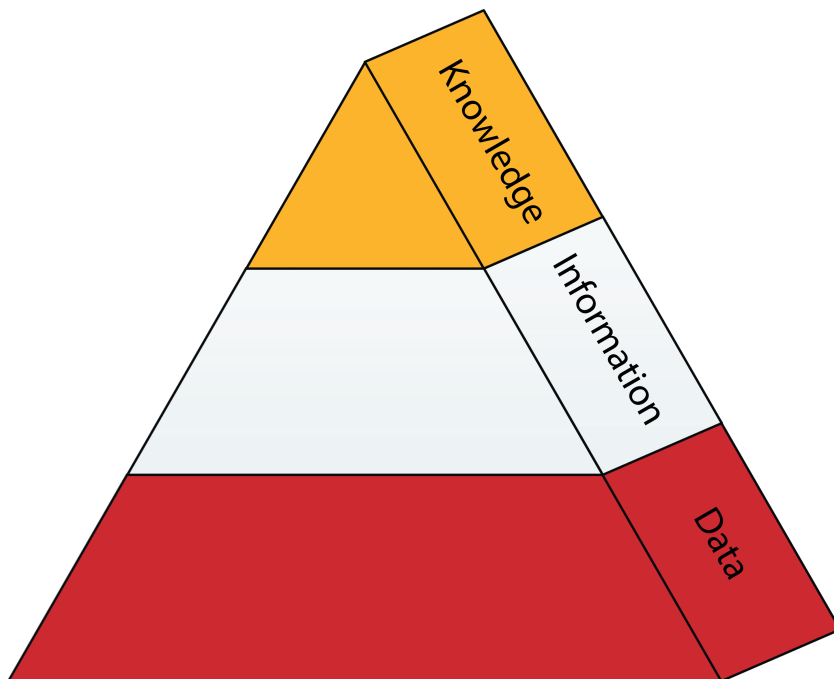


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Fuzzy Ontology for Knowledge Mobilisation and Decision Support



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Fuzzy Ontology for Knowledge Mobilisation and Decision Support

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Abstract

A growing concern for organisations is how they should deal with increasing amounts of collected data. With fierce competition and smaller margins, organisations that are able to fully realize the potential in the data they collect can gain an advantage over the competitors.

It is almost impossible to avoid imprecision when processing large amounts of data. Still, many of the available information systems are not capable of handling imprecise data, even though it can offer various advantages. Expert knowledge stored as linguistic expressions is a good example of imprecise but valuable data, i.e. data that is hard to exactly pinpoint to a definitive value. There is an obvious concern among organisations on how this problem should be handled; finding new methods for processing and storing imprecise data are therefore a key issue. Additionally, it is equally important to show that tacit knowledge and imprecise data can be used with success, which encourages organisations to analyse their imprecise data.

The objective of the research conducted was therefore to explore how fuzzy ontologies could facilitate the exploitation and mobilisation of tacit knowledge and imprecise data in organisational and operational decision making processes.

The thesis introduces both practical and theoretical advances on how fuzzy logic, ontologies (fuzzy ontologies) and OWA operators can be utilized for different decision making problems. It is demonstrated how a fuzzy ontology can model tacit knowledge which was collected from wine connoisseurs. The approach can be generalised and applied also to other practically important problems, such as intrusion detection. Additionally, a fuzzy ontology is applied in a novel consensus model for group decision making. By combining the fuzzy ontology with Semantic Web affiliated techniques novel applications have been designed. These applications show how the mobilisation of knowledge can successfully utilize also imprecise data.

An important part of decision making processes is undeniably aggregation, which in combination with a fuzzy ontology provides a promising basis for demonstrating the benefits that one can retrieve from handling imprecise data. The new aggregation operators defined in the thesis often provide new possibilities to handle imprecision and expert opinions. This is demonstrated through both theoretical examples and practical implementations. This thesis shows the benefits of utiliz-

ing all the available data one possess, including imprecise data. By combining the concept of fuzzy ontology with the Semantic Web movement, it aspires to show the corporate world and industry the benefits of embracing fuzzy ontologies and imprecision.

Sammanfattning

Organisationer har idag stora utmaningar med att hantera ett viktigt element som kan skapa konkurrensfördelar; kunskap. Moderna informationssystem samlar kontinuerligt in mängder av data som innehåller användbar kunskap, men som inte utnyttjas till fullo. Hårdare konkurrens och mindre marginaler innebär att organisationer som utnyttjar sin ihopsamlade data kommer att ha en konkurrensfördel gentemot sina konkurrenter.

Då stora mängder data skall processeras är det nästintill omöjligt att fullständigt undvika oprecis och diffus data. Samtidigt är många av dagens informationssystem inte kapabla att hantera oprecis data, fastän den kan innehålla värdefull information. Ett exempel på oprecis men värdefull data är verbal information från experter, med andra ord data som är svår att definitivt fastställa till ett specifikt värde. Att hantera underförstådd kunskap är en utmaning för organisationer; att utveckla nya metoder för att processera och lagra oprecis data är därför väsentligt. Därutöver är det viktigt att demonstrera hur underförstådd kunskap och oprecis data framgångsrikt kan användas, vilket förhoppningsvis inspirerar organisationer och företag att mer än tidigare beakta även oprecis kunskap.

Det huvudsakliga målet med den här avhandlingen är att undersöka hur ontologier som kan arbeta med oprecis data kan underlätta användningen och mobiliseringen av underförstådd kunskap och oprecis data för beslutsstödsprocesser och operativ och strategisk ledning i organisationer.

Avhandlingen introducerar både praktiska och teoretiska framsteg för hur logik och ontologier för oprecisa observationer (eng. “fuzzy logic” och “fuzzy ontologies”) och OWA operatorer (eng. “OWA operators”) kan användas för att stöda olika beslutsstödsprocesser. Avhandlingen visar även hur ontologier kan ge begreppsunderlag för att hantera underförstådd kunskap. Exemplet som beskrivs i avhandlingen behandlar olika typer av vin och data som samlats in från vinkonässörer. Den här ansatsen kan generaliseras och appliceras för att stöda arbetet också med andra praktiska problem såsom intrångsdetektering. Därtill används en ontologi som en central aktör i en ny konsensusmodell för gruppbeslutsfattande. Då ontologier kombineras med tekniker som utvecklats för den semantiska webben så blir det möjligt att konstruera nya applikationer. De här applikationerna visar hur en mobilisering av kunskap kan utnyttja oprecisa data.

En viktig del av beslutsfattandet är att kunna aggregera element till större

helheter för att skapa översikter. Aggregation är användbart tillsammans med de utvecklade ontologierna, speciellt eftersom de kan utnyttja även oprecis data. De nya aggregationsoperatorerna som definieras i avhandlingen erbjuder nya möjligheter att hantera oprecisa data och expertkunskap. Det här visas mera ingående med hjälp av både praktiska och teoretiska exempel.

Avhandlingen demonstrerar de fördelar man kan erhålla genom att utnyttja tillgänglig data, inklusive oprecisa data. Genom att kombinera ontologier med data och information från den semantiska webben strävar avhandlingen efter att visa fördelarna med att kunna använda data och information som samlats in från verkligheten.

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A handwritten signature in black ink, consisting of a large, stylized 'R' followed by a long horizontal stroke that tapers to the right.

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Bromarf, 10.5.2014

List of original publications

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Part I

Research Summary

Chapter 1

Introduction

Knowledge has always been an important way for individuals and groups to distinguish themselves. For the people living in the stone ages, knowledge about different tools made them better prepared for basic tasks, such as making fire and finding food. As groups, knowledge about how one can defend a village against other tribes was valuable information to possess. In modern times, the same basic notion is still crucial. The value received from knowledge has taken different characteristics over time and nowadays knowledge is being used and shared in, seemingly, endless contexts. Nevertheless, the core notion that “knowledge is power” is still more than relevant.

As information technologies, and society as a whole, are constantly advancing and extending the boundaries of human capability it has created a world where data is being collected and stored all the time. The methods employed for finding patterns in data have become more advanced, offering more rigorous predictions of the possible scenarios and developments that could occur. Although these ideas have been embraced on every level of the society, this has assuredly influenced the functionality of modern companies. The advantages that companies strive to achieve towards their competitors are not necessarily as dramatic as inventing the wheel or discovering fire; it is more and more coming down to the details. Inevitably this process has reached a stage where one has to utilize knowledge and information which is not straightforward to handle. Companies and persons in charge of analysing data are faced with the challenge that the collected data is not precise and easily processable. This data still contains useful information and therefore cannot be overlooked, especially as organisations are competing with shrinking margins [80].

Most companies are capable of collecting data from their internal processes and storing it in various information systems. Data refers to static raw material which can or cannot have meaning in itself. In a business context, the millions of automatically generated Excel spreadsheets, containing rows and rows of symbols, can be seen as data. By applying different methods to generate meaning and

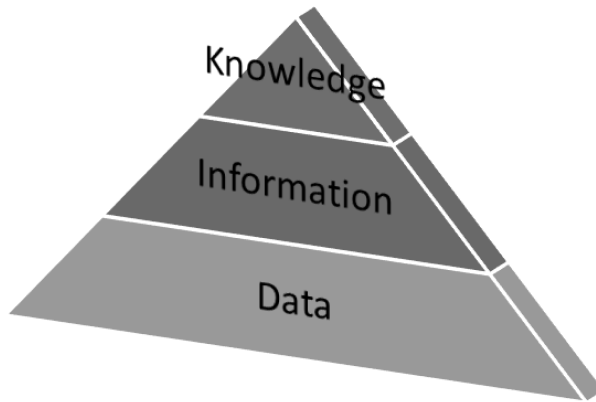


Figure 1.1: Data-Information-Knowledge

purpose from the data, information can be extracted to facilitate the decision making. For example, if 10 spreadsheets are combined and new values are extracted from the static data, then some kind of information has been created. And, greatly simplified, one can retrieve knowledge from this information, referring to the final phase of the pyramid in Figure 1.1, in this final step one aims at understanding the meaning of the information and acts accordingly. The knowledge stage requires previous experience and knowledge to make valuable conclusions [3, 22, 43]. It is important that the process of retrieving knowledge from information is influenced by other external and internal factors, to emphasize, excellent information alone does not necessary create knowledge [22, 83].

An expert is a good example of a mechanism that turns information into knowledge to support decision making. This transformation process is supported by the experts' tacit knowledge (e.g. previous experiences). The definition of an expert generally refers to a person that has extensive knowledge of a specific domain. In the context of expert systems, an expert is the main source of knowledge. The required knowledge is retrieved from human experts and modelled in the knowledge base, i.e. in terms of rules. The success of representing expert knowledge depends largely on the knowledge engineer in charge of collecting and combining the retrieved knowledge [166]. Expert knowledge expressed with linguistics terms represents an example which is tacit by nature, but still contains useful information. According to Polanyi [230] tacit knowledge implies that "we can know more than we can tell", making it hard to capture and transfer among individuals.

Defining and understanding the differences between explicit and tacit knowledge can be cumbersome (and it is still partly an uncharted area), Figure 1.2 shows the widely used iceberg explanation [271]. This representation illustrates how much of our knowledge is explicit and how much is tacit as well as different examples of features that are explicit or tacit. There exist different estimations on the distribution of an individual's knowledge, with the widely agreed division of 10

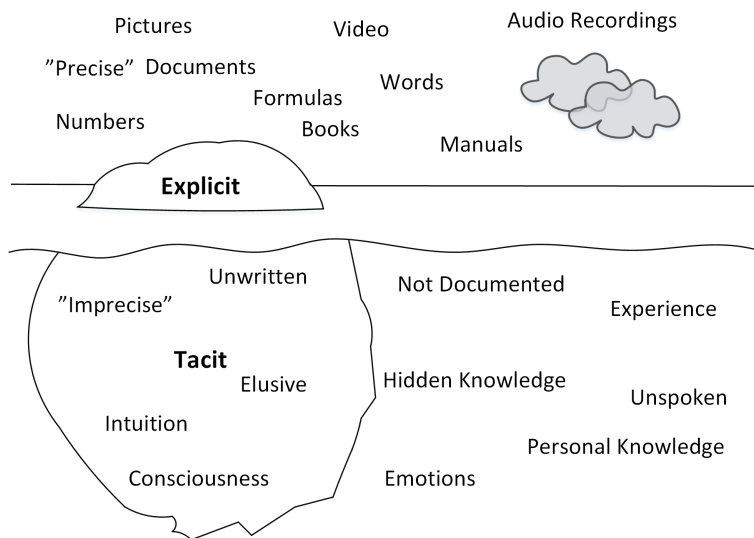


Figure 1.2: Explicit vs. Tacit Knowledge

percent explicit and 90 percent tacit [29]. This creates an obvious problem for organisations that aim at storing and analysing this imprecise data, as tacit knowledge is not easy to handle and work with, especially compared to more traditional and straightforward data sources; nevertheless the abundance of this knowledge makes it impossible to overlook [39, 159]. In this thesis, imprecision is used to refer to data that is hard to exactly pinpoint to a definitive value. This might be due to the fact that the data is retrieved from several sources or that linguistic terms have been used. For example, it might not be possible to state that a value is 5.6 exactly, but rather that it is somewhere near 5.6.

The increasing number of companies active in the field of Analytics [153], has created a demand for methods and information systems that are capable of handling imprecise data, with numerous signs indicating that this demand will continue to rise. With the increased pace of decision making in business and industrial sectors, employees need to quickly gain access to guidance or advice when and where it is required [197]. This is basically a vital function for organisations that wish to survive in today's economy [299]. The knowledge retrieved from this data needs to be distributed to the employees, as mobility and the need for constant access to data is quickly becoming an essential part of our life. There is neither time nor possibility for employees to postpone decisions until they reach an office as the decision needs to be taken immediately. For instance, maintenance personnel fixing a broken machine, would benefit from receiving relevant guidance from a system in real-time. As many of the real-time decision making problems show resemblance to previous incidents, experts and their knowledge provide highly valuable assets in many situations [59, 83].

Fuzzy logic was introduced by Zadeh [313], as a way to describe objects with the use of imprecise definitions. By using fuzzy logic, computer systems can create rules that are not limited to true/false statements. Having truth values that can move between completely true and completely false means that uncertainty can be incorporated into the reasoning model, and at the same time, information expressed with linguistic terms can be utilized.

The combination of fuzzy logic and ontologies (i.e. fuzzy ontologies) is a promising approach to address the issues related to mobilising imprecise and tacit knowledge [62]. Fuzzy ontologies are strongly connected and influenced by the Soft Computing movement, included in the larger field of Computational Intelligence and Analytics.

Ontology, as such, provides a way of modelling knowledge and simultaneously creates better prerequisites for advanced reasoning. Gruber [115] has defined ontologies, in the context of computer science, as descriptions of concepts and relations between agents of communities. Although ontologies are sometimes seen as taxonomies, they provide more knowledge about the domain modelled [114]. By utilizing ontologies for modelling knowledge, it becomes possible to create systems which can implement more advanced reasoning processes.

By combining the advantages of fuzzy logic and ontologies, fuzzy ontologies make it possible to store and analyse imprecise and tacit knowledge. This feature can be utilized to hinder knowledge losses when, for instance, experts retire from an organisation [59, 167]. Naturally it implies that organisations are deprived of all the knowledge acquired by the expert / employee, it is essential to find solutions and methods for storing their tacit knowledge for future use when the expert is no longer with the organisation.

An important part of decision making is the process of aggregating data (numerical values) to create a reduced set of values that can be used for comparing alternatives. The ordered weighted averaging operator introduced by Yager [307] is a widely applied aggregation tool, especially in the context of decision making. Developing new extensions of the OWA operator is very important, as the numerous aggregation operators available are suitable for very specific problems.

1.1 Background

To better grasp the problems present in the research field, in this section a short introduction is presented, to provide the basis for the research objectives and the research questions. The underlying issue of this thesis is that companies are constantly compelled to make decisions under uncertainty or by using imprecise information. However, this should not automatically imply that the results produced should be less reliable than the results retrieved from precise data.

Imprecision refers to the fact that some values can be hard to estimate and impossible to categorise as belonging to a specific category. This imprecision might

indicate that the data is situated in between categories or that one cannot exactly predict how it will evolve, nevertheless, this is often how the human brain makes decisions, using huge amounts of imprecise and uncertain information to create predictions [277, 280, 329].

From a different point of view, imprecision refers to the quality of the object description, based on a selected model/environment [243], having strong similarities to semantic accuracy. In other words, one cannot completely specify the real description of an object, only that the value is in a specific interval. It is possible to argue that one could eliminate imprecision by creating more precise sensors and methods for collecting data. However, imprecision is a part of our model of the world and cannot be overlooked if we want to imitate human experts and create advanced reasoning with tacit knowledge in an artificial way [262].

Soft Computing techniques can be helpful for managing this situation and imitating the decision making processes of experts. The term Soft Computing refers to a set of techniques that use computational power to solve problems that include imprecise and uncertain information, drawing inspiration from functions inherent in the human brain [318]. By employing these techniques computers and information systems can handle issues and solve problems, even though they do not have precise information available for all stages of the processes.

1.1.1 From AI Towards CI

Artificial Intelligence (AI) was established as a research field in the mid-1950s, with the main purpose of artificially solving problems that require intelligence. Due to Hollywood movies and science-fiction novels, this new research field attracted a lot of interest from the public. This created a somewhat inaccurate picture of what kind of intelligence we actually can achieve today. As constructing an intelligent robot in the real world is not as easy as animating the same robot for a film sequence, there is a need to sort out these misunderstandings and misinterpretations.

Kordon [175] states that the most valuable feature of human intelligence is to predict the future based on previous experiences, available data and patterns [127]. These predictions tend to be limited to a specific field of knowledge. By attempting to mimic this process, AI researchers create experts systems that aim at producing accurate predictions inside this framed space. A long-term goal of this research field is to completely reproduce an experts brain, in a computer environment, and to utilize knowledge in the same way as a human expert but with the added advantage of vast amounts of computer power. However, the current situation in the AI field is far from achieving this goal, with numerous doubtful voices questioning whether it is even possible to achieve it with the techniques available today [67, 93, 99]. The following are examples on traditional AI techniques, used for “capturing the expert in the box”: Knowledge Management, Expert Systems and Case Based Reasoning [175].

As a way of distinguishing Artificial Intelligence from more embellished developments, Computational Intelligence (CI) was introduced as a term for describing a new branch that is separate from AI. In the 1960-1970s, as AI grew in popularity and produced numerous expert systems, it once again became clear that having access to knowledge is a clear advantage. The ability for AI to create expert systems based on domain knowledge, however, turned out to be its biggest handicap in widespread use. The field began to lose its special position and the opinions started to shift towards a more general theory about intelligence, compared to the one offered by AI. This movement changed the views on what computers could and should do, as previous visions might have been slightly optimistic, for instance Simon [259] predicted that computers and machines would be able to do any work that humans can by 1985 (predicted in the 1960's) [14].

The main idea behind CI is that computers should be able to perform tasks other than processing already pre-stored knowledge produced by humans. As the new research area started to become successful, it became clear that AI was not the only possible solution for creating intelligence, and that CI was a worthy successor (or companion) [99]. From an applied point of view, Kordon [175] defines three major differences between the two terms:

- **Representing Intelligence.** While AI stores domain specific expert knowledge in the system, CI extracts the knowledge from the available data.
- **Processing Intelligence.** AI is more fond of using symbolic reasoning methods, where CI utilizes numerical calculations.
- **Environment Interaction.** AI aims at changing the environment after the created solutions, whereas CI adopts and learns from the environment.

Duch [93] states that CI focuses on problems which are difficult to solve using the traditional AI methods, but are easily solved by humans and animals. In other words, it is concerned with problem solving that requires intelligence and instincts. By studying why and how this can be accomplished, researchers hope to mimic these functions. CI can therefore be seen as a combination of information techniques and biology, however, as the field is quite broad, this statement is not valid for all techniques included in the CI arsenal.

A common feature among the CI techniques is that they study problems where traditional computer science algorithms or solutions are ineffective or impossible to create. These problems cannot be solved by increasing computer power and time, but require completely new ways of execution [66, 67, 93]. More specifically, AI is often based on domain experts knowledge where CI tries to extract knowledge from data. CI techniques can create and produce knowledge from the available data, whereas AI is limited to pre-defined knowledge. This means that AI uses human knowledge and collected data and tries to fit and adapt the environment after that knowledge, compared to CI which adds more numerical calculations and

therefore is able to also learn from the environment. AI is therefore more limited to a specific domain, based on specific knowledge, where CI learns and adapts its knowledge base as the domain knowledge and environment change [30, 297]

A well-known illustration of the difference between AI and CI originates from Liebowitz [191]:

“If you are a dog lover, build expert systems; if you are a cat lover, build neural networks”

Liebowitz argues that expert systems require extensive human input, so the user should be knowledgeable and fond of interacting with the system. Neural networks, the most used CI technique, on the other hand, are more independent and seldom in need of any attention. These systems basically handle themselves and need very little human input.

For a more formal definition of what Computational Intelligence is, one can turn to Bezdek’s [28] definition:

“A system is computational intelligent when it: deals with only numerical (low-level) data, has pattern recognition components, does not use knowledge in the artificial intelligence sense; and additionally when it (begins to) exhibit (i) computational adaptivity, (ii) computational fault tolerance, (iii) speed approaching human-like turnaround, and (iv) error rates that approximate human performance.”

A different and simplified definition is given by Duch [93]:

“Computational intelligence is a branch of science studying problems for which there are no effective computational algorithms.”

The Computational Intelligence field is constantly evolving and as a consequence of this researchers still, to some extent, disagree on what CI exactly is. It will still be a while before the field has reached a stage where one could reach consensus about a general definition. However, it seems to be more widely agreed on which areas belong to CI. The common feature of these methods is that they are capable of autonomously acquiring and integrating knowledge and also that they can be used in both a supervised and unsupervised learning mode.

Imprecise information is present abundantly in the CI-techniques. Fuzzy logic is generally considered to belong to these methods, even though its functionality differs slightly from the other techniques. Fuzzy logic offers a useful tool for handling uncertainty, an issue which is impossible to avoid if one wants to create completely new, non-AI, techniques. In other words, as CI is expanding its field of use, it will influence the decision making processes more and more. This makes the introduction of Soft Computing techniques unavoidable, as one cannot avoid imprecise information in different business and industry contexts [319].

Computational Intelligence and Soft Computing techniques are strongly connected with Analytics. Many of the techniques developed in the CI and AI fields have later diverged and been implemented for Analytics. For instance, machine learning was originally devised as an AI technique enabling computers to learn, now the algorithms and methods developed are frequently used in different fields of Analytics. As the datasets are growing larger and larger for every day that goes by, it means that the techniques implemented for retrieving value from the data needs to be more advanced. The idea that CI and AI provide, the intelligent machines, suits the goals of Analytics well.

1.1.2 Analytics

Defining Analytics can be equally as cumbersome as defining Computational Intelligence. INFORMS (The Institute for Operations Research and the Management Sciences), the largest society in the world for professionals in the field of Operations Research (OR), Management Science (MS) and Analytics states that the difference between OR, MR and Analytics is not easy to establish. However, they emphasise the different features offered by the methods, as OR and MS tend to be aimed more towards the tools and techniques used, while Analytics emphasizes the actual analytical process and how the application and process together impact the organisation.

Analytics can be seen as an area aimed at finding patterns in data. This is achieved by combining Statistics, Computer Programming and Operations Research to approach problems in the business and industry sectors [174]. Analytics has a tendency to be combined with Visual Analytics to better visualize and present the results to aid decisions [81]. INFORMS supports the view that Analytics can be divided into three subcategories: Prescriptive Analytics, Predictive Analytics and Descriptive Analytics. They, subsequently, aim at the following [83, 108]:

- Evaluating and determining new ways to operate
- Predicting future options and possible trends
- Preparing and analysing historical data

The term Analytics has lately been used, e.g. by software creators, as a buzzword to gather all the different functions available under one roof [240]. The most common application of Analytics is to study business data for predicting and improving business performance [80]. This is especially visible when we consider the developed business applications. Today almost every department of an organisation can make use of Analytics, examples can be taken from areas such as: sales, marketing, supply chain optimization and fraud detection [27].

Businesses are, nevertheless, still faced with the same challenges that were present when Analytics was first introduced: The volume of structured and unstructured data. Complex, large data sets and the challenge to handle them are

referred to as Big Data. According to Havens et al. [125], this refers to data that is too large to be loaded into a computer's working memory, in other words, that the data amount is too huge to handle in a practical way [241].

Nowadays, Big Data is increasingly treated as an enterprise asset that yields actionable business insights, instead of being viewed as an obstacle. More and more enterprises seek to explore the potentials of their Big Data in order to discover facts they did not know before and to support more effective decision making processes [241]. The forerunners in Analytics are today utilizing information technologies and Big Data to make decisions even on a moment-to-moment basis, or at least on a day-to-day basis. The main problems presently relate to a different issue: after all this analysed information is produced, it should be delivered to the right persons at the right time, for aiding them in making the right decisions [44, 196]. Additionally, Analytics should be more adapted to handling imprecise data abundant in business environments.

One of the problems with the traditional computer systems, for instance used for analytical purposes, is that they are based on Boolean logic, creating limitations regarding the reasoning functions [246, 317]. The ability to deal with imprecise information and produce precise answers is a vital feature of a human brain, however, there is a lack of suitable techniques for applying this approach also from a computational point of view [221, 320, 321].

As a result, Soft Computing, a subarea of Computational Intelligence, is increasing in importance within Analytics. On one hand it is clear that new, more powerful computers make it possible to solve much larger and more complex problems than before. On the other hand, though organisations have access to all this computing power, the techniques and models used are ineffective for solving different kinds of problems as well as for analysing data [318, 319]. The possibilities offered by Soft Computing would also make systems more suitable for handling Big Data, as allowing computers to be imprecise can result in more effective and therefore less time consuming decision making processes [244].

1.1.3 Soft Computing and Fuzzy Logic

The Soft Computing movement has embraced fuzzy logic, as it offers a possible solution for the problems inherent in decision making with expert-based tacit knowledge. Objects in the real world very seldom have clearly-defined memberships to groups, because, it is difficult to exactly pinpoint what an object could be described as. Fuzzy logic makes it possible to describe an object with the use of imprecise definitions, a useful feature when dealing with tacit and imprecise knowledge [313, 314].

Instead of limiting the choices to 1 or 0, fuzzy logic makes it possible to use any real number between 0 and 1, for defining the different degrees of truth, i.e. membership values. The membership values to different groups, for instance: 0.45, 0.99 and 0.02 indicate how similar an object is with respect to the properties that

are connected to that group. By combining different techniques with fuzzy logic, computer systems can work and reason as humans, with the additional benefit of the processing power [175].

To address one of the issues that can limit this development, Castro [63] states that fuzzy logic might cause the number of rules to grow exponentially inverse, in comparison to the accuracy level. Kordon [175] supports this statement by observing that larger sets of rules and variables might create a system that is not practical in an applied context, due to excessive calculations. This goes hand in hand with the possible problems of scaling up the fuzzy systems and the problems one can encounter when maintaining the fuzzy logic based systems [97]. These issues are usually approached by combining fuzzy logic with other techniques to utilize fuzzy logic and overcome its drawbacks at the same time.

With the massive amounts of collected data available, a system for creating some kind of order in all the chaos is required. In the Semantic Web, ontologies are the main technology for creating interoperability on a semantic level. This is achieved by creating a formal illustration of the data, which thanks to its formality can be shared and reused all over the Web. More specifically, an ontology formulates and models the relationship between the concepts in a given domain [79]. By using ontologies, one opens a gateway to introduce fuzzy logic to the whole Semantic Web community, as ontologies are highly compatible and can be used together with several techniques, integrating and sharing the defined information [128].

Although the use of fuzzy logic together with ontologies (i.e. fuzzy ontologies) has increased steadily for both the Semantic Web and for decision support, there is a lack of available applications showing the actual benefits of ontologies and specifically fuzzy ontologies. This has, inevitably, diminished the utilization of fuzzy ontologies and ontologies for the Semantic Web. Lukasiwicz and Straccia [198] and Straccia [268] facilitate the introduction of fuzzy logic into the Semantic Web by creating a bridge between these two areas, making it possible to implement fuzzy logic by using the already established Web Ontology Language language (OWL). This development can open the door for new applied approaches for modelling imprecise knowledge.

Recently there has been an increasing effort to introduce more users to the benefits of fuzzy ontologies for various purposes [268], however, it has not yet attracted the interest of the general audience. There is an imminent need to spark the discussion on how and for what purpose fuzzy ontologies are most suitable to be employed and in what combinations fuzzy ontologies could be used for optimizing the generated benefits.

There has also been a spike in the developments of applications based on type-2 fuzzy ontologies [50, 179, 181, 182]. This can be another approach to introduce fuzzy ontologies to the masses. More users would result in more ontologies, which due to compatibility benefits would strengthen the usability of fuzzy ontologies overall, as well as demonstrate that modelling uncertainty is not as cumbersome as it is usually perceived. A successful structure for creating fuzzy ontologies is based

on OWL and extended with fuzzy logic by Bobillo and Straccia [36, 37, 39–41]. This novel approach forms the basis for the technical developments presented in this thesis.

1.2 Research Objectives

Companies are today facing serious problems in dealing with information and data. At the same time knowledge created using data from different sources has evolved into a resource that few companies can afford to neglect. There is an obvious need to handle this conflict, as companies are basically forced into collecting and analysing data. If the companies fail to take advantage of this movement, they might quite quickly fall off the wagon [107, 157]. This statement can be supported by the fact that numerous companies are investing in R&D projects related to these issues. Even larger country-wide programs have been initiated, such as the Data to Intelligence (D2I) program, collecting over 25 large Finnish companies with the aim to “boost Finnish international competitiveness through intelligent (context-sensitive, personalized, proactive) data processing technologies and services that add measurable value”. Finding new ways to handle and analyse data is certainly a topic that generates interest ¹.

The main method for approaching this problem is to develop fuzzy ontologies to tackle knowledge management and knowledge mobilisation problems that are present in industrial cases. By modelling and storing tacit expert knowledge, it is possible to ease the knowledge losses as employees, for various reasons, leave the organisation. At the same time, these applications will make use of the massive amounts of unused data available in companies. Carlsson et al. [56–58] state that knowledge mobilisation will change how we view knowledge management. Instead of collecting information from experts, and later distributing that information around the company, knowledge mobilisation allows for context-adaptive fast information whenever the user is in need of it.

Knowledge mobilisation usually has 4 different functionalities [56–58]:

- The forming of new knowledge
- The development of new algorithm for knowledge mobilisation purposes
- Finding knowledge in data (Big Data)
- Activate knowledge on the move

Being successful in all four phases could fully utilize the use of ICT for knowledge management. Fuzzy ontology has qualities that could offer a possible solution for this problem. The results presented in this thesis also hope to provide some

¹<http://www.datatointelligence.fi/>

advances regarding the mobilisation of knowledge and what form it will take in modern organisations.

The first step of the research is to develop a fuzzy ontology that can be used as a test environment for experimenting to identify the benefits of fuzzy logic and ontologies. The Fuzzy Wine Ontology case by Carlsson et al. [56,57,59] is chosen to form the basis for the test environment to be developed. Wines and their possible food combinations are by nature imprecise, meaning that wine drinkers tend to listen quite a lot to experts and their advices. It has to be acknowledged that every individual has an unique taste regarding what wine they like the most, however, the aim is to show how tacit expert knowledge can be used to generate decision support. The test environment is adopted for use in other projects by adjusting it for the specific purposes and requirements; thereby testing the usefulness and adaptiveness of fuzzy ontologies.

As an increasing part of the knowledge stored in companies is expressed as expert knowledge, this has lately attracted an elevated amount of interest, especially concerning the way knowledge management affects organisations. Companies will, at the latest, notice if they are lacking capabilities in managing and storing knowledge when their employees are approaching retirement age. When these experts leave the organization, they will take their knowledge with them. As a significant percentage of companies can be considered to depend on their internal knowledge for achieving success, they need to find suitable methods for keeping that acquired knowledge inside the organisation. This refers to both measured data as well as tacit knowledge. From an organisational point of view, it is essential to be able to make use of all this collected information in an automatic fashion. Experts tend to make use of linguistic expressions when communicating their opinion. By successfully modelling this linguistic data and combining it with precisely measured information, one can create methods suitable for knowledge management purposes in organisations of today.

Aggregation operators are a vital part of the functions undergoing inside the fuzzy ontology applications, as they provide ways for combining different information instances. The family of Ordered Weighted Averaging operators (OWA operators) [307] is often used for aggregating values in models aimed for the Semantic Web. Creating new extensions of the OWA operator and thereby extending their scope is an important part of the development of fuzzy ontologies for supporting decision making processes. The developed fuzzy ontology applications and new extensions of OWA operators are applied and adapted for various problems, illustrating how they could aid the decision making process.

Group Decision Making (GDM) situations are of special interest due to their complicated nature. When several decision makers are involved into the procedures it automatically means that other factors, such as weapons of influence and hierarchical structures, can influence the end result and undervalue opinions and information. These tendencies are clearly visible in situations where the participants

are very knowledgeable, for instance a group of experts, in these situations other factors besides pure knowledge definitely influence the outcomes. An objective is to study how fuzzy ontologies could aid in making this process more effortless and smooth. This can be done for instance by reducing the set of alternatives that the group should decide among, or by providing suggestions on what alternative might be the most suitable, to form the basis for the experts' decisions.

The research objective of this thesis can be summarized as to explore how fuzzy logic and ontologies could facilitate the exploitation and mobilisation of tacit knowledge and imprecise data in organisational and operational decision making processes. This is conducted focusing on the notion that there is a need to utilize the tacit expert knowledge abundant in today's organisation, before it is too late. By showing how imprecise and tacit knowledge could be incorporated into decision support systems, it can be demonstrated that this knowledge can be stored and utilized, even though the expert is no longer active. These tools provide organisations with considerable benefits and at the same time, they validate the fact that fuzzy ontologies are useful for modelling imprecise data and for creating applications aimed for the Semantic Web. In the long run making fuzzy ontologies an usable tool also for the general user. The research questions presented in the next section offer more details regarding the different steps conducted in this thesis.

1.3 Research Questions

The previously identified research objectives can be approached by providing answers to the following research questions: These specific questions emerged as a result of a thorough analysis of the current state-of-the-art regarding the representation and applications of imprecise and tacit knowledge for decision making purposes.

- RQ 1: How can tacit and imprecise knowledge be represented and processed by a fuzzy ontology?
- RQ 2: Can aggregation operators improve fuzzy ontology representation and reasoning by extending their scope to incorporate:
 - (i) Different representations of imprecise information?
 - (ii) Group Decision Making?
- RQ 3: In what way can type-2 fuzzy sets improve the performance of knowledge mobilisation systems and how can they be incorporated in the ontology building process?
- RQ 4: What techniques and methods are sufficient for a fuzzy ontology application to handle expert knowledge expressed as imprecise data?

- RQ 5: How can fuzzy ontologies be applied to support decision making processes for the purpose of knowledge mobilisation?

The research questions introduced here give hints on how the problems were conquered. As a basis for the research, first an overview is provided on the current situation regarding recent developments in the fields of Soft Computing, the Semantic Web and fuzzy ontologies. The first question aims more towards showing why it makes sense to use fuzzy ontologies to represent imprecise knowledge. These preliminary discussions form the foundation for the future developments, which aim at extending the current state of the art with new findings.

With the second and third research questions, the research is extended into investigating how fuzzy ontologies and specifically OWA operators can improve the handling of imprecise information. The thesis takes a more technical approach for answering the fourth and fifth research questions by exploring how the theories presented and developed can be applied for solving practical decision making problems. At this phase, the three-step method: Protégé – fuzzyDL – Java is evaluated and other alternative methods are discussed. This technical approach has its limitations; a goal is therefore to find possible useful uses of the approach in its current form and also to provide solutions to the limitations.

The fourth and fifth questions aspire to summarize the results gained from the previous research questions and thereby provide some guidelines on how one could utilise expert knowledge for supporting decision making. The last research question deals with knowledge mobilisation issues and shows how the support systems created can be made mobile.

1.4 Structure of the Thesis

In order to accomplish the research objectives defined in section 1.2 and answering the research questions in 1.3, the thesis is structured as follows.

Chapter 1, **Introduction**, introduces the motivations leading up to the thesis. The introduction shows how the thesis fits into the current situation in the research field, as well as proclaims the contributions originating from the results produced. In addition, the Research Objectives 1.2, Research Questions 1.3 and the Structure 1.4 of the thesis are presented.

Chapter 2, **Methodology**, introduces the relevant methods and theories used as the basis for the research conducted. The main fields presented are: Action Design Research 2.1, Decision Support Systems 2.2, Analytics 2.3, Positivism 2.4 and also some Philosophical Questions 2.5 are discussed.

Chapter 3, **State-of-the-Art - Fuzzy Ontology, Group Decision Making and Aggregation Operators**, presents a literature review and a state-of-the-art concerning

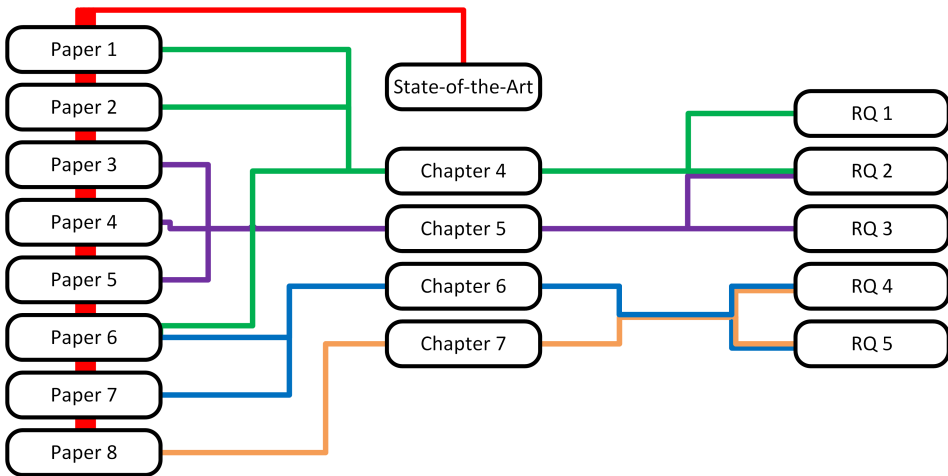


Figure 1.3: The outline of the thesis

the topics covered in this thesis.

The contribution received from in this chapter is to provide a overview of the current state-of-the-art situation in the research fields. All **research papers** included in the thesis contribute to this chapter.

Chapter 4, **A New Consensus Model for Group Decision Making**, presents an approach to using fuzzy ontologies for aiding in the process of reaching consensus in a group environment.

It is well known that involving more people (and their individual opinions) in a decision making process does not automatically make the end result better. This is a consequence of several reasons; one is the observation that there are always one or more individuals that are better at making their opinions seem more relevant compared to others. This is especially relevant when the group members are experts in their topic. If this use of weapons of influence takes place, the traditional group decision making models fail. However, there are still valuable benefits to gain from combining different opinions and experiences in these situations. Developing support for these kinds of processes is therefore highly relevant and can produce useful results, in case the limitations and issues are taken into consideration properly.

The use of these weapons of influence can be handled by introducing fuzzy ontologies into the process. One can take into consideration that some participants are more talented at influencing others. At the same time, it becomes possible to include a larger set of alternatives into the decision making process. By introducing a linguistic extension to the model, one can more sufficiently handle descriptions of the alternatives and attributes, which are both dynamic and vague. The Fuzzy Wine Ontology 4.1, is presented in detail in this chapter. This ontology and its

concepts serve as the main ontology implemented throughout the thesis.

The contributions in this chapter aims at providing answers to **Research Question 1** and partly to **Research Question 2**. The basis for the results presented in this chapter can be found in **papers 1** and **2**. Although the contributions from paper **6** are mainly discussed in Chapter 6, it contributed also to this chapter, especially the part covering the Fuzzy Wine Ontology (Section 4.1):

Paper 1

Pérez, I.J., Wikström, R., Mezei, J., Carlsson, C., Anaya, K. and Herrera-Viedma, E. (2013). Linguistic Consensus Models Based on a Fuzzy Ontology.

Paper 2

Pérez, I.J., Wikström, R., Mezei, J., Carlsson, C. and Herrera-Viedma, E. (2013). A New Consensus Model for Group Decision Making Using Fuzzy Ontology.

Paper 6

Wikström, R. (2013). Ontology of Imprecision and Fuzzy Ontology Applications.

Chapter 5, **Aggregation Operators and Fuzzy Numbers in Decision Making**, presents new variations of the OWA operators, used for supporting decision making processes.

Aggregation operators play a fundamental role in decision making, especially when there are numerous criteria with a conflicting nature present [307]. When imprecise data is introduced in the decision making process, it becomes important to develop appropriate solutions for handling it in the aggregation process, for instance in the context of fuzzy ontologies. This is imminent when the involved knowledge and data are provided by experts.

When utilizing expert knowledge for knowledge-based systems there is a need to find new ways to represent these elements. A possible approach is to implement interval-valued fuzzy sets, type-2 fuzzy ontology and OWA operators for the aggregation process. By combining interval-valued fuzzy numbers (IVFN) with different OWA operators, such as the ordered weighted averaging distance (*OWAD*) operator and the induced ordered weighted averaging operator (*IOWAD*) new definitions can be constructed.

As these new definitions satisfy important properties (e.g. monotonicity), the new extensions can be employed for aggregating information in fuzzy ontologies

in order to aid decision makers with finding the most similar objects to a given case.

This chapter is mostly based on the contributions from **papers 3, 4 and 5**. However, **paper 8** functions as an extension of the work presented in **paper 5**. The contributions in this chapter mainly aim at providing answers to **Research Questions 2 and 3**.

Paper 3

Mezei, J. and Wikström, R. (2013). Aggregation Operators and Interval-Valued Fuzzy Numbers in Decision Making.

Paper 4

Mezei, J., Wikström, R. and Carlsson, C. (2014). Aggregating Linguistic Expert Knowledge with Type-2 Fuzzy Ontology.

Paper 5

Mezei, J. and Wikström, R. (2013). OWAD Operators In Type-2 Fuzzy Ontologies.

Chapter 6, **Fuzzy Ontology Applications**, offers some examples on how fuzzy ontologies can work as the basis for applications aimed at mobilising knowledge.

The Semantic Web is currently demanding new methods and systems that can make use of imprecise information. As the amount of data collected grows constantly, overlooking imprecise and uncertain data is not feasible. Ontologies are regularly used for structuring knowledge for the Semantic Web, however, the traditionally used ontologies are not suitable for all contexts. Introducing fuzzy logic into this concoction creates a basis for new applications suitable for the Semantic Web.

The main contribution in this chapter lies in the combination of mobile technology and fuzzy ontologies with the goal of facilitating the mobilisation of knowledge. This would give the users the possibility to receive decision support through their mobile devices, regardless of the context and location they are in. To illustrate and validate this approach, different kinds of web platform applications have been developed to help users with choosing a suitable wine. Additionally, a version developed for the Android mobile platform is presented. These applications open the door for future developments in the knowledge mobilisation field, as it is demonstrated how one can use free and available techniques for utilizing tacit and imprecise knowledge.

This chapter is mostly based on the contributions from **papers 6 and 7**. Examples of fuzzy ontology applications are also presented in **papers 1, 2, 6 and 8**. The contributions in this chapter provide answers to **Research Questions 4 and 5**.

Paper 6

Wikström, R. (2013). Ontology of Imprecision and Fuzzy Ontology Applications.

Paper 7

Morente, J.A., Wikström, R., Herrera-Viedma, E. and Carlsson, C. (2014) Mobile Decision Support with Fuzzy Ontology.

Chapter 7, **Fuzzy Ontology for Real-Life Decisions**, presents some applications and solutions developed for solving real-life problems. This chapter provides a more practical view on how fuzzy ontologies can aid decision making and problem solving.

As the access to internet extends all over the world and the introduction of applications with semantic features is slowly starting to take off, it creates an environment that offers increasingly more opportunities for misuse. This means that security measures of different kinds are increasing in importance, which is especially relevant for organisations such as financial institutions. An attack towards a financial institute has lucrative rewards for the attackers, both material (funds) and immaterial (media attention). One critical problem as new types of intrusions appear continuously, is that novel detection systems have to be designed to be able to identify attacks that have never been experienced before, which naturally is cumbersome.

By utilizing insights provided by security experts one could create systems aimed at identifying these anomalies. By applying type-2 similarity measures for intrusion detection a framework based on fuzzy ontology and similarity measures to incorporate expert knowledge and represent imprecise information in the intrusion detection process is developed. This chapter presents the security situation, the similarity measures and the fuzzy ontology for intrusion detection, in more detail.

This chapter is mostly based on the contribution from **paper 8**. The results in this chapter validate the proposed solutions for **Research Question 4 and 5**.

Paper 8

Wikström, R., and Mezei, J. (2014). Intrusion Detection with Type-2 Fuzzy Ontologies.

Chapter 8, **Summary & Conclusions**, presents some discussions and conclusions as well as a summary of the contributions. Limitations, future research opportunities and possible directions are also pointed out. Thereafter, the **Bibliography** and **Publications** are included.

Chapter 2

Methodology

*“We can know more than we can tell”
- Polanyi*

Defining what information system (IS) research is and how one should study and develop information systems have been debatable questions, starting from the definition issues raised by e.g. Dickson et al. [90] and Ives et al. [154]. Research conducted inside the realm of the information systems discipline tends to be a combination of many different areas, for example business research and computer science. This creates an interdisciplinary environment, where the goal is to apply theories for solving the problems that occur in practical situations [24, 250]. This creates the need for interdisciplinary research in order to study how IS can be applied, for instance, inside organisations [42, 98].

Two widespread fields in IT and applied IS research are behavioural and Design Sciences, two paradigms that have slightly different goals and methodologies [201]. Behavioural research originates from e.g. sociology, psychology and natural science research methods and mainly aims at developing and justifying theories. The methods explain or predict how e.g. information systems affect organisations. The main issues studied with this research approach relate to the interactions between technology and people. Design Science, on the contrary, has its roots in engineering and, simplified, focuses on problem-solving. Based on existing theories, new artefacts are designed and implemented to solve pre-defined problems [141].

It should be noted that IS is not equivalent to IT-research. IT-research refers to a more comprehensive research field, subsuming the different subtopics, including IS. The definitions of what information systems actually are have been proven to vary greatly among users, supporting the claim that IS research is moving freely in an interdisciplinary environment [204]. In 1995, Silver et al. [256] stated that a physical Information System consists of 5 components: Hardware, Software, Data, Procedures and People. However, as a consequence of rapid developments in the area, defining IS research is more cumbersome. A recent definition is given by

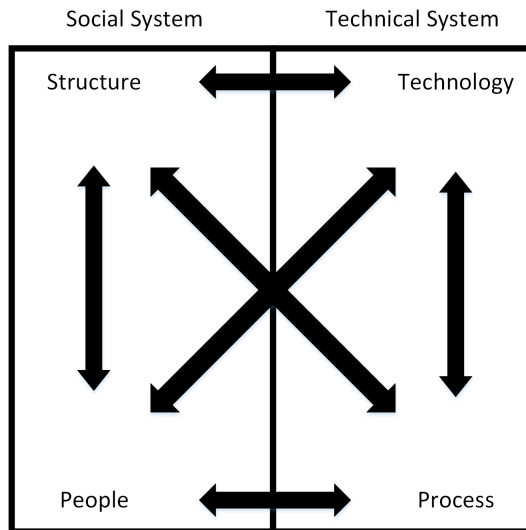


Figure 2.1: Information System Components [229]

Piccoli [229], who proposes that information systems consist of 4 key components, which all should be taken into consideration when conducting IS research and implementing IS in organisations:

- **Structure.** The design of an organisation. This includes, for instance, how the responsibilities are divided and how the reporting is performed.
- **Technology.** The technical solutions offered by the system.
- **People.** The individuals directly involved with the information system, with each individual having specific IT-skill levels.
- **Process.** The series of steps needed to complete a business activity. One example can be, receiving an order and processing it.

The components are all interconnected and affected by the changes performed inside the structure (see Figure 2.1). All these four components are necessary in an information system and they all need to be successfully employed for the whole system to function properly. In other words, one cannot fix all issues just by acquiring new technological solutions, if the other 3 components are lagging behind. This notion of “Systemic Effects” is important to stress. By overlooking one or several parts, one cannot expect that the system works in a fully satisfactory way [229].

A characteristic of IS research is that different research methodologies are used and combined for achieving the goals. In the early development of IS, methodologies like TACS (Tradition and Common Sense) were used, however, these have been abandoned or subsumed into the commonly used methods of today [287].

The available methodologies tend to be suitable for different steps in the IS development process, creating new combinations of already available methodologies [184, 213]. As countless different methodologies exist, the number of possible combinations are abundant [156]. It is always the researchers' responsibility to identify the most promising combinations and justify its choice.

This thesis can be positioned in the intersection of the business and the computational domains. Due to the nature of the projects undertaken for this thesis, Action Design Research (2.1), was a logical choice as primary methodology, as the IT artefacts developed were deliberately adapted and considered to be formed from the context they were created in/for. The developments of IT-artefacts carried out for the research was partly supported by meetings with the industrial partners and possible users of the applications. This approach open for possibilities to create and develop solutions that the users actually need [250]. At the same time, the feedback and gradual evaluations created good opportunities to improve the artefacts, including the reasoning processes conducted in the background. More specifically, the study presented drew inspiration and support from both Design Science and Action Research. The combination of these methodologies into Action Design Research created a good theoretical background to further build upon.

As improving organisational decision making on the operational level, especially how tacit expert knowledge can be utilized for this purpose, is the main application area for the research conducted, an introduction to the methods and recent developments of Decision Support Systems (2.2) is also presented in this chapter.

The emerging field of Analytics (2.3) and the provided methods and ways of thinking were implemented during the research project. Especially the business oriented branch of Analytics provides useful support and insights for the overall research process. At the same time, Positivism (2.4) worked as the main school of thinking for the mathematical advancements developed and validated. In other words, the main methodology Action Design Research draws influences and support from Decision Support Systems, Analytics and Positivism.

The Philosophical Questions (2.5) presented are touching upon the problems active in the thesis as a whole. There are a lot of unsolved problems regarding the creation and definition of intelligence, which naturally is a cumbersome challenge, as it is hard to define and comprehend something as diffuse as intelligence. The last section therefore presents a discussion circling around these subjects.

2.1 Action Design Research

Action Design Research (ADR) or Action Design Science was proposed as a solution for reinstating the original goal of IS research, namely to develop and apply IT artefacts in organisations [250]. Hevner et al. [141] states that the main goal in IS research is to find ways to improve the effectiveness and efficiency of organiza-

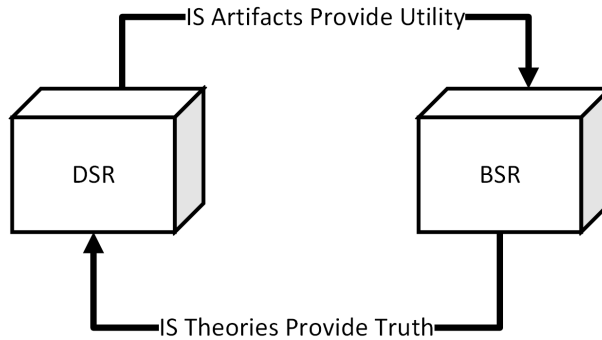


Figure 2.2: The complementary nature of Design Science Research and Behavioral Science Research [141]

tions. To achieve this, IS needs to build upon both Behavioural Science and Design Science, as they are inseparable in the contexts of information systems. Figure 2.2 shows in what sense Design Science and Behavioural Science are interacting.

Action Design Research originates from Action Research and Design Science:

Design Science

Design Science or design in general has been and is still central in most disciplines [141]. Hevner et al. [141] state that Design Science addresses two key issues regarding IS research; the role of the IT-artefact in IS research and the perceived lack of professional relevance.

Design Science has been applied in IS research in different ways for decades, although the paper by Hevner et al. [141] is the main point of reference regarding how one should conduct Design Science research in the context of Information Systems. To solve the issues with the contradicting nature of design and behavioural sciences and to solve the two key issues in IS research, Hevner et al. [141] introduced a framework that explains how IS research, implementing both sides, can be conducted in a successful way. As the research should work in a cycle, design science creates artefacts that are evaluated and studied in behavioural research, which then encourages further developments on the Design Science side. Design Science can, simplified, be defined as a method employed for solving problems.

Some disadvantages concerning Design Science have also been pointed out. Van et al. [285] state that Design Science generates a lot of data, creating problems when analysing and re-analysing the collected data. Hevner and Chatterjee [140] wrote that as DS is often performed in a specific domain, additional research might be needed in order to generalise the findings. It has also been pointed out that Design Science has to be performed with a stable theoretical base. If this is not upheld

the risk is that one creates a well designed artefact with no real use [141].

Action Research

The other cornerstone in ADR, Action Research, aims at understanding action processes [10]. The method for achieving this is to study how and why certain events actually happen and to draw conclusions and generalisations from these events, not limiting the conclusions only to the specific event studied. The term “Action Research ” was initially introduced by Kurt Lewin in 1946 [186], as there was a concern that one should find new methods for dealing with the critical social problems active at that time. Starting from his contribution, Action Research has developed into a key method for conducting organisational research.

Rapoport [235, p. 1] defines Action Research as:

”Action research aims to contribute to the practical concerns of people in an immediate problematic situation and to the goals of social science by joint collaboration within a mutually acceptable ethical framework“

In organisationally based Action Research, there are traditionally 5 phases to be followed when conducting Action Research [270]:

- Diagnostics: Identifying and defining the problem
- Action Planing: Defining the possible solutions to the problem
- Action taking: Selecting a solution
- Evaluation: Studying the consequence of the solution chosen
- Specify learning: Identifying the advantages / disadvantages generated

Action Research, formally, moved into the IS field thanks to the contribution by Wood-Harper [302] and was later on established as a valid method for IS research [15–17]. There is an ongoing discussion whether Action Research is a science at all, when evaluated from a positivist point of view. However, Action Research is assumed to represent a different kind of science, that produces knowledge which can extend the capacity and knowledge of the members in the organisation or context studied [270]. Discoveries from implementing Action Research have also been questioned due to its possible subjectivity, as practitioners indirectly might influence the results of the research according to their own believes, i.e. there is a need to emphasize a critical mindset [168]. Walsham [291] raised the concern about the extensive time consumption when performing interpretive research. Using another method, which is less time consuming, might make it possible to conduct several case studies in the same time frame.

Action Design Research

Based on previous work [18, 141], Sein et al. [250] proposed a solution that employs the Design Research method and simultaneously tries to create an innovative IT-artefact to solve organisational problems, and at the same time learn from the overall process. The ADR method aims at solving two main challenges; (i) define a problem in a certain organisational context and (ii) construct and evaluate an IT artefact that aims to solve the defined issues. The method cannot work with a stage-by-stage process, where one step is conducted and concluded before the next one is initiated, as ADR aims for continuous re-evaluation efforts. There are, however, defined stages and principles for ADR, presented next.

- Stage 1: Problem Formulation
- Stage 2: Building, Intervention, and Evaluation
- Stage 3: Reflection and Learning
- Stage 4: Formalization and Learning

Initially, the formulation of the problem is defined. The idea or basis for the project can originate from different kinds of sources, such as literature reviews or experiences by practitioners. The actual problem formulation might be supported by pre-investigations conducted by the participants. During this phase, the initial goal of the research is defined and the different roles of the instances participating are agreed upon. By extensively defining the goals and the task in the beginning, as well as from where the problem originates and draws its inspiration, one can more securely and confidentially continue on with the project.

One of the principles of ADR is that it should be practice-inspired, drawing inspiration from actual problems but aiming for the creation of new knowledge that is applicable also for other contexts than the initial problem. The problems imminent when handling imprecise and vague data in Decision Support Systems and Decision Making form the main inspiration for the research conducted. The aim is to present solutions for handling imprecise information in an operational context.

The second stage in ADR, Building, Intervention, and Evaluation (BIE), generates the design and initiates the purpose of the IT artefact, so that it fits the organizational use and may solve the issue which started the project. This process takes numerous iterations and cycles of changes and re-designs, during which the artefact is created and recreated, and also tested and evaluated. As the end users already at this stage can affect the end product, this stage ideally consumes significant time and effort. The BIE process can be dominated both by the IT-side as well as by the organisation. Analytics and Decision Making serve as the main tool and environment for inspiration of this research, offering both techniques and methods for building and evaluating artefacts.

The third part of ADR, Reflection and Learning, is conducted simultaneously with the two first stages. This stage pinpoints the fact that ADR involves more than the solution of a specific issue, one also needs to remember the research side. There is a need to draw wider conclusions and define general theories based on the results from the projects. Understanding and modelling information expressed through the use of language, e.g. by experts, is the general theme applied and conducted during this stage of the presented research.

As to bring closure to ADR, the Formalization and Learning section presents ideas and methods for formalizing the new knowledge discovered during the previous stages. This hopefully creates a general method that can be successfully applied for similar problems. Sein et al. [250] suggest following three steps when conducting the formalization: (i) reflect on the design and redesign during the project; (ii) evaluate adherence to principles; (iii) analyse intervention results according to stated goals.

Susman and Evered [270] state that as methods for studying organisations have become more advanced, this process has at the same time created less useful results for practitioners. Regardless of what method or principles form the bases of the research, Duan et al. [92] state that IS researchers should focus their developments on the requirements and inputs received from the users, and design and develop systems that follow these requirements. It is important to remember that IS research should aim towards transferring the research results to practitioners.

Creating something practically useful was an important task for the thesis. The contributions aimed at in this thesis were motivated by actual problem solving issues in different research projects: regular meetings were held with the partners, where the artefacts and their impact on the organisational work were constantly discussed and reviewed. This feedback was one of the central contributions required for the developed applications and used to develop their functionality. The feedback and evaluations received after the application was tested contributed with key information and guidelines for future development. Interaction with wine connoisseurs and wine amateurs was also central during the development and rule extraction process carried out for the Fuzzy Wine Ontology.

Chapter 7, presents an example of how the developed solutions and concepts have been applied for similar contexts and situations, but solving completely different issues.

2.2 Decision Support Systems

As decision making and the creation of Decision Support Systems (DSS) play a vital part in Analytics and the developments of the Artificial Intelligence field [146], the following section will introduce DSS in more detail and present some recent research directions. The applications presented later on in the thesis were created to aid with different kinds of decision making.

DSS (Decision Support System) research began with publications by, e.g. [8, 109, 258]; since then, the field has established itself as a broad and innovative area. A Decision Support System consists of three elements: an user interface subsystem, a database subsystem, and a model processing subsystem [121]. With the help of this structure, users are able to manage and analyse data for decision making purposes [7]. To ease the use of this system, the users usually access the system through an user interface. With the increasing popularity of the internet and the cloud possibilities, this has today embraced a more web based approach, where mobile devices provide the user the possibility to constantly have access to different decision support systems [77].

Knowledge is becoming more and more mobile, simultaneously, the traditional knowledge management methods will have to adapt to this change [253]. Users are today demanding (and expecting) decision support in all kinds of everyday situations, where everything, from choosing travel routes to what clothes to wear is assisted by a mobile device [286]. Even though increased decision support might make persons more apathetic, behavioural and physiological studies conducted about human behaviour and reasoning in decision making have clearly pointed out why we desperately need decision making support. Tversky and Kahneman are forerunners in this field. They have found that human decision making is not as fact-based as we would like to believe, as decisions and estimates are easily influenced by surrounding events. It is clear that decision makers of all kinds are in need of different kinds of help when making decisions [163, 164].

Using experts and their tacit knowledge optimally when making decisions has always been a challenge for decision makers [159]; however, different methods, such as fuzzy sets [313], make it possible to include also imprecise data into DSS, and extract useful knowledge from it. Based on current DSS research, it is possible to state that handling and computing with imprecise data and making this knowledge mobile and context adaptive is a very important research topic for the DSS community.

Combining this approach with group decision making, makes it possible to aid a group of users to reach consensus. Already in the 1980's, DSS was applied for solving group decision making problems. Logically, a Group Decision Support System (GDSS) aims at helping a group to reach consensus, whereas the traditional DSS's are aimed at helping an individual decision maker [113]. This aid can work in different ways, for instance, the support could minimize the differences between the different opinions of the group members, making a final consensus easier, or include external expert knowledge into the decision making process, to ease decision making.

In Group Decision Making (GDM), more preferences and factors are required to be taken into consideration, compared to individually tailored decision support; this makes the process and the development of GDM systems more complex. However, the possible benefits received from applying GDM have more potential.

Handling uncertainty is an important task when applying analytical methods,

as the goal is to achieve some kind of decision support, when choosing between options. The system needs to produce a limited number of alternatives. It is not feasible to provide the end result as a bunch of possibilities that may or may not occur. In the optimal situation the user is shown all the different alternatives, however, this would greatly limit the main task, which is to provide decision support. In other words, one needs to be rather precise and direct at some point in the process, as the user should be provided with a limited amount of alternatives to decide among, i.e. making the final decision greatly simplified.

It is highly debatable whether it is actually possible to construct reliable models based on uncertain and imprecise information, for instance when modelling tacit knowledge. By combining DSS with different methods and theories, such as fuzzy logic, one can incorporate uncertain factors into the calculations. In many cases, the users themselves are capable of choosing between a limited set of alternatives, if one manages to take uncertainty and imprecision into consideration but still provide this feature, then the users can themselves evaluate the final alternatives. This can be solved, for instance, by providing a degree of uncertainty regarding a specific alternative [57, 88, 198, 326].

2.3 Analytics

It is generally agreed that Analytics refers to the extensive use of ICT techniques to aid and support decision making and carrying out decisions. A well known definition was coined by Davenport [82, p. 7]:

“The extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact based management to drive decisions and actions“

As businesses today depend more and more on automated support for decision making, the interest in using Analytics has naturally increased, especially for profit-seeking organisations, as it offers new possibilities to increase the profit margins. The employees, on different levels, use information and data to make decisions and occasionally, decisions are made based solely on assumptions, experience, emotions or even based on a “hunch”. Research has concluded that this is not an appropriate method for reaching an optimal decision [4, 142, 143, 165], although exceptions exist. Human intuition tends to anchor to the wrong facts, which means that one needs to be careful when trying to incorporate human intuition into reasoning processes. Analytics therefore moves towards more advanced decision support systems, where the system points the decision makers in the right direction and removes some of the non-fact-based decisions but still utilizes some of the positive human “hunches” [11, 92].

2.3.1 Business Analytics (BA)

Analytics has gained enormous attention from the business sector, as companies are using Analytics for improving competitiveness and profitability [80, 190, 218]. Business Analytics (BA) is generally the term used for describing Analytics applied in a business context. Brynjolfsson [49] claims that this revolutionises innovation, as Analytics and information technologies are changing the whole structure and behaviour of companies. It provides businesses with new and better insights, with new methods and techniques constantly developed [174].

Oliveira et al. [218] argue that the main goal of BA is to increase the information processing capabilities of the organisation. However, many companies are only blindly aiming at increasing performance generally, instead of actually figuring out what kind of problems are needed to be solved. Having access to relevant knowledge would make it possible to adjust the decisions to the actual situation. By extracting useful information and patterns from the business data, the systems produce predictions for the future as well as suggestions to improve the current situation [199].

It may seem obvious that technology itself does not solve all the problems, but it is important to remember. The problem is that the promise to provide decision makers with information and knowledge has led to the rapid rise in popularity for BA, creating the illusion that Analytics and computers will solve all our problems. This has never been the case and it is still not the case. One has to remember that also other factors, like the persons using the system, will have an even greater impact on the end result [155, 279].

There are three main uses of Analytics: Descriptive Analytics, Predictive Analytics and Prescriptive Analytics. Descriptive and predictive are currently dominating the field, although, Prescriptive Analytics, the most challenging but at the same time the most rewarding approach has lately gained an increased interest. Figure 2.3 presents Delen and Demirkans [83] take on how BA is structured.

Descriptive Analytics

Descriptive Analytics is also referred to as business reporting and aims at finding explanations to what is currently happening and what has happened. This goal is basically achieved by producing different kinds of reports, using simple and traditional methods, such as OLAP. The users create charts and reports about different instances in an organisation, such as sales or budget. With the help of these reports, informed decisions are made, as the user can pinpoint the current opportunities and problems in the organisation, obtaining a rough overall picture which can help with steering the whole organisation towards the right direction. As visual and understandable reports are key in this area, Visual Analytics has a tendency to be mostly used for descriptive purposes [83, 100].

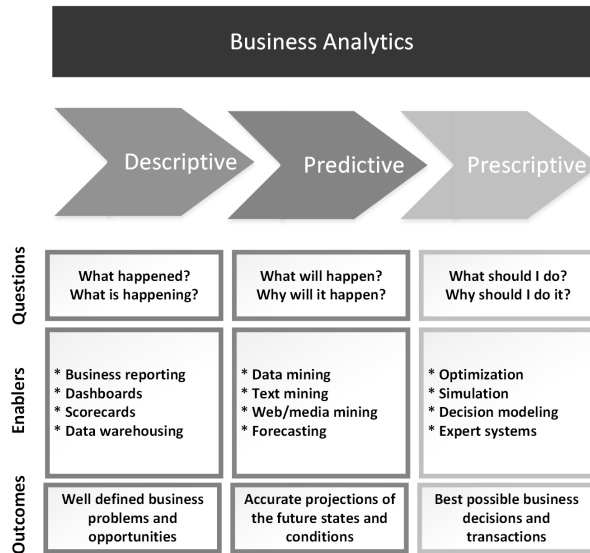


Figure 2.3: The three subareas of Business Analytics [83]

Predictive Analytics

Shmueli et al. [255] state that by predictive models, one usually refers to models that instead of explaining existing phenomena, are aimed at predicting the future or new observations with high accuracy. Predictive Analytics makes use of historical data to predict future developments. This is achieved by detecting patterns or relationships in the data, and then envisioning these relationships forward in time [100]. Examples of predictive models could be to predict future box-office sales based on online movie ratings [85]. By including more mathematical features when analysing the data, the process aims at finding patterns that represent the relationships between the different data instances, that are not detectable with traditional methods, thereby providing answers to what and why certain changes will happen in the future. A central goal is therefore to predict the future developments and also explain why the developments will happen. Examples of techniques used for this purpose are, for instance: data mining, text mining, time series analysis and agent technology [47, 84].

Prescriptive Analytics

Prescriptive Analytics could be seen as the third and final stage of the Business Analytics process. In this stage the aim is to produce answers on how different goals can be reached. Different kinds of optimizations are conducted to identify the best ways to reach pre-defined objectives. For instance, from a financial point of view, when one might want to create a low risk stock portfolio, prescriptive methods are used to create a portfolio which fulfils one's initial requirements [100].

As another example, a company might want to maximise the profit earned from a product by finding the ideal price at any given situation.

The algorithms used are based on a mixture of data and expert knowledge. Popular techniques include: optimization modeling, simulation modeling and multi-criteria decision modeling [83,94]. The mathematically supported techniques have also successfully been used to take into account uncertain data when making decisions [100]. There are significant differences between the three stages, especially regarding the tools and methods used. However, applications and models tend to make use of the whole Business Analytics spectrum.

2.3.2 Big Data in Analytics

An important reason for the increased usage of Analytics in the world of business is definitely the Big Data phenomenon. It has been estimated that the world produces 1.2 zettabytes (10^{21}) of electronic data each year, which ranges from the huge amounts of scientific data that is collected from experiments to Twitter and Facebook messages [304]. A big part of this data originates from companies, that are storing data at an incredible pace. According to Sakr et al. [242], Facebook serves 570 billion page views, stores 3 billion new photos per month and manages 25 billion pieces of content (i.e. status, comments), monthly.

Big Data can be defined as data that is too large to be loaded into the working memory of the computer [125] making the dataset too large or too unstructured to handle with conventional techniques. For instance, in a case where numerous different data types are combined, the analysis can be complex to manage. In addition to data size and data complexity, Douglas [91] defined big data from the perspective of three V's (volume, variety and velocity) which has later been extended with another V (veracity) by Zikopoulos et al. [327].

As Big Data also means complexity, it is a serious problem to overcome when implementing fuzzy ontologies for handling expert knowledge. The basic calculations tend to be relatively straightforward to compute, however, with an increasing amount of alternatives it inevitably creates a complex environment. Big Data and its possible solutions are therefore a relevant topic to take into consideration when creating decision support with fuzzy ontologies.

A recent study of 3,000 executives, managers and analysts working across over 30 industries and 100 countries [177] found that:

- Top performing organisations use Analytics five times more than lower performers
- Organisations that strongly agreed that “the use of business information and Analytics differentiates them within their industry” were twice as likely to be top performers as lower performers

- Compared to low performers, top performers were twice as likely to use Analytics to guide future strategies and twice as likely to use insights to guide day-to-day operations and make decisions based on rigorous analysis

The challenge of handling Big Data has not hindered an increasing amount of companies to explore the potentials in order to discover facts they did not know before and to support a more effective decision making process. Demirkan and Delen [86] expect that this increased interest in developing and studying Big Data will continue to soar also in the future. They call this age for the “Petabyte age”, characterized by the fact that traditional methods for analyzing and handling data are beginning to show their limits. As a result of this, several possible solutions for handling Big Data have been suggested [248]. Parallelization of the analysis process and a new approach on the algorithm side are general directions suggested.

It also has to be pointed out that even though one could handle Big Data, there is an issue with transporting it [248]. The network systems of today are not designed for distributing these kinds of data amounts, therefore, new approaches for distributing knowledge based on Big Data is needed. Schadt et al. [248] state that it is crucial to develop interoperable sets of analysis tools that can be run on different computational platforms depending on which is best suited for the given application.

Apart from this, one has to recognise the fact that the Big Data phenomenon is a bit of a buzzword and has received a lot of media attention due to this. In fact, some studies claim that both the treats and possibilities are exaggerated. A recent survey by SAS [247] shows that only about 12 percent of organisations are implementing or executing a Big Data strategy of any kind. As it is a fairly new movement, early adopters are sure to adapt Big Data before the rest will follow; however, there seems to be several open questions still about what Big Data actually is. One has to be critical and reasonable when dealing with the new methods and possibilities proposed in connection with Big Data.

2.4 Positivism

The theories about positivism emerged already during ancient times and have been debated and reformulated ever since. Auguste Comte suggested that knowledge passes through three stages: theological - metaphysical - positive. As the knowledge reached a positive stage, one could draw laws from that knowledge that could be implemented in society [21, 51].

The research conducted in this thesis was supported and improved by the development of new extensions to mathematical models. For developing mathematical models, the positivist view of the world is a crucial factor. To be able to prove that mathematical formulas and extensions are valid in the physical world, one need to conclude and believe that knowledge is based on experience that has been collected through experiments or observations. This knowledge should be seen as real and

valid knowledge representing the truth [76]. This means that the world operates based on a set of established laws, in other words that the laws apply both to the society as well as to the physical reality. In this way, all the results retrieved from the model that are behaving according to the definition, will work as a validation for the model as a whole.

An important fact to remember is the principle of falsifiability, stating that all scientific theories should be able to show what discovery or proof would falsify the whole theory. In other words, none of the theories can be proven to be completely true, as they are all awaiting the falsification; they are true until shown otherwise [231, 232]

Conducting research using the Scientific Method has, in one sense, never been easier, as the access to data and experiments is easily acquired online. Especially in fields connected to computers (which today include basically all fields), it has become possible for basically anyone to download and rerun programs and pieces of code, for the purpose of reproducing results and validate a theory [263].

As stated before, there is an ongoing scientific debate on how IS research should be conducted [172, 239, 298] and the different schools of thought have their limitations and benefits. The traditional debate between positivism and interpretivism has been upset by the introduction of new concepts such as critical realism, which could be seen as situated between these two realms, and post-positivism, which is based on positivism but adapts the theories to the current world view. Positivism has also been proclaimed as dead and outdated, partly because it has clear limitations when studying, for instance, human behaviour [51, 171, 228]. Regardless, as the research conducted in this thesis uses fuzzy numbers to store linguistic information expressed by experts, there is a need to state that these procedures are valid also for real world situations.

2.5 Philosophical Questions

The philosophical questions circulating the research areas of this thesis are certainly interesting, especially the discussion about how one could ever define something as abstract as intelligence. In one sense this seems like a waste of time, as the functionality of the systems should be the key, not whether they are intelligent or not (or whether they resemble human intelligence or not). However, if the goal is to create something that can be considered to be intelligent, then one needs to have a clear picture of what intelligence is, which would make it considerably easier to achieve. There are several schools in this field, with some stating that we will never create something which can show intelligence and others stating that we have already created intelligent machines, although not producing human intelligence [45, 106, 226, 322].

Heuristics and problem solving methods based on heuristics knowledge are interesting to take into account at this point. With heuristics, one refers to a problem

solving method which is fast but not always optimal, i.e. they can be used for finding a satisfactory solution in a short amount of time [224]. As Big Data and imprecise information create a lot of possibilities to over-analyse data (consuming time and resources), heuristics could aid with speeding up the problem solving process. This becomes increasingly more important as the problems are becoming more and more complex, making it hard for a single decision maker to grasp every detail. In these cases our intuition and decision making capabilities tend to fail as we lean more on heuristics and naturally the biases included. Being aware of both the negative as well as the positive effects of using heuristics is therefore important [272, 281].

In the following two Sections (2.5.1 and 2.5.2), some open questions are addressed and elaborated on. The goal is to address the research conducted in this thesis from a philosophical point of view.

2.5.1 Understanding and Modelling Language

Using human language and expressions in combination with computer systems immediately creates contradictions, as computer languages are not structured in a similar way as human languages and the reasoning process of humans is fundamentally different compared to computers. However, completely disregarding human language is unavoidable if one wants to fully utilize tacit knowledge. This incompatibility is mainly due to the fact that computers lack human experience, as they have not lived a human life. This creates issues with understanding sentences that contain tacit information, requiring a background story and knowledge to fully comprehend [249].

An issue worth discussing, acknowledged by, e.g. [244, 249], is why we demand that computers should fully comprehend and understand information expressed in human languages, as no human being fully understands their own native language in all situations and contexts. Is there a consensus that computers are not allowed to make any mistakes? As a first step, presumably it would be easier to achieve a non-perfect computer instead of a perfect, fail proof, computer.

One of the problems this boils down to is the ability to quickly grasp a situation and categorise the information after importance. A human user, due to previous experiences and stored patterns, can quite automatically distinguish the important issues in a context. For instance, if you enter an otherwise normal room, and notice a bomb lying in the middle of the room, you would quite quickly concentrate your available resources towards that object. However, a computer, not specifically designed to deal with bombs, would use its time and resources for analysing all objects in the room. This is, logically, not the best possible approach.

Ontology is one of the tools that researchers are suggesting as a solution for the above mentioned issues. As ontologies can show the relationships between instances and elements in a given context, they create a background story that can aid computers in understanding the overall picture. Ontologies are easily connected

with each other meaning that different context based ontologies can be combined into an ontology spanning over several contexts, this greatly aids the computers possibility to comprehend and understand human language [246]. If the computer, that entered the room containing the bomb, would have been aware of the fact that bombs are seldom situated in the middle of the room, it would probably have acted differently. Regarding the understanding of specific words, ontologies can instantly be shared, meaning that machines are automatically updated as a new word is introduced, making the maintenance of these computers greatly simplified.

An interesting thought is offered by Haugeland [123] when he states that the main problem with computers is that they, frankly, do not care. In other words they do not have the need, desire and reason to understand spoken language. This refers back to the initial idea that computers need to have the background story before they can fully grasp the new material provided to them. As they lack the human life and upbringing, they have no understanding what it means to be human and to share our values in life. Without providing the system with, at least, some insights into our world, it will definitely limit the functionality when computers are faced with the spoken language.

2.5.2 Artificial General Intelligence

Few researchers active in the field of Artificial Intelligence can surely claim that humanity will not, in the future, be able to create Artificial Intelligence of some kind. As new types of computer systems, that tend to be more based on biological advancements instead of just metallic structures, are being developed, the developments move more and more towards the human model, which we consider to be intelligent. The new ideas flourishing in the computer field will create computers that possess, today unimaginable, features. We have not only implemented biological features into our machines, but we are more and more connecting ourselves with mechanical devices providing us with extra features and possibilities.

There is a fear that by creating more intelligent machines, it would have a negative effect on humanity; however, the computers are limited to resources, meaning that they can not grow or function outside their limitations (precisely like humans). They are and will stay inside the boundaries defined by the designers. In other words, the computers and their Artificial Intelligence will exist in numerous different contexts and forms, with some having emotions and some having physical functions, all depending on their specific tasks. It is natural to be hesitant towards new developments and movements, however, steam engines created the same fuzz and insecurity when they were introduced [127].

The fact that we are more and more relying on different systems to provide us with guidelines and advice at all stages and contexts of life, our way of behaving and reasoning is also changing. Due to this, it is reasonable to debate how this will change our definition of intelligence and what we consider to be intelligent. The next generations of humans will probably view intelligence from another

perspective, as they will lack the same experience and background as the current generations. Today a simple task such as finding the right bus that goes via ones home requires different reasoning processes. How will individuals view this task in the future, if they have never been forced to perform that task, as the mobile device would have automatically instructed them to, for instance, jump onto bus nr. 42. One needs to pay attention to this also when designing Decision Support Systems that aid human decision makers. The systems should aim at mainly guiding and supporting the decision making, leaving room and space for the reflections and thoughts expressed by the users themselves. The new devices and systems that aid us in making good decision and survey our behaviour provide useful and life-saving benefits. It is not reasonable to assume that the developments in this field would slow down or stop,

The problem of defining and clearly stating what is intelligent and what is not intelligent has created some discussions; this is especially interesting when we are becoming increasingly more dependent on machines and computers, and as the line between human and computer is becoming more blurry, it creates further definition problems. Current systems are, intellectually, limited to certain contexts and domains. Even though they would behave in an intelligent fashion in a given context, they would not be capable of performing anything in another domain. This tendency appears frequently in Artificial Intelligence research, and due to this, [106, 226, 288, 295] defined a new research field called Artificial General Intelligence. The field aims towards creating an intelligence that is not limited to a specific context. This goal can be supported by defining intelligence as [301]: “the ability to behave appropriately under unpredictable conditions”.

When using fuzzy logic for the reasoning process, computers can be assigned to build their results on similarities with previous events and experiences. One can move away from the “if-then” rules, that in one sense limit the reasoning process to pre-defined scenarios. By removing this limitation, one can create systems that learn over time and resemble the functionalities of a human brain, such as creating predictions based on observed patterns [127].

By combining the best features of today’s systems, it is maybe possible to create a system that could adapt itself to new situations and contexts, somewhat proving the point that one can create something with general intelligence. In order to create a more realistic and useful general intelligence, there is a need for completely new methods, such as the ones being studied inside the boundaries of Computational Intelligence; it is not enough to try to work with traditional methods. New ideas, such as neural networks, ontologies and the studies of brain patterns are necessary pieces.

A possible solution to this issue was proposed by Haugeland [124] in 1985. He introduced the term Synthetic Intelligence that simplified states that machine intelligence is not limited to being artificial, but can exist in a more genuine form. Researchers should not try to imitate human intelligence with computers, but create a genuine, new intelligence that only computers can produce. In other words, one

should not be fixed with creating intelligence similar to what human intelligence constitutes of, but rather develop something intelligent based on the limitations that comes with being a computer.

As is can be noticed, there is a lot of doubts and questions still unresolved regarding the creation of Artificial Intelligence. However, it is a fact that the development in this field has gained increased speed and it is unlikely that it will slow down in the foreseeable future. One needs to remember that regardless of what one defines as intelligent, computers are being equipped more and more with advanced reasoning functions, which will create completely new support systems for humanity, which, if used properly, could aid with solving some of the critical issues and problems in our society today.

2.6 Summary

This chapter has introduced the main methodologies used for the research conducted and the novel results devised. The positivist world view and the Action Design Research methodology presented were used as the main pair of scientific inspiration. The methods were applied in the context of Analytics and decision making and created an entirety that represents the basis for this thesis.

The approach chosen raises several philosophical questions regarding the definition of intelligence and how and whether human knowledge can be modelled and used in information systems. Therefore these questions were discussed in more detail, to provide some sort of understanding on what philosophical thoughts were the inspirations for this thesis.

In the next Chapter, recent publications and foundational research results regarding Soft Computing, Fuzzy Ontology, Group Decision Making and Aggregation Operators are presented.

Chapter 3

State-of-the-Art

Fuzzy Ontology, Group Decision Making and Aggregation Operators

The society has dramatically changed during the last decades, essentially due to the possibility for basically anyone to easily access information and knowledge. This is usually referred to as the internet. However, the success of the internet originates from the fact that humans have adopted and embraced technology in a completely different way than ever before. These technical developments created a movement that has resulted in a world where it is relatively hard to cope without using any technical device. Very few people could have imagined how much these technologies actually would influence our daily lives [126, 193].

Individuals, groups and communities depend more and more on the support and aid received from devices of different kind. The desire for new features and functionalities is constantly growing, due to both human curiosity and laziness, but most likely due to the perceived usefulness. This results in an urge to develop new, ground-breaking methods and artefacts that can be used by the society.

The internet itself is, of course, situated in the center of new developments, with the Semantic Web movement leading the way [26]. This movement aims for taking the development to the next phase. Originally, one accessed the internet purely to receive information, and gradually, as the techniques evolved, it became possible also to add information to web pages, creating a read-write version of the internet. This introduced the concepts of communities (and its benefits) and flourished with websites such as Wikipedia.com or Facebook.com, websites where the users themselves are the ones creating the content (and value). A natural step for the future development is to introduce inputs that are generated in an automatic fashion, by the computers themselves [105].

To achieve this, one needs support and solutions from different research fields, one being Soft Computing and specifically the offered techniques needed for handling uncertainty, imprecision and tacit knowledge. Creating methods for handling these issues is vital for developing semantic applications for the Semantic Web. To better grasp the current situation surrounding this thesis, an extensive state-of-

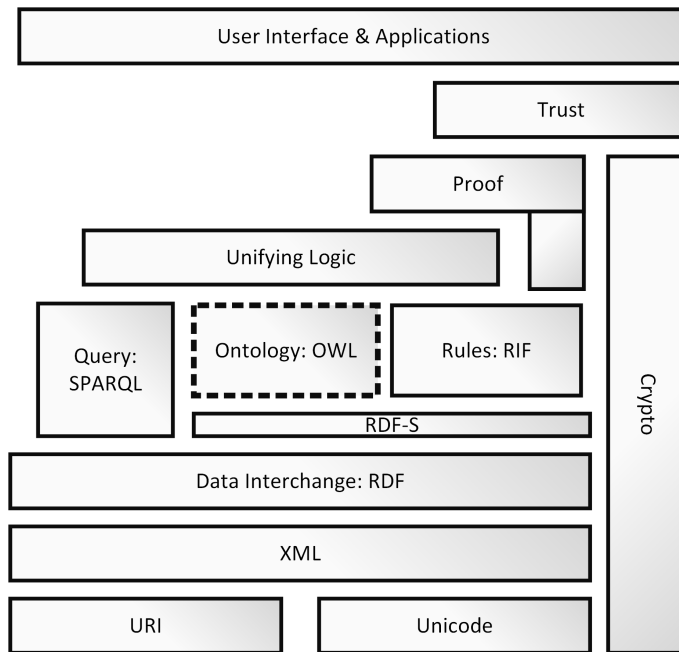


Figure 3.1: Version 4 of the Semantic Web “Birthday Cake” by Berners-Lee [25, 105]

the-art review has been conducted, to work as a basis for the novel developments presented later on in the thesis. The following chapter presents some of the recent developments in: Fuzzy Logic and The Semantic Web 3.1, Group Decision Making and Reaching Consensus 3.2 and Aggregation Operators (focusing on OWA operators) 3.3.

3.1 Fuzzy Ontology and the Semantic Web

The rapid evolution of the internet has created a demand for more automation and machine processable information. The Semantic Web offers completely new ways for processing and using information. Figure 3.1 shows the well known “Birthday Cake” diagram [25], explaining the structure of the Semantic Web. As can be noted, ontologies and the main ontology modelling language OWL, are situated in the middle of the cake, connecting the more data emphasized parts with the rule segments.

The birthday cake uses Unicode and URI (Uniform Resource Identifier) as the base foundation. This level represents the basic building stones of the Semantic Web, in which basic instances of data are created. Unicode provides a digital representation of the human language by offering an universal character encoding standard for characters and text. This makes it possible to encode multilingual

words and share and create global software. Currently, Unicode can represent and encode over 1 million different characters, enough to represent all the written languages of the world [283].

URIs provide a way for locating resources, both abstract and physical objects, for instance: an image, a pdf, and a person. It provides a string of characters that function as the unique identifier for the resource. The uniformity makes it possible to use different types of identifier in the same context, even if the access mechanisms used are different. By being able to identify specific entities, it facilitates the interaction between web-based resources [202].

Moving upwards in the cake, the next step is RDF, XML and similar techniques, offering a way to represent and combine the information expressed on a basic level. This can be presented as a “triple” , for instance, “X ownsA Car”. RDF provides syntax for representing information about resources, i.e. representing metadata; such as the title, the author and the date of creation for web-based documents. RDF was created for working together with URI and representing properties and metadata about instances defined with URI [200].

XML (Extensible Markup Language) is markup language that provides a way for encoding data into web documents, readable by both humans and machines. It was designed with functionality, simplicity and usability in mind. Drawing aid from Unicode, XML offers a possibility to share and create web-based documents, removing the language limitations [48].

Ontologies are then applied on these two levels with the goal of providing more metadata about this modelled data, as well as expressing the relationships and connections between the instances. Query-languages such as SPARQL also belong to this third level. After all these steps are implemented they can together be used for handling the rules and logics, the next feature to be included into the set-up. This logic would make inferences, answer queries and make decisions automatically.

The following two layers take on a less technical role. If one has a system up and running, based on specified rules, one also needs a method for validating and proving that the results are actually coming from the one claiming to send the information. Even if such a system was actualized, it still requires that the real users believe in this system and trust that it is actually correct. The whole Semantic Web package is then transmitted to the users via a user interface of some kind. The basic notion behind the cake is that all the higher levels depend on and build upon the previous lower levels, i.e. to reach a fully working Semantic Web, one needs to implement all levels of the cake. Crypto, or security measures of different kinds are surveying all the technically oriented levels [26].

3.1.1 Ontology

Ontologies provide a structure that can represent and explain how the vast amounts of data available (for instance online) are connected and what their internal

relationships are [96]. As ontologies can handle imprecise knowledge [39], model complex relations and easily be reused with other Semantic Web techniques, they were the natural choice to use for the cases worked on in this thesis.

The idea of ontologies was originally defined by Aristotle. During history it has been used by philosophers as a synonym for metaphysics or the study of existence. The ontological argument, referred to as the “Great Chain of Being”, used by, among others, Anselm of Canterbury [1033–1109], was popular during the medieval times in Europe. It states that the Supreme Being was the highest term in a scale of terms ranging downwards to infinity. This notion lives on still, although the Supreme Being is represented as the class **Thing** and actually represents the top class, from which everything else originates. If one would create an ontology about books, the library containing the books could work as the Supreme Being.

During the last 20 years, the term ontology has gained in popularity also in computer science and information systems fields. This is partly due to the search for Artificial Intelligence, as the researchers recognized that the key issue for developing advanced AI systems was to capture and represent knowledge in a feasible way. If this was possible, then the system would be able to view problems from the same point of view as humans, which would improve the automated reasoning [114,215].

There are several ontology definitions available, but the definition by Gruber [114, p. 1] is often referred to and is suitable to build upon:

“An ontology is an explicit specification of a conceptualization”

In this context, a conceptualisation represents the structure of the domain being modelled, i.e. how the instances are related and observed. By explicitly specifying this conceptualisation, one defines the concepts by using explicit terms and definitions [114, 116]. The main goal is to express knowledge about the individuals and instances in the ontology, as well as their relationships to each other. Usually, a specific domain is modelled, where the individuals have something in common, e.g. cars, with the different individuals as car brands or car models. In this way, most ontologies have a natural limitation to a specific domain [217]. An ontology could also be seen as a complex, domain specific vocabulary, that organizes and integrates data. They make it possible to link together all the information available on the Web, as well as to include real world resources, such as public libraries [128]. Also, ontologies have different roles depending on the context in which they are being used; on the Semantic Web, they represent the main technology for creating interoperability on a semantic level. The formal illustration of data can be shared and reused all over the Web. In other words, an ontology formulates and models the relationship between the concepts in a given domain [79].

In many applications, the information that can be used in the decision making process is available in the form of an ontology. However, classical (crisp / Boolean)

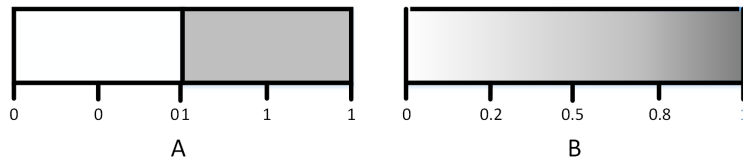


Figure 3.2: (A) Boolean Logic (B) Fuzzy Logic

ontologies are not appropriate to represent imprecise and vague knowledge [245]: To handle this problem, the concept of fuzzy ontology has been introduced, using the theories about fuzzy logic in combination with ontologies. With this consolidation, it becomes possible to model the domain and include the tacit and imprecise knowledge that is inherent in that context.

3.1.2 Fuzzy Logic

Fuzzy sets theory and fuzzy logic were originally proposed by Zadeh in 1965 [313]. The motivation was the fact that objects in the real world seldom have clearly-defined memberships to groups. In classical set theory, elements can exclusively belong to a set or not, but with fuzzy set theory it becomes possible for elements to belong to sets to some degree. Fuzzy logic is a branch in the extensive fuzzy set theory, where it represents a logical system which is able to deal with imprecise and uncertain knowledge. Incorrectly, fuzzy logic is sometimes used to refer to the whole fuzzy set theory.

It is also important to stress the fact that by implementing fuzzy logic it does not automatically mean that the end results will be imprecise or vague, one can produce as precise answers as one desires [175].

The basic difference between Boolean (crisp) logic and fuzzy logic is how the membership degree to different groups is defined and viewed. Boolean logic is limited to the values 0 and 1, or true or false, meaning that an instance either belongs or does not belong to a set. This is illustrated in Figure 3.2(A). As long as the value is on the left side of the defined value, it will be valued as 0 (false) and as soon as it has a higher value as the specific value it will tip over to the true side (1). With fuzzy logic, Figure 3.2(B), the membership value moves in a continuum between 0 and 1. This means that it can partly belong and partly not belong to the set at the same time. This gives more options when modelling imprecise data, making it possible to indicate that even though the membership value is not 1, it still has some similarities with the set and therefore, for instance, has the value 0.8.

The usefulness of fuzzy sets can be illustrated with the help of the following simple example. In the contexts of outside temperature, one wants to define how many degrees it should be outside before it is referred to as “cold”. Of course, this varies greatly based on the location one lives in and the person himself or herself. Regardless, if one would define -10 as cold, using Boolean logic, it would mean

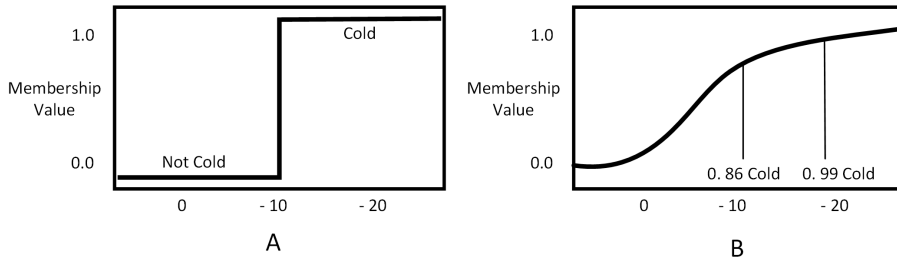


Figure 3.3: (A) Boolean Logic (B) Fuzzy Logic

that everything colder than -10 is referred to as “cold” and everything warmer is referred to as “not cold”. There is, however, a clear difference between -10 and -30, although they are both defined as “cold”. Figure 3.3(A) shows an illustration of this case expressed as Boolean. The fuzzy logic approach is to define “cold” with the use of the function presented in Figure 3.3(B). In that case, -10 is defined as having a membership value of 0.86 to “cold”, this means that -10 certainly can be considered as cold, however, -20, that has a membership value of 0.99, is definitely colder than -10.

This shows a clear benefit when using fuzzy logic, especially when one models imprecise and tacit knowledge. By using this approach, one can model the linguistic expressed knowledge provided, for instance, by experts in different fields.

The mathematical definition of a fuzzy set is:

Definition 1 ([313]). *Let X be a nonempty set. A fuzzy subset A of X is characterized by its membership function*

$$\mu_A : X \rightarrow [0, 1]$$

where $\mu_A(x)$ is interpreted as the degree of membership of element x in fuzzy set A for each $x \in X$

The possibility to use fuzzy logic to model imprecision, has over the years resulted in several applications and research projects. Several of these applications have later on been launched as fully working consumer / business products, implementing the theories of fuzzy logic [175]. Examples of these can be found already starting from the 1980’s and 1990’s, where fuzzy logic was successfully implemented in products for the home appliance industry [290], transportation [275] or improving the features of cameras / video cameras [254].

3.1.3 Fuzzy Ontology

The concept and idea of using fuzzy ontology as an extension of classical ontology has emerged during the last decade, with the hope of dealing with imprecise

and vague concepts [33]. As there are clear benefits with using fuzzy logic instead of crisp logic, these same features apply also for fuzzy ontologies, but adds the benefits received from the ontological side. Even though, Pena [225] already in the 1980's stated that using fuzzy logic in ontologies would be beneficial, research about fuzzy ontologies did barely exist before the start of this century. Pena mentioned, for instance, the following advantages with using fuzzy ontologies:

- Positing fuzzy predicates usually simplifies our theories in most scientific fields
- Fuzzy predicates are much more plausible, and give us a much more attractive and cohesive world view, than their crisp counterparts
- Degree-talk and comparative constructions

Lately, this statement has been supported several times [33,148,198,246]. Contrary to classical ontology, there exists no unique definition of fuzzy ontology: it is usually anchored to the specific domain or application area. Bobillo therefore simplified and generalised the definition by stating that a fuzzy ontology is [33, p. 67]:

“An ontology which uses fuzzy logic to provide a natural representation of imprecise and vague knowledge, and eases reasoning over it ”

A more mathematical definition will also be implemented in this thesis, in which, a fuzzy ontology is defined as a set of fuzzy relations [59,223]:

$$R_i : A_i \times B_i \rightarrow [0, 1]. \quad (3.1)$$

R_i can represent different types of relationships or dependencies:

$$\begin{aligned} &\{a_i \in A_i\} \text{ is_part_of } \{b_i \in B_i\}, \\ &\{a_i \in A_i\} \text{ has_property } \{b_i \in B_i\}, \end{aligned}$$

with $R_i(a_i, b_i)$ describing the degree of the strength of the relation. The values of the relation are usually determined by experts or estimated using different sources of information [266]. Baader et al. [13] and Calegari et al. [55] provide a definition of a fuzzy ontology which is more illustrative:

Definition 2. *A fuzzy ontology is a quintuple*

$$O_F = \{I, C, R, F, A\}$$

where:

I = the set of individuals,

C = the set of concepts,

R = the set of relations,

F = the set of fuzzy relations

A = the set of axioms

After the fuzzy ontology is created, the reasoning can be performed using different classes of a fuzzy description logic. The *fuzzyDL* reasoner is the most used reasoner in this thesis [33]. This reasoner and some others are presented in more detail in Section 3.1.5.

Even though research conducted with fuzzy ontologies can be considered to be a young research field, there has, in recent years, been an increased amount of publications about fuzzy ontologies, as the field is beginning to “pick up speed”. Examples of some domains in which fuzzy ontologies have been applied are:

- Information retrieval [324]
- E-learning [102]
- Medically aimed applications [223]
- Weather forecasting [278]
- Terrorism prevention [152]
- Intrusion detection [46, 89, 274]
- Change management [158]

Aiding decision making processes with support received from fuzzy ontologies is the general application area for the research conducted in this thesis. As it can be noted, the use of fuzzy logic is not limited to this area alone.

Decision making with a fuzzy ontology

Since the introduction of fuzzy logic in the context of decision making [23], fuzzy sets and possibility theory have become widely used alternatives to model uncertainty. When facing incomplete, imprecise or vague information, decision support systems based on fuzzy modelling provide useful tools, offering the decision makers aid and insights which otherwise would have gone unnoticed.

For decision making processes, it is possible to store the information in the form of an ontology [267]. However, as concluded before, Boolean based, crisp ontologies are not appropriate to handle imprecise and tacit knowledge [246]: This issue can be handled by introducing fuzzy ontology into the contexts of decision making. In recent years, this approach has been widely supported as decision making has been identified as one of the most potential application areas of fuzzy ontology/fuzzy description logic [2, 59, 192, 267].

Fuzzy sets can, for instance, be incorporated into the contexts of decision making by implementing fuzzy relations:

Example 1. A fuzzy relation R_i can be seen as the evaluation of a set of different alternatives (A_i) based on a set of given criteria (B_i). From this observation, the values of the relation can be interpreted as

$$R_i(a_j, b_k) = \begin{cases} 1, & \text{if } a_j \text{ definitely satisfies criterion } b_k \\ \alpha \in]0, 1[, & \text{if } a_j \text{ more or less satisfies criterion } b_k \\ 0, & \text{if } a_j \text{ does not satisfy criterion } b_k \text{ at all} \end{cases}$$

As it has been stated before, it should be noted that there is not always a need to use fuzzy values, as some of the attributes can be clearly defined with crisp values.

3.1.4 Type-2 Fuzzy Ontology

The originally proposed fuzzy set (also called type-1 fuzzy set) received criticism as the membership function itself was not imprecise and it was not possible to define it as imprecise either. Type-2 fuzzy sets were therefore introduced by Zadeh [315], adding this feature to fuzzy sets.

Type-2 fuzzy sets make it possible to model and minimize the imprecision, in a more effective way than when using type-1 fuzzy sets. In comparison to type-1 fuzzy sets, where the membership values are crisp, type-2 fuzzy sets are characterized by having fuzzy values as membership functions, making it possible to include uncertainty and imprecision also in the membership function itself. The three-dimensional membership function of type-2 fuzzy sets enables a better modelling of imprecision, creating more options to define different opinions.

Figure 3.4 shows a visualisation of a type-2 fuzzy set, where the three dimensional structure is visualised. The gray triangle represents an excerpt from the whole type-2 fuzzy set, showing that the membership function itself is uncertain. Type-2 fuzzy sets create an interval moving in three dimensions, creating a space in which all the possible values can be situated.

A special class of type-2 fuzzy sets is the class of interval-valued fuzzy sets (IVFS). Interval-valued fuzzy sets play an important part in the research conducted in this thesis and at the same time they are the most used subclass of type-2 fuzzy sets. IVFS's have proved to be useful for computational intelligence problems, because they specify interval-valued degrees of membership to each element, as there is a lack of objective procedures for selecting a crisp membership degree for the elements in a fuzzy set [315]. An interval-valued fuzzy set is formally defined as:

Definition 3 ([110]). An interval-valued fuzzy set A defined on X is given by

$$A = \{(x, [\mu_A^L(x), \mu_A^U(x)])\}, x \in X,$$

where $\mu_A^L(x), \mu_A^U(x) : X \rightarrow [0, 1]; \forall x \in X, \mu_A^L(x) \leq \mu_A^U(x)$, the ordinary fuzzy set $\mu_A^L(x)$ is called a lower fuzzy set and $\mu_A^U(x)$ is called an upper fuzzy set of A .

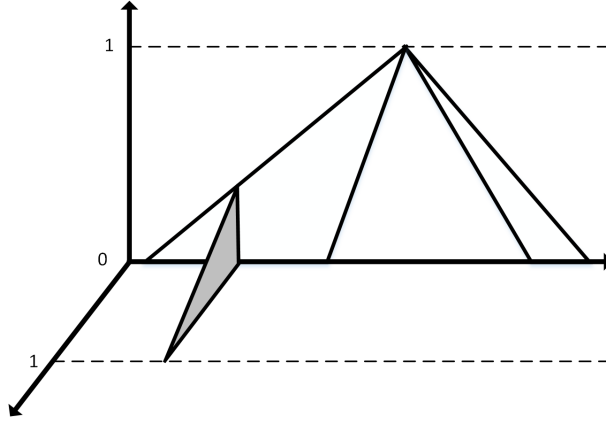


Figure 3.4: A Type-2 Fuzzy Set

The notation $\bar{\mu}_A(x) = [\mu_A^L(x), \mu_A^U(x)]$ is used for the interval assigned to x . $\bar{\mu}_A(x)$ can be seen as an interval-valued function from X to $[I] = \{[a, b] : a \leq b, a, b \in I\}$. All interval-valued fuzzy sets on X are denoted by $IVF(X)$. Since every $A \in IVF(\mathbb{R})$ is uniquely associated with the corresponding membership function, throughout the thesis the notation $A(x) = \bar{\mu}_A(x)$ and similarly for the upper and lower fuzzy sets are used. A subclass of $IVF(\mathbb{R})$: interval-valued fuzzy numbers (IVFN), is simply the case when $A^L(x)$ and $A^U(x)$ are ordinary fuzzy numbers.

For the α -level sets of $A^L(x)$ and $A^U(x)$ the notations $[A^L(x)]^\alpha = [a_1(\alpha), a_2(\alpha)]$, $[A^U(x)]^\alpha = [a^1(\alpha), a^2(\alpha)]$ and $[A]^\alpha = ([A^L(x)]^\alpha, [A^U(x)]^\alpha)$ are used. The arithmetic operations of interval-valued fuzzy numbers can be defined using γ -cuts and the Extension Principle [315].

If $A, B \in IVFN$ with upper and lower membership functions $A^L(x)$, $A^U(x)$ and $B^L(x)$, $B^U(x)$, then the α -cuts of the upper and lower membership functions of $A * B$, where $*$ $\in \{+, -, *\}$ are the following:

$$[(A * B)^U]^\alpha = [a^1(\alpha), a^2(\alpha)] * [b^1(\alpha), b^2(\alpha)]$$

and

$$[(A * B)^L]^\alpha = [a_1(\alpha), a_2(\alpha)] * [b_1(\alpha), b_2(\alpha)].$$

If $A \in IVFN$, then $B \in \mathcal{F}$ is an embedded fuzzy number of A if

$$A^L(x) \leq B(x) \leq A^U(x),$$

for all $x \in \mathbb{R}$. The set of all the embedded fuzzy numbers of $A \in IVFN$ will be denoted by $\mathcal{F}(A)$.

In this thesis the mean value of $A \in IVFN$ [61] is used extensively:

Definition 4. The mean (or expected) value of $A \in IVFN$ is defined as

$$E(A) = \int_0^1 \alpha (M(U_\alpha) + M(L_\alpha)) d\alpha, \quad (3.2)$$

where U_α and L_α are uniform probability distributions defined on $[A^U]^\alpha$ and $[A^L]^\alpha$, respectively, and M stands for the probabilistic mean operator.

Although the applications using type-2 fuzzy sets are more limited than type-1 fuzzy sets, some interesting approaches have been presented. Gu and Zhang [118] created a browser-based application, where type-2 fuzzy sets were applied for modelling expert knowledge. Based on the input from the user, the system uses stored expert knowledge for generating house buying advice.

The same differences and benefits regarding type-1 and type-2 fuzzy sets are valid also for type-1 and type-2 fuzzy ontologies. By increasing the possibilities to model uncertainty and imprecision, one has a greater opportunity to capture, for instance, tacit knowledge. Introducing type-2 fuzzy sets in combination with ontologies offers a significant step towards modelling imprecision and implementing tacit knowledge into different reasoning processes and problem solving scenarios.

In this thesis we will define the interval type-2 fuzzy ontology as a set of fuzzy relations [59, 223]:

$$R_i : A_i \times B_i \rightarrow I_{\leq}^2, \quad (3.3)$$

where $I_{\leq}^2 = \{[a, b] \subseteq [0, 1] \mid a \leq b\}$.

R_i represents the same relationships or dependencies as in 3.1.

Recently, combinations of type-2 fuzzy sets and ontologies have started to appear more frequently among publications, although one can clearly see that the combination is a fairly unexplored territory. Li et al. [187] introduced a type-2 fuzzy version of the description logic *ALC* (Attributive Concept Language with Complements) and implemented it together with type-2 fuzzy OWL. This contribution supports the claim that type-2 fuzzy ontologies can deal with imprecise knowledge more efficiently than type-1 fuzzy ontologies.

Lee et al. [179–181] have successfully applied type-2 fuzzy ontologies for applications aimed at personal diabetic-diet recommendations. Currently, the application is based on the Fuzzy Markup Language, but the goal is to apply it also for OWL. Bukhari and Kim [50] have created a type-2 fuzzy ontology and applied it on a multi-agent platform to create a fully automatic air ticket booking system.

These successful application-centred articles show that there is a market and a need for type-2 fuzzy ontologies and the benefit they provide.

3.1.5 Software and Techniques

The artefacts devised in this thesis draw upon several techniques. Both new ideas and well-known techniques were employed. An underlying idea was to use open source and free techniques as much as possible. This supports the general idea behind the Semantic Web, where information is accessible, reusable and modifiable

by anyone, making it possible for new revolutionizing applications to be invented and constructed. By limiting access to knowledge and knowledge management techniques, it would certainly limit the overall success of the whole Semantic Web movement.

This section presents the main techniques used for creating the applications presented in this thesis. One could even claim that some of these techniques are and will be the base for future developments for the Semantic Web.

OWL

The Web Ontology Language (OWL) is a family of knowledge representation languages for creating ontologies. The language provides classes, properties and entities that make it possible to create ontologies that can be subsumed and used by other Semantic Web techniques [145].

OWL is formally supported by the World Wide Web Consortium (W3C) and is proposed as the standard language to be used when creating ontologies for internet use. It would greatly increase the usability if all knowledge would be expressed using the same language, i.e. even though there might exist other options, choosing one and sticking with it is definitely beneficial in this case. OWL was designed with the notion that it should work together with information stored in RDF (Resource Description Framework), although OWL works on a higher level, creating order and structure from the information expressed with RDF [144, 145].

Recently, OWL ontologies have been applied in several contexts. Valiente et al. [284] created Onto-ITIL, an OWL ontology that aims at easing the integration of business information and IT. The ontology, simplified, makes it easier to minimize the gap between customer needs and the IT services that actually are provided to customers. Bastinos et al. [20] created a multi-criteria decision making method for OWL ontologies. It adds decision making support to ontologies, which, for instance, can be used in knowledge management systems. The decision making process is, in other words, included in the ontology itself. Haghghi et al. [122] used ontologies and OWL for intelligent decision support for medical emergency management. They also stated that there is still no generic agreement on how ontologies aimed for knowledge management and decision-making should be constructed. Chen [69] adopted ontology techniques to develop methods for retrieving empirical knowledge from models and using it for problem solving and decision support.

The recent publications clearly show the general direction for the ontology community as a whole, i.e. that ontologies are being used more and more for decision making purposes. Additionally, OWL has established itself as the main ontology modelling language for creating ontologies. However, there are still numerous possible improvements and implementations yet to be discovered [20], for instance, the utilization of tacit and imprecise knowledge in ontologies. This would be an important step, in order for the Semantic Web to reach its full potential.

Java

The Java language was originally developed by Gosling [111] (amongst others), and is today established as one of the main programming languages, especially for internet affiliated purposes. Although the language was originally created for use in embedded consumer-electronic applications, it gradually evolved into a language applied for online purposes.

Java can be defined as [194]:

“A general-purpose concurrent class-based object-oriented programming language, where minimizing the implementation dependencies is the key goal”

This should allow a program code to function platform independently, throughout the internet [160]. As Java is a popular language, it implies that there is a lot of support to be found from different communities created around the language; at the same time there are plenty of interesting applications available to draw inspiration from.

An interesting example of what Java can be used for is presented by Durillo and Nebro [95]; they developed a Java framework called jMetal, including a graphical user interface (GUI), which can be used for solving multi-objective optimization problems. For the research carried out in this thesis, Java worked as the main environment for handling, displaying and distributing the fuzzyDL queries and results between the server and the user. With the use of Java, in combination with only the fuzzyDL reasoner, it is possible to solve complex DM problems, avoiding the use of the command prompt.

Java is also the language used for creating the different servers implemented for deploying the applications. The GlassFish server (glassfish.java.net), is an open-source application server supported by Oracle. As of May 2014, version 4.0 is the latest update available for download. The Tomcat application server (tomcat.apache.org) is an open-source server developed by the Apache Software Foundation (ASF). In May 2014, version 8 is the latest version available for download.

Protégé

The development process of ontologies has been greatly supported by the creation of software aimed at making the ontology modelling process more feasible. The most noticeable software for OWL ontology creation is, undoubtedly, Protégé,¹ an ontology creation tool that was originally developed as a metatool for use in the area of knowledge-acquisition in medical planning [214].

Knublauch et al. [173] noticed that the demand for a software that could model ontologies using OWL was crucial, especially due to the emergence of the Semantic Web and the increased desire to capture knowledge in different ways. They

¹The software is available at <http://protege.stanford.edu/>

therefore developed an OWL plug-in for Protégé, enabling developers to save and edit OWL ontologies, avoiding a direct treatment of OWL syntaxes. Today, Protégé is an open-source tool that supports a wide range of different languages, such as RDF and XML.

For the applications and ontologies created in this thesis, the two most important benefits of Protégé are:

- The possibility to create ontologies in OWL, avoiding the direct treatment of OWL syntaxes.
- The plugins that help with enhancing its functionality, e.g. the Fuzzy OWL plugin [39] and the Matrix plug-in.

The *fuzzyDL* Reasoner

A Description Logic (DL) could be seen as a frame-based knowledge representation language, with the basic goal of capturing knowledge; this goal coincides with the goal of the Semantic Web, especially for the OWL language where Description Logic is central. The combination of DL and OWL alone does not make it suitable for handling imprecise and uncertain data [266, 268]. Therefore, Straccia [266] took the first step towards enabling the use of fuzzy sets for ontologies written in OWL by developing a fuzzy version of $SHOIN^{(D)}$, which is the DL language used in the OWL-DL version of OWL ontologies (OWL 2 is based on $SROIQ^{(D)}$ and OWL-Lite is based on $SHIF^{(D)}$). In [267], Straccia introduced the idea that fuzzy Description Logic is a suitable method for dealing with Multi-Criteria Decision Making (MCDM) problems.

To further develop the possibility to use fuzzy OWL ontologies for different reasoning purposes, the *fuzzyDL* system was created by Bobillo and Straccia [36]; it is an expressive fuzzy description logic reasoner, i.e. it makes it possible to reason with fuzzy description logic modelled in OWL. The *fuzzyDL* reasoner, included in the system, is able to extend the Description Logic $SHIF(D)$ with fuzzy sets and also reason with that model. This allows the user to define fuzzy concepts by using left-shoulder, right-shoulder, triangular and trapezoidal membership functions [39]. With [37], the first steps towards modelling fuzzy ontologies in OWL 2 was successfully conducted: the *fuzzyDL* system supports the latest version of the Web Ontology Language. In [37], the first steps towards developing a *fuzzyDL* plug-in for Protégé were taken and later completed in [39].

Recently, Bobillo and Straccia [38, 41] stated that aggregation operators have this far been overlooked. Nevertheless, they show that by integrating aggregation operators, such as weighted average or OWA operators with fuzzy ontologies, several new application areas can be approached.

Thanks to the possibility of using *fuzzyDL* together with OWL ontologies, the door for combining fuzzy OWL ontologies with Semantic Web applications is open. This observation and the fact that OWL is the main ontology language

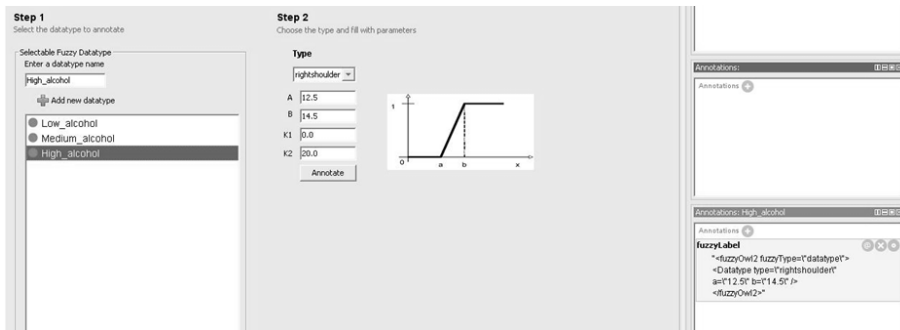


Figure 3.5: Excerpt from the *fuzzyDL* plug-in for Protégé

used for the Semantic Web, are the main reasons for using the *fuzzyDL* reasoner for the research carried out in this thesis. The different fuzzy ontologies modelled in OWL support the reasoning processes by using the *fuzzyDL* reasoner and the Gurobi optimizer.

fuzzyDL plug-in

To make use of the *fuzzyDL* reasoner more convenient, Bobillo and Straccia [39] developed a plug-in² for Protégé that integrates OWL with the *fuzzyDL* reasoner, offering the possibility to add, for instance, fuzzy datatypes, fuzzy modified concepts and weighted concepts to the OWL based ontology. The plug-in also translates the .owl file automatically to a format processable by the *fuzzyDL* reasoner, making it possible to submit queries directly to the reasoner by using Protégé.

The graphical user interface of this plug-in makes it an important step towards including fuzzy logic in OWL and making fuzzy logic available for the general user, as defining fuzzy membership functions for the OWL ontology can be performed in a simple way. At the same time this will make it possible to deal with the vague information that has been troublesome for the Semantic Web techniques.

Gurobi Optimizer

The programs created for handling optimization problems are constantly becoming more sophisticated. Well known software includes CPLEX, XPRESS and Gurobi. Gurobi is capable of solving linear programming (LP), quadratic programming (QP), quadratically constrained programming (QCP), mixed integer linear programming (MILP), mixed-integer quadratic programming (MIQP), and mixed-integer quadratically constrained programming (MIQCP) [119].

²The software is available at <http://gaia.isti.cnr.it/straccia/software/fuzzyDL/fuzzyDL.html>

Gurobi was created by Zonghao Gu, Edward Rothberg and Robert Bixby [31], where the last names inspired the name of the optimizer. Gurobi was designed with multi-core processors in mind, in other words, it is well suited for modern computers. Gurobi is today considered to be one of the top optimization suites available and is, according to conducted experiments, the fastest LP-solver available [120].

In this thesis, the Gurobi optimizer was solely used in connection with fuzzyDL to aid with the conducted calculation processes.

Other Fuzzy Logic based software and reasoners

Other software solutions for reasoning with fuzzy ontologies implementing fuzzy sets have been developed:

DeLorean (DEscription LOGic REasoner with vAGueNess), is a fuzzy rough Description Logic (DL) reasoner; it supports fuzzy rough extensions of the fuzzy DLs $SROIQ^{(D)}$ and $SHOIN^{(D)}$, i.e. also OWL 2. [33]. The reasoner is basically a translator between the fuzzy ontology language and the normal OWL language. The translated version still contains semantic features and can be reasoned with using a normal DL reasoner [34, 35].

FiRE is a Java-based, fuzzy reasoning engine based on the fuzzy Description Logic $f_{KD} - SHIN$. The FiRE engine was, probably, the first graphical software which used fuzzy logic in the DL knowledge base [260, 264].

The Fuzzy Markup Language (FML) is a fuzzy logic-based markup language that can be implemented for describing the functionality of a fuzzy system. It is based on XML and works as a middleware between the hardware running the application and the fuzzy control system. FML can also be applied for ontology purposes [1, 2].

The Fuzzy Ontology Framework (FOF) [261] aims at integrating object-oriented programming classes, written in .NET, with OWL based fuzzy ontologies. By implementing ontologies (and fuzzy ontologies) into new techniques, such as OPP and .Net, and at the same time creating adaptable and flexible software, it effectively shows the benefits and compatibility of ontologies.

ONTOSEARCH2 is an ontology search engine that can implement fuzzy logic. Originally, the engine made it possible to search and query web ontologies and then store them using tractable Description Logic; by utilizing SPARQL, one can query the stored ontologies. By combining this with a fuzzyDL-lite query engine, it became possible to handle general fuzzy queries [220, 276].

DLMEDIA [269] is an ontology mediated multimedia information retrieval system, where ontologies serve as the layer used for defining the concepts and relations of the domain. It implements a representation language that resembles the fuzzy Description Logic developed by [265, 266, 268].


Directive	Individual Dominance
	Minority Influence
	Majority Rules
Participatory	Consensus

Figure 3.6: The spectrum of GDM methods

3.2 Group Decision Making and Reaching Consensus

Decision making in a group setting offers a lot of advantages and limitations at the same time. Reaching a consensus is a complicated process as there are different opinions involved. The different group members may all have personal reasons for requiring certain criteria to be fulfilled. These reasons might not even be based on facts, but be influenced by other reasons. Nevertheless, more persons involved in the process also mean that the amount of knowledge should be higher in the group than in a single individual. More knowledge should, if handled correctly, result in a better decision.

From an organisational point of view, encouraging group decision making processes results in a more motivated work force. As people are involved in the process, they also feel more involved in the company strategy and overall goals. There is a need to develop methods to fully utilize group knowledge, and the reasoning, such as the use of tactics and weapons of influence that might shift the groups decision towards a non-knowledge based decision.

Group Decision Making

Group decision making has a rather long scientific tradition, with the first articles published already in the late 1970's [32, 185]. Group decision making is still an active research field: new algorithms for supporting different aspects of the decision making process and adding new functionalities are consistently being introduced. Examples of recent publications include the article by Yu et al. [311], where a distance-based group decision making methodology is proposed in order to solve multi-person multi-criteria decision making problems in case of emergencies such as earthquakes and hurricanes. In [304], a support model for group decision making that uses multiplicative relations, consistency and consensus measures to assist the decision making process is presented. Lan et al. [176] employ induced uncertain linguistic OWA operators for creating a group decision making algorithm.

There are several methods that can be applied for group decision making. Figure 3.6 shows the major characteristics regarding the GDM methods, classified

along a spectrum, starting from directive and going towards participatory decision making.

The methods that are situated closer to the directive range imply that the decision is made by a small number of decision makers. An example of a directive method is the individual dominance method, where one person in the group has the authority or power to make a final decision, regardless of the other participants' opinions. On the other hand, the methods that are situated closer to the participatory range imply that the decision is made by all the parties involved. For example, the majority rule method usually involves a group voting of some kind, where the alternative receiving the most votes wins. The consensus method follows the same basic idea, a consensual agreement is achieved through group discussion, where all the participants are able to voice their personal opinion regarding the decision [169].

Although a lot of material is available regarding how GDM processes should be conducted, there are still areas, such as dealing with uncertainty, that are not fully charted. The introduction of new technological advancements also changes the setting for the performance of GDM. There have been some recent developments regarding these topics. Choudhury et al. [74] used fuzzy preference relations for handling uncertain factors when reaching consensus in a group. Yue [312] developed an approach to aggregate interval data into interval-valued intuitionistic fuzzy information and applied it for GDM purposes. Khalili-Damghani and Sadi-Nezhad [170] created a novel hybrid fuzzy multiple criteria GDM approach for project selection.

3.3 Aggregation Operators

In many situations and contexts, it is a necessary task to aggregate across different criteria, creating an overall value that can be used for decision making. In other words, aggregation refers to the process of combining numerical values into a single number, representing the original set of numbers [112]. A context where aggregation is frequently used is in the previously presented group decision making. There is a possibility that there exist different relationships between the criteria used in the aggregation. This can be approached by introducing different weights into the aggregation process, assigning some values a stronger influence on the final aggregated value.

Many different aggregation approaches take for granted that the values, that should be taken into consideration, are based on precise data. Naturally, this is seldom the case, especially as data collection methods and systems are becoming more advanced and complex; it means that more imprecise and uncertain data has to be modelled. This problem becomes even more noticeable when one considers the human factor (e.g. expert knowledge) which is more and more inherent in decision making processes and therefore, inevitably, in aggregation. Bellman and

Zadeh [23] and Zimmermann [328] highlighted this dilemma already in the 1970's.

Aggregation can and should be used in a lot of different contexts, and it has become a key factor for reasoning and making decisions with the help of ontologies. For instance, Bobillo and Straccia [41] successfully applied aggregation operators in fuzzy description logic. Aggregation operators in combination with ontologies offer a good package for processing and modelling imprecise information and tacit knowledge.

3.3.1 OWA Operators

Yager [307] stated that aggregation operations are based on two extremes; one extreme is where the goal is to satisfy all the criteria and the other extreme is when one wants to satisfy any criterion. This can be approached by introducing “and” and “or” operators. For example, one wants to find the most suitable alternative, amongst a set of alternatives, where each alternative has 4 measures to consider. Using the “and” approach, the alternative which has the highest overall value, when all 4 measures are combined, will be chosen. If the “or” approach is used, the alternative which has the single highest measure (regardless of the other measures), will be selected. Yager [307] therefore introduced the ordered weighted averaging (OWA) operator for dealing with this phenomenon. Since then, the OWA operator has been extended and redeveloped numerous times.

Definition 5 ([307]). *An OWA function is a mapping $OWA_{\mathbf{w}} : [0, 1]^N \rightarrow [0, 1]$ with an associated vector $\mathbf{w} = (w_1, \dots, w_N)$ such that $\sum_{i=1}^N w_i = 1$ and $w_i \in [0, 1] \forall i$.*

Furthermore,

$$OWA_{\mathbf{w}}(a_1, \dots, a_N) = \sum_{i=1}^N w_i a_{(i)}$$

where $a_{(j)}$ is the j -th largest element of the multiset $A = \langle a_1, \dots, a_N \rangle$.

If we have an OWA operator of dimension $n = 3$ and the following weights:

$$W = \begin{bmatrix} 0.2 \\ 0.5 \\ 0.3 \end{bmatrix},$$

and elements in the set:

$$A = \begin{bmatrix} 3 \\ 12 \\ 8 \end{bmatrix},$$

applying the OWA operator on W and A would give an aggregated value of:

$$(0.2)(12) + (0.5)(8) + (0.3)(3) = 7.3.$$

OWA operators have proven to be especially useful when extending the purpose of t-norms and t-conorms. The t-norms and t-conorms can be viewed as binary operations that can be utilized in probabilistic metric spaces and multi-valued logic [103].

Definition 6 ([103]).

A t-norm T is defined as a symmetric, associative and non-decreasing function $T: [0, 1]^2 \rightarrow [0, 1]$ satisfying boundary condition $T(1, x) = x$ for all $x \in [0, 1]$.

A t-conorm S is defined as a symmetric, associative and non-decreasing function $S: [0, 1]^2 \rightarrow [0, 1]$ satisfying boundary condition $S(0, x) = x$ for all $x \in [0, 1]$.

T-conorms can often be too polarized towards the *and* and *or* operators. To classify the location of an OWA operator between *and* and *or*, Yager [307] introduced a measure of *orness*, associated with any vector w :

$$orness(\mathbf{w}) = \frac{1}{N-1} \sum_{i=1}^N (N-i)w_i \quad (3.4)$$

The induced ordered weighted averaging (IOWA) operator was introduced by Yager [310]. In this generalisation of the original OWA operator, the general OWA operator is induced by another variable, the order inducing value (u_i). In this approach, the arguments are ordered based on the u_i values. The IOWA operator basically works by aggregating the pairs that have been specified. The procedure for calculating the OWA aggregation of these OWA pairs is defined as:

$$F(\langle u_1, a_1 \rangle, \dots, \langle u_n, a_n \rangle) = \sum_{j=1}^n w_j b_j \quad (3.5)$$

where b_j is the a_i value of the OWA pair having the j -th largest u_i value.

The IOWA operator allows decision makers to aggregate complex objects whose ordering may not be easily accomplished, but which may be ordered with respect to some other properties [310]. Another relevant extension of the OWA operator is the heavy OWA operator, this extension makes it possible to define a larger class of aggregation operators, including not only mean operators but also totalling operators [308]:

Definition 7. A heavy OWA operator of dimension n is a mapping $f: \mathbb{R}^n \rightarrow \mathbb{R}$ that has an associated weighting vector W of dimension n with $w_j \geq 0$ and $1 \leq \sum_{j=1}^n w_j \leq n$, such that:

$$f(a_1, a_2, \dots, a_n) = \sum_{j=1}^n w_j b_j \quad (3.6)$$

where b_j is the j -th largest element of the bag $\langle a_1, \dots, a_n \rangle$.

Based on the concept of OWAD (ordered weighted averaging distance) operators, similarity measures for interval-valued fuzzy numbers (IVFN's) (cf. Section 3.1.4) are defined in this thesis. The definition of an OWAD operator, by Xu and Chen [306] is therefore introduced next:

Definition 8. An OWAD operator of dimension n is a mapping $OWAD: \mathbb{R}^n \times \mathbb{R}^n \rightarrow [0, 1]$ that has an associated weighting vector W with $\sum_{j=1}^n w_j = 1$ and $w_j \in [0, 1]$ such that:

$$OWAD \left(\langle \mu_1^{(1)}, \mu_1^{(2)} \rangle, \dots, \langle \mu_n^{(1)}, \mu_n^{(2)} \rangle \right) = \sum_{j=1}^n w_j D_j,$$

where D_j represents the j th largest of the $|\mu_i^{(1)} - \mu_i^{(2)}|$.

To better utilize information expressed with linguistic terms for decision making purposes, the Linguistic OWA [132] was introduced:

Definition 9. If $\{a_1, \dots, a_m\}$ represents an ordered set of labels then the LOWA operator ϕ is defined as:

$$\begin{aligned} \phi\{a_1, \dots, a_m\} &= W \times B^T = C^m\{w_k, b_k, k = 1, \dots, m\} \\ &= w_1 \odot b_1 \oplus (1 - w_1) \odot C^{m-1}\{\beta_h, b_h, h = 2, \dots, m\}, \end{aligned}$$

where $W = [w_1, \dots, w_m]$, is a weighting vector, such that, $w_i \in [0, 1]$ and $\sum_i w_i = 1$; $\beta_h = w_h / \sum_2^m w_k$, $h = 2, \dots, m$, and B is the associated ordered label vector. Each element $b_i \in B$ is the i th largest label in the collection a_1, \dots, a_m .

The general process of applying the different OWA operators that have been defined consists of three steps [326]:

- reorder the input arguments in descending order;
- determine the weights for the operator;
- use the OWA weights to aggregate the re-ordered arguments.

OWA operators can be used as part of a fuzzy ontology and be applied for decision making purposes. By including OWA operators in ontologies one can increase the effectiveness of the reasoning process. The OWA operators can be implemented in order to combine concepts, which means that one can create new operators which are combinations of previously defined concepts [59, 62].

3.3.2 OWA operators for Decision Making

Creating different extensions of the OWA operator has been a popular topic since the OWA was established and acknowledged. The new extensions can be motivated by the fact that decision making contexts and the use of aggregation have been extended into previously unexplored areas. As the well-known aggregation technique provides a good solution to most problems, the extensions of the OWA operators can provide some extra features and benefits for a specific scenario or context. This means that there is a need and desire to continue developing OWA operators and to adapt them to specific contexts.

A certainly successful area for the OWA operator is the decision making field. Merigó and Gil-Lafuente [208] used fuzzy induced generalised aggregation operators for improving multi-person decision making processes. This offers the possibility to use different aggregation methods in the same approach, but still keeping the option to choose the aggregation methods that one considers to be important. Carlsson et al. [59] applied OWA operators and fuzzy ontology to support decision making. Lan et al. [176] used induced uncertain linguistic OWA operators for group decision making, and in [305], different linguistic ordered weighted geometric-based aggregation operators (LOWG) and linguistic preference relations were used to solve a group decision making problem.

3.4 Summary

This chapter has introduced the current state-of-the-art on Fuzzy Ontologies, Group Decision Making and Aggregation Operators. The definitions and concepts introduced here form the basis for the models and support technology developed in this thesis.

Decision making and group decision making have become increasingly more important in organisations. More complex data and different alternatives in combination with a fast paced work environment have created a situation where decision support systems have roles of growing importance. This development has made the weaknesses of these systems more visible, as increased use creates more opportunities for failure. A serious weakness is the lack of proper tools, methods and instruments for dealing with tacit knowledge and imprecise data.

The recent developments of fuzzy ontologies (both type-1 and type-2) and the introduction of aggregation operators, such as the OWA operators, in fuzzy ontologies have turned out to be a possible solution to these problems. An important step towards finding a solution was made by Straccia and Bobillo [36, 37, 266, 268], when they introduced fuzzy logic in Description Logics, which offers a method for handling the limitations of having to deal with imprecise data in ontologies.

Fuzzy ontologies and aggregation operators can be applied for several contexts, to deal with decision making problems of different kinds. The complexity and diversity of decision making problems make them an interesting area to develop and

extend. The discussed combination of fuzzy logic and ontologies makes it possible to model imprecise knowledge and, using aggregation operators, retrieve valuable information from this knowledge. These techniques and methods fit well into the Semantic Web movement. These new techniques and methods are being applied with the goal of including more semantics understanding, automated reasoning and decision making features into the internet.

Chapter 4

A New Consensus Model for Group Decision Making

Reaching consensus in a group setting creates new obstacles for making good decisions. In a group environment, different decision makers have their own opinions that will affect their desired decision as well as negotiating behaviour. Apart from this, decisions makers are currently faced with an array of information sources and already sorting among this pile of information is itself cumbersome.

To better illustrate how the contributions in this Chapter can be applied, a dinner party is used as the setting for testing the developed consensus model. The attendants need to decide what wine they should drink during the dinner, and the aim of the model is to help with choosing a wine that everyone can agree on. The ontology used for this example is the Fuzzy Wine Ontology, which is more extensively presented in Section 4.1, although the ontology will be employed also for other purposes further on in the thesis.

This Chapter addresses the use of fuzzy ontologies in GDM problems; where the computations performed in the consensus model are based on previous research results. Therefore, a more thorough introduction to group decision making algorithms and consensus reaching processes is presented in Section 4.2 leading up to a new consensus model.

The contributions developed in this Chapter can be divided into two parts. As decision making sometimes deals with an extensive number of alternatives, it is shown how fuzzy ontology can be employed to deal with large sets of alternatives; this is the main theme of Section 4.3. Secondly, a new negotiation process to influence group decision behaviour is presented. The model is based on two different points of reference (consensual and social) and consequently the consensus model uses two kinds of criteria to guide the negotiation process among experts; this is presented in more detail in Section 4.4. In addition, a linguistic extension of the consensus model is presented in Section 4.5. Finally, Section 4.6 presents some examples where the new consensus model is implemented and Section 4.7 gives a

discussion and summary.

4.1 The Fuzzy Wine Ontology

The Fuzzy Wine Ontology was created to work as a place-holder for industrial applications, as the ontologies and applications that are created for industrial purposes usually contain classified information making them unsuitable as examples and for publication purposes. The idea to use wines as case examples is not a new phenomenon, however, the goal with the Fuzzy Wine Ontology is to create a complex-enough context where different methods and approaches can be tested. This can be achieved by modelling wines using both precise data and expert-based tacit knowledge. The wines are suitable as an example case due to the fact that there are numerous advices and rules on how different wines should be combined with different contexts. This kind of advice can be expressed, for instance, by using linguistic expressions [56, 58].

The Fuzzy Wine Ontology was originally created and executed in Excel, however, with the development of a more semantically aimed internet (The Semantic Web), there was a need to implement the ontology in a more practical format. The OWL language was chosen as the language to use, basically because it is supported by W3C and can be combined with all the relevant techniques for the Semantic Web. The possibility to add fuzzy logic to OWL [266], made it the only logical choice [300].

The OWL based ontology was created using Protégé and the fuzzy OWL plugin. This OWL version of the Fuzzy Wine Ontology is divided into different subclasses. Figure 4.1 presents a simplified graphical structure of the Fuzzy Wine Ontology, presenting the four main classes which all influence the choice of the wines: the Context, the Drinker, the Food and the Wine.

First of all, the ontology contains different contexts, for which the most suitable wines need to be chosen. It is assumed that different dinner settings require different types of wine. In other words, certain wines might be more suitable for specific scenarios. For instance, a business oriented dinner requires both a “good quality wine” as well as a “wine known to be favoured by the guests”. If one is planning a picnic in the woods, the preferences are definitely different compared to a business dinner, i.e. the environment and setting surrounding the wine drinking situation affect the choice of the wine. Some examples of included contexts or scenarios are presented next, however, it is important to stress that the rules have been created for demonstration purposes and might be a bit stereotypical.

- **Business Dinner**

Wine for a business context should not contain high alcohol level, nor be low priced. Also, the choice of wine might be adapted to the business guests background, i.e. by giving a specific country a higher weight one could favour a wine from the guest’ home country.

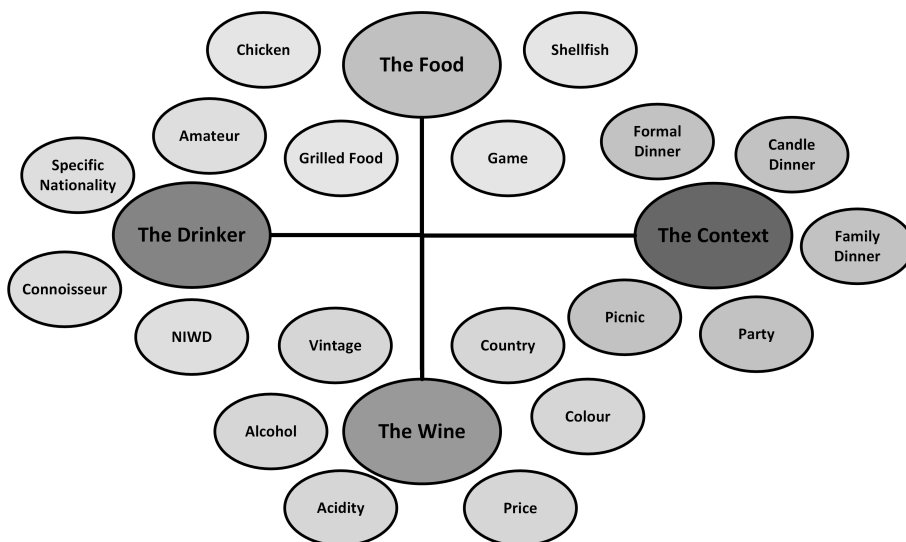


Figure 4.1: Graphically illustrated structure of the Fuzzy Wine Ontology

- **Candle Dinner**

Wine for a candle context should be a red wine, with low acidity and high alcohol level.

- **Family Dinner**

Wine for a family context should be with low alcohol level, not highly priced or with high acidity level.

- **Party**

Wine for parties should be inexpensive, i.e. low alcohol (to keep guests awake) and novello (widely available). This principle is, of course, based more on general agreements than connoisseur opinions, but it works as an example that even these kinds of rules can be included in a complex ontology. It would also be possible to define Party Wines as a food; however, the principles that this category is based on make it better suited as a context.

- **Picnic**

Wine for a picnic context should be from 2012 or newer, not highly priced with medium alcohol level.

Another part of the ontology consists of different types of wine drinkers. Although this is also a bit stereotypical, the point is to show that also the individual preferences (and previous choices) can contribute to the selection of the most suitable wine. All wine drinkers have their individual taste, which means that everyone has certain criteria and preferences for selecting wines that may or may not go against any recommendations. Examples of different drinkers are:

- **NIWD (Not Interested Wine Drinker)**

Wine for a drinker that is not interested in wines should mainly be based on the price. The biggest difference for these users is found in the price and the colour of the wine.

- **Connoisseur**

For this ontology, it is assumed that connoisseurs and experts drinkers are looking for a wine from the higher price segment, the cheap wines are therefore given a lower weight for this type of users.

- **Drinker with a specific Nationality.**

Different nationalities, especially those that have their own wine production, have a slight tendency to prefer to drink wines from their home country. This should affect the end result of the computation. For example, if the user is from France, the french wines could be given a higher weight in the calculation process.

- **Amateur**

A wine for an amateur drinker should not be highly priced nor exclusive.

Most recommendations for pairing wines are based upon the type of food that the wines will be consumed with. Different attributes and contexts fit well together with different types of food and spices. Also, wines tend to be consumed together with a dish of some kind, which gives the Food-Wine pairing a key position when retrieving the most suitable wine. Even though the other circumstances might influence the desired wine, the food being consumed is still the central factor. Examples of food categories included in the fuzzy wine ontology are:

- **Chicken**

Wines consumed together with chicken should be white or light red, not full bodied or high priced.

- **Shellfish**

Wine for shellfish should be from 2007 or newer, dry and white.

- **Grilled Food**

Wine for grilled food should be a novello wine with high alcohol and high acidity, preferably a red wine.

- **Game**

Game suits well with a red, full to medium bodied wine that has high acidity level and alcohol level.

Most of the information about the wines and their pairing-principles is described using connoisseurs-based tacit knowledge, with precise data available for some attributes. This tacit knowledge was collected from numerous wine connoisseur forums / website, for instance: (cellartracker.com, klwines.com, wineperspective.com, winesfromspain.com and snooth.com). Additionally books and academic publications were used, such as Bastian et al. [19]. The precise data, i.e. the alcohol level and price of the wines was primarily retrieved from the Finnish alcohol monopoly Alko (alko.fi). In the Fuzzy Wine Ontology the following attributes are collected for the wines:

- **Country**

The place where the wine is produced has a huge impact on the final product as the weather and the different grapes give each wine a special character. Different countries and regions have their own supporters. In the fuzzy wine ontology, four countries of origin are included: France, Spain, Italy, and USA. It would be possible to extend the ontology by specifying this preference in more detail, for instance by defining in which vineyard or region the wine was produced. However, limiting the option to a country level is satisfactory in this application.

- **Colour**

As with the country category, colour is also based on crisp logic, as it is assumed that a wine can be either red, rosé or white. It is possible to argue that some wines could have membership value in more than one class. However, the three wine colours used are considered to be enough for most cases and scenarios, therefore, fuzzy logic is not implemented for this category. Involving amber coloured wines etc., would only limit the functionality of the applications. The different grapes used for producing the wines gives the wine different properties that combine better with different foods. For instance, red wines tend to combine well with meaty food, even though not all red wines are perfect for this combination. Even so, the colour of the wine greatly affects the choice of the wine to be consumed.

- **Price**

Many wine drinkers make their choice based mainly on the price of the wine, judging other values such as acidity and alcohol level secondary. Therefore, it is impossible to not include the price of the wines in the ontology, even though they hardly affect the actual taste of the wine. The price has to be included for the sake of making it possible to find the cheaper wines, if one has a smaller budget. It is also possible to argue that spending an extra amount of money on an expensive wine creates a more distinguished atmosphere, which in turn makes the wine “taste” better.

- **Acidity**

The acidity level of the wine is essential for the taste. If the level is too low, in comparison to other wine properties, it will create a flat and gloomy wine, while if the level is too high, the wine will be sour.

- **Alcohol**

The alcohol level does not only affect the drinkers' mental capabilities, but different alcohol levels demand different supportive properties. A bad mixture creates a poorly tasting wine.

- **Vintage**

The vintage of the wine is important to consider, as wines develop different characteristics over time. Some wines therefore have to be stored for a while, before their right tastes and properties begin to emerge.

The wine properties all have pre-defined limitations. Defining a value outside these limitations would create an inconsistent knowledge base and result in an error. As several of the properties included have natural limitations, i.e. the alcohol level of wines is never under 0 percent, implementing these boundaries minimizes the errors in the ontology. Table 4.1 presents the defined boundaries.

Attribute	Limitation
Acidity	$0 \leq \text{Acidity} \leq 10$
Alcohol	$0 \leq \text{Alcohol} \leq 20$
Vintage	$1990 \leq \text{Vintage} \leq 2012$
Price	$0 \leq \text{Price} \leq 200$

Table 4.1: Attribute Limitations

The presented attributes are then divided into subattributes, such as: low alcohol, medium alcohol and high alcohol. Each category is represented by a membership function applied to generate the membership value to that specific category. Figure 4.2 shows the membership values of Alcohol. Trapezoidal shaped fuzzy numbers are used to create the membership functions, using the notation $A = (a, b, c, d)$, where $[b, c]$ is the core of the fuzzy number and a and d are the left and right endpoints of the support, respectively (illustrated in Figure 4.3). The right-shoulder, left-shoulder and triangular functions are special cases of the trapezoidal function. Table 4.2 shows how the different membership values were defined for the subclasses included in the fuzzy ontology.

The most recent version of the fuzzy ontology contains over 600 wines. The information about the specific wines was collected from the Finnish alcohol company Alko. The pairing principles (e.g. what food suites which wines) were based on recommendations given by wine experts and literature written by connoisseurs.

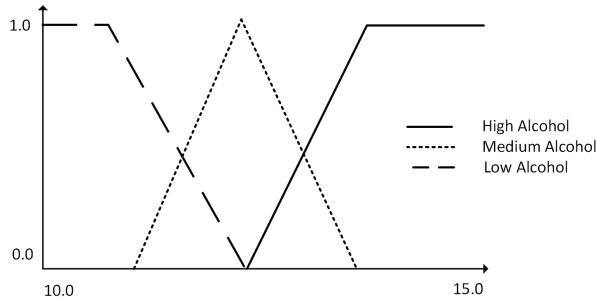


Figure 4.2: The membership values of alcohol

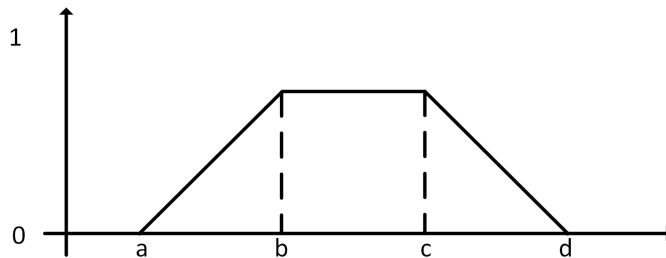


Figure 4.3: A Trapezoidal Fuzzy Number

With the presented structure, the fuzzy wine ontology creates a complex-enough test environment for fuzzy ontology based applications, combining both crisp values and fuzzy values. An example of a crisp value could be the colour of the wine, whereas a fuzzy value could be the linguistic term "sweet". Table 4.3 presents four wines with some selected crisp / fuzzy values and figure 4.4 shows an excerpt from the Fuzzy Wine Ontology, modelled in Protégé.

There are some imminent issues with creating a fuzzy wine ontology as combining wine and food is very much based on individual taste and preferences. If someone enjoys drinking a certain type of wine together with a certain type of food, it is probably the best solution, even though the general guidelines show something completely different.

Attribute	Low	Medium	High	
Acidity	(0.0,0.0,4.5,5.4)	(4.7,5.4,5.4,6.2)	(5.3,6.0,10.0,10.0)	
Alcohol	(0.0,0.0,9.0,12.5)	(10.0,12.5,12.5,15.0)	(12.5,14.5,20.0,20.0)	
Price	(0.0,0.0,6.5,15.5)	(6.0,14.0,14.0,22.5)	(15.5,23.0,200.0,200.0)	
	Novello	Regular	Old	Exclusive
Vintage	(2010,2012,2014,2014)	(2008,2010,2010,2012)	(2005,2007,2007,2009)	(1800,1800,2000,2005)

Table 4.2: The different membership values

In a sense, this implies that there is neither correct nor wrong wine for a specific context, as people might enjoy something that is the complete opposite to the

Wine	France	White	High_Price	Medium_Acidity	Medium_Alcohol
Chablis Grand Cru Les Preuses	1	1	1	0,37	0,80
Briego Vendimia Seleccionada	0	0	0	0,37	0,60
Tiempo Briego	0	0	0,38	0,85	0,60
René Barbier Rosado	0	0	0,19	0,70	0,80

Table 4.3: Four wines and their crisp / fuzzy membership values

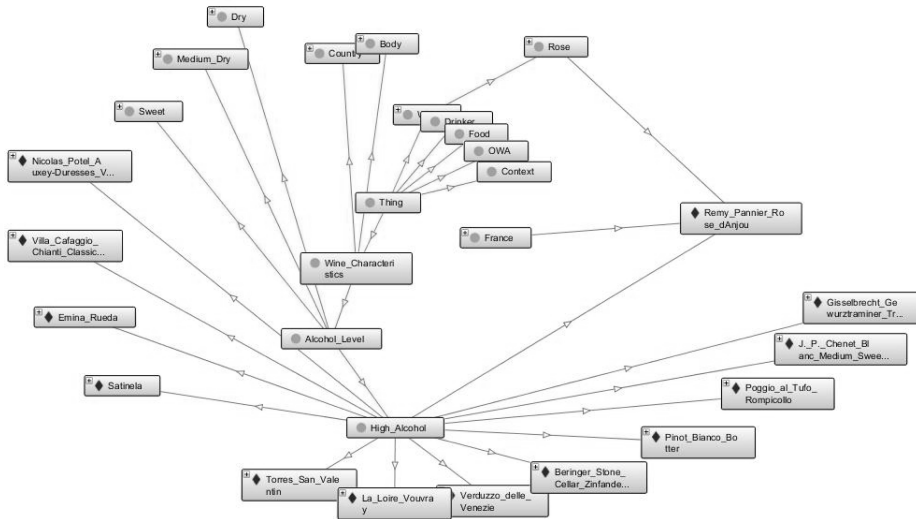


Figure 4.4: Excerpt from the Fuzzy Wine Ontology

provided advice. It is therefore difficult to give any definitive answer to the questions that should be answered with the Fuzzy Wine Ontology. Nevertheless, the general purpose of the wine ontology is to prove that it is possible to transmit the knowledge retrieved from the experts and present them in a useful way to amateurs. By handling uncertain and imprecise data with fuzzy logic one can at least point the user towards the right direction, even though the users themselves should make the final decision.

4.1.1 Wine Selection Examples

To illustrate how to compute which wines suite which scenario to the highest degree, the following section presents simple examples, in which game is served in a business dinner setting.

A wine suitable for **Game** should have the following characteristics:

- High alcohol

- High acidity
- Red (colour)
- Full (body)

A **Business Dinner** should emphasize the following values:

- High alcohol
- Not Low price
- Spanish

It is known that the dinner guest prefers wines that have high alcohol level and were produced in Spain; low priced wines are given a negative impact on the end results, therefore the notion: (Not Low price). The next step is to implement the OWA operators to separately compute the membership values for the food and the context, for each wine included in the process.

The different weights for the OWA operators are defined as:

Business Dinner: 0.4 High alcohol, 0.3 (Not Low price), 0.3 Spanish

Game: 0.25 High alcohol, 0.25 High acidity, 0.25 Red (color), 0.25 Full (body)

OWA combining Business Dinner and Game:

0.5 Business Dinner 0.5 Game

The following example presents how one final ranking value is calculated for one wine. First, all the membership values for different concepts are calculated; the value of Not Low Price is calculated as 1-Low Price. The example shows the wine Marqués de Vitoria Crianza membership value for the scenario:

Wine: Marqués de Vitoria Crianza.

A Medium bodied, Spanish red wine.

Alcohol level: 13,5

Acidity level: 5.5

Price: 12.99

The different membership values are combined as:

$$(0.4 * 0.25) + (0.3 * (1-0.22)) + (0.3 * 1) = 0.634$$

$$(0.25 * 0.25) + (0.25 * 0.29) + (0.25 * 1.0) + (0.25 * 0.75) = 0.5725$$

Marqués de Vitoria Crianza membership value for this scenario is (with equal weights for Business Dinner (the context) and Game (the food)):

$$\text{Business Dinner + Game: } (0.5 * 0.634) + (0.5 * 0.5725) = 0.60325$$

The membership value, 0.60325 can then be used to compare Marqués de Victoria Crianza with other wines. The higher the value is, the more suitable the wine is for the specified scenario.

4.2 Methods for Group Decision Making

A Classic GDM situation consists of a problem description and a set of possible alternatives, denoted as $X = \{x_1, x_2, \dots, x_n\}$, ($n \geq 2$), and a group of two or more experts, denoted as $E = \{e_1, e_2, \dots, e_m\}$, ($m \geq 2$). The experts are driven by their own ideas, attitudes, motivations and knowledge, which influence their opinions about the set of alternatives that needs to be considered to achieve a common solution. By introducing a linguistic term set S , with a certain granularity, a linguistic group decision making problem can be formulated [129, 131]. The decision model used for the GDM purposes in this thesis is composed of two different processes and is presented in more detail next [54, 60, 134, 138, 162]:

1. *Consensus process*: The process refers to how the maximum degree of an agreement among the experts regarding the alternatives is obtained. This is crucial as, in any decision process, it is preferable that the experts reach a high degree of consensus regarding a solution set of alternatives before obtaining the final solution.
2. *Selection process*: The process describes how to obtain a solution set of alternatives from the opinions provided by the experts on the alternatives. This consists of two phases: aggregation and exploitation. The aggregation phase defines a collective opinion according to the preferences provided by the experts. The exploitation phase transforms the global information about the alternatives into a global ranking.

Preference relations are utilized as the task is to order a set of alternatives according to the decision makers' preferences and opinions. This creates a binary relation, that is a set that consists of ordered pairs, indicating what alternatives the decision maker prefers over other alternatives. For instance, a person might prefer to receive two bananas instead of three apples, i.e. the first alternative is more preferred to the second. The problem arises when the one providing preference relations finds it hard to differ between the available alternatives, especially when one is limited to using either true or false. Quite a lot of these situations are fuzzy by nature. By modelling the preferences with fuzzy sets the offers greater flexibility, as the decision maker can specify the uncertainty [219]. For the consensus model it is assumed that the experts give their preferences by using fuzzy preference relations, which can be defined as:

Definition 10 ([219]). A fuzzy preference relation (FPR) P on a set of alternatives X is a fuzzy set on the product set $X \times X$, i.e., it is characterized by a membership function $\mu_P : X \times X \rightarrow [0, 1]$.

where $\mu_{P^k} = p_{ij}^k$ denotes the preference degree of the alternative x_i over x_j for expert k . P^k can be used without loss of generality. The preferences provided by the experts are allowed to be inconsistent [71, 161].

If the cardinality of X is small, the preference relation may be conveniently represented by an $n \times n$ matrix, $P^k = (p_{ij}^k)$, where $p_{ij}^k = \mu_{P^k}(x_i, x_j)$ ($\forall i, j \in \{1, \dots, n\}$) is interpreted as the preference degree, i.e. how much the alternative x_i is preferred to x_j by the expert e_k , where the value of p_{ij}^k indicates:

- $p_{ij}^k = 1/2$ indicates indifference between x_i and x_j ($x_i \sim x_j$)
- $p_{ij}^k = 1$ indicates that x_i is absolutely preferred to x_j
- $p_{ij}^k > 1/2$ indicates that x_i is preferred to x_j ($x_i \succ x_j$)
- $p_{ij}^k < 1/2$ indicates that x_j is preferred to x_i ($x_i \prec x_j$)
- $p_{ij}^k = 0$ indicates that x_j is absolutely preferred to x_i

When aggregating experts' preferences, the fuzzy preference relations method is an effective tool for modelling decision processes [139, 161]. In comparison with, for instance, preference orderings or utility functions, fuzzy preference relations are more informative, as they allow for the pairwise comparison of alternatives. This means that users have much more freedom to express their preferences [71].

4.2.1 A Group Decision Making Algorithm

The GDM applications developed for this thesis are based on the following group decision making algorithm by Pérez et al. [227]:

1. *Providing information step*: In this first step, the experts provide their preferences based on a set of alternatives using preference relation matrices.

The experts give their degree of preference for each possible alternative and the preference relation matrices are built using the given information. Linguistic values belonging to the balanced linguistic term set $S = \{s_0, s_1, \dots, s_{n-1}\}$ are the instances used by the experts to express their preference degrees. When the set of preference matrices, based on all the experts preferences $\{P_1, P_2, \dots, P_m\}$ is completed, the aggregation step begins.

2. *Aggregation step*: The preference relation matrices are aggregated in order to obtain a collective preference matrix. For that purpose, the mean operator, ϕ , is used over the indexes of the linguistic labels as follows:

$$C_{ij} = \phi(P_{ij}^{1..m}) = \frac{\sum_{k=1}^m \text{index}(P_{ij}^k)}{m} \quad (4.1)$$

where the *index* function returns the index of a label m and P_{ij}^k represents the linguistic degree of preference of alternative i over j for the expert k . The matrix C is now numerical and using the collective preference matrix, a ranking of the alternatives can be calculated.

3. *Selection step*: As the collective preference matrix was calculated in the previous step, a ranking of the alternatives is now obtained as follows. Two degrees [133, 227] are used for this purpose:

- *Quantifier-guided dominance degree (GDD)*: This operator suggests which alternatives dominate others, that is, which alternatives are preferred by the experts over the other alternatives. The higher GDD value an alternative is, the better it is. The GDD value for alternative i is defined as:

$$GDD_i = \phi(c_{i1}, c_{i2}, \dots, c_{i(i-1)}, c_{i(i+1)}, \dots, c_{in}) \quad (4.2)$$

where c_{ij} is the collective matrix value for the row i and column j and ϕ is the mean operator.

- *Quantifier-guided non-dominance degree (GNDD)*: This operator is applied to show which alternatives are not dominated by others, i.e. alternatives which are not preferred by other alternatives. The GNDD value for alternative i is defined as:

$$GNDD_i = \phi(1 - c_{1i}^s, 1 - c_{2i}^s, \dots, 1 - c_{(i-1)i}^s, 1 - c_{(i+1)i}, 1 - c_{ni}^s) \quad (4.3)$$

where

$$c_{ji}^s = \max\{c_{ji} - c_{ij}, 0\} \quad (4.4)$$

To calculate the ranking between the alternatives, a t-norm is applied for the GDD and the GNDD values. The higher the resulting value, the more preferred that alternative is.

Example

To better show how the algorithm works on a dinner context, an example with the preferences expressed as linguistic terms, is presented.

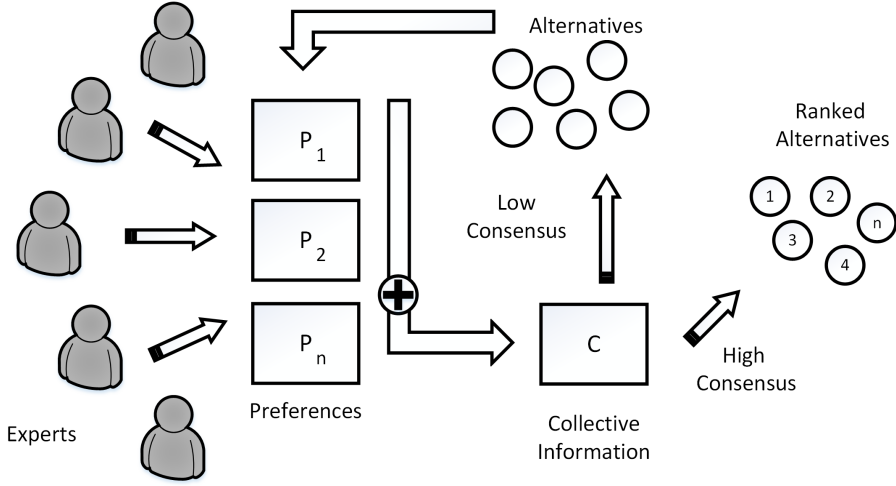


Figure 4.5: Group decision making process scheme

The group that wants to reach consensus consists of three dinner guests, denoted as e_1, e_2 and e_3 . They should decide among four wines that the ontology has singled out (w_1, w_2, w_3 and w_4). The dinner guests use the balanced linguistic term set S to describe the grade of preference between every two wines. The goal is to find a wine which satisfies all participants to as high a degree as possible.

The balanced linguistic term set can be defined as:

$$S = \{s_1 : \text{very_low}, s_2 : \text{quite_low}, s_3 : \text{low}, s_4 : \text{medium}, \\ s_5 : \text{high}, s_6 : \text{quite_high}, s_7 : \text{very_high}\}$$

Where each linguistic expression represents an index value in the interval $[0,6]$, i.e. $s_1 = 0$ and $s_7 = 6$. Based on their expressed preferences, the preference relation matrices P_i are built for each dinner guest:

$$P_1 = \begin{pmatrix} - & s_2 & s_1 & s_3 \\ s_7 & - & s_6 & s_5 \\ s_3 & s_4 & - & s_5 \\ s_1 & s_1 & s_2 & - \end{pmatrix} \quad P_2 = \begin{pmatrix} - & s_3 & s_1 & s_2 \\ s_5 & - & s_7 & s_6 \\ s_4 & s_4 & - & s_3 \\ s_2 & s_1 & s_1 & - \end{pmatrix} \quad P_3 = \begin{pmatrix} - & s_1 & s_1 & s_2 \\ s_7 & - & s_6 & s_7 \\ s_5 & s_3 & - & s_2 \\ s_3 & s_1 & s_2 & - \end{pmatrix}$$

By applying (4.1), the matrix C is calculated. Even though the results were given in the interval $[0,6]$, it is possible to make a domain change and express them in the interval $[0,1]$. The matrices for both domains are shown below:

$$C_{[0,6]} = \begin{pmatrix} - & 1 & 0 & 1.33 \\ 5.33 & - & 5.66 & 5 \\ 3 & 2.66 & - & 2 \\ 1 & 0 & 0.66 & - \end{pmatrix}$$

$$C_{[0,1]} = \begin{pmatrix} - & 0.1666 & 0 & 0.2216 \\ 0.8883 & - & 0.9433 & 0.8333 \\ 0.5 & 0.4433 & - & 0.3333 \\ 0.1666 & 0 & 0.11 & - \end{pmatrix}$$

Using C and (4.2) and (4.3), the GDD and GNDD degree values are calculated. The t-conorm *maximum* has been used to compute the final ranking. The resulting values for each of the alternatives are shown in Table 4.4. The final ranking of alternatives in the group decision making process is $\{w_2, w_3, w_1, w_4\}$. This means that wine w_2 is the most preferred wine among the dinner guests and w_4 is the least preferred option.

Alternatives (wines)	GDD	GNDD	$T(GDD, GNDD)$
w_1	0.1294	0.5927	0.5927
w_2	0.8883	1	1
w_3	0.4255	0.8333	0.8333
w_4	0.0922	0.6294	0.6294

Table 4.4: Results of the selection process for the decision making example.

4.2.2 Consensus Reaching Process

To aid the consensus reaching process in a group is an important task for the research carried out in this thesis. To be able to define and study the process, it is assumed that consensus is a measurable parameter, where the maximum value corresponds to total agreement, and the minimum value means complete disagreement. The different consensus degrees can be used to measure the current level of consensus in the ongoing decision process. It is also assumed that the fuzzy preference relations are representations of the experts' preferences; if this is assumed, it is possible to compute the consensus degrees by using three different steps [134, 135, 203]:

- Pairs of alternatives
- Alternatives
- Relations

As long as the experts do not agree about the final results, the process can be repeated in order to allow them to modify their opinions and make them come closer to a consensus. By using consensus measures, one can check whether the experts have reached an agreement. If the consensus value is low, it is reasonable to initiate another decision making round; if consensus is high, it means that almost all experts agree which makes it unnecessary to repeat the process again. Consensus measures can also be used to advise users on how to modify their opinions in order to reach a higher consensus. In other words, the process could indicate that a specific expert needs to adjust his / her preferences towards the preferences of other group members in order to reach a high consensus value. The mathematical process defined can be illustrated in a scheme, presented in Figure 4.5.

The computation of the consensus degrees is carried out as follows:

1. For each pair of experts, e_k, e_l ($k < l$), a similarity matrix, $SM^{kl} = (sm_{ij}^{kl})$, is created where

$$sm_{ij}^{kl} = \left(1 - |p_{ij}^k - p_{ij}^l|\right).$$

2. Then, the consensus matrix, CM , is determined by aggregating all the similarity matrices using the arithmetic mean as the aggregation function ϕ :

$$cm_{ij} = \phi(sm_{ij}^{12}, sm_{ij}^{13}, \dots, sm_{ij}^{1m}, sm_{ij}^{23}, \dots, sm_{ij}^{(m-1)m}).$$

3. As the similarity and consensus matrices are computed the next step is to obtain the consensus degrees at three different levels so that a global consensus degree can be obtained:

- (a) *Consensus degree on pairs of alternatives.* The consensus degree for a pair of alternatives (x_i, x_j) , denoted cop_{ij} , is the consensus degree among all the experts for that pair of alternatives:

$$cop_{ij} = cm_{ij}.$$

- (b) *Consensus degree on alternatives.* The consensus degree for alternative x_i , denoted ca_i , is the consensus degree among all the experts on that alternative:

$$ca_i = \frac{\sum_{j=1; j \neq i}^n (cop_{ij} + cop_{ji})}{2(n-1)}.$$

- (c) *Consensus degree on the relation.* The consensus degree for the relation, denoted CR , is the global consensus degree among all the experts' opinions:

$$CR = \frac{\sum_{i=1}^n ca_i}{n}.$$

The consensus values presented here reside in the interval $[0,1]$, however, they can be expressed linguistically by using a balanced linguistic term set $S = \{s_i, \dots, s_n\}$, provided that the following expression is applied:

$$LR_r = s_{(k+j)} | k = \text{round}(r \cdot (n - j)) \quad (4.5)$$

where $r \in [0, 1]$ is the numerical value that should be expressed linguistically, LR_r is its linguistic representation and s_k is a linguistic value that belongs to S .

Normally, to achieve consensus among the experts, it is necessary to provide the whole group of experts with advice during the process. For instance, how far the group is from consensus, what are the most controversial issues, whose preferences are most in disagreement with the rest of the group and how preference changes would influence the consensus degree. If one includes a moderator into this process, he / she can play a key role. The moderator is a person who does not participate in the discussion but knows the preferences of each expert and the level of agreement during the consensus process. The moderator supervises and drives the process towards consensus

Figure 4.6 presents a consensus model, where it is assumed that the experts, at some point, disagree; this means that the decision making process will be iterative and several discussion rounds need to be conducted. The experts can be suggested to change their preferences according to the advice received from the moderator of the process. In each round, the consensus measures are computed to check the current agreement existing among experts. If the consensus is low, it might be beneficial to initiate another round of discussion and voting. If the consensus is high enough, the selection process might be finalised [60, 73, 138].

4.3 A Fuzzy Ontology for Handling Large Sets of Alternatives in the Contexts of GDM

In decision making, the number of possible alternatives can be extensive and it is not feasible to present a large number of them to the decision makers. To better utilize the knowledge of the experts, there is a need to reduce the set of alternatives, creating a reasonable number for the decision makers to evaluate. By employing a fuzzy ontology to describe a decision making problem, a smaller set of alternatives can be produced, ruling out inadequate alternatives and keeping the better ones.

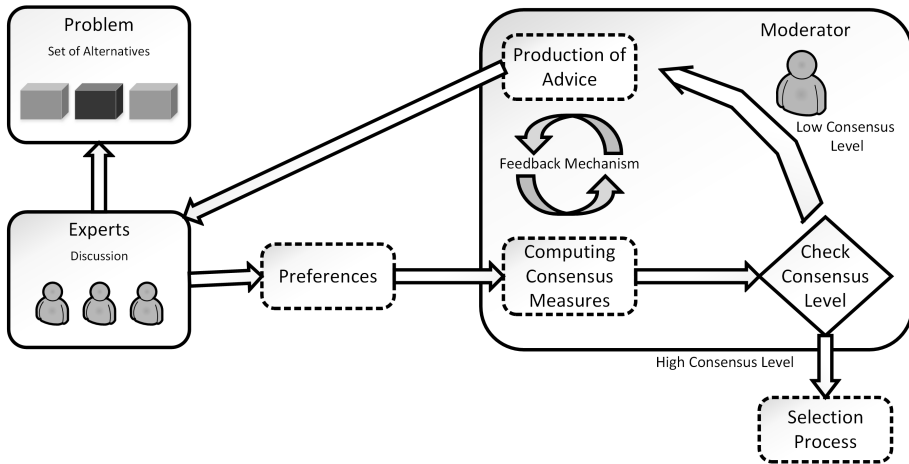


Figure 4.6: The Consensus Reaching Process

The Fuzzy Wine Ontology can be used as an example context, where the huge number of available wines makes the decision making cumbersome. If one presents hundreds of similar wines for an expert to decide among, it becomes a challenging task; if the list was pre-filtered before it reached the expert, the knowledge and time of the expert could be utilized more efficiently. As even small differences would impact the decision, nuances might be overlooked if there are huge numbers of wines to consider.

Initially, the experts define which criteria they consider to be the most relevant for the given situation. By using the reasoning system of a fuzzy ontology, the alternatives which satisfy the set of criteria to the highest degree can be identified. The aggregation of different attributes is a central part of this procedure.

Example 1

For the first example, four different attributes are used. The end goal is to find out which alternative satisfies these attributes the most. By using OWA, this can be solved in the following way:

$$\arg \max_i OWA$$

$$\begin{aligned} &R(x_i, \text{attribute_A}), R(x_i, \text{attribute_B}), \\ &R(x_i, \text{attribute_C}), R(x_i, \text{attribute_D}) \end{aligned} \quad (4.6)$$

Using an OWA operator, the obtained values are combined, creating the final values needed for the final decisions. The weights are defined as $\mathbf{w} \approx (w_1, w_2, w_3, w_4)$ and the attributes as $\mathbf{b} \approx \{\text{Criterion1}, \text{Criterion2}\}$. The values of the weights are chosen by the experts, pinpointing which criterion should receive more value compared to the others. The experts do not have to be part of the decision making group. It is also possible to decide the weights by using databases and

excluding the use of experts completely at this stage.

The vector associated with the OWA operator can be defined as $\mathbf{w} \approx (0.20, 0.50, 0.20, 0.10)$. Five different alternatives are considered, with different values for the different attributes. The solutions for (4.6) can be obtained as:

$$\begin{aligned} f(x_1) &= 0.20 \cdot 0.9 + 0.50 \cdot 0.55 + 0.20 \cdot 0.35 + 0.10 \cdot 0.2 \approx 0.545 \\ f(x_2) &= 0.20 \cdot 0.5 + 0.50 \cdot 0.23 + 0.20 \cdot 0.10 + 0.10 \cdot 0.02 \approx 0.237 \\ f(x_3) &= 0.20 \cdot 1.0 + 0.50 \cdot 0.9 + 0.20 \cdot 0.78 + 0.10 \cdot 0.25 \approx 0.831 \\ f(x_4) &= 0.20 \cdot 0.6 + 0.50 \cdot 0.5 + 0.20 \cdot 0.25 + 0.10 \cdot 0.09 \approx 0.429 \\ f(x_5) &= 0.20 \cdot 0.77 + 0.50 \cdot 0.70 + 0.20 \cdot 0.3 + 0.10 \cdot 0.0 \approx 0.564 \end{aligned}$$

As the goal is to find the alternative that satisfies the equation the most, the following problem needs to be solved:

$$\arg \max_{i=1,2,3,4,5} \{f(x_i)\}$$

Solution $i = 3$ gives the highest value in this example and this alternative is therefore the most suitable option. By identifying the top n alternatives, one can limit the set of alternatives provided to the experts. Therefore they do not receive only one answer, but a set of acceptable answers. This means that the experts can take into consideration also the third best option, which in reality could prove to be the most suitable alternative.

Example 2

For this example, 10 different alternatives are used. The goal is to find the top 3 alternatives. The attributes are limited to 3, and the first attribute will receive the most weight, as it is the most important:

$$\arg \max_i OWA$$

$$R(x_i, \text{attribute_A}), R(x_i, \text{attribute_B}), R(x_i, \text{attribute_C}) \quad (4.7)$$

The weight vector for the OWA operator is defined as $\mathbf{w} \approx (0.60, 0.25, 0.15)$ and the solutions for (4.7) can be obtained as:

$$f(x_1) = 0.60 \cdot 0.94 + 0.25 \cdot 0.75 + 0.15 \cdot 0.6 \approx 0.889$$

$$f(x_2) = 0.60 \cdot 0.7 + 0.25 \cdot 0.12 + 0.15 \cdot 0.01 \approx 0.452$$

$$f(x_3) = 0.60 \cdot 1.0 + 0.25 \cdot 0.99 + 0.15 \cdot 0.65 \approx 0.945$$

$$f(x_4) = 0.60 \cdot 0.8 + 0.25 \cdot 0.75 + 0.15 \cdot 0.68 \approx 0.770$$

$$f(x_5) = 0.60 \cdot 0.8 + 0.25 \cdot 0.70 + 0.15 \cdot 0.0 \approx 0.655$$

$$f(x_6) = 0.60 \cdot 0.85 + 0.25 \cdot 0.70 + 0.15 \cdot 0.1 \approx 0.700$$

$$f(x_7) = 0.60 \cdot 0.5 + 0.25 \cdot 0.45 + 0.15 \cdot 0.4 \approx 0.473$$

$$f(x_8) = 0.60 \cdot 0.9 + 0.25 \cdot 0.45 + 0.15 \cdot 1.0 \approx 0.893$$

$$f(x_9) = 0.60 \cdot 1.0 + 0.25 \cdot 0.66 + 0.15 \cdot 0.24 \approx 0.801$$

$$f(x_{10}) = 0.60 \cdot 0.5 + 0.25 \cdot 0.72 + 0.15 \cdot 0.78 \approx 0.723$$

To find the alternative that satisfies the equation the most, the following problem should be solved:

$$\arg \max_{i=1, \dots, 10} \{f(x_i)\}$$

The alternatives that have the 3 highest values are $i = x_3, x_8, x_1$ and are the most suitable solutions for this problem. As alternative 8 and 1 are quite similar, human experts could better decide about the subtle differences not detectable by the computation.

4.4 The Negotiation Process: Influencing Group Decision Behaviour

The negotiation process can be initiated when a suitable discussion subset has been obtained, for instance by implementing the procedure presented in Section 4.3. When the set of alternatives is chosen, each expert e_k expresses his/her preferences about the selected alternatives by means of a FPR P^k . Then, the model can compute the current level of agreement achieved among the experts (CR).

The next step depends on the consensus measure CR calculated, if it is not high enough and if the number of rounds has not reached a maximum number of iterations, there is a need to modify the opinions of the experts, in other words, a negotiation phase has to be started. At this stage, one can implement tactics or weapons of influence to convince some of the experts to change their minds in order to reach a higher consensus.

A popular approach to solve this issue is to simulate a group negotiation session by applying a feedback mechanism [54]. In the consensus reaching process, this can replace the feedback provided by the moderator. The problem is to find

ways of convincing experts to change their individual positions and support them in obtaining and agreeing on a feasible solution [227]. To solve this problem, a three steps negotiation process was developed. The three steps work in the following way:

- Fix the points of reference so that the negotiation can narrow the gaps between the positions of experts, and move towards an optimal and consensual solution.
- Calculate additional consensus measures, proximity measures [130].
- Utilize the proximity measures and the points of reference to build a new feedback mechanism, working as a recommender system [233, 234, 238]. The experts receive some advice and, if they take the recommendations into account, they will change their preferences in order to obtain a higher consensus level [137, 203].

Obtaining fuzzy preference relations as points of reference

To represent the group opinion, a collective FPR is used. $P^c = (p_{ij}^c)$, is obtained by aggregating all individual preference relations $\{P^1, P^2, \dots, P^m\}$. This produces a value showing the global preference between every pair of alternatives based on the majority of experts' opinions. An OWA operator ϕ_Q is used to perform the aggregation, guided by a fuzzy linguistic non-decreasing quantifier Q [307]:

$$p_{ij}^c = \phi_Q(p_{ij}^1, \dots, p_{ij}^m).$$

This means that P^c is used as point of reference P^r to push the negotiation process forward. The main advantage of this approach becomes visible when experts are willing to follow the recommendations, as the experts that are hindering the agreement are identified and guided in the right direction. However, to convince an expert to modify his/her preferences based only on the fact that consensus can be reached faster, does not seem feasible. Based on research by Cialdini [75], social proof is a powerful weapon that can be used to influence people. The principle states that people tend to imitate other peoples' behaviour when making decisions, i.e. if several individuals have decided in favour of a particular alternative, the remaining individuals are more likely to follow them, as that alternative is perceived as more favourable. It has been shown that both children and adults can be nudged towards a certain decision, just by informing them that a certain alternative has been chosen a lot before.

At this stage, the fuzzy ontology is again employed; the query is this time refined in order to obtain the most suitable solution according to the knowledge stored and modelled by the fuzzy ontology. Due to this, one can use this generated result, which is based on expert knowledge, as weapon of influence to persuade

some experts towards reaching consensus. At the same time, as the solution is considered to be suitable by the fuzzy ontology, one can create a good initial proposal for the experts to start discussing about.

The fuzzy ontologies can be used for providing fuzzy utility values for each alternative of the discussion subset, as described in Section 4.1.1. Using the transformation function [71, 72] it is possible to obtain the optimal alternative, P^o . By using the fuzzy ontology to process the initial set of alternatives, presented in Section 4.3, one can obtain a utility score based on the chosen criteria. The obtained set of alternatives A_1, \dots, A_n have the corresponding utility values u_1, \dots, u_n . The higher the value of u_i , the more acceptable is the alternative A_i . Assuming that the utility values follow a positive ratio scale, Chiclana et al. [71, 72] determined a generic form of a reciprocal fuzzy preference relation, based on the utility values, through a transforming function h as:

$$p_{ij}^o = h(u_i, u_j) = \begin{cases} \frac{s(u_i)}{s(u_i) + s(u_j)}, & \text{if } (u_i, u_j) \neq (0, 0) \\ \frac{1}{2}, & \text{if } (u_i, u_j) = (0, 0) \end{cases}$$

where $s : [0, 1] \rightarrow \mathbb{R}^+$ is any non-decreasing and continuous function satisfying $s(0) = 0$. For the model developed, the function $s(x) = x^2$ was chosen, resulting in the following formula:

$$p_{ij}^o = \begin{cases} \frac{u_i/u_j}{u_i/u_j + u_j/u_i}, & \text{if } (u_i, u_j) \neq (0, 0) \\ \frac{1}{2}, & \text{if } (u_i, u_j) = (0, 0) \end{cases} \quad (4.8)$$

where u_i/u_j can be interpreted as the preference intensity of A_i to A_j .

For this negotiation model, the proposal is to use the optimal FPR P^o as a new point of reference P^r from which one can produce advice for the experts. This means that those experts whose opinions are far away from the most suitable solution provided by the ontology, will be asked to change their preferences as that would benefit the whole group (see Figure 4.7). Thus, the negotiation process is carried out in two ways simultaneously, optimal and consensual. Where the optimal solution is provided by the fuzzy ontology and the consensual solution is reached through negotiations. This should facilitate the consensus reaching and reduce the possibility that the process will stagnate or stop.

Computing the Proximity Measures

The purpose of applying proximity measures is to evaluate the agreement between individual experts' opinions and a feasible solution. As this needs to be computed for each expert, the two points of reference P^r (P^C and P^O) are used in order to establish the current direction of the negotiation process. Therefore, the proximity measures are computed as:

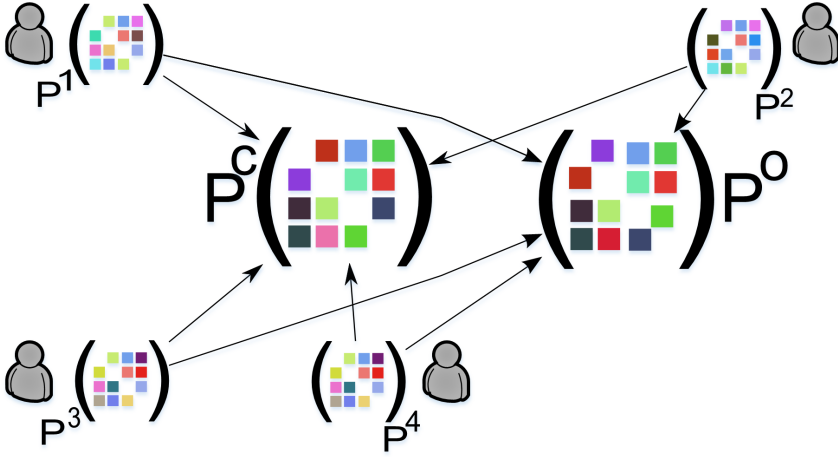


Figure 4.7: Points of reference of the negotiation process

1. For each expert, e_k , two proximity matrices, $PM^{kr} = (pm_{ij}^{kr})$, are created where

$$pm_{ij}^{kr} = \left(1 - |p_{ij}^k - p_{ij}^r|\right).$$

2. Three different levels of proximity measures are computed:

- (a) *Proximity measures on pairs of alternatives*, pp_{ij}^{kr} . Measuring the proximity between the preferences of each pair of alternatives per expert e_k and each point of reference P^r :

$$pp_{ij}^{kr} = pm_{ij}^{kr}.$$

- (b) *Proximity measure on the alternatives*, pa_i^{kr} . Measuring the proximity between the preferences on each alternative x_i of the expert e_k and each point of reference P^r :

$$pa_i^{kr} = \frac{\sum_{z=1}^n pp_{iz}^{kr}}{n}.$$

- (c) *Proximity measure on the relation*, pr^{kr} . Measuring the global proximity between the preferences of each expert e_k and each point of reference P^r :

$$pr^{kr} = \frac{\sum_{z=1}^n pa_z^{kr}}{n}.$$

Managing Large Sets of Alternatives

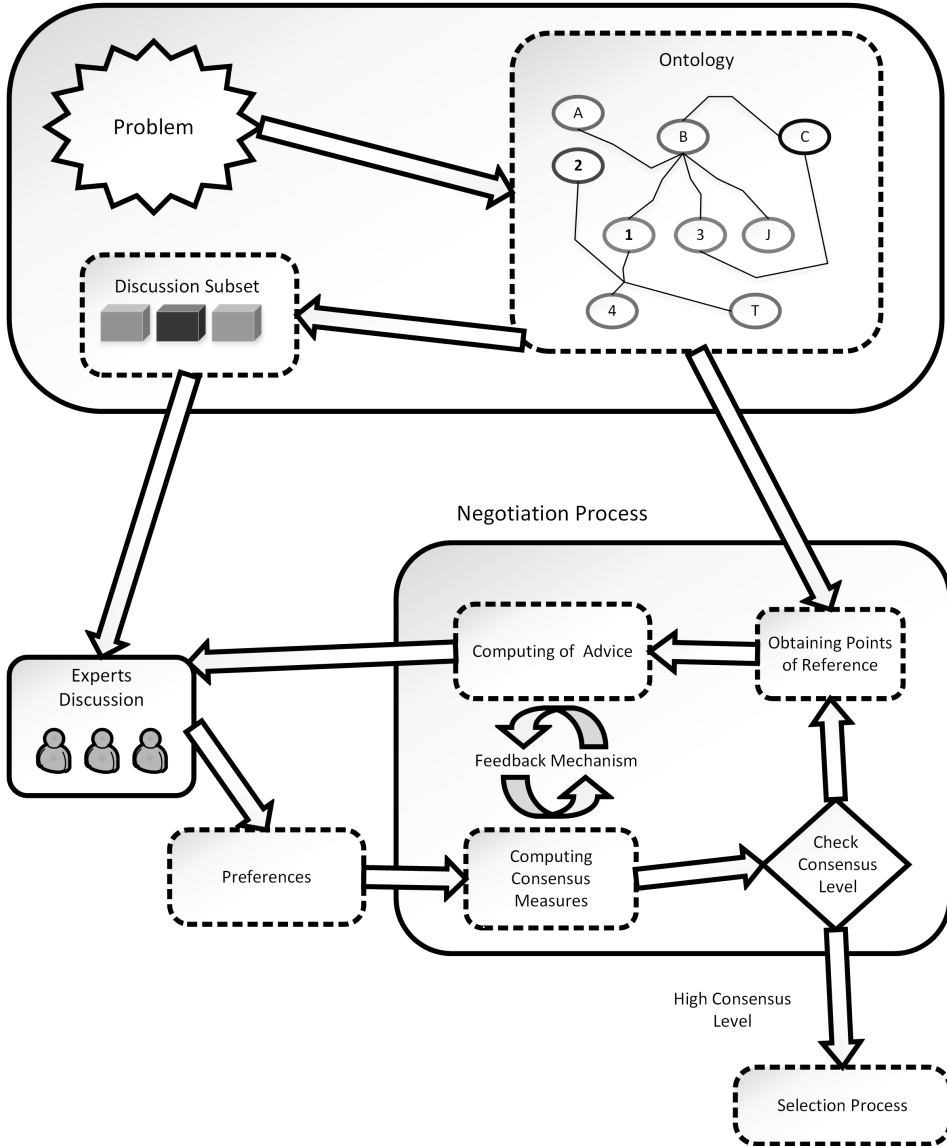


Figure 4.8: New consensus reaching process based on a fuzzy ontology

Advising Experts: The Feedback Mechanism

When the proximity measures have been computed, for each expert and for both points of reference (the collective solution P^c and the optimal solution P^o), the next step is to identify those experts who should modify their preferences and to create some simple rules to drive the negotiation process forward. To achieve this, the advice to the experts for achieving a good and consensual solution is built in two phases: the identification phase and the recommendation phase.

- *Identification phase:*

The goal of this phase is to identify the experts, alternatives and pairs of alternatives that contribute the least to achieving a high degree of consensus, i.e. those that are far away from the optimal solution.

1. *Identification of experts.* The set of experts, $EXPCH$, that should receive advice on how to change some of their preference values is identified:

$$EXPCH_c = \{k \mid pr^{kc} < \gamma_1\}$$

$$EXPCH_o = \{k \mid pr^{ko} < \gamma_2\}$$

where γ is the minimum proximity level required for the expert that needs to be changed.

2. *Identification of alternatives.* The alternatives which associated assessments should be taken into account by the above experts is identified:

$$ALT_{kc} = \{x_i \in X \mid pa_i^{kc} < \gamma_1 \wedge k \in EXPCH_c\}$$

$$ALT_{ko} = \{x_i \in X \mid pa_i^{ko} < \gamma_2 \wedge k \in EXPCH_o\}$$

3. *Identification of pairs of alternatives.* Here, the particular pairs of alternatives (x_i, x_j) whose respective assessments p_{ij}^k the expert e_k should change is determined:

$$PALT_{kc} = \{(x_i, x_j) \mid pp_{ij}^{kc} < \gamma \wedge x_i \in ALT_{kc} \wedge k \in EXPCH_c\}$$

$$PALT_{ko} = \{(x_i, x_j) \mid pp_{ij}^{ko} < \gamma \wedge x_i \in ALT_{ko} \wedge k \in EXPCH_o\}$$

- *Recommendation phase:*

In this phase we use two different rules for recommending what preferences the experts should modify.

1. *Rules to increase the consensus level.* The direction of change that should be applied to the preference assessment for each expert $e_k \in EXPCH_c$, p_{ij}^k , with $(x_i, x_j) \in PALT_{kc}$, is calculated using the following two direction rules:

- If $p_{ij}^k > p_{ij}^c$, the expert e_k should decrease the assessment associated to the pair of alternatives (x_i, x_j) in order to increase the consensus level.
- If $p_{ij}^k < p_{ij}^c$, the expert e_k should increase the assessment associated to the pair of alternatives (x_i, x_j) in order to increase the consensus level.

2. *Rules to improve the quality of the solution.* Simultaneously, the direction of change that should be applied to the preference assessment for each expert $e_k \in EXPCH_o$, p_{ij}^k , with $(x_i, x_j) \in PALT_{ko}$, is calculated using the following two direction rules:

- If $p_{ij}^k > p_{ij}^o$, the expert e_k should decrease the assessment associated to the pair of alternatives (x_i, x_j) in order to improve the quality of the solution received from the ontology (social proof).
- If $p_{ij}^k < p_{ij}^o$, the expert e_k should increase the assessment associated to the pair of alternatives (x_i, x_j) in order to improve the quality of the solution received from the ontology (social proof).

The main advantage of the proposed consensus model lies in the persuasive and convincing power of the society. At each consensus stage, not only those experts whose minds are far away from the consensual solution receive recommendations, but also those that are far away from the optimal solution retrieved from the fuzzy ontology will receive some feedback. It reduces the opinion changing aversion of the experts [136] which means that stagnation can be avoided more effectively. Also, the model itself can more precisely model real world GDM scenarios and the group can therefore reach consensus more seamlessly.

Figure 4.8 illustrates the presented consensus model. By employing the fuzzy ontology for both filtering among the alternatives and proposing a possible solution for the problem, it gives the experts a good starting point for further negotiations. In Section 4.6, the proposed consensus model is demonstrated with a practical example, implementing the Fuzzy Wine Ontology (see Section 4.1).

4.5 A Linguistic Extension to the Consensus Model

Including linguistic expressions into the consensus model presented in Section 4.4 would provide the experts with another way of expressing their preferences and opinions for the alternatives. The linguistic consensus model is conducted following the same process as the already defined consensus model, with some exceptions.

Instead of using fuzzy preference relations (FPR), the fuzzy linguistic preference relation (FLPR) P^h is implemented for each expert e_k . FLPR is a fuzzy set of the product set $X \times X$, characterized by a linguistic membership function [5, 296]:

$$\mu_P : X \times X \longrightarrow S.$$

where the value $\mu_{Ph}(x_i, x_j) = p_{ij}^k$ is interpreted as the linguistic preference degree of the alternative x_i over x_j for the expert e_k . When FLPR is used to represent the collective opinion of the group, the FLPR, $P^c = (p_{ij}^c)$, is obtained by aggregating all individual preference relations $\{P^1, P^2, \dots, P^m\}$. This produces a value showing the global preference between every pair of alternatives based on the majority of experts' opinions.

In this linguistic extension, a LOWA operator ϕ_Q is used to carry out the aggregation, guided by a fuzzy linguistic non-decreasing quantifier Q [307, 316]:

$$p_{ij}^c = \phi_Q(p_{ij}^1, \dots, p_{ij}^m).$$

This means that P^c is used as point of reference P^r . The LOWA operator is more suitable when handling linguistic information, compared to other OWA operator extensions [132].

When computing proximity measures, the linguistic extension differs slightly from the original model. In the first step, where the two proximity matrices, $PM^{kr} = (pm_{ij}^{kr})$, for each expert, e_k , are created, the following formula is used:

$$pm_{ij}^{kr} = 1 - \frac{|I(p_{ij}^k) - I(p_{ij}^r)|}{g}.$$

In step 2, part B in the original consensus model (See 2b) when the proximity measure of the alternatives pa_i^{kr} is calculated, the measure of the proximity between the preferences of each alternative x_i of the expert e_k and each point of reference P^r is instead obtained as:

$$pa_i^{kr} = \frac{\sum_{z=1; z \neq i}^n pp_{iz}^{kr}}{2(n-1)}.$$

This linguistic extension of the new consensus model presented in 4.4 implements LOWA operators and fuzzy linguistic preference relations (FLPR) into the previously defined model. The introduction of linguistic variables is a step towards making the models more user friendly and also better suited for dealing with imprecise data and tacit knowledge.

4.6 Using the Consensus Model to Select a Wine

The following Section aims at illustrating how the presented consensus model can be implemented in a practical situation. A basic application, designed with a mobile context in mind, was created to facilitate the ease of use. The application was designed to work through the web browser and can therefore be accessed and used by most smart phones. The different technical applications developed are presented

more extensively in Chapter 6, whereas this Section concentrates on numerical examples.

The scenario used in the first example is a formal dinner where fish is served. Three OWA operators are used for retrieving the most suitable wine from the Fuzzy Wine Ontology. One is implemented for calculating the formal value, one for the fish value and one for combining the two previously calculated values.

The OWA operators are assigned with the following values:

- **Formal Dinner:**

- Weights $\mathbf{w} \approx (0.40, 0.25, 0.35)$
- Attributes $\mathbf{b} \approx \mathbf{MediumPrice, RegularYear, MediumAlcohol}$

- **Fish:**

- Weights $\mathbf{w} \approx (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$
- Attributes $\mathbf{b} \approx \mathbf{NovelloYear, Dry, White}$

The following should therefore be solved

$$\arg \max_i OWA(R(x_i, \mathbf{Formal\ Dinner}), R(x_i, \mathbf{Fish})) \quad (4.9)$$

The values retrieved from calculation 4.9 are then combined with the use of a third OWA, producing the final value:

- **Formal Dinner and Fish:**

- Weights $\mathbf{w} \approx (0.5, 0.5)$
- Attributes $\mathbf{b} \approx \mathbf{Formal\ Dinner, Fish}$

The 5 best wines retrieved from the ontology are chosen, having the following values: $(0,75, 0.74, 0.73, 0.64, 0.51)$. Using (4.8) the preference relations are obtained, the result is presented in Table 4.5. For the next phase, three experts are asked to express their opinion in terms of a fuzzy preference relation about these 5

P^O	A_1	A_2	A_3	A_4	A_5
A_1	0,50	0,51	0,52	0,58	0,68
A_2	0,49	0,50	0,51	0,57	0,68
A_3	0,48	0,49	0,50	0,56	0,67
A_4	0,42	0,43	0,44	0,50	0,61
A_5	0,32	0,32	0,33	0,39	0,50

Table 4.5: The preference relation of the 5 wines based on the values produced by the fuzzy ontology

e_1	A_1	A_2	A_3	A_4	A_5
A_1	0,50	0,20	0,60	0,50	0,70
A_2	0,80	0,50	0,90	0,80	1,00
A_3	0,40	0,10	0,50	0,40	0,60
A_4	0,50	0,20	0,60	0,50	0,70
A_5	0,30	0,00	0,40	0,30	0,50

e_2	A_1	A_2	A_3	A_4	A_5
A_1	0,50	0,60	0,55	0,55	0,70
A_2	0,40	0,50	0,45	0,45	0,60
A_3	0,45	0,55	0,50	0,50	0,65
A_4	0,45	0,55	0,50	0,50	0,65
A_5	0,30	0,40	0,35	0,35	0,50

e_3	A_1	A_2	A_3	A_4	A_5
A_1	0,50	0,35	0,80	0,75	0,50
A_2	0,65	0,50	0,95	0,90	0,65
A_3	0,20	0,05	0,50	0,45	0,20
A_4	0,25	0,10	0,55	0,50	0,25
A_5	0,50	0,35	0,80	0,75	0,50

Table 4.6: The initial preference relations for 5 wines by 3 experts

wines, these preference matrices are presented in Table 4.6. The aggregated preference relation is calculated using an OWA operator with the weights $\mathbf{w} \approx (\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$.

The consensus value received after the first round is $CR = 0.77$, however, the minimum required value was set to 0.9. To reach a higher consensus value, the new consensus model was employed and the steps are presented in Table 4.7. The lowest initial proximity values belonged to the third expert. The recommended changes for that expert in the first round were therefore the following: increase the preference of A_2 over A_3 and decrease the preference of A_4 over A_2 , resulting in a consensus value of $CR = 0.80$. After 4 steps, a high enough consensus value is reached. Based on the final preference relations, the best wine is chosen as A_5 . The ontology recommended A_1 as the best choice, however the experts consensus value between A_1 and A_5 is minimal.

4.7 Summary

This Chapter has introduced a new consensus model for group decision making as well as a linguistic extension of the same model. It has also been demonstrated that fuzzy ontologies are suitable for handling a large set of alternatives and that they

Step	pr^{1c}	pr^{2c}	pr^{3c}	pr^{1o}	pr^{2o}	pr^{3o}	e_1	e_2	e_3	CR
0	0,90	0,88	0,88	0,86	0,96	0,80	–	–	+(2,3), -(4,3)	0,77
1	0,90	0,90	0,91	0,86	0,96	0,84	+(2,5), -(4,5)	–	–	0,80
2	0,97	0,91	0,91	0,93	0,96	0,83	–	–	+(2,3), -(3,5)	0,84
3	0,95	0,94	0,93	0,93	0,96	0,89	–	–	+(1,5), -(1,3)	0,87
4	0,94	0,96	0,96	0,93	0,96	0,97	–	–	–	0,90

Table 4.7: The Negotiation Process

are capable of narrowing the set down to a more feasible one.

The desire to achieve consensus is an important task, not only in profit-seeking organisations, but in all areas of life. By introducing new models, such as the consensus model presented in this Chapter, the aim is to create models for facilitating these ongoing processes and adapt them to different situations. As it is impossible to fully satisfy everyone in a group setting, involving everyone and reaching a compromise is more satisfying than having a single person making all the decisions, without taking the rest of the opinions into consideration.

The Fuzzy Wine Ontology and its objective have been introduced in more detail. The ontology has also been implemented in the consensus model, showing that fuzzy ontologies can represent knowledge expressed in an imprecise format, i.e. based on knowledge retrieved from experts.

By implementing different OWA operators for retrieving the best alternatives (e.g. wines) from the ontology and including them into the group decision making problem, a step has been taken towards validating the fact that aggregation operators in combination with fuzzy ontologies provide an useful tool for modelling and utilizing tacit knowledge.

In Chapter 5, new extensions of OWA operators will be presented and in Chapter 6 and Chapter 7 applications based on fuzzy ontologies are introduced. Although some of these results were created for other purposes, than specifically for GDM, they can be combined with the consensus reaching process. For example, in an intrusion detection application for financial organisations that is governed by experts, the consensus reaching process could be implemented to support their decisions.

Chapter 5

Aggregation Operators and Fuzzy Numbers in Decision Making

Extending OWA operators with new variations is a necessary task when developing new solutions for decision making problems, as utilizing various aggregation operators is one of the key approaches when making decisions [207]. One can utilize different nuances of the aggregation operators for very specific aggregation tasks. The importance of aggregation operators becomes even more crucial when imprecise data is included in the aggregation process [205, 309]

The goal of this chapter is to introduce new OWA operators and to show how they contribute to the functionality of fuzzy ontologies. The functionality of these definitions is then illustrated with practically aimed examples. The first Section 5.1 presents the IVFN-based OWA operators that have been developed and Section 5.2 presents novel similarity measures and OWAD-based definitions.

5.1 Induced Ordered Weighted Averaging Operator for IVFN

This Section presents the new definitions of the induced ordered weighted averaging (IOWA) operator when generalised for interval-valued fuzzy numbers (IVFN's). The definitions of different fuzzy extensions of the OWA operator [68, 207, 208] are special cases of the new definitions introduced in this section. By extending the induced OWA operator (3.5) with imprecise arguments and order inducing variables, it becomes possible to handle more imprecision in the aggregation process.

To illustrate the basic differences between a general OWA operator and the induced OWA operator (3.5), an IOWA-based numerical example is presented:

If we have 3 OWA pairs $\langle u_i, a_i \rangle$ [310]:

$$\langle 2, 0.3 \rangle, \langle 4, 1 \rangle, \langle 6, 0.2 \rangle$$

and the following weights to use for aggregation:

$$W = \begin{bmatrix} 0.7 \\ 0.2 \\ 0.1 \end{bmatrix}$$

First, the OWA pairs are ordered based on the variable u_i :

$$\begin{aligned} &\langle 6, 0.2 \rangle \\ &\langle 4, 1 \rangle \\ &\langle 2, 0.3 \rangle \end{aligned}$$

From this, the ordered list of the a_i values is retrieved (defined as vector B):

$$B = \begin{bmatrix} 0.2 \\ 1 \\ 0.3 \end{bmatrix}$$

If F is applied, we receive:

$$F(\langle u_i, a_i \rangle) = (0.7)(0.2) + (0.2)(1) + (0.1)(0.3) = 0.37$$

5.1.1 The Quasi IVFN-IOWA operator

By allowing the order induced variable to be expressed as an IVFN, it is possible to include additional information into the aggregation process, not simply limiting the aggregation process to the order of the arguments. The following definition describes the Quasi version of the IVFN-IOWA operator:

Definition 11 ([209]). *A Quasi IVFN-IOWA operator of dimension n is a mapping $f : IVFN^n \times IVFN^n \rightarrow IVFN$ that has an associated weighting vector W of dimension n with $w_j \in [0, 1]$ and $\sum_{j=1}^n w_j = 1$, such that:*

$$f(\langle U_1, A_1 \rangle, \langle U_2, A_2 \rangle, \dots, \langle U_n, A_n \rangle) = g^{-1} \left(\sum_{j=1}^n w_j g(B_j) \right) \quad (5.1)$$

where B_j is the A_i value of the pair $\langle U_i, A_i \rangle$ having the j th largest U_i ; U_i is the order inducing variable represented in the form of IVFN's; A_i is the argument variable represented in the form of IVFN's, and $g : IVFN^m \rightarrow IVFN$ is a continuous strictly monotone function.

Theorem 5.1.1 ([209]). *If f is a Quasi IVFN-IOWA operator, then it is commutative, monotone, idempotent, and bounded, as the following properties are satisfied:*

1. f is commutative:

$$f(\langle U_1, A_1 \rangle, \langle U_2, A_2 \rangle, \dots, \langle U_n, A_n \rangle) = f(\langle U'_1, A'_1 \rangle, \langle U'_2, A'_2 \rangle, \dots, \langle U'_n, A'_n \rangle)$$

where $(\langle U'_1, A'_1 \rangle, \langle U'_2, A'_2 \rangle, \dots, \langle U'_n, A'_n \rangle)$ is any permutation of the arguments.

2. f is monotone: if $A_i \geq B_i$ for all i , then

$$f(\langle U_1, A_1 \rangle, \langle U_2, A_2 \rangle, \dots, \langle U_n, A_n \rangle) \geq f(\langle U_1, B_1 \rangle, \langle U_2, B_2 \rangle, \dots, \langle U_n, B_n \rangle)$$

3. f is idempotent:

$$f(\langle U_1, A \rangle, \langle U_2, A \rangle, \dots, \langle U_n, A \rangle) = A$$

4. f is bounded:

$$\min_i \{A_i\} \leq f(\langle U_1, A_1 \rangle, \langle U_2, A_2 \rangle, \dots, \langle U_n, A_n \rangle) \leq \max_i \{A_i\}$$

Proof. The first and third statements follow from the definition of the Quasi IVFN-IOWA operator and the arithmetical operations of IVFN's. The monotonicity follows from the properties of the function g and the linearity of the mean value. The boundedness can be proven by comparing the mean value of the aggregated value to the minimum and maximum as follows:

$$\begin{aligned} E(f(\langle U_1, A_1 \rangle, \langle U_2, A_2 \rangle, \dots, \langle U_n, A_n \rangle)) &= E \left[g^{-1} \left(\sum_{j=1}^n w_j g(B_j) \right) \right] \geq \\ E \left[g^{-1} \left(\sum_{j=1}^n w_j g(\min_i \{A_i\}) \right) \right] &= E \left[g^{-1} \left(g(\min_i \{A_i\}) \sum_{j=1}^n w_j \right) \right] \\ &= E(\min_i \{A_i\}) \end{aligned}$$

using that $\sum_{j=1}^n w_j = 1$, and

$$\begin{aligned} E(f(\langle U_1, A_1 \rangle, \langle U_2, A_2 \rangle, \dots, \langle U_n, A_n \rangle)) &= E \left[g^{-1} \left(\sum_{j=1}^n w_j g(B_j) \right) \right] \leq \\ E \left[g^{-1} \left(\sum_{j=1}^n w_j g(\max_i \{A_i\}) \right) \right] &= E \left[g^{-1} \left(g(\max_i \{A_i\}) \sum_{j=1}^n w_j \right) \right] \\ &= E(\max_i \{A_i\}) \end{aligned}$$

where B_j is the A_i value of the pair $\langle u_i, A_i \rangle$ having the j th largest u_i . □

5.1.2 The IVFN-IOWA operator

Choosing different functions as g , we obtain special cases of the Quasi IVFN-IOWA operator. By setting $g(x) = x^2$, we obtain the quadratic IVFN-IOWA operator. The case of $g(x) = x$ corresponds to the IVFN-IOWA operator, it is therefore useful to formulate a definition for this case, as this is the most used version of the Quasi operator.

Definition 12 ([209]). *An IVFN-IOWA operator of dimension n is a mapping IVFN-IOWA : $\mathbb{R}^n \times IVFN^n \rightarrow IVFN$ that has an associated weighting vector W of dimension n with $w_j \in [0, 1]$ and $\sum_{j=1}^n w_j = 1$, such that:*

$$IVFN-IOWA(\langle u_1, A_1 \rangle, \langle u_2, A_2 \rangle, \dots, \langle u_n, A_n \rangle) = \sum_{j=1}^n w_j B_j, \quad (5.2)$$

where B_j is the A_i value of the FIOWA pair $\langle u_i, A_i \rangle$ having the j th largest u_i , u_i is the order inducing variable and A_i is the argument variable represented in the form of IVFN's.

If f is an IVFN-IOWA operator then it is commutative, monotone, idempotent, and bounded. These properties automatically follow from the Theorem 5.1.1 and from the fact that IVFN-IOWA is a special case of the Quasi IVFN-IOWA operator.

5.1.3 The IVFN-IHOWA operator

As a next step, the definition of the heavy OWA operator [308] is extended to interval-valued fuzzy numbers. This Quasi IVFN-IHOWA operator allows for the sum of the weights to be more than 1, i.e. it can take any value in the $[1, n]$ interval.

Definition 13 ([211]). *The Quasi IVFN-IHOWA operator of dimension n is a mapping $f : IVFN^n \times IVFN^n \rightarrow IVFN$ that has an associated weighting vector W of dimension n with $w_j \in [0, 1]$ and $1 \leq \sum_{j=1}^n w_j \leq n$, such that:*

$$f(\langle U_1, A_1 \rangle, \langle U_2, A_2 \rangle, \dots, \langle U_n, A_n \rangle) = g^{-1} \left(\sum_{j=1}^n w_j g(B_j) \right) \quad (5.3)$$

where B_j is the A_i value of the pair $\langle U_i, A_i \rangle$ having the j th largest U_i ; U_i is the order inducing variable represented in the form of IVFN's; A_i is the argument variable represented in the form of IVFN's, and $g : IVFN^n \rightarrow IVFN$ is a continuous strictly monotone function.

This operator is only idempotent in the case when $\sum_{j=1}^n w_j = 1$, otherwise the aggregated value $A \sum_{j=1}^n w_j$ is obtained when all the arguments are equal to A . The commutative, monotone and bounded properties are formulated in the following theorem.

Theorem 5.1.2 ([211]). *If f is a Quasi IVFN-IHOWA operator, then the following properties are satisfied:*

1. f is commutative:

$$f(\langle U_1, A_1 \rangle, \langle U_2, A_2 \rangle, \dots, \langle U_n, A_n \rangle) = f(\langle U'_1, A'_1 \rangle, \langle U'_2, A'_2 \rangle, \dots, \langle U'_n, A'_n \rangle)$$

where $(\langle U'_1, A'_1 \rangle, \langle U'_2, A'_2 \rangle, \dots, \langle U'_n, A'_n \rangle)$ is any permutation of the arguments.

2. f is monotone: if $A_i \geq B_i$ for all i , then

$$f(\langle U_1, A_1 \rangle, \langle U_2, A_2 \rangle, \dots, \langle U_n, A_n \rangle) \geq f(\langle U_1, B_1 \rangle, \langle U_2, B_2 \rangle, \dots, \langle U_n, B_n \rangle)$$

3. f is bounded:

$$\min_i \{A_i\} \leq f(\langle U_1, A_1 \rangle, \langle U_2, A_2 \rangle, \dots, \langle U_n, A_n \rangle) \leq \sum_{j=1}^n A_j$$

Proof. The commutativity follows from the definition of the operator and the arithmetical operations of IVFN's. The monotonicity follows from the properties of the function g and the linearity of the mean value. The boundedness can be proven by comparing the mean value of the aggregated value to the minimum and the total operator ($\sum_{j=1}^n A_j$). \square

5.1.4 Examples

To better illustrate how the presented definitions can be used, this Section will presents some examples, both numerical and practical, that demonstrate their benefits.

Numerical Example

To illustrate the presented concept, we will calculate the aggregation of triangular-shaped IVFN's (the upper and lower fuzzy numbers are triangular fuzzy numbers). The upper and lower triangular fuzzy numbers can be represented as $A^L = (a, \alpha, \beta)$ and $A^U = (a, \theta, \tau)$ respectively, where a stands for the center, (α, β) and (θ, τ) denotes the left and right width of the fuzzy numbers. The mean value of a trapezoidal IVFN can be expressed as [61]

$$E(A) = a + \frac{\beta - \alpha}{12} + \frac{\tau - \theta}{12}.$$

In this example we use the following three trapezoidal IVFN's:

$$\begin{aligned} A_1^L &= (4, 1, 3), A_1^U = (4, 3, 4), \\ A_2^L &= (3, 2, 5), A_2^U = (3, 4, 6), \\ A_3^L &= (9, 2, 2), A_3^U = (9, 4, 4), \end{aligned}$$

The corresponding order inducing variables and weights are:

$$\begin{aligned} u_1 &= 3, u_2 = 2, u_3 = 6. \\ W &= (0.2, 0.4, 0.4). \end{aligned}$$

The aggregation can be calculated as:

$$\text{IVFN-IOWA}(\langle 3, A_1 \rangle, \langle 2, A_2 \rangle, \langle 6, A_3 \rangle) = 0.2 * A_3 + 0.4 * A_1 + 0.4 * A_2.$$

Using the arithmetic of IVFN's, the aggregated value, A , is obtained as:

$$\begin{aligned} \text{the lower fuzzy number } A^L &= (4, 1.2, 2.6) \text{ and} \\ \text{the upper fuzzy number } A^U &= (4, 2.8, 3.6). \end{aligned}$$

Project selection utilizing the IVFN-IOWA operator

According to Lee et al. [183], research and development (R&D) projects are important factors in the field of information technology (IT). This is due to the fact that innovations are crucial to ensure the profitability of a company in the IT sector; selecting the best R&D projects is therefore an important part of the decision making processes within companies.

For this example, we implement the IVFN-IOWA operator for the purpose of project selection. A multi-attribute decision making problem with multiple experts can be processed using the following steps:

- Step 1. The selection of criteria and alternatives: the appropriate set of selection criteria $C = \{c_1, \dots, c_m\}$ and the set of potential alternative solutions $A = \{a_1, \dots, a_n\}$ are defined.
- Step 2. Defining the evaluation measure: in this example the experts express their opinion concerning to what extent an alternative satisfies a criterion by using linguistic labels represented by interval-valued fuzzy numbers. One possible representation using IVFN's is presented in Table 5.1, utilizing trapezoidal shaped upper and lower fuzzy numbers.
- Step 3. The experts specify their opinion: every expert $E_j, j \in \{1, \dots, l\}$ provides his/her evaluation in the form of a matrix $(A_{ab}^j)_{n \times m}$ where $A_{ab}^j \in \{\text{very low, low, medium, high, very high}\}$.
- Step 4. The opinions are aggregated into one decision matrix: every expert E_j is associated with a weight w_j such that $w_j \in [0, 1], \sum_{j=1}^l w_j = 1$. The weights define the importance of the experts within the group. Using these weights, the individual evaluations are aggregated using the arithmetic operations of IVFN's; the result is denoted by $(A_{ab})_{n \times m}$.

	Upper fuzzy number	Lower fuzzy number
Very Low	(0,0,0.2,0.4)	(0,0,0.15,0.3)
Low	(0,0.2,0.4,0.6)	(0.1,0.25,0.35,0.5)
Medium	(0.2,0.4,0.6,0.8)	(0.3,0.45,0.5,0.7)
High	(0.4,0.6,0.8,1)	(0.5,0.65,0.75,0.9)
Very High	(0.6,0.8,1,1)	(0.7,0.85,0.95,1)

Table 5.1: Linguistic labels represented by trapezoidal IVFN's

- Step 5. Individually aggregating every alternative: using the matrix of aggregated payoffs, the overall evaluation for every alternative is obtained individually by employing the IVFN-IOWA operator. The alternative with the highest value will be selected and an ordering for the alternatives is established.

E_1	C_1	C_2	C_3	C_4	C_5
A_1	low	medium	very low	low	medium
A_2	high	low	very high	low	very low
A_3	medium	medium	medium	medium	high
A_4	low	very high	high	low	medium

E_2	C_1	C_2	C_3	C_4	C_5
A_1	high	medium	low	very high	medium
A_2	low	very low	high	medium	high
A_3	low	very high	medium	very low	high
A_4	medium	very high	low	very low	medium

E_3	C_1	C_2	C_3	C_4	C_5
A_1	medium	high	very low	high	medium
A_2	medium	medium	very high	very low	medium
A_3	low	high	very high	low	medium
A_4	very high	medium	high	medium	medium

Table 5.2: Preference relations of the 4 alternatives constructed by 3 experts

In this example the decision-makers should consider the following 5 criteria when evaluating the possible R&D projects available:

1. Competitiveness of technology
2. The potential size of market
3. Environmental and safety benefits

4. Return on development cost
5. Opportunity of project result implementation

The preferences are expressed using trapezoidal IVFN's as described in Table 5.1. The preference matrices specified by the 3 experts for the 4 alternative projects considered are listed in Table 5.2. The weights used in this example for representing the importance of the experts are: $S = (0.1, 0.6, 0.3)$. The aggregated payoff matrices for the four alternatives can be produced using the importance weights of the experts and arithmetical operation on IVFN's (weighted average).

Lower	C_1	C_2	C_3	C_4	C_5
A_1	4	3	1	5	2
A_2	2	4	3	1	5
A_3	4	3	1	2	5
A_4	5	4	3	1	2

Table 5.3: Order Inducing Values

Alternative	Lower fuzzy number	Upper fuzzy number	Mean value	Ranking
A_1	(0.31,0.45,0.55,0.70)	(0.22,0.40,0.60,0.80)	0.501	3
A_2	(0.32,0.45,0.56,0.69)	(0.23,0.40,0.60,0.78)	0.502	2
A_3	(0.30,0.42,0.54,0.67)	(0.22,0.38,0.58,0.75)	0.482	4
A_4	(0.34,0.48,0.59,0.72)	(0.24,0.43,0.63,0.80)	0.529	1

Table 5.4: The obtained evaluation of the 4 alternatives

The weights of the IVFN-IOWA are $W = (0.1, 0.15, 0.25, 0.35, 0.15)$. Considering the possibility that the R&D projects have different characteristics, induced ordering variables are introduced to emphasize different criteria for different alternatives (see Table 5.3). The final results of the project selection process are shown in Table 5.4. The mean value is employed to obtain the final ordering. The alternative with the best payoff is A_4 , and the order is the following: $A_4 \succ A_2 \succ A_1 \succ A_3$.

Special cases: numerical comparison

To further illustrate the advantages of the proposed aggregation operators the following problem is approached: selecting a wine which is similar to (i) a set of preferences or (ii) an ideal wine. The Fuzzy Wine Ontology 4.1 is implemented as the main source of knowledge.

4 different wines are considered as alternatives as well as 3 criteria (Alcohol, Acidity, Price) with preferences specified in a specific context. Decision-makers are asked to specify to what degree they think a given wine satisfies a predefined criterion level. For example, if it is required that the wine should fit the context of

E_1	Alcohol	Acidity	Price
A_1	low	medium	very low
A_2	high	very low	very high
A_3	medium	medium	medium
A_4	low	very high	high

Table 5.5: The preference relation of the wines

"Business Dinner", we can estimate how the alcohol level of an alternative wine is similar to the alcohol level of an ideal wine which would be the most suitable for that context.

Using the matrix of payoffs, we obtain the overall evaluation for every alternative individually by employing the IVFN-IOWA operator. The alternative with the highest value will be selected and an ordering for the alternatives is established.

	Upper fuzzy number	Lower fuzzy number
U_1	(0.5,1,1.5,2)	(0.75,1.2,1.4,1.75)
U_2	(0.25,0.75,1,1.25)	(0.5,0.8,0.9,1.1)
U_3	(1,1.25,1.5,2.25)	(1.2,1.3,1.4,2)

Table 5.6: Order Inducing Values

The preference matrix specified for choosing one of four wines based on three criteria is listed in Table 5.5. The order inducing variables are presented in Table 5.6. Using different special cases of the generalised IVFN-IHOWA, we can obtain the different rankings of the wines in Table 5.7. The weights of the different OWA operators are specified as $W = (0.5, 0.3, 0.2)$, for the heavy OWA we use $W = (0.4, 0.9, 0.2)$.

Notably, employing different operators results in different rankings. For example, the new operators result in different rankings than the fuzzy average. The order inducing variables and the weights in the heavy OWA provide more freedom to the decision maker to express the preferences regarding the importance of different attributes with respect to each other and it becomes possible to incorporate this into the weights of the operator.

For the second case, when a wine is chosen based on its similarity to an ideal

Mean	Fuzzy min	Fuzzy max	Fuzzy average	IVFN-IOWA	IVFN-IHOWA
A_1	0.12 (3)	0.50 (3)	0.31 (4)	0.28 (4)	0.59 (3)
A_2	0.12 (3)	0.88 (1)	0.57 (2)	0.51 (2)	0.56 (4)
A_3	0.50 (1)	0.50 (3)	0.50 (3)	0.45 (3)	0.75 (2)
A_4	0.30 (2)	0.88 (1)	0.63 (1)	0.56 (1)	1.05 (1)

Table 5.7: The obtained evaluation of the 4 alternatives (the rankings are indicated in the parenthesis after the mean values)

wine, we assume that there is a wine which has been chosen on a previous occasion as the best for the context but it is not available at the moment. Using the same four alternatives as in the previous case one can estimate which one of these four is the most similar to the ideal wine by applying the IVFN-IOWAD operator. Also in this case, Table 5.5 is utilized even though the interpretation of the labels is different: for example, if the ideal wine has a high alcohol level it means that A_1 and A_4 are similar to the ideal wine to a low degree, whereas A_2 can be considered to be similar to a high degree. Using the order inducing variable from Table 5.6, we obtain that the most similar wine is A_4 , followed by A_2 , A_3 , and A_1 , as: $0.56 \succ 0.51 \succ 0.45 \succ 0.28$.

5.2 Ordered Weighted Averaging Distance Operator for IVFN

In this section some enhancements regarding Ordered Weighted Averaging Distance Operators (OWAD) and how they can be applied for interval-valued fuzzy numbers in the context of decision making problems is presented. To illustrate how these new definitions are used, Section 5.2.5 presents some examples implementing these new definitions.

5.2.1 Similarity Measures for Interval-valued Fuzzy Sets

Similarity measures are an important technique for handling imprecise information in the context of information systems [292]. The easily understandable functionality behind these measures, i.e. comparing how similar two instances are, has contributed to their popularity. This is also the case regarding intrusion detection systems, where numerous applications and implementations are based on similarity measures. An example of an intrusion detection system, implementing both fuzzy ontology and similarity measures is presented in Chapter 7.

By looking at the literature on similarity measures for interval-valued fuzzy sets, three main groups that originate from different approaches to construct similarities can be found (cf. [211] for a more detailed discussion):

1. *Similarity based on distance measures*: The traditional way to obtain the similarity from a normalized distance measure d is to calculate

$$s(A, B) = 1 - d(A, B).$$

The most commonly used distance measures are the Hamming distance and Euclidean distance. In this group of measures, there are two main approaches: (i) calculating the distance directly from the interval-valued membership functions [52] or (ii) transforming the interval-valued fuzzy sets into type-1 fuzzy sets and calculate the distances of the obtained fuzzy sets [87]. There

exist numerous proposals for both approaches mainly using the definitions of [52] and [87] as a basis and improving these definitions in different ways (for example incorporating weighting functions).

2. *Similarity based on set-theoretic measures and arithmetic operations:* In this group of measures, the most general formula was given by Bustince [53] with t-norms and interval valued grade indicators. One of the most common approaches is to use the Jaccard index as the basis of similarity measures. As in the previous case, there are two main ways to apply this measure: (i) calculating the Jaccard index of the upper membership values and the lower membership values separately and combine them to obtain an overall similarity [325]; (ii) calculating the similarity directly from the interval-valued memberships [303].
3. *Similarity based on type-1 fuzzy sets:* In this group of measures, we can find methods that employ the similarity of embedded fuzzy sets [212] or aggregate the similarity of the upper and lower membership functions to obtain a new similarity measure [101].

Additionally, there exist a few approaches to determining the similarity for general type-2 fuzzy sets that can naturally be applied to interval-valued fuzzy sets (as special cases of general type-2 fuzzy sets). For example McCulloh et al. [206] created a framework to extend any similarities of interval-valued fuzzy sets to general type-2 fuzzy sets.

5.2.2 Distance for IVFN

In order to extend the OWAD operator (see definition 8) into the family of IVFN's, an appropriate distance function needs to be chosen i.e. $d : IVFN \times IVFN \rightarrow \mathbb{R}$. This distance measure has to satisfy the following properties:

1. Non-negativity: $d(A_1, A_2) \geq 0$
2. Commutativity: $d(A_1, A_2) = d(A_2, A_1)$
3. Reflexivity: $d(A, A) = 0$
4. Triangle inequality: $d(A_1, A_2) + d(A_2, A_3) \geq d(A_1, A_3)$.

There exist different definitions of distances for interval-valued fuzzy sets (and as a special case, for IVFN's) based on traditional distance measures, e.g. by Grzegorzewski [117], Wang [294] and Zheng and Guo [323]. For the OWAD extensions presented here, the mean value of an interval-valued fuzzy number (4) is employed for measuring the distance of IVFN's.

The distance between two IVFN's, $d : \text{IVFN} \times \text{IVFN} \rightarrow \mathbb{R}$, is defined as:

$$d(A, B) = |E(A) - E(B)|. \quad (5.4)$$

It is easy to see that this distance satisfies the four properties of a distance measure:

1. Non-negativity: $|E(A) - E(B)| \geq 0$
2. Commutativity: $|E(A) - E(B)| = |E(B) - E(A)|$
3. Reflexivity: $|E(A) - E(A)| = 0$
4. Triangle inequality: $|E(A) - E(B)| + |E(B) - E(C)| \geq |E(A) - E(C)|$.

5.2.3 The Quasi IVFN-IOWAD operator

Definition 14 ([210]). A *Quasi IVFN-IOWAD operator of dimension n* is a mapping $f : \text{IVFN}^n \times \text{IVFN}^n \times \text{IVFN}^n \rightarrow \mathbb{R}$ that has an associated weighting vector W of dimension n with $w_j \in [0, 1]$ and $\sum_{j=1}^n w_j = 1$, such that:

$$f(\langle U_1, A_1, B_1 \rangle, \langle U_2, A_2, B_2 \rangle, \dots, \langle U_n, A_n, B_n \rangle) = g^{-1} \left(\sum_{j=1}^n w_j g(D_j) \right), \quad (5.5)$$

where D_j is the $d(A_i, B_i)$ value of the triplet $\langle U_i, A_i, B_i \rangle$ having the j th largest U_i and $g : \mathbb{R} \rightarrow \mathbb{R}$ is a continuous, strictly monotone function.

Theorem 5.2.1 ([210]). If f is an *Quasi IVFN-IOWAD operator*, then the following properties are satisfied:

1. f is commutative:

$$\begin{aligned} f(\langle U_1, A_1, B_1 \rangle, \langle U_2, A_2, B_2 \rangle, \dots, \langle U_n, A_n, B_n \rangle) = \\ f(\langle U'_1, A'_1, B'_1 \rangle, \langle U'_2, A'_2, B'_2 \rangle, \dots, \langle U'_n, A'_n, B'_n \rangle), \end{aligned}$$

where $(\langle U'_1, A'_1 \rangle, \langle U'_2, A'_2 \rangle, \dots, \langle U'_n, A'_n \rangle)$ is any permutation of the arguments.

2. f is monotone: if $d(A_i^1, B_i^1) \geq d(A_i^2, B_i^2)$ for all i , then

$$\begin{aligned} f(\langle U_1, A_1^1, B_1^1 \rangle, \langle U_2, A_2^1, B_2^1 \rangle, \dots, \langle U_n, A_n^1, B_n^1 \rangle) = \\ f(\langle U_1, A_1^2, B_1^2 \rangle, \langle U_2, A_2^2, B_2^2 \rangle, \dots, \langle U_n, A_n^2, B_n^2 \rangle). \end{aligned}$$

3. f is idempotent: if $d(A_i, B_i) = d(A_j, B_j) = d, \forall i, j$, then

$$f(\langle U_1, A_1, B_1 \rangle, \langle U_2, A_2, B_2 \rangle, \dots, \langle U_n, A_n, B_n \rangle) = d.$$

4. f is bounded:

$$\begin{aligned} \min_i \{d(A_i, B_i)\} &\leq \\ f(\langle U_1, A_1, B_1 \rangle, \langle U_2, A_2, B_2 \rangle, \dots, \langle U_n, A_n, B_n \rangle) &\leq \\ \max_i \{d(A_i, B_i)\}. \end{aligned}$$

Proof. The proofs are straightforward consequences of the definition and the arithmetic operations on interval-valued fuzzy sets, therefore only the boundedness is proven. It can be proven by comparing the aggregated value to the minimum and maximum as follows:

$$\begin{aligned} \min_i \{d(A_i, B_i)\} &= g^{-1} \left(g(\min_i \{d(A_i, B_i)\}) \right) = \\ g^{-1} \left(\sum_{j=1}^n w_j g(\min_i \{d(A_i, B_i)\}) \right) &\leq g^{-1} \left(\sum_{j=1}^n w_j g(D_j) \right) = \\ f(\langle U_1, A_1, B_1 \rangle, \langle U_2, A_2, B_2 \rangle, \dots, \langle U_n, A_n, B_n \rangle) \end{aligned}$$

and

$$\begin{aligned} \max_i \{d(A_i, B_i)\} &= g^{-1} \left(g(\max_i \{d(A_i, B_i)\}) \right) = \\ g^{-1} \left(\sum_{j=1}^n w_j g(\max_i \{d(A_i, B_i)\}) \right) &\geq g^{-1} \left(\sum_{j=1}^n w_j g(D_j) \right) = \\ f(\langle U_1, A_1, B_1 \rangle, \langle U_2, A_2, B_2 \rangle, \dots, \langle U_n, A_n, B_n \rangle). \end{aligned}$$

□

Note 1. One special case of this definition is the generalised IVFN-IOWAD operator, where $g(x) = x^\alpha$, $\alpha \in \mathbb{R}$, and it takes the following form:

$$\left(\sum_{j=1}^n w_j D_j^\alpha \right)^{\frac{1}{\alpha}}.$$

5.2.4 The IVFN-IOWAD operator

A special case of the Quasi IVFN-IOWAD is the IVFN-IOWAD operator, presented next.

Definition 15 ([210]). An IVFN-IOWAD operator of dimension n is a mapping $f : \mathbb{R}^n \times IVFN^n \times IVFN^n \rightarrow \mathbb{R}$ that has an associated weighting vector W of dimension n with $w_j \in [0, 1]$ and $\sum_{j=1}^n w_j = 1$, such that:

$$f(\langle u_1, A_1, B_1 \rangle, \langle u_2, A_2, B_2 \rangle, \dots, \langle u_n, A_n, B_n \rangle) = \sum_{j=1}^n w_j D_j, \quad (5.6)$$

where D_j is the $d(A_i, B_i)$ value of the triplet $\langle u_i, A_i, B_i \rangle$ having the j th largest u_i , where u_i is the order inducing variable and A_i, B_i are the argument variable represented in the form of IVFN's.

Theorem 5.2.2 ([210]). *Based on the theorem provided for the Quasi IVFN-IOWAD operator, if f is a IVFN-IOWAD operator, then it is commutative, monotone, idempotent, and bounded.*

5.2.5 Examples

To better illustrate how the presented definitions can be used, this Section will present a numerical example calculating the OWA-distance of triangular-shaped IVFN's and secondly some explanations on how OWAD operators can be employed for fuzzy ontologies are presented.

Numerical example

To illustrate the OWAD concept, we will calculate the OWA-distance of triangular-shaped IVFN's (the upper and lower fuzzy numbers are triangular fuzzy numbers) choosing $g(x) = x$, which is a special case of the definition, an IVFN-IOWAD operator. In the example we will use the following six triangular IVFN's:

$$\begin{aligned} A_1^L &= (6, 3, 2), A_1^U = (6, 4, 3), \\ A_2^L &= (8, 5, 4), A_2^U = (8, 7, 6), \\ A_3^L &= (2, 2, 4), A_3^U = (3, 3, 6), \\ B_1^L &= (6, 3, 3), B_1^U = (6, 4, 4), \\ B_2^L &= (7, 4, 3), B_2^U = (7, 5, 4), \\ B_3^L &= (2, 1, 1), B_3^U = (2, 3, 3), \end{aligned}$$

The corresponding order inducing variables and weights are defined as:

$$\begin{aligned} u_1 &= 4, u_2 = 1, u_3 = 7. \\ W &= (0.1, 0.5, 0.4). \end{aligned}$$

The aggregation can be calculated as

$$\begin{aligned} &f(\langle 4, A_1, B_1 \rangle, \langle 1, A_2, B_2 \rangle, \langle 7, A_3, B_3 \rangle) \\ &= 0.1|E(A_3 - B_3)| + 0.5|E(A_1 - B_1)| + 0.4|E(A_2 - B_2)| \\ &= 0.625. \end{aligned}$$

OWAD Operators for Fuzzy Ontologies

For this example, it is assumed that the relation specifying different relationships between individuals and concepts takes IVFN's as values. I.e. by implementing IVFN's in a fuzzy ontology, they can represent different types of relationships between individuals and concepts (e.g., 'belongs-to', 'has-a'). The fuzzy quantities range in the $[0, 1]$ interval, 1 and 0 indicate a strong and weak relationship, respectively.

The information for the fuzzy ontology can be obtained from experts. Instead of using the set of IVFN's with support in the $[0, 1]$ interval as the range of the relation, the experts could utilize a reasonable set of linguistic descriptions to assess the value of the relationships in the ontology. For this purpose, linguistic variables represented by trapezoidal IVFN's can be employed.

When a fuzzy ontology is employed as a decision support system, the first step is to create a subset of the concepts used to describe specific cases or situations. Based on the descriptions and the ontology relations, we can choose the object which provides the most satisfactory solution.

The process of using a fuzzy ontology and the OWAD operators as decision support tools can be summarized in the following steps:

- **Step 0. Creating the ontology:** using expert knowledge the individuals, $I = \{i_1, i_2, \dots, i_n\}$, and the concepts, $C = \{c_1, c_2, \dots, c_m\}$, are defined using fuzzy relations to specify the relationships between the individuals and objects.
- **Step 1. Specifying the context:** defining a subset of the concepts, $C_l = \{c_{l_1}, c_{l_2}, \dots, c_{l_k}\}$, it can sufficiently describe a given case. Experts can specify the connection between the case and the concepts using *IVFN's*; using the same set of linguistic variables used in previous examples (Table 5.1). Trapezoidal shaped upper and lower fuzzy numbers are implemented. If we have more experts, the opinions will be aggregated by employing an OWA operator.
- **Step 2. Defining the importance of the concepts:** the decision maker is able to specify importance weights associated with every element in the defined subset C_l . These values will be used as order inducing variables in the aggregation step.
- **Step 3. Calculating the distance:** using a case description and the order inducing variables provided by the experts together with a set of OWA weights, the distance of the case from the individuals in the ontology employing the Quasi IVFN-IOWAD operator can be calculated.
- **Step 4. Choosing the closest solution:** when the distances are obtained, the individuals that have the smallest distance from the case description will be

chosen as possible solutions. These solutions can then be presented for the decision maker to e.g. evaluate or confirm.

Scenarios illustrating these definitions will be presented in Chapter 7.

5.3 Summary

This Chapter has introduced different generalisations of the OWA operator, applying interval-valued fuzzy numbers as arguments of the aggregation process. Furthermore, novel generalisations of the induced OWAD operators have been introduced, where the operator is applied on interval-valued fuzzy numbers based on the mean value of IVFN's. Further, it has been proven that the different introduced extensions of the OWA operator satisfy important properties, such as commutativity and monotonicity.

A lot of decision making problems tend to become unmanageable due to complexity. By utilizing fuzzy numbers and linguistic variables one can create suitable description of complicated situations. I.e. the process of aggregating imprecise information described by fuzzy variables plays a crucial role in the decision making process. Developing new variations of the OWA operator is therefore a necessary task.

To show the usability of these novel definitions, some examples are presented to demonstrate the usability of the new OWA definitions as well as validate their produced benefits, for instance by employing the OWA operators in fuzzy ontologies for aggregating information.

The definitions developed in this Chapter is utilized from a more practical perspective in both Chapter 6 and Chapter 7, where they are applied for aggregating the imprecise information needed for producing different types of advice.

Chapter 6

Fuzzy Ontology Applications

In a fast-paced business environment, there is an need for distributing and sharing the collective knowledge that exists and is being created in organisations. Previous chapters in this thesis have presented methods for utilizing and storing imprecise and tacit knowledge. The development of new mobile technologies, e.g. for the Semantic Web, has opened the door for new possibilities to distribute this information effectively [251].

The mobilisation of knowledge will change the business processes of today, as users will be able to receive illustrative, real time advice and support regardless of where they are currently operating. As an example, maintenance personnel could wear a pair of eyeglasses that are connected to the organisations database and the user could receive step-by-step instructions on how to perform the reparation of a broken product; this could work even if the person wearing the classes has no previous experience and knowledge about that particular problem and solution. The expertise of the user in combination with detailed information and instructions received through the eyeglasses will make the whole process possible.

In this chapter, we show how information technologies in combination with fuzzy ontology can utilize and mobilise tacit knowledge; this is demonstrated by presenting different versions of novel web platform and Android applications.

6.1 The Structure of the Applications

This Section introduces the initial application structure developed for mobilising knowledge with the help of fuzzy ontologies, presenting the basic building stones of the server and the graphical user interface (GUI). This structure was used as a basis for the further advancements presented later on in this Chapter.

As the context for the developed applications, a dinner setting is used, where the participants should decide what wine they want to drink with their food. The Fuzzy Wine Ontology 4.1 was used as the main source of knowledge.

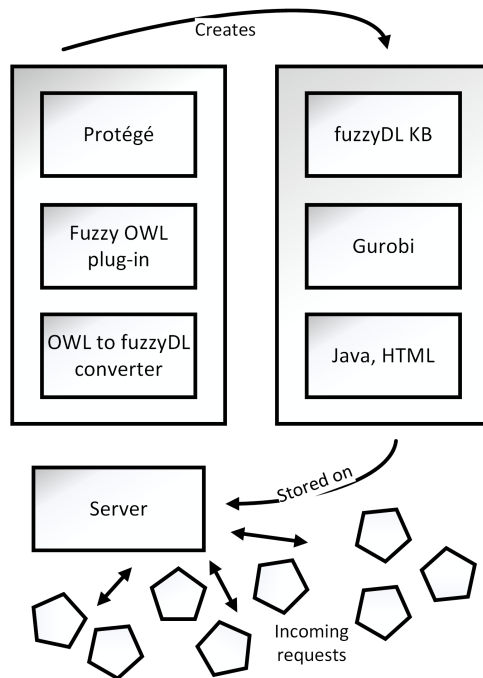


Figure 6.1: Technical structure of the application

6.1.1 The Server Side

The server side is the main component of the applications developed, as most of the computation is performed on the server. The different clients connecting to the server mainly works as senders and receivers of information, i.e. little computation is performed on the client devices themselves.

Figure 6.1 presents the basic set-up of the application. The Fuzzy Wine Ontology was modelled as an OWL ontology in Protégé and then converted from .owl format to a *fuzzyDL* processable format. The knowledge base created is stored as a .txt file on the server, which allows for the Java program to directly access the fuzzy ontology [39,41].

Application servers that can be used for managing these files are, for instance, the Glassfish server or the Tomcat server. They handle the Java /HTML program, stored as a .war file, the *fuzzyDL* reasoner, the Fuzzy Wine Ontology knowledge base and the Gurobi optimizer, files and program that are stored on the server. This Section introduces the basic structure supporting the applications.

6.1.2 The Client Side

The client side refers to the GUI created for facilitating the usability of the applications.

Java

The Java language together with the *fuzzyDL* API [36] make it possible to combine the *fuzzyDL* reasoner and the fuzzy ontology with any Java compatible program. The Fuzzy Wine Ontology, stored as a *fuzzyDL* text file is imported into the Java program. The different instances, in this case wines, are individually imported using the following code segment:

```
Individual a = kb.getIndividual("a");
```

The same code segment can be used also for importing other elements, such as concepts and roles. The imported instances are then connected with different properties and a relationship is established among them.

```
Concept conceptB = Concept.some("propertyC", conceptB);
```

For constructing the different scenarios, we employ OWA operators. As an example, if one wants to create a scenario based on the food being eaten (e.g. shellfish, game) and the context (e.g. friends, business dinner) three different OWA operators are created to perform this task: (i) to calculate the food values; (ii) for the context descriptions, and (iii) to combine the previous two OWA operators. Before defining the OWA operators, arrays containing the concepts and weights of the OWA operators are created. The following example defines the Grilled Food concept: (0.25 High Alcohol, 0.25 High Acidity, 0.25 Red, 0.25 Novello).

```
ArrayList<Double> context1 = new ArrayList
<Double>();

context.add(0.25);
context.add(0.25);
context.add(0.25);
context.add(0.25)

ArrayList<Concept> context2 = new ArrayList
<Concept>();

context2.add(conceptA);
context2.add(conceptB);
context2.add(conceptC);
context2.add(conceptD);

OwaConcept Grilled_Food = new OwaConcept(context1, context2);
```

A similar OWA operator is created to represent another concept (in this case the context, e.g. a Business Dinner). The third OWA operator is implemented to combine the food and the context OWA operators; in this case both the food and the context are given equal weights:

```

ArrayList<Double> Scenario1 = new ArrayList
<Double>();

Scenario1.add(0.5);
Scenario1.add(0.5);

ArrayList<Concept> Scenario2 = new ArrayList
<Concept>();

Scenario2.add(Context);
Scenario2.add(Food);

OwaConcept Scenario = new OwaConcept (Scenario1,
    Scenario2);

```

For the Java program to retrieve the best individuals for a certain occasion, the values of the final OWA operator have to be computed. The following code segment shows how the scenario is calculated for 10 individuals. Although this code segment is executed in a more automated fashion in the applications, this presents the simplest and most basic approach:

```

int n = 10;
Solution[] sol = new Solution[n];

sol[0] = (new MaxSatisfiableQuery(Scenario,
individualA.solve(kb.clone())));

sol[1] = (new MaxSatisfiableQuery(Scenario,
individualB.solve(kb.clone())));

.
.

```

This results in a calculated scenario value for each individual, values that can be used for whatever purpose one wants, for instance, to create a list, descending from the highest to the lowest individual value.

HTML

For the basic version of the web platform application HTML pages are used to collect the input from the user, send it to the server and display the result produced by the server structure. This is performed by using a `form action` function. Figure 6.2 shows a screenshot from the front-page GUI with the different available alternatives. The user chooses the context and the specific food. The query is then submitted to the server. The following code segment is an excerpt from that html page:

The structure presented in this section served as the base construct for further developments shown in the following sections.

6.2 The GDM Application

The previous Section presented the basic structure and application developed by combining the architecture and initial application with a decision support algorithm. A novel decision support system has been created, aiding a group of decision makers to reach consensus. To improve the functionality and speed of the system, also the users' location and context are taken into account.

The Fuzzy Wine Ontology serves, also for this application, as the main source of knowledge. The first goal is to retrieve a list of suitable wines from the fuzzy ontology that the users can discuss and vote for. By implementing consensus measures and decision support algorithms, the users continue the decision making process by providing individual preferences on the most suitable alternatives. Based on this, the consensus measures and guidelines are calculated and provided to the participants to help them to reach a decision.

To show the versatility of this approach, two different versions were developed: the web platform application presented in Section 6.2.1 and the Android application presented in Section 6.2.2. The web platform version is executed in a web browser, and can be accessed by basically any device that has access to the internet. The Android version is naturally limited to devices supporting Android apps. Figure 6.3 presents the activity diagram of the developed applications, consisting of the following steps:

1. **Location search:** The location of the user is retrieved using the IP location in the web platform version and the IP location or GPS for the Android application. The IP address or the GPS coordinates are then submitted to Google Services in order to retrieve information about the actual location of the device used to access the application. Thanks to the IP address, devices that do not have a GPS component can still use the application.
2. **Fuzzy Ontology search:** When the location of the user has been determined, the Fuzzy Wine Ontology search starts. The following parameters are used to guide the search:
 - (a) *Context:* Context refers to the scenario surrounding the dinner, influencing the choice of the wine. Three options are available: Candle, Friends and Formal.
 - (b) *Food:* The type of food that the users are going to consume greatly affects the choice of wine. Five food options are available in the application: Game, Fish, Grilled food, Chicken and Shellfish.

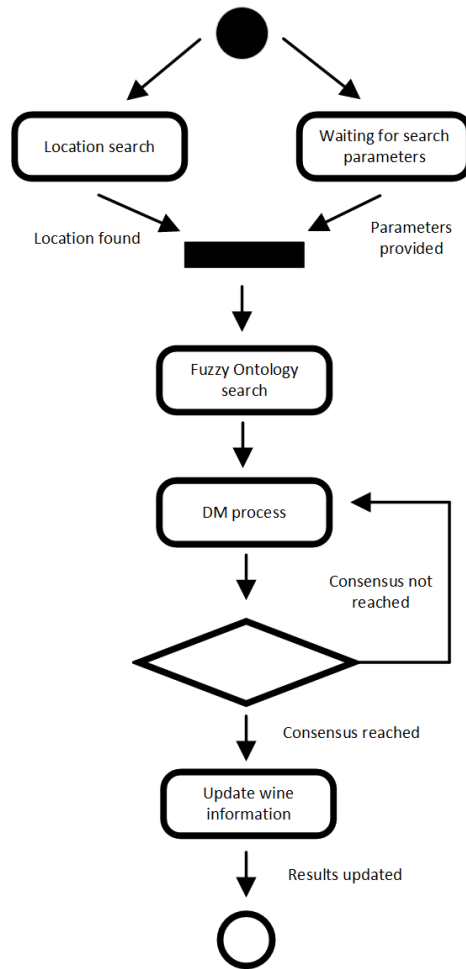


Figure 6.3: Web platform and Android application activity diagram.

- (c) *Number of people*: The total number of people participating in the decision making process. This parameter will only be used in a group decision making process and it is not used when querying the Fuzzy Wine Ontology .
- (d) *Number of wines*: The number of wines that the fuzzy ontology search should return. This feature allows users to control the number of search results, in order to choose how many wines they want to decide among in the decision making process.

It is a fact that different criteria can be equally valid when a wine is chosen; in order to broaden the perspective, several searches with different criteria are carried out in the fuzzy ontology search step. Due to this, the users are given more options when choosing their favourite wine. All in all four searches

with four different criteria are conducted:

- (a) *Most famous wine*: This wine can be considered to be the most famous wine of the location where the users are, i.e. a wine that is typically consumed among the natives. This criterion allows users to taste a wine that is characteristic of the place that they are visiting.
- (b) *Lowest price wine*: This search retrieves the lowest priced wine from the fuzzy ontology. This can be utilized by people who are not fond of wines or people who want to choose an economic option.
- (c) *Best wines according to the context and food*: This option retrieves, using the fuzzy ontology and the available wines of the location, a list of the best wines for the context and food specified by the user.
- (d) *Most voted wine*: This criteria takes into account results from previous group decision making processes in order to recommend a specific wine. From the wines available in the location, the one that has been chosen the most is selected.

If there is not a most voted wine available (no wine from that location has ever been selected by any users), then this criterion is not taken into account.

By computing these four criteria above, based on the parameters specified by the users, a list of different wines is presented to the user.

3. **Decision Making process**: With the use of the fuzzy wine ontology, a list of wines based on different criteria has been created; from this list the users must decide which wine to choose. Both the web platform application and the Android application implement a group decision algorithm that can assist the decision making process. The algorithm implements the following steps:

- (a) *Providing preferences*: A questionnaire is offered to each of the users in order to collect their preferences. Using the retrieved information, a preference relation matrix for the decision making calculation is built for each user.
- (b) *Decision making calculation*: Using the preference matrices, the group decision making algorithm is executed to produce a ranking of the selected wines, and consensus information to the users.
- (c) *Temporary decision making results*: Based on the consensus information the users can decide whether to choose the first ranked wine or to continue modifying their preferences. If they choose the second option, the *a* and *b* steps are repeated, however, this time advice is supplied to the users in order to point their modifications towards the right direction.

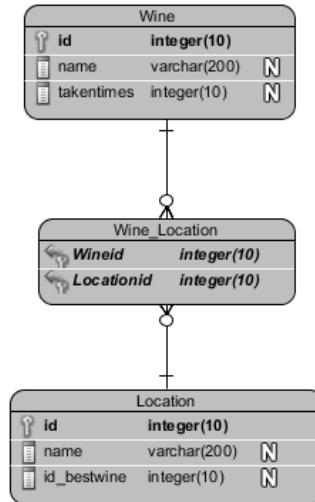


Figure 6.4: Wine-Location database entity-relation diagram.

(d) *Final result*: When consensus is high enough or users are tired of modifying their preferences, the first ranked wine is chosen and the group decision making process ends.

4. **Updating wine information**: After the group decision making process is finalised, the wine-location database is updated (e.g. the number of times each wine has been chosen). Posterior decisions will therefore be available as feedback for wine drinkers that later use the application.

A database is used to store information about which wines are available in each location and how many times a wine has been chosen. The nature of the database and its features make it possible to update the wines and locations stored in the wine-location database at any time. Its entity-relation diagram is presented in Figure 6.4. It consists of two tables and one relationship:

- **Wine table**: This table stores all the wines that are included in the fuzzy ontology, regardless of their locations. For each wine, the number of times that the wine has been chosen is stored in the *takentimes* field.
- **Location table**: This table stores all the locations available. Thanks to this structure, the wine-location association process is dynamic and scalable, information about which wines are available in each location can be added and updated whenever it is needed.
- **Wine_Location relationship**: This many-to-many relationship stores information about which wines are associated with what locations. A wine can

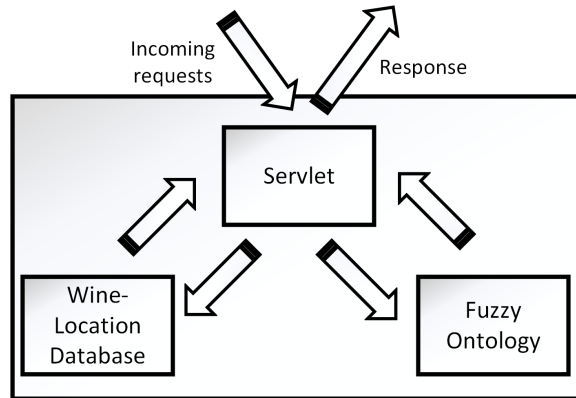


Figure 6.5: The extended server structure

be associated with multiple locations and in each location there are several wines.

The overall server structure is presented in Figure 6.5; it extends the structure presented in Figure 6.1 with the Wine-Location database. Incoming requests from the devices are handled by the server servlet, dealing with the fuzzy ontology API and the wine-location database. When a fuzzy ontology search is performed, the servlet retrieves from the database the wines that are affiliated with the users' location, and sends the query to the fuzzy ontology. When the fuzzy ontology returns the wine list results, the servlet sends the resulting information to the device that has made the request. It has to be pointed out that both the Web browser and the Android application share the same ontology and wine-location database; thanks to this, decision making results and wine information are shared by the two versions which avoids redundancy issues and eases the information updating task.

6.2.1 Web Platform Application

The web platform application was developed for mobile devices that do not have an Android operating system installed. As it is executed through a web browser, it can be used from any device that has internet connection. In this application, the server servlet handles the communication, presents the results to the user and carries out the group decision making process. In other words, all the computational effort is resolved there, giving the servlet an important role. The following software is implemented for constructing the web platform application:

- The web platform was implemented using JSP, Javascript and the Java language.
- A Tomcat server or a Glassfish server is used for running the servlet.

Figure 6.6: Providing information to the fuzzy ontology (web platform)

- MYSQL is used for building the Wine-Location database.
- The connection between the server and the database uses JDBC.
- Netbeans IDE was used as the development environment.

Example

To show how the web platform application works, an example is presented, illustrated with relevant screenshots from the application.

Four people are about to enjoy a dinner at a restaurant located in Aguilar de la Frontera, a town in Córdoba, Spain. It is an informal dinner among friends and they are planing to eat grilled food. They want to use the fuzzy ontology to find four wines to decide among.

After all the required information has been entered on the web page (Figure 6.6), the results from the fuzzy ontology, adopted to the location, are shown (Figure 6.7) and the decision making process can be initiated. Each one of the participants fills in the questionnaire presented in Figure 6.8 and, after that, the first results are displayed (Figure 6.9). Now, the friends can decide to repeat the decision making process pressing the *vote again* link if they feel that the consensus level is not high enough, or they can even choose to select *the most chosen wine* or a *famous wine*

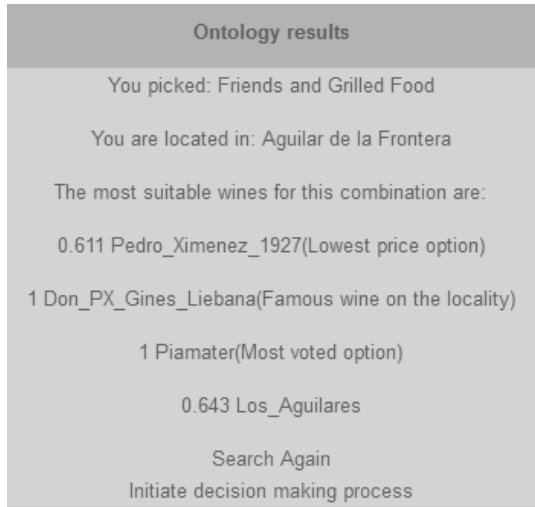


Figure 6.7: Ontology Results (web platform)

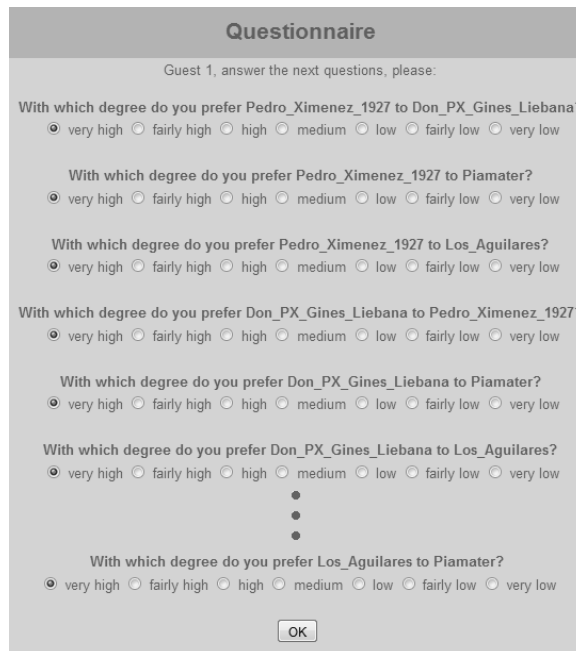


Figure 6.8: Questionnaire Screenshot (web platform)

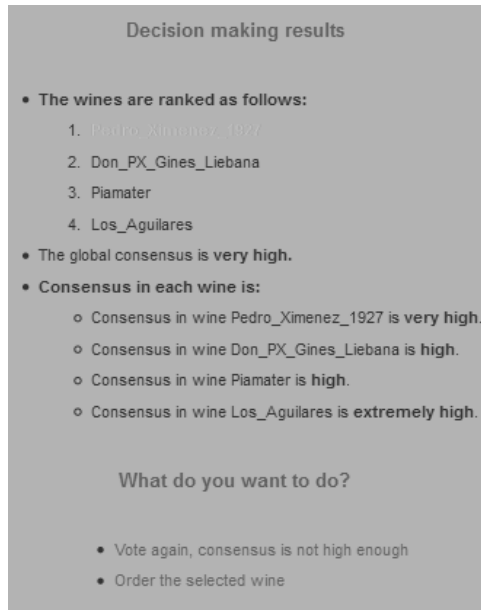


Figure 6.9: Decision Making Results (web platform)

from the location. However, because consensus is high, they decide not to go for another decision making round and select the wine: **Pedro_Ximenez_1927**.

6.2.2 The Android Application

The developed Android application also follows a client-server model, in order to perform the computationally demanding operations more fluently. Figure 6.10 shows the sequence diagram of the application, showing when the application communicates with the server. All in all three client-server requests are performed:

The softwares implemented to create the Android application resemble the ones implemented for the web platform version. This is mostly due to the fact that most of the computation is performed on the same server, regardless of the application used, where JSP, Javascript and Java are the core components. Java was also used for programming the Android application itself. Sockets are used in the Android application-server communication to share the fuzzy ontology search results. To increase the security of the whole application, the connection between the Android application and the database is conducted through the server, i.e. not directly via a JSP script. Eclipse IDE, Netbeans IDE and the Software Development Kit provided by Android were the development environments used.

To demonstrate the graphical user interface of the Android application, screenshots based on the same example as the one presented in Section 6.2.1 are presented:

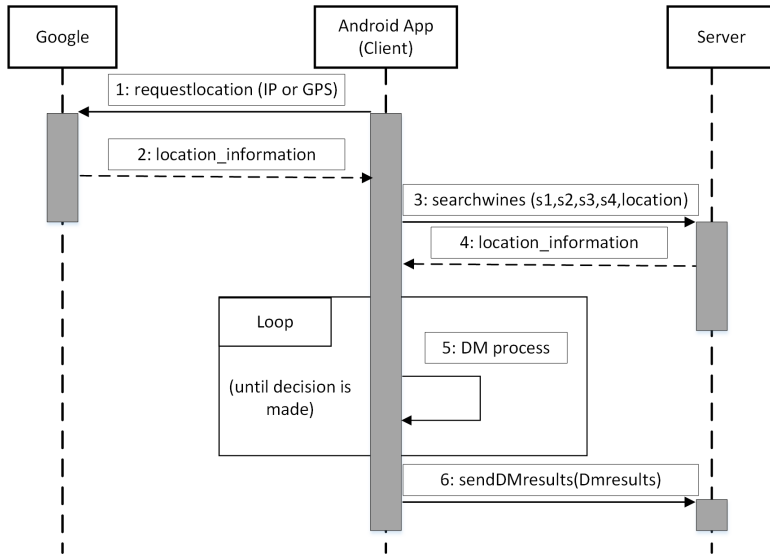


Figure 6.10: Sequence diagram for the Android application

- Figure 6.11 shows the input part of the Android application as well as the initial fuzzy ontology results screen.
- Figure 6.12 shows an example of a question from the questionnaire. Questions are showed one by one to the users to improve the readability. The figure also shows the results displaying screen.

6.3 Summary

This Chapter has introduced applications that utilize tacit knowledge and imprecise data in a mobile context. The developed novel applications show that by combining a fuzzy ontology with decision support algorithms, it is possible to utilize imprecise information to create mobile decision support. Demonstrating that imprecise expert knowledge, traditionally stored and analysed in non-mobile devices, can be distributed and successfully managed using mobile devices. This mobilisation of knowledge will make it possible for users to receive support for their decisions, based on imprecise data, regardless of where they are.

For the applications presented in this Chapter, the Fuzzy Wine Ontology was used as the main source of knowledge. In the context of wines, information is imprecise as it comes from the opinions of wine connoisseurs who express themselves in a terminology that is imprecise through the concepts and the language used. Without the capability of fuzzy ontology to model and manage imprecise knowledge, the development of this application could not have been possible.

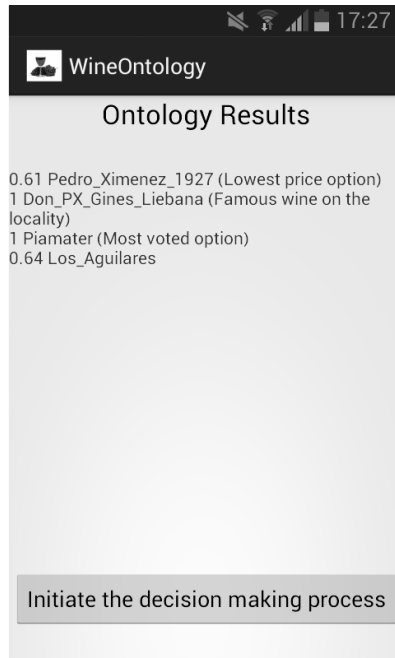
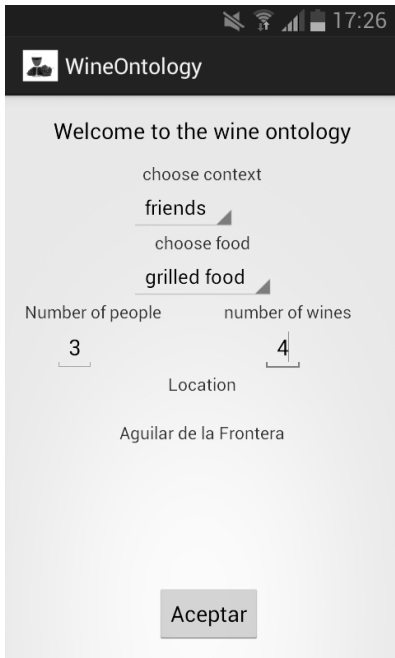


Figure 6.11: Search information screenshot and wine ontology results screenshot (Android application)

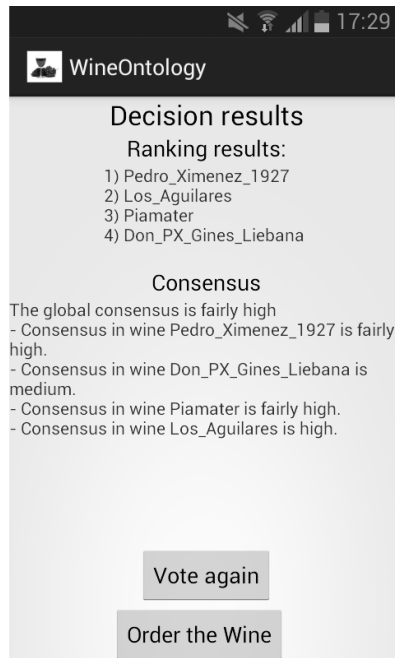
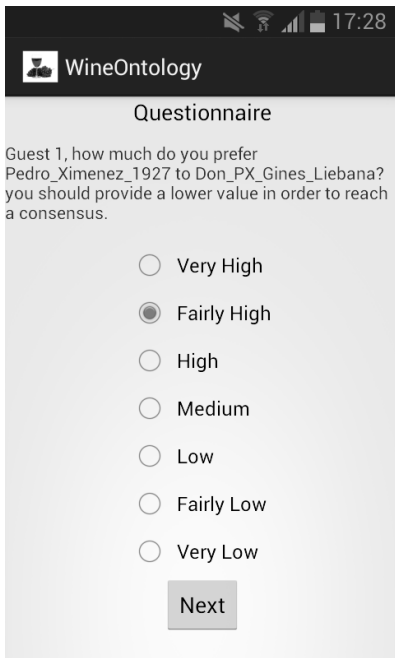


Figure 6.12: Questionnaire screenshot and temporary results decision screenshot (Android application)

The applications demonstrate how wine connoisseur knowledge can be transformed into useful advice and distributed to amateurs. Also, it becomes possible for the participants to use the applications as a basis for discussion and voting procedures. As the location is introduced in the computation, the alternatives that are not available are omitted in order to avoid impossible choices and to speed up the computations. As the applications have been designed to be used also with mobile devices, the dinner guests can use the applications in real time at the restaurant where they are seated.

The underlying goal with the structure presented in this Chapter is to present an example of how one can build applications by utilizing imprecise data. The used structure can be applied to resolve many other situations apart from the ones presented.

Chapter 7

Fuzzy Ontology for Real-Life Decisions

This chapter is aimed at applying the theories and techniques that have been developed in this thesis, for solving problems that are found imminent in real-life and thereby showing the practical benefits from implementing the theoretical contributions presented in this thesis. The technical application and its graphical user interface is based on the structure presented in Chapter 6, where, for instance, *fuzzyDL* and OWL are used for creating fuzzy ontologies that can be used as knowledge bases for mobile applications.

One approach to demonstrate the benefits of fuzzy ontologies is to model a fuzzy ontology by developing and implementing similarity measures that can be used for intrusion detection purposes. The mathematical contributions presented in Chapter 5 were used for calculating the similarities between the new entities detected and the previously stored entities in the knowledge base. Although the methods used for intrusions are seldom limited to a specific context, the fuzzy ontology was created with the mindset to find risks that are relevant for financial institutions. The fuzzy intrusion detection ontology was developed as a simple application, to show a practical example of how a fuzzy ontology can aid intrusion detection by computing the risk for certain intrusions to occur.

With the intention to support the arguments for developing an intrusion detection system with similarity measures and a fuzzy ontology, a short literature review about intrusion detection systems in financial institutes is presented. The similarity measures for interval-valued fuzzy sets are introduced and presented more thoroughly in Chapter 5. The contributions from this chapter address three concerns that are not widely recognized for intrusion detection systems:

- Making use of expert knowledge to identify anomalies
- Representation of (imprecise) information about previous intrusion cases
- Utilizing imprecise descriptions to identify the potential risks of an intrusion

7.1 Intrusion Detection

Intrusion detection systems (IDS's) are important for supervising networks, especially as the number of intrusion events is increasing rapidly due to the widespread use of internet. Normally an intrusion detection system works as a decision support system that helps to identify potentially dangerous activities by utilizing real-time information and event reports of previous intrusion cases. There are two main approaches to conduct intrusion detection: (i) misuse detection (known patterns of intrusion are compared to present activities) and (ii) anomaly detection (activities that deviate from normal system behaviour but cannot be matched to any previous cases) [6, 274].

As sensors and data collection methods are improving, intrusion detection systems are forced to process a constantly increasing amount of information and alerts (also including false alerts) [216]. A fair part of this information consists of imprecise and vague knowledge [195]. Dickerson et al. [89] suggested that fuzzy ontologies could be implemented for analysing this vague knowledge, especially for analysing anomalies, as it would be possible to find cases that are similar in a fuzzy sense, but not in any crisp sense. Detecting anomalies is an important way to find unwanted behaviour, not only for intrusion detection purposes but also in e.g. fraud detection and military surveillance.

Similarity measures proved to be successful in anomaly detection implementations [65]. For instance, kernel based similarity measures (cosine and binary [189]) together with text processing techniques were used to detect host-based intrusions by Sharma et al. [252]. By applying similarity measures on the collected intrusion alerts (modelled as a fuzzy ontology), one can find the similarity to different attack strategies. By anticipating the attack strategy (or at least what it is similar to), one can predict the coming moves by the attacker.

Expert knowledge plays a crucial role in identifying anomalies and assessing the potential loss that can be caused by an intrusion. Even though IDS's are generally moving towards more automation by excluding human experts, it has even been stated that it is necessary to include experts in IDS, as fully automated reliable systems seem impossible to achieve [64]. There are systems which are able to detect malwares and intrusions based on behavioural patterns; however, few come even close to automatically decide if the spotted abnormality is a malware or not, and therefore depend on experts to make the final decision [150, 293].

Experts usually express themselves using linguistic terms, i.e. "the activity level is quite high" and "one should deactivate some of the measures". These imprecise linguistic terms, fully understandable for other experts, are hard to interpret for a computer. Computers are designed to compute precise data, but the linguistic terms are imprecise.

Using a fuzzy ontology to represent available information in terms of interval-valued fuzzy sets, with a combination of similarity analysis and expert opinions, it creates a promising tool for identifying and measuring the risks of misuse and

anomalies. The support system aims at providing information to the users concerning two types of decisions: (i) identifying suspicious activities that can indicate intrusions, and (ii) recommendation on countermeasures for any given case.

7.2 Intrusion Detection with Type-2 Fuzzy Ontology

According to Internet World Stats¹, roughly 1/3 of the Earth's population has access to the internet. With the penetration rate rapidly increasing, it naturally means that not only private users are active online but also an increasing number of businesses. With more users and businesses connected to the internet, there is a growing risk of intrusions and other complications. In this context, intrusion detection systems are becoming more and more important.

Applications and software that help users to protect their computing and communication equipment from viruses and malware constitute an important research topic. Ontology has proven to be useful for detecting intrusion, as it offers possibilities to analyse patterns that intruders are generating and to detect previously unknown attack methods [188].

Dai et al. [78] observe that hackers tend to be one step ahead of all security systems, creating an endless circle of data losses and a constant demand for new software to fix the previous errors. As hackers and their methods are adaptive, behaviour-based approaches have gained an increasing interest from the sides that try to protect data. These approaches are more effective when dealing with previously unknown attacks [12, 150].

Malware is the common term used for describing a software that performs attacks on computers and simultaneously implements different techniques to avoid being detected by intrusion detection software. Wagener et al. [289] propose a possible solution to this problem; they apply similarity and distance measures on malware behaviour to create a better classification of the malware. Comparisons of similarity and distance measures for identifying malware have also been carried out, e.g. by [9]. Due to the complexity of malware, fuzzy ontology is an promising approach for aiding with intrusion detection tasks by utilizing expert knowledge.

7.2.1 Financial institutions

A financial institution offers financial services, working as an intermediary by providing, for instance: loans, deposits, currency exchanges and investments. Banks and insurance companies are examples of financial institutions. The institutions own sensitive data and also significant amounts of monetary funds, which make them interesting objects for cyber-attacks.

It has to be noted that not all intrusion attempts are conducted for personal gain, such as stealing funds, but more as a challenge for achieving credibility in online

¹internetworldstats.com/stats.htm

communities or getting noted by the global media. The financial institutions are attractive targets for this purpose, as people tend to react when their savings are “in danger”; the security systems protecting the institutions are challenging to break, and the hackers who manage to break them deserve some credit. Recently, there has been a global increase in attacks directed towards financial institutions. As these institutions can be considered prime targets on a nationwide scale, the treat of cyber terrorism cannot be overlooked [147,222].

In other words, there is a high risk that the intrusion attacks are directed towards the financial sector [237]. Reports indicate that bank website outage hours are increasing every month and more and more online banking frauds occur. An old but still active financial malware is called Zeus. It was noticed already in 2006, and since then it has been re-modelled and re-customized several times so that each version requires more preventive work by the security systems. Currently, there is even a market for trading with “plug-ins” created for Zeus and, naturally, this malware is not the only one available. Recently, there has been several publications about preventing different types of attacks specifically aimed at the financial sector [178,236].

7.2.2 Fuzzy Ontology For Intrusion/Malware Detection

Lately, there has been an increase in using ontologies for the purpose of intrusion and malware detection. Undercoffer et al. [282] constructed an ontology for intrusion detection in the context of computer attacks, using the DAML+OIL ontology modelling language (a precursor to OWL). Simmonds et al. [257] developed an ontology to defend against attacks aimed at networks and emphasized that one should also prepare for the consequences of an successful attack and find out how the designed system should react in that scenario.

With the rapid development of mobile devices, a completely new field was created that is vulnerable to intrusions and malwares. Chiang and Tsaur [70] took the first steps towards implementing ontologies also for protecting mobile devices. They modelled an ontology based on the behaviours of known mobile malware. Hung et al. [151] created an extensive ID ontology, which also included a feature allowing users to model the ontology application on a conceptual level. This broadens the possible range of users, meaning that even non-expert users could contribute to intrusion detection.

However, it has been stated several times that traditional, non-fuzzy ontologies are not suitable to deal with imprecise and vague knowledge [148, 198]. Avoiding imprecise data in the online world is close to impossible, and hence, the introduction of fuzzy ontologies is gaining increased interest in the research community [46, 89, 274]. Huang et al. [148–150] developed an Interval Type-2 Fuzzy Set ontology, as a novel approach to malware behavior analysis (MiT). They aim to find possible solutions to the problem with imprecise data and behavioural patterns. Using the Fuzzy Markup Language and the Web Ontology Language, they

managed to create a fully operational system, which is able to analyse collected data and to extract behaviour information. Tafazzoli et al. [273] created a fuzzy malware ontology designed for the Semantic Web. The ontology represents relevant concepts inherent in the malware field. The relationships between different malware are modelled with the help of fuzzy linguistic terms, such as: “weak relation” and “very good relation”. Considering that it was created with the Semantic Web in mind, it can be used to share information online.

As it can be noticed, there are a fair number of positive results with implementing fuzzy ontologies. It is therefore justified to state that further research is needed on how fuzzy ontologies can benefit the work on intrusion detection.

7.3 The Fuzzy Financial Institution Ontology

The fuzzy financial institution ontology was modelled in OWL using Protégé and utilizing the Fuzzy OWL plug-in. The information about intrusion risks was collected from different computer security companies and reports, e.g. from The Kaspersky Lab² and S2sec³.

Figure 7.1 presents an overview of the ontology structure. The ontology is structured in classes according to the intrusion type, e.g. **DDos**, **Malware_and_Viruses** and **Data_Breaches**. Each one of these general classes has more specified subclasses, such as: **Phishing**, **Win32**, **Gauss** and **Zeus**. These subclasses are populated with individuals representing specific intrusions, such as previously recorded intrusion attempts. All the individual instances have a set of previously stored values or behaviours showing how the intrusion was conducted. Using similarity measures, these values are compared with the new intrusions detected.

7.3.1 The Fuzzy Financial Institution Application

An application for retrieving information from the fuzzy ontology was constructed using Java. The technical structure of the application follows the same design as the wine selection applications presented in Chapter 6. The goal of the application is to demonstrate the basic functionality of the fuzzy ontology in a graphical way. The main idea behind the application is that human experts make use of the produced results but still make the final decision, i.e. it supports the decisions that need to be made by the experts. The application works in the following way:

- Initially, the user decides among a couple of pre-defined example threats that have been “registered”. Naturally, the registration and comparison of the possible intrusions would be automatic in a real world intrusion detection system (Figure 7.2A).

²kaspersky.com/

³21sec.com/

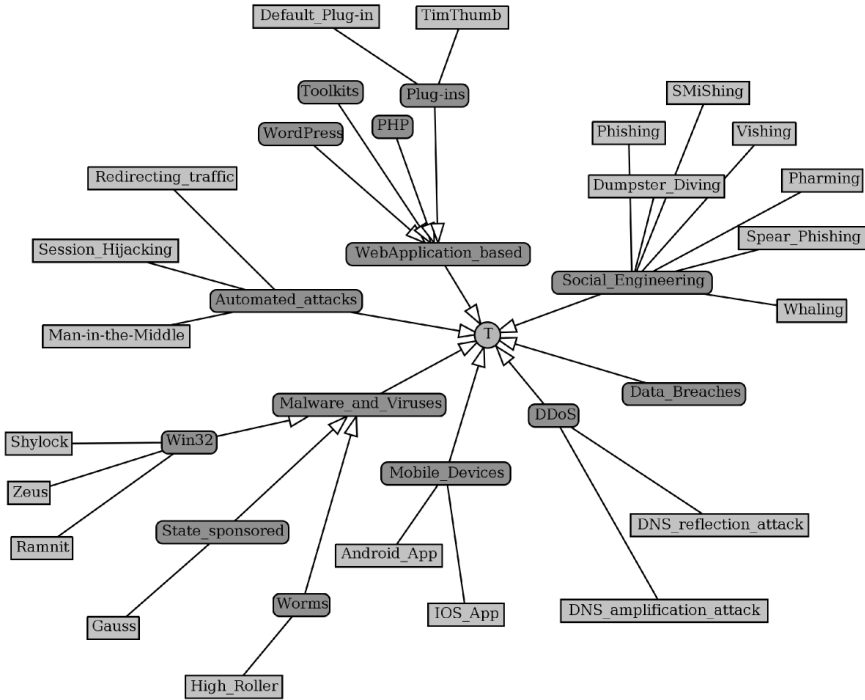


Figure 7.1: The Structure of the Ontology

- The intrusion chosen is thereafter modelled with interval type-2 fuzzy sets. The previously registered intrusions are retrieved from the ontology and the similarities with the current intrusion are computed.
- The results of the computation, i.e. how likely the detected abnormally is to previously detected and stored intrusions and which previous intrusion it resembles the most, is presented to the user (Figure 7.2B).
- The user has the possibility to view other similar intrusions (Figure 7.2C), which offer the human experts an opportunity to receive a more comprehensive picture of the situation.

It has to be acknowledged that the functions in the application are only basic, but the structure of the application and the techniques can easily be extended and combined with other applications and techniques.

7.3.2 Examples of Intrusion Detection Scenarios

As to further demonstrate the possible usability of the application proposed, a couple of scenarios are introduced, showing how the fuzzy ontology could aid in de-

The Fuzzy Ontology Intrusion Detection

Version 1.0

Check for intrusions:

Behavior Type 1	▼
Behavior Type 1	
Behavior Type 2	
Behavior Type 3	
Behavior Type 4	
Behavior Type 5	

A

You picked: Behavior1

Value 1 is 95 % similar to Zeus_Intrusion_nr45 **More Details**

Value 2 is 59 % similar to Zeus_Intrusion_nr32 **More Details**

Value 3 is 67 % similar to Gauss_Intrusion_nr2 **More Details**

Value 4 is 85 % similar to Zeus_Intrusion_nr45 **More Details**

Value 5 is 75 % similar to Zeus_Intrusion_nr5 **More Details**

It is **Highly** likely that the detected intrusion is an **Zeus-based malware**.

B

You picked: Behavior1

More details regarding Value 3

Value 3 is 67 % similar to Gauss_Intrusion_nr2 **0.66-0.68**

Value 3 is 65 % similar to Zeus_Intrusion_nr54 **0.65-0.66**

Value 3 is 64 % similar to Zeus_Intrusion_nr1 **0.65-0.65**

Value 3 is 62 % similar to Zeus_Intrusion_nr7 **0.60-0.64**

C

Figure 7.2: Example of a fuzzy intrusion detection user interface

etecting possible intrusions. The usability of OWAD operators is also demonstrated, as the scenarios are solved by employing the operator.

Scenario 1

This scenario deals with a possible malware attack from the widely used Zeus malware. For this scenario, the advice generated by the system is assessed by human experts, after which a decision is made that combine both the ontology result and the expert assessments.

The process starts as the surveillance system notices an abnormal behaviour. The recorded values are automatically processed by the intrusion detection system and it generates results showing how likely it is that the detected abnormality is an intrusion attempt. This example displays the following result:

Value 1 is 98 % similar to Zeus_Intrusion_nr45

Value 2 is 23 % similar to Zeus_Intrusion_nr32

Value 3 is 77 % similar to Gauss_Intrusion_nr2

Value 4 is 45 % similar to Zeus_Intrusion_nr45

Value 5 is 89 % similar to Zeus_Intrusion_nr5

*There is a **High** probability that the detected intrusion is a **Zeus-based malware***

The values represent different measures that are relevant to the behaviour of the intrusion. For the Zeus Malware, they could represent: (i) amount of hazardous

.php files detected (ii) amount of hazardous .exe files detected or (iii) amount of functions reporting a malfunction. The detected files could be compared with different lists that contain hazardous files that occur frequently in different types of intrusions.

In the next step, the human expert would assess the results generated by the ontology. The expert has the option to see not only the most similar case, but also the whole list of generated similarities. For instance, the expert could notice that *Zeus_Intrusion_nr12* and *Zeus_Intrusion_nr50* had a 44 % and 43 % similarity to value 4, respectively. By being able to view a bigger picture, it supports the expert's decision. Based on the expert's decision, the defence system takes appropriate actions, which will be more efficient as the intrusion method is likely to be known.

Scenario 2

For this scenario, we assume that a denial-of-service attack (Dos) is occurring, initiated with the purpose of overloading an institution's online system, and to create chaos which would consume both time and money to sort out. In this scenario the experts are excluded, as Dos attacks requires immediate action and cannot wait for human input.

System administrators of online systems can easily define what the normal range of data traffic is, using historical data, and also define when the crucial limits are reached. Using fuzzy interval values, one can model when the values are closing in on the critical limits using linguistic terms, such as: "low risk", "medium risk" and "high risk" to indicate how close the amount of data traffic is to the critical limit. This means that one can observe even small risks, when several slightly suspicious factors (which would not have been noticed in a non-fuzzy system) together can indicate possible intrusions.

A bank usually registers the following logins in its online banking system:

Average logins per hour: 1000
Record-high, logins per hour: 1500
Record-low, logins per hour: 500

In other words, it usually moves between 500 and 1500 logins per hour. By using type-2 fuzzy sets, one can define that if the numbers of logins go over 1500, the online banking system is considered to be "Highly trafficked" and as it reaches close to 2000, it becomes more and more "Critical". However, the system does not need to shut down if the logins exceed a critical limit; only if several similar measures are starting to reach a critical level, the system can conclude that a possible attack is occurring. The fuzzy ontology can define what kind of Dos attack is most likely taking place and adjust the counter measures according to that knowledge, by quickly shutting down the system before it crashes and wait for maintenance personnel to arrive and make the final decision. In this way one could avoid the

costly maintenance work caused by a real crash.

7.4 Summary

Applications and systems that are implementing fuzzy ontologies and aiming at improving real-life processes are needed to validate the practical use of fuzzy ontologies. This chapter aims at presenting some advancements regarding this issue.

One possible application area for fuzzy ontology is intrusion detection systems which are becoming more and more essential to handle the risks associated with network activities. New intrusion detection systems should be capable of protecting an organisation not only from increasing numbers of attacks but also from more and more sophisticated intrusion strategies. A promising solution would be to include expert knowledge in the detection process in combination with a fuzzy ontology for handling the linguistic and imprecise terms used by the experts. In the presented verification case the combination of fuzzy logic and ontologies can transform expert knowledge into a systematic description which is processable with computational methods. The fusion of type-2 fuzzy ontologies and similarity measures to identify possible means of intrusion often provide benefits to organisations that cannot be achieved by other methods.

To support the results produced by the ontology and to provide additional information which is essential to identifying anomalies, expert opinions expressed in terms of linguistic information and modelled by interval-valued fuzzy numbers are employed. As numerous intrusions can occur at the same time, the proposed system can estimate the seriousness of the different activities. Based on this, the decision makers can employ limited resources in a more optimal way and minimize potential losses.

Chapter 8

Summary & Conclusion

This final Chapter is dedicated to summarising the contributions presented in the thesis and to show how the research objectives have been met and the research questions answered. Initially, a short Summary (8.1) of the contributions developed in the thesis is given. The Research Questions (8.2) are worked through one by one and the relations to the presented contributions are identified, leading up to the Research Objective (8.3). Based on these results, some Discussion & Limitations (8.4) and Future Research Directions (8.5) are presented.

8.1 Summary

Companies and organisations are required to process an increasing amount of data in order to be competitive in the market. The nature of the collected data creates several serious issues that should be solved. A critical issue is how one should deal with imprecise data, which, for instance, has been retrieved from experts and is stored as linguistic expressions. Avoiding to utilize the collected data is not a feasible option, as employees need to receive decision support to improve their work performance. Additionally, as expert employees retire or leave the organisations, it means that all their acquired knowledge will disappear; to secure future use of this knowledge is therefore important.

The contributions developed in this thesis show how fuzzy ontologies can be used to give sufficiently good representations of imprecise data. This makes it possible to represent, for instance, tacit knowledge in knowledge bases, which makes it possible to create different types of decision support systems, for instance to aid decision makers in a group setting. This is demonstrated in the thesis by introducing a novel consensus model, where the fuzzy ontology has a central role in both pre-processing the set of alternatives as well as aiding in the negotiation process.

As aggregation operators have an important role in solving decision making problems, it is natural to combine different aggregation operators with fuzzy ontologies, which opens the door for new decision support applications and simulta-

neously improves the outputs of the calculations. The well-known OWA operator was extended and implemented as an aggregation operator in the thesis. This is shown by presenting some developed mobile applications, where the fuzzy ontology is used to give decision support for the users of the application.

By developing applications that work also in a mobile context, it becomes possible to provide users with context-adaptive support, regardless of where they are, further improving the work performance. This is an important feature in the global market of today, making it possible to distribute and utilize unique insights from one expert all over the organisation.

8.2 The Research Questions, Revisited

This Section revisits the research questions and shows the contributions and results that have been worked out. The main methodology used to work through the research questions was Action Design Research (ADR). In the following the relation between the research questions and the four steps of ADR: (i) Problem Formulation, (ii) Building, Intervention, and Evaluation, (iii) Reflection and Learning, and (iv) Formalization and Learning will also be discussed. Naturally, some of the research questions are linked to several steps of the ADR process. Tacit knowledge and how it can be represented and processed are strongly connected with the extensive state-of-the-art review which has been carried out; the knowledge that was built in this way helped to create a good basis for anchoring the first step of ADR, Problem Formulation.

Initially, the formulation of the research objective and research questions was supported by both the extensive state-of-the-art review and meetings and discussions with employees of different organisations. These organisations have collected large amounts of data, and imprecise data, retrieved from experts, constitutes a fair part of the knowledge base. During this process, it became clear that there is a need to develop new methods for dealing with imprecise data as the organisations lack suitable methods for both storing and utilizing the data for decision support; the research questions were posed in order to deal with and solve this issue.

The goal of this research, exploring how fuzzy ontology can be used for analysing imprecise data, is clearly practice-inspired. The problem formulation is based on actual problems and aims at developing solutions that are applicable also in other contexts, which is an important feature of ADR.

RQ 1. How can tacit and imprecise knowledge be represented and processed by a fuzzy ontology?

The first research question addresses the initial problem, how and if fuzzy ontologies are suitable for both storing and processing imprecise knowledge. This is discussed more extensively in Chapter 4. The problem is approached by extracting rules from experts and representing them with the help of fuzzy logic. The

fuzzy representations can then be included in a fuzzy ontology, systematically representing expert knowledge. The Fuzzy Wine Ontology, a fuzzy ontology that is constructed with tacit knowledge retrieved from wine connoisseurs is introduced. By modelling the wines in the OWL language in combination with the fuzzyDL extension, it is shown that tacit and imprecise knowledge can be represented in a knowledge base. As fuzzyDL adds fuzzy concepts to the standard OWL language, it means that the fuzzy ontology / knowledge base can be utilized by all software that can handle OWL. This makes the knowledge base suitable and compatible for use on the Semantic Web and adds the benefits of fuzzy concepts.

Furthermore, it is shown that a fuzzy ontology created in OWL can be used as the main source of knowledge for different decision support systems. The novel consensus model described in Chapter 4 validates this claim. The possibility to receive decision support in a group context can, for instance, aid and enhance the effectiveness of video conferences conducted between experts and maintenance personnel. The results received from reasoning with the fuzzy ontology are the same or similar to results received from non-automatic calculations. This shows that automatically retrieved results, based on tacit knowledge from the fuzzy ontology produce similar decisions as human experts would make.

RQ 2: Can aggregation operators improve fuzzy ontology representation and reasoning by extending their scope to incorporate (i)-(ii)?

Aggregation operators often provide important benefits when building decision support, as they offer a way to aggregate several values into a single value that represents the whole set. The OWA operator provides a way to represent different aggregations using one single definition but modifying the weights. Defining new extensions of the OWA operator results in aggregation operators that are customised for certain problems and specific cases. This can be utilized for case-adapted representations of imprecise information and to create advice for participants in group decisions.

This research question mostly follows the second step of the ADR method: Building, Intervention, and Evaluation. The OWA operators have been developed and adapted to fit the problem specifications. Several different OWA operators were developed, each suited to solve different issues connected with the problem identified. The third step of the ADR method, Reflection and Learning is also visible in this research question. The OWA operators that were developed to solve specific practical problems can be developed into general theories.

(i) Different representations of imprecise information

The thesis has introduced several extensions of the OWA operator. The extensions combine interval valued fuzzy numbers (IVFN) with induced weights and distance

measures. By implementing the Induced Ordered Weighted Averaging (IOWA) operator on IVFN's, the Quasi IVFN-IOWA and IVFN-IOWA are introduced. Also an IVFN-Induced Heavy Ordered Weighted Averaging (IHOWA) operator is defined. With the heavy OWA operator the weights in the aggregation process can exceed the value 1 and by inducing the weights of the OWA operator when applied for IVFN's, they offer more flexibility when handling imprecision in the aggregation process.

Distance measures (i.e. the Ordered Weighted Averaging Distance operator) are also applied on IVFN's which results in the Quasi IVFN-IOWAD operator and the IVFN-IOWAD operator. By measuring and aggregating the distance between the mean values of the IVFN's we obtain easily understandable results, as the similarity between instances are shown. It has also been shown that the defined OWA operators satisfy important properties, such as commutativity and monotonicity.

The developed OWA operators have successfully been applied, both in numerical examples and for real-life applications. It was demonstrated that they offer new options for representing and expressing imprecise information, for instance when utilizing linguistic labels.

(ii) Group Decision Making

The thesis demonstrates how aggregation operators can be used for support in group decision making situations. A novel consensus model with a linguistic extension uses the OWA operator for different purposes. The OWA operator can aggregate the values retrieved from the fuzzy ontology, to create a smaller set of alternatives for the decision makers to discuss about. This reduces the amount of information that the decision makers need to embrace, which helps to focus their limited time and resources on what is important.

In the consensus model, the OWA operator also greatly supports the processes of retrieving the best alternative from the fuzzy ontology. The proposed solution is the main point of reference for the advice given to the decision makers. It is clear that OWA operators are useful in a fuzzy ontology to help with group decision making problems.

RQ 3: In what way can type-2 fuzzy sets improve the performance of knowledge mobilisation systems and how can they be incorporated in the ontology building process?

Type-2 fuzzy sets, in comparison with type-1 fuzzy sets, offer more ways to express imprecision, both for experts providing their estimates and for operators inserting data into a knowledge base. This gives type-2 fuzzy sets clear benefits in improving the performance of developed systems and in facilitating the creation of fuzzy

ontologies, as they make it possible to better incorporate imprecise data received from multiple experts.

In this thesis type-2 fuzzy sets and interval valued fuzzy numbers have been applied to improve the performance and the creation of fuzzy ontologies for the developed decision support systems. It has been demonstrated; both in theory and in practice that it is beneficial to use type-2 fuzzy sets (cf. Chapter 5). It is shown how experts can express their preferences using linguistic labels, represented by a specific trapezoidal IVFN. By aggregating the opinions into one single matrix and thereafter using one of the defined OWA operators for each individual evaluation, it becomes possible to easily rank the different alternatives.

The same theoretical approach can be implemented also in practical applications. The use of IVFN's makes it possible to include more complex tacit and imprecise knowledge in the computational process. Additionally, it becomes possible to deal more efficiently with inputs from the user, if they are expressed with linguistic labels. It is clear that by incorporating type-2 fuzzy sets, it becomes possible to deal with imprecision more efficiently.

This research question is situated in the same two steps of the ADR method as the previous research question, i.e. in the Building, Intervention, and Evaluation step and in the Reflection and Learning step. The research question is slightly more devoted to the validation and generalisation of the developed OWA operators and draws more inspiration from the Reflection and Learning step.

RQ 4: What techniques and methods are sufficient for a fuzzy ontology application to handle expert knowledge expressed as imprecise data?

It needs to be acknowledged that his problem is cumbersome to solve and it might be that a satisfactory answer is impossible to achieve. This is due to the fact that imprecise data and expert knowledge are strongly affected by the personal opinion of both the expert and the implementer. Nevertheless, it is a positive development that research on ontologies is constantly producing better techniques and methods, improving the handling of this problem. The research question is therefore devoted to show techniques that sufficiently well handle expert knowledge expressed as imprecise data, well aware of the current limitations.

The previous research questions have shown that it is possible to use fuzzy ontologies to model and process imprecise data (e.g. tacit knowledge). To further validate the approach and to show how applications that utilize imprecise data can be created, the thesis has introduced two main variants of fuzzy ontology based applications, both based on expert knowledge (discussed more in Chapters 6 and 7).

The first implementation utilizes the Fuzzy Wine Ontology and builds decision support to aid the users to select which wine they should drink for their dinner.

The second application uses expert knowledge in combination with historical data to detect and prevent intrusion. The applications were created using Semantic Web compatible techniques. The extended compatibility of these techniques facilitates the transition to mobile contexts.

The results produced by the applications are similar to the actual advice received from the experts. This is valid even though the applications process previously unknown instances, i.e. the modelled expert knowledge can be applied in previously unknown cases and data sets. It has to be stated that the suggested approach is far from flawless; there are several parts that need to be developed further if the use of fuzzy ontologies is to become more widespread. Nevertheless, the presented results clearly show that there are available techniques, and combinations of techniques, that are capable of handling imprecise data that is retrieved from experts. It is also shown that, besides handling imprecise data, this approach can successfully be used in applications for building automated decision support.

RQ 5: How can fuzzy ontologies be applied to support decision making processes for the purpose of knowledge mobilisation?

The answer to this research question builds on the results presented in the answers to research question 4, where applications that utilize tacit knowledge and imprecise data were introduced. The next step is to implement this in the context of knowledge mobilisation, i.e. to make the applications both mobile and context adaptive.

This has been demonstrated by creating both a web platform and an Android application that use the Fuzzy Wine Ontology as the knowledge base. The web platform version allows all mobile devices that have a web browser installed to access the knowledge base through a web page. The Android version works on all devices that run the Android operating system.

The solution presented in the thesis uses a server where the fuzzy ontology knowledge base is stored and processed. The mobile devices connect to the server through different applications, utilizing the same knowledge base. Additionally, the mobile devices have access to the processing power of the server. This means that the knowledge base is stored and the calculations are processed in the server, facilitating the updating of the knowledge base and increasing the speed of the calculations. The applications modify the instances included in the computation based on the location of the mobile device and adapt the retrieved advice to the context and the location of the user. The applications and the structure presented (cf. Figure 6.1) show that it is possible to use fuzzy ontologies for knowledge mobilisation purposes.

The fourth and fifth research questions both follow the second step of ADR, Building, Intervention, and Evaluation and the fourth step, Formalization and Learning. The applications and the mobilisation of the applications were created simultaneously with other developments. This makes it possible to change and adapt

the applications to a desired goal, even if the goal might be modified during the process. The different developments that were carried out are included in the final IT-artefacts, i.e. the Fuzzy Wine Ontology-based applications and the intrusion detection application. It is also shown and explained how the developed artefacts can be generalised and applied to other similar cases. In other words, it is possible to use the presented approach as a basis for other applications and projects.

8.3 The Research Objective, Revisited

The research questions and their answers presented in the previous section support the research objective undertaken: to find new ways to handle and analyse imprecise data. As stated before, organisations are faced with a cumbersome challenge: to handle and process an increasing amount of imprecise data. This data should not only be analysed, it should also be mobilised and offered to the users whenever and wherever needed. The thesis supports this by exploring how fuzzy logic and ontologies could facilitate the exploitation and mobilisation of knowledge in organisational and operational decision making processes. This is achieved by developing fuzzy ontologies and aggregation operators for knowledge management and knowledge mobilisation problems.

The new research results presented support the initial assumption that fuzzy ontologies based on expert knowledge can be successfully created with the help of Semantic Web affiliated techniques. It is also shown that a novel extension to the OWA operator can be used to aggregate both type-1 and type-2 fuzzy sets. The aggregated values can successfully be used to support decision making and group decision making. Additionally, the OWA operators are useful for aggregating values needed for decision support; as it was shown in two applications.

The thesis has demonstrated how fuzzy ontology can facilitate the mobilisation of knowledge. The presented research is a step towards storing expert-based tacit knowledge in information systems. In this way, imprecise data and tacit knowledge can be utilized even if the expert is not present. This creates a good basis for developing more advanced mobile, context-adaptive decision support systems. As the applications developed are based on Semantic Web affiliated techniques, the thesis also helps to introduce fuzzy ontologies to the non-professional user. This could make it possible for basically anyone to create a fuzzy ontology and to combine and share it over the Semantic Web. This would create a snowball effect, as the number of users and available fuzzy ontologies grows, it would simultaneously improve the benefits received.

8.4 Discussion & Limitations

The following section presents some discussion and thoughts about the topics that have been discussed in this thesis. Additionally, some possible limitations for the research are presented.

Future developments in the IT-field will definitely change our current world-view in several ways and naturally, this development will affect also organisations and companies. The rapid development of the IT-field creates an immense demand for new techniques [104], that provide an edge towards the competitors [80]. Both Analytics and Soft Computing fit this description well, offering new possibilities for organisations to handle and analyse data.

Although Soft Computing has been around for awhile, it feels like the potential of the research field has only recently started to show. This possible potential is supported by the introduction of biologically inspired methods. Techniques such as neural networks, evolutionary computation and fuzzy logic have been proven to provide considerable benefits when solving problems, especially where there is a lack of information about the problem itself. Soft Computing could also provide a solution to the problem of “bringing the expert out from the box”, i.e creating decision support systems that are able to work in previously unknown domains.

Analytics is becoming a key part of many modern organisations. Although there has been a lot of technical development, organisations are still facing the same challenges as when Analytics was first introduced: the size and complexity of the data that should be analysed. This phenomenon is usually referred to as Big Data. It might be that the threat of Big Data is a bit exaggerated, as the technical development will rather quickly adapt to and start to match the increasing amounts of data, however, the complexity of the data collected might prove to be more cumbersome.

Loshin [196] mentions the following issues as critical for the future of Analytics: interoperability among analytical software, the quality of the data, the complexity of the systems and the actual benefits received from Analytics. Also here, complexity tends to be a common concern. It is a fact that the quality and complexity of the collected data makes the analysis more demanding, requiring that a decision maker either improves the quality of data itself or improves the methods and algorithms applied for processing the data.

The forerunners in Analytics are today making decisions on a moment-to-moment basis, or at least on a day-to-day basis. These organisations are now trying to make this information more mobile, so that people can have access to analytical tools and calculations regardless of where they currently are situated. It can be assumed that this mobilisation of both tools and data will continue and even start to pick up speed.

The Action Design Research methodology implemented for this thesis was introduced only a couple of years ago (the article by Sein et al. [250] was published

in 2011). Even though there is a limited amount of successful implementations to compare with, the methodology and the provided ideas supported the process of approaching the research objectives. The practically-inspired thoughts in combination with both a Design and Action Research approach was beneficial for supporting the research process. The general notion behind ADR, that IT-artefacts are and should be shaped and built to meet the needs of the end-users is well in line with the key idea of this thesis. Additionally, the idea that the objective, artefact-centred Design Science can successfully be combined with subjective Action Research, provides an interesting basis to expand from. Future implementations of this methodology will certainly validate the approach, which is a positive development, as there is a need for new methodologies in IS-research.

It has to be acknowledged that the positivist approach has been criticised as being incompatible with parts of ADR. This criticism may not always be justified, as the positivist approach to conducting research fits well with parts of ADR. Nevertheless, there is a need to further validate and investigate the shared concepts.

The thesis does not claim to present any solution regarding the philosophical questions presented in Chapter 3. It seems quite clear that the road towards creating intelligent machines is already well on its way. With the development of new techniques (e.g. fuzzy ontologies) and more powerful computers (e.g. quantum computers), the possibilities to reach the goal are increasing. As it seems unlikely that humanity would suddenly stop developing more advanced computer systems, it is only a matter of time before we can create an Artificial General Intelligence (AGI). The road leading to the first AGI applications will be lined with numerous intelligent applications and systems, making the introduction of a fully functioning AGI machine less intimidating.

Even if this thesis has been mostly focused on the benefits of using fuzzy ontologies and OWA operators for different purposes, there is another side of the coin. There exist limitations that should be addressed in order for fuzzy ontologies to reach their full potential.

A key issue that is currently hindering the use of fuzzy ontologies is the speed of computation. This is not an issue when performing simpler computations; for instance, Excel can easily handle a value in the interval $[0,1]$ instead of using only 0 or 1. However, as the calculations become more complex, for instance when one processes linguistic expressions to solve a complex decision problem, the computation time becomes an issue. In this thesis, as the created applications are both context adaptive and mobile, there was a need to find temporary solutions to reduce the computation time. A solution was to limit the set of alternatives before the computation was initiated, by retrieving only the alternatives that are available or logically possible for that specific problem.

This issue should not be seen as an impossible problem to overcome, as this is mostly due to the lack of suitable programs to perform the tasks. The techniques

used for this thesis were initially designed for slightly different purposes. As the development continues, new methods and programs more suitable for dealing with these issues will be developed. It is also a fact that there is seldom a need to process the whole fuzzy knowledge base, as most problem situations can be solved well enough by only processing a limited data set.

8.5 Future Research

Mobile devices of all kinds are becoming more and more common and are used in different decision making contexts, solving tasks that were impossible to manage a couple of years ago. This movement will change the way decisions are made in our everyday life, supporting informed and rational decision making regardless of where we are. To support this movement there is a need to develop new techniques to perform analyses and computations and to find new methods for handling and modelling the data.

The terms fuzzy logic and fuzzy ontology are a bit misleading, resulting in misunderstandings about how they are used and what they are capable of. As fuzzy ontologies could develop into one of the cornerstones of the Semantic Web, there is a need for a clarification about what the terms actually imply. Both the Semantic Web and fuzzy ontology research would benefit from a clearer definition and an extended awareness among researchers and users.

It would also be important to make it clear why fuzzy ontologies and methods for dealing with imprecision are needed, as there are opinions against using imprecise data. An important fact to state for future discussion is that it is impossible to avoid imprecise data, regardless of how advanced sensor systems we use, as there will always be imprecision of some kind when humans are involved. It can also be argued that imprecision is beneficial and leads to better decisions.

The Fuzzy Wine Ontology based applications introduced in the thesis demonstrate the benefits one can receive from implementing fuzzy ontologies. As the application is anchored to a topic that is well known to most people, it aspires to introduce the concept of fuzzy ontology to the general public as well as the industry. It would be beneficial to continue developing the Fuzzy Wine Ontology and extend it with new features, such as: selecting multiple wines for a dinner or adopting the retrieved results based on previous choices. This would support the process of introducing and explaining fuzzy ontologies to organisations.

It is also clear that there is a need to define new variants of the OWA operator. There are numerous possible implementation areas which means that there is a need to create operators that are modified for specific purposes. The same fact applies to the creation of new consensus models to support group decision making, as there is a lot to gain from improving and maximising the use of knowledge in GDM problems.

The thesis introduces some advances in the design and development of decision

support systems using fuzzy ontology. Some examples are developed to show how this structure can be made mobile, through smart phones and other mobile devices. With this, the author hopes to inspire future research and developments, both in academia and in the private sector, on how expert knowledge can be utilized in a fast-paced and mobile context.

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Robin Wikström

Fuzzy Ontology for Knowledge Mobilisation and Decision Support

Utilizing imprecise data

The objective of the research conducted was to explore how fuzzy ontologies could facilitate the exploitation and mobilisation of tacit knowledge and imprecise data in organisational and operational decision making processes.

This thesis shows the benefits of utilizing all the available data one possesses, including imprecise data. By combining the concept of fuzzy ontology with the Semantic Web movement, it aspires to show the corporate world and industry the benefits of embracing fuzzy ontologies and imprecision.



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