investors and managers.

2.5.3 Data Envelopment Analysis (DEA)

The DEA approach is one of the basic non-parametric approaches which is employed to measure efficiency and productivity of alternatives (Mansouri, *et al.,* 2004). A hybrid decision making system using DEA and linguistic fuzzy models was developed by Jassbi, et al. (2016) to select the best supplier in the presence of multiple decision makers. Zerafat, et al. (2009) used the concept of DEA to introduce a new mathematical method for selecting the best alternative in a group decision making environment with a case study. The introduced model was a multi-objective function which was converted into a multi-objective linear programming model from which the optimal solution was obtained.

2.5.4 Integrated Approaches

To further simplify and address the problems associated with multi-person decision making, two or more decision methods have been combined and employed in a multi-person decision environment. In order to examine the improvement fields of an Iran automobile industry, Yousefi and Hadi-Vencheh (2010) proposed an integrated model by combining Analytic Hierarchy Process (AHP) and Technique for Ordering Preference by Similarity to Ideal Solution (TOPSIS). The results of two techniques were combined to find the final ranking and they further used a Data Envelopment Analysis (DEA) model as a basis for comparing the reliability of the results of the two techniques. Rouyendegh (2011) applied a unification of Intuitionistic fuzzy TOPSIS and DEA to a model of group decision making in the evaluation of departments in a university by aggregating individual opinions of decision makers for rating the importance of criteria and alternatives.

Angiz, et al. (2012) suggested the integration of AHP with a Data Envelopment Analysis (DEA) based preferential aggregation method. This integrated method manipulated the preferential weights and ranking aspect of each decision maker in coming up with an optimization model that will then determine the best efficiency score of each alternative. These efficiency scores are then used to rank the alternatives and determine the group decision weights. Guo (2013) utilized an intuitionistic fuzzy weighted averaging (IFWA) operator to aggregate individual opinions of decision makers into a group opinion. Intuitionistic fuzzy entropy was then used to obtain the entropy weights of the criteria. Finally, TOPSIS method was combined with an intuitionistic fuzzy set to select appropriate IS project in group decision making environment.

Table 2.2: A brief summary of some major multi-person decision making methods.

Methods Applied	Authors	Problem Addressed
TOPSIS	Personnel Selection (Shih, *et al.*, 2007).	Extended TOPSIS for group decision making in the selection of an online manager.
AHP	E-portfolio selection (Mu, *et al.*, 2009).	Development of an e-Portfolio selection model based on the AHP methodology for group decision making.
DEA	Personnel Selection (Zerafat, *et al.*, 2009).	Selecting the best alternative in a group decision making environment by using the concept of DEA to introduce a new mathematical model.
AHP-DEA	Evaluation and selection of travel spots (Angiz, *et al.*, 2012).	Ranking of alternatives by integrating AHP group decision making method with a DEA-based preferential aggregation method.
AHP-TOPSIS	Automobile Selection (Yousefi and Hadi-Vencheh, 2010).	Integrating AHP and TOPSIS to examine the improvement fields of Iran automobile industry.
Fuzzy TOPSIS	Supply Chain Coordination (Singh and Benyoucef, 2013).	Presented a fuzzy TOPSIS and soft consensus based group decision making in MCDM problems of strategic selection and supply chain.
Fuzzy TOPSIS – DEA	Evaluation of university departments (Rouyendegh, 2011).	A unification of Fuzzy TOPSIS and Data Envelopment Analysis (DEA) to select the department that has the largest score due to its highest efficiency and performance.

2.6 Multi-Person Multi-Attribute Decision Problem – New Approach

Another objective of the current study is to develop a matchmaking approach that can be implemented to address various multi-person decision problems. In order to attain this goal, a matchmaking algorithm is proposed to aid in multi-person decision making. The crux of this approach revolves around the introduction of attribute description vector in the improved matchmaking algorithm which will aid to effectively capture the preferences of multiple decision makers with no restriction on the number in order to effectively achieve a successful decision process. Although the proposed method is not novel, it extends an existing algorithm to improve its capability. Its application which has been carried out for the very first time by the researcher proves to be robust, less arduous and efficient.

The approach – based on the vector analysis approach – aids in improving multi-person decision accuracy and enhancing decision transparency, thereby increasing decision effectiveness which will further lead to the minimization of selecting incompetent alternative. The approach also addresses the problems faced during a decision process in a multi-person environment and therefore provides an effective solution to the research questions highlighted in chapter 1. In a concise survey of the reviewed literature, it is indisputable that almost none of the research studies on matchmaking considered the critical issue of decision making in a multi-person environment. Additionally, the efficiencies of the above mentioned variety of the existing multi-person decision making methods have been questioned because they are extensions of single decision making methods which function by aggregating the preferences of several decision makers. This function imposes additional computational resources, especially for a large number of decision makers.

In the current study, an attempt is made to develop a new method that is less complicated, less time-consuming for multi-person multi-attribute decision making. However, doing so requires an effort to solve the multi-person decision problem in a different way – by reformulating the decision dilemma as a vector analysis approach. To make the matchmaking approach successful in a multi-person multi-attribute decision process, vector representation of constraints and distance metrics are introduced in the implementation of the existing Hunt ForTune Matchmaking Algorithm so that a more robust algorithm can be established. The proposed model will encompass several knowledge and skills features that the matchmaking algorithm exhibits. The anticipated new matchmaking algorithm – proposed in the present study – will allow for the representation of different types of constraints and capturing of the preferences of all the decision makers into a single reference profile to make the decision process efficient and valid to decision makers.

The study objectives listed in chapter 1 should be achieved while developing and implementing an effective matchmaking approach for multi-person multi-attribute decision making. Effective in this regard means adequately capturing and processing the preferences of multiple decision makers.

2.7 Summary of Related Research on Matchmaking Systems

Different matchmaking systems that support various types of constraints have been employed in diverse environments to solve various decision problems and obtain maximum positive results. In Table 2.3 various matchmaking systems – and the type of constraints supported – are briefly discussed.

Table 2.3: Cross Dimensional Analysis of Various Matchmaking Systems

Matchmaking System	**Types of Constraints**	**Matchmaking Process**
GRAPPA (Veit, *et al.*, 2001)	Hard constraints Soft constraints	Uses distance function to compute similarity of profiles. The best matches are returned in a ranked format.
Weighted Tree (Bhavsar, *et al.*, 2004)	Range Value Preferential Value	Uses tree matching algorithm to compute similarity. Attributes of profiles are represented as node-labelled, arc-labelled and arc-weighted trees.
Matchmaking in learning networks (Kester, *et al.*, 2007)	Not Specified	Uses database to store details of learning contents, learner information and available resources. Latent semantic analysis is used to match request with resources.

Description logic-based neoclassic (Noia, *et al.*, 2003)	Range value Preferential value	Matches are divided into potential and partial categories. Ranks matching profiles within these categories.
Web-Services Technologies (Li and Horrocks, 2003)	Range value	DAML-S based ontology and description logic reasoner are used to compare service description.
Ontology-driven matchmaking system (Mohaghech and Razzazi, 2004)	Not Clearly defined	Nodes represent hard and soft skills. Ontologies are used to specify similarity among skills.
Linguistic approach (Ojha and Pradhan, 2006)	Range value	The distance between buyer's profile and product feature profile is computed. The less the distance, the more the similarity between product and buyer. Ranks based on similarity value.
Vague knowledge bases for matchmaking in P2P e-marketplaces (Ragone, *et al.*, 2007)	Hard and Soft constraints Range value Preferential Alternate	Uses a hybrid combination of descriptive languages, Fuzzy Rules, and Utility theory to find the most promising alternatives. The alternatives were chosen by computing the similarity between two profiles and returning the top-matching profiles based on the similarity scores.
Hunt ForTune Matchmaking System (Joshi, *et al.*, 2010)	Hard and Soft constraints Range Value Preferential Alternate Value Hidden Cost	Profiles are captured using a set of nodes and are represented as a quadruple of constraints. Calculates similarity values between the two profiles and locates the closest matches.

2.8 Summary of Chapter 2

An inappropriate decision making process and ineffective decision making method can undoubtedly lead to failure in the outcome of the decision process. In recent years, there has been a growing concern for decision making in the presence of multiple decision makers in various organizations. This is due to the fact that most decision problems are increasingly involving interaction that requires a collective effort. multi-person decision problem is a great burden to all forms and types of organizations irrespective of size. The success of an organization, firm or country and its ability to progressively and profitably compete in a global economy can be attributed to the presence of effective, reliable and necessary resources – personnel or material resources. However, the utilization of an inferior decision making tool will rather result in the wastage of resources thereby leading to tremendous failure.

The work done by Patalano and LeClair (2011), portrays that indecisiveness – an individual difference of measure of chronic difficulty and delay in decision making – does not influence decisions carried out in a multi-person environment. Rather, the presence of multiple decision makers does contribute to increased confidence in the outcomes of a decision process. The study of inappropriate and complex decision making is a critical matter and there has been a growing interest in addressing this inappropriateness and complexity in decision making as more decision making scenarios take place in a multi-person decision environment (Jassbi, *et al.*, 2014; Lunenburg, 2010; Ozer and Lane, 2010).

Organizations, institutions and government institutions have to take steps in making rational decisions during a decision process in order to eliminate any form of bias or corruption in the decision process as this will tarnish the reputation of the firm and the economy. Research has shown that a decision process carried out in a multi-person decision environment is a necessary step in eliminating such biases in a decision process. In this regard, a multi-person decision making process calls for a more prudent consideration of factors that consists of both time and computational complexities.

In this chapter, a matchmaking algorithm was proposed to support multi-person decision making. Complex multi-person decision making is a common dilemma faced in all sectors of the economy. Complex and inappropriate multi-person decision making is a plight which has not been satisfactorily addressed. The proposed matchmaking algorithm has the aim of eliminating this complexity issue of multi-person decision making by capturing and conveniently representing all decision makers' preferences using a vector attribute analysis – rather than aggregating individual preferences which causes computational complexity and inefficiency as seen in other multi-person decision methods.

To achieve this goal, the proposition is to improve Joshi's matchmaking algorithm (Joshi, *et al.,* 2010) and implement it in a multi-person decision making environment to address the current predicament while simultaneously averting time-consuming and computational complexities. Hence, an approach that can effortlessly handle problems encountered in a multi-person decision environment is highly anticipated. As far as it is known, this is the first time this kind of research has been carried out. It can therefore be argued that this is an original contribution to the problems and complexities of multi-person multi-attribute decision making. Additionally, the proposed method contributes significantly to the aspect of decision theory by improving decision accuracy and enhancing decision transparency thereby increasing decision effectiveness. In Chapter 3, the methodology is described. The method employed in the validation of the proposed multi-person matchmaking approach is also discussed. The experimental results and evaluations are presented in Chapter 4.

CHAPTER 3

METHODOLOGY

3.0 Introduction

The methodology applied in the present study is based on an effective and efficient matchmaking algorithm – with the aim of conveniently capturing and processing the preferences of multiple decision makers into a single reference profile. The two concepts introduced – reference requisites profile and client competence profile – will effectively assist in formulating the multi-person, multi-attribute decision plight using the vector analysis approach. The competences of an alternative are captured in client competence profile while the expected requirements from the alternatives are captured in the reference requisites profile. The model of Joshi et al. (2010) matchmaking algorithm and matching process is particularly significant in this regard. It will be discussed how Joshi's algorithm functions and the researcher's improved version.

To make the Joshi's approach successful in a multi-person decision environment, the matchmaking algorithm is improved by the introduction of vector representation of constraints and distance metrics – with the main focus of a matching reference requisites profile and client competence profile. In order to achieve this, a matchmaking algorithm (Joshi et al. 2010) can be considered as a vital solution. A matchmaking algorithm – for capturing preferences of multiple decision makers with no restriction on the number is needed to enhance the selection of alternatives among different types of constraints and also effectively achieve a successful decision process. Modelling the task of multi-person decision process as a matchmaking problem to support multiple decision makers requires relationships between the competence of the alternatives and the expected requirements by the decision makers. The proposed decision method will not only help in ensuring that the most competent alternatives are ranked first and chosen, but also rank the other alternatives based on their performances. Moreover, the proposed method will also aid in improving decision accuracy and enhancing decision transparency thereby increasing decision effectiveness.

3.1 Hunt ForTune Matchmaking Algorithm

The matchmaking method was first proposed with the objective to assist in e-commerce by searching the space of possible matches between demand and supply and finding a match between the trading intentions of the market participants (Joshi, *et al.*, 2009; Noia, *et al.*, 2003) and was later implemented in different environments to solve various decision problems and obtain maximum positive results (Al Rabea and Al Fraihat, 2012; Bellur and Kulkarni, 2007; Joshi, *et al.*, 2009; Noia, *et al.*, 2003; Kester, *et al.*, 2007; Olugbara, *et al.*, 2015). Matchmaking is the process of optimally pairing up alternatives from two groups (client and target) for possible matches between the groups using through similarity computation (Joshi, *et al.*, 2009; Schmid, *et al.*, 2014). Matchmaking systems' features and success largely depends on how effectively alternatives' profiles from two groups (client and target) are represented, the selection criteria, criteria weights estimation and a reliable distance metric to ascertain the impact of criteria weights on the selection and ranking of alternatives (Joshi, *et al.*, 2009). A successful matchmaking system should possess specific features such as scalable algorithm, ability to capture various types of data or constraints, domain independence, and categorization of matchmaking results, amongst others (Kester, *et al.*, 2007; Bhavsar, *et al.*, 2004).

In the Hunt ForTune Matchmaking algorithm, a profile is represented as a set of constraints, such that P = $\{C_1, C_2, C_3, \ldots C_m\}$. Each constraint is a quadruple consisting of decision criteria Ci=<a, d, f, p>, where a is an attribute, d is a set of values to describe an attribute, f shows the flexibility of a constraint and p is the priority of a constraint. Details of the type of constraints and their modelling can be seen in Joshi, *et al.*, (2010). A short introduction of the elements is further described below:

Attribute (*a*): An attribute represents a facet such as qualification, selection tests, and rating codes. This field is always a string.

Description (*d*): This represents a set of values that can be assigned to an attribute of a constraint like 80, <40,60,80>, <50,…,70>, Football. This field takes all possible member values such as alphabetic strings, numerical values, a logical expression, a range value or an alpha-numeric expression.

Flexibility (*f*): Flexibility indicates whether the constraint is a hard or a soft constraint with values {Yes, No}. A {No} indicates the rigidness of the constraint whereas a {Yes} value represents a soft constraint.

Priority (*p*): This describes the relative priority of soft constraints among other soft constraints. All soft constraints are initialized with the priority values of 1. The value of *p* can be any real value greater than 0.

The Hunt ForTune matchmaking algorithm compares the constraints of two profiles, if the attributes are the same, then the similarity value is computed by checking the description values of these attributes. If the description values are the same, the priority values of both constraints are multiplied together, but if the description values are different, the flexibility of both constraints are considered. Although, when hard constraints in the two profiles do not match, the relative difference between the two corresponding description values of these attributes is computed and will later be used to compute the similarity value (Joshi, *et al.,* 2010). Given two profiles for matching, the Hunt Fortune Matchmaking algorithm finds an optimal decision alternative by computing the product of the similarity values.

In addition to the special features listed earlier, the Hunt ForTune matchmaking algorithm supports other features such as preferential constraints which facilitates participants to indicate the relative importance among constraints, thereby customizing the results of the matchmaking process to suit their needs which makes it unique and imperative in this study (Joshi, *et al.,* 2010; Olugbara, *et al.,* 2015). But as most of the real-world decision process take place in environments involving multiple decision makers, multiple alternatives which usually have conflicting attributes and different data types, the existing Hunt ForTune matchmaking algorithm cannot satisfy such decision making needs, which is what the model in this study intends to address.

3.2 Multi-Person Hunt ForTune Matchmaking Method

The multi-person matchmaking method was tested by positioning data into two profiles – reference requisites profile and client competence profile. Fundamentally, the method should rank alternatives that are aligned to the expected requirements enumerated in the reference requisites profile with the intention to support multiple decision making – by performing an in-depth matching of the reference requisites profile with the client competence profile. The ranking of alternatives is determined by their similarity values. The higher the similarity value, the closer the alternative meets the expected requirements and placed high in the rankings. To validate the effectiveness of the multi-person matchmaking-based decision process, novel matching theoretical mathematical technique was employed to study and compare the effect of alternative selection on the matchmaking ranking result. The evaluation of the efficiency, accuracy and effectiveness of the multi-person matchmaking is determined using the Hausdorff matching method.

3.3 Implementation of the Multi-Person Hunt ForTune Matchmaking Method

The focus of this research work is to implement the existing Hunt ForTune matchmaking algorithm to effectively process the preferences of multiple decision makers. The proposed implementation is composed of capturing the preferences of all the decision makers into a single reference profile using the vector analysis approach. To make the matchmaking algorithm successful in group decision making, vector representation of constraints and distance metrics are introduced in the implementation of the existing Hunt ForTune Matchmaking Algorithm so that a more robust algorithm can be established. The detailed procedure is described in the following steps.

Firstly, two profiles will be constructed: the reference profile capturing the DMs expected requirements from the alternatives and the client profile capturing the DMs preference values of each alternative to be evaluated. Each profile P, will contain all the necessary constraints. Each constraint is described in terms of an attribute, a set of values to describe an attribute, the flexibility of a constraint and the priority of a constraint. For a general definition, the vector analysis approach is introduced to effectively capture all DMs preferences as a description for each constraint.

In the next step, the similarity value of each constraint is determined in terms of performance with respect to each criteria by comparing the attributes of each client profile with the attributes of the reference profile. If both attributes are the same, an intermediate similarity value of 1 is given by checking the description vector between both profiles. If the description values are not the same, an intermediate similarity value is calculated by considering the flexibility of both constraints. In the case where both reference and client profiles contain hard constraints, the similarity of that attribute is the pairwise comparison between the description and the priority values of both profiles is computed using a reliable similarity metric. Additionally, if either both profiles or one profile contains a soft constraint, the similarity value of that attribute are the values of the compromise count factors α and β, which are used when there is a case of compromise match and Omission Penalty is a parameter that penalizes the omission of a given constraint.

The usage of these parameters is well elaborated in Figure 3.1. The pairwise comparison in this algorithm can be gotten by using an efficient and reliable similarity metric. For the purpose of this study, various mathematical expressions to compute the similarity between two profiles or objects will be discussed in the next section. Finally, the overall similarity value of each profile, which determines the ranking and also a selection of the best decision alternative is calculated as the product of similarity values. The alternatives can then be ranked according to the descending order of the value of the similarity. That is, the decision alternative with the highest similarity value is ranked as the most preferred.

3.4 Multi-Person Matchmaking Profile Representation

In this section, the modelling of the reference requisites profile and the client competence profile is discussed, using the dataset as described by Joshi et al. (2010) that models both the profiles as a set of constraints. In the proposed multi-person matchmaking method, the profile representation is constructed from the parameters listed below:

a. Alternatives are modelled as profiles
b. Criteria are modelled as constraints
c. Preference values of multiple decision makers are modelled as a vector of attribute descriptions.

A constraint is a rule that describes the requisites and competence specified by the decision makers involved in the decision process – and a profile is formally represented as a set of constraints:

$$C_i =< a,< d_1, d_2, d_3,..., d_n >, f ,< p_1, p_2, p_3,..., p_n >> \qquad (3.1)$$

$$C =< C_1, C_2,..., C_m > \qquad (3.2)$$

From Equation (3.1), the i^{th} term is a quadruple constraint parameter. Accordingly, the preferences of decision makers for each attribute are collected as an attribute description vector. The attribute, its description vector, flexibility and priority vector are compactly represented as a 4-tuple profile.

Algorithm multipersonMatchmaking()

Ci: reference profile

Cj: Alternative profile

Let α = 0.98 and β = 0.96

Omission Penalty = 0.05

(1) **if** (Ci.a == Cj.a) **then**

(2) **if** (isSame(Ci.d, Cj.d)) **then**

(3) return $S(C_i,C_j)$ = 1;

(4) **elseif** (Ci.f == No) AND (Cj.f == No) **then**

(5) return $S(C_i,C_j)$ = similarity((Ci.p,Cj.p)(Ci.d,Cj.d))

(6) **elseif** (Ci.f == Yes) AND (Cj.f == Yes) **then**

(7) return $S(C_i,C_j)$ = β

(8) **else**

(9) return $S(C_i,C_j)$ = α

(10) **endif**

(11) Ci++; //move on to next Ci;

(12) Cj++; //move on to next Cj;

(13) return $S(C_i,C_j)$

(14) **endif**

(15) **elseif** (Ci.a < Cj.a) **then**

(16) ci++; //move on to next Ci;

(17) return $S(C_i,C_j)$ = Omission Penalty

(18) **end elseif**

(19) **elseif** (Ci.a > Cj.a) **then**

(20) cj++; //move on to next Cj;

(21) return $S(C_i,C_j)$ = Omission Penalty

(22) **end elseif**

(23) Calculate the similarity S(Pi,Pj) of the two profiles Pi,Pj by taking the product of N similarities as follows:

$$S(Pi,Pj) = \prod_{k=1}^{N} S_k(ci,cj)$$

(24) **stop**

Figure 3.1: Implemented Multi-Person Hunt ForTune Matchmaking Algorithm

3.5 Matchmaking Similarity Computations and Majority Voting Technique

A similarity metric is a real-valued function that quantifies the similarity between two objects or data points. For various matchmaking problems, similarity metrics are essential and therefore applied in matching profiles. Therefore the concept of similarity is important in many algorithms as it is necessary to measure the similarity of different objects, and thus, form an essential part in many applications that involve clustering, classification, recognition, or retrieval (Ghany, *et al.*, 2014). With a large number of similarity metrics having been introduced in the literature, selecting an appropriate one for a particular task is crucial, since the success of the related application may depend critically on this choice. Similarity metrics vary depending on the data types used.

As previously mentioned, the matchmaking algorithm computes the similarity between two profiles P_x and P_y as a function of the constraint of attributes, descriptions, flexibility and priority. For example, let m be the number of constraints for P_x and n the number of constraints for P_y. The similarity score S(Pi, Pj) between two profiles Pi, Pj is calculated by taking the product of N similarities using the following product formula:

$$S(Pi,Pj)=\prod_{k=1}^{N} S_k(ci,cj) \tag{3.3}$$

It is important to note that the relative difference routine in Joshi, et al. (2010) model has been replaced with a similarity measure in this current work because of the vector representation of attribute description. This similarity routine will enable the researcher compare the attribute vector description of both profiles, retrieve and generate a ranked list of alternatives from the most competent to the least competent alternative. Finally, the similarity between the two profiles is calculated such that the maximum value of 1 corresponds to the highest similarity and minimum value of 0 corresponds to the least similarity.

There are various similarity metrics proposed by different authors to aid in the matching and measuring of similarity between any two objects as well as solving various problems of classification, selection and retrieval (Cha, 2007; Choi, *et al.*, 2010; Ghany, *et al.*, 2014; Deza and Deza, 2009; Merigo and Casanovas, 2011; Hatzigiorgaki and Skodras, 2003; Khapli and Bhalchandra, 2011). For the purpose of this study, different similarity metrics were studied and scrutinized with the aim of identifying their advantages and confines in order to select the most appropriate measure to achieve the present study's aims. After in-depth experimentations and testing, five similarity metrics were chosen to be employed in the multi-person matchmaking algorithm because of their popularity in similarity measurement and their performances in various multi-person decision processes experimented by the researcher.

Additionally, after every similarity metric employed in this study makes a prediction for each experiment, the final ranking of alternatives will be determined using the majority voting technique. This is due to the fact that decisions made by majority voting are likely to be more accurate than a single prediction or prediction made by the minority (Landemore, 2010). Majority voting is a technique that combines the different predictions or votes for each instance and the final output prediction is the one that receives more than half of the votes (Rokach, 2010). Consequently, in this study, the final decision result is made by a majority vote of the ranking of alternatives with preference given to the ranks determined by at least three (3) of the similarity metrics in order to produce improved results.

The similarity metrics described below were found to be more suitable for addressing the research problems of the current study – due to their abilities to support multi-person decision making thereby minimizing incompetent alternative shortlisting. Moreover, these formulas were further extended to ensure that they possess normalization capabilities, take the attribute priority into consideration and eliminate zero values for the denominator. Mathematically, it is not possible to divide by 0 (zero) therefore, a small value of 0.001 was added to the denominator to eliminate the possibilities of diving by 0. The extended formulas that were finally applied in this study are briefly summarized in the subsection below.

3.5.1 Soergel Index

The Soergel Index has been employed mostly in the field of molecular fingerprints similarity calculations (Cereto-Massague, et al., 2015; Bajusz, et al., 2015). In the course of experimentation and testing of similarity metrics, it was noted that the results derived from using Soergel index proved to be reliable. As a result, it was not necessary to divide equation (3.4) by a constant.

$$Sim(P,Q) = 1 - \left(\frac{\sum_{i=1}^{d} | P_i - Q_i |}{\sum_{i=1}^{d} \max(P_i, Q_i) + 0.001} \right) \tag{3.4}$$

3.5.2 Wave Hedges Index

The Wave Hedges Index has been applied to various fields such as compressed domain image retrieval, landscape retrieval (Hatzigiorgaki and Skodras, 2003; Jasiewicz, et al., 2013). In order to eliminate the errors encountered when dealing with negative values and points having 0 as a value, the commonly used Wave Hedges Index has been modified as seen in Equation (3.5). Furthermore, dividing Equation (3.5) by a constant n normalizes the similarity value, thereby increasing the level of accuracy by ensuring that the similarity value falls between [0, 1].

$$Sim(P,Q) = 1 - \frac{1}{n} \sum_{i=1}^{n} \left(\frac{w_i \, | P_i - Q_i |}{\max(P_i, Q_i) + 0.001} \right) \tag{3.5}$$

3.5.3 Canberra Similarity

This measure is very popular in content-based image retrieval applications (Liu and Yang, 2013). It has the advantage of a relatively low computational complexity and high retrieval efficiency. It resembles Sorensen but in this study it has been altered to normalize the absolute difference of the individual level and is defined as:

$$Sim(P,Q) = 1 - \frac{1}{n} \sum_{i=1}^{n} \left(\frac{w_i \, | P_i - Q_i |}{(P_i + Q_i) + 0.001} \right) \tag{3.6}$$

3.5.4 Euclidean Metric

This is one of the commonest distance metrics. It is a simple yet powerful way to determine the similarity between two data objects. It has been prominently used for classification in diverse areas such as image retrieval (Schuster, et al., 2015). In this study, the general Euclidean metric has been modified to Equation (3.7) so as to integrate weights as well as normalize similarity values.

$$Sim(P,Q) = 1 - \frac{1}{n}\sum_{i=1}^{n}\left(\frac{w_i(P_i - Q_i)^2}{(P_i + Q_i)^2 + 0.001}\right) \tag{3.7}$$

3.5.5 Sorensen Index

This is also called Bray-Curtis Distance. Just like Soergel Index, the results derived from using this similarity metric proved to be reliable. This could be as a result of the separate summation for the numerator and the denominator. For the purpose of similarity measure, it is defined in this study as:

$$Sim(P,Q) = 1 - \left(\frac{\sum_{i=1}^{n} \mathrm{w_i} \,|\, \mathrm{P_i} - \mathrm{Q_i} \,|}{\sum_{\mathrm{i=1}}^{\mathrm{n}} (\mathrm{P_i} + \mathrm{Q_i}) + 0.001}\right) \tag{3.8}$$

3.6 Limitation of the Multi-Person Hunt ForTune Matchmaking Method

In a typical matchmaking scenario, two profiles are always matched to determine the similarity between them. However, in a multi-person decision process, the researcher came across a decision problem that cannot be conveniently represented using the multi-person matchmaking method. In unique cases, one may encounter a situation where the constraints of the reference profile has not been explicitly proven as the maximum requirement or a situation where the client profile holds superiority in the decision making process thus making the matching process more challenging. In order to effectively make the right decision, the reference profile should not only be matched with the client profile, but the client profile should also be matched to the reference profile. The results derived from these matching process will enable the decision maker determine how similar the profiles are. As a result of this major limitation, the researcher introduced the idea of 'Hausdorff' into the matchmaking process.

3.7 Hausdorff-Based Matchmaking

The Hausdorff distance is the maximum distance of one set to the nearest point in another set. It is a means of determining the resemblance and the quality of a match between the two sets

(Wang, *et al.*, 2016). It is a measure of how much two sets resemble each other with respect to their positions (Zhu, *et al.*, 2004). Given two finite sets $A = \{a_1, a_2, ..., a_m\}$ and $B = \{b_1, b_2, ...b_n\}$, the Hausdorff distance H(A,B) is defined as:

$$H(A, B) = \max\{h(A, B), h(B, A)\} \tag{3.9}$$

where

$$h(A, B) = \max_{a \in A}\left\{\min_{b \in B}\{d(a, b)\}\right\} \tag{3.10}$$

The elements of the sets A and B are a and b respectively, and d(a, b) is any metric between these elements. The two distances h(A,B) and h(B,A) are called the directed Hausdorff distance (Zhu, *et al.*, 2004).

Different authors have applied Hausdorff distance to aid in solving various similarity problems between different types of objects in diverse domains. Jesorsky, et al. (2001) used the Hausdorff distance as a similarity metric between a general face model and possible instances of the object within the image for face detection. Rotter, et al. (2005) used Hausdorff for fast shape matching. They attempted to simplify the computation of the Hausdorff distance between graphical image objects. Di Lorenzo and Di Maio (2006) applied the Hausdorff distance in melody space as a new approach to address the melodic similarity problem by measuring the nearness between two music pieces. Using an illustrative example, Fu (2015) used Hausdorff to solve stochastic multi-attribute decision problems. Wang, et al. (2016) proposed a Haudorff based hesitant fuzzy linguistic numbers for multi-attribute decision making.

Since in this study, similarity has been considered instead of distance, the following definition has been used for the directed Hausdorff distance:

$$h(A, B) = \max_{a \in A}\left\{\max_{b \in B}\{d(a, b)\}\right\} \tag{3.11}$$

A number of authors have related distance with similarity (Cha, 2007; Goshtasby, 2012) as:

$$Similarity = 1 - Distance \tag{3.12}$$

If distance is normalized to give a maximum value of 1 for maximum possible distance between two points, this corresponds to the two points to be none similar. However, the distance value of 0 corresponds to the two points being similar with maximum similarity value of 1 (Shimodaira, 2014). This study considers normalization to give a better interpretation to similarity metrics.

In order to successfully integrate Hausdorff distance into the matchmaking process, two profiles will also be needed – reference and client profile. The weighted similarity metrics in section 3.5 will be used to compute the Hausdorff score between each client profile and the reference profile – h(A,B) – as well as between the reference profile and the client profile – h(B,A). Ultimately, the final score between the profiles is determined by taking the maximum Hausdorff score – max(h(A,B),h(B,A) – which is then used to rank the alternatives from best to worst. Through various decision problems shown in chapter 4, the feasibility of this method is verified.

The Hausdorff distance plays a crucial role in the matchmaking process and offers several relevant advantages:

a) It does not just match client profiles with the reference profiles, but also matches the reference profile with client to profile to further determine how similar both profiles are. Thereby establishing how reasonable the reference profile is.
b) It takes the maximum similarity value between both profiles to determine the ranking of alternatives.

3.8 Summary of Chapter 3

In this chapter, the researcher discusses the methodological design. The researcher starts off by introducing the Joshi's Hunt ForTune matchmaking algorithm and then unpacked the profile representation and description of profile elements as well as explaining what a constraint is. Most importantly, the proposed multi-person Hunt Fortune Matchmaking method which allows the convenient capturing and representation of preferences of multiple decision makers is introduced and explained. The implementation of the proposed method is described and the multi-person Hunt Fortune Matchmaking Algorithm is also presented. The researcher further went on to explain the concept of reference profiles and client profiles and also portrayed how these profiles are represented in the proposed multi-person Hunt Fortune Matchmaking method.

Furthermore, determining the similarity between two profiles was the crux of this study. Therefore it was extremely substantial to study and test different similarity metrics in order to select the appropriate ones that could be applied to this study. In decision theory weights carry a critical effect on the outcome of the decision process and the proposed method uses the vector analysis approach to represent weights and description of attributes, it was therefore essential to select the similarity metrics that could conveniently accommodate the vector approach. A list of the similarity metrics applied in this study has been described in section 3.5. Additionally, Hausdorff distance was introduced into the matchmaking process to address the limitation described in section 3.7. The researcher defines Hausdorff distance and also shows the major variants of Hausdorff distance found in literature. The researcher went on to define as well as explain the Hausdorff distance as related to matchmaking and mentioned the role Haudorff plays in a matchmaking process. The Hausdorff – based matchmaking was also administered to validate the results derived from applying proposed multi-person Hunt Fortune Matchmaking method in solving various decision problems.

To achieve objectives of this study, the researcher actually needed to embody the constraints well and most importantly proposed multi-person Hunt Fortune Matchmaking method and similarity metrics were the centre of this work. Because the success of this proposed method massively relies on how well the multi-person Hunt Fortune Matchmaking algorithm is defined. The researcher is convinced that the introduction of the proposed multi-person hunt fortune matchmaking method has successfully contributed to the success of decision theory as the results presented in Chapter 4 visibly portrays the effectiveness, efficiency and reliability of the multi-person hunt fortune matchmaking algorithm.

CHAPTER 4

EXPERIMENTAL RESULTS AND ANALYSIS

4.0 Introduction

In this section (Chapter 4), the results are presented and evaluations are described that were performed in the present study (the experiment) using multi-person matchmaking algorithm and Hausdorff distance to examine diverse decision problems faced in the education domain. The main focus of all the experiments is on matching the profiles of different alternatives against reference profiles. The purpose of the experiment is to solve the predicament of choosing the perfect set of alternatives – among competing alternatives – as a multi-attribute decision problem to support multi-person decision making.

In order to do the research project appropriately, the researcher delved into different decision problems which are frequently encountered in the education domain. The purpose with the experiments was threefold:

a. Comparing the effectiveness of Vague Knowledge Bases for Matchmaking in P2P e-Marketplaces (Ragone, *et al.*, 2007) and the Hunt ForTune matchmaking system (Joshi, et al. 2010) in Chapter 2. (Thereby achieving the first research objective of the current study).
b. Developing and implementing the multi-person based Hunt ForTune matchmaking algorithm to solve various decision problems – personnel selection, government policy selection, sport evaluation, Mancala game strategy selection – in the presence of multiple decision makers presented in this chapter (thereby achieving the second research objective of the study).
c. Validating the results derived through the proposed multi-person matchmaking algorithm using the Hausdorff distance for matchmaking (thereby accomplishing the third research objective of this study).

In order to pursue the objectives of the study, a variety of case studies were used. These case studies – personnel selection, government policy evaluation and selection, sport evaluation and Mancala game strategy selection were used to illustrate the effects and the results derived from using the matchmaking method in a multi-person decision environment. These case studies were chosen as decision problems in this study because they represent diverse application areas where decision making could be cumbersome, tricky but yet necessary. The focus of these case studies was to evaluate, rank and decide on the best and prospective alternatives or choices according to their performances which is determined by their similarity values. To give a proper account of the results and evaluations that were performed, the discussions are presented under two major headings – the multi-person matchmaking process and the Hausdorff validation procedure.

4.1 The Multi-Person Matchmaking Process

The steps described in section 3.3 (Chapter 3) were applied in solving the various decision problems listed earlier. As previously mentioned, in matchmaking two profiles are mandatory for matching and selecting. Accordingly, the reference profiles and alternative competence profiles for each decision problem in this study are constructed based on the decision data involved in the decision process. Furthermore, these profiles are represented in the model described in section 3.4 (Chapter 3).

4.1.1 Personnel Selection

Consider the following problem. A local chemical company wants to recruit an online manager. The relevant criteria to be evaluated include knowledge tests (language test, professional test and safety rule test), skill tests (professional skills and computer skills) and interviews (panel interviews and 1-on-1 interviews). There are 17 qualified personnel and four decision makers are responsible for the selection (Shih, et al. 2007). In order to illustrate the application of the multi-person matchmaking method to the personnel selection problem, Figure 4.1 shows how the reference profile information is represented in the proposed multi-person matchmaking method.

RP = {

<language_test, <100, 100, 100,100>, No, <1,1,1,1> >

<professional_test, <100,100,100,100>, No, <1,1,1,1> >

<safety_rule_test, <100, 100,100,100>, No, <1,1,1,1> >

<professional_skill, <100, 100, 100, 100>, No, <1,1,1,1> >

<computer_skill, <100, 100, 100, 100>, No, <1,1,1,1> >

<panel_interview, <100, 100, 100, 100>, No, <1,1,1,1> >

<1-on-1_interview, <100, 100, 100, 100>, No, <1,1,1,1> >

}

Figure 4.1: Personnel Reference Requisite Profile in a Quadruple Format

Table 4.1 shows the similarity score calculation result when the profiles of 17 prospective personnel (P01 to P17) applying for a job position are matched against the reference profile shown in figure 4.1. These scores were derived using the algorithm shown in figure 3.1 and also the similarity metrics described in section 3.5. The table columns Score indicates the overall similarity values between each personnel profile and the reference profile and the columns – Rank – shows the ranking of personnel according to performance from best to worst. Furthermore, the client (personnel) competence profiles of the 17 candidates matched against the reference profile is attached in Appendix A (at the end of the document).

Table 4.1: Comparative results and rankings using the different similarity metrics in the Proposed Matchmaking Algorithm for Personnel Selection.

PERSONNELS	Soergel		Wave Hedges		Canberra		Euclidean		Sorensen	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
P01	0.8012	5	0.8012	5	0.8829	5	0.9835	5	0.8833	5
P02	0.7218	**15**	0.7218	**15**	0.8131	**12**	0.9343	**17**	0.8208	**15**
P03	0.8306	3	0.8306	3	0.9006	3	0.9853	**4**	0.9032	3
P04	0.7478	**12**	0.7478	**12**	0.8432	**14**	0.9684	**12**	0.8436	**13**
P05	0.7506	11	0.7506	11	0.8447	11	0.9682	**13**	0.8468	11
P06	0.8109	4	0.8109	4	0.8904	4	0.9865	**3**	0.8906	4
P07	0.7472	**13**	0.7472	**13**	0.8444	**13**	0.9711	**11**	0.8446	**12**
P08	0.7827	8	0.7827	8	0.8698	8	0.9792	8	0.8704	8
P09	0.8840	2	0.8840	2	0.9364	2	0.9953	2	0.9366	2
P10	0.7643	10	0.7643	10	0.8570	10	0.9757	10	0.8574	10
P11	0.6803	**16**	0.6803	**16**	0.7907	**16**	0.9465	**15**	0.7908	**16**
P12	0.6687	**17**	0.6687	**17**	0.7797	**17**	0.9390	**16**	0.7818	**17**
P13	0.7795	9	0.7795	9	0.8679	9	0.9791	9	0.8681	9
P14	0.7919	6	0.7919	6	0.8771	6	0.9825	6	0.8772	6
P15	0.7327	**14**	0.7327	**14**	0.8330	**15**	0.9662	**14**	0.8334	**14**
P16	0.8859	1	0.8859	1	0.9375	1	0.9955	1	0.9378	1
P17	0.7901	7	0.7901	7	0.8752	7	0.9813	7	0.8756	7

Comparing the results in table 4.1 derived from using the different similarity metrics, it can be seen that the ranks of alternatives (personnels) in the proposed multi-person matchmaking method are rather consistent. Although there are minimal variations with the ranking of some personnels, the ranks of the first ten and the last three personnels do not change except in the case of the Euclidean metric. All similarity metrics agreed with the ranks of P01, P07, P08, P09, P10, P13, P14 and P16. This has demonstrated that the proposed method is an efficient alternative solution to multi-person multi-attribute decision problems.

4.1.2 Government Policy Selection

In the following problem regarding political management (Merigo, 2011), a country planning its fiscal policy employs the expertise of a 3 groups of decision makers to consider the economic situation of the world economy. These decision makers evaluated five alternatives (A01-A05) based on five criteria (S1-S5) formulated from the state of the economic situation. Their decision data was represented in a triangular fuzzy format. In order to effectively represent fuzzy preferences of each group of experts using the proposed method, the fuzzy preferences of each group of experts had to be represented and analysed individually. Figure 4.2 shows how the reference profile information is represented in the proposed multi-person matchmaking method.

RP = {
<S1, <100,100,100,100,100,100,100,100,100>, No, <1,1,1,1,1,1,1,1,1> >
<S2, <100,100,100,100,100,100,100,100,100>, No, <1,1,1,1,1,1,1,1,1> >
< S3, <100,100,100,100,100,100,100,100,100>, No, <1,1,1,1,1,1,1,1,1> >
< S4, <100,100,100,100,100,100,100,100,100>, No, <1,1,1,1,1,1,1,1,1> >
< S5, <100,100,100,100,100,100,100,100,100>, No, <1,1,1,1,1,1,1,1,1> >
}

Figure 4.2: Policy Reference Requisite Profile in a Quadruple Format

Table 4.2 shows the similarity score calculation result when the profiles of 5 different government policies (A01 to A05) to be considered and selected are matched against the reference profile shown in figure 4.2. These scores were derived using the algorithm shown in figure 3.1 and also the similarity metrics described in section 3.5. The table columns – Score – indicates the overall similarity values between each government policy profile and the reference profile and the columns Rank shows the ranking of policies according to performance from best to worst. The client competence profiles of the alternatives matched against the reference profile are attached in Appendix B (at the end of the document).

Table 4.2: Comparative results and rankings using the different similarity metrics in the Proposed Matchmaking Algorithm for Government Policy Selection.

Alternatives	Soergel		Wave Hedges		Canberra		Euclidean		Sorensen	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
A01	0.4878	4	0.4878	4	0.6336	4	0.8697	2	0.6440	4
A02	0.4956	2	0.5031	2	0.6432	2	0.8670	3	0.6572	2
A03	0.4927	3	0.4927	3	0.6345	3	0.8632	4	0.6470	3
A04	0.4337	5	0.4337	5	0.5616	5	0.7831	5	0.5887	5
A05	0.5250	1	0.5466	1	0.6887	1	0.9042	1	0.6987	1

From table 4.2, it can be seen that the ranks of alternatives in the proposed multi-person matchmaking method are rather consistent using three of the similarity metrics. Although there are a couple of changes with the ranking of three of the alternatives using the Euclidean metric, the ranks of the first and last three alternatives do not change. This has further indicated that the proposed method can be a reliable and less complicated alternative solution to multi-person multi-attribute decision problems irrespective of data size.

4.1.3 Sport Evaluation

The following decision problem considered non-homogeneous alternatives in a group decision making process (Olugbara and Nepal, 2012). A survey involving 34 respondents was conducted where the respondent expressed affinity for at least one sport. Ten sports were evaluated based on five criteria including enjoyment, technicality, values, risk and popularity. Each of these criteria was further divided into sub-criteria which are enjoyment, technicality, values, risk and popularity – and were evaluated based on a measurement instrument of 7-point semantic differential scale. Due to the fact that there was no fixed number of decision makers for each sport, 10 different reference profiles were constructed from this experiment as each sport was evaluated by at least 3 decision makers. Figure 4.3 is a sample representation of how the reference profile information is represented in the proposed multi-person matchmaking method.

RP = {

<enjoyment, <21,21,21>, No, <1,1,1> >

<technicality, <3,3,3>, No, <1,1,1 > >

< value, <21,21,21>, No, <1,1,1> >

< risk, <2,2,2>, No, <1,1,1> >

< popularity, <21,21,21>, No, <1,1,1> >

}

Figure 4.3: Sample Sport Reference Requisite Profile in a Quadruple Format

Enjoyment, value and popularity were considered benefit criteria – the higher the scores, the better – thus the effects of these criteria were maximized while technicality and risk were cost criteria – the lower the scores, the better – thus the effects were minimized (Olugbara and Nepal, 2012). As a result, the attribute description values of the reference profile in figure 4.3 was constructed based on the benefit and cost criteria specifications.

Table 4.3 shows the similarity score calculation result when the profiles of 10 different sports to be evaluated are matched against 10 different reference profiles. These scores were derived using the algorithm shown in figure 3.1 and also the similarity metrics described in section 3.5. The table columns Score indicates the overall similarity values between each alternative (sport) profile and the reference profile and the columns Rank shows the ranking of alternatives (sports) according to performance from best to worst. The client competence profiles of the alternatives (sports) matched against the different reference profiles are attached in Appendices C and D respectively (at the end of the document).

Table 4.3: Comparative results and rankings using the different similarity metrics in the Proposed Matchmaking Algorithm for Sport Evaluation.

Sports	Soergel		Wave Hedges		Canberra		Euclidean		Sorensen	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Hockey	0.5381	10	0.5467	10	0.6309	10	0.7716	10	0.6372	10
Volleyball	0.6609	2	0.6992	2	0.7746	2	0.8868	1	0.7595	2
Baseball	0.6024	7	0.6180	7	0.6993	7	0.8249	7	0.7083	7
Basketball	0.5797	9	0.5862	9	0.6683	9	0.8030	9	0.6777	9
Swimming	0.6597	3	0.6859	3	0.7659	3	0.8867	2	0.7558	3
Rugby	0.6237	5	0.6362	6	0.7112	6	0.8312	6	0.7120	6
Ping-Pong	0.6136	6	0.6517	5	0.7269	5	0.8451	5	0.7250	5
Tennis	0.6313	4	0.6701	4	0.7490	4	0.8699	4	0.7328	4
Wrestling	0.5975	8	0.6041	8	0.6880	8	0.8213	8	0.6872	8
Soccer	0.6947	1	0.7283	1	0.7903	1	0.8842	3	0.7733	1

Likewise, from table 4.3 the ranks of alternatives (sports) in the proposed multi-person matchmaking method are consistent using three of the similarity measures. Although there are few displacements with the ranking of some of the alternatives using the Euclidean metric, the ranks of the majority of the alternatives do not change. All similarity metrics agreed with the ranks of Hockey, Baseball, Basketball, Tennis and Wrestling. This has also proven that the proposed method can be an efficient alternative solution to multi-person multi-attribute decision problems irrespective of data size and type.

4.1.4 Mancala Game Strategy Selection

One open problem in decision making being considered in this study is the Mancala strategy selection. This is identified as a form of decision problem because there are three major areas of conflict – where one can decide to either fight one's opponent, debate with one's opponent or outwit one's opponent. Additionally, Mancala – which is classified as a board game – has been used to model interactions and decision making processes in the business world (Oderanti and De Wilde, 2011; Donkers, *et al.*, 2001). Most business firms (decision makers) can identify the moves that a rival could make in response to each of its strategies and then the firm can plan counter-strategies to outwit its rival. Basically, decision making in this scenario is the capability of the business firms (decision makers) to execute a strategy following some conscious tactical choices which will either positively or negatively affect profit of a business (Akinyemi, *et al.*, 2009; Oderanti and De Wilde, 2011).

A lot of research work and methods have been proposed in literature in the quest of exploring good heuristics and strategies in solving this decision problem (Divilly, *et al.*, 2013; Olugbara, *et al.*, 2006; Akinyemi, et al., 2013; Olugbara, *et al*., 2007; Olugbara, *et al*., 2006; Randle, *et al.*, 2012; Oderanti and De Wilde, 2011; Smith, 2007). While a decision maker knows information about oneself which will be modelled as the reference profile in this study incomplete and various information is known about the rival – which will be modelled as the client profile in this study. It should be noted that every player is allowed a maximum of 6 moves. The focus of this experiment is on determining the best strategy in diverse variants of Mancala. Figure 4.4 is a sample representation of how the reference profile – solvable Mancala positions using the endgame in (Olugbara, *et al.*, 2006; Donkers, *et al.*, 2001) is represented in the proposed multi-person matchmaking method.

RP = {
<P6, <7,5,3,1,2,2,0,1,0,0,0,0>, No, <1,1,1,1,1,1,1,1,1,1,1,1> >
<P1, <7,5,3,1,2,0,0,1,0,0,0,0>, No, <1,1,1,1,1,1,1,1,1,1,1,1> >
<P5, <0,6,4,2,3,1,0,1,0,0,0,0>, No, <1,1,1,1,1,1,1,1,1,1,1,1> >
<P6, <0,6,4,2,0,2,0,1,0,0,0,0>, No, <1,1,1,1,1,1,1,1,1,1,1,1> >
<P2, <0,6,4,2,0,0,0,1,0,0,0,0>, No, <1,1,1,1,1,1,1,1,1,1,1,1> >
<P3, <0,0,5,3,1,1,0,1,0,0,0,0>, No, <1,1,1,1,1,1,1,1,1,1,1,1> >
<P6, <0,0,0,4,2,2,0,1,0,0,0,0>, No, <1,1,1,1,1,1,1,1,1,1,1,1> >
<P4, <0,0,0,4,2,0,0,1,0,0,0,0>, No, <1,1,1,1,1,1,1,1,1,1,1,1> >
<P5, <0,0,0,0,3,1,0,1,0,0,0,0>, No, <1,1,1,1,1,1,1,1,1,1,1,1> >
<P6, <0,0,0,0,0,2,0,1,0,0,0,0>, No, <1,1,1,1,1,1,1,1,1,1,1,1> >
}

Figure 4.4: Mancala Position Reference Profile in a Quadruple Format

The endpoint of this Mancala experiment is to determine which position in each strategy is the best. As a result, eight (8) client profiles are modelled 4 known and 4 unknown strategies representing different variants of the Mancala game (Martin, *et al.*,2014; Randle, et al., 2013). Therefore, the immediate similarity value of each attribute in the client profile will be calculated in order to determine which position in each strategy will result in a win irrespective of the move the rival or opponent makes. The position with the maximum similarity value is taken as the solvable position.

Table 4.4 shows the similarity score calculation result when the profiles of different Mancala strategies are matched against the reference profile shown in figure 4.4. These scores were derived using the algorithm shown in figure 3.1 and Soergel Index similarity metric described in section 3.5. The table column Score indicates the immediate similarity values between each attribute in the client profile and the corresponding attribute in the reference profile and the column Solvable Positions shows which attribute is the best, that is which position in each strategy is solvable.

Table 4.4: Calculating the Immediate Similarity Value of each constraint using Soergel Index in the Proposed Matchmaking Algorithm for Mancala Game Strategy Selection.

Constraints	Score	Solvable Positions
<P6,<7,5,3,1,2,0,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	P6
<P5,<7,5,3,1,0,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9165	
<P4,<7,5,3,0,3,2,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8728	
<P3,<7,5,0,2,3,3,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8838	
<P2,<7,0,4,2,3,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8983	
<P1,<0,6,4,2,3,3,1,0,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9666	
<P5,<7,5,3,1,0,1,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9129	P1
<P4,<7,5,3,0,3,0,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8664	
<P3,<7,5,0,2,3,1,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8664	
<P2,<7,0,4,2,3,1,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8798	
<P1,<0,6,4,2,3,1,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	
<P6,<0,6,4,2,3,0,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8769	P5
<P5,<0,6,4,2,0,2,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	
<P4,<0,6,4,0,4,2,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8497	
<P3,<0,6,0,3,4,2,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9072	
<P2,<0,0,5,3,4,2,1,0,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9374	
<P6,<0,6,4,2,0,0,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	P6
<P4,<0,6,4,0,1,3,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8625	
<P3,<0,6,0,3,1,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8821	
<P2,<0,0,5,3,1,3,1,0,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9523	

<P6,<3,3,3,3,3,0,4,4,4,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8847	P1
<P5,<3,3,3,3,0,4,4,4,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8789	
<P4,<3,3,3,0,4,4,4,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8562	
<P3,<3,3,0,4,4,4,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8748	
<P2,<3,0,4,4,4,3,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8781	
<P1,<0,4,4,4.3,3,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8989**	
<P6,<4,4,4,4,4,0,5,5,5.5,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8812	P1
<P5,<4,4,4.4,0,5,5,5,5,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8764	
<P4,<4,4,4,0,5,5,5,5,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8504	
<P3,<4,4,0,5,5,5,5,4,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8643	
<P2,<4,0,5,5,5,5,4,4,4,4,4.4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8713	
<P1,<0,5,5,5,5,4,4,4,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8875**	
<P6,<5,5,5,5,5,0,6,6,6,6,6,5>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0 .167,0.167,0.167,0.167≫	0.8788	P1
<P5,<5,5,5,5,0,6,6,6,6,6,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8713	
<P4,<5,5,5.0,6,6,6,6,6,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8469	
<P3,<5,5,0,6,6,6,6,6,5,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8581	
<P2,<5,0,6,6,6,6,6,5,5,5,5,5>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0 .167,0.167,0.167,0.167≫	0.8636	
<P1,<0,6,6,6,6,6,5,5,5,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8803**	
<P6,<6,6,6,6,6,0,7,7,7,7,7,7>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8742**	P6
<P5,<6,6,6,6,0,7,7,7,7,7,7,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8678	
<P4,<6,6,6,0,7,7,7,7,7,7,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8446	
<P3,<6,6,0,7,7,7,7,7,7,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8539	
<P2,<6,0,7,7,7,7,7,7,6,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8585	
<P1,<0,7,7,7,7,7,7,6,6,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8724	

Table 4.4 shows the possible solvable positions that can guarantee a win in any Mancala strategy selection problem. These positions can be derived using the weighted Soergel Index similarity metric described in section 3.5 (Chapter 3). The highlighted figures are derived by computing the immediate similarity values between the different client profiles and the reference profiles.

Table 4.5 shows the similarity score calculation result when the profiles of different Mancala strategies are matched against the reference profile shown in figure 4.4. These scores were derived using the algorithm shown in figure 3.1 and Wave Hedges Index similarity metric described in section 3.5. The table column – Score – indicates the immediate similarity values between each attribute in the client profile and the corresponding attribute in the reference profile and the column – Solvable Positions – shows which attribute is the best position in which each strategy is solvable.

Table 4.5: Calculating the Immediate Similarity Value of each constraint using the Wave Hedges Index in the Proposed Matchmaking Algorithm for Mancala Game Strategy Selection.

Constraints	**Score**	**Solvable Positions**
<P6,<7,5,3,1,2,0,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	P6
<P5,<7,5,3,1,0,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9548	
<P4,<7,5,3,0,3,2,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9513	
<P3,<7,5,0,2,3,3,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9559	
<P2,<7,0,4,2,3,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9462	
<P1,<0,6,4,2,3,3,1,0,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9629	
<P5,<7,5,3,1,0,1,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9525	P1
<P4,<7,5,3,0,3,0,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9443	
<P3,<7,5,0,2,3,1,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9443	
<P2,<7,0,4,2,3,1,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9304	

<P1,<0,6,4,2,3,1,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	
<P6,<0,6,4,2,3,0,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9467	P5
<P5,<0,6,4,2,0,2,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	
<P4,<0,6,4,0,4,2,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9374	
<P3,<0,6,0,3,4,2,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9617	
<P2,<0,0,5,3,4,2,1,0,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9548	
<P6,<0,6,4,2,0,0,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	P6
<P4,<0,6,4,0,1,3,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9536	
<P3,<0,6,0,3,1,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9478	
<P2,<0,0,5,3,1,3,1,0,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9629	
<P6,<3,3,3,3,3,0,4,4,4,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8925	P1
<P5,<3,3,3,3,0,4,4,4,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8840	
<P4,<3,3,3,0,4,4,4,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8655	
<P3,<3,3,0,4,4,4,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8794	
<P2,<3,0,4,4,4,3,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8812	
<P1,<0,4,4,4.3,3,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.9003**	
<P6,<4,4,4,4,4,0,5,5,5.5,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8897	P1
<P5,<4,4,4.4,0,5,5,5,5,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8854	
<P4,<4,4,4,0,5,5,5,5,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8608	
<P3,<4,4,0,5,5,5,5,4,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8727	
<P2,<4,0,5,5,5,5,4,4,4,4,4.4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8782	
<P1,<0,5,5,5,5,4,4,4,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8905**	
<P6,<5,5,5,5,5,0,6,6,6,6,6,5>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.16	**0.8898**	P6

7,0.167,0.167,0.167		
<P5,<5,5,5,5,0,6,6,6,6,6,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8822	
<P4,<5,5,5.0,6,6,6,6,6,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8585	
<P3,<5,5,0,6,6,6,6,6,5,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8678	
<P2,<5,0,6,6,6,6,6,5,5,5,5,5>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8729	
<P1,<0,6,6,6,6,6,5,5,5,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8868	
<P6,<6,6,6,6,6,0,7,7,7,7,7,7>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8863**	P6
<P5,<6,6,6,6,0,7,7,7,7,7,7,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8807	
<P4,<6,6,6,0,7,7,7,7,7,7,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8569	
<P3,<6,6,0,7,7,7,7,7,7,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8648	
<P2,<6,0,7,7,7,7,7,7,6,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8688	
<P1,<0,7,7,7,7,7,7,6,6,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8810	

Table 4.5 shows the possible solvable positions that can guarantee a win in any Mancala strategy selection problem. These positions can be derived using the weighted Wave Hedges Index similarity metric described in section 3.5 (Chapter 3). The highlighted figures are derived by computing the immediate similarity values between the different client profiles and the reference profiles.

Table 4.6 shows the similarity score calculation result when the profiles of different Mancala strategies are matched against the reference profile shown in figure 4.4. These scores were derived using the algorithm shown in figure 3.1 and Canberra Similarity metric described in section 3.5. The table column – Score – indicates the immediate similarity values between each attribute in the client profile and the corresponding attribute in the reference profile and the column Solvable Positions shows which attribute is the best position in which each strategy is solvable.

Table 4.6: Calculating the Immediate Similarity Value of each constraint using Canberra Similarity in the Proposed Matchmaking Algorithm for Mancala Game Strategy Selection.

Constraints	Score	Solvable Positions
<P6,<7,5,3,1,2,0,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	P6
<P5,<7,5,3,1,0,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9165	
<P4,<7,5,3,0,3,2,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9536	
<P3,<7,5,0,2,3,3,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9620	
<P2,<7,0,4,2,3,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9539	
<P1,<0,6,4,2,3,3,1,0,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9652	
<P5,<7,5,3,1,0,1,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9596	P1
<P4,<7,5,3,0,3,0,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9443	
<P3,<7,5,0,2,3,1,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9485	
<P2,<7,0,4,2,3,1,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9304	
<P1,<0,6,4,2,3,1,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	
<P6,<0,6,4,2,3,0,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9506	P5
<P5,<0,6,4,2,0,2,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	
<P4,<0,6,4,0,4,2,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9397	
<P3,<0,6,0,3,4,2,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9655	
<P2,<0,0,5,3,4,2,1,0,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9592	
<P6,<0,6,4,2,0,0,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	P6
<P4,<0,6,4,0,1,3,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9583	
<P3,<0,6,0,3,1,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9516	
<P2,<0,0,5,3,1,3,1,0,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9652	

<P6,<3,3,3,3,3,0,4,4,4,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9033	P1
<P5,<3,3,3,3,0,4,4,4,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8941	
<P4,<3,3,3,0,4,4,4,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8521	
<P3,<3,3,0,4,4,4,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8863	
<P2,<3,0,4,4,4,3,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8907	
<P1,<0,4,4,4.3,3,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.9091**	
<P6,<4,4,4,4,4,0,5,5,5.5,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9008	P1
<P5,<4,4,4.4,0,5,5,5,5,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8938	
<P4,<4,4,4,0,5,5,5,5,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8666	
<P3,<4,4,0,5,5,5,5,4,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8808	
<P2,<4,0,5,5,5,5,4,4,4,4,4.4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8861	
<P1,<0,5,5,5,5,4,4,4,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.9015**	
<P6,<5,5,5,5,5,0,6,6,6,6,6,5>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.16 7,0.167,0.167,0.167	**0.8994**	P6
<P5,<5,5,5,5,0,6,6,6,6,6,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8908	
<P4,<5,5,5.0,6,6,6,6,6,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8641	
<P3,<5,5,0,6,6,6,6,6,5,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8759	
<P2,<5,0,6,6,6,6,6,5,5,5,5,5>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.16 7,0.167,0.167,0.167≫	0.8814	
<P1,<0,6,6,6,6,6,5,5,5,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8968	
<P6,<6,6,6,6,6,0,7,7,7,7,7,7>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8961**	P6
<P5,<6,6,6,6,0,7,7,7,7,7,7,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8886	
<P4,<6,6,6,0,7,7,7,7,7,7,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8622	
<P3,<6,6,0,7,7,7,7,7,7,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8729	
<P2,<6,0,7,7,7,7,7,7,6,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8773	
<P1,<0,7,7,7,7,7,7,6,6,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8919	

Table 4.5 shows the possible solvable positions that can guarantee a win in any Mancala strategy selection problem. These positions can be derived using the weighted Canberra Similarity metric described in section 3.5 (Chapter 3). The highlighted figures are derived by computing the immediate similarity values between the different client profiles and the reference profiles.

Table 4.7 shows the similarity score calculation result when the profiles of different Mancala strategies are matched against the reference profile shown in figure 4.4. These scores were derived using the algorithm shown in figure 3.1 and Euclidean Similarity metric described in section 3.5. The table column Score indicates the immediate similarity values between each attribute in the client profile and the corresponding attribute in the reference profile and the column Solvable Positions shows which attribute is the best position in which each strategy is solvable.

Table 4.7: Calculating the Immediate Similarity Value of each Attribute using Euclidean Metric in the Proposed Matchmaking Algorithm for Mancala Game Strategy Selection.

Constraints	Score	Solvable Positions
<P6,<7,5,3,1,2,0,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	P6
<P5,<7,5,3,1,0,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9697	
<P4,<7,5,3,0,3,2,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9567	
<P3,<7,5,0,2,3,3,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9695	
<P2,<7,0,4,2,3,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9645	
<P1,<0,6,4,2,3,3,1,0,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9687	
<P5,<7,5,3,1,0,1,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9687	P1
<P4,<7,5,3,0,3,0,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9443	
<P3,<7,5,0,2,3,1,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9485	

<P2,<7,0,4,2,3,1,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9304	
<P1,<0,6,4,2,3,1,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	
<P6,<0,6,4,2,3,0,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9561	P5
<P5,<0,6,4,2,0,2,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	
<P4,<0,6,4,0,4,2,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9428	
<P3,<0,6,0,3,4,2,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9703	
<P2,<0,0,5,3,4,2,1,0,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9656	
<P6,<0,6,4,2,0,0,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	P6
<P4,<0,6,4,0,1,3,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9652	
<P3,<0,6,0,3,1,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9564	
<P2,<0,0,5,3,1,3,1,0,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9687	
<P6,<3,3,3,3,3,0,4,4,4,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8904	P1
<P5,<3,3,3,3,0,4,4,4,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8797	
<P4,<3,3,3,0,4,4,4,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8521	
<P3,<3,3,0,4,4,4,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8682	
<P2,<3,0,4,4,4,3,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8762	
<P1,<0,4,4,4.3,3,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8935**	
<P6,<4,4,4,4,4,0,5,5,5.5,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8605	P1
<P5,<4,4,4.4,0,5,5,5,5,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8639	
<P4,<4,4,4,0,5,5,5,5,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8337	
<P3,<4,4,0,5,5,5,5,4,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8505	
<P2,<4,0,5,5,5,5,4,4,4,4,4.4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8565	
<P1,<0,5,5,5,5,4,4,4,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8749**	

<P6,<5,5,5,5,5,0,6,6,6,6,6,5>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8437	P1
<P5,<5,5,5,5,0,6,6,6,6,6,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8335	
<P4,<5,5,5.0,6,6,6,6,6,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8173	
<P3,<5,5,0,6,6,6,6,6,5,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8323	
<P2,<5,0,6,6,6,6,6,5,5,5,5,5>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8388	
<P1,<0,6,6,6,6,6,5,5,5,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8559**	
<P6,<6,6,6,6,6,0,7,7,7,7,7,7>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8268	P1
<P5,<6,6,6,6,0,7,7,7,7,7,7,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8168	
<P4,<6,6,6,0,7,7,7,7,7,7,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.7873	
<P3,<6,6,0,7,7,7,7,7,7,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8155	
<P2,<6,0,7,7,7,7,7,7,6,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8208	
<P1,<0,7,7,7,7,7,7,6,6,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8383**	

Table 4.7 shows the possible solvable positions that can guarantee a win in any Mancala strategy selection problem. These positions can be derived using the weighted Euclidean Similarity metric described in section 3.5 (Chapter 3). The highlighted figures are derived by computing the immediate similarity values between the different client profiles and the reference profiles.

Table 4.8 shows the similarity score calculation result when the profiles of different Mancala strategies are matched against the reference profile shown in figure 4.4. These scores were derived using the algorithm shown in figure 3.1 and Sorensen Index similarity metric described in section 3.5. The table column – Score – indicates the immediate similarity values between each attribute in the client profile and the corresponding attribute in the reference profile and the column – Solvable Positions – shows which attribute is the best position in which each strategy is solvable.

Table 4.8: Calculating the Immediate Similarity Value of each Attribute using the Sorensen Index in the Proposed Matchmaking Algorithm applied to the Mancala Game Strategy Selection.

Constraints	Score	Solvable Positions
<P6,<7,5,3,1,2,0,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	P6
<P5,<7,5,3,1,0,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9443	
<P4,<7,5,3,0,3,2,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8972	
<P3,<7,5,0,2,3,3,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9109	
<P2,<7,0,4,2,3,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9269	
<P1,<0,6,4,2,3,3,1,0,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9814	
<P5,<7,5,3,1,0,1,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9411	P1
<P4,<7,5,3,0,3,0,0,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8887	
<P3,<7,5,0,2,3,1,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8887	
<P2,<7,0,4,2,3,1,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9061	
<P1,<0,6,4,2,3,1,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	
<P6,<0,6,4,2,3,0,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9026	P5
<P5,<0,6,4,2,0,2,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	
<P4,<0,6,4,0,4,2,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8634	
<P3,<0,6,0,3,4,2,1,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9358	
<P2,<0,0,5,3,4,2,1,0,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9615	
<P6,<0,6,4,2,0,0,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**1.0000**	P6
<P4,<0,6,4,0,1,3,0,1,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8831	
<P3,<0,6,0,3,1,3,1,1,0,0,0,0>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9089	
<P2,<0,0,5,3,1,3,1,0,0,0,0,0>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9722	

<P6,<3,3,3,3,3,0,4,4,4,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9119	P1
<P5,<3,3,3,3,0,4,4,4,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9050	
<P4,<3,3,3,0,4,4,4,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8737	
<P3,<3,3,0,4,4,4,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8998	
<P2,<3,0,4,4,4,3,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9041	
<P1,<0,4,4,4.3,3,3,3,3,3,3,3>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.9275**	
<P6,<4,4,4,4,4,0,5,5,5.5,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9078	P1
<P5,<4,4,4.4,0,5,5,5,5,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9019	
<P4,<4,4,4,0,5,5,5,5,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8645	
<P3,<4,4,0,5,5,5,5,4,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8857	
<P2,<4,0,5,5,5,5,4,4,4,4,4.4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8953	
<P1,<0,5,5,5,5,4,4,4,4,4,4,4>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.9152**	
<P6,<5,5,5,5,5,0,6,6,6,6,6,5>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.9049	P1
<P5,<5,5,5,5,0,6,6,6,6,6,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8953	
<P4,<5,5,5.0,6,6,6,6,6,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8587	
<P3,<5,5,0,6,6,6,6,6,5,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8766	
<P2,<5,0,6,6,6,6,6,5,5,5,5,5>,NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8847	
<P1,<0,6,6,6,6,6,5,5,5,5,5,5>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.9067**	
<P6,<6,6,6,6,6,0,7,7,7,7,7,7>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167	**0.8991**	P6
<P5,<6,6,6,6,0,7,7,7,7,7,7,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8906	
<P4,<6,6,6,0,7,7,7,7,7,7,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8547	
<P3,<6,6,0,7,7,7,7,7,7,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8701	
<P2,<6,0,7,7,7,7,7,7,6,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8773	
<P1,<0,7,7,7,7,7,7,6,6,6,6,6>, NO,<0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167,0.167≫	0.8968	

Table 4.8 shows the possible solvable positions that can guarantee a win in any Mancala strategy selection problem. These positions can be derived using the weighted Sorensen Index similarity metric described in section 3.5 (Chapter 3). The highlighted figures are derived by computing the immediate similarity values between the different client profiles and the reference profiles.

4.2 Hausdorff Validation Procedure

The quality of the performance of the multi-person matchmaking algorithm is further demonstrated by applying the Hausdorff distance to matchmaking scenarios. Hausdorff distance has been generally used in similarity computations to determine if two points (reference profile and client profile) similarities correspond to nearness – similar profiles imply nearness to each other (Di Lorenzo and Di Maio, 2006). As earlier mentioned, one important advantage of Hausdorff distance is the possibility of comparing client profile with reference profiles and vice versa. As a result, the maximum between the two Hausdorff scores are used to rank the alternatives in this study while applying the Hausdorff distance.

The following subsections show the results derived from using the Hausdorff distance for each of the experiments in section 4.1. Each experimental result is displayed in three columns. The client profile column shows each attribute description in the client profiles – represented as individual elements. The results derived from matching the reference profile with the client profiles – h(A,B), results derived from matching the client profiles with the reference profile – h(B,A), and the maximum Hausdorff score between each element in the client and ideal reference profile – max(h(A,B),h(B,A) – labelled as Score.

4.2.1 Personnel Selection

Table 4.9 shows the reference profile of the personnel selection problem with preferences of four decision makers (DM1 – DM4) for seven attributes.

Table 4.9: Reference Profile

Attributes	DM1	DM2	DM3	DM4
Language Test	100	100	100	100
Professional Test	100	100	100	100
Safety Rule Test	100	100	100	100
Professional Skills	100	100	100	100
Computer Skills	100	100	100	100
Panel Interview	100	100	100	100
1-on-1 Interview	100	100	100	100

In tables 4.10 – 4.14, shows the results derived from using the weighted similarity metrics shown in section 3.5 (Chapter 3) to calculate the Hausdorff scores between the client profiles and the reference profile and vice versa. The figures in the column Score are used to rank the alternatives from best to worst.

Table 4.10: Calculating Hausdorff Scores using the Weighted Soergel Index for Personnel Selection.

S/N	Attributes	DM1	DM2	DM3	DM4	h(A,B)	h(B,A)	Score
P01	Language Test	80	80	80	80	0.9893	0.9930	**0.9930**
	Professional Test	70	70	70	70	0.9587	0.9821	0.9821
	Safety Rule Test	85	85	85	85	0.9923	0.9923	0.9923
	Professional Skills	77	77	77	77	0.9652	0.9803	0.9803
	Computer Skills	76	76	76	76	0.9743	0.9861	0.9861
	Panel Interview	80	85	75	90	0.9618	0.9707	0.9707
	1-on-1 Interview	75	80	70	85	0.9414	0.9655	0.9655
P02	Language Test	85	85	85	85	0.9919	0.9919	**0.9919**
	Professional Test	65	65	65	65	0.9518	0.9793	0.9793
	Safety Rule Test	76	76	76	76	0.9858	0.9912	0.9912
	Professional Skills	80	80	80	80	0.9697	0.9773	0.9773
	Computer Skills	75	75	75	75	0.9732	0.9839	0.9839
	Panel Interview	65	60	70	60	0.8857	0.9662	0.9662
	1-on-1 Interview	75	70	77	70	0.9278	0.9602	0.9602
P03	Language Test	78	78	78	78	0.9882	0.9946	**0.9946**
	Professional Test	90	90	90	90	0.9862	0.9862	0.9862
	Safety Rule Test	72	72	72	72	0.9835	0.9941	0.9941
	Professional Skills	80	80	80	80	0.9697	0.9849	0.9849
	Computer Skills	85	85	85	85	0.9839	0.9893	0.9893
	Panel Interview	90	80	80	90	0.9670	0.9775	0.9775

	1-on-1 Interview	85	85	90	55	0.9393	0.9735	0.9735
P04	Language Test	75	75	75	75	0.9866	0.9919	**0.9919**
	Professional Test	84	84	84	84	0.9780	0.9793	0.9793
	Safety Rule Test	69	69	69	69	0.9817	0.9912	0.9912
	Professional Skills	85	85	85	85	0.9773	0.9773	0.9773
	Computer Skills	65	65	65	65	0.9625	0.9839	0.9839
	Panel Interview	65	55	68	62	0.9153	0.9662	0.9662
	1-on-1 Interview	70	60	72	72	0.9170	0.9602	0.9602
P05	Language Test	84	84	84	84	0.9914	0.9919	**0.9919**
	Professional Test	67	67	67	67	0.9545	0.9793	0.9793
	Safety Rule Test	60	60	60	60	0.9764	0.9912	0.9912
	Professional Skills	75	75	75	75	0.9621	0.9773	0.9773
	Computer Skills	85	85	85	85	0.9839	0.9839	0.9839
	Panel Interview	75	75	50	70	0.9277	0.9662	0.9662
	1-on-1 Interview	80	80	55	75	0.9250	0.9602	0.9602
P06	Language Test	85	85	85	85	0.9919	0.9919	**0.9919**
	Professional Test	78	78	78	78	0.9697	0.9793	0.9793
	Safety Rule Test	82	82	82	82	0.9894	0.9912	0.9912
	Professional Skills	81	81	81	81	0.9712	0.9773	0.9773
	Computer Skills	79	79	79	79	0.9775	0.9839	0.9839
	Panel Interview	80	75	77	75	0.9474	0.9662	0.9662
	1-on-1 Interview	80	85	82	75	0.9474	0.9602	0.9602
P07	Language Test	77	77	77	77	0.9876	0.9909	**0.9909**
	Professional Test	83	83	83	83	0.9766	0.9766	0.9766
	Safety Rule Test	74	74	74	74	0.9847	0.9900	0.9900
	Professional Skills	70	70	70	70	0.9546	0.9742	0.9742
	Computer Skills	71	71	71	71	0.9689	0.9818	0.9818
	Panel Interview	65	70	65	67	0.9252	0.9617	0.9617
	1-on-1 Interview	70	60	72	75	0.9195	0.9549	0.9549
P08	Language Test	78	78	78	78	0.9882	0.9903	**0.9903**
	Professional Test	82	82	82	82	0.9752	0.9752	0.9752
	Safety Rule Test	72	72	72	72	0.9835	0.9894	0.9894
	Professional Skills	80	80	80	80	0.9697	0.9727	0.9727
	Computer Skills	78	78	78	78	0.9764	0.9807	0.9807
	Panel Interview	70	75	75	75	0.9457	0.9595	0.9595
	1-on-1 Interview	60	65	67	85	0.9224	0.9522	0.9522
P09	Language Test	85	85	85	85	0.9919	0.9946	**0.9946**
	Professional Test	90	90	90	90	0.9862	0.9862	0.9862
	Safety Rule Test	80	80	80	80	0.9882	0.9941	0.9941
	Professional Skills	88	88	88	88	0.9818	0.9849	0.9849
	Computer Skills	90	90	90	90	0.9893	0.9893	0.9893
	Panel Interview	80	95	90	90	0.9748	0.9775	0.9775

	1-on-1 Interview	85	85	85	92	0.9659	0.9735	0.9735
P10	Language Test	89	89	89	89	0.9941	0.9941	**0.9941**
	Professional Test	75	75	75	75	0.9656	0.9848	0.9848
	Safety Rule Test	79	79	79	79	0.9876	0.9935	0.9935
	Professional Skills	67	67	67	67	0.9500	0.9833	0.9833
	Computer Skills	77	77	77	77	0.9753	0.9882	0.9882
	Panel Interview	70	75	68	65	0.9308	0.9752	0.9752
	1-on-1 Interview	75	80	78	70	0.9349	0.9708	0.9708
P11	Language Test	65	65	65	65	0.9812	0.9839	**0.9839**
	Professional Test	55	55	55	55	0.9380	0.9587	0.9587
	Safety Rule Test	68	68	68	68	0.9811	0.9823	0.9823
	Professional Skills	62	62	62	62	0.9242	0.9546	0.9546
	Computer Skills	70	70	70	70	0.9678	0.9678	0.9678
	Panel Interview	50	62	60	65	0.9089	0.9324	0.9324
	1-on-1 Interview	60	65	65	70	0.9087	0.9204	0.9204
P12	Language Test	70	70	70	70	0.9839	0.9839	**0.9839**
	Professional Test	64	64	64	64	0.9504	0.9587	0.9587
	Safety Rule Test	65	65	65	65	0.9794	0.9823	0.9823
	Professional Skills	65	65	65	65	0.9470	0.9546	0.9546
	Computer Skills	60	60	60	60	0.9571	0.9678	0.9678
	Panel Interview	60	65	50	45	0.8975	0.9324	0.9324
	1-on-1 Interview	65	75	60	50	0.8977	0.9204	0.9204
P13	Language Test	95	95	95	95	0.9973	0.9973	**0.9973**
	Professional Test	80	80	80	80	0.9725	0.9931	0.9931
	Safety Rule Test	70	70	70	70	0.9823	0.9971	0.9971
	Professional Skills	75	75	75	75	0.9621	0.9924	0.9924
	Computer Skills	70	70	70	70	0.9678	0.9946	0.9946
	Panel Interview	75	80	65	70	0.9380	0.9887	0.9887
	1-on-1 Interview	75	80	75	75	0.9368	0.9867	0.9867
P14	Language Test	70	70	70	70	0.9839	0.9919	**0.9919**
	Professional Test	80	80	80	80	0.9725	0.9793	0.9793
	Safety Rule Test	79	79	79	79	0.9876	0.9912	0.9912
	Professional Skills	80	80	80	80	0.9697	0.9773	0.9773
	Computer Skills	85	85	85	85	0.9839	0.9839	0.9839
	Panel Interview	80	75	80	75	0.9489	0.9662	0.9662
	1-on-1 Interview	70	72	70	75	0.9257	0.9602	0.9602
P15	Language Test	60	60	60	60	0.9785	0.9930	**0.9930**
	Professional Test	78	78	78	78	0.9697	0.9821	0.9821
	Safety Rule Test	87	87	87	87	0.9923	0.9923	0.9923
	Professional Skills	70	70	70	70	0.9546	0.9803	0.9803
	Computer Skills	66	66	66	66	0.9635	0.9861	0.9861

	Panel Interview	70	75	65	60	0.9259	0.9707	0.9707
	1-on-1 Interview	65	70	70	65	0.9138	0.9655	0.9655
P16	Language Test	92	92	92	92	0.9957	0.9957	**0.9957**
	Professional Test	85	85	85	85	0.9793	0.9890	0.9890
	Safety Rule Test	88	88	88	88	0.9929	0.9953	0.9953
	Professional Skills	90	90	90	90	0.9849	0.9879	0.9879
	Computer Skills	85	85	85	85	0.9839	0.9914	0.9914
	Panel Interview	90	92	85	88	0.9747	0.9820	0.9820
	1-on-1 Interview	95	90	80	90	0.9688	0.9788	0.9788
P17	Language Test	86	86	86	86	0.9925	0.9930	**0.9930**
	Professional Test	87	87	87	87	0.9821	0.9821	0.9821
	Safety Rule Test	80	80	80	80	0.9882	0.9923	0.9923
	Professional Skills	70	70	70	70	0.9546	0.9803	0.9803
	Computer Skills	72	72	72	72	0.9700	0.9861	0.9861
	Panel Interview	80	70	75	70	0.9404	0.9707	0.9707
	1-on-1 Interview	85	75	80	75	0.9421	0.9655	0.9655

The goal of this experiment is to decide which client profile among all the client profiles shown in the table is the best. The figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Soergel Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). As can be seen in table 4.15, the highlighted figures are used to rank the client profiles.

Table 4.11: Calculating Hausdorff Scores using Weighted the Wave Hedges Index for Personnel Selection.

S/N	Attributes	DM1	DM2	DM3	DM4	h(A,B)	h(B,A)	Score
P01	Language Test	80	80	80	80	0.9893	0.9930	**0.9930**
	Professional Test	70	70	70	70	0.9587	0.9821	0.9821
	Safety Rule Test	85	85	85	85	0.9923	0.9923	0.9923
	Professional Skills	77	77	77	77	0.9652	0.9803	0.9803
	Computer Skills	76	76	76	76	0.9743	0.9861	0.9861
	Panel Interview	80	85	75	90	0.9618	0.9707	0.9707
	1-on-1 Interview	75	80	70	85	0.9414	0.9655	0.9655
P02	Language Test	85	85	85	85	0.9919	0.9919	**0.9919**
	Professional Test	65	65	65	65	0.9518	0.9793	0.9793

	Safety Rule Test	76	76	76	76	0.9858	0.9912	0.9912
	Professional Skills	80	80	80	80	0.9697	0.9773	0.9773
	Computer Skills	75	75	75	75	0.9732	0.9839	0.9839
	Panel Interview	65	60	70	60	0.8857	0.9662	0.9662
	1-on-1 Interview	75	70	77	70	0.9278	0.9602	0.9602
P03	Language Test	78	78	78	78	0.9882	0.9946	**0.9946**
	Professional Test	90	90	90	90	0.9862	0.9862	0.9862
	Safety Rule Test	72	72	72	72	0.9835	0.9941	0.9941
	Professional Skills	80	80	80	80	0.9697	0.9849	0.9849
	Computer Skills	85	85	85	85	0.9839	0.9893	0.9893
	Panel Interview	90	80	80	90	0.9670	0.9775	0.9775
	1-on-1 Interview	85	85	90	55	0.9393	0.9735	0.9735
P04	Language Test	75	75	75	75	0.9866	0.9919	**0.9919**
	Professional Test	84	84	84	84	0.9780	0.9793	0.9793
	Safety Rule Test	69	69	69	69	0.9817	0.9912	0.9912
	Professional Skills	85	85	85	85	0.9773	0.9773	0.9773
	Computer Skills	65	65	65	65	0.9625	0.9839	0.9839
	Panel Interview	65	55	68	62	0.9153	0.9662	0.9662
	1-on-1 Interview	70	60	72	72	0.9170	0.9602	0.9602
P05	Language Test	84	84	84	84	0.9914	0.9919	**0.9919**
	Professional Test	67	67	67	67	0.9545	0.9793	0.9793
	Safety Rule Test	60	60	60	60	0.9764	0.9912	0.9912
	Professional Skills	75	75	75	75	0.9621	0.9773	0.9773
	Computer Skills	85	85	85	85	0.9839	0.9839	0.9839
	Panel Interview	75	75	50	70	0.9277	0.9662	0.9662
	1-on-1 Interview	80	80	55	75	0.9250	0.9602	0.9602
P06	Language Test	85	85	85	85	0.9919	0.9919	**0.9919**
	Professional Test	78	78	78	78	0.9697	0.9793	0.9793
	Safety Rule Test	82	82	82	82	0.9894	0.9912	0.9912
	Professional Skills	81	81	81	81	0.9712	0.9773	0.9773
	Computer Skills	79	79	79	79	0.9775	0.9839	0.9839
	Panel Interview	80	75	77	75	0.9474	0.9662	0.9662
	1-on-1 Interview	80	85	82	75	0.9474	0.9602	0.9602
P07	Language Test	77	77	77	77	0.9876	0.9909	**0.9909**
	Professional Test	83	83	83	83	0.9766	0.9766	0.9766
	Safety Rule Test	74	74	74	74	0.9847	0.9900	0.9900
	Professional Skills	70	70	70	70	0.9546	0.9742	0.9742
	Computer Skills	71	71	71	71	0.9689	0.9818	0.9818
	Panel Interview	65	70	65	67	0.9252	0.9617	0.9617
	1-on-1 Interview	70	60	72	75	0.9195	0.9549	0.9549
P08	Language Test	78	78	78	78	0.9882	0.9903	**0.9903**
	Professional Test	82	82	82	82	0.9752	0.9752	0.9752

	Safety Rule Test	72	72	72	72	0.9835	0.9894	0.9894
	Professional Skills	80	80	80	80	0.9697	0.9727	0.9727
	Computer Skills	78	78	78	78	0.9764	0.9807	0.9807
	Panel Interview	70	75	75	75	0.9457	0.9595	0.9595
	1-on-1 Interview	60	65	67	85	0.9224	0.9522	0.9522
P09	Language Test	85	85	85	85	0.9919	0.9946	**0.9946**
	Professional Test	90	90	90	90	0.9862	0.9862	0.9862
	Safety Rule Test	80	80	80	80	0.9882	0.9941	0.9941
	Professional Skills	88	88	88	88	0.9818	0.9849	0.9849
	Computer Skills	90	90	90	90	0.9893	0.9893	0.9893
	Panel Interview	80	95	90	90	0.9748	0.9775	0.9775
	1-on-1 Interview	85	85	85	92	0.9659	0.9735	0.9735
P10	Language Test	89	89	89	89	0.9941	0.9941	**0.9941**
	Professional Test	75	75	75	75	0.9656	0.9848	0.9848
	Safety Rule Test	79	79	79	79	0.9876	0.9935	0.9935
	Professional Skills	67	67	67	67	0.9500	0.9833	0.9833
	Computer Skills	77	77	77	77	0.9753	0.9882	0.9882
	Panel Interview	70	75	68	65	0.9308	0.9752	0.9752
	1-on-1 Interview	75	80	78	70	0.9349	0.9708	0.9708
P11	Language Test	65	65	65	65	0.9812	0.9839	**0.9839**
	Professional Test	55	55	55	55	0.9380	0.9587	0.9587
	Safety Rule Test	68	68	68	68	0.9811	0.9823	0.9823
	Professional Skills	62	62	62	62	0.9242	0.9546	0.9546
	Computer Skills	70	70	70	70	0.9678	0.9678	0.9678
	Panel Interview	50	62	60	65	0.9089	0.9324	0.9324
	1-on-1 Interview	60	65	65	70	0.9087	0.9204	0.9204
P12	Language Test	70	70	70	70	0.9839	0.9839	**0.9839**
	Professional Test	64	64	64	64	0.9504	0.9587	0.9587
	Safety Rule Test	65	65	65	65	0.9794	0.9823	0.9823
	Professional Skills	65	65	65	65	0.9470	0.9546	0.9546
	Computer Skills	60	60	60	60	0.9571	0.9678	0.9678
	Panel Interview	60	65	50	45	0.8975	0.9324	0.9324
	1-on-1 Interview	65	75	60	50	0.8977	0.9204	0.9204
P13	Language Test	95	95	95	95	0.9973	0.9973	**0.9973**
	Professional Test	80	80	80	80	0.9725	0.9931	0.9931
	Safety Rule Test	70	70	70	70	0.9823	0.9971	0.9971
	Professional Skills	75	75	75	75	0.9621	0.9924	0.9924
	Computer Skills	70	70	70	70	0.9678	0.9946	0.9946
	Panel Interview	75	80	65	70	0.9380	0.9887	0.9887
	1-on-1 Interview	75	80	75	75	0.9368	0.9867	0.9867
P14	Language Test	70	70	70	70	0.9839	0.9919	**0.9919**

	Professional Test	80	80	80	80	0.9725	0.9793	0.9793
	Safety Rule Test	79	79	79	79	0.9876	0.9912	0.9912
	Professional Skills	80	80	80	80	0.9697	0.9773	0.9773
	Computer Skills	85	85	85	85	0.9839	0.9839	0.9839
	Panel Interview	80	75	80	75	0.9489	0.9662	0.9662
	1-on-1 Interview	70	72	70	75	0.9257	0.9602	0.9602
P15	Language Test	60	60	60	60	0.9785	0.9930	**0.9930**
	Professional Test	78	78	78	78	0.9697	0.9821	0.9821
	Safety Rule Test	87	87	87	87	0.9923	0.9923	0.9923
	Professional Skills	70	70	70	70	0.9546	0.9803	0.9803
	Computer Skills	66	66	66	66	0.9635	0.9861	0.9861
	Panel Interview	70	75	65	60	0.9259	0.9707	0.9707
	1-on-1 Interview	65	70	70	65	0.9138	0.9655	0.9655
P16	Language Test	92	92	92	92	0.9957	0.9957	**0.9957**
	Professional Test	85	85	85	85	0.9793	0.9890	0.9890
	Safety Rule Test	88	88	88	88	0.9929	0.9953	0.9953
	Professional Skills	90	90	90	90	0.9849	0.9879	0.9879
	Computer Skills	85	85	85	85	0.9839	0.9914	0.9914
	Panel Interview	90	92	85	88	0.9747	0.9820	0.9820
	1-on-1 Interview	95	90	80	90	0.9688	0.9788	0.9788
P17	Language Test	86	86	86	86	0.9925	0.9930	**0.9930**
	Professional Test	87	87	87	87	0.9821	0.9821	0.9821
	Safety Rule Test	80	80	80	80	0.9882	0.9923	0.9923
	Professional Skills	70	70	70	70	0.9546	0.9803	0.9803
	Computer Skills	72	72	72	72	0.9700	0.9861	0.9861
	Panel Interview	80	70	75	70	0.9404	0.9707	0.9707
	1-on-1 Interview	85	75	80	75	0.9421	0.9655	0.9655

As the goal of this experiment is to decide which client profile among all the client profiles shown in the table is the best. The figures under the columns labelled – h(A,B) and h(B,A) – in table 4.11 are derived using the weighted Wave hedges Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). As can be seen in table 4.15, the highlighted figures are used to rank the client profiles.

Table 4.12: Calculating Hausdorff Scores using Weighted the Canberra Similarity for Personnel Selection.

S/N	Attributes	DM1	DM2	DM3	DM4	h(A,B)	h(B,A)	Score
P01	Language Test	80	80	80	80	0.9940	0.9963	**0.9963**
	Professional Test	70	70	70	70	0.9757	0.9904	0.9904
	Safety Rule Test	85	85	85	85	0.9959	0.9959	0.9959
	Professional Skills	77	77	77	77	0.9803	0.9895	0.9895
	Computer Skills	76	76	76	76	0..9854	0.9925	0.9925
	Panel Interview	80	85	75	90	0.9789	0.9843	0.9843
	1-on-1 Interview	75	80	70	85	0.9667	0.9815	0.9815
P02	Language Test	85	85	85	85	0.9956	0.9956	**0.9956**
	Professional Test	65	65	65	65	0.9708	0.9888	0.9888
	Safety Rule Test	76	76	76	76	0.9920	0.9952	0.9952
	Professional Skills	80	80	80	80	0.9832	0.9877	0.9877
	Computer Skills	75	75	75	75	0.9847	0.9913	0.9913
	Panel Interview	65	60	70	60	0.9143	0.9817	0.9817
	1-on-1 Interview	75	70	77	70	0.9581	0.9785	0.9785
P03	Language Test	78	78	78	78	0.9934	0.9972	**0.9972**
	Professional Test	90	90	90	90	0.9928	0.9928	0.9928
	Safety Rule Test	72	72	72	72	0.9904	0.9969	0.9969
	Professional Skills	80	80	80	80	0.9832	0.9920	0.9920
	Computer Skills	85	85	85	85	0.9913	0.9944	0.9944
	Panel Interview	90	80	80	90	0.9820	0.9881	0.9881
	1-on-1 Interview	85	85	90	55	0.9634	0.9860	0.9860
P04	Language Test	75	75	75	75	0.9923	0.9956	**0.9956**
	Professional Test	84	84	84	84	0.9880	0.9888	0.9888
	Safety Rule Test	69	69	69	69	0.9892	0.9952	0.9952
	Professional Skills	85	85	85	85	0.9877	0.9877	0.9877
	Computer Skills	65	65	65	65	0.9773	0.9913	0.9913
	Panel Interview	65	55	68	62	0.9476	0.9817	0.9817
	1-on-1 Interview	70	60	72	72	0.9505	0.9785	0.9785
P05	Language Test	84	84	84	84	0.9953	0.9956	**0.9956**
	Professional Test	67	67	67	67	0.9728	0.9888	0.9888
	Safety Rule Test	60	60	60	60	0.9853	0.9952	0.9952
	Professional Skills	75	75	75	75	0.9784	0.9877	0.9877
	Computer Skills	85	85	85	85	0.9913	0.9913	0.9913
	Panel Interview	75	75	50	70	0.9559	0.9817	0.9817
	1-on-1 Interview	80	80	55	75	0.9551	0.9785	0.9785
P06	Language Test	85	85	85	85	0.9956	0.9956	**0.9956**

	Professional Test	78	78	78	78	0.9830	0.9888	0.9888
	Safety Rule Test	82	82	82	82	0.9942	0.9952	0.9952
	Professional Skills	81	81	81	81	0.9841	0.9877	0.9877
	Computer Skills	79	79	79	79	0.9874	0.9913	0.9913
	Panel Interview	80	75	77	75	0.9702	0.9817	0.9817
	1-on-1 Interview	80	85	82	75	0.9707	0.9785	0.9785
P07	Language Test	77	77	77	77	0.9930	0.9950	**0.9950**
	Professional Test	83	83	83	83	0.9872	0.9872	0.9872
	Safety Rule Test	74	74	74	74	0.9912	0.9945	0.9945
	Professional Skills	70	70	70	70	0.9733	0.9859	0.9859
	Computer Skills	71	71	71	71	0.9818	0.9900	0.9900
	Panel Interview	65	70	65	67	0.9551	0.9791	0.9791
	1-on-1 Interview	70	60	72	75	0.9522	0.9753	0.9753
P08	Language Test	78	78	78	78	0.9934	0.9947	**0.9947**
	Professional Test	82	82	82	82	0.9864	0.9864	0.9864
	Safety Rule Test	72	72	72	72	0.9904	0.9942	0.9942
	Professional Skills	80	80	80	80	0.9832	0.9850	0.9850
	Computer Skills	78	78	78	78	0.9867	0.9894	0.9894
	Panel Interview	70	75	75	75	0.9689	0.9777	0.9777
	1-on-1 Interview	60	65	67	85	0.9535	0.9737	0.9737
P09	Language Test	85	85	85	85	0.9956	0.9972	**0.9972**
	Professional Test	90	90	90	90	0.9928	0.9928	0.9928
	Safety Rule Test	80	80	80	80	0.9934	0.9969	0.9969
	Professional Skills	88	88	88	88	0.9903	0.9920	0.9920
	Computer Skills	90	90	90	90	0.9944	0.9944	0.9944
	Panel Interview	80	95	90	90	0.9864	0.9881	0.9881
	1-on-1 Interview	85	85	85	92	0.9817	0.9860	0.9860
P10	Language Test	89	89	89	89	0.9969	0.9969	**0.9969**
	Professional Test	75	75	75	75	0.9803	0.9920	0.9920
	Safety Rule Test	79	79	79	79	0.9931	0.9966	0.9966
	Professional Skills	67	67	67	67	0.9701	0.9912	0.9912
	Computer Skills	77	77	77	77	0.9861	0.9938	0.9938
	Panel Interview	70	75	68	65	0.9590	0.9869	0.9869
	1-on-1 Interview	75	80	78	70	0.9627	0.9845	0.9845
P11	Language Test	65	65	65	65	0.9886	0.9905	**0.9905**
	Professional Test	55	55	55	55	0.9600	0.9757	0.9757
	Safety Rule Test	68	68	68	68	0.9888	0.9896	0.9896
	Professional Skills	62	62	62	62	0.9645	0.9733	0.9733
	Computer Skills	70	70	70	70	0.9811	0.9811	0.9811
	Panel Interview	50	62	60	65	0.9425	0.9603	0.9603
	1-on-1 Interview	60	65	65	70	0.9447	0.9531	0.9531

P12	Language Test	70	70	70	70	0.9905	0.9905	**0.9905**
	Professional Test	64	64	64	64	0.9698	0.9757	0.9757
	Safety Rule Test	65	65	65	65	0.9875	0.9896	0.9896
	Professional Skills	65	65	65	65	0.9679	0.9733	0.9733
	Computer Skills	60	60	60	60	0.9732	0.9811	0.9811
	Panel Interview	60	65	50	45	0.9329	0.9603	0.9603
	1-on-1 Interview	65	75	60	50	0.9355	0.9531	0.9531
P13	Language Test	95	95	95	95	0.9986	0.9986	**0.9986**
	Professional Test	80	80	80	80	0.9847	0.9965	0.9965
	Safety Rule Test	70	70	70	70	0.9896	0.9985	0.9985
	Professional Skills	75	75	75	75	0.9784	0.9961	0.9961
	Computer Skills	70	70	70	70	0.9811	0.9973	0.9973
	Panel Interview	75	80	65	70	0.9638	0.9942	0.9942
	1-on-1 Interview	75	80	75	75	0.9641	0.9932	0.9932
P14	Language Test	70	70	70	70	0.9905	0.9956	**0.9956**
	Professional Test	80	80	80	80	0.9847	0.9888	0.9888
	Safety Rule Test	79	79	79	79	0.9931	0.9952	0.9952
	Professional Skills	80	80	80	80	0.9832	0.9877	0.9877
	Computer Skills	85	85	85	85	0.9913	0.9913	0.9913
	Panel Interview	80	75	80	75	0.9711	0.9817	0.9817
	1-on-1 Interview	70	72	70	75	0.9568	0.9785	0.9785
P15	Language Test	60	60	60	60	0.9866	0.9963	**0.9963**
	Professional Test	78	78	78	78	0.9830	0.9904	0.9904
	Safety Rule Test	87	87	87	87	0.9959	0.9959	0.9959
	Professional Skills	70	70	70	70	0.9733	0.9895	0.9895
	Computer Skills	66	66	66	66	0.9780	0.9925	0.9925
	Panel Interview	70	75	65	60	0.9553	0.9843	0.9843
	1-on-1 Interview	65	70	70	65	0.9485	0.9815	0.9815
P16	Language Test	92	92	92	92	0.9978	0.9978	**0.9978**
	Professional Test	85	85	85	85	0.9888	0.9943	0.9943
	Safety Rule Test	88	88	88	88	0.9962	0.9975	0.9975
	Professional Skills	90	90	90	90	0.9920	0.9937	0.9937
	Computer Skills	85	85	85	85	0.9913	0.9955	0.9955
	Panel Interview	90	92	85	88	0.9865	0.9906	0.9906
	1-on-1 Interview	95	90	80	90	0.9832	0.9889	0.9889
P17	Language Test	86	86	86	86	0.9960	0.9963	**0.9963**
	Professional Test	87	87	87	87	0.9904	0.9904	0.9904
	Safety Rule Test	80	80	80	80	0.9934	0.9959	0.9959
	Professional Skills	70	70	70	70	0.9733	0.9895	0.9895
	Computer Skills	72	72	72	72	0.9825	0.9925	0.9925
	Panel Interview	80	70	75	70	0.9655	0.9843	0.9843
	1-on-1 Interview	85	75	80	75	0.9674	0.9815	0.9815

As the goal of this experiment is to decide which client profile among all the client profiles shown in the table is the most preferred. The figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Canberra Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). As can be seen in table 4.15, the highlighted figures are used to rank the client profiles.

Table 4.13: Calculating Hausdorff Scores using the Weighted Euclidean Metric for Personnel Selection.

S/N	Attributes	DM1	DM2	DM3	DM4	h(A,B)	h(B,A)	Score
P01	Language Test	80	80	80	80	0.9993	0.9997	**0.9997**
	Professional Test	70	70	70	70	0.9957	0.9993	0.9993
	Safety Rule Test	85	85	85	85	0.9997	0.9997	0.9997
	Professional Skills	77	77	77	77	0.9974	0.9993	0.9993
	Computer Skills	76	76	76	76	0.9980	0.9995	0.9995
	Panel Interview	80	85	75	90	0.9978	0.9989	0.9989
	1-on-1 Interview	75	80	70	85	0.9955	0.9987	0.9987
P02	Language Test	85	85	85	85	0.9996	0.9996	**0.9996**
	Professional Test	65	65	65	65	0.9938	0.9991	0.9991
	Safety Rule Test	76	76	76	76	0.9989	0.9996	0.9996
	Professional Skills	80	80	80	80	0.9981	0.9990	0.9990
	Computer Skills	75	75	75	75	0.9978	0.9993	0.9993
	Panel Interview	65	60	70	60	0.9517	0.9985	0.9985
	1-on-1 Interview	75	70	77	70	0.9933	0.9983	0.9983
P03	Language Test	78	78	78	78	0.9992	0.9999	**0.9999**
	Professional Test	90	90	90	90	0.9996	0.9996	0.9996
	Safety Rule Test	72	72	72	72	0.9984	0.9998	0.9998
	Professional Skills	80	80	80	80	0.9981	0.9996	0.9996
	Computer Skills	85	85	85	85	0.9993	0.9997	0.9997
	Panel Interview	90	80	80	90	0.9984	0.9994	0.9994
	1-on-1 Interview	85	85	90	55	0.9922	0.9993	0.9993
P04	Language Test	75	75	75	75	0.9989	0.9996	**0.9996**
	Professional Test	84	84	84	84	0.9990	0.9991	0.9991
	Safety Rule Test	69	69	69	69	0.9980	0.9996	0.9996

	Professional Skills	85	85	85	85	0.9990	0.9990	0.9990
	Computer Skills	65	65	65	65	0.9952	0.9993	0.9993
	Panel Interview	65	55	68	62	0.9875	0.9985	0.9985
	1-on-1 Interview	70	60	72	72	0.9904	0.9983	0.9983
P05	Language Test	84	84	84	84	0.9996	0.9996	**0.9996**
	Professional Test	67	67	67	67	0.9946	0.9991	0.9991
	Safety Rule Test	60	60	60	60	0.9963	0.9996	0.9996
	Professional Skills	75	75	75	75	0.9969	0.9990	0.9990
	Computer Skills	85	85	85	85	0.9993	0.9993	0.9993
	Panel Interview	75	75	50	70	0.9901	0.9985	0.9985
	1-on-1 Interview	80	80	55	75	0.9909	0.9983	0.9983
P06	Language Test	85	85	85	85	0.9996	0.9996	**0.9996**
	Professional Test	78	78	78	78	0.9979	0.9991	0.9991
	Safety Rule Test	82	82	82	82	0.9994	0.9996	0.9996
	Professional Skills	81	81	81	81	0.9983	0.9990	0.9990
	Computer Skills	79	79	79	79	0.9985	0.9993	0.9993
	Panel Interview	80	75	77	75	0.9960	0.9985	0.9985
	1-on-1 Interview	80	85	82	75	0.9966	0.9983	0.9983
P07	Language Test	77	77	77	77	0.9991	0.9995	**0.9995**
	Professional Test	83	83	83	83	0.9988	0.9988	0.9988
	Safety Rule Test	74	74	74	74	0.9987	0.9995	0.9995
	Professional Skills	70	70	70	70	0.9953	0.9987	0.9987
	Computer Skills	71	71	71	71	0.9969	0.9991	0.9991
	Panel Interview	65	70	65	67	0.9910	0.9981	0.9981
	1-on-1 Interview	70	60	72	75	0.9909	0.9977	0.9977
P08	Language Test	78	78	78	78	0.9992	0.9995	**0.9995**
	Professional Test	82	82	82	82	0.9987	0.9987	0.9987
	Safety Rule Test	72	72	72	72	0.9984	0.9994	0.9994
	Professional Skills	80	80	80	80	0.9981	0.9985	0.9985
	Computer Skills	78	78	78	78	0.9984	0.9990	0.9990
	Panel Interview	70	75	75	75	0.9955	0.9978	0.9978
	1-on-1 Interview	60	65	67	85	0.9908	0.9974	0.9974
P09	Language Test	85	85	85	85	0.9996	0.9999	**0.9999**
	Professional Test	90	90	90	90	0.9996	0.9996	0.9996
	Safety Rule Test	80	80	80	80	0.9993	0.9998	0.9998
	Professional Skills	88	88	88	88	0.9994	0.9996	0.9996
	Computer Skills	90	90	90	90	0.9997	0.9997	0.9997
	Panel Interview	80	95	90	90	0.9990	0.9994	0.9994
	1-on-1 Interview	85	85	85	92	0.9986	0.9993	0.9993
P10	Language Test	89	89	89	89	0.9998	0.9998	**0.9998**
	Professional Test	75	75	75	75	0.9972	0.9995	0.9995
	Safety Rule Test	79	79	79	79	0.9992	0.9998	0.9998

	Professional Skills	67	67	67	67	0.9941	0.9995	0.9995
	Computer Skills	77	77	77	77	0.9982	0.9996	0.9996
	Panel Interview	70	75	68	65	0.9924	0.9992	0.9992
	1-on-1 Interview	75	80	78	70	0.9946	0.9991	0.9991
P11	Language Test	65	65	65	65	0.9976	0.9983	**0.9983**
	Professional Test	55	55	55	55	0.9884	0.9957	0.9957
	Safety Rule Test	68	68	68	68	0.9979	0.9982	0.9982
	Professional Skills	62	62	62	62	0.9917	0.9953	0.9953
	Computer Skills	70	70	70	70	0.9967	0.9967	0.9967
	Panel Interview	50	62	60	65	0.9849	0.9930	0.9930
	1-on-1 Interview	60	65	65	70	0.9883	0.9917	0.9917
P12	Language Test	70	70	70	70	0.9983	0.9983	**0.9983**
	Professional Test	64	64	64	64	0.9934	0.9957	0.9957
	Safety Rule Test	65	65	65	65	0.9973	0.9982	0.9982
	Professional Skills	65	65	65	65	0.9932	0.9953	0.9953
	Computer Skills	60	60	60	60	0.9933	0.9967	0.9967
	Panel Interview	60	65	50	45	0.9790	0.9930	0.9930
	1-on-1 Interview	65	75	60	50	0.9830	0.9917	0.9917
P13	Language Test	95	95	95	95	1.0000	1.0000	**1.0000**
	Professional Test	80	80	80	80	0.9983	0.9999	0.9999
	Safety Rule Test	70	70	70	70	0.9982	1.0000	1.0000
	Professional Skills	75	75	75	75	0.9969	0.9999	0.9999
	Computer Skills	70	70	70	70	0.9967	0.9999	0.9999
	Panel Interview	75	80	65	70	0.9939	0.9999	0.9999
	1-on-1 Interview	75	80	75	75	0.9951	0.9998	0.9998
P14	Language Test	70	70	70	70	0.9983	0.9996	**0.9996**
	Professional Test	80	80	80	80	0.9983	0.9991	0.9991
	Safety Rule Test	79	79	79	79	0.9992	0.9996	0.9996
	Professional Skills	80	80	80	80	0.9981	0.9990	0.9990
	Computer Skills	85	85	85	85	0.9993	0.9993	0.9993
	Panel Interview	80	75	80	75	0.9962	0.9985	0.9985
	1-on-1 Interview	70	72	70	75	0.9929	0.9983	0.9983
P15	Language Test	60	60	60	60	0.9966	0.9997	**0.9997**
	Professional Test	78	78	78	78	0.9979	0.9993	0.9993
	Safety Rule Test	87	87	87	87	0.9997	0.9997	0.9997
	Professional Skills	70	70	70	70	0.9953	0.9993	0.9993
	Computer Skills	66	66	66	66	0.9955	0.9995	0.9995
	Panel Interview	70	75	65	60	0.9908	0.9989	0.9989
	1-on-1 Interview	65	70	70	65	0.9899	0.9987	0.9987
P16	Language Test	92	92	92	92	0.9999	0.9999	**0.9999**
	Professional Test	85	85	85	85	0.9991	0.9998	0.9998

	Safety Rule Test	88	88	88	88	0.9998	0.9999	0.9999
	Professional Skills	90	90	90	90	0.9996	0.9997	0.9997
	Computer Skills	85	85	85	85	0.9993	0.9998	0.9998
	Panel Interview	90	92	85	88	0.9992	0.9996	0.9996
	1-on-1 Interview	95	90	80	90	0.9987	0.9995	0.9995
P17	Language Test	86	86	86	86	0.9997	0.9997	**0.9997**
	Professional Test	87	87	87	87	0.9993	0.9993	0.9993
	Safety Rule Test	80	80	80	80	0.9993	0.9997	0.9997
	Professional Skills	70	70	70	70	0.9953	0.9993	0.9993
	Computer Skills	72	72	72	72	0.9972	0.9995	0.9995
	Panel Interview	80	70	75	70	0.9945	0.9989	0.9989
	1-on-1 Interview	85	75	80	75	0.9958	0.9987	0.9987

Likewise, the figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Euclidean metric described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). As can be seen in table 4.15, the highlighted figures are used to rank the client profiles.

Table 4.14: Calculating Hausdorff Scores using the Weighted Sorensen Index for Personnel Selection.

S/N	Attributes	DM1	DM2	DM3	DM4	h(A,B)	h(B,A)	Score
P01	Language Test	80	80	80	80	0.9940	0.9963	**0.9963**
	Professional Test	70	70	70	70	0.9757	0.9904	0.9904
	Safety Rule Test	85	85	85	85	0.9959	0.9959	0.9959
	Professional Skills	77	77	77	77	0.9803	0.9895	0.9895
	Computer Skills	76	76	76	76	0..9854	0.9925	0.9925
	Panel Interview	80	85	75	90	0.9789	0.9843	0.9843
	1-on-1 Interview	75	80	70	85	0.9667	0.9815	0.9815
P02	Language Test	85	85	85	85	0.9956	0.9956	**0.9956**
	Professional Test	65	65	65	65	0.9708	0.9888	0.9888
	Safety Rule Test	76	76	76	76	0.9920	0.9952	0.9952
	Professional Skills	80	80	80	80	0.9832	0.9877	0.9877
	Computer Skills	75	75	75	75	0.9847	0.9913	0.9913
	Panel Interview	65	60	70	60	0.9143	0.9817	0.9817
	1-on-1 Interview	75	70	77	70	0.9581	0.9785	0.9785

P03	Language Test	78	78	78	78	0.9934	0.9972	**0.9972**
	Professional Test	90	90	90	90	0.9928	0.9928	0.9928
	Safety Rule Test	72	72	72	72	0.9904	0.9969	0.9969
	Professional Skills	80	80	80	80	0.9832	0.9920	0.9920
	Computer Skills	85	85	85	85	0.9913	0.9944	0.9944
	Panel Interview	90	80	80	90	0.9820	0.9881	0.9881
	1-on-1 Interview	85	85	90	55	0.9634	0.9860	0.9860
P04	Language Test	75	75	75	75	0.9923	0.9956	**0.9956**
	Professional Test	84	84	84	84	0.9880	0.9888	0.9888
	Safety Rule Test	69	69	69	69	0.9892	0.9952	0.9952
	Professional Skills	85	85	85	85	0.9877	0.9877	0.9877
	Computer Skills	65	65	65	65	0.9773	0.9913	0.9913
	Panel Interview	65	55	68	62	0.9476	0.9817	0.9817
	1-on-1 Interview	70	60	72	72	0.9505	0.9785	0.9785
P05	Language Test	84	84	84	84	0.9953	0.9956	**0.9956**
	Professional Test	67	67	67	67	0.9728	0.9888	0.9888
	Safety Rule Test	60	60	60	60	0.9853	0.9952	0.9952
	Professional Skills	75	75	75	75	0.9784	0.9877	0.9877
	Computer Skills	85	85	85	85	0.9913	0.9913	0.9913
	Panel Interview	75	75	50	70	0.9559	0.9817	0.9817
	1-on-1 Interview	80	80	55	75	0.9551	0.9785	0.9785
P06	Language Test	85	85	85	85	0.9956	0.9956	**0.9956**
	Professional Test	78	78	78	78	0.9830	0.9888	0.9888
	Safety Rule Test	82	82	82	82	0.9942	0.9952	0.9952
	Professional Skills	81	81	81	81	0.9841	0.9877	0.9877
	Computer Skills	79	79	79	79	0.9874	0.9913	0.9913
	Panel Interview	80	75	77	75	0.9702	0.9817	0.9817
	1-on-1 Interview	80	85	82	75	0.9707	0.9785	0.9785
P07	Language Test	77	77	77	77	0.9930	0.9950	**0.9950**
	Professional Test	83	83	83	83	0.9872	0.9872	0.9872
	Safety Rule Test	74	74	74	74	0.9912	0.9945	0.9945
	Professional Skills	70	70	70	70	0.9733	0.9859	0.9859
	Computer Skills	71	71	71	71	0.9818	0.9900	0.9900
	Panel Interview	65	70	65	67	0.9551	0.9791	0.9791
	1-on-1 Interview	70	60	72	75	0.9522	0.9753	0.9753
P08	Language Test	78	78	78	78	0.9934	0.9947	**0.9947**
	Professional Test	82	82	82	82	0.9864	0.9864	0.9864
	Safety Rule Test	72	72	72	72	0.9904	0.9942	0.9942
	Professional Skills	80	80	80	80	0.9832	0.9850	0.9850
	Computer Skills	78	78	78	78	0.9867	0.9894	0.9894
	Panel Interview	70	75	75	75	0.9690	0.9777	0.9777
	1-on-1 Interview	60	65	67	85	0.9541	0.9737	0.9737

P09	Language Test	85	85	85	85	0.9956	0.9972	**0.9972**
	Professional Test	90	90	90	90	0.9928	0.9928	0.9928
	Safety Rule Test	80	80	80	80	0.9934	0.9969	0.9969
	Professional Skills	88	88	88	88	0.9903	0.9920	0.9920
	Computer Skills	90	90	90	90	0.9944	0.9944	0.9944
	Panel Interview	80	95	90	90	0.9866	0.9881	0.9881
	1-on-1 Interview	85	85	85	92	0.9817	0.9860	0.9860
P10	Language Test	89	89	89	89	0.9969	0.9969	**0.9969**
	Professional Test	75	75	75	75	0.9803	0.9920	0.9920
	Safety Rule Test	79	79	79	79	0.9931	0.9966	0.9966
	Professional Skills	67	67	67	67	0.9701	0.9912	0.9912
	Computer Skills	77	77	77	77	0.9861	0.9938	0.9938
	Panel Interview	70	75	68	65	0.9592	0.9869	0.9869
	1-on-1 Interview	75	80	78	70	0.9629	0.9845	0.9845
P11	Language Test	65	65	65	65	0.9886	0.9905	**0.9905**
	Professional Test	55	55	55	55	0.9600	0.9757	0.9757
	Safety Rule Test	68	68	68	68	0.9888	0.9896	0.9896
	Professional Skills	62	62	62	62	0.9645	0.9733	0.9733
	Computer Skills	70	70	70	70	0.9811	0.9811	0.9811
	Panel Interview	50	62	60	65	0.9428	0.9603	0.9603
	1-on-1 Interview	60	65	65	70	0.9447	0.9531	0.9531
P12	Language Test	70	70	70	70	0.9905	0.9905	**0.9905**
	Professional Test	64	64	64	64	0.9698	0.9757	0.9757
	Safety Rule Test	65	65	65	65	0.9875	0.9896	0.9896
	Professional Skills	65	65	65	65	0.9679	0.9733	0.9733
	Computer Skills	60	60	60	60	0.9732	0.9811	0.9811
	Panel Interview	60	65	50	45	0.9339	0.9603	0.9603
	1-on-1 Interview	65	75	60	50	0.9370	0.9531	0.9531
P13	Language Test	95	95	95	95	0.9986	0.9986	**0.9986**
	Professional Test	80	80	80	80	0.9847	0.9965	0.9965
	Safety Rule Test	70	70	70	70	0.9896	0.9985	0.9985
	Professional Skills	75	75	75	75	0.9784	0.9961	0.9961
	Computer Skills	70	70	70	70	0.9811	0.9973	0.9973
	Panel Interview	75	80	65	70	0.9640	0.9942	0.9942
	1-on-1 Interview	75	80	75	75	0.9641	0.9932	0.9932
P14	Language Test	70	70	70	70	0.9905	0.9956	**0.9956**
	Professional Test	80	80	80	80	0.9847	0.9888	0.9888
	Safety Rule Test	79	79	79	79	0.9931	0.9952	0.9952
	Professional Skills	80	80	80	80	0.9832	0.9877	0.9877
	Computer Skills	85	85	85	85	0.9913	0.9913	0.9913
	Panel Interview	80	75	80	75	0.9712	0.9817	0.9817
	1-on-1 Interview	70	72	70	75	0.9567	0.9785	0.9785

P15	Language Test	60	60	60	60	0.9866	0.9963	**0.9963**
	Professional Test	78	78	78	78	0.9830	0.9904	0.9904
	Safety Rule Test	87	87	87	87	0.9959	0.9959	0.9959
	Professional Skills	70	70	70	70	0.9733	0.9895	0.9895
	Computer Skills	66	66	66	66	0.9780	0.9925	0.9925
	Panel Interview	70	75	65	60	0.9558	0.9843	0.9843
	1-on-1 Interview	65	70	70	65	0.9486	0.9815	0.9815
P16	Language Test	92	92	92	92	0.9978	0.9978	**0.9978**
	Professional Test	85	85	85	85	0.9888	0.9943	0.9943
	Safety Rule Test	88	88	88	88	0.9962	0.9975	0.9975
	Professional Skills	90	90	90	90	0.9920	0.9937	0.9937
	Computer Skills	85	85	85	85	0.9913	0.9955	0.9955
	Panel Interview	90	92	85	88	0.9866	0.9906	0.9906
	1-on-1 Interview	95	90	80	90	0.9835	0.9889	0.9889
P17	Language Test	86	86	86	86	0.9960	0.9963	**0.9963**
	Professional Test	87	87	87	87	0.9904	0.9904	0.9904
	Safety Rule Test	80	80	80	80	0.9934	0.9959	0.9959
	Professional Skills	70	70	70	70	0.9733	0.9895	0.9895
	Computer Skills	72	72	72	72	0.9825	0.9925	0.9925
	Panel Interview	80	70	75	70	0.9657	0.9843	0.9843
	1-on-1 Interview	85	75	80	75	0.9676	0.9815	0.9815

Similarly, the figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Sorensen Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). As can be seen in table 4.15, the highlighted figures are used to rank the client profiles.

Table 4.15 shows the results of the evaluation of profile matching and similarity computation using Hausdorff distance in matchmaking by taking the maximum Hausdorff score in order to observe the changes in the rankings of alternatives. For the dataset, the researcher performs the evaluation by integrating weights into the Hausdorff distance computation – as weights play a vital role in matchmaking. The result in table 4.15 shows some changes in ranking when the weighted similarity metrics mentioned in section 3.5 (chapter 3) are employed in the Hausdorff process.

Table 4.15: Effects of evaluation of Hausdorff distance with weighted Similarity metrics on profile matching.

PERSONNELS	Soergel		Wave Hedges		Canberra		Euclidean		Sorensen	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
P01	0.9930	6	0.9930	6	0.9963	6	0.9997	6	0.9963	6
P02	0.9919	9	0.9919	9	0.9956	9	0.9996	9	0.9956	9
P03	0.9946	3	0.9946	3	0.9972	3	0.9999	2	0.9972	3
P04	0.9919	10	0.9919	10	0.9956	10	0.9996	10	0.9956	10
P05	0.9919	11	0.9919	11	0.9956	11	0.9996	11	0.9956	11
P06	0.9919	12	0.9919	12	0.9956	12	0.9996	12	0.9956	12
P07	0.9909	14	0.9909	14	0.9950	14	0.9995	14	0.9950	14
P08	0.9903	15	0.9903	15	0.9947	15	0.9995	15	0.9947	15
P09	0.9946	4	0.9946	4	0.9972	4	0.9999	3	0.9972	4
P10	0.9941	5	0.9941	5	0.9969	5	0.9998	5	0.9969	5
P11	0.9839	16	0.9839	16	0.9905	16	0.9983	16	0.9905	16
P12	0.9839	17	0.9839	17	0.9905	17	0.9983	17	0.9905	17
P13	0.9973	1	0.9973	1	0.9986	1	1.0000	1	0.9986	1
P14	0.9919	13	0.9919	13	0.9956	13	0.9996	13	0.9956	13
P15	0.9930	7	0.9930	7	0.9963	7	0.9997	7	0.9963	7
P16	0.9957	2	0.9957	2	0.9978	2	0.9999	4	0.9978	2
P17	0.9930	8	0.9930	8	0.9963	8	0.9997	8	0.9963	8

From table 4.15, there are changes in the ranking of alternatives under the different similarity metrics as compared to the results using the multi-person matchmaking algorithm in table 4.1. Although it can be noticed that all similarity metrics agreed with the ranks of P01, P02, P04, P05, P06, P07, P08, P10, P11, P12, P13, P14, P15 and P17, there is little to no disparity between the Hausdorff scores which makes this result undependable and arguable. This further demonstrates that the multi-person matchmaking algorithm is a reliable and less complicated alternative in multi-person multi-attribute decision problems.

4.2.2 Government Policy Selection

Table 4.16 shows the reference profile for the selection of government policies with preferences of three groups of experts (Experts 1, Experts 2, Expert 3) analysing five policy alternatives (A01-A05) by considering 5 possible states of nature (S1 – S5). As mentioned in Section 4.1.2, in order to effectively represent fuzzy preferences of each group of experts using the proposed method, the fuzzy preferences of each group of experts had to be represented and analysed individually.

Table 4.16: Reference Profile.

Policy States	Experts 1			Experts 2			Experts 3		
S1	100	100	100	100	100	100	100	100	100
S2	100	100	100	100	100	100	100	100	100
S3	100	100	100	100	100	100	100	100	100
S4	100	100	100	100	100	100	100	100	100
S5	100	100	100	100	100	100	100	100	100

In tables 4.17 – 4.21, the results derived from using the weighted similarity metrics described in section 3.5 (Chapter 3) to calculate the Haudorff values between the client profiles and the reference profile vice versa. These values are displayed in the second and third columns respectively. Finally, the figures in the last column – Score –is used to rank the alternatives from best to worst.

Table 4.17: Calculating Hausdorff Scores using the Weighted Soergel Index for Government Policy Selection.

Alternatives	Policy states	Experts 1			Experts 2			Experts 3			h(A,B)	h(B,A)	Score
A01	S1	60	70	80	40	50	60	30	40	50	0.8400	0.8400	0.8400
	S2	70	80	90	60	70	80	40	50	60	0.8833	0.8833	0.8833
	S3	40	50	60	50	60	70	30	40	50	0.8300	0.8300	0.8300
	S4	50	60	70	50	60	70	50	60	70	0.8800	0.8800	0.8800
	S5	60	70	80	60	70	80	60	70	80	0.9000	0.9000	**0.9000**
A02	S1	40	50	60	40	50	60	40	50	60	0.8333	0.8333	0.8333
	S2	30	40	50	30	40	50	70	80	90	0.8533	0.8533	0.8533

	S3	60	70	80	40	50	60	60	70	80	0.8800	0.8800	0.8800
	S4	70	80	90	70	80	90	30	40	50	0.8800	0.8800	0.8800
	S5	60	70	80	60	70	80	60	70	80	0.9000	0.9000	**0.9000**
A03	S1	30	40	50	70	80	90	20	30	40	0.8167	0.8167	0.8167
	S2	50	60	70	50	60	70	50	60	70	0.8667	0.8667	0.8667
	S3	50	60	70	40	50	60	50	60	70	0.8567	0.8567	0.8567
	S4	60	70	80	80	90	100	60	70	80	0.9200	0.9200	**0.9200**
	S5	70	80	90	60	70	80	40	50	60	0.8833	0.8833	0.8833
A04	S1	80	90	100	40	50	60	10	20	30	0.8567	0.8567	0.8567
	S2	70	80	90	30	40	50	20	30	40	0.9000	0.9000	**0.9000**
	S3	40	50	60	40	50	60	40	50	60	0.9000	0.9000	0.9000
	S4	40	50	60	40	50	60	40	50	60	0.8667	0.8667	0.8667
	S5	30	40	50	70	80	90	80	90	100	0.9000	0.9000	0.9000
A05	S1	20	30	40	70	80	90	50	60	70	0.8333	0.8333	0.8333
	S2	60	70	80	60	70	80	60	70	80	0.8267	0.8267	0.8267
	S3	70	80	90	50	60	70	60	70	80	0.8333	0.8333	0.8333
	S4	50	60	70	50	60	70	50	60	70	0.8333	0.8333	0.8333
	S5	60	70	80	60	70	80	60	70	80	0.9067	0.9067	**0.9067**

Just like in the previous experiment, the figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Soergel Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to rank the client profiles from best to worst in table 4.22.

Table 4.18: Calculating Hausdorff Scores using Weighted the Wave Hedges Index for Government Policy Selection.

Alternatives	**Policy states**	**Experts 1**			**Experts 2**			**Experts 3**			**h(A,B)**	**h(B,A)**	**Score**
A01	S1	60	70	80	40	50	60	30	40	50	0.8400	0.8400	0.8400
	S2	70	80	90	60	70	80	40	50	60	0.8833	0.8833	0.8833
	S3	40	50	60	50	60	70	30	40	50	0.8300	0.8300	0.8300
	S4	50	60	70	50	60	70	50	60	70	0.8800	0.8800	0.8800
	S5	60	70	80	60	70	80	60	70	80	0.9000	0.9000	**0.9000**
A02	S1	40	50	60	40	50	60	40	50	60	0.8333	0.8333	0.8333
	S2	30	40	50	30	40	50	70	80	90	0.8533	0.8533	0.8533

	S3	60	70	80	40	50	60	60	70	80	0.8800	0.8800	0.8800
	S4	70	80	90	70	80	90	30	40	50	0.8800	0.8800	0.8800
	S5	60	70	80	60	70	80	60	70	80	0.9000	0.9000	**0.9000**
A03	S1	30	40	50	70	80	90	20	30	40	0.8167	0.8167	0.8167
	S2	50	60	70	50	60	70	50	60	70	0.8667	0.8667	0.8667
	S3	50	60	70	40	50	60	50	60	70	0.8567	0.8567	0.8567
	S4	60	70	80	80	90	100	60	70	80	0.9200	0.9200	**0.9200**
	S5	70	80	90	60	70	80	40	50	60	0.8833	0.8833	0.8833
A04	S1	80	90	100	40	50	60	10	20	30	0.8567	0.8567	0.8567
	S2	70	80	90	30	40	50	20	30	40	0.9000	0.9000	**0.9000**
	S3	40	50	60	40	50	60	40	50	60	0.9000	0.9000	0.9000
	S4	40	50	60	40	50	60	40	50	60	0.8667	0.8667	0.8667
	S5	30	40	50	70	80	90	80	90	100	0.9000	0.9000	0.9000
A05	S1	20	30	40	70	80	90	50	60	70	0.8333	0.8333	0.8333
	S2	60	70	80	60	70	80	60	70	80	0.8267	0.8267	0.8267
	S3	70	80	90	50	60	70	60	70	80	0.8333	0.8333	0.8333
	S4	50	60	70	50	60	70	50	60	70	0.8333	0.8333	0.8333
	S5	60	70	80	60	70	80	60	70	80	0.9067	0.9067	**0.9067**

Likewise, the figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Wave Hedges Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to rank the client profiles from best to worst in table 4.22.

Table 4.19: Calculating Hausdorff Scores using the Weighted Canberra Similarity for Government Policy Selection.

Alternatives	**Policy states**	**Experts 1**			**Experts 2**			**Experts 3**			**h(A,B)**	**h(B,A)**	**Score**
A01	S1	60	70	80	40	50	60	30	40	50	0.8906	0.8906	0.8906
	S2	70	80	90	60	70	80	40	50	60	0.9258	0.9258	0.9258
	S3	40	50	60	50	60	70	30	40	50	0.8831	0.8831	0.8831
	S4	50	60	70	50	60	70	50	60	70	0.9255	0.9255	0.9255
	S5	60	70	80	60	70	80	60	70	80	0.9403	0.9403	**0.9403**
A02	S1	40	50	60	40	50	60	40	50	60	0.8876	0.8876	0.8876

	S2	30	40	50	30	40	50	70	80	90	0.8982	0.8982	0.8982
	S3	60	70	80	40	50	60	60	70	80	0.9245	0.9245	0.9245
	S4	70	80	90	70	80	90	30	40	50	0.9195	0.9195	0.9195
	S5	60	70	80	60	70	80	60	70	80	0.9403	0.9403	**0.9403**
A03	S1	30	40	50	70	80	90	20	30	40	0.9004	0.9004	0.9004
	S2	50	60	70	50	60	70	50	60	70	0.9403	0.9403	**0.9403**
	S3	50	60	70	40	50	60	50	60	70	0.9394	0.9394	0.9394
	S4	60	70	80	80	90	100	60	70	80	0.9156	0.9156	0.9156
	S5	70	80	90	60	70	80	40	50	60	0.9403	0.9403	0.9403
A04	S1	80	90	100	40	50	60	10	20	30	0.8709	0.8709	0.8709
	S2	70	80	90	30	40	50	20	30	40	0.8727	0.8727	0.8727
	S3	40	50	60	40	50	60	40	50	60	0.8876	0.8876	0.8876
	S4	40	50	60	40	50	60	40	50	60	0.8876	0.8876	0.8876
	S5	30	40	50	70	80	90	80	90	100	0.9380	0.9380	**0.9380**
A05	S1	20	30	40	70	80	90	50	60	70	0.8661	0.8661	0.8661
	S2	60	70	80	60	70	80	60	70	80	0.9156	0.9156	0.9156
	S3	70	80	90	50	60	70	60	70	80	0.9072	0.9072	0.9072
	S4	50	60	70	50	60	70	50	60	70	0.9527	0.9527	**0.9527**
	S5	60	70	80	60	70	80	60	70	80	0.9258	0.9258	0.9258

Similarly, the figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Canberra Similarity described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to rank the client profiles from best to worst in table 4.22.

Table 4.20: Calculating Hausdorff Scores using the Weighted Euclidean metric for Government Policy Selection.

Alternatives	**Policy states**	**Experts 1**			**Experts 2**			**Experts 3**			**h(A,B)**	**h(B,A)**	**Score**
A01	S1	60	70	80	40	50	60	30	40	50	0.9586	0.9586	0.9586
	S2	70	80	90	60	70	80	40	50	60	0.9790	0.9790	0.9790
	S3	40	50	60	50	60	70	30	40	50	0.9553	0.9553	0.9553
	S4	50	60	70	50	60	70	50	60	70	0.9816	0.9816	0.9816
	S5	60	70	80	60	70	80	60	70	80	0.9882	0.9882	**0.9882**
A02	S1	40	50	60	40	50	60	40	50	60	0.9603	0.9603	0.9603
	S2	30	40	50	30	40	50	70	80	90	0.9590	0.9590	0.9590
	S3	60	70	80	40	50	60	60	70	80	0.9798	0.9798	0.9798
	S4	70	80	90	70	80	90	30	40	50	0.9709	0.9709	0.9709
	S5	60	70	80	60	70	80	60	70	80	0.9882	0.9882	**0.9882**
A03	S1	30	40	50	70	80	90	20	30	40	0.9588	0.9588	0.9588
	S2	50	60	70	50	60	70	50	60	70	0.9882	0.9882	**0.9882**
	S3	50	60	70	40	50	60	50	60	70	0.9869	0.9869	0.9869
	S4	60	70	80	80	90	100	60	70	80	0.9772	0.9772	0.9772
	S5	70	80	90	60	70	80	40	50	60	0.9882	0.9882	0.9882
A04	S1	80	90	100	40	50	60	10	20	30	0.9252	0.9252	0.9252
	S2	70	80	90	30	40	50	20	30	40	0.9382	0.9382	0.9382
	S3	40	50	60	40	50	60	40	50	60	0.9603	0.9603	0.9603
	S4	40	50	60	40	50	60	40	50	60	0.9603	0.9603	0.9603
	S5	30	40	50	70	80	90	80	90	100	0.9783	0.9783	**0.9783**
A05	S1	20	30	40	70	80	90	50	60	70	0.9362	0.9362	0.9362
	S2	60	70	80	60	70	80	60	70	80	0.9772	0.9772	0.9772
	S3	70	80	90	50	60	70	60	70	80	0.9722	0.9722	0.9722
	S4	50	60	70	50	60	70	50	60	70	0.9913	0.9913	**0.9913**
	S5	60	70	80	60	70	80	60	70	80	0.9790	0.9790	0.9790

The figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Euclidean metric described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to rank the client profiles from best to worst in table 4.22.

Table 4.21: Calculating Hausdorff Scores using he Weighted Sorensen Index for Government Policy Selection.

Alternatives	Policy states	Experts 1			Experts 2			Experts 3			h(A,B)	h(B,A)	Score
A01	S1	60	70	80	40	50	60	30	40	50	0.8957	0.8957	0.8957
	S2	70	80	90	60	70	80	40	50	60	0.9300	0.9300	0.9300
	S3	40	50	60	50	60	70	30	40	50	0.8867	0.8867	0.8867
	S4	50	60	70	50	60	70	50	60	70	0.9265	0.9265	0.9265
	S5	60	70	80	60	70	80	60	70	80	0.9412	0.9412	**0.9412**
A02	S1	40	50	60	40	50	60	40	50	60	0.8889	0.8889	0.8889
	S2	30	40	50	30	40	50	70	80	90	0.9043	0.9043	0.9043
	S3	60	70	80	40	50	60	60	70	80	0.9265	0.9265	0.9265
	S4	70	80	90	70	80	90	30	40	50	0.9280	0.9280	0.9280
	S5	60	70	80	60	70	80	60	70	80	0.9412	0.9412	**0.9412**
A03	S1	30	40	50	70	80	90	20	30	40	0.8913	0.8913	0.8913
	S2	50	60	70	50	60	70	50	60	70	0.8844	0.8844	0.8844
	S3	50	60	70	40	50	60	50	60	70	0.8889	0.8889	0.8889
	S4	60	70	80	80	90	100	60	70	80	0.8889	0.8889	0.8889
	S5	70	80	90	60	70	80	40	50	60	0.9451	0.9451	**0.9451**
A04	S1	80	90	100	40	50	60	10	20	30	0.9085	0.9085	0.9085
	S2	70	80	90	30	40	50	20	30	40	0.9412	0.9412	**0.9412**
	S3	40	50	60	40	50	60	40	50	60	0.9412	0.9412	0.9412
	S4	40	50	60	40	50	60	40	50	60	0.9167	0.9167	0.9167
	S5	30	40	50	70	80	90	80	90	100	0.9412	0.9412	0.9412
A05	S1	20	30	40	70	80	90	50	60	70	0.8750	0.8750	0.8750
	S2	60	70	80	60	70	80	60	70	80	0.9167	0.9167	0.9167
	S3	70	80	90	50	60	70	60	70	80	0.9085	0.9085	0.9085
	S4	50	60	70	50	60	70	50	60	70	0.9547	0.9547	**0.9547**
	S5	60	70	80	60	70	80	60	70	80	0.9300	0.9300	0.9300

The figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Sorensen Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to rank the client profiles from best to worst in table 4.22.

Table 4.22 shows the results of the evaluation of profile matching and similarity computation using Hausdorff distance in matchmaking to observe the changes in the rankings of alternatives. For the dataset, the researcher performs the evaluation by integrating weights into the Hausdorff distance computation – as weights play a vital role in matchmaking. The results in table 4.22 show some changes in ranking when the weighted similarity metrics mentioned in section 3.5 (Chapter 3) are employed in the Hausdorff process.

Table 4.22: Effects of evaluation of Hausdorff distance with weighted Similarity metrics on profile matching.

Alternatives	Soergel		Wave Hedges		Canberra		Euclidean		Sorensen	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
A01	0.9000	3	0.9000	3	0.9403	2	0.9882	2	0.9412	3
A02	0.9000	4	0.9000	4	0.9403	3	0.9882	3	0.9412	4
A03	0.9200	1	0.9200	1	0.9403	4	0.9882	4	0.9451	2
A04	0.9000	5	0.9000	5	0.9380	5	0.9783	5	0.9412	5
A05	0.9067	2	0.9067	2	0.9527	1	0.9913	1	0.9547	1

From table 4.22, there are changes in the ranking of alternatives under the different similarity metrics as compared to the results derived using the multi-person matchmaking algorithm in table 4.2. After the overall maximum score of each client profile is determined, the ranking is performed from high to low to decide on the best profile. Applying the majority voting technique, it can be asserted that **A05** is the best while **A04** is the worst.

4.2.3 Sport Evaluation

As explained in section 4.1.3, 10 different reference profiles were constructed from this experiment due to the fact that there were no fixed number of decision makers for each sport, that is each sport was evaluated by a minimum of 3 decision makers and maximum of 23 decision makers. Table 4.23 shows a sample representation of the reference profile of 8 decision makers analysing the different sports based on five attributes. The complete reference profiles can be seen in Appendix E (at the end of the document).

Table 4.23: Reference Profile.

Attributes	**DM1**	**DM2**	**DM3**	**DM4**	**DM5**	**DM6**	**DM7**	**DM8**
Enjoyment (C1)	21	21	21	21	21	21	21	21
Technicality (C2)	3	3	3	3	3	3	3	3
Values (C3)	21	21	21	21	21	21	21	21
Risk (C4)	2	2	2	2	2	2	2	2
Popularity (C5)	21	21	21	21	21	21	21	21

Table 4.24 shows the datasets for the ten sports that were evaluated. As mentioned earlier in section 4.1.3, there were no fixed number of decision makers to evaluate a particular sport. As a result, each sport was evaluated by different numbers of decision makers, thereby resulting in diverse dimensions of the dataset.

Table 4.24: Evaluation of Ten Sports.

Attributes	**Sports**	**Preferences of different decision makers (DM1 –DM23)**					
C1	Hockey	3	20	13	13	14	
C2		11	18	13	13	4	
C3		13	7	9	9	8	
C4		7	9	12	12	14	
C5		3	5	9	17	15	
C1	Volley ball	19	7	20	21	12	20
C2		18	5	3	4	3	3
C3		17	16	20	16	8	12
C4		9	5	4	7	4	14
C5		15	3	14	21	13	18
C1	Baseball	18	3	14			
C2		4	9	6			
C3		15	16	15			
C4		7	4	14			
C5		20	3	18			

C1	Basket ball	15	3	20	12	11	9	19	13
C2		21	11	8	19	14	12	12	17
C3		19	14	21	15	11	5	19	14
C4		10	6	13	8	8	7	12	4
C5		21	3	21	5	13	10	21	11

C1	Swimming	15	21	15	7	10	21	21	16	16	13	18	21	21
C2		6	6	15	14	15	3	8	15	7	3	3	3	5
C3		11	10	7	21	10	21	11	15	9	16	16	4	13
C4		10	6	8	6	7	7	4	21	9	6	5	17	3
C5		13	3	21	14	14	21	20	15	17	19	20	15	12

C1	Rugby	21	7	11	21	7	15	21	13
C2		3	9	14	9	20	13	8	11
C3		9	19	16	21	20	19	21	8
C4		8	5	10	11	12	13	14	11
C5		13	3	11	16	16	18	21	16

C1	Ping-Pong	20	3	20	14	3	21	19	19
C2		3	12	3	3	3	3	6	3
C3		6	14	8	11	3	4	13	9
C4		8	2	5	6	3	7	9	2
C5		4	3	11	14	11	11	12	17

C1	Tennis	8	12	10	8	18	21	17	16	17	16	6	20	19
C2		16	12	13	5	3	3	16	14	3	4	6	3	3
C3		12	11	6	5	13	12	19	20	18	20	19	10	11
C4		5	2	6	5	9	3	12	9	9	3	14	7	4
C5		3	11	12	16	14	21	21	18	19	14	21	15	13

C1	Wrestling	14	8	14	15	15	12	15	20	9	10
C2		20	15	21	12	21	14	7	10	7	15
C3		20	15	20	16	18	9	19	18	17	11
C4		8	5	10	12	14	8	8	14	14	12
C5		20	4	21	14	15	14	15	21	14	16

C1	Soccer	19	18	15	21	21	21	21	15	21	21	21	21	21	19	19	19	21	21	21	18	14	13	13
C2		3	21	21	4	9	3	10	8	4	8	3	9	21	3	3	4	3	3	5	3	10	6	4
C3		9	6	19	21	21	15	21	18	21	12	21	3	15	14	17	7	18	21	19	10	5	18	19

C4		11	3	10	3	8	8	13	8	8	8	7	5	12	11	14	6	9	10	14	6	6	10	11
C5		19	4	21	21	21	21	13	21	21	19	21	17	18	21	19	20	21	21	21	21	16	17	21

In tables 4.25 – 4.29, shows the results derived from using the weighted similarity metrics shown in section 3.5 (Chapter 3) to calculate the Hausdorff scores between the client profiles and the reference profile and vice versa. The figures in the column Score are used to rank the alternatives from best to worst.

Table 4.25: Calculating Hausdorff Scores using the Weighted Soergel Index for Sport Evaluation.

Sport Name	h(A,B)	h(A,B)	Score
Hockey	0.8897	0.9323	0.9323
	0.9393	0.8945	**0.9393**
	0.9231	0.9323	0.9323
	0.9011	0.8798	0.9011
	0.8979	0.9323	0.9323
Volleyball	0.9379	0.9561	**0.9561**
	0.9228	0.9228	0.9228
	0.9561	0.9561	0.9561
	0.8816	0.8970	0.8970
	0.9362	0.9561	0.9561
Baseball	0.9471	0.9516	**0.9516**
	0.9103	0.9103	0.9103
	0.9403	0.9516	0.9516
	0.8846	0.8887	0.8887
	0.9516	0.9516	0.9516
Basketball	0.8818	0.9555	**0.9555**
	0.9503	0.8809	0.9503
	0.9555	0.9555	0.9555
	0.8788	0.8709	0.8788
	0.9282	0.9555	0.9555
Swimming	0.9149	0.9597	**0.9597**
	0.9187	0.9187	0.9187
	0.9597	0.9597	0.9597
	0.8772	0.8943	0.8943
	0.9332	0.9597	0.9597
Rugby	0.9248	0.9689	**0.9689**

	0.9255	0.8881	0.9255
	0.9689	0.9689	0.9689
	0.8982	0.8739	0.8982
	0.9385	0.9689	0.9689
Ping-Pong	0.8997	0.9110	0.8997
	0.9485	0.9485	**0.9485**
	0.9110	0.9110	0.9110
	0.8982	0.9142	0.8982
	0.9032	0.9110	0.9032
Tennis	0.8882	0.9665	**0.9665**
	0.9500	0.8781	0.9500
	0.9665	0.9665	0.9665
	0.8982	0.8688	0.8982
	0.9490	0.9665	0.9665
Wrestling	0.9063	0.9518	**0.9518**
	0.9052	0.9052	0.9052
	0.9518	0.9518	0.9518
	0.8762	0.8853	0.8853
	0.9495	0.9518	0.9518
Soccer	0.9639	0.9810	**0.9810**
	0.9090	0.9090	0.9090
	0.9588	0.9810	0.9810
	0.8811	0.8878	0.8878
	0.9810	0.9810	0.9810

Just like in the previous experiments, the figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Soergel Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to rank the client profiles from best to worst in table 4.30.

Table 4.26: Calculating Hausdorff Scores using the Weighted Wave Hedges Index for Sport Evaluation.

Sport Name	h(A,B)	h(A,B)	Score
Hockey	0.8796	0.9323	**0.9323**
	0.9323	0.8970	0.9323
	0.9231	0.9323	0.9323
	0.9011	0.8815	0.9011
	0.8979	0.9323	0.9323
Volleyball	0.9379	0.9561	0.9561

	0.9618	0.9618	**0.9618**
	0.9561	0.9561	0.9561
	0.9008	0.9230	0.9230
	0.9362	0.9561	0.9561
Baseball	0.9471	0.9516	**0.9516**
	0.9376	0.9376	0.9376
	0.9403	0.9516	0.9516
	0.8965	0.9069	0.9069
	0.9516	0.9516	0.9516
Basketball	0.8818	0.9555	**0.9555**
	0.9503	0.8871	0.9503
	0.9555	0.9555	0.9555
	0.8788	0.8749	0.8788
	0.9282	0.9555	0.9555
Swimming	0.8662	0.9597	**0.9597**
	0.9270	0.9270	0.9270
	0.9597	0.9597	0.9597
	0.8909	0.8999	0.8999
	0.9332	0.9597	0.9597
Rugby	0.9248	0.9689	**0.9689**
	0.9255	0.9017	0.9255
	0.9689	0.9689	0.9689
	0.8982	0.8830	0.8982
	0.9385	0.9689	0.9689
Ping-Pong	0.9063	0.9518	**0.9518**
	0.9396	0.9396	0.9396
	0.9518	0.9518	0.9518
	0.8948	0.9083	0.9083
	0.9495	0.9518	0.9518
Tennis	0.8997	0.9110	0.9110
	0.9759	0.9759	**0.9759**
	0.9192	0.9110	0.9192
	0.9127	0.9324	0.9324
	0.9032	0.9110	0.9110
Wrestling	0.8882	0.9665	**0.9665**
	0.9500	0.8835	0.9500
	0.9665	0.9665	0.9665
	0.8982	0.8708	0.8982
	0.9490	0.9665	0.9665
Soccer	0.9639	0.9810	**0.9810**
	0.9432	0.9435	0.9435
	0.9588	0.9810	0.9810
	0.8811	0.9113	0.9113
	0.9810	0.9810	0.9810

The figures under the columns labelled h(A,B) and h(B,A) are derived using the weighted Wave Hedges Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to rank the client profiles from best to worst in table 4.30.

Table 4.27: Calculating Hausdorff Scores using the Weighted Canberra Similarity for Sport Evaluation.

Sport Name	h(A,B)	h(A,B)	Score
Hockey	0.9130	0.9524	**0.9524**
	0.9524	0.9208	0.9524
	0.9471	0.9524	0.9524
	0.9330	0.9015	0.9330
	0.9220	0.9524	0.9524
Volleyball	0.9582	0.9721	**0.9721**
	0.9715	0.9715	0.9715
	0.9721	0.9721	0.9721
	0.9293	0.9443	0.9443
	0.9544	0.9721	0.9721
Baseball	0.8970	0.9767	**0.9767**
	0.9497	0.9497	0.9497
	0.9767	0.9767	0.9767
	0.9192	0.9243	0.9243
	0.9457	0.9767	0.9767
Basketball	0.9168	0.9702	**0.9702**
	0.9679	0.9097	0.9679
	0.9702	0.9702	0.9702
	0.9111	0.8910	0.9111
	0.9457	0.9702	0.9702
Swimming	0.9681	0.9681	**0.9681**
	0.9535	0.9535	0.9535
	0.9588	0.9681	0.9681
	0.9266	0.9286	0.9286
	0.9677	0.9681	0.9681
Rugby	0.9508	0.9793	**0.9793**
	0.9465	0.9220	0.9465
	0.9793	0.9793	0.9793
	0.9300	0.9022	0.9300
	0.9735	0.9793	0.9793

Ping-Pong	0.9278	0.9795	**0.9795**
	0.9662	0.9049	0.9662
	0.9795	0.9795	0.9795
	0.9295	0.8881	0.9295
	0.9661	0.9795	0.9795
Tennis	0.9221	0.9331	0.9331
	0.9820	0.9820	**0.9820**
	0.9388	0.9331	0.9388
	0.9405	0.9534	0.9534
	0.9295	0.9331	0.9331
Wrestling	0.9372	0.9668	**0.9668**
	0.9529	0.9529	0.9529
	0.9668	0.9668	0.9668
	0.9233	0.9285	0.9285
	0.9660	0.9668	0.9668
Soccer	0.9787	0.9874	**0.9874**
	0.9571	0.9571	0.9571
	0.9710	0.9874	0.9874
	0.9130	0.9318	0.9318
	0.9874	0.9874	0.9874

The figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Canberra Similarity described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to rank the client profiles from best to worst in table 4.30.

Table 4.28: Calculating Hausdorff Scores using the Weighted Euclidean Metric for Sport Evaluation.

Sport Name	h(A,B)	h(A,B)	Score
Hockey	0.9570	0.9796	**0.9796**
	0.9791	0.9569	0.9791
	0.9796	0.9796	0.9796
	0.9756	0.9344	0.9756
	0.9564	0.9796	0.9796
Volleyball	0.9845	0.9919	**0.9919**
	0.9847	0.9847	0.9847
	0.9919	0.9919	0.9919
	0.9684	0.9728	0.9728

	0.9779	0.9919	0.9919
Baseball	0.9390	0.9963	**0.9963**
	0.9804	0.9804	0.9804
	0.9963	0.9963	0.9963
	0.9593	0.9605	0.9605
	0.9637	0.9963	0.9963
Basketball	0.9631	0.9903	**0.9903**
	0.9903	0.9556	0.9903
	0.9890	0.9903	0.9903
	0.9573	0.9266	0.9573
	0.9708	0.9903	0.9903
Swimming	0.9933	0.9933	**0.9933**
	0.9762	0.9762	0.9762
	0.9834	0.9933	0.9933
	0.9686	0.9599	0.9686
	0.9876	0.9933	0.9933
Rugby	0.9834	0.9928	**0.9928**
	0.9753	0.9539	0.9753
	0.9928	0.9928	0.9928
	0.9728	0.9332	0.9728
	0.9814	0.9928	0.9928
Ping-Pong	0.9532	0.9655	0.9655
	0.9909	0.9909	**0.9909**
	0.9678	0.9655	0.9678
	0.9779	0.9807	0.9807
	0.9655	0.9655	0.9655
Tennis	0.9773	0.9868	**0.9868**
	0.9727	0.9727	0.9727
	0.9868	0.9868	0.9868
	0.9638	0.9576	0.9638
	0.9867	0.9868	0.9868
Wrestling	0.9782	0.9951	**0.9951**
	0.9877	0.9400	0.9877
	0.9951	0.9951	0.9951
	0.9720	0.9175	0.9720
	0.9874	0.9951	0.9951
Soccer	0.9960	0.9960	**0.9960**
	0.9769	0.9769	0.9769
	0.9871	0.9960	0.9960
	0.9582	0.9620	0.9620
	0.9952	0.9960	0.9960

Likewise, The figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Euclidean metric described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to rank the client profiles from best to worst in table 4.30.

Table 4.29: Calculating Hausdorff Scores using the Weighted Sorensen Index for Sport Evaluation.

Sport Name	h(A,B)	h(A,B)	Score
Hockey	0.9248	0.9567	**0.9567**
	0.9567	0.9185	0.9567
	0.9483	0.9567	0.9567
	0.9347	0.8995	0.9347
	0.9304	0.9567	0.9567
Volleyball	0.9654	0.9743	**0.9743**
	0.9485	0.9485	0.9485
	0.9743	0.9743	0.9743
	0.9166	0.9228	0.9228
	0.9617	0.9743	0.9743
Baseball	0.9140	0.9767	**0.9767**
	0.9448	0.9448	0.9448
	0.9767	0.9767	0.9767
	0.9121	0.9197	0.9197
	0.9595	0.9767	0.9767
Basketball	0.9264	0.9739	**0.9739**
	0.9704	0.9026	0.9704
	0.9739	0.9739	0.9739
	0.9137	0.8862	0.9137
	0.9558	0.9739	0.9739
Swimming	0.9710	0.9723	**0.9723**
	0.9368	0.9368	0.9368
	0.9627	0.9723	0.9723
	0.9195	0.9130	0.9195
	0.9723	0.9723	0.9723
Rugby	0.9570	0.9826	**0.9826**
	0.9509	0.9123	0.9509
	0.9826	0.9826	0.9826

	0.9321	0.8935	0.9321
	0.9633	0.9826	0.9826
Ping-Pong	0.9398	0.9398	0.9398
	0.9691	0.9691	**0.9691**
	0.9367	0.9398	0.9398
	0.9321	0.9406	0.9406
	0.9352	0.9398	0.9398
Tennis	0.9314	0.9812	**0.9812**
	0.9702	0.8994	0.9702
	0.9812	0.9812	0.9812
	0.9321	0.8836	0.9321
	0.9706	0.9812	0.9812
Wrestling	0.9445	0.9713	**0.9713**
	0.9316	0.9316	0.9316
	0.9713	0.9713	0.9713
	0.911	0.9088	0.9110
	0.9709	0.9713	0.9713
Soccer	0.9808	0.9900	**0.9900**
	0.9355	0.9355	0.9355
	0.9761	0.9900	0.9900
	0.9161	0.9119	0.9161
	0.9900	0.9900	0.9900

The figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Sorensen Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each client profile is chosen to represent the performance of that particular client. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to rank the client profiles from best to worst in table 4.30.

Table 4.30 shows the results of the evaluation of profile matching and similarity computation using Hausdorff distance in matchmaking to observe the changes in the rankings of alternatives. For the dataset, the researcher performs the evaluation by integrating weights into the Hausdorff distance computation – as weights play a vital role in matchmaking. The results in table 4.30 show some changes in ranking when the weighted similarity metrics mentioned in section 3.5 (Chapter 3) are employed in the Hausdorff process.

Table 4.30: Effects of evaluation of Hausdorff distance with weighted similarity metrics on profile matching.

Sports	Soergel		Wave Hedges		Canberra		Euclidean		Sorensen	
	Score	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
Hockey	0.9393	10	0.9323	10	0.9524	10	0.9796	10	0.9567	10
Volleyball	0.9561	5	0.9618	5	0.9721	6	0.9919	6	0.9743	5
Baseball	0.9516	8	0.9516	9	0.9767	5	0.9963	1	0.9767	4
Basketball	0.9555	6	0.9555	7	0.9702	7	0.9903	8	0.9739	6
Swimming	0.9597	4	0.9597	6	0.9681	8	0.9933	4	0.9723	7
Rugby	0.9689	2	0.9689	3	0.9793	4	0.9928	5	0.9826	2
Ping-Pong	0.9485	9	0.9518	8	0.9795	3	0.9909	7	0.9691	9
Tennis	0.9665	3	0.9759	2	0.9820	2	0.9868	9	0.9812	3
Wrestling	0.9518	7	0.9665	4	0.9668	9	0.9951	3	0.9713	8
Soccer	0.9810	1	0.9810	1	0.9874	1	0.9960	2	0.9900	1

From table 4.30, there is a lot of disparity in the ranking of the sports as compared to the results using the multi-person matchmaking algorithm in table 4.3. Hockey is the only sport regarded as the least preferred irrespective of the similarity metric applied. The multi-person matchmaking method has further proven to be optimum considering there is little to no disparity in the ranking of alternatives irrespective of the similarity metric employed. This indicates that the multi-person matchmaking algorithm is useful in multi-person multi-attribute decision problems.

4.2.4 Mancala Game Strategy Selection

As explained in section 4.1.4, the endpoint of this experiment is to determine which position in each strategy is solvable and can result in a win. Using the Hausdorff-based matching process, the maximum score of each position in each strategy will be obtained in order to determine the winning position irrespective of the move the rival or opponent makes. The position with the maximum score is taken as the solvable position because the higher the

Hausdorff score, the higher the chances of a solvable position. Table 4.31 shows the reference profile (S1,…,S12 denote strategy).

Table 4.31: Reference Profile

S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
7	5	3	1	2	2	0	1	0	0	0	0
7	5	3	1	2	0	0	1	0	0	0	0
0	6	4	2	3	1	0	1	0	0	0	0
0	6	4	2	0	2	0	1	0	0	0	0
0	6	4	2	0	0	0	1	0	0	0	0
0	0	5	3	1	1	0	1	0	0	0	0
0	0	0	4	2	2	0	1	0	0	0	0
0	0	0	4	2	0	0	1	0	0	0	0
0	0	0	0	3	1	0	1	0	0	0	0
0	0	0	0	0	2	0	1	0	0	0	0

Table 4.32: Calculating Hausdorff Scores using the Weighted Soergel Index for Mancala Game Strategy Selection.

Positions	Strategies											h(A,B)	h(B,A)	Score
P06	**7**	**5**	**3**	**1**	**2**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P05	7	5	3	1	0	3	1	1	0	0	0	0	0.9710	0.9710	0.9710
P04	7	5	3	0	3	2	0	1	0	0	0	0	0.9848	0.9848	0.9848
P03	7	5	0	2	3	3	0	1	0	0	0	0	0.9583	0.9583	0.9583
P02	7	0	4	2	3	3	1	1	0	0	0	0	0.9358	0.9358	0.9358
P01	0	6	4	2	3	3	1	0	0	0	0	0	0.9666	0.9666	0.9666
P05	7	5	3	1	0	1	1	1	0	0	0	0	0.9696	0.9696	0.9696
P04	7	5	3	0	3	0	0	1	0	0	0	0	0.9833	0.9833	0.9833
P03	7	5	0	2	3	1	0	1	0	0	0	0	0.9564	0.9564	0.9564
P02	7	0	4	2	3	1	1	1	0	0	0	0	0.9332	0.9332	0.9332
P01	**0**	**6**	**4**	**2**	**3**	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P06	0	6	4	2	3	0	1	1	0	0	0	0	0.9814	0.9814	0.9814
P05	**0**	**6**	**4**	**2**	**0**	**2**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P04	0	6	4	0	4	2	0	1	0	0	0	0	0.9648	0.9648	0.9648
P03	0	6	0	3	4	2	1	1	0	0	0	0	0.9364	0.9364	0.9364
P02	0	0	5	3	4	2	1	0	0	0	0	0	0.9374	0.9374	0.9374

P04	**0**	**6**	**4**	**2**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P03	0	6	4	0	1	3	0	1	0	0	0	0	0.9607	0.9607	0.9607
P02	0	6	0	3	1	3	1	1	0	0	0	0	0.9297	0.9297	0.9297
P01	0	0	5	3	1	3	1	0	0	0	0	0	0.9523	0.9523	0.9523
P06	3	3	3	3	3	0	4	4	4	3	3	3	0.8847	0.8847	0.8847
P05	3	3	3	3	0	4	4	4	3	3	3	3	0.8823	0.8823	0.8823
P04	3	3	3	0	4	4	4	3	3	3	3	3	0.8874	0.8874	0.8874
P03	3	3	0	4	4	4	3	3	3	3	3	3	0.8775	0.8775	0.8775
P02	3	0	4	4	4	3	3	3	3	3	3	3	0.8781	0.8781	0.8781
P01	**0**	**4**	**4**	**4**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**0.8989**	**0.8989**	**0.8989**
P06	4	4	4	4	4	0	5	5	5	5	4	4	0.8812	0.8812	0.8812
P05	4	4	4	4	0	5	5	5	5	4	4	4	0.8794	0.8794	0.8794
P04	4	4	4	0	5	5	5	5	4	4	4	4	0.8834	0.8834	0.8834
P03	4	4	0	5	5	5	5	4	4	4	4	4	0.8755	0.8755	0.8755
P02	4	0	5	5	5	5	4	4	4	4	4	4	0.8718	0.8718	0.8718
P01	**0**	**5**	**5**	**5**	**5**	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**0.8875**	**0.8875**	**0.8875**
P06	5	5	5	5	5	0	6	6	6	6	6	5	0.8788	0.8788	0.8788
P05	5	5	5	5	0	6	6	6	6	6	5	5	0.8774	0.8774	0.8774
P04	**5**	**5**	**5**	**0**	**6**	**6**	**6**	**6**	**6**	**5**	**5**	**5**	**0.8807**	**0.8807**	**0.8807**
P03	5	5	0	6	6	6	6	6	5	5	5	5	0.8741	0.8741	0.8741
P02	5	0	6	6	6	6	6	5	5	5	5	5	0.8679	0.8679	0.8679
P01	0	6	6	6	6	6	5	5	5	5	5	5	0.8803	0.8803	0.8803
P06	6	6	6	6	6	0	7	7	7	7	7	7	0.8742	0.8742	0.8742
P05	6	6	6	6	0	7	7	7	7	7	7	6	0.8731	0.8731	0.8731
P04	**6**	**6**	**6**	**0**	**7**	**7**	**7**	**7**	**7**	**7**	**6**	**6**	**0.8759**	**0.8759**	**0.8759**
P03	6	6	0	7	7	7	7	7	7	6	6	6	0.8704	0.8704	0.8704
P02	6	0	7	7	7	7	7	7	6	6	6	6	0.8651	0.8651	0.8651
P01	0	7	7	7	7	7	7	6	6	6	6	6	0.8724	0.8724	0.8724

The figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Soergel Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each strategy is chosen to represent the performance of that particular strategy. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to show the possible solvable position in each Mancala strategy. The higher the maximum score, the higher the chances of these positions resulting in a win because it implies that the reference profile is solvable.

Table 4.33: Calculating Hausdorff Scores using the Weighted Wave Hedges Index for Mancala Game Strategy Selection.

Positions	Strategies												h(A,B)	h(B,A)	Score
P06	**7**	**5**	**3**	**1**	**2**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P05	7	5	3	1	0	3	1	1	0	0	0	0	0.9675	0.9675	0.9675
P04	7	5	3	0	3	2	0	1	0	0	0	0	0.9814	0.9814	0.9814
P03	7	5	0	2	3	3	0	1	0	0	0	0	0.9698	0.9698	0.9698
P02	7	0	4	2	3	3	1	1	0	0	0	0	0.9525	0.9525	0.9525
P01	0	6	4	2	3	3	1	0	0	0	0	0	0.9629	0.9629	0.9629
P05	7	5	3	1	0	1	1	1	0	0	0	0	0.9652	0.9652	0.9652
P04	7	5	3	0	3	0	0	1	0	0	0	0	0.9814	0.9814	0.9814
P03	7	5	0	2	3	1	0	1	0	0	0	0	0.9698	0.9698	0.9698
P02	7	0	4	2	3	1	1	1	0	0	0	0	0.9583	0.9583	0.9583
P01	**0**	**6**	**4**	**2**	**3**	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P06	0	6	4	2	3	0	1	1	0	0	0	0	0.9722	0.9722	0.9722
P05	**0**	**6**	**4**	**2**	**0**	**2**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P04	0	6	4	0	4	2	0	1	0	0	0	0	0.9756	0.9756	0.9756
P03	0	6	0	3	4	2	1	1	0	0	0	0	0.9617	0.9617	0.9617
P02	0	0	5	3	4	2	1	0	0	0	0	0	0.9548	0.9548	0.9548
P04	**0**	**6**	**4**	**2**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P03	0	6	4	0	1	3	0	1	0	0	0	0	0.9675	0.9675	0.9675
P02	0	6	0	3	1	3	1	1	0	0	0	0	0.9571	0.9571	0.9571
P01	0	0	5	3	1	3	1	0	0	0	0	0	0.9629	0.9629	0.9629
P06	3	3	3	3	3	0	4	4	4	3	3	3	0.8925	0.8925	0.8925
P05	3	3	3	3	0	4	4	4	3	3	3	3	0.8840	0.8840	0.8840
P04	3	3	3	0	4	4	4	3	3	3	3	3	0.8798	0.8798	0.8798
P03	3	3	0	4	4	4	3	3	3	3	3	3	0.8794	0.8794	0.8794
P02	3	0	4	4	4	3	3	3	3	3	3	3	0.8817	0.8817	0.8817
P01	**0**	**4**	**4**	**4**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**0.9003**	**0.9003**	**0.9003**
P06	4	4	4	4	4	0	5	5	5	5	4	4	0.8897	0.8897	0.8897
P05	4	4	4	4	0	5	5	5	5	4	4	4	0.8854	0.8854	0.8854
P04	4	4	4	0	5	5	5	5	4	4	4	4	0.8764	0.8764	0.8764
P03	4	4	0	5	5	5	5	4	4	4	4	4	0.8727	0.8727	0.8727
P02	4	0	5	5	5	5	4	4	4	4	4	4	0.8782	0.8782	0.8782
P01	**0**	**5**	**5**	**5**	**5**	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**0.8905**	**0.8905**	**0.8905**
P06	**5**	**5**	**5**	**5**	**5**	**0**	**6**	**6**	**6**	**6**	**6**	**5**	**0.8898**	**0.8898**	**0.8898**

P05	5	5	5	5	0	6	6	6	6	6	5	5	0.8822	0.8822	0.8822
P04	5	5	5	0	6	6	6	6	6	5	5	5	0.8768	0.8768	0.8768
P03	5	5	0	6	6	6	6	6	5	5	5	5	0.8708	0.8708	0.8708
P02	5	0	6	6	6	6	6	5	5	5	5	5	0.8729	0.8729	0.8729
P01	0	6	6	6	6	6	5	5	5	5	5	5	0.8868	0.8868	0.8868
P06	**6**	**6**	**6**	**6**	**6**	**0**	**7**	**7**	**7**	**7**	**7**	**7**	**0.8863**	**0.8863**	**0.8863**
P05	6	6	6	6	0	7	7	7	7	7	7	6	0.8807	0.8807	0.8807
P04	6	6	6	0	7	7	7	7	7	7	6	6	0.8734	0.8734	0.8734
P03	6	6	0	7	7	7	7	7	7	6	6	6	0.8685	0.8685	0.8685
P02	6	0	7	7	7	7	7	7	6	6	6	6	0.8688	0.8688	0.8688
P01	0	7	7	7	7	7	7	6	6	6	6	6	0.8810	0.8807	0.8810

The figures under the columns labelled h(A,B) and h(B,A) are derived using the weighted Wave Hedges Index described in section 3.5 (Chapter 3). Therefore the overall maximum value Score from each strategy is chosen to represent the performance of that particular strategy. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to show the possible solvable position in each Mancala strategy. The higher the maximum score, the higher the chances of these positions resulting in a win because it implies that the reference profile is solvable.

Table 4.34: Calculating Hausdorff Scores using the Weighted Canberra Similarity for Mancala Game Strategy Selection.

Positions	**Strategies**												**h(A,B)**	**h(B,A)**	**Score**
P06	**7**	**5**	**3**	**1**	**2**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P05	7	5	3	1	0	3	1	1	0	0	0	0	0.9694	0.9694	0.9694
P04	7	5	3	0	3	2	0	1	0	0	0	0	0.9833	0.9833	0.9833
P03	7	5	0	2	3	3	0	1	0	0	0	0	0.9759	0.9759	0.9759
P02	7	0	4	2	3	3	1	1	0	0	0	0	0.9600	0.9600	0.9600
P01	0	6	4	2	3	3	1	0	0	0	0	0	0.9652	0.9652	0.9652
P05	7	5	3	1	0	1	1	1	0	0	0	0	0.9675	0.9675	0.9675
P04	7	5	3	0	3	0	0	1	0	0	0	0	0.9833	0.9833	0.9833
P03	7	5	0	2	3	1	0	1	0	0	0	0	0.9740	0.9740	0.9740
P02	7	0	4	2	3	1	1	1	0	0	0	0	0.9609	0.9609	0.9609
P01	**0**	**6**	**4**	**2**	**3**	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P06	0	6	4	2	3	0	1	1	0	0	0	0	0.9722	0.9722	0.9722

P05	**0**	**6**	**4**	**2**	**0**	**2**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P04	0	6	4	0	4	2	0	1	0	0	0	0	0.9795	0.9795	0.9795
P03	0	6	0	3	4	2	1	1	0	0	0	0	0.9655	0.9655	0.9655
P02	0	0	5	3	4	2	1	0	0	0	0	0	0.9592	0.9592	0.9592
P04	**0**	**6**	**4**	**2**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P03	0	6	4	0	1	3	0	1	0	0	0	0	0.9722	0.9722	0.9722
P02	0	6	0	3	1	3	1	1	0	0	0	0	0.9628	0.9628	0.9628
P01	0	0	5	3	1	3	1	0	0	0	0	0	0.9652	0.9652	0.9652
P06	3	3	3	3	3	0	4	4	4	3	3	3	0.9033	0.9033	0.9033
P05	3	3	3	3	0	4	4	4	3	3	3	3	0.8941	0.8941	0.8941
P04	3	3	3	0	4	4	4	3	3	3	3	3	0.8912	0.8912	0.8912
P03	3	3	0	4	4	4	3	3	3	3	3	3	0.8863	0.8863	0.8863
P02	3	0	4	4	4	3	3	3	3	3	3	3	0.8907	0.8907	0.8907
P01	**0**	**4**	**4**	**4**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**0.9091**	**0.9091**	**0.9091**
P06	4	4	4	4	4	0	5	5	5	5	4	4	0.9008	0.9008	0.9008
P05	4	4	4	4	0	5	5	5	5	4	4	4	0.8938	0.8938	0.8938
P04	4	4	4	0	5	5	5	5	4	4	4	4	0.8880	0.8880	0.8880
P03	4	4	0	5	5	5	5	4	4	4	4	4	0.8816	0.8816	0.8816
P02	4	0	5	5	5	5	4	4	4	4	4	4	0.8861	0.8861	0.8861
P01	**0**	**5**	**5**	**5**	**5**	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**0.9015**	**0.9015**	**0.9015**
P06	**5**	**5**	**5**	**5**	**5**	**0**	**6**	**6**	**6**	**6**	**6**	**5**	**0.8994**	**0.8994**	**0.8994**
P05	5	5	5	5	0	6	6	6	6	6	5	5	0.8908	0.8908	0.8908
P04	5	5	5	0	6	6	6	6	6	5	5	5	0.8868	0.8868	0.8868
P03	5	5	0	6	6	6	6	6	5	5	5	5	0.8804	0.8804	0.8804
P02	5	0	6	6	6	6	6	5	5	5	5	5	0.8814	0.8814	0.8814
P01	0	6	6	6	6	6	5	5	5	5	5	5	0.8968	0.8968	0.8968
P06	**6**	**6**	**6**	**6**	**6**	**0**	**7**	**7**	**7**	**7**	**7**	**7**	**0.8961**	**0.8961**	**0.8961**
P05	6	6	6	6	0	7	7	7	7	7	7	6	0.8886	0.8886	0.8886
P04	6	6	6	0	7	7	7	7	7	7	6	6	0.8836	0.8836	0.8836
P03	6	6	0	7	7	7	7	7	7	6	6	6	0.8778	0.8778	0.8778
P02	6	0	7	7	7	7	7	7	6	6	6	6	0.8773	0.8773	0.8773
P01	0	7	7	7	7	7	7	6	6	6	6	6	0.8919	0.8919	0.8919

The figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Canberra Similarity described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each strategy is chosen to represent the performance of that particular strategy. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to show the possible solvable position in each Mancala strategy.

Table 4.35: Calculating Hausdorff Scores using the Weighted Euclidean Metric for Mancala Game Strategy Selection.

Positions	Strategies												h(A,B)	h(B,A)	Score
P06	**7**	**5**	**3**	**1**	**2**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P05	7	5	3	1	0	3	1	1	0	0	0	0	0.9716	0.9716	0.9716
P04	7	5	3	0	3	2	0	1	0	0	0	0	0.9855	0.9855	0.9855
P03	7	5	0	2	3	3	0	1	0	0	0	0	0.9834	0.9834	0.9834
P02	7	0	4	2	3	3	1	1	0	0	0	0	0.9692	0.9692	0.9692
P01	0	6	4	2	3	3	1	0	0	0	0	0	0.9687	0.9687	0.9687
P05	7	5	3	1	0	1	1	1	0	0	0	0	0.9706	0.9706	0.9706
P04	7	5	3	0	3	0	0	1	0	0	0	0	0.9855	0.9855	0.9855
P03	7	5	0	2	3	1	0	1	0	0	0	0	0.9824	0.9824	0.9824
P02	7	0	4	2	3	1	1	1	0	0	0	0	0.9680	0.9680	0.9680
P01	**0**	**6**	**4**	**2**	**3**	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P06	0	6	4	2	3	0	1	1	0	0	0	0	0.9722	0.9722	0.9722
P05	**0**	**6**	**4**	**2**	**0**	**2**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P04	0	6	4	0	4	2	0	1	0	0	0	0	0.9843	0.9843	0.9843
P03	0	6	0	3	4	2	1	1	0	0	0	0	0.9703	0.9703	0.9703
P02	0	0	5	3	4	2	1	0	0	0	0	0	0.9656	0.9656	0.9656
P04	**0**	**6**	**4**	**2**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P03	0	6	4	0	1	3	0	1	0	0	0	0	0.9791	0.9791	0.9791
P02	0	6	0	3	1	3	1	1	0	0	0	0	0.9698	0.9698	0.9698
P01	0	0	5	3	1	3	1	0	0	0	0	0	0.9687	0.9687	0.9687
P06	3	3	3	3	3	0	4	4	4	3	3	3	0.9183	0.9183	0.9183
P05	3	3	3	3	0	4	4	4	3	3	3	3	0.9076	0.9076	0.9076
P04	3	3	3	0	4	4	4	3	3	3	3	3	0.9068	0.9068	0.9068
P03	3	3	0	4	4	4	3	3	3	3	3	3	0.9018	0.9018	0.9018
P02	3	0	4	4	4	3	3	3	3	3	3	3	0.9041	0.9041	0.9041
P01	**0**	**4**	**4**	**4**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**0.9214**	**0.9214**	**0.9214**
P06	4	4	4	4	4	0	5	5	5	5	4	4	0.9162	0.9162	0.9162
P05	4	4	4	4	0	5	5	5	5	4	4	4	0.9057	0.9057	0.9057
P04	4	4	4	0	5	5	5	5	4	4	4	4	0.9037	0.9037	0.9037
P03	4	4	0	5	5	5	5	4	4	4	4	4	0.8990	0.8990	0.8990
P02	4	0	5	5	5	5	4	4	4	4	4	4	0.8983	0.8983	0.8983
P01	**0**	**5**	**5**	**5**	**5**	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**0.9160**	**0.9167**	**0.9167**

P06	5	5	5	5	5	0	6	6	6	6	6	5	0.9133	0.9133	0.9133
P05	5	5	5	5	0	6	6	6	6	6	5	5	0.9031	0.9031	0.9031
P04	5	5	5	0	6	6	6	6	6	5	5	5	0.9012	0.9012	0.9012
P03	5	5	0	6	6	6	6	6	5	5	5	5	0.8950	0.8950	0.8950
P02	5	0	6	6	6	6	6	5	5	5	5	5	0.8945	0.8945	0.8945
P01	**0**	**6**	**6**	**6**	**6**	**6**	**5**	**5**	**5**	**5**	**5**	**5**	**0.9086**	**0.9115**	**0.9115**
P06	6	6	6	6	6	0	7	7	7	7	7	7	0.9103	0.9103	0.9103
P05	6	6	6	6	0	7	7	7	7	7	7	6	0.9003	0.9003	0.9003
P04	6	6	6	0	7	7	7	7	7	7	6	6	0.8983	0.8983	0.8983
P03	6	6	0	7	7	7	7	7	7	6	6	6	0.8921	0.8921	0.8921
P02	6	0	7	7	7	7	7	7	6	6	6	6	0.8904	0.8904	0.8904
P01	**0**	**7**	**7**	**7**	**7**	**7**	**7**	**6**	**6**	**6**	**6**	**6**	**0.9011**	**0.9078**	**0.9011**

The figures under the columns labelled h(A,B) and h(B,A) are derived using the weighted Euclidean metric described in section 3.5 (Chapter 3). Therefore the overall maximum value Score from each strategy is chosen to represent the performance of that particular strategy. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to show the possible solvable position in each Mancala strategy. The higher the maximum score, the higher the chances of these positions resulting in a win because it implies that the reference profile is solvable.

Table 4.36: Calculating Hausdorff Scores using Weighted the Sorensen Index for Mancala Game Strategy Selection.

Positions	**Strategies**												**h(A,B)**	**h(B,A)**	**Score**
P06	**7**	**5**	**3**	**1**	**2**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P05	7	5	3	1	0	3	1	1	0	0	0	0	0.9841	0.9841	0.9841
P04	7	5	3	0	3	2	0	1	0	0	0	0	0.9920	0.9920	0.9920
P03	7	5	0	2	3	3	0	1	0	0	0	0	0.9761	0.9761	0.9761
P02	7	0	4	2	3	3	1	1	0	0	0	0	0.9602	0.9602	0.9602
P01	0	6	4	2	3	3	1	0	0	0	0	0	0.9814	0.9814	0.9814
P05	7	5	3	1	0	1	1	1	0	0	0	0	0.9833	0.9833	0.9833
P04	7	5	3	0	3	0	0	1	0	0	0	0	0.9912	0.9912	0.9912
P03	7	5	0	2	3	1	0	1	0	0	0	0	0.9750	0.9750	0.9750
P02	7	0	4	2	3	1	1	1	0	0	0	0	0.9583	0.9583	0.9583
P01	**0**	**6**	**4**	**2**	**3**	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P06	0	6	4	2	3	0	1	1	0	0	0	0	0.9902	0.9902	0.9902
P05	**0**	**6**	**4**	**2**	**0**	**2**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**

P04	0	6	4	0	4	2	0	1	0	0	0	0	0.9804	0.9804	0.9804
P03	0	6	0	3	4	2	1	1	0	0	0	0	0.9607	0.9607	0.9607
P02	0	0	5	3	4	2	1	0	0	0	0	0	0.9615	0.9615	0.9615
P04	**0**	**6**	**4**	**2**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**1.0000**	**1.0000**	**1.0000**
P03	0	6	4	0	1	3	0	1	0	0	0	0	0.9777	0.9777	0.9777
P02	0	6	0	3	1	3	1	1	0	0	0	0	0.9555	0.9555	0.9555
P01	0	0	5	3	1	3	1	0	0	0	0	0	0.9722	0.9722	0.9722
P06	3	3	3	3	3	0	4	4	4	3	3	3	0.9119	0.9119	0.9119
P05	3	3	3	3	0	4	4	4	3	3	3	3	0.9092	0.9092	0.9092
P04	3	3	3	0	4	4	4	3	3	3	3	3	0.9150	0.9150	0.9150
P03	3	3	0	4	4	4	3	3	3	3	3	3	0.9033	0.9033	0.9033
P02	3	0	4	4	4	3	3	3	3	3	3	3	0.9041	0.9041	0.9041
P01	**0**	**4**	**4**	**4**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**0.9275**	**0.9275**	**0.9275**
P06	4	4	4	4	4	0	5	5	5	5	4	4	0.9078	0.9078	0.9078
P05	4	4	4	4	0	5	5	5	5	4	4	4	0.9056	0.9056	0.9056
P04	4	4	4	0	5	5	5	5	4	4	4	4	0.9104	0.9104	0.9104
P03	4	4	0	5	5	5	5	4	4	4	4	4	0.9008	0.9008	0.9008
P02	4	0	5	5	5	5	4	4	4	4	4	4	0.8959	0.8959	0.8959
P01	**0**	**5**	**5**	**5**	**5**	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**0.9152**	**0.9152**	**0.9152**
P06	5	5	5	5	5	0	6	6	6	6	6	5	0.9049	0.9049	0.9049
P05	5	5	5	5	0	6	6	6	6	6	5	5	0.9031	0.9031	0.9031
P04	**5**	**5**	**5**	**0**	**6**	**6**	**6**	**6**	**6**	**5**	**5**	**5**	**0.9072**	**0.9072**	**0.9072**
P03	5	5	0	6	6	6	6	6	5	5	5	5	0.8990	0.8990	0.8990
P02	5	0	6	6	6	6	6	5	5	5	5	5	0.8907	0.8907	0.8907
P01	0	6	6	6	6	6	5	5	5	5	5	5	0.9067	0.9067	0.9067
P06	6	6	6	6	6	0	7	7	7	7	7	7	0.8991	0.8991	0.8991
P05	6	6	6	6	0	7	7	7	7	7	7	6	0.8976	0.8976	0.8976
P04	**6**	**6**	**6**	**0**	**7**	**7**	**7**	**7**	**7**	**7**	**6**	**6**	**0.9012**	**0.9012**	**0.9012**
P03	6	6	0	7	7	7	7	7	7	6	6	6	0.8941	0.8941	0.8941
P02	6	0	7	7	7	7	7	7	6	6	6	6	0.8869	0.8869	0.8869
P01	0	7	7	7	7	7	7	6	6	6	6	6	0.8968	0.8968	0.8968

The figures under the columns labelled – h(A,B) and h(B,A) – are derived using the weighted Sorensen Index described in section 3.5 (Chapter 3). Therefore the overall maximum value – Score – from each strategy is chosen to represent the performance of that particular strategy. These highlighted scores are derived by taking the maximum value between h(A,B) and h(B,A). These highlighted figures are used to show the possible solvable position in each Mancala strategy. The higher the maximum score, the higher the chances of these positions resulting in a win because it implies that the reference profile is solvable.

4.3 Comparative results of Multi-Person Hunt ForTune Matchmaking method and Hausdorff-based Matchmaking

In this section the results of all experiments will be briefly discussed and compared in order to validate the results obtained from using the proposed multi-person Hunt ForTune Matchmaking method. The majority voting technique explained in section 3.5 will be used to determine the final ranking of alternatives with preference given to the ranks determined by at least three (3) of the similarity metrics in order to produce improved results.

4.3.1 Personnel Selection

Applying the majority voting technique to the results in Table 4.1 and Table 4.15, based on the number of similarity metrics that agreed on the ranking positions of alternatives, the best five personnels according to the proposed method are **P16>P09> P03>P06>P01** and the worst five personnel are **P07>P15>P02>P11>P12**. According to Hausdorff distance, the best five personnel are **P13>P16>P03>P09>P10** and the worst five personnels are **P14>P07>P08>P11>P12.** Comparatively, the final ranking of both methods, it can be noticed that certain personnel such as P03, P09 and P16 were constantly classified among the best performed while personnel P07, P11 and P12 were grouped as the worst performed personnel. The fact that there is some level of consistency in the similarity values obtained from the proposed method shown in table 4.1 as opposed to the Hausdorff scores in Table 4.15 has demonstrated that the proposed method that the proposed method is an alternative solution to multi-person multi-attribute decision problems.

4.3.2 Government Policy Selection

From Table 4.2, it can be clearly said that the final ranking of alternatives is in the following order **A05>A02>A03>A01>A04**. Comparing the result with that from Table 4.22, it can be noticed that there is no uniformity in the ranking of alternatives irrespective of alternatives. By applying the majority voting technique for both multi-person Hunt ForTune Matchmaking method and Hausdorff-based matchmaking, it can be asserted that **A05** is choosing the best while **A04** is the worst irrespective of the similarity metric applied. This has further indicated that the proposed method can be a reliable and less complicated alternative solution to multi-person multi-attribute decision problems irrespective of data size.

4.3.3 Sport Evaluation

In this particular experiment, all similarity metrics agreed with the ranks of very few sports. Results derived from applying the proposed method shown in Table 4.3 portrays that Soccer, Volleyball and Swimming are considered top 3 sports while Wrestling, Basketball and Hockey are the least preferred sports by applying the majority voting technique. Likewise, in Table 4.30 applying the majority voting technique, the Hausdorff-based matchmaking agreed on Soccer as the 1^{st} sport, Volleyball, as the 5^{th} sport and Hockey as the 10_{th} sport irrespective of the similarity metric applied. Although it can be noted that "Soccer" is still ranked the most preferred sport while "Hockey" is ranked as the least preferred sport irrespective irrespective of the method, the Hausdorff-based matchmaking still made it difficult to decipher which sport is ranked on which position because all five similarity metrics barely agreed on the position of most sports. This weakness has also proven that the proposed method can be an efficient alternative solution to multi-person multi-attribute decision problems irrespective of data size and type

4.3.3 Mancala Game Strategy Selection

Table 4.37 and Table 4.38 summarizes the results derived from applying the proposed multi-person Hunt ForTune Matchmaking method and Hausdorff-based matchmaking method to the Mancala game strategy selection respectively.

Table 4.37: Multi-person Hunt ForTune Matchmaking method for Mancala Game Strategy Selection.

Strategies	Soergel	Wave Hedges	Canberra	Euclidean	Sorensen
S1	P06	P06	P06	P06	P06
S2	P01	P01	P01	P01	P01
S3	P05	P05	P05	P05	P05
S4	P06	P06	P06	P06	P06
S5	P01	P01	P01	P01	P01
S6	P01	P01	P01	P01	P01
S7	P01	P06	P06	P01	P01
S8	P06	P06	P06	P01	P06

Table 4.38: Hausdorff-Based Matchmaking method for Mancala Game Strategy Selection.

Strategies	Soergel	Wave Hedges	Canberra	Euclidean	Sorensen
S1	P01	P01	P01	P01	P01
S2	P05	P05	P05	P05	P05
S3	P02	P02	P02	P02	P02
S4	P01	P01	P01	P01	P01
S5	P06	P06	P06	P06	P06
S6	P06	P06	P06	P06	P06
S7	P03	P01	P01	P06	P03
S8	P03	P01	P01	P06	P03

Applying the Majority Voting Technique to the Table 4.37 and 4.38 respectively, it can be asserted that the final ranking of winning positions in each strategy for the proposed Multi-person Hunt Fortune Matchmaking Method is **P06, P01, P05, P06, P01, P01, P06, P06.** While the final ranking for the Hausdorff process can only be explicitly defined for the first six (6) strategies as **P01, P05, P02, P01, P06, P03**. This can be as a result of different reasons such inadequate variations in the Hausdorff scores or incompatibility of a particular similarity metric. This experiment has given the proposed Multi-person Hunt Fortune Matchmaking Method an additional advantage in the sense that for both the known and unknown strategies investigated in this experiment, the proposed method has yet again proven to produce efficient results.

4.4 Summary of Chapter 4

In this chapter, the results and evaluations performed to realize the research objectives as well as to address the main research question of this study has been discussed. The researcher started off by citing the main objectives which were achieved from this research work and how they were achieved. The experiments performed in this study were chosen as case studies because the covered a wide variety of decision making in a multi-person decision environment. Comparing the results derived in this study with the results derived using the Group TOPSIS (Shih, et al. 2007; Olugbara and Nepal, 2012) and Fuzzy probabilistic ordered weighted averaging (FPOWA) operator (Merigo, 2011) respectively, the proposed multi-person matchmaking method has proven to be less complex in terms of time and computational functionalities.

Furthermore, the researcher then proceeded to illustrate diverse experiments and discuss the results under two main headings: Multi-Person Matchmaking Process and Hausdorff validation procedure. It is conspicuous from the outcome that the Multi-Person Matchmaking method is useful for the selection of alternatives in any form of multi-person decision environment as the results derived produced a greater level of accuracy. Although, the results derived from using both the Multi-Person Matchmaking method and the Hausdorff-based matchmaking process somewhat correlated, it can be asserted that the objectives of this study were achieved as the result from the proposed Multi-Person Matchmaking method was consistent irrespective of the similarity metric applied.

In the next chapter, a summary, future work and conclusion of the study are presented.

CHAPTER 5

SUMMARY, FURTHER STUDY AND CONCLUSION

5.0 Introduction

In this section (Chapter 5), contains the summary, further study and conclusion of the present study. The summary subsection describes the successful demonstration of the proposed methodology carried out by the researcher and how each research objective was achieved. Duuring the course of research, the researcher discovered possible areas where the proposed methodology can be applied, these areas are listed in subsection 5.2 – further study. Finally, an overall conclusion of the present study os being described in subsection 5.3.

5.1 Summary

The researcher has successfully demonstrated the useful applications of the Hunt ForTune matchmaking algorithm, to examine several decision processes in a multi-person decision environment. An effective multi-person multi-attribute matchmaking algorithm has been developed to convert attribute preferences elicited by multiple decision makers into a vector attribute description format using the vector analysis approach. The methodology of this study has provided an exhaustive explanation to demonstrate that regular decision making methods need to be reviewed. The current multi-person matchmaking method can accommodate a situation where decisions have to be made by multiple decision makers while avoiding time and computational complexities. The recipe of decision failure in alternative shortlisting is as a result of a phenomenon where biases and uncertainties are present.

Finally, a resolution is proposed to resolve this predicament if incompetent shortlisting – by developing a matchmaking algorithm which can be implemented to conveniently capture and process preferences of multiple decision makers, match client competence profiles with reference profiles and finally rank alternatives according to the similarities between the profiles. To recap, the development and validation of a new algorithm – to support multi-person decision making – has the following goals:

a) To compare the effectiveness of two state-of-the-art matchmaking systems in literature for solving decision problems;

b) To develop and implement a matchmaking approach to solve different multi-person decision problems frequently encountered by decision makers;

c) To evaluate and validate the multi-person matchmaking algorithm for various decision problems using a novel matching theoretical mathematical technique.

The matchmaking algorithm of Joshi, et al. (2010) was empirically extended to suit the current research question. The algorithm developed in this study provides functionalities for processing multiple decision makers' preferences for alternatives and then calculating their similarity values. In addition, the extended algorithm protects the complexity of having to restructure the constraints representation format (quadruple format) as well as eliminating the time-consuming process of aggregating the preferences of individual decision makers into a unified format. In a nutshell, the achievements of the present project are as follows:

a) An extended matchmaking algorithm was pioneered to aid in an automated decision making process in a multi-person decision making environment.

b) Vector analysis approach was introduced to enhance the capability of a multi-person matchmaking system through vector formulation of attribute description.

c) The representation of the preferences of multiple decision makers as a vector of attribute descriptions in the extended matchmaking algorithm aids, to effectively capture the preferences of multiple decision makers with no restriction on the number in order to effectively achieve a successful decision process.

d) The Hausdorff-based matchmaking was introduced to validate the process and outcome of the proposed multi-person matchmaking method.

e) The proposed new algorithm has proven to be robust, less arduous and can be effectively used in all forms of decision problems involving multiple decision makers.

5.2 Further Study

In summarizing the present study's findings, some research deficiencies were identified. The multi-person decision problem was investigated by formulating and representing the preferences of multi decision makers using a vector analysis approach. The Joshi, et al. (2010) matchmaking algorithm was a useful baseline for the re-engineering of a new mutli-persons matchmaking algorithm to achieve the study's objectives.

The current study revealed that using a matchmaking algorithm for multi-person decision making and the introduction of the vector analysis approach can indeed assist in improving decision making in an environment involving multiple decision makers as well as eliminating any form of biases and computational complexities. This matchmaking algorithm has been applied in the current study to various multi-person decision making instances. Consequently, the following aspects are recommended for further study:

a) Firstly, a survey needs to be carried out to explicitly determine which similarity metric is the most reliable and should be applied to the proposed multi-person matchmaking method irrespective of data type and decision domain.
b) Secondly, further study on the improvement of the efficiency of the algorithm, in particular, the aspect of weight elicitation in matchmaking is highly recommended.
c) Furthermore, a second project is recommended to apply the multi-person matchmaking method in an educational domain, particularly for the admission of students.

5.3 Conclusion

Based on the results of the present empirical study, the following conclusions were deduced:

a) There is a distinctive capturing and representation of the preferences of all decision makers involved in the decision process as the steps involved in the proposed model are less complicated and robust.
b) The proposed model can be used without being integrated with any other method for selection, evaluation and ranking.
c) Some similarity metrics perform constantly better than others depending on the type of data involved in the decision process.
d) The improved Hunt ForTune matchmaking algorithm produced the optimal and efficient solutions in the all experiments irrespective of similarity metrics employed thereby proving to be effective.
e) This improved version synthesizes the criteria into a single integrated attribute and represents it as a vector constraint with the weights also assigned in a vector format.

It was discussed how the proposed system accomplished the research objectives of the present study. The work of Joshi, et al. (2010) is valuable in this regard – it offers many additional features – as compared to other matchmaking systems. It was also identified that the major problem with the original Hunt ForTune matchmaking algorithm was its inability to solve multi-person decision problems. The researcher has proposed an improved algorithm to resolve these problems. The researcher has also tested the effectiveness of the proposed algorithm with some experiments. Additionally, the effect of the different similarity metrics on the ranking of alternatives has been approached in the present work. The choice on which similarity metrics to use in a particular matchmaking problem depends fully on the decision maker and the application domain as different similarity metrics can be more or less useful for certain types of data and applications. The results derived from the experiments prove that the proposed algorithm is efficient, robust and reliable.

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Appendix A: Client Competence Profiles Matched Against Reference Profile in Figure 4.1 for Personnel Selection in Section 4.1.1

Personnel 1 = {

<language_test, <80,80,80,80>, No, <0.066,0.042,0.060,0.047> >

<professional_test, <70, 70, 70,70>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <87, 87, 87, 87>, No, <0.066, 0.082,0.051,0.037> >

<professional_skill, <77, 77, 77,77>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <76, 76, 76, 76>, No, <0.130,0.118,0.100,0.081> >

<panel_interviews, <80,85,75,90>,No, <0.216,0.215,0.203,0.267> >

<1-on-1_interview, <75,80,70,85>, No, <0.196,0.255,0.285,0.326> >

}

Personnel 2 = {

<language_test, <85, 85, 85, 85>, No, <0.066, 0.042,0.060,0.047> >

<professional_test, <65, 65, 65,65>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <76, 76, 76, 76>, No, <0.066,0.082,0.051,0.037> >

<professional_skill, <80, 80, 80,80>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <75, 75, 75, 75>, No, <0.130,0.118,0.100,0.081> >

<panel_interviews, <65,60,70,60>, No, <0.216,0.215,0.203,0.267> >

<1-on-1_interview, <75,70,77,70>, No, <0.196,0.255,0.285,0.326> >

}

Personnel 3 = {

<language_test, <78,78,78,78>, No, <0.066,0.042,0.060,0.047>>

<professional_test, <90,90,90, 90>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <72,72,72,72>, No, <0.066,0.082,0.051,0.037> >

<professional_skill, <80,80,80,80>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <85,85,85,85>, No, <0.130,0.118,0.100,0.081> >

<panel_interviews, <90,80, 80, 90>, No, <0.216, 0.215,0.203,0.267> >

<1-on-1_interview, <85,85,90,55>, No, <0.196,0.255, 0.285,0.326> >

}

Personnel 4 = {

<language_test, <75, 75, 75, 75>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <84, 84, 84,84>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <69, 69, 69, 69>, No, <0.066,0.082, 0.051, 0.037> >

<professional_skill, <85, 85, 85,85>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <65, 65, 65, 65>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <65,55,68,62>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <70,60,72,72>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 5 = {

<language_test, <84, 84, 84, 84>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <67, 67, 67,67>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <60, 60, 60, 60>, No, <0.066,0.082,0.051,0.037> >

<professional_skill, <75, 75, 75,75>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <85, 85, 85, 85>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <75,75,50,70>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <80,80,55,75>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 6 = {

<language_test, <85, 85, 85, 85>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <78, 78, 78,78>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <82, 82, 82, 82>, No, <0.066, 0.082, 0.051,0.037> >

<professional_skill, <81, 81, 8181>, No, <0.130,0.176,0.167, 0.133> >

<computer_skills, <79, 79, 79, 79>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <80,75,77,75>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <80,85,82,75>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 7 = {

<language_test, <77, 77, 77, 77>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <83, 83, 83,83>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <74, 74, 74, 74>, No, <0.066, 0.082, 0.051,0.037> >

<professional_skill, <70, 70, 70,70>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <71, 71, 71, 71>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <65,70,65,67>, No, <0.216, 0.215, 0.203,0.267> >

<1-on-1_interview, <70,60,72,75>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 8 = {

<language_test, <78, 78, 78, 78>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <82, 82, 82,82>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <72, 72, 72, 72>, No, <0.066, 0.082, 0.051,0.037> >

<professional_skill, <80, 80, 80,80>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <78, 78, 78, 78>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <70,75,75,82>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <60,65,67,85>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 9 = {

<language_test, <85, 85, 85, 85>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <90, 90, 90,90>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <80, 80, 80, 80>, No, <0.066, 0.082, 0.051,0.037> >

<professional_skill, <88, 88, 88,88>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <90, 90, 90, 90>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <80,95,90,90>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <85,85,85,92>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 10 = {

<language_test, <89, 89, 89, 89>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <75, 75, 75,75>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <79, 79, 79, 79>, No, <0.066, 0.082, 0.051,0.037> >

<professional_skill, <67, 67, 67,67>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <77, 77, 77, 77>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <70,75,68,65>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <75,80,78,70>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 11 = {

<language_test, <65, 65, 65, 65>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <55, 55, 55,55>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <68, 68, 68, 68>, No, <0.066, 0.082, 0.051,0.037> >

<professional_skill, <62, 62, 62,62>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <70, 70, 70, 70>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <50,62,60,65>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <60,65,65,70>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 12 = {

<language_test, <70, 70, 70, 70>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <64, 64, 64,64>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <65, 65, 65, 65>, No, <0.066, 0.082,0.051,0.037> >

<professional_skill, <65, 65, 65,65>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <60, 60, 60, 60>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <60,65,50,45>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <65,75,60,50>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 13 = {

<language_test, <95, 95, 95, 95>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <80, 80, 80,80>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <70, 70, 70, 70>, No, <0.066, 0.082, 0.051,0.037> >

<professional_skill, <75, 75, 75,75>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <70, 70, 70, 70>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <75,80,65,70>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <75,80,75,75>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 14 = {

<language_test, <70, 70, 70, 70>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <80, 80,80,80>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <79, 79, 79, 79>, No, <0.066, 0.082,0.051,0.037> >

<professional_skill, <80, 80, 80,80>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <85, 85, 85, 85>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <80,75,80,75>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <70,72,70,75>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 15 = {

<language_test, <60, 60, 60, 60>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <78, 78, 78,78>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <87, 87, 87, 87>, No, <0.066, 0.082, 0.051,0.037> >

<professional_skill, <70, 70, 70,70>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <66, 66, 66, 66>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <70,75,65,60>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <65,70,70,65>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 16 = {

<language_test, <92, 92, 92, 92>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <85, 85, 85,85>, No, <0.196,0.112,0.134,0.109> >

<safety_rule_test, <88, 88, 88, 88>, No, <0.066, 0.082, 0.051,0.037> >

<professional_skill, <90, 90, 90,90>, No, <0.130,0.176,0.167,0.133> >

<computer_skills, <85, 85, 85, 85>, No, <0.130, 0.118, 0.100,0.081> >

<panel_interviews, <90,92,85,88>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <95,90,80,90>, No, <0.196, 0.255, 0.285, 0.326> >

}

Personnel 17 = {

<language_test, <86, 86, 86, 86>, No, <0.066, 0.042, 0.060, 0.047> >

<professional_test, <87, 87, 87, 87>, No, <0.196, 0.112, 0.134, 0.109> >

<safety_rule_test, <80, 80, 80, 80>, No, <0.066, 0.082, 0.051, 0.037> >

<professional_skill, <70, 70, 70, 70>, No, <0.130, 0.176, 0.167, 0.133> >

<computer_skills, <72, 72, 72, 72>, No, <0.130, 0.118, 0.100, 0.081> >

<panel_interviews, <80,70,75,70>, No, <0.216, 0.215, 0.203, 0.267> >

<1-on-1_interview, <85,75,80,75>, No, <0.196, 0.255, 0.285, 0.326> >

}

Appendix B: Client Competence Profiles Matched Against Reference Profile in Figure 4.2 for Government Policy Selection in Section 4.1.2

Policy 1 = {
<S1, <60,70,80,40,50,60,30,40,50>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S2, <70,80,90,60,70,80,40,50,60>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S3, <40,50,60,50,60,70,30,40,50>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S4, <50,60,70,50,60,70,60,70,80>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S5, <60,70,80, 60,70,80, 60,70,80>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
}

Policy 2 = {
<S1, <40,50,60,40,50,60,40,50,60>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S2, <30,40,50,30,40,50,70,80,90>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S3, <60,70,80,40,50,60,60,70,80>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S4, <70,80,90,70,80,90,30,40,50>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S5, <60,70,80, 60,70,80, 60,70,80>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
}

Policy 3 = {
<S1, <30,40,50,60,70,80,20,30,40>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S2, <50,60,70,50,60,70,50,60,70>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S3, <50,60,70,50,60,70,50,60,70>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S4, <60,70,80,80,90,100,60,70,80>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S5, <70,80,90, 60,70,80, 40,50,60>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
}

Policy 4 = {
<S1, <80,90,100,40,50,60,10,20,30>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S2, <70,80,90,30,40,50,20,30,40>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S3, <40,50,60,40,50,60,40,50,60>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S4, <40,50,60,40,50,60,40,50,60>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S5, <30,40,50, 70,80,90, 80,90,100>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
}

Policy 5 = {
<S1, <20,30,40,70,80,90,50,60,70>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S2, <60,70,80,60,70,80,60,70,80>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S3, <70,80,90,50,60,70,60,70,80>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S4, <50,60,70,50,60,70,50,60,70>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
<S5, <60,70,80, 60,70,80, 60,70,80>, No, <0.3,0.3,0.3,0.3,0.3,0.3,0.4,0.4,0.4> >
}

Appendix C: Client Competence Profiles Matched with Appendix D for Sport Evaluation in Section 4.1.3

Hockey = {

<Enjoyment, <3,20,13,13,14>, No, <0.3010,0.3010,0.3010,0.3010,0.3010>>

<Technicality, <11,18,13,13,4>, No,<0.1545,0.1545,0.1545,0.1545,0.1545> >

<Values, <13,7,9,9,13>, No, <0.1495,0.1495,0.1495,0.1495,0.1495> >

<Risk, <7,9,12,12,14>, No, <0.2036,0.2036,0.2036,0.2036,0.2036> >

<Popularity, <3,5,9,17,15>, No,<0.1914,0.1914,0.1914,0.1914,0.1914> >

}

Volleyball = {

<Enjoyment, <19,7,20,21,13,20>, No, <0.3010,0.3010,0.3010,0.3010,0.3010,0.3010> >

<Technicality, <18,5,3,4,3,3>, No, <0.1545,0.1545,0.1545,0.1545,0.1545,0.1545> >

<Values, <17, 16, 20, 16, 8, 12>, No, <0.1495, 0.1495, 0.1495, 0.1495, 0.1495,0.1495> >

<Risk, <9, 5, 4, 7, 4, 14>, No, <0.2036, 0.2036, 0.2036, 0.2036, 0.2036,0.2036> >

<Popularity, <15, 3, 14, 21, 13, 18>, No, <0.1914, 0.1914, 0.1914, 0.1914, 0.1914, 0.1914> >

}

Baseball = {

<Enjoyment, <18, 3, 14>, No, <0.3010, 0.3010, 0.3010> >

<Technicality, <4, 9, 6>, No, <0.1545, 0.1545, 0.1545> >

<Values, <15, 16, 15>, No, <0.1495, 0.1495, 0.1495> >

<Risk, <7, 4, 14>, No, <0.2036, 0.2036, 0.2036> >

<Popularity, <20, 3, 18>, No, <0.1914, 0.1914, 0.1914> >

}

Basketball = {

<Enjoyment, <15, 3, 20, 12, 11, 9, 19, 13>, No, <0.3010, 0.3010, 0.3010, 0.3010, 0.3010, 0.3010, 0.3010, 0.3010> >

<Technicality, <21, 11, 8, 19, 14, 12, 12, 17>, No, <0.1545, 0.1545, 0.1545, 0.1545, 0.1545, 0.1545, 0.1545, 0.1545> >

<Values, <19, 14, 21, 15, 11, 5, 19, 14>, No, <0.1495, 0.1495, 0.1495, 0.1495, 0.1495, 0.1495, 0.1495, 0.1495> >

<Risk, <10, 6, 13, 8, 8, 7, 12, 4>, No, <0.2036, 0.2036, 0.2036, 0.2036, 0.2036, 0.2036, 0.2036, 0.2036> >

<Popularity, <21, 3, 21, 5, 13, 10, 21, 11>, No, <0.1914, 0.1914, 0.1914, 0.1914, 0.1914, 0.1914, 0.1914, 0.1914> >

}

Swimming = {

<Enjoyment, <15,21,15,17,10,21,21,16,16,13,18,21,21>,

No,<0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010, 0.3010,0.3010,0.3010> >

<Technicality, <6,6,15,4,15,3,8,15,7,3,3,3,5>, No,

<0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545, 0.1545> >

<Values, <11,10,7,21,10,21,11,15,9,16,16,4,13>, No,

<0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495, 0.1495,0.1495> >

<Risk, <10,6,8,6,7,7,4,12,9,6,5,7,3>, No, <0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,

0.2036,0.2036,0.2036,0.2036,0.2036> >

<Popularity, <13,3,21,14,14,21,20,15,17,19,20,15,12>,

No,<0.1914,0.1914,0.1914,0.1914,0.1914,0.1914,0.1914,0.1914,0.1914,0.1914, 0.1914, 0.1914,0.1914> >

}

Rugby = {

<Enjoyment, <21,17,11,21,7,15,21,13>, No, <0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010> >

<Technicality, <3,9,14,9,20,13,8,11>, No, <0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545> >

<Values, <9,19,16,21,20,19,21,8>, No, <0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495> >

<Risk, <8,5,10,11,12,13,14,11>, No, <0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036> >

<Popularity, <13,3,11,16,16,18,21,16>, No, <0.1914,0.1914,0.1914,0.1914,0.1914, 0.1914,0.1914,0.1914> >

}

Ping-Pong = {

<Enjoyment, <20,3,20,14,3,21,12,19>, No, <0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010> >

<Technicality, <3,12,3,3,3,3,6,3>, No, <0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545> >

<Values, <6,14,8,11,3,4,13,9>, No, <0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495> >

<Risk, <8,2,5,6,3,7,9,2>, No, <0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036> >

<Popularity, <4,3,11,14,11,11,12,17>, No, <0.1914,0.1914,0.1914,0.1914,0.1914, 0.1914,0.1914,0.1914> >

}

Tennis = {

<Enjoyment, <8,12,10,8,18,21,17,16,17,16,6,20,19>, No,

<0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010, 0.3010, 0.3010, 0.3010,0.3010> >

<Technicality, <16,12,13,5,3,3,16,14,3,4,6,3,3>, No,

<0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545, 0.1545, 0.1545> >

<Values, <12,11,6,5,13,21,19,20,18,20,19,10,11>, No,

<0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495, 0.1495,0.1495> >

<Risk,<5,2,6,5,9,11,12,9,9,3,14,7,4>,

No,<0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036> >

<Popularity, <3,11,12,16,14,21,21,18,19,14,21,18,13>,

No,<0.1914,0.1914,0.1914,0.1914,0.1914,0.1914,0.1914,0.1914,0.1914,0.1914, 0.1914, 0.1914,0.1914> >

}

Wrestling = {

<Enjoyment, <14,8,14,15,15,12,15,20,9,10>, No, <0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010, 0.3010,0.3010> >

<Technicality, <20,15,21,12,21,14,7,20,7,15>, No, <0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545, 0.1545,0.1545> >

<Values, <20,15,20,16,18,9,19,18,17,11>, No, <0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495, 0.1495,0.1495> >

<Risk, <8,5,10,12,14,8,8,14,14,12>, No, <0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036> >

<Popularity, <20,4,21,14,15,14,15,21,14,16>, No, <0.1914,0.1914,0.1914,0.1914,0.1914, 0.1914,0.1914,0.1914, 0.1914,0.1914> >

}

Soccer = {

<Enjoyment, <19,18,15,21,21,21,21,15,21,12,21,21,21,19,19,19,21,21,21,18,14,13,13>, No,<0.3010,0.3010,0.3010,0.3010,0.3010,0.3010, 0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010,0.3010, 0.3010> >

<Technicality, <3,21,21,4,9,3,10,8,4,8,3,9,21,3,3,4,3,3,5,3,10,6,4>, No, <0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545, 0.1545,0.1545,0.1545,0.1545,0.1545, 0.1545,0.1545,0.1545,0.1545,0.1545,0.1545,0.1545, 0.1545, 0.1545,0.1545> >

<Values, <9,6,19,21,21,15,21,18,21,12,21,3,15,14,17,7,18,21,19,10,5,18,19>, No, <0.1495,0.1495,0.1495,0.1495,0.1495,0.1495, 0.1495,0.1495, 0.1495,0.1495,0.1495,0.1495,0.1495, 0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495,0.1495, 0.1495,0.1495> >

<Risk, <11,3,10,3,8,8,13,8,8,8,7,5,12,11,14,6,9,10,14,6,6,10,11>, No, <0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036, 0.2036,0.2036,0.2036,0.2036,0.2036, 0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036,0.2036, 0.2036,0.2036> >

<Popularity,<19,4,21,21,21,21,13,21,21,19,21,17,18,21,19,20,21,21,21,21,16,17,21>,No,<0.1914,0.1914,0.1914,0.1914,0.1914, 0.1914, 0.1914, 0.1914, 0.1914,0.1914,0.1914,0.1914,0.1914, 0.1914,0.1914,0.1914,0.1914,0.1914,0.1914,0.1914,0.1914, 0.1914, 0.1914> >

}

Appendix D: Reference Profiles Matched for Sport Evaluation in Section 4.1.3

Hockey = {

<Enjoyment, <21,21,21,21,21>, No, <1,1,1,1,1> >

<Technicality, <3,3,3,3,3>, No, <1,1,1,1,1> >

<Values, <21,21,21,21,21,21>, No, <1,1,1,1,1> >

<Risk, <2,2,2,2,2>, No, <1,1,1,1,1> >

<Popularity, <21,21,21,21,21>, No, <1,1,1,1,1> >

}

Volleyball = {

<Enjoyment, <21,21,21,21,21,21>, No, <1,1,1,1,1,1> >

<Technicality, <3,3,3,3,3,3>, No, <1,1,1,1,1,1> >

<Values, <21,21,21,21,21,21>, No, <1,1,1,1,1,1> >

<Risk, <2,2,2,2,2,2>, No, <1,1,1,1,1,1> >

<Popularity, <21,21,21,21,21,21>, No, <1,1,1,1,1,1> >

}

Baseball = {

<Enjoyment, <21,21,21 >, No, <1,1,1> >

<Technicality, <3,3,3>, No, <1,1,1> >

<Values, <21,21,21 >, No, <1,1,1> >

<Risk, <2,2,2 >, No, <1,1,1 > >

<Popularity, <21,21,21>, No, <1,1,1> >

}

Basketball = {

<Enjoyment, <21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1> >

<Technicality, <3,3,3,3,3,3,3,3,3>, No, <1,1,1,1,1,1,1,1,1> >

<Values, <21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1> >

<Risk, <2,2,2,2,2,2,2,2,2>, No, <1,1,1,1,1,1,1,1,1> >

<Popularity, <21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1> >

}

Swimming = { <Enjoyment, <21,21,21,21,21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1> > <Technicality, <3,3,3,3,3,3,3,3,3,3,3,3,3>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1> > <Values, <21,21,21,21,21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1> > <Risk, <2,2,2,2,2,2,2,2,2,2,2,2,2>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1> > <Popularity, <21,21,21,21,21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1> > }
Rugby = { <Enjoyment, <21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1> > <Technicality, <3,3,3,3,3,3,3,3>, No, <1,1,1,1,1,1,1,1> > <Values, <21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1> > <Risk, <2,2,2,2,2,2,2,2>, No, <1,1,1,1,1,1,1,1> > <Popularity, <21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1> > }
Ping-Pong = { <Enjoyment, <21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1> > <Technicality, <3,3,3,3,3,3,3,3>, No, <1,1,1,1,1,1,1,1> > <Values, <21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1> > <Risk, <2,2,2,2,2,2,2,2>, No, <1,1,1,1,1,1,1,1> > <Popularity, <21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1> > }
Tennis = { <Enjoyment, <21,21,21,21,21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1> > <Technicality, <3,3,3,3,3,3,3,3,3,3,3,3,3>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1> > <Values, <21,21,21,21,21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1> > <Risk, <2,2,2,2,2,2,2,2,2,2,2,2,2>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1> > <Popularity, <21,21,21,21,21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1> > }
Wrestling = { <Enjoyment, <21,21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1,1> > <Technicality, <3,3,3,3,3,3,3,3,3,3>, No, <1,1,1,1,1,1,1,1,1,1> > <Values, <21,21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1,1> > <Risk, <2,2,2,2,2,2,2,2,2,2>, No, <1,1,1,1,1,1,1,1,1,1> > <Popularity, <21,21,21,21,21,21,21,21,21,21>, No, <1,1,1,1,1,1,1,1,1,1> > }

Soccer = {

<Enjoyment, <21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21>, No,
<1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1> >

<Technicality, <3,3,3,3,3,3,3,3,3,3,3,3,3,3,3,3,3,3,3,3,3,3,3>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1> >

<Values, <21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21>, No,
<1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1> >

<Risk, <2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2,2>, No, <1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1> >

<Popularity, <21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21,21>, No,
<1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1> >

}

Appendix E: Reference Profiles Matched with data in Table 4.24 for Sport Evaluation in Section 4.2.3

Attributes	Sports	Preferences of different decision makers (DM1 –DM23)												
C1	Hockey	21	21	21	21	21								
C2		3	3	3	3	3								
C3		21	21	21	21	21								
C4		2	2	2	2	2								
C5		21	21	21	21	21								
C1	Volley-ball	21	21	21	21	21	21							
C2		3	3	3	3	3	3							
C3		21	21	21	21	21	21							
C4		2	2	2	2	2	2							
C5		21	21	21	21	21	21							
C1	Baseball	21	21	21										
C2		3	3	3										
C3		21	21	21										
C4		2	2	2										
C5		21	21	21										
C1	Basket-ball	21	21	21	21	21	21	21	21					
C2		3	3	3	3	3	3	3	3					
C3		21	21	21	21	21	21	21	21					
C4		2	2	2	2	2	2	2	2					
C5		21	21	21	21	21	21	21	21					
C1	Swim-ming	21	21	21	21	21	21	21	21	21	21	21	21	21
C2		3	3	3	3	3	3	3	3	3	3	3	3	3
C3		21	21	21	21	21	21	21	21	21	21	21	21	21
C4		2	2	2	2	2	2	2	2	2	2	2	2	2
C5		21	21	21	21	21	21	21	21	21	21	21	21	21
C1	Rugby	21	21	21	21	21	21	21	21					
C2		3	3	3	3	3	3	3	3					
C3		21	21	21	21	21	21	21	21					
C4		2	2	2	2	2	2	2	2					
C5		21	21	21	21	21	21	21	21					
C1	Ping-Pong	21	21	21	21	21	21	21	21					
C2		3	3	3	3	3	3	3	3					
C3		21	21	21	21	21	21	21	21					
C4		2	2	2	2	2	2	2	2					
C5		21	21	21	21	21	21	21	21					

C1	Tennis	21	21	21	21	21	21	21	21	21	21	21	21	21										
C2		3	3	3	3	3	3	3	3	3	3	3	3	3										
C3		21	21	21	21	21	21	21	21	21	21	21	21	21										
C4		2	2	2	2	2	2	2	2	2	2	2	2	2										
C5		21	21	21	21	21	21	21	21	21	21	21	21	21										
C1	Wrest-ling	21	21	21	21	21	21	21	21	21	21													
C2		3	3	3	3	3	3	3	3	3	3													
C3		21	21	21	21	21	21	21	21	21	21													
C4		2	2	2	2	2	2	2	2	2	2													
C5		21	21	21	21	21	21	21	21	21	21													
C1	Soccer	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21
C2		3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
C3		21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21
C4		2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
C5		21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21