THE e-DECISIONAL COMMUNITY: AN INTEGRATED KNOWLEDGE SHARING PLATFORM

By

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STATEMENT OF ORIGINALITY

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I hereby certify that components of the work embodied in this thesis are from published papers of which I am a joint author. My contribution to these papers covers knowledge and experience management, knowledge representation, multi agent system, virtual organisations, and knowledge measurements and warrants inclusion of their parts in the body of my thesis.

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LIST OF ACRONYMS

ACL	Agent Communication Language
API	Application Programming Interface
CC	Cloud Computing
CML	Collective Management Layer
CoP	Community of Practice
DDNA	Decisional DNA
DF	Derivative Follower
FIPA	Foundation for Intelligent Physical Agents
GA	Group Agent
GT	Game Theory
HTTP	Hyper-Text Transfer Protocol
IaaS	Infrastructure as a Service
IEEE	Institute of Electrical and Electronics Engineers
IML	Individual Management Layer
ISO	International Organization for Standardization
KaaS	Knowledge as a Service
KAL	Knowledge-based Application Layer
KBVO	Knowledge Based Virtual Organizations
KE	Knowledge Engineering
KM	Knowledge Management
KOS	Knowledge-Oriented Services
KQML	Knowledge Query and Manipulation Language
MAS	Multi-Agent System
MY	Myoptimal
OWL	Web Ontology Language
PA	Personal Agent
PaaS	Platform as a Service
REST	Representational State Transfer
RF	Reputation Follower
SaaS	Software as a Service
SKMS	Smart Knowledge Management System
SOA	Service-Oriented Architecture
SOAP	Secure Object Access Protocol
SOE	Set of Experience
SOEKS	Set of Experience Knowledge Structure
SQL	Structured Query Language
VO	Virtual Organization
XML	eXtensible Markup Language

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ABSTRACT

In today's knowledge oriented economy, the ability to make accurate decisions becomes crucial for any organization or individual for adapting to new demands and conditions in the environment. Additionally, technology allows for ubiquitous access to knowledge and information from different places and devices at any time, which has created a new generation of highly informed customers and enterprises; thus, precise decisions have become more important in order to increase customer fidelity, maintain competitive advantage, and reduce reaction times and costs.

In spite of all the advances in the field of Knowledge Management, and more specifically in the area of Knowledge Sharing, most of the existing solutions for capturing, storing, and reusing knowledge require a high degree of expert intervention; for instance, expert forums or document bases. Moreover, the process of finding an appropriate solution for a given problem becomes complex when the amount of information and knowledge available increase everyday. Furthermore, unlike traditional organizational assets, knowledge has a unique intangible nature and is highly embedded in the workforce and the business processes, making it hard to measure and estimate its actual availability.

The e-Decisional Community aims at proposing a set of guidelines for the development of a large scale platform to share knowledge and experience in order to support decision-making processes in organizations. The main idea behind the platform is that experiential knowledge is gathered from the constant interaction between users and organizations and from the software applications that they use on a daily basis. Knowledge exchange and evaluation is performed in a semi-automatic way by using smart agent technology, a set of indicators that reflect human behaviour, and an automatized knowledge-based market environment. Additionally, the most important contribution of this research is the definition of a semi-automatic way of assessing quantity and quality of knowledge. The e-Decisional Community is able to provide estimated measures of quantity and quality

of knowledge, endowing organizations with a novel set of tools for assessing the knowledge that resides in their workers and business processes.

Several conceptual elements of this thesis have been implemented in a testing prototype, and the experimental results that were obtained show that the platform has a great potential for reducing the workload on experts, as well as response times for providing accurate solutions. Consequently, overall organizational efficiency is increased because workers can focus on their core tasks without worrying about additional management duties for their knowledge-based systems, such as solution classification, or knowledge quality assessment.

CHAPTER 1:
RESEARCH MOTIVATION AND BACKGROUND

Knowledge management (KM) technologies have been the centre of attention for some researchers in the scientific community. Nowadays, KM has become a critical element for organizations that need to collaborate with others when pursuing a common objective, given the importance of knowledge as a mayor asset that guarantees competitive advantage in a rapidly changing, economic-driven environment (Zhang, Tang, Liu, and You 2008).

Due to the advances in KM technologies and the need for inter-organizational cooperation, knowledge sharing (KS) related activities have become crucial in any KM strategy. Knowledge-sharing promotes the creation of knowledge clusters and networks which make organizations more competitive, and also facilitates skills and knowledge upgrading (Baskerville and Dulipovici 2006). As a consequence, several theories and proposals on KS can be found in literature, and most of them are a valuable contribution to the area of knowledge engineering (KE). They are concerned with providing technical support for KS between entities in various ways and using different approaches such as folksonomies, social networks, amongst others.

Diverse technologies have converged to supply new and interesting solutions for KS and other KM related issues, such as knowledge extraction, representation, storage/retrieval and evolution. One of these proposals is the Smart Knowledge Management System (SKMS), which defines the processes and components required to capture, store, improve, reuse, and transmit experience through generations of decision makers (Sanin and Szczerbicki 2008a). Also, software agents and Grid computing have spawned countless proposals, ranging from personal suggestion agents or smart document-based knowledge extraction to more advanced approaches like the knowledge grid (Zhuge 2005).

More recently, the term Cloud Computing has emerged as a trend in the computing world creating the opportunity to share and exchange information on a large scale. It is based upon concepts such as Web 2.0 and virtualization; and uses Grid computing as its infrastructure support (Foster, Yong, Raicu, and Lu 2008). This new vision, where almost everything is provided as a service, opens the door for new research opportunities and the scientific community is starting to focus its efforts around this new model; thus, the KM field is not the exception, with some general ideas about clouds and knowledge management sketched recently (Delic and Riley 2009).

Based on the previous ideas and research opportunities, this thesis presents a proposal called the e-Decisional Community. This community allows for many individuals and organizations to share experiential knowledge, and supports complex decision-making processes. In the e-Decisional Community new knowledge is created and evolves through constant interactions amongst entities or groups of entities. It is based on concepts from software agents, grid computing, and Cloud computing in order to model complex human interactions, provide coordinated problem solving and knowledge sharing at large scales. Moreover, some important features like trust and reputation, knowledge quality and quantity measurement, dynamic group formation, and a market environment are proposed as key elements in the e-Decisional Community.

1.1. ENABLING TECHNOLOGIES

This section presents a review of the different technologies that enable the development of the e-Decisional Community, and their applications in the field of KM.

1.1.1. Smart Knowledge Management System, SOEKS and DDNA

Knowledge has been an important asset for individuals, organizations, and society through the ages. Today's enterprises need to react and adapt to changes rapidly, and they are conscious that proper KM processes will help them survive in a dynamic environment.

Managers and decision makers in general, base their current decisions on lessons learned from previous similar situations (Sanin and Szczerbicki 2005a). However, much of an organization's experience is not properly capitalized at all because of inappropriate knowledge administration, leading to decision reprocessing, high response times, and lack of flexibility to adapt in dynamic environments. The SKMS provides the means to decision makers by defining a set of four macro processes and components required to capture, store, improve, reuse, and transmit experience (Sanin and Szczerbicki 2008a). The SKMS dynamically transforms large amounts of data and information from diverse sources into knowledge, supporting decision-making processes at any level of the organizational hierarchy.

The SKMS is based on the concepts of Decisional DNA (DDNA) and Set Of Experience Knowledge Structure (SOEKS). DDNA is a structure that captures decisional fingerprints inside organizations and is built from formal decision events. Each decision event is transformed into a SOEKS creating a decisional gene. Subsequently, many genes are grouped to generate a decisional chromosome and many chromosomes comprise a DDNA strand. Consequently, DDNA captures the inference strategies of enterprises (Sanin and Szczerbicki 2008b). SOEKS and DDNA can be exchanged using an XML-based representation (Sanin and

Szczerbicki 2005b) and ontologies (Toro, Sanín, Szczerbicki, and Posada 2008); therefore, DDNA supports knowledge discovery and storage, as well as inter- and intra-organizational KS. The SOEKS has been successfully applied in industrial environments, specifically for maintenance purposes, in conjunction with augmented reality techniques (Toro et al. 2007), and in the fields of finances and energy research (Sanin, Mancilla-Amaya, Szczerbicki, and CayfordHowell 2009).

1.1.2. Software Agents

Software agents (or simply agents) represent an active research area where many efforts have been made to develop human-like behaviour in computer systems. According to Wooldridge and Jennings (1995), these systems have special characteristics that make them unique: (1) autonomy; (2) social ability; (3) reactivity; (4) proactivity; (5) mobility; (6) veracity; (7) benevolence; (8) rationality. As a consequence, agents are used in many KM approaches because they provide an appropriate way for modelling organizational knowledge. In fact, Van Elst and Abecker (2001) describe four characteristics of KM that support the use of agent-based systems: (1) Knowledge is distributed inside organizations; (2) KM goals are not often a high priority to knowledge workers; (3) Knowledge work as well as KM in general requires complex interactions and proactive behaviour; and (4) KM deals with dynamic environments.

Previous work on KM based on agents was concerned with text mining, automated suggestions, and smart document access (De Rezende, Pereira, Xexeo, and De Souza 2007; Kim, Choi, Kim, and Hwang 2007), distributed organizational memories (Abecker, Bernardi, and Van Elst 2003; Gandon and Dieng-Kuntz 2002), agent-based architectures (Vizcaino, Soto, Portillo, and Piattini 2007), and use of ontologies in multi-agent systems (MAS) among others. It is evident that there is a strong relationship between software agent technology and KM, with many interesting proposals being developed. Nevertheless, there is still some work to do in a number of particular aspects (Van Elst, Dignum, and Abecker 2004): (1) Interaction between human and software agents; (2) agent architectures and KM concepts (e.g., trust, rights); (3) methodological and engineering aspects; (4) evaluation of agent-based KM.

1.1.3. Grid Computing

Since the mid 1990s, Grid technology has provided a robust and highly scalable infrastructure for coordinated problem-solving. However, as the complexity of undertaken problems increases, the requirements surrounding the grid have become more complex and demanding. Efforts like the Semantic Grid provide new capabilities to users and as pointed out by De Roure, Jennings, and Shadbolt (2005), topics like semantic service description, smart interaction, autonomous behaviour, knowledge technologies, amongst others, should be addressed in future research efforts.

In fact, many researchers have focused their attention to knowledge technologies and grid research. Zhuge (2004) presents the Knowledge Grid as a highly distributed collaborative environment, where explicit knowledge resources—for example, information or services with their semantic descriptions—are managed to support decision-making processes and cooperative work. Another step in this direction is the knowledge grid system proposed by Cannataro and Talia (2004), which explores management of knowledge discovery applications on the grid, providing mechanisms to integrate data-mining tools, computing, and storage resources by means of grid services orchestrated by users.

Regardless of its powerful attributes, grid technology concepts need to be improved with ideas from other areas in order to fulfil the elements proposed by De Roure, Jennings, and Shadbolt (2005). Software agents, as described in the previous section, offer some unique attributes that are common to the research topics defined for the grid (Foster, Jennings, and Kesselman 2004). Elements like autonomous behaviour, community management, advanced coordination, and negotiation techniques are being used in the grid to make it more resilient and efficient; two examples of this are presented by Gil (2006) and Norman et al. (2004), who describe new ways to make grid environments more robust and to dynamically manage virtual organizations in electronic commerce scenarios, both based on agents.

1.1.4. Cloud Computing

Cloud computing (CC) has recently emerged as a new computing trend that is attracting efforts from the scientific community, but as other authors have stated, there is no consensus on what CC is (Youseff, Butrico, and Da Silva 2008; Foster, Yong, Raicu, and Lu 2008). However, Cloud Computing can be understood as a computing model where end-user applications (i.e., Software as a Service (SaaS)), platforms (i.e., Platform as a Service (PaaS)), and hardware/software infrastructures (i.e., Infrastructure as a Service (IaaS)) are provided as services to users over the Internet.

Cloud computing is closely related to grids according to Foster, Yong, Raicu, and Lu (2008). Clouds are an evolution of grid technology, but with different requirements in areas such as business models, applications and abstractions. The cloud takes full advantage of developments in virtualization technology, the Semantic Web and grid computing in order to provide different services on-demand.

There is increasing interest in the scientific community regarding CC, leading to different proposals for the implementation of cloud-based environments being developed. For example, Zhan et al. (2009) present a cloud-computing system to consolidate heterogeneous workloads in organizations. Others propose the use of human organizational principles to develop client CC environments, which facilitate knowledge and experience transfer between people (Hewitt 2008). Moreover, cloud-based KM systems have been envisaged by Delic and Riley (2009), who state that knowledge clouds will interconnect users across several organizations and data centres, thus, supporting the "Intelligent Enterprise." The "Intelligent Enterprise" is an entity that behaves intelligently and uses the Internet as its base for providing services and performing operations.

1.2. RESEARCH OPPORTUNITY

This chapter has briefly introduced the importance of knowledge for organizations and their strategies. Strategic decisions require appropriate knowledge about the environment and the organization, and the best way guarantee success when a decision is made is by assuring the availability and high quality of knowledge. Consequently, the proposal presented in this thesis aims at facilitating the exchange of experiential knowledge between individuals and organizations, with the intention of supporting decision-making processes. Based on the aforementioned idea, and the opportunities and relations presented previously, the main objective of the research described in this thesis is to:

- *Provide guidelines for the development of a large-scale environment to share knowledge and experience represented as SOEKS and DDNA, in order to support decision-making processes across different organizational levels.*

With the intention of supporting the development of the KS environment described by the main goal, several sub-aims have been defined as follows:

- *Provide the means for capturing, storing, reusing, and evolving individual and collective experience at large scales in organizational environment*: in order to be able to adapt quickly to new demands and conditions in the environment, organizations should be able to collect experience and reuse it in order to make accurate decisions. The e-Decisional Community provides the means to manage the increasing amount of knowledge that comes from heterogeneous sources in today's organizations.
- *Integrate concepts from different technologies into the fields of KM and KE*: as presented previously in this chapter, several technologies have been applied to KM research. The e-Decisional Community integrates concepts from different

technologies to create an innovative environment for semi-automated experience management.

- *Support the daily activities of individuals and organizations by using human-inspired behaviour*: the e-Decisional Community is meant to support decision making on a daily basis and in a semi-automated way with little user interaction. Consequently, the platform employs a behavioural approach that models human interactions, in order to provide more accurate results when tasks are performed solely by the system.
- *Create a knowledge-based market environment in which experience can be traded*: experience is a valuable asset for every individual and every organization, and like any other asset, it must have a cost associated to it. This ensures that contributors are rewarded for their efforts, and reduces the chance of free riding. Moreover, organizations should be able to determine how much their "know-how" is worth, and use this measure to define the terms of agreements with other enterprises.
- *Provide the required mechanisms for knowledge assessment*: assessing knowledge with the intention of setting a price for it becomes an important contribution made by the e-Decisional Community. Specifically, the platform provides quality and quantity assessment mechanisms for knowledge, which are a major step forward in KM research given the complexity of such tasks because of the intangible nature of knowledge.

1.3. THESIS OUTLINE

With the goal of describing the research process involved for the development of the e-Decisional Community, this thesis has been structured in seven chapters. Instead of devoting a whole chapter to literature review, every chapter in this thesis is comprised by a background section of its own. The main idea behind this approach is to make every chapter as independent as possible, and make them self-contained to avoid unnecessary repetitions. Similarly, the experimental prototype of the e-Decisional Community is described in an incremental way throughout the entire document. This approach allows highlighting and evaluating technical details separately depending on the topic that is presented in each chapter, until the final model is presented.

The thesis structure is also meant to follow describe the more general features and concerns of the research process first, and then elaborates on the specific contributions that are made to the fields of KM and KE. The chapter structure defined for this document is as follows:

- *Chapter 1*: is concerned with describing the overall motivation and aims of the research, as well as some general information related to the technologies and concepts that support the global idea of the e-Decisional Community.

- *Chapter 2*: introduces the conceptual model for the e-Decisional Community, describing its features, capabilities, and initial design. This chapter sets the global guidelines for the development of the e-Decisional Community. The details about the implementation and development of the e-Decisional Community are unfolded in the following chapters.

- *Chapter 3*: presents the elements that are considered important to resemble human behaviour in the platform. A detailed analysis of existing theories on human behaviour is presented, and as a result a set of features are selected. This chapter focuses on trust and reputation as key elements to foster KS in large groups or communities of users. The first iteration of the experimental prototype is presented in this chapter.

- *Chapter 4*: describes the quality assessment mechanism proposed for the e-Decisional Community. This mechanism is based on a set of attributes taken from existing research on data and information quality, and are adapted to the context of the e-Decisional Community in order to provide an estimate measure of experiential knowledge. To validate this proposal, the experimental prototype was improved and it is presented in this chapter, along with the experimental results that were obtained.

- *Chapter 5*: explains the quantity assessment mechanism that has been proposed for the e-Decisional Community. Quantity is also one of the quality attributes mentioned previously; therefore, this chapter integrates some elements from chapter 4, and expands them with the new quantity model. The new experimental prototype iteration and new experimental results are presented in this chapter.

- *Chapter 6*: presents the market environment for the e-Decisional Community. This chapter integrates the concepts of reputation, trust, quality, and quantity described in the previous chapters, and applies them to the specific scenario of knowledge trading in the platform. The final iteration of the experimental prototype is presented, along with the results obtained from the market experiments.

- *Chapter 7*: provides some concluding remarks about the research process presented in the thesis, including achievements and contributions. This chapter also presents the current status of the prototype implementation, the elements that remain for future development and the lessons learnt from the entire process. Finally, ideas for new research opportunities in the future as sketched with the objective of defining a roadmap that will hopefully conclude with the deployment of the e-Decisional Community in organizational environments.

It is worth noting that all the proposed aspects of the platform are not completely developed in this document because of the technical and theoretical extension of the elements involved; nonetheless, this thesis describes the major theoretical concepts and concerns that are faced by the e-Decisional Community with the intention of building new knowledge and making a contribution to the research community.

CHAPTER 2: THE E-DECISIONAL COMMUNITY

As illustrated in the previous chapter, Knowledge Management (KM) has become a key success factor in diverse fields, given the importance of knowledge as a significant organizational asset. The ability to learn from past experiences and adapt to rapidly changing conditions, determines which organizations will prevail in today's global economy. Consequently, managers are more conscious about the importance of knowledge as part of their strategies, and are giving a higher priority to KM- related activities.

Knowledge Sharing (KS) is one activity that has received the attention of the research community in recent times, because knowledge is useful only if it is accessible to all users, and can be used to solve problems and make decisions (Lao, Xiao, Wang, and Qin 2008). In order to support decision-making processes, knowledge and experience have to be transmitted across individuals and organizations. In fact, Hustad (2004) states that KS is performed at different levels: between individuals, from individuals to groups, between groups, and from groups to organizations. Therefore, KS can be considered as the basic element of any knowledge-oriented process, because it fosters collaboration, and facilitates experiential knowledge discovery, use, and distribution. Several approaches have been developed to support collaboration and KS using different technologies such as ontologies, folksonomies, wikis, and social networks (Kings, Gale, and Davies 2007). Concrete examples of these efforts can be found in projects like Palette (Vidou et al. 2006), Wikipedia (Foundation 2012), or SQUIDZ (Kings, Gale, and

Davies 2007). However, in spite of the existing advancements in technology, improving KS by means of autonomous mechanisms and the use of a domain-independent knowledge representation, still remains as a research area to be explored

The e-Decisional Community is proposed as new technological platform, designed to promote knowledge sharing, and knowledge improvement through generations of decision makers. KS in the e-Decisional Community is supported by a market environment, in which knowledge represented as SOEKS and DDNA is provided as a service. The platform is based on conceptual principles from other technologies, i.e. software agents, grid computing, and cloud computing. The objective behind such combination of elements is to offer support for autonomous, intelligent, and coordinated KS at a large scale. Also, the e-Decisional Community is able to facilitate the exchange of ideas amongst different groups of interest in an organization.

This chapter introduces the general elements proposed for the e-Decisional Community, starting with its global vision and main features. Then, the conceptual model and architecture are presented, describing the different layers and services that comprise the platform. Subsequently, a detailed analysis of the different alternatives for transmitting SOEKS and DDNA using software agents is offered. Finally, summary and brief conclusions on this chapter are presented. The main goal of this chapter is to provide a general outline of the e-Decisional Community, and the details of the platform's implementation and formal models will be unfolded in the following chapters.

2.1. GLOBAL VISION OF THE E-DECISIONAL COMMUNITY

According to Vidou et al. (2006), organizations are comprised of many interconnected groups of interest, called Communities of Practice (CoPs). Communities of Practice are "groups of people who share a passion for something that they know how to do, and who interact regularly in order to learn how to do it better" (Wenger 2004 p:2). Consequently, the e-Decisional Community is designed as a CoP, providing the means for groups to perform their activities using the latest advances in technology. The interaction between users with similar interests provides the means for efficient experience discovery and utilization, because employees are expected to collaborate more actively and willingly with their peers than other participants that do not belong to a group, and hence do not have the same motivation to share their knowledge, i.e. achieve a common goal. In addition, the e-Decisional Community is not just a data/text-mining tool, or a smart document repository. It is a dynamic and scalable platform for problem-solving activities amongst individuals and organizations. The main concern addressed by the e-Decisional Community is the way experience represented as SOEKS and DDNA is passed on, and evolves through generations of decision makers in an autonomous and smart fashion.

Figure 1 depicts the global vision of the e-Decisional Community. The platform integrates different organizations and their employees. Also, three major levels are identified: bottom, middle, and top level. At the bottom level of the platform, software agents representing workers in an organization interact autonomously with each other in knowledge-related activities. Every group of agents at the bottom level can be seen as a multi-agent system. Interactions are delimited by a set of objectives established by the organizational unit each agent belongs to; therefore, cooperation makes experiential knowledge grow and evolve for that given business unit. In a similar way, organizational divisions at the middle level can cooperate and collaborate amongst themselves. These higher-level interactions give place to a composition of Multi-Agent System (MAS), with the purpose of fulfilling a collection of well-defined organizational aims.

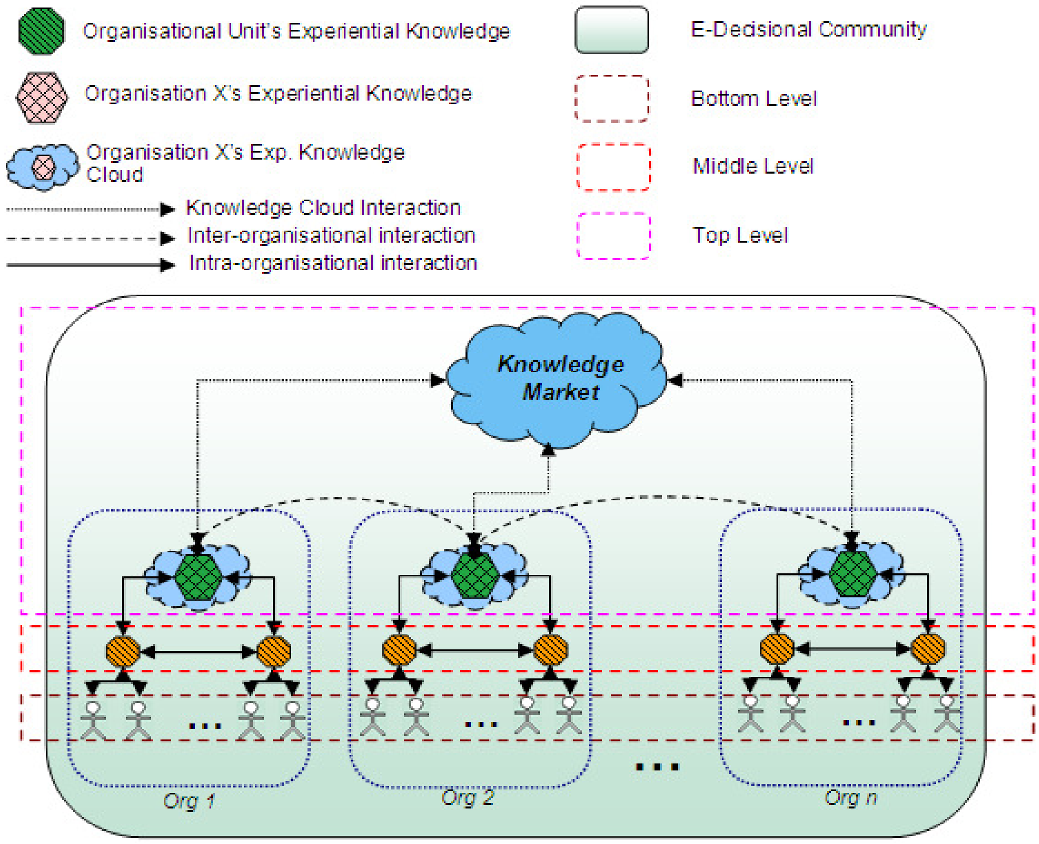

Figure 1. Global Vision of the e-Decisional Community

At the top level, many different organizations can interact to share knowledge in a scenario that is motivated by strategic alliances, or producer-consumer relationships. Using a Cloud Computing approach, organizations may create their own clouds, interact with each other, and provide knowledge on-demand. These interactions are motivated by economic principles for instance alliances, and producer-consumer relationships. In fact, the interconnection of different business partners will generate a much larger cloud, stimulating the creation of a large-scale knowledge market, in which knowledge is the main asset, and it is sold or exchanged as part of collective strategies. It is worth clarifying that the market mechanism used for inter-organization negotiation, is also used by individual agents in order to exchange queries and answers for knowledge-based tasks. The market mechanism used by the e-Decisional Community is explained in detail in chapter 6.

2.2. E-DECISIONAL COMMUNITY FEATURES

In order to support decision-making processes in organizations, the e-Decisional Community shall provide the following features:

- ***People-oriented:*** the platform is a tool that provides knowledge-oriented problem solving capabilities, in which people can take advantage of today's computational improvements to support complex decision-making processes in organizations.

- ***Agent-based capabilities:*** characteristics from software agents are provided to model complex human interactions and support intelligent KM processes, in highly distributed and complex environments.

- ***Constant evolution:*** knowledge evolution and refinement is achieved by constantly updating existing experiences with data and information from the real world, which is provided by the users and the software applications they use.

- ***Community formation:*** there are tasks that cannot be executed successfully in an individual fashion; therefore, grouping based on objectives and knowledge is supported in a dynamic manner.

- ***Well-defined interactions:*** agents and services participating must interact in an orderly fashion. Therefore, protocols and interaction schemes are defined to establish proper communication, role assignment, and permission policies.

- ***Conflict resolution:*** negotiation techniques and conflict resolutions mechanisms are provided to solve disputes caused by accessing scarce resources, or by conflicting beliefs and experiences.

- ***Security and trust***: it is clear that a secure environment is a key requirement for any distributed system these days, especially when Internet is used as the primary communication channel. Also, knowledge, and knowledge sources, must be reliable to make the right decisions; therefore, the concept of decisional trust presented by Sanin and Szczerbicki (2009b) is extended to include more features that reflect human-like behaviour.

2.3. CONCEPTUAL MODEL

The proposed conceptual model for the e-Decisional Community is comprised of four layers: knowledge-based application layer, collective and individual management layers, and knowledge-oriented services layer. The platform is conceptualized on top of the SKMS, to extend the capabilities of the latter by using DDNA and SOEKS for knowledge representation and exchange. Figure 2 depicts the conceptual model for the KS platform.

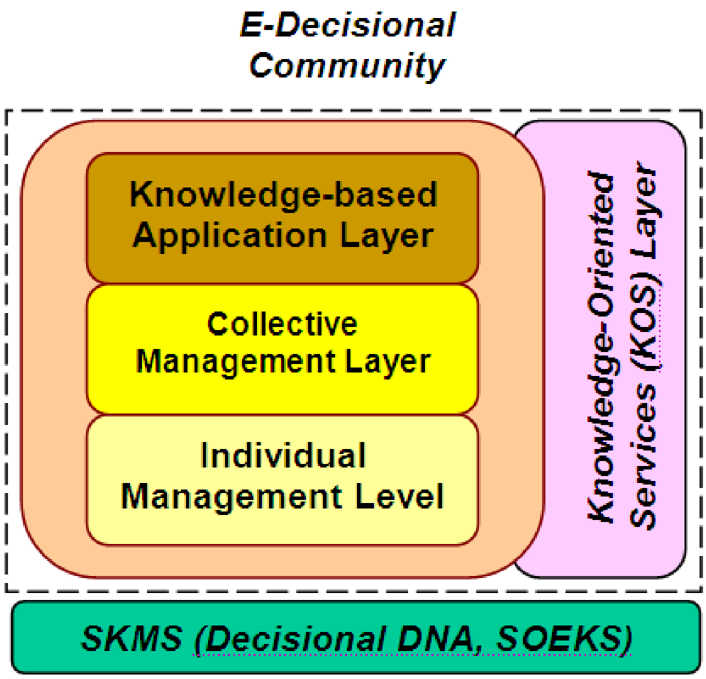

Figure 2. Proposed conceptual model for the e-Decisional Community

All the layers in the conceptual model make extensive use of knowledge-oriented services (KOS) to provide appropriate KS capabilities. KOS support interactions between different entities at all levels of the hierarchy illustrated in Figure 1; however, in order to do so properly, they need to be part of a coordinated strategy.

Since the e-Decisional Community is based on software agents' principles, well-defined interaction policies are used to coordinate KOS execution, delineate the proper mechanisms for resource access, and articulate individual and collective strategies.

Each one of the layers in the conceptual model has a set of responsibilities and capabilities, as follows:

- ***Knowledge-based Application Layer (KAL):*** this layer provides end-user access to the whole platform functionality. Web 2.0 or mobile applications may be used by workers to interact with other peers or groups to solve problems, make decisions, and feed the system with information based on their daily activities. Knowledge-based applications can use complementing technologies such as augmented reality, to improve interaction with the environment and capture experiential data from different sources.

- ***Collective management layer (CML):*** dynamic teamwork management, inter and intra-organizational interactions, cooperation, and global policies, among other mechanisms, are provided by this layer to support collaborative work. Groups and organizations are represented as heterogeneous MAS; thus, multiple MAS can interact between each other using well-defined protocols and policies provided by the CML. During the interaction process, new experiential knowledge is created or inferred, increasing the expertise level of the entire enterprise. Virtual organization formation and management based on knowledge objectives is also supported at this level, and the details of this process are presented in chapter 3.

- ***Individual management layer (IML):*** individuals in an organization are represented by software agents. Consequently, knowledge exchange, collaboration, and dynamic teamwork formation, can be performed in an autonomous fashion resembling human behaviour. Moreover, agents can remember users' behaviour in order to proactively initiate knowledge-based tasks. In this layer, agents act as an entry point to the KOS provided by the platform and are able to create an individual's decisional fingerprint that can be used, for example, as a performance or reputation indicator. This layer provides all the required mechanisms to support the aforementioned functionality.

- ***Knowledge-Oriented Services Layer (KOS):*** knowledge-oriented services deliver a wide range of features oriented to promote proper KS inside organizations. The services provided by this layer are: access to DDNA and SOEKS repositories; access to yellow and white pages directories; role definitions; trust and reputation services; knowledge quantity and quality assessment services; knowledge market transaction history. Coordinated execution of KOS is defined by the interaction protocols of the CML and IML.

- ***SKMS, Decisional DNA and SOEKS:*** this is not a layer of the e-Decisional Community. However, the four macro processes defined by the SKMS (diagnosis, prognosis, solution, and knowledge), along with its knowledge-capturing and representation mechanisms, constitute the foundation on which KS in the e-Decisional Community is supported. More details about the SKMS can be found in (Sanin and Szczerbicki 2008a).

2.4. CONCEPTUAL ARCHITECTURE

In the e-Decisional Community, users access the platform using mobile or Web 2.0 knowledge-based applications as explained in the previous section. Consequently, protocols like HTTP or SOAP, and architectural approaches such as REpresentational State Transfer REST must be employed. In addition, applications in the KAL make use of software agents to access the e-Decisional Community's functionality. Each user is represented by a personal agent (PA), which acts in his/her behalf inside the community and provides access to KOS. Personal agents know about their roles, interaction restrictions, trust relationships, and reputation of other entities by means of specialized KOS.

Numerous PAs may share a temporary or permanent interest for a specific topic, which leads to a dynamic group formation. When various agents form a coalition (i.e., a MAS), they are represented by a group agent (GA). Therefore, multiple MAS are viewed as complex agents that interact similarly to how individual PAs do, but with higher level goals and interests. In a similar way, interaction between organizations is carried out using GAs that represent them. GAs are able to solve more complex problems or make critical decisions, because they can use the experience from many individuals or groups. Figure 3 illustrates the conceptual architecture for the e-Decisional Community.

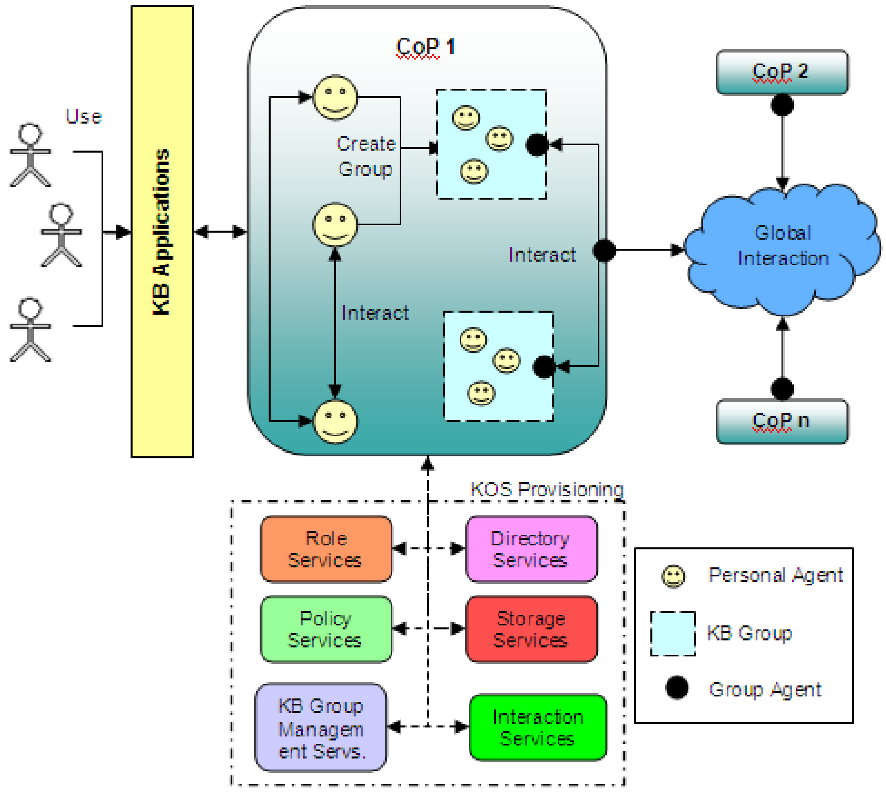

Figure 3. Conceptual Architecture for e-Decisional Community

The conceptual architecture for the e-Decisional Community defines six KOS categories oriented to assist experience diffusion. Services may be provided on-demand for external or internal entities, and an organization can provide a customized type of KOS on the Cloud if required. The service categories defined for the e-Decisional Community are:

- ***Role services:*** this service category acts as a repository where organizational roles are mapped, defining the corresponding behaviours, responsibilities, capacities, goals, and permissions. Roles can be dynamically taken by any entity.

- ***Directory services:*** provides white and yellow pages services, in order to query for individuals, knowledge resources, or services.

- ***Policy services:*** stores the organizational policies for dealing with different issues. For example, policies for uncertainty management, service distribution, rewards/punishment, and others, are stored for dynamic querying.

- ***Knowledge storage services:*** these services provide storage and retrieval capabilities for individual, collective, and organizational experience. Providing secure, reliable, location-independent, and fast access to SOEKS and DDNA structures is the main concern of this service category.

- ***Knowledge-based group management services:*** dynamic formation of groups based on knowledge objectives is a key feature of the e-Decisional Community. As a consequence, a specific category of services is devoted to support this aspect. Trust, negotiation, reputation, quality and quantity of knowledge, and knowledge transaction history, constitute the key elements that are provided to support cooperative problem resolution and decision making.

- ***Interaction services:*** this set of services contains the definition of all the protocols that are used inside the CoP to guarantee orderly interaction. These protocols are employed to coordinate the communication flow between the different entities involved in a knowledge negotiation process, or knowledge transaction.

2.5. TRANSMITTING SOEKS AND DDNA INSIDE THE E-DECISIONAL COMMUNITY USING SOFTWARE AGENTS

Users of the e-Decisional Community are able to access the platform via heterogeneous computing devices from different locations, with different processing capabilities and under variable network conditions. Also, organizational policies might be in place and could restrict shared knowledge. As a consequence, the way in which agents in the community transmit their knowledge has to be flexible, and must adapt to different usage conditions presented by the clients. In this section, a review of different agent communication and knowledge representation languages is presented, with the intention of defining the set of mechanisms to be used in the e-Decisional Community for knowledge transmission between agents.

2.5.1. Knowledge Representation Platforms and Ontology Languages

This section presents existing languages for knowledge representation and manipulation. Several proposals were reviewed and analysed in regards to their significance for the e-Decisional Community, but for the sake of simplicity this section only presents details about the most relevant.

The Simple HTML Ontology Extensions (SHOE), allows annotating web pages with semantic content that can be used by software agents to extract knowledge (Heflin, Hendler, and Luke 1998). SHOE supports the process of knowledge acquisition from the web, and provides information that can be represented as SOEKS and used for decision-making. However, SHOE has a low popularity because it is not a widely recognized standard like OWL (W3C 2004). Standards offer the possibility to use several open source tools and APIs (e.g. Protégé-owl API) to extract and manipulate knowledge in a much powerful way than SHOE.

Another approach comes from the Knowledge Grid environment (Zhuge 2008), a large-scale distributed environment where shared knowledge resources are categorized in three dimensions used to identify content and storage locations. The dimensions are: category, level and location. The knowledge level dimension is also divided in four categories: Concepts, Axioms, Rules and Methods (Zhuge 2002). In order to query and perform operations on the different knowledge grids, an important part of Zhuge's proposal is the Knowledge Grid Operation Language (KGOL) (Zhuge and Liu 2003). KGOL provides all the required operations to produce, access, and manage knowledge. Its syntax and set of operations are very similar to the ones provided by SQL, and the results of each operation are returned as XML documents or XML documents fragments.

The dimensions and categories proposed by the Knowledge Grid can be represented in the SOEKS XML format (Sanin and Szczerbicki 2005b). For example, the <category> section can be directly related to the category dimension proposed by the knowledge grid. Also, the location of a resource can be mapped by using a <creation> section. Finally, the level dimension can be related directly to elements from DDNA and the SOEKS as follows: concepts $\rightarrow$ variables, axioms $\rightarrow$ functions, rules $\rightarrow$ rules, and method $\rightarrow$ set of solutions presented to users. As a result, the inter-operation between the knowledge grid and the e-Decisional Community is possible, due to the similarities between the former and the SOEKS.

Finally, the Web Ontology Language (OWL) offers mechanisms for information processing by computer programs. DDNA and SOEKS can be represented using ontologies and OWL (Sanin, Szczerbicki, and Toro 2007), exploiting powerful representation, querying and inference capabilities. For instance, the ability to perform advanced queries on large sets of information with an optimal response time can be achieved by means of Reflexive Ontologies (RO) (Toro, Sanín, Szczerbicki, and Posada 2008).

2.5.2. Agent Communication Languages (ACL)

This section discusses different approaches developed for communication and knowledge transfer between agents, briefly describing their features, advantages, disadvantages, and relevance to the e-Decisional Community context.

In first place, the Knowledge Query and Manipulation Language (KQML) (Finin, Fritzson, McKay, and McEntire 1994) is a language/protocol that defines message formats and handling procedures, which allow agents to engage in knowledge-sharing processes, independently of the content representation. KQML is a popular language for agent communication, and was used by several systems as presented in (Haustein and Luedecke 2000); however, KQML has some drawbacks that have been pointed out in previous work referring to interoperability issues (Haustein and Luedecke 2000), lack of extensibility (Moore 1999), and the use of non-standard dialects of the language (Dignum 2000). SOEKS can be stored in XML or OWL (Sanin, Szczerbicki, and Toro 2007; Sanin and Szczerbicki 2005b), and these formats can be used as a content representation language in conjunction with KQML to promote knowledge-based interactions between autonomous entities, and support complex decision-making processes.

In second place, FIPA-ACL (FIPA 2002a) defines a set of performatives and message parameters that are used to handle agent interactions in any context. It provides independence from the content language used i.e. it is a wrapper. This language has been adopted as a standard for communications in many agent development platforms, like JADE (Telecom-Italia 2012) or JACK (Howden, Ronnquist, Hodgson, and Lucas 2001), among others.

SOEKS and Decisional DNA can be shared among physical agents, such as robots or cognitive embedded systems (Zhang, Sanin, and Szczerbicki 2010; Sanin, Mancilla-Amaya, Zhang, and Szczerbicki 2012). In this situation, FIPA's specification is a suitable alternative to handle interactions because it provides standard intercommunication between the physical world and the virtual world in which other software agents exist. In spite of its advantages, FIPA-ACL has received some criticism. Dignum (Dignum 2000) mentions that FIPA-ACL is based on multi-modal logics and as a consequence, some agents may lack the ability to act according to them. Also, FIPA-ACL, as well as KQML, does not offer performatives to express future commitment; thus, agents cannot make promises to each other regarding future events.

Finally, the Formal Language for Business Communications (FLBC) is another language proposal based on speech act theory that aims at providing automated message handling in electronic communications. In a FLBC based system, messages consist of assertions and declarations which are typically used in inference procedures. Also, systems based on this approach can have semantic access to the messages knowing the meaning and contents of what is transmitted (Kimbrough and Moore 1997). FLBC is meant to provide independence from the content language and it supports XML (Moore 2001). Thus, this platform would facilitate the transmission of SOEKS and DDNA in its simplest format, but it would not be possible to use the OWL representation of DDNA. However, it is possible to translate an OWL ontology into an XML tree which allows for content querying and manipulation, but major reasoning capabilities provided by OWL are lost and cannot be exploited.

2.5.3. Selection process of an ACL and Ontology Language for the e-Decisional Community

Previous sections have illustrated how DDNA and SOEKS may be transmitted and represented using different protocols and ontology-based languages. The next step in the design process of the e-Decisional Community is to perform a selection process to determine which technologies are most suitable for experience transmission. In order to do so, evaluation criteria was established to measure the suitability of each tool, as follows:

- *Standard-based*: communications between an instance of the e-Decisional Community and other knowledge-bases systems should be carried out in a standard way.

- *Inference capabilities*: languages must provide advanced inference capabilities, which facilitate discovery of new knowledge. These capabilities are complemented by the rational abilities of autonomous agents.

- *Compactness*: languages or protocols should provide a compact way for representing/transmitting knowledge in environments with memory, storage space, and bandwidth restrictions.

- *Java compliance*: since the SOEKS API has been implemented in Java, it is desirable that open source libraries or development frameworks are also developed in Java.

- *Currently supported and active*: languages and protocols should be part of active initiatives, which guarantees their constant improvement, development, and support.

Table 1 presents the results of the evaluation process. The following conventions were used: Y= the criterion is satisfied, N= the criterion is not satisfied, NA= the criterion is not applicable, ?= not determined. The inference capabilities criterion was not applied to ACLs. Also, extensibility and compactness criteria were not applied to ontology languages.

Table 1. Evaluation of ACL and ontology languages

TOOL	STANDARD	INFERENCE	COMPACT	JAVA COMP.	ACTIVE
KQML	Y	N/A	Y	Y	N
FIPA-ACL	Y	N/A	Y	Y	Y
FLBC	N	N/A	N	?	?
XOL(Karp, Chaudhri,	N	N	N/A	N	N

and Thomere 2000)					
SHOE	N	Y	N/A	N	N
KGOL	N	N	N/A	?	N
OWL	Y	Y	N/A	Y	Y

Table 1 shows that FIPA and OWL are the strongest options in each category. The selection of FIPA-ACL for agent communications is driven by the fact that it supports communication between and virtual agents. Also, FIPA is implemented by a variety of Java-based agent platforms, assures interoperability, and can be used in restrictive environments (e.g. mobile devices). On the ontology language category, OWL is the obvious choice not only because of its well-known features, but also because it has been used in the past as a representational format for SOEKS and DDNA with excellent results. Entities can transmit OWL encapsulated in FIPA messages to assure standard inter-agent communication, and compatibility with other agent-based systems.

2.5.4. Alternatives for SOEKS and DDNA transmission in the e-Decisional Community

After presenting the different ACL and ontology languages alternatives, and selecting the most suitable ones for use in the e-Decisional Community, the next step is to establish the different ways in which SOEKS and DDNA are shared between agents. Restrictions such as security, network bandwidth, or processing and storage capacity may prevent agents from exchanging some of their experience; therefore, alternative options for sharing knowledge must be provided to deal with such scenarios. One sharing alternative would not suit all the possible scenarios that might arise while KS is being performed in organizations; for that reason, this section outlines a set of possibilities that might be used depending on different environment restrictions that might limit KS.

The first option that is proposed is to share entire SOEKS. The main advantage of this strategy is simplicity, because no complex operations are required to manipulate each set of experience for it to be transmitted. This alternative of transmission allows for KS between agents similarly to what happens when a person seeks advice from other. The person that was asked for help transmits his/her solution (i.e. experience) to the person who requested it; however, in the end the requestor is the one who makes a decision whether to use the new knowledge or not. This approach is suitable for environments with low or none restrictions on network communications, and processing or storage capacity. Also, this approach works best if there are no restrictions on confidentiality of knowledge; otherwise, SOEKS should be altered in order to avoid transmitting sensitive elements. The main disadvantage of this alternative is that large sets of information may exceed storage or memory capacity of physical agents, such as robots or embedded systems.

The second option is sharing subsets of a SOEKS. As mentioned earlier, some organizations may impose restrictions on the KS environment. Then, what can be done to deal with organizational policies, security or privacy measures? An example of this situation can be found in the medical field. Medical information given by a patient to his/her doctor is, in most cases, confidential and cannot be revealed without authorization. Consequently, a set of experience based on the medical information of a patient can be subject of such restrictions, allowing only a part of the entire set to be shared.

Transmitting just a subset of the set of experience is a solution to the former situation, and is achieved by using the priority and weight characteristics defined for the elements comprising a SOEKS (Sanin and Szczerbicki 2009a). An agent can evaluate the aforementioned values, and decide to transmit only those within a pre-established threshold. A receiving agent then evaluates the new knowledge, and decides if should incorporated into its knowledge base. The evaluation of weight and priority of the SOEKS' elements enable the use of the Pareto principle, where 20% of the functions can define 80% of the decision; thus, guaranteeing that entities are able to share representative pieces of knowledge, and make complex decisions based on different samples. The second alternative is more suitable than the first one when entities with physical restrictions are involved in the KS process.

The third option is sharing examples of valid or invalid SOEKS. The previous alternatives assume that knowledge given to entities is accurate and correct; however, the dynamic context in which an entity is executed may cause knowledge to be invalid or inaccurate. Also, when privacy and security restrictions are enforced, a teacher/student example could be beneficial for KS because it educates agents about different concepts using examples that do not disclose sensitive information. For the third alternative, the entire solution for a problem is not exchanged by agents, and entities must “learn” their own solutions. Similar approaches have been explored by other authors; for example, Afsharchi and Far (2006) present a new way of improving agent communications by using example-based interactions. In the context of the e-Decisional Community, users posit a priority value to pick the best solution among a range of possibilities. This value is used later by autonomous entities to identify positive and negative examples for the solution of a problem. Agents are trained to learn what type of solution is appropriate under different circumstances and afterwards, they can act as trainers for others in the community. Examples can be exchanged as a complete SOEKS or subsets of SOEKS, taking into account the restrictions and the benefits of the previous alternatives.

Table 2 summarizes the different alternatives for KS using SOEKS and DDNA in the e-Decisional Community. Sharing complete SOEKS is suitable for environments with low or medium physical and privacy related restrictions. It is also suitable for physical agents and virtual agents to share knowledge; however, physical agents might be limited by the size of the SOEKS files they can process and store. If the SOEKS files are small enough, agents should be able to share complete experiences using the first option. On the other hand, sharing SOEKS fragments is more appropriate for environments with higher levels of restriction for their operation. By using the second option, physical agents or agents in mobile devices should be able to handle more SOEKS without worrying about processing or storage restrictions. Finally, sharing SOEKS examples is a hybrid strategy that can use complete SOEKS or fragments of SOEKS to teach other agents in the system without revealing sensitive knowledge.

Table 2. Summary of KS strategies using SOEKS and DDNA

OPTION	PHYSICAL RESTRICTIONS (E.G., BANDWIDTH, STORAGE)	SECURITY/PRIVACY/POLICY RESTRICTIONS	PHYSICAL/VIRTUAL AGENTS
Share entire SOEKS	Low/Medium	Low/Medium	Both
Share SOEKS fragments	Medium/High	Medium/High	Both
Share examples	All	High	Both

2.6. *HOW TO MEASURE THE USEFULNESS OF THE KNOWLEDGE SHARED IN THE E-DECISIONAL COMMUNITY?*

In addition to the previously described alternatives for KS based on SOEKS in the e-Decisional Community a measure for the effectiveness of KS is needed; for that reason, all knowledge interactions require users and agents alike to give feedback on the experience they use. Knowledge feedback helps in the process of measuring knowledge usefulness, supporting the creation of reputation and trust indicators, assisting agents in selecting the most knowledgeable peers for cooperation, and allowing organizations to measure the overall quality of their knowledge. The e-Decisional community provides trust and reputation mechanisms as a way to guarantee trustworthiness. The details of this model are presented in chapter 3. Also, knowledge quantity and quality assessment mechanisms are supported by the platform, and are introduced in chapters 4 and 5.

2.7. SUMMARY

In this chapter, the general features for a CoP that allows sharing of experiential knowledge across different organizational levels were presented. The e-Decisional Community is based upon the principles of different computing technologies, namely: software agents, grid and cloud computing. As a consequence of this approach, eight global features have been presented as the main concern in the work presented in this thesis.

Also, a brief analysis on existing mechanisms that are essential to support KS in the e-Decisional Community was offered. This is the basis for the development of knowledge-based interactions that will help organizations be more competitive by optimizing discovery and use of experiential knowledge. As a result of the previously mentioned analysis, three main strategies for SOEKS and DDNA transmission between agents were identified. The purpose of these strategies is to provide different alternatives for KS in the presence of different restrictions for the platform.

CHAPTER 3: HUMAN BEHAVIOUR MODELLING FOR THE E-DECISIONAL COMMUNITY

As mentioned in section 2.4, one of the features defined for the e-decisional community is dynamic group formation, to support the execution of knowledge intensive tasks when an individual's knowledge is not enough to provide a suitable solution. Given that the e-decisional community incorporates grid computing concepts into the KM field, dynamic groups are based on the concept of virtual organizations (VOs) defined by Foster, Kesselman and Tuecke (2001); however, in the e-Decisional Community shared resources do not refer to computers, software or data. Resources in the context of the e-Decisional Community are knowledge and experience represented by as SOEKS and DDNA. As a consequence, these dynamic groups are called knowledge-based virtual organizations (KBVOs). KBVOs are not actually limited to inter-organizational relations, and they are generalized to include every single group of interest and organizational unit in an enterprise. Each KVBO has diverse knowledge resources to share, and different policies/rules to access knowledge; therefore, every gathering of workers can be represented as a separate KBVO and the entire system as a composition of organizations.

Also, as presented in the previous chapter, the e-Decisional Community is a people-oriented platform; thus, the study of social and human behavioural factors surrounding collaboration in groups is of great importance. Since the concept of KBVOs encompasses every person and every group of persons in an organization, a comprehensive literature review has been performed to identify elements that can be introduced into the e-Decisional Community to reflect human behaviour, and make the KBVO model as complete as possible.

This chapter presents the requirements for KBVO in the e-Decisional Community. Firstly, a theoretical background on social dynamics in virtual teams and organizations is presented, along with some practical applications in the fields of agents, grid and cloud computing. Then, the requirements for KBVOs in the e-Decisional Community are presented along with the conceptual relationships between the comprising elements. Finally, a model to measure trust and reputation is presented, along with a validation prototype and experimental results. The experimental prototype and results presented in this Chapter represent the first iteration in the development process of the e-Decisional Community. Following Chapters will present refined versions of the initial prototype and results.

3.1. REVIEW ON SOCIAL DYNAMICS IN VIRTUAL GROUP INTERACTIONS

Virtual interactions have become increasingly popular, not only as an entertainment mechanism but also as a new way to perform work-related activities and exploit emergent business opportunities. However, the success of such environments in any organization depends not only upon technological factors but also on social and behavioural elements related directly to the workforce and the enterprises.

Researchers have analysed virtual environments from different perspectives in order to understand them better and make them more efficient. For instance, Spaulding (2010) uses a value chain approach, along with social contracts and trust theory, to determine how an enterprise can obtain value from its interaction with different types of virtual communities. Lin, Standing, and Liu (2008) present a model that can be used in projects involving virtual teams and argue that social factors like relationship building, communication, and cohesion influence the performance and satisfaction of the group.

Other researchers have studied the elements surrounding KS in virtual environments. For instance, Koh and Kim (2004) study how community KS is related to virtual community outcomes in e-Business. Also, Lin, Hung, and Chen (2009) analyse the perceptions, behaviours, and contextual factors that have a direct incidence in KS inside organizations. According to them, elements like reciprocity, perceived advantage, and trust can influence KS behaviour. Similarly, Panteli and Sockalingam (2005) propose a framework in which trust and conflict are considered as important elements in knowledge-oriented processes, and proper management of these aspects may lead to improved KS in virtual environments. Additionally, Ahn et al. (2005) propose a system that facilitates knowledge use in collaborative environments, by capturing, evolving, and reusing contextual information about knowledge. This proposal is based on the idea that knowledge is generated and used on a specific context, which makes it relevant and increases its importance in specific situations. Finally, social capital theory, social cognitive theory, and autopoiesis have also been used in an attempt to better understand how experience and knowledge are created, shared, and structured in organizations (Chiu, Hsu, and Wang 2006; Pamkowska 2008).

Besides the behavioural and situational approaches described earlier, an organization must devise adequate plans and strategies to embrace virtual organizations. KM strategies that allow virtual organizations and communities to acquire competitive advantage have been explored. Elements like policies, performance measures, fast adaptation, and knowledge as a basis for process integration are some of the components that researchers like Burn and Ash (2002) have proposed to assure optimal decision making. Moreover, when several organizations need to engage in a productive interaction, commitments and responsibilities from each part must be evaluated. Contracts are widely used to guarantee that a service or resource is provided, to specify the characteristics of an agreement, and to define rewards or penalties. Hoffner, Field, Grefen, and Ludwig (2001) present a framework that explores management of virtual business relationships in an automated and efficient way. This is achieved by defining, among others, a contract framework and a virtual market technology to assist enterprises in the process of searching for partners and negotiating contracts' characteristics.

3.2. TECHNOLOGICAL APPLICATIONS OF SOCIAL DYNAMICS IN SOFTWARE AGENTS, GRID AND CLOUD COMPUTING

As explained in Chapter 2, the e-Decisional Community integrates principles from different technologies, including software agents and grid computing. In this section, applications of social elements in the fields of software agents and grid computing are shown to illustrate the relationship between social dynamics and computational solutions.

Organizational theories can be used to model human organizations, as well as computer systems. Organizational theories have been applied in MAS, to represent elements like rules, norms, relationships, and structure of organizations. Argente, Julian, and Botti (2006) present a detailed study on human organizational structures and the way MAS can be modelled under such point of view. They also propose possible implementation patterns to suit different structures such as bureaucracies, matrixes, or virtual organizations.

Other features of human behaviour like association by interests and trust can be implemented in agent-based solutions. For instance, Li, Montazemi, and Yuan (2006) developed a methodology that finds buddies using reinforcement learning and satisfaction indicators. Their methodology was tested using a music selection scenario, proving that agents are capable of finding other entities with similar musical interests just as humans would do. Also, a framework for collaborative trust in MAS based on the concepts of mutual trust, shared risks, and common goals, is presented by Mokhtar, Wajid, and Wang (2007).

Knowledge sharing is unlikely to be successful unless organizational members adopt appropriate practices, and in order to assist this process, Roda, Angehrn, Nabeth, and Razmerita (2003) created a framework and an agent system called K-InCA. K-InCA helps users embrace knowledge sharing practices using pedagogical strategies, which are supported on an intervention model (i.e., a set of rules), a change domain (i.e., collection of behaviours for the organization), a user model (i.e., individual preferences, competencies and needs), and a set of expert agents.

In addition, concepts from software agents have been applied in grid computing, as part of several efforts to develop new solutions that incorporate ideas from both worlds (Norman et al. 2004). Some proposals in this regard, such the one presented by Patel et al. (2005), define the elements required to create VOs using the concepts of trust, reputation, quality of service, and policies. Likewise, a framework for agent-based modelling of VOs in the grid is proposed by Zhai, Qu, and Gao (2004). In this modelling framework, agents can represent resources or they can be grouped into VOs. Individual agents or groups are represented by master agents who interact at a higher level. In addition to the previous VO proposals, contracts are also applied in the grid as introduced by Zuzek et al.(2008), who formally define a model for VO formation through contract negotiation implemented in the FiVO framework. Additional work that integrates social dynamics, software agents, and grid computing includes estimation of performance based on reputation and cooperation of agents in the semantic grid (Dragoni, Gaspari, and Guidi 2006; Papaioannou and Stamoulis 2009).

Finally, another application example is represented by the knowledge grid, a proposal that allows users to share heterogeneous knowledge resources and collaborate to execute tasks and make decisions (Zhuge 2008). The knowledge grid features a virtual knowledge service market, an environment where entities exchange knowledge at given prices (Zhuge and Guo 2007). This process includes four stages:

(1) advertisement of knowledge, (2) advertisement of demands, (3) negotiation of price, and (4) renegotiation until an agreement is achieved.

3.3. KNOWLEDGE-BASED VIRTUAL ORGANIZATIONS (KBVO)

Previous sections have described several elements that may influence the process of knowledge sharing in virtual organizations or teams, and the relationship that exists between such factors and technology. Based on the previous ideas, this section presents the required elements to reflect human behaviour in the e-Decisional Community, and support the execution of knowledge intensive tasks via KVBOs when cooperation between agents is required to provide suitable solutions for a given problem.

3.3.1. Requirement definition for KVBOs

As a people-oriented platform, the e-Decisional Community must use indicators, measurements, and mechanisms that reflect human behaviour in a computer-based environment. By using the previous items, the e-Decisional Community is able to give support for software agents to engage in KS activities like real people would do. Consequently, features that are common in literature, and therefore widely used and accepted, have been selected as part of the e-Decisional Community, and are presented in Table 3. In addition, as part of the requirements for KBVO formation in the e-Decisional Community, the life cycle for such groups must be defined. A commonly accepted life cycle model for virtual organizations is used, based on four stages as described by Preece et al. (2000): requirement identification; partner selection; task execution; group dissolution. These stages along with the items concepts in Table 3 are the foundation to support KVBO's life cycle.

Table 3. Elements to be used in the e-Decisional Community for Dynamic Community Formation

FEATURE	REFERENCED IN	FEATURE	REFERENCED IN
Trust	(Koh and Kim 2004), (Lin, Hung, and Chen 2009),	**Community size and age**	(Chiu, Hsu, and Wang 2006)

	(Panteli and Sockalingam 2005),(Patel et al. 2005),(Zhai, Qu, and Gao 2004), (Zhuge and Guo 2007) ,(Papaioannou and Stamoulis 2009)		
Reputation (personal, group)	(Patel et al. 2005),(Zhuge and Guo 2007),(Lin, Standing, and Liu 2008)	**Rewards/Punishment**	(Patel et al. 2005),(Lin, Standing, and Liu 2008)
Performance	(Papaioannou and Stamoulis 2009),(Patel et al. 2005), (Chiu, Hsu, and Wang 2006)	**Coordination and Communication**	(Koh and Kim 2004)
Knowledge Quality and Quantity	(Norman et al. 2004),(Patel et al. 2005), (Koh and Kim 2004)	**Community Promotion**	(Panteli and Sockalingam 2005)
Community Participation	(Zhuge and Guo 2007),(Norman et al. 2004)	**Conflict**	(Patel et al. 2005),(Hoffner, Field, Grefen, and Ludwig 2001)
Quality of KS	(Lin, Standing, and Liu 2008)	**Contracts**	(Zuzek et al. 2008),(Lin, Standing, and Liu 2008)
Satisfaction	(Zhuge and Guo 2007),(Preece 2000)		

Figure 4 illustrates the existing relationships between the concepts defined previously in Table 3. In the diagram, (+) indicates a positive impact and (-) a negative impact, to represent the influence of one concept on another. These relationships are used in the e-Decisional Community to provide accurate metrics to measure the quality of the KS process and the quality of knowledge itself. Furthermore, services like satisfaction assessment, group advertisement, and service contracting are provided, and described in detail throughout the following chapters.

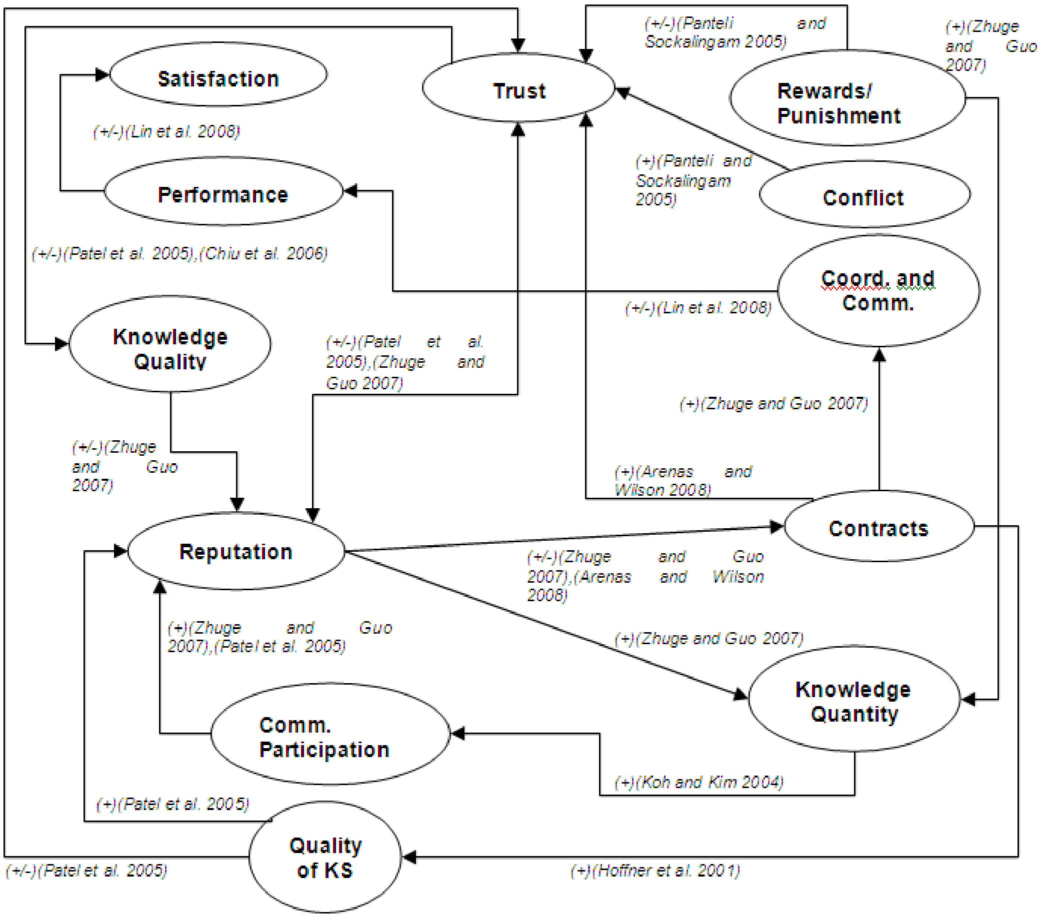

Figure 4. Identified relationships for KBVO formation.

A quick overview of Table 3 shows that trust is considered as a key aspect in group dynamics, and it can act as a driving factor surrounding community formation for decision making. However, trust does not refer only to the degree of confidence between entities but also to the precision and usefulness of the knowledge they share. In addition, reputation, quality of knowledge sharing (QoKS), contracts, conflict, and rewards/punishment are important characteristics related to trust.

Reputation can be a motivating factor for individuals or groups to share knowledge. In order to have higher reputation in the community, entities can share more knowledge and participate more actively. However, this could not be enough to increase reputation, since shared knowledge must be of acceptable quality to other members. Reputation can decrease as a result of sharing large amounts of "bad" or untrustworthy knowledge and vice versa.

Contracts are used with the purpose of creating a formal agreement between entities relating to knowledge provisioning. In order to create a contract, agents must advertise their knowledge, and carry out a bid process to select the most suitable proposal. According to Arenas and Wilson (2008), contracts can be used along with reputation-based recommendations to build trust. Agents can ask other peers for an opinion about possible partners to provide knowledge, based on their previous experiences. Furthermore, well-managed conflict or contracts can also help in the process of building trust among entities, because in the early stages of a relationship trust can be built on rules (Panteli and Sockalingam 2005). In addition, communication and coordination are elements that can have a great influence in the process of contract creation and the performance of a group. Good coordination leads to better task execution, and appropriate communication between entities allows them to promote their knowledge, make bids, and carry on negotiation processes.

Other concepts shown in Table 3 such as community promotion, and community size and age are not illustrated in the diagram because they are independent assessments, i.e. they are not related to other concepts. For example, the number of members in a group and the period of time they have been interacting together can be independently measured, indicating their possible level of expertise. Also, community promotion refers to the process of advertising knowledge services and experience, in the context of the e-Decisional Community. Therefore, it is assumed that this process is willingly carried out by agents regardless of any other factors; nevertheless, the final decision of whether to engage (or not) in knowledge sharing processes is still affected by the other elements presented in this section.

3.4. TRUST AND REPUTATION MODELS FOR THE E-DECISIONAL COMMUNITY

This section presents the conceptual model developed to represent trust and reputation in the e-Decisional Community, as the first step towards the creation of a knowledge market. Trust and reputation were selected mainly because their degree of importance according to Figure 4 is the highest (i.e., the number of connecting relationships with other concepts). During this section it is assumed that an agent a_i is part of a system Ω which has at least two agents, $\Omega = \{a_1, a_2, a_3, ..., a_n\}; n >= 2$. The trust and reputation models introduced in this section are a based on different concepts from existing research, and are not designed as a novel proposal since it is of the scope of this thesis.

3.4.1. Background

Several proposals have explored trust and reputation for agent-based systems and VOs in great detail, using sophisticated mathematical models such as the ones presented in (Yu and P. Singh 2002; Patel 2006; Hermoso, Centeno, Billhardt, and Ossowski 2008). Also, Zacharia, Moukas, and Maes (2000) present a reputation mechanism that can be used in any marketplace, including knowledge marketplaces as described in (Zacharia, Moukas, Boufounos, and Maes 2000). However, most of the previous examples do not deal explicitly with KS activities, and their computational complexity is also considered as a drawback for the e-Decisional Community because complex operations are required to obtain reputation values or store an agent's transaction history. Computational intensive processes become restrictive for the e-Decisional Community when knowledge participants are embedded systems or small physical agents. Therefore, the way in which reputation and trust are assessed in the e-Decisional Community must take into account such restrictions, and offer an almost effortless way for agents to evaluate the trustworthiness of others.

Jurca and Faltings (2005) developed a simple reputation mechanism for P2P environments, which computes reputation information using an average-based aggregation rule. This approach is a perfect match for the needs of the e-Decisional Community because it can be implemented in a centralized or semi-centralized way, and can be used by traditional software agents or embedded systems because of its simplicity. The reputation mechanism presented in the following sections uses a similar approach to the one developed by Jurca and Faltings. However, a key difference in the e-Decisional Community is that reputation is seen as a measure of collective trust. Trust in the e-Decisional Community is based on feedback from users and agents, and is designed to measure the dependability of entities in the system. Similarly to some of the proposals presented earlier, feedback is considered as a simple way of evaluating the degree of satisfaction in a transaction, and determining how much trust should be posited in an agent.

Unlike the different alternatives for SOEKS and DDNA transmission presented in Chapter 2, trust and reputation have to be standard across the platform. It is not possible to have different mechanisms for every kind of agent, or for every type of environment. Unified trust and reputation mechanisms are the best alternative for interoperability, ease of implementation, and information coherence between different instances of the e-Decisional Community.

3.4.2. Trust Model

In the context of the e-Decisional Community, every interaction between agents can have two possible outcomes like in a Bernoulli trial: success or failure. Consequently, the interaction result between two agents is defined as:

$$I(a_i, a_j) \in \{SUCCESS, FAILURE\}; \forall i \neq j$$

Equation 1. Possible interaction result between agents

This approach is oriented toward knowing how much trust should be placed in an agent based on the outcomes of previous interactions. In other words, agent A wants to know in advance what is the probability of a success before interacting with agent B, using its experience to calculate such result. To model this behaviour, Laplace's rule of succession was used to define *T*, the level of trust between two agents, as follows:

$$T(a_i, a_j) = \frac{S(I(a_i, a_j)) + 1}{H(I(a_i, a_j)) + 2}; \forall i \neq j \wedge 0 \leq T(a_i, a_j) \leq 1$$

Equation 2. Trust between two agents

In Equation 2, $S(I(a_i,a_j))$ is the total is number of successful interactions between agents a_i and a_j , and $H(I(a_i,a_j))$ is the total number of interactions between the agents including failures.

Additionally, following Zhuge's and Guo's approach presented in (Zhuge and Guo 2007), trust decays over time making older results less significant. This is an important element in the trust model for the e-Decisional Community because recent interactions have a greater effect on the final trust evaluation. As a consequence, the decay factor λ is introduced to automatically decrease trust levels among agents when there are no new interactions. Therefore, the value of trust after a periodic decay is calculated by:

$$T(a_i, a_j) = T(a_i, a_j) - (T(a_i, a_j) \cdot \lambda);\ 0 \leq \lambda < 1$$

Equation 3. Trust decay over time

3.4.3. Reputation Model

Reputation in the e-Decisional Community is basically an average of the trust that many agents have placed on another one over time. If agent A reports a high level of trust in agent B, reputation of B in the community increases and vice versa. In addition, because reputation decays over time reputation is also affected.

The reputation level $R(a_i)$ for an agent a_i is simply the accumulation of previous reputation levels divided among the total number of opinions (feedback) from other agents $F(a_i)$:

$$R(a_i) = \frac{1}{F(a_i)} \cdot \sum_{k=1}^{F(a_i)} R_k(a_1); 0 \leq R_k(a_i) \leq 1 \wedge F(a_i) \geq 1$$

Equation 4. Reputation of an agent in the e-Decisional Community

When the system runs for the first time and there is no record of previous interactions between agents, reputation is used by entities as the initial trust level. In addition, when a new agent enters the system, its reputation level is 0.5, because it is not possible to indicate beforehand whether it is a trustworthy agent or not.

3.5. CASE STUDY AND EXPERIMENTS

This section presents the initial version of the prototype for the e-Decisional Community, and the results obtained in the first set of experiments.

3.5.1. Experimental prototype v 1.0

An agent prototype was developed using JADE 4.0 (Telecom-Italia 2012) and Java SE 6 (Oracle 2011).Also, as part of this process, an initial API version for the e-Decisional Community was generated. The refinement of the prototype and API is described in the following chapters of this thesis.

As presented in Chapter 2, the e-Decisional Community defines four basic layers: Individual Management Layer (IML), Collective Management Layer (CML), Knowledge-Based Application Layer (KAL), and Knowledge-Oriented Services Layer (KOS). The initial version of the API includes basic functionality for the IML and KOS, and also provides abstract methods for developers to implement guaranteeing that agents can be customized if required. Figure 5presents the initial package structure for the API.

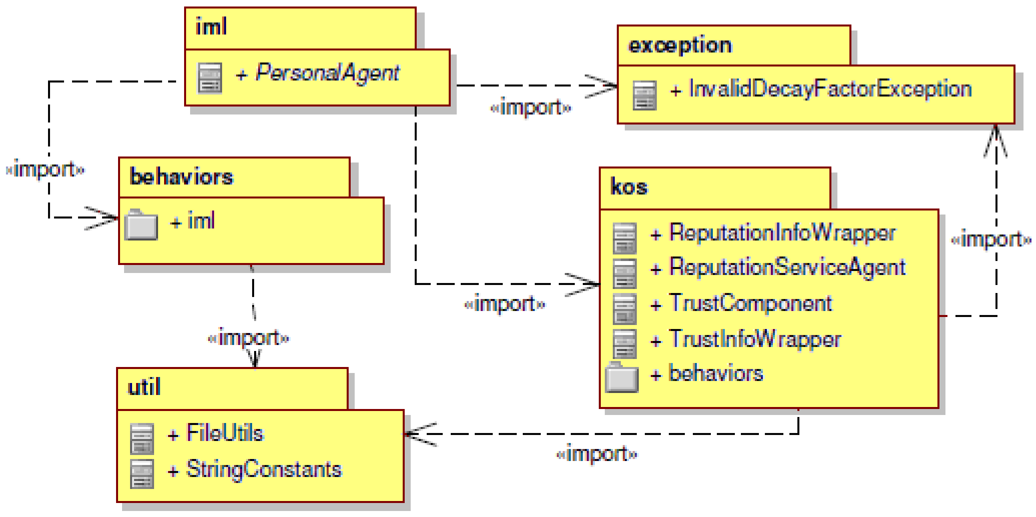

Figure 5. Package Structure of the first experimental prototype.

The IML provides the capacity to create personal agents that represent human workers. Also, KOS for reputation and trust are provided to support the activities performed by the personal agents. It is important to notice that the reputation service is modeled as single agent (centralized service), which possesses global knowledge about the reputation of every entity in the system. Each peer must register itself against the reputation service agent when they enter the system. Afterwards, the service recalculates trust on-demand each time it receives feedback from other agents.

On the other hand, trust is designed as a component that personal agents use individually to asses the trustworthiness of their peers. Trust components are part of an agent's mental state, and provide separation between an agent's individual perception of trust towards others, and the global reputation provided by the reputation service.

3.5.2. Experiment Design and Configuration

The goal of the initial experiments is to validate how trust changes over time because of automatic decay, and after obtaining feedback for sharing experience represented as SOEKS. Also, the behavior of the reputation indicators is examined under these conditions.

A test application was developed using the first version of the API. In this application, it is assumed that all agents know each other, and that they belong to the same organizational group. The application's context is the following: an agent wants to know about a cheap mechanic to fix a car. The interaction is started by an initial query issued by an agent, who defines a budget for the mechanical repairs. Then, the other agents in the system respond to the query, if and only if, the average cost per repair of their known mechanics is less or equal to the one proposed by the initiator agent. Based on the result of each interaction, agents recalculate trust and report the new value to the reputation service.

To simulate "bad" agents the `java.util.Random` object is used to generate random *true* or *false* values. When an agent's knowledge does not satisfy the budget conditions and the random value is *true*, the agent responds, thus, simulating a "deceptive" agent. In any other cases, the agents respond based on the value of the random variable

For the experiments, one dummy agent and ten working agents were created. The dummy agent's only task was to send a message to trigger a reaction in the working agents, as explained previously. To facilitate the process of trust measurement, one working agent was taken as a reference point by reading its trust values with respect the other nine agents. The reputation levels were measured periodically from the reputation service agent, and 50 independent trials were executed. In addition, each agent has a behavior that ran periodically to decay trust at a rate of 10% each time.

3.5.3. Experimental Results

The graphics presented in this section illustrate the trust level from an agent, called AG1 towards other agents in the system. For the sake of simplicity, four agents out of the remaining nine have been selected because the results illustrate different scenarios that can be found in the e-Decisional Community. Figure 6 illustrates the following behaviors:

- *AG7*: Depicts the behavior of a trustworthy agent that keeps a "good" behavior for the duration of the experiment.

- *AG4*: Shows an "intermediate" behavior; trust values for this agent stay around 0.6 in average for the majority of the tests.

- *AG8*: Shows how an agent starts with a sequence of "bad" responses, and after changing its attitude, it gains trust from the others again. It takes a long time for reputation to start increasing again after several misbehaviors.

- *AG9*: Illustrates how an agent has low trust after repeatedly replying with inaccurate information. In this case reputation keeps going down during the experiments.

Figure 7 illustrates the way in which the decay factor affects trust over time. A stair-like behavior in values can be clearly appreciated, confirming that trust decays λ percent when agents do not interact with each other, as expected. After a new interaction is accomplished, trust is recalculated again and increases/decreases by a small amount. In this series of experiments, trust decays only if agents have not interacted in the last minute. For applications in an organizational context, this time scale should be extended to days or weeks to resemble human behavior in a better way.

Finally, Figure 8 shows the behavior of reputation through time. As expected, the diagram shows that reputation behaves depending on trust, just as defined in the model. The variations in the reputation values also show a more stable behavior than trust, in the sense that variations due to success or failure are not reflected as drastically as in Figure 6 and Figure 7. This means that a bad opinion about a fellow agent does not necessarily have a great impact on the perceived reputation inside the community; to seriously affect reputation, an agent must have several bad reviews from its peers.

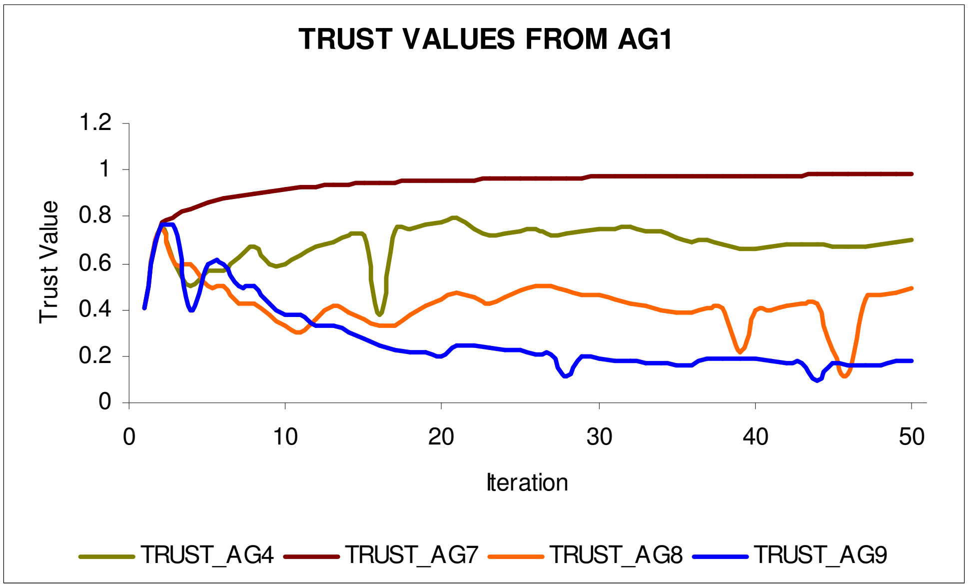

Figure 6. Trust values obtained in the initial experiments for AG1

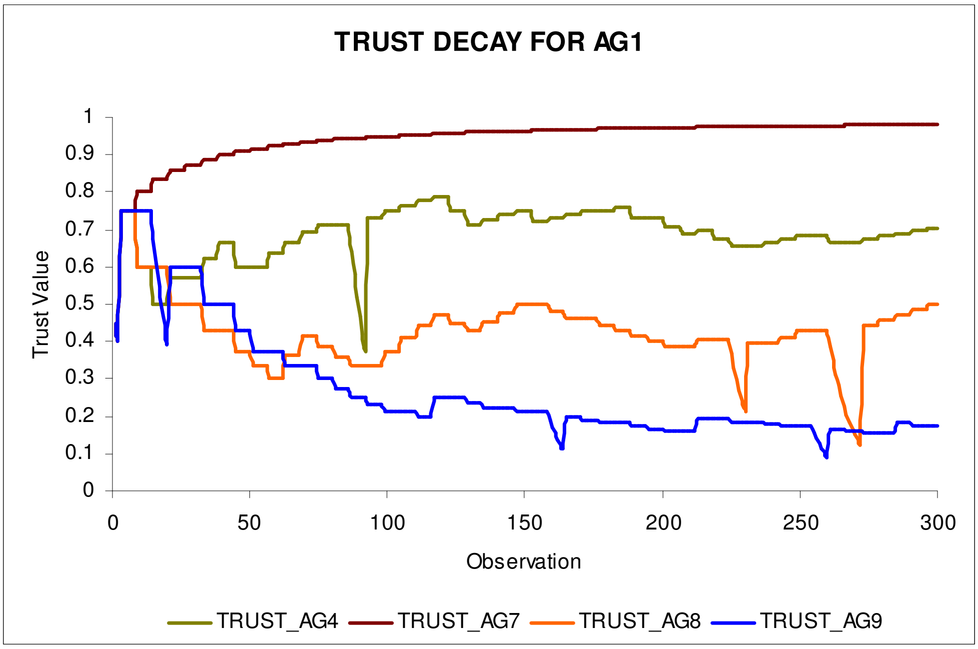

Figure 7. Trust decay in AG1 for the initial experiments

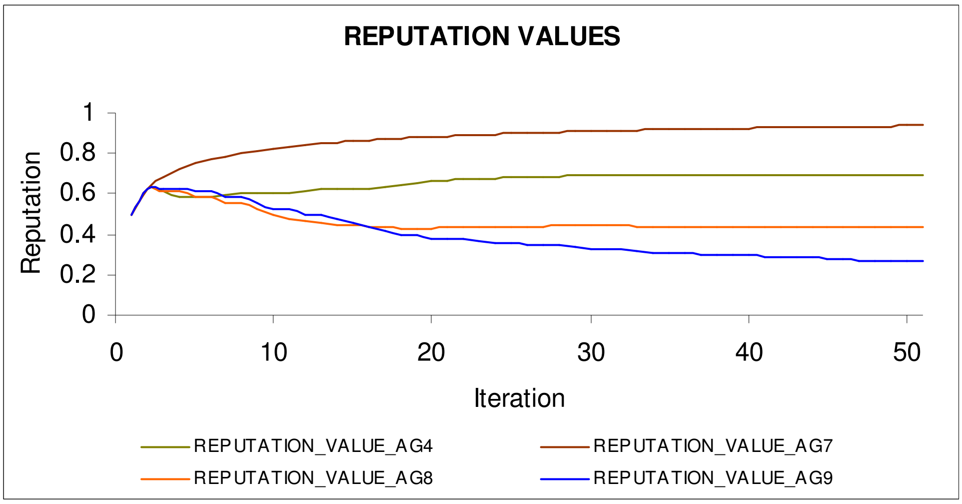

Figure 8. Reputation values in the community for the initial experiments

3.6. SUMMARY

The social and technical aspects of KBVOs have been presented and discussed in this Chapter, with the main goal of establishing a set of initial requirements to support dynamic groups in the e-Decisional Community for automated knowledge sharing and decision making.

It is worth remembering that the trust and reputation models described in the previous sections are not intended to be a novel proposal. Instead, they are aimed at supporting the development of the e-Decisional Community by taking into account different ideas and concepts and apply them to create a knowledge market using SOEKS and DDNA.

Finally, the results obtained in the experiments reflect to a certain degree human behaviour in the e-Decisional Community. For instance, the perceived trust towards a peer can be drastically changed by a single misleading act. After losing trust in an agent who has being deceitful, it takes a long time and effort from that agent to regain the lost trust. On the other hand, if an entity always contributes with accurate knowledge the perceived trust towards that agent remains high. These attitudes are inherent to humans and are reflected in the set of experiments described earlier.

CHAPTER 4: KNOWLEDGE QUALITY MEASUREMENT

As mentioned in section 2.6 of chapter 2, all knowledge interactions require users and agents to give feedback on the experience they use. Knowledge feedback supports the creation of reputation and trust indicators, assists agents in selecting the other peers for cooperation, helps in the process of measuring knowledge usefulness, and allows organizations to measure the overall quality of their knowledge. So far, the role of trust and reputation has been presented as the initial indicators that support KS sharing via KVBOs. This chapter keeps exploring the requirements defined for KBVOs and introduces a novel mechanism to measure quality of experiential knowledge represented as SOEKS and DDNA. The measurement model described in this Chapter integrates the relationships identified previously on Figure 4 in chapter 3, to offer an effective way of sharing knowledge by evaluating agents on how knowledgeable they are on different topics.

Knowledge quality is used in the e-Decisional Community as the main criteria to select other peers for cooperation; thus, providing a robust support for organizational decision-making and problem solving activities. Quality measurement is based on a set of domain-independent attributes that are evaluated by agents and users alike. The main differences between other knowledge measurement proposals and the one used by the e-Decisional Community are:

- The evaluation process is semi-automatic reducing the impact of biased judgements and the workload on users.

- The quality attributes used in the measurement process can be applied in different areas in a standard way.

- The proposed model shows that it is possible to obtain a percentage of knowledge that represents an approximate measure of an individual's knowledge.

The remaining of this chapter is structured as follows: first, a review of existing research on quality assessment is presented. Second, the model for knowledge quality measurement in the e-Decisional Community is described. Finally, the second iteration of the experimental prototype is depicted along with the experimental results and analysis.

4.1. BACKGROUND AND MOTIVATION

Organizations have acknowledged the importance of quality as a strategic factor that can determine their survival in the industry. Quality has been traditionally oriented towards delivering superior products, increasing revenues, and guaranteeing customer satisfaction. In addition, consumers have become more demanding and knowledgeable, thus creating additional pressure for managers who need to devise new ways to react to their customers' high expectations. As a consequence, organizations have begun to understand the importance of knowledge in their strategies. By using appropriate knowledge management processes, organizations are able to reuse their experience to make accurate decisions, save time and money, and provide added value (i.e., higher quality) to their products and services.

Proper support for decision-making processes requires high-quality knowledge; otherwise, managers may be led to make a wrong decision, generating a negative impact on their organizations and customers. Quality and knowledge have become crucial elements in the process of obtaining a competitive advantage in today's knowledge-oriented economy, and their integration has attracted several efforts from research community, which has provided alternative solutions for this new concern (Linderman et al. 2004; Supekar, Patel, and Lee 2004; Rao and Osei-Bryson 2007). However, this is an area of research that allows for further improvement due to the difficulty in measuring an intangible asset such as knowledge.

According to Nonaka's definition, knowledge can be classified as tacit or explicit (Nonaka 1994). Tacit knowledge is based on personal experiences and an understanding of the surrounding environment, which makes it hard to formalize. On the other hand, explicit knowledge can be codified and represented using a common language that others can understand. Given that tacit knowledge is hard to assess, an approximate measure of an individual's knowledge can only be acquired if there is a way to explicitly represent it and quantify it.

Knowledge quality measurement is a topic that has attracted the efforts of several researchers but still presents many challenges. There is no exact way to measure an asset like knowledge mainly because existing measurement criteria are not precise (Tongchuay and Praneetpolgrang 2008). The following sub-sections present an overview of current research related to knowledge quality measurement with the intention of clarifying the concepts involved, and portraying the need for a new quality assessment mechanism like the one proposed for the e-Decisional Community.

4.1.1. Quality

There is no consensus in literature about the meaning of quality. There are several definitions of quality, and all seem to be based on the specific context in which they are used. For instance, Seawright and Young (1996) present a variety of definitions of quality and the relationships between them, and classified them into seven categories as follows: strategic, transcendent, multidimensional, manufacturing based, value based, product based, and user based. These definitions influence each other and, according to Seawright and Young, the understanding of these associations can help an organization compete in a better way. Reeves and Bednar (1994) describe the advantages and disadvantages of different definitions of quality and state that each one is appropriate under different situations. Some definitions of quality include the concepts of quality as excellence, as value, as conforming to specifications, as a way to meet/exceed expectations, and from the customer's point of view. These definitions of quality are also related to the categories defined by Seawright and Young but a unique definition of quality seems to be hard to find.

The proposal presented in this thesis looks at quality from the value point of view. For the e-Decisional Community knowledge and experience are assets that provide a company with the means to adapt and respond rapidly and appropriately to changes in the environment. This can also be seen as providing an organization with added value from its day-today operations. Following the definition presented in (Seawright and Young 1996), value-based quality is an extension of user-based quality, in which a product satisfies users' needs. More precisely, value-based quality is defined as excellence or fit for use. In the e-Decisional Community, knowledge must be adequate to solve an organizational problem with the best possible result in order to be considered of good quality. In this context, the user is an organization (or worker) and the need is represented by the solution for the problem at hand.

4.1.2. Knowledge Measurement

Following the knowledge definition presented by Nonaka (1994), it seems difficult to provide an exact measure of an individual's tacit knowledge. Even when knowledge can be formalized and socialized, thus becoming explicit, its evaluation will depend on many variables such as personal attitudes or the very same environment in which people interact. For instance, Steedman (2003) questioned the different proposals on knowledge measurement from the perspective of economics. He argued that the "stock of knowledge" might not be cardinally measured, and that many other authors have treated it as if it was a "...single magnitude with a cardinal measure...” (Steedman 2003 p:127), without any justification. Steedman also says that many existing proposals in literature lack a solid conceptual foundation, and only when theory produces clear indicators it will be possible to identify magnitudes and measure knowledge accurately.

Despite this limitation, other proposals have attempted to solve the question of how to measure knowledge. Bontis (2001) presented a literature review on the different models that have been used to measure intellectual capital. Unfortunately, all of the cases presented in (Bontis 2001) are context specific, and no agreement on a standard way of measuring knowledge assets is derived. List, Schiefer, and Bruckner (2001) presented a workflow-based approach to measure knowledge based on the premise that knowledge is embedded in organizational procedures and daily practices or develops over time throughout experience and action. In addition, Hunt (2003) defined the concept of personal knowledge and presented a method to measure it that is related to the ways in which motivated people acquire and use knowledge to execute their actions. This measure addresses the shortcomings of existing multiple-choice tests, including elements like sureness and misinformation as part of the final scores, to produce more meaningful results. According to Hunt, the addition of these elements helps in the process of evaluating whether knowledge is acquired and retained appropriately for further use and determining whether a person is uninformed or misinformed.

These approaches represent a step toward formalizing the process of knowledge measurement. However, most of these efforts do not provide standardized indicators to assess knowledge, mainly because they are highly coupled with the context in which they are used. The approach presented in this article aims at measuring knowledge in such a way that it can be used to support decision-making processes in different domains.

4.1.3. Knowledge Quality Measurement

A number of research efforts have addressed the issue of measuring quality of knowledge. This seems like a daunting task based on the elements presented in the previous sections, given the lack of a general consensus in the areas of quality and knowledge measurement. Some of the existing proposals focus on knowledge quality; others integrate process-oriented views for quality assurance or define quality guidelines for knowledge-based systems.

Tongchuay and Praneetpolgrang (2008) presented a conceptual framework and a set of metrics for knowledge management systems based on information quality elements. The framework used the IEEE 1061 and ISO 9000 standards (IEEE 1993; Standarization 2011) , skills from experts, and the eight dimensions of quality defined by Garvin (1987). This proposal is a step toward the formalization of quality indicators; however, it demands a high degree of human intervention to provide values for each metric. Similarly, Lee, Lee, Ryu, and Kang. (2007) defined a set of properties to increase quality in knowledge management systems based on the four modes of knowledge circulation defined in (Nonaka 1994). For each circulation mode, attributes based on elements from data and information quality are defined and prioritized according to the opinion of several experts. Rao and Osei-Bryson (2007) proposed a set of quality dimensions for knowledge-based systems. These dimensions aim at measuring quality at different levels of the system, including the ontology level, knowledge items, knowledge retainers (i.e., knowledge storage), and the usage level. A broad set of indicators comprise each dimension, many of which have been defined previously by other researchers.

The semantic Web has also been subject of research about quality, as presented by Supekar, Patel, and Lee (2004), who developed quantitative and qualitative measures for the increasing number of ontologies from different domains. An ontology of features that characterizes quality in the semantic Web was proposed, and multiple-attribute decision-making techniques were applied to rank different sources. This allows software agents and knowledge engineers to accurately judge the quality of ontologies on the Semantic Web.

Other research efforts like the ones presented in (Zhao and Bryar 2001; Paulzen, Duomi, Perc, and Cereijo-Roibas 2002; Linderman et al. 2004; Molina, Lloréns-Montes, and Ruiz-Moreno 2007) have studied the integration of quality management practices with knowledge management. In this way, organizations are able to guarantee the quality of their knowledge from a process-oriented point of view. In addition, through process assessment and control, a measure on the quality of knowledge assets can be obtained.

It is apparent that there are many research efforts that concentrate on the quality of knowledge. However, none of them deals explicitly with experiential knowledge, and most do not provide an automated solution for quality measurement. In many cases, a high degree of human intervention is required in order to define and evaluate different quality indicators. Therefore, it is possible that subjective opinions might influence the final estimates, leading to inaccurate decisions.

4.2. QUALITY MEASUREMENT IN THE E-DECISIONAL COMMUNITY

This section presents the proposed approach for semi-automatic quality measurement of explicit knowledge, describing the criteria and the model that supports it.

4.2.1. Knowledge Quality Attributes

As explained in the previous section, measuring an entity's knowledge is only possible if there is a way to explicitly represent it and quantify it. Consequently, knowledge quality measurement in the e-Decisional Community is based on a set of nine attributes extracted from existing literature on data and information quality. The main reason for basing the proposal presented in this section on data and information elements is that they play an important role in the creation of knowledge, as described by Davenport and Prusak (1998). Raw data are transformed into relevant information, which is then used (i.e., applied to solve a problem) by organizations or users to create knowledge; however, other researchers, such as Tuomi (1999), have argued that in order to interpret and transform data, previous knowledge is required. A detailed presentation of this issue and more information can be found in (Tuomi 1999). In addition, because the process of quality assessment is meant to be semi-automatic, the best approach is to define a set of items that the agents participating in the e-Decisional Community can measure. Data an information quality approaches provide a rich list of elements that can be adapted for this purpose, as the ones described by Fox, Levitin, and Thomas (1994), Wand and Wang (1996) and Pipino, Lee, and Wang (2002).

The proposed quality measure attributes were selected based on their number of appearances in literature. This is usually an indication of their relevance and also shows that there is a consensus about their role in quality measurement. The selection process was as follows: first, a list was defined based on 64 items identified during the literature review. These items were ranked according to the number of appearances in the reviewed papers. A Pareto analysis was performed to reduce the number of possibilities. As a result of this first iteration, the number of attributes was reduced to 27. In the second iteration, citations to third-party papers were reviewed. Some of the initial papers contained summary tables that pointed to other authors who have also considered some of the attributes crucial; for instance, a list of citations of quality attributes in literature was provided in (Wand and Y. Wang 1996). The number of third-party references was added to the filtered list of the first step. Finally, a second Pareto analysis was performed to obtain an attribute list with 14 items illustrated in Figure 9. Notice that in the illustration the 80% threshold is marked by the red vertical line.

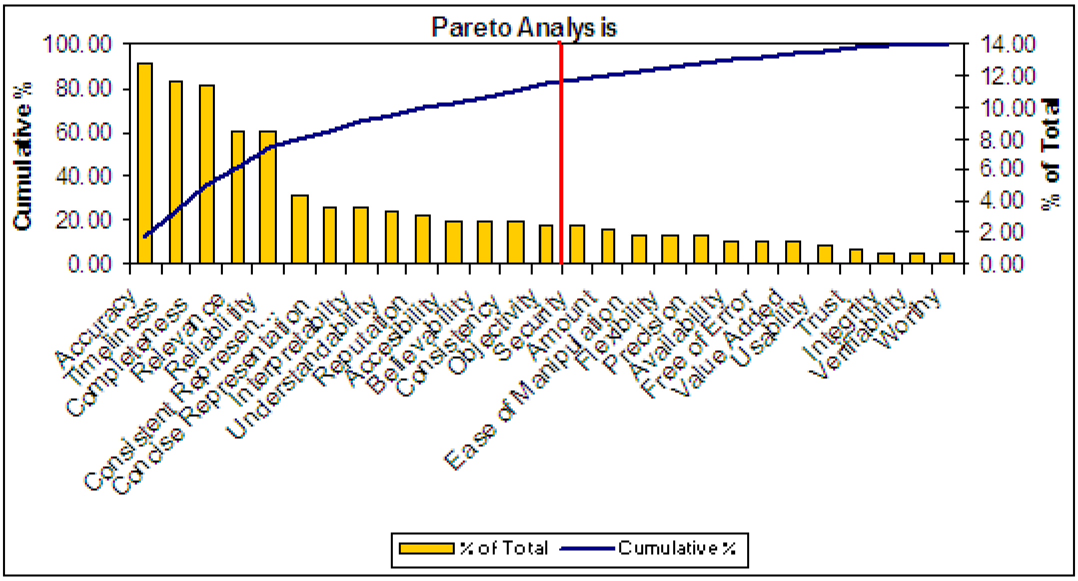

Figure 9. Pareto Analysis Result

An analysis of the preliminary attributes was performed to determine their suitability for use in a knowledge-oriented context. Firstly, consistency and conciseness of representation were removed from the list, because the current SOEKS implementation inherently ensures them. Consistency is defined as satisfying a set of predefined constraints (Fox, Levitin, and Thomas 1994), and conciseness refers to the extent to which elements are compactly represented (Pipino, Lee, and Wang 2002). In the context of the e-Decisional Community, SOEKS's constraints force every single element to comply with predefined conditions since its creation, guaranteeing consistency; moreover, SOEKS provides compact representations in XML and OWL formats, which ensures conciseness. Secondly, reliability was also disregarded, because it refers to the capacity of the system to behave under uncertain conditions or to produce the same outputs through time (Guida and Mauri 1993; Wand and Y. Wang 1996), which requires additional elements that are outside the scope this proposal.

Other attributes such as interpretability and accessibility are ensured. Interpretability of knowledge refers to the degree to which data and information are in an appropriate language, symbols, and units (Pipino, Lee, and Wang 2002). Given that agents are the main traders of knowledge, this indicator is assumed to be satisfied, because entities must be able to interpret and manipulate SOEKS and DDNA in its different formats. Finally, accessibility is assumed to be ensured because agents always have access to their repositories or can cooperate to obtain new external knowledge.

Table 4 presents the final list of attributes obtained after the depuration process, along with their definitions from the literature. These definitions are adapted and applied to knowledge in the context of the e-Decisional Community. The amount of knowledge is an attribute that was not in the Pareto analysis shown in Figure 9, but was added to the final list because measuring the amount of knowledge in the e-Decisional Community will allow the platform to provide an estimate of the depth of an agent's knowledge. The formal model to measure knowledge quantity is presented in the following chapter of this thesis.

Table 4. Final List of Quality Attributes

INDICATOR	DEFINITION
Accuracy	Degree of closeness of its value v to some value v', considered correct for an entity and an attribute. (Sometimes v' is referred to as the standard.) (Fox, Levitin, and Thomas 1994).
Timeliness	The extent to which the knowledge is up-to-date for the task at hand (Pipino, Lee, and Wang 2002).
Completeness	-Measure of the knowledge represented by nodes that have been acquired, applied or tested, related to the total number required by the task, divided by the total number of nodes (Overbeek, van Bommel, and Proper 2011). -Knowledge is sufficient and not missing in order to complete a task (Pipino, Lee, and Wang 2002).
Relevance	Relevance is concerned with whether acquired knowledge is deemed appropriate during the fulfillment of a task or not (Overbeek, van Bommel, and Proper 2011).
Understandability	The level of expressiveness that allows for the meaning of knowledge to be understood easily (Lee, Lee, Ryu, and Kang 2007).
Reputation	Knowledge highly regarded in terms of its source or content (Pipino, Lee, and Wang 2002).
Believability	The extent to which knowledge is regarded as true or credible (Fox, Levitin, and Thomas 1994).

Objectivity	Knowledge is unbiased (Pipino, Lee, and Wang 2002).
Amount	-The level of appropriateness for quantity of provided knowledge to be used in current affairs (Lee, Lee, Ryu, and Kang 2007). -The extend to which the volume of Knowledge is appropriate for the task at hand (Pipino, Lee, and Wang 2002).

4.2.2. Obtaining values for the Quality Attributes

Attributes are grouped depending on how their values can be obtained and three different ways were identified: from the user, from the agent, or using SKMS.

All values have a range from zero to one. The values from the SKMS category are calculated by the prognosis macro process as part of the creation of a SOEKS. Values from the SKMS category are aimed at reducing the possibilities of duality and providing each SOEKS with a set of distinctive features. When a new experience is created by an agent, the same techniques used by the SKMS will be applied to the new knowledge element in order to recalculate the truth and precision values of the SOEKS. More information about this process can be found in (Sanin and Szczerbicki 2008a).

The values of the agent category contribute to automation of the measurement process. For instance, if an agent is not able to respond to a user query, it must engage in a message exchange with other entities that might have an adequate solution. In this case, knowledge is incomplete for that particular question; hence, the completeness attribute is modified by the agent. Completeness can be calculated using a similar approach to the one proposed by Overbeek, van Bommel, and Proper (2011). Additionally, reputation of knowledge sources is an attribute that has already been implemented, as described in chapter 3.

The user category contains the attributes that are left for the final user to evaluate. This approach allows the system to receive feedback from the real world and adjust its behavior accordingly. In addition, it is considered that this kind of soft approach will improve the quality knowledge measurements, given that final evaluations will contain both the user opinions and the more objective system perspective. Table 5 presents the quality characteristics grouped by the source for their values and a brief description of their relevance to the e-Decisional Community.

Table 5. Features of the Quality Attributes

ATTRIBUTE	DESCRIPTION	DEFAULT VALUE
	User Category (Values obtained from user feedback)	
Timeliness	Indicates if an agent's knowledge is updated according to the user's needs. For instance, if a user works with historical information, knowledge might not need to be recently updated.	Default value is 1. Knowledge is assumed to meet the timeliness criterion by default.
Relevance	Indicates if a solution proposed by an agent is relevant to the problem at hand.	Default value is 0. 5. An intermediate value is assigned as default because the system cannot determine beforehand how relevant an experience is.
Understandability	Refers to the way a solution is presented to the user, if it makes sense and can be understood. It is the responsibility of the agent to provide solutions to the application layer in a human-readable format.	Default value is 0. A user must evaluate a SOEKS' understandability each time it is used.
Objectivity	Is knowledge unbiased? User feedback based on a personal perspective might influence knowledge. Therefore, when a solution is shared, users have the opportunity to evaluate its impartiality.	Default value is 1. Knowledge is assumed to be objective when a new SOEKS is created.
	Agent Category (Values automatically calculated by agents)	
Amount	The amount of knowledge in a certain area.	Default value 0. Model is presented in Chapter 5.
Completeness	Indicates if knowledge is sufficient to perform certain tasks.	Default value is 1. When a new experience is created, it is assumed that it has been and still is sufficient to solve similar

		problems.
Reputation	The reputation of a knowledge source based on previous knowledge interactions with other agents. Reputation may be affected negatively if an agent possesses "inaccurate' knowledge.	Defined by the system. Default value when an agent registers is 0.5. Refer to Chapter 3 for details.
	SKMS Category (Values extracted from the SOEKS)	
Believability	It is the truth value of the SOEKS.	Default value defined by the Prognosis Macro-Process. See (Sanin and Szczerbicki 2008a) for more information.
Accuracy	It is the precision value of the SOEKS.	Default value defined by the Prognosis Macro-Process. See (Sanin and Szczerbicki 2008a) for more info.

4.3. FORMAL MODEL TO QUANTIFY KNOWLEDGE IN THE E-DECISIONAL COMMUNITY

As explained earlier, it is hard to obtain an exact measure of knowledge because it is a continuously evolving and changing organizational asset. Therefore, it is important to recall that the knowledge measurements presented herein are approximations of the actual quality of knowledge held by users and agents. Knowledge quality inside the e-Decisional Community is measured in two steps: (1) calculate the quality of each individual experience, that is, each SOEKS belonging to an agent, and (2) calculate the quality of all the experiences of an entity based on the individual measures from step 2.

Quality for individual SOEKS is defined as the average of all of the quality attributes' values. All attributes have the same weight, because it is assumed that an agent's expertise in calculating completeness or reputation is as important as user feedback on the other attributes. Reputation is used in the final stage of the process, which is described later in this section. Consequently, the quality measure *Q* of an individual SOEKS in the e-Decisional Community is defined as:

$$Q(soe_j a_i) = \frac{1}{8}\sum_{1}^{k} QA(soe_j a_i)_k ; 1 \le k \le 8$$

Equation 5. Quality measure for individual SOEKS

Where:

1. $QA(soe_j a_i) = \left\{ \begin{matrix} QA_{accuracy}, QA_{timeliness}, \\ QA_{complete}, QA_{relevance}, \\ QA_{unders\tan d}, QA_{believe}, \\ QA_{objectivity}, QA_{amount} \end{matrix} \right\}$ Is the set of 8 quality attributes for an individual experience that belongs to an agent. Reputation is not counted in this set, for now.

2. $S(a_i) = \{soe_1 a_i soe_2 a_i, ..., soe_m a_i\}$ Is the set of SOEKS belonging to agent $a_i \in \Omega$, where $m \ge 0$ is the total number of SOEKS for that agent.

3. $\Omega = \{a_1, a_2, a_3, ..., a_n\}; n >= 2$ Is the set of agents in the system.

After calculating the quality for each individual SOEKS belonging to an agent, the next step is to calculate the overall quality measure for all the SOEKS in the set $S(a_i)$. The values of quality measures for individual SOEKS can be distributed in several ways; hence, there is not a standard model that can be used to predict a specific behavior in these values. Consequently, using an arithmetic mean as in the first step is more likely to provide inaccurate information about the overall quality, because the central value does not represent in detail the behavior of an entity's knowledge over time. Furthermore, an arithmetic mean is not appropriate if the platform needs to provide accurate predictions of future quality values, trend analysis, or rates of change at a given point in time.

For the previously discussed reasons, overall quality calculations are performed using regression analysis. This statistical tool offers the means to discover the equation that best fits a set of data samples (i.e., individual quality measures) in order to perform complex analyses. Total quality can be understood as the area under the best-fitting curve (or line): as the area increases, so does the final quality value. This means that if individual SOEKS quality measures have low values, they will cover a small area under the curve and vice versa. As the result, the overall quality for an agent in the system, $Q_{Overall}(a_i)$ is obtained by integrating the best-fit equation as follows:

$$Q_{Overall}(a_i) = \int_1^n fit(x) \cdot dx$$

Equation 6. Overall Quality for an agent's SOEKS

Where n is the total number of individual SOEKS quality measures, and $fit(x)$ is the best-fit equation for the data. Because there is not a standard unit of measurement for knowledge, the final value is given as a percentage with respect to the possible maximum area under the curve. For example, let us assume that an agent $a_i \in \Omega$ has a total of 50 experiences in its knowledge repository. In this scenario, the agent is a "guru" and the individual knowledge quality for each one of its SOEKS is 1. In this situation, the best-fit equation is a line in the form $y=mx+b$, with $m=0$ and $b=1$. Consequently, the area under the curve is given by the area of the rectangle with length=50 and width=1. Therefore, the area is 50, which is equivalent to a 100% knowledge quality. This scenario is depicted by Figure 10.

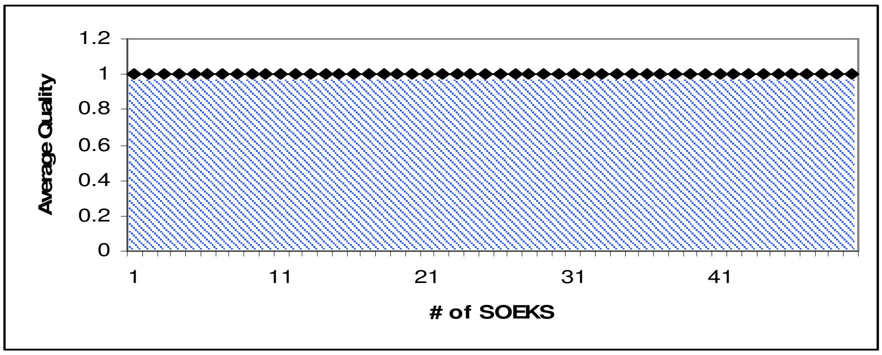

Figure 10. Ideal case of knowledge quality

Now, suppose that another agent $a_j \in \Omega$ is introduced to the system. This new agent also has 50 SOEKS, but the regression for this case results in a seventh-degree polynomial with a coefficient of determination R2=0.991. Figure 11 illustrates the scenario.

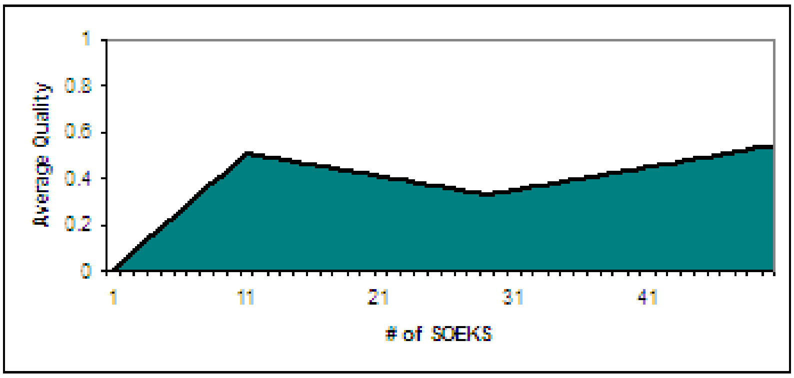

Figure 11. Example quality for an agent whose data fits a 7th degree polynomial equation

The area under the curve can be calculated by integrating the best-fit equation following Equation 6. According to this result, and keeping in mind that an area of 50 is equivalent to 100% quality, the final measure for overall quality of agent a_j is 38.62%. The process is illustrated below:

$$Q_{Overall}(a_j) = \int_1^{50} \begin{matrix}(0.05 + 0.0021\,x + 0.016x^2 - 0.001x^3 + 8.82\cdot 10^{-5}x^4 - \\ 2.11\cdot 10^{-6}x^5 + 2.54x^6 - 1.22\cdot 10^{-10}x^7)\cdot dx\end{matrix} = 19.31 \approx 38.62\%$$

Until now, the use of all quality attributes has been explained but one: reputation. Reputation is a key element that reflects how much trust is posited in an agent inside the community and is used to determine the probability of future success based on previous interactions. Reputation is used in the final step of quality calculations, and the final value obtained is used a way of assessing other peers for engaging in cooperative tasks that are supported by knowledge-based virtual organizations; therefore, the agents with lower quality are less likely to be selected when a query is issued. For these reasons, the total quality value of an agent is given by the following formula:

$$Q_{Total}(a_i) = R(a_i) \cdot Q_{Overall}(a_i)$$

Equation 7. Total quality of an agent's knowledge

Where $R(a_i)$ is the reputation of an agent $a_i \in \Omega$, as defined chapter 3. This approach helps in the process of deciding which agent to select when there are several agents with similar $Q_{Overall}$ values.

4.4. CASE STUDY AND EXPERIMENTS

In order to perform a set of independent experiments with the intention of validating how quality measures affect the possibility of an agent being selected for cooperation, the initial prototype presented in chapter 3 was improved in order to include the quality functionality described previously. This section presents the improvements that were made, as well as the configurations for the new set of incremental experimental tests.

4.4.1. Experimental prototype v 2.0

The second prototype was implemented using Java 6 (Oracle 2011), and JADE 4.0.1 (Telecom-Italia 2012) just like its predecessor. In addition, new mathematical and statistical libraries were included in order to support the process of regression and estimation of knowledge quality. The new open source libraries that were used are Symja 0.0.7a (Symja 2011) and Statcato 0.9.2 (Yau 2011).

Figure 12 presents a simplified class diagram for the new experimental prototype. The features for quality measurement were implemented in the Individual

Management Layer (IML) defined in Chapter 2. The classes that contain the new functionality are `QualityAttributes`, `QualityAttributesCache` and `QualityFileManager`.

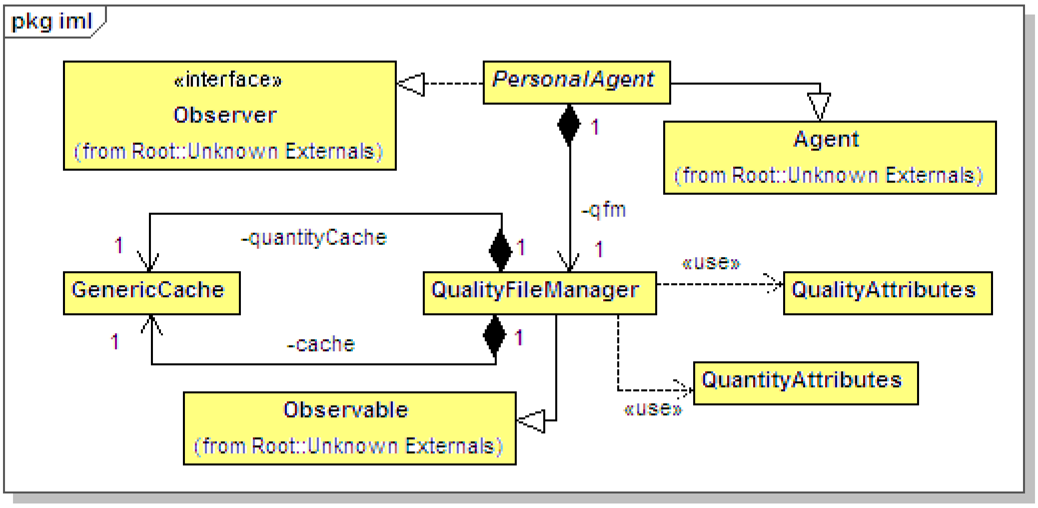

Figure 12. Simplified Class-Diagram for the experimental prototype v 2.0

The `QualityAttributes` class holds the quality attributes for an individual SOEKS, and it is also in charge of calculating the average quality according to Equation 5. The `QualityFileManager` class administers the Master Quality File (MQF) for each agent. The MQF is a file that stores the information about individual quality measures for several SOEKS, which are provided by the `QualityAttributes` class. The MQF has as many entries as SOEKS exist for an agent, and each agent has one observable MQF. The `QualityAttributesCache` class represents an exact copy of the MQF in memory, in order to increase the performance of the system.

The prototype relies on a global Knowledge Quality Service (KQS). This service is an agent that is in charge of: i) Performing the regression analysis; ii) Calculating as described in equation 5; iii) Keeping record of the quality for all agents; and iv) Providing information for group formation processes. When an agent enters the system, it sends a message to the KQS asking to be registered. Following this, the KQS performs all the required calculations and creates a new entry in its registry. When an agent's MQF is modified, it sends a message to the KQS, which will recalculate quality based on the new values and overwrite the existing registry entry. Entries in the KQS are indexed by the agent's name, area, and subarea of knowledge. Therefore, an agent may have many entries in the KQS registry under its name, but each one of them will belong to the quality of knowledge in different topics.

In order to perform the regression analysis, some classes from the Statcato (Yau 2011) project were used. These classes are: `BasicStatistics`, `CorrelationRegression`, `MultipleRegression2`, and `HelperFunctions`. As a result, the prototype is able to support seven different types of regression: linear, quadratic, cubic, logarithmic, power, exponential, and polynomial. The polynomial regression is calculated up to *n-1* degrees, with *n* being the total number of samples. Although it is considered that a seventh degree polynomial is sufficient in most cases, in this prototype's scenario it is desired that at least the polynomial model provides a high fit when all others have failed to do so. This approach assures a higher precision in the assessment of quality with a large number of data samples.

When the KQS executes the regression, it evaluates all the previously mentioned possibilities and uses the coefficient of determination R2 to choose the best fit. Once the best fit is chosen, the following step is to calculate the area under the curve. This is achieved by using the Symja (2011) library. In this process, the lower bound for the integral will always be 1 (at point 0 no experience is assumed), and the upper bound is given by the number of data samples that are provided by an agent. Then, simply by using the `Integrate` command, the KQS is able to determine the overall quality of knowledge.

Each time an agent requests the creation of dynamic KBVO, the first message is sent to the KQS, which returns a list of the highest ranked agents. Then, the initiator agent queries the reputation service and obtains the reputation values for the candidates. Then, Q_{Total} is calculated for each nominee as described in Equation 7. With these values, the initiator sends messages to all the selected agents to initiate the cooperative work.

4.4.2. Experiment design and Configuration

The experimental agent system was comprised of 10 agents. In each experiment, one agent sent a request for the creation of a group and then the system evaluated the request and calculated overall quality values and reputation to return a list of the highest ranked agents. The experiments were repeated 100 times.

Quality measures for individual SOEKS were generated using a random number generator; these values were changed between iterations of the experiment. In addition, once the final list of agents was returned to the requester, overall quality values were used to simulate the process of user feedback through time and its effects on quality. Each agent had 200 SOEKS in their respective repositories.

4.4.3. Experimental Results

Figure 13shows the experimental results obtained after measuring the number of times agents are selected as part of a knowledge-based virtual organization based only on the quality of their overall knowledge $Q_{Overall}$. Due to the precision of double values used to represent quality measures in the prototype, small variations in the final measures will have a noticeable impact on the final outcome and on the possibility of an agent of being selected or not as part of a group. Also, due to the random values generated between trials, all of the agents were selected the same number of times on average. This situation helps illustrate a scenario in which all of the organizational members are knowledgeable on a particular topic and can contribute and learn as equals. In a real application, this should be achieved only after constant collaboration and expansion of knowledge throughout the entire organization. This is a desired state in the system, given that it will reduce the dependency on expert agents, and if some entities leave others can take their place in the knowledge sharing process.

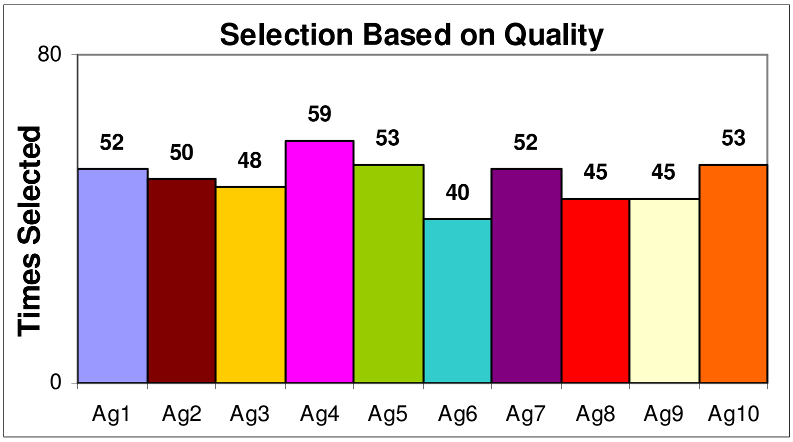

Figure 13. Selection of Agents Based on Overall Knowledge Quality

Figure 14 and Figure 15 present a detailed analysis of the quality assessment process for agents 4 and 6. Here agents 4 and 6 were selected because they represent opposite cases in the selection process described previously. The graphics show the relationship between overall knowledge, reputation, and the total quality, Q_{Total}, for each of the aforementioned agents.

Figure 14. Effect of reputation over quality for agent 4

During the experiments it was observed that both agents had individual quality values around 50% for their SOEKS. Reputation for agent 6 had values between 30 and 40%, and agent 4 maintained a reputation around 40% for the majority of the iterations. Reputation has a great impact on the final quality values, Q_{Total}, and it is an effective method for dealing with duality in results and an adequate way of making informed decisions about agents in the community.

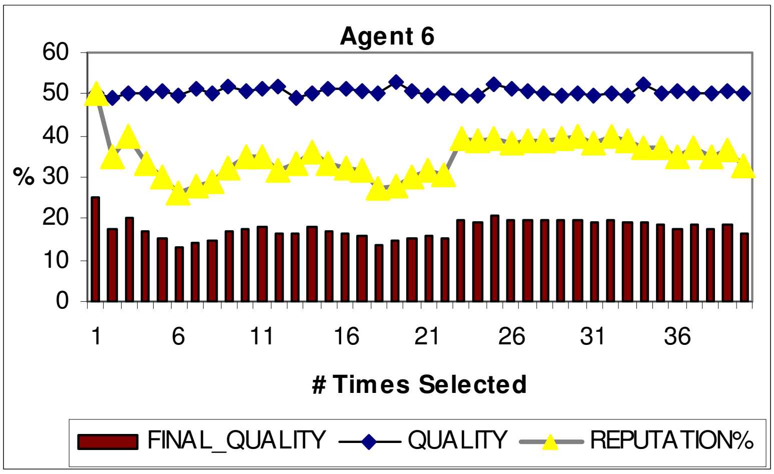

Figure 15. Effect of reputation over quality for agent 6

In addition, the use of reputation enhances the platform with a basic ability to resemble social human behaviour in group environments. People usually ask for advice from others who can provide new knowledge and are highly regarded inside a group. Based on the previous remarks, a question arises: how is it possible that two agents with similar quality measures for their SOEKS can have such different reputation values? This behaviour can be attributed to the randomness used in the experiments, because random recalculation of values is performed between iterations. In addition, trust is recalculated to simulate the usefulness of the knowledge provided.

Reputation values for agent 6 illustrate a condition that can be encountered in real life; that is, misinformation. The scenario in Figure 15 portrays a situation described by Hunt (2003), who stated that people can strongly believe that they are correct even when they are not and might use erroneous beliefs to make decisions. Hunt makes the following remark: “A sure-but-wrong belief, used confidently as a basis for making decisions and taking actions, may lead to surprising errors in performance—sometimes with tragic results.” (Hunt 2003 p:105). In the e-Decisional Community, this means that a user gives a high score to its SOEKS quality attributes based on a mistaken personal conviction; therefore, an agent will have high SOEKS quality and will probably be selected for cooperation. After several interactions, other agents=users might realize that the knowledge provided by the misinformed entity is incorrect. Consequently, trust levels for that agent must be adjusted, affecting its global reputation and reducing the number of times it is selected for cooperation, as illustrated by the experiments.

4.5. SUMMARY

The model presented in this chapter represents a new approach to measuring knowledge quality. The quality estimations assist users and agents in the process of increasing the effectiveness of their decisions and save time. In addition, knowledge quality measures can be used as a way to enforce service level agreements when several organizations engage in cooperative tasks; for instance, quality can be used as a metric to evaluate knowledge delivery or as a way to evaluate possible peers based on their reputation and overall quality. Additionally, quality measurement as described in this article can be applied in several domains, given that DDNA and SOEKS provide a domain-independent knowledge representation (Sanin, Mancilla-Amaya, Szczerbicki, and CayfordHowell 2009).

Finally, the development of a metric to quantify knowledge needs to be integrated with the current quality model for it to be complete. Nonetheless, a simple count of the number of SOEKS is not a fully appropriate approach to estimate the knowledge depth, and the complexity of SOEKS (e.g., the number of variables and functions) must be considered in order to provide an accurate quantity measure. The following chapter introduces a formal model to quantify knowledge in the e-Decisional Community, taking into account the previous ideas.

CHAPTER 5: KNOWLEDGE QUANTITY MEASUREMENT

Measuring knowledge quantity has been the focus of active research in recent times. Organizations plan their projects and activities based on the availability of their assets, ranging from manufactured elements to computer services and infrastructure. In today's economy, knowledge has become the most valuable resource for many organizations, and its proper use often determines the survival of enterprises in a competitive environment. However, determining how much knowledge is accessible is not as simple as counting how many units of a product are on inventory. This Chapter describes an approach for knowledge quantification that offers a way of estimating the "depth" of an agent's knowledge in an automated way.

Knowledge quantity in the e-Decisional Community is used to provide better resource planning for organizations, but most importantly, it is a key attribute in the quality assessment model for the platform presented previously. Additionally, knowledge quantity was also identified as an element related to trust, and community participation in section 3.3.1. By defining a mechanism to assess knowledge quantity, it would be possible to develop other KBVO attributes in the future. The remaining of this chapter is structured as follows: firstly, a background on knowledge quantification is provided. Secondly, the concepts of quantity dimensions and quantity vector are presented as a way of quantifying knowledge in the e-Decisional Community. Finally, the second third iteration of the experimental prototype and experimental results are described.

5.1. BACKGROUND AND MOTIVATION

Is it possible to quantify knowledge? Why do organizations need to measure knowledge? Some researchers argue that it might be impossible to give a cardinal measure for knowledge (Bodrow 2006; Steedman 2003); however, a number of initiatives have tried to overcome this issue. In fact, many proposals highlight the significance of quantifying knowledge for sustaining competitive advantage (Metwally 2008), measuring knowledge convergence (Weinberger, Stegmann, and Fischer 2007), or as a necessary precondition for quality in shared database environments (Cress, Barquero, Schwan, and Hesse 2007). These opportunities and the increasing importance of knowledge in today's global economy are the motivation behind the quantity measurement approach presented in this chapter.

In today's industrial world natural resources and manual labour are not the only and most important economic resources. Knowledge has become the most valuable economic resource for enterprises around the globe (Bodrow 2006), and it needs to be measured just like any other asset. Knowledge measuring has been the centre of attention for several members of the research community in recent years. For instance, Bodrow (2006) consolidated the different theoretical aspects and tools for knowledge management in Europe. Bodrow's study states that it is impossible to measure knowledge in countable units as it has no quantitative features like physical assets. This idea is reinforced by MacKinnon, Levitt and Nissen (2005) who propose to measure knowledge as a percentage of what can be known about a topic, and not as a countable unit. Moreover, MacKinnon, Levitt and Nissen use knowledge quantity as part of a theoretical framework based on ideas from inventory and supply chain management, in which knowledge is perceived as analogous to physical goods, and is intended to optimize knowledge flows. This is an effort aimed at reusing existing research on manufactured goods, applied to the knowledge management field.

Additionally, knowledge is critical for the success of projects in different areas; however, since most of an organization's knowledge resides in its workers and processes, appropriate knowledge management techniques are required to achieve the maximum rate of success. As a consequence of this new tendency, workers have become more knowledge-driven (Ramirez and Steudel 2008; Dahooie, Afrazeh, and Hosseini 2011), and are able to solve problems and identify opportunities using their skills. These characteristics differ significantly from the ones possessed by the previous generation of industrial workers whose skills were based on manual and repetitive tasks.

A challenge that comes with a knowledge-driven workforce is how to measure the actual work that is performed. Unlike manual labour, measuring knowledge work is not a simple matter of counting the units of produced items. Elements like the intensity in communication, structure, complexity, or creativity and innovation, should be examined when quantifying the amount of knowledge work in an organization. By using formal quantification frameworks, it is possible for managers to promote knowledge and skills, identify knowledge groups, and increase profits by improving the process of a product or service. Such frameworks define mathematical models that can be used to assess knowledge work; however, these frameworks are highly dependant on scores given by top management, leading to a high degree of subjectivity in the final measures and increasing the workload of experts (Ramirez and Steudel 2008; Dahooie, Afrazeh, and Hosseini 2011). Other traditional approaches commonly used to measure knowledge of workers in organizations, like multiple choice tests or direct subjective ratings, usually require the researcher to be more knowledgeable about the domain than the test subjects (Borgatti and Carboni 2007), and do not take into account knowledge dimensions or elements presented in other proposals as illustrated by Ramirez and Steudel (2008) or Dahooie and Afrazeh (2011).

Taking into account the previous ideas and opportunities, the proposal for knowledge quantification presented in this chapter aims to create an automatic way of assessing quantity, thereby increasing the effectiveness of the decisions made by organizations. It is considered that the formal method presented in the following sections is a novel contribution to the field of KM, because it provides an accurate estimate of knowledge quantity based on the actual experience held by individuals, which must be represented as SOEKS and DDNA.

5.2. QUANTITY MEASUREMENT MECHANISM

As presented in the previous section, assessing the quantity of knowledge held by individuals and organizations is not an easy task, and obtaining a precise "amount" for it may not be possible, just yet. Therefore, the approach used in the e-Decisional Community does not provide a "count" of knowledge as the final measure, but instead, it estimates the final "amount" based on what an agent knows in relation to what is known by all the other agents in the system. The value obtained as a result of this process is then used as an attribute in the process of knowledge quality assessment described in chapter 4.

5.2.1. Quantity Dimensions and Quantity Vector

Quantity estimation of explicit knowledge in the e-Decisional Community is based on three dimensions: subareas of knowledge, experiences (i.e. number of SOEKS), and "depth" of knowledge. These dimensions are used to create a quantity vector, and its magnitude divided by the magnitude of the ideal case (i.e. all dimensions are 1) represents an agent's estimated quantity of knowledge, i.e. a normalized quantity of knowledge. The values of each one of the dimensions are ratios between the elements that an agent possesses and the total number of elements in the system; consequently, each dimension, as well as the final quantity estimate, will have a value between zero and one. The ratio approach is based on the vision presented by MacKinnon, Levitt and Nissen (2005), and suits to perfection the features provided by the SOEKS, because every experience is a SOEKS which can be counted and used to estimate the final quantity. The dimensions defined for the vector follow existing proposals on knowledge work measuring (Ramirez and Steudel 2008; Dahooie, Afrazeh, and Hosseini 2011), and they were selected because they are inherent to the way DDNA classifies experiences in a system.

The first dimension in the vector is comprised of the subareas of knowledge (i.e. the Decisional Chromosomes) known to an agent, because knowledge from similar topics may be required when responding to queries. This approach is meant to foster innovation and facilitate the discovery of new knowledge by incorporating solutions that, at first glance, are not directly related to the query topic, but belong to the same area. This is easily accomplished because DDNA strands group chromosomes according to their main area of knowledge, facilitating the process of finding related subareas; nevertheless, DDNA strands represent independent decision processes, and as such, there is no way of finding the relationship amongst different strands. Therefore, supporting the first dimension on DDNA strands is not a suitable approach. It can also be argued that the first dimension could be based on the SOEKS' list of subjects; however, this idea allows a high degree of granularity that is neither efficient nor practical. Areas and subareas of knowledge can be standardized across the organization, based on the different roles, competencies, and responsibilities of each position. However, in the e-Decisional Community the subject list of each SOEKS is seen as a way of tagging knowledge; therefore, the values of this field cannot be standardized, making the measuring and classification of knowledge more difficult. The subject list is used as a way to filter and browse through the multiple alternatives presented to the final user in order to make an informed decision.

The next dimension refers to how much experience an agent has in an area of knowledge, and this is measured by counting all the SOEKS in related subareas. Given that each SOEKS represents a past decision, several SOEKS will reflect the multiple decisions made by an individual. The outcome of those decisions is irrelevant in the process of quantifying knowledge, because it is assumed that an individual or an agent can learn from negative or positive experiences alike. This is a key feature of the SOEKS and makes it different from other proposals, which usually discard the negative experiences (e.g. neural networks). In the SOEKS and DDNA approach, "bad" experiences can also be used to infer new rules that will affect the behaviour of the entire system.

The final dimension refers to the "depth" of knowledge. The idea of "depth" in the presented approach refers to how many variables, functions, constraints and rules an agent knows about a certain topic; in other words, this dimension is concerned with the details of each experience. It is considered that the SOEKS count of the previous dimension is not by itself an accurate solution to measure "depth". For instance, two agents may have the same experience count (i.e. number of SOEKS), and have knowledge about the same variables, except for one. Therefore, the agent that has information about the extra variable is assumed to have a more in-depth knowledge about a topic because its "known universe" of elements is bigger. This vision allows the e-Decisional Community to provide a more accurate estimation of quantity and more comprehensive view of knowledge, since both "width" and "depth" of knowledge are represented by the second and third dimensions.

As mentioned previously, each dimension is calculated as a ratio between what is known to an agent and what is known by the entire system. This approach is similar to the one used in traditional tests (e.g. multiple choice tests), where a score is given based on the number of correct/incorrect answers given when a particular area of knowledge is being evaluated, i.e. possessed knowledge/total knowledge. This is an efficient and well-known method for estimating the quantity of an individual's knowledge in the absence of a standard unit of measure, and the relative values obtained from this process can be used for benchmarking/diagnosis purposes in an organization. For instance, if a position requires specific knowledge in a topic, and an agent does not score well in any of the dimensions for that topic, managers may decide that further training is required, or even that the training process itself needs to be redesigned to obtain some improvement.

5.2.2. Formal Model Description

Let us assume that there are *n* agents in the system defined by the set $\Omega = \{a_1, a_2, ..., a_n\}$, and each agent has knowledge about several topics in the set $T(a_i) = \{t_1 a_i, t_2 a_i, ..., t_q a_i\}$. Also, agents have several SOEKS in their repositories defined as $S(a_i) = \{soe_1 a_i, soe_2 a_i, ..., soe_m a_i\}$, and every SOEKS is comprised by a number of elements, namely variables, functions, constraints and rules; in other words, each SOEKS is a set in the form $soe_m a_i = \{V(soe_m a_i), F(soe_m a_i), C(soe_m a_i), R(soe_m a_i)\}$. The values of each quantity dimension (D_i) for an agent a_i in the system are calculated as follows:

$$D_1(a_i) = \frac{|T(a_i)|}{\left|\bigcup_{j=1}^{n} T(a_j)\right|} \; ; \; n = |A| \; ; \left|\bigcup_{j=1}^{n} T(a_j)\right| > 0$$

Equation 8. Value for the first quantity dimension

$$D_2(a_i) = \frac{|S(a_i)|}{\left|\bigcup_{j=1}^{n} S(a_j)\right|} \; ; n = |A| \; ; \left|\bigcup_{j=1}^{n} S(a_j)\right| > 0$$

Equation 9. Value for the second quantity dimension

$$D_3(a_i) = \frac{\left|\bigcup_{k=1}^{m} soe_k a_i\right|}{\left|\bigcup_{j=1}^{n}\bigcup_{r=1}^{m} soe_r a_j\right|} \; ; n = |A| \text{ and } m = |S| \text{ for each agent; } \left|\bigcup_{j=1}^{n}\bigcup_{r=1}^{m} soe_r a_j\right| > 0$$

Equation 10. Value for the third quantity dimension

The previous formulae entail the e-Decisional Community, or any other platform that implements DDNA, to provide a way of recording all the topics and SOEKS in the system as well as updating these elements to reflect changes in the environment. Based on the previous ideas, the estimate amount of knowledge, QA_{amount}, held by an agent is given by the magnitude of the knowledge vector $\vec{v}$ divided by the magnitude of the optimal case vector $\vec{o}$, as presented in Equation 11. The knowledge vector has its origin at (0, 0, 0), which is the default state of "no knowledge".

$$QA_{amount}(a_i) = \frac{|\vec{v}|}{|\vec{o}|} = \frac{\sqrt{D_1(a_i)^2 + D_2(a_i)^2 + D_3(a_i)^2}}{\sqrt{3}}$$

Equation 11. Estimated quantity of knowledge.

Let us illustrate the application of this approach with a simple example. Assume a system with two agents, in which all the agents know about one area, and two subareas of knowledge. The variables, functions, rules and constraints in the system are equal for both agents, for a total of ten elements in the example. Finally, one of the agents has 3 SOEKS in its repository and the other one has 2. Every SOEKS is assumed to be unique, meaning that the agents have knowledge about different SOEKS' elements combinations that produce different outcomes. For this case, the values of the quantity dimensions and the estimated quantity are as follows:

$$D_1(a_1) = D_1(a_2) = \frac{2}{2} = 1.0$$

$$D_2(a_1) = \frac{|S(a_1)|}{|S(a_1)| + |S(a_2)|} = \frac{3}{3+2} = 0.6 \quad D_2(a_2) = \frac{|S(a_2)|}{|S(a_1)| + |S(a_2)|} = \frac{2}{3+2} = 0.4$$

$$D_3(a_1) = D_3(a_2) = \frac{10}{10} = 1$$

$$QA_{amount}(a_1) = \frac{\sqrt{1.0^2 + 0.6^2 + 1.0^2}}{\sqrt{3}} = 0.88 \quad QA_{amount}(a_2) = \frac{\sqrt{1.0^2 + 0.4^2 + 1.0^2}}{\sqrt{3}} = 0.84$$

The previous example shows how small differences in an agent's experience can affect the final quantity value, and the possibility of being selected for cooperation based only on this indicator. However, when the number of elements stored in the system grows, these differences might not be as notorious, and the system should provide a larger precision in the numerical values to achieve greater accuracy. Also, it can be observed that the outcome of each decision is irrelevant in this approach, emphasizing the fact that individuals learn from the good and bad experiences alike. Moreover, the automatic nature of the quantification process reduces the workload on human experts, and adds an "objective" dimension to the system by reducing the influence of biased opinions, while still allowing the users to be in control and make decisions. It is worth remembering that the e-Decisional Community is meant to support day-to-day operations, and even when some tasks are automated by the platform, users are the ones that know the real context in which their knowledge is used; hence, it is desirable that the users act as the final decision-makers.

5.3. CASE STUDY AND EXPERIMENTS

Following the approach of the previous chapters, this section presents the improvements made to the initial prototype in order to validate the proposed quality assessment mechanism. The latest prototype details, configuration, and experimental results are presented in the following sections.

5.3.1. General Design Considerations

The main goal of the prototype is to validate the relationship of the attributes proposed in this chapter as well as chapter 4, and their impact in the process of assessing quality and quantity for dynamic group formation. A key feature in the prototype's design is that the main services provided by the platform, i.e. reputation, quality, and quantity, are handled by specialized agents which hold global information that can be accessed by the rest of the community. The agents that represent the users hold in their mental states information about personal quality, quantity, and trust levels for known peers. In order to update their trust levels, and advertise their quality and quantity information, the agents in the community use a simple REQUEST-REPLY scheme to send information back and forth to the service agents. In this way, the responsibilities inside the platform are distributed, and in case of failure, any of the main services agents can contribute to the process of information recovery, and can operate at a basic level without disrupting the operation of the entire system. Also, if a worker agent is down, its information can be kept alive in the system for others to query, and also to maintain a historical record.

5.3.2. Experimental Prototype v 3.0

Following the previous prototype, the latest version was developed using Java SE 6 (Oracle 2011), JADE 4.0.1 (Telecom-Italia 2011), Symja 0.0.7a (Symja 2011) and Statcato 0.9.2 (Yau 2011). Additionally, the SOEKS API was used in order to manipulate the SOEKS structures. The SOEKS API it is a Java library developed by the Knowledge Engineering Research Team of The University of Newcastle, Australia. The prototype is comprised of ten worker agents and three service agents for reputation, quality, and quantity. Agents are not performing a concise cooperative task since this is out of the scope of the initial validation. Also, having three service agents reduces the workload, avoids bottlenecks, and minimizes dependency on "super" agents. Future improvements in this area include the implementation of a market-based mechanism to negotiate knowledge, and the use of FIPA compliant protocols to execute tasks and exchange problem-specific knowledge.

Figure 16 presents a simplified class diagram for the IML package. The diagram shows the details for the `QuantityAtributes` and `QualityAttributes` classes, which provide the basic measurement indicators. It is worth noticing that the `QualityAttributes` class does not hold information about knowledge quantity directly. There are two reasons for this; firstly, it is easier to maintain and improve independent classes if the approach is to be modified. Secondly, quality and quantity are calculated in different stages, meaning that the required information may not be complete at the same time. When an agent becomes active in the community, it first registers its quantity information and then its quality. Soon after, the quality agent will request the quantity information from the quality service in order to obtain the final measure, guaranteeing that all the required information is available when needed.

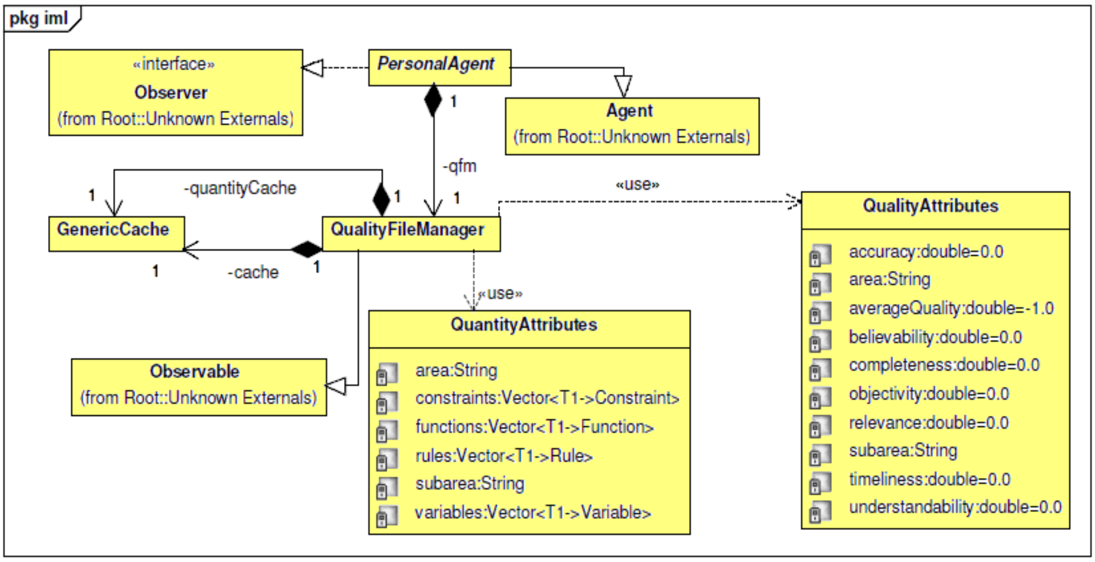

Figure 16. Class diagram for the IML package in prototype 3.0

The service agents are in charge of performing the complex calculations required to obtain quality and quantity values, and maintaining a registry with all the information. Figure 17 presents the class diagram for the KOS package, showing the different operations that the agents perform in the system. In general, all the agents provide handles for registration and information retrieval requests. More specifically, the knowledge quality agent uses some functionality provided by the Statcato (Yau 2011) and Symja (Symja 2011) libraries in order to perform regressions, and calculate the area that represents the quality of an agent's knowledge. The knowledge quantity agent maintains a global count of all the variables, functions, rules and constraints in the system. This is achieved by comparing every element sent by the worker agents on a one-to-one basis, by means of the comparison methods provided by the SOEKS API. Finally, the reputation agent calculates reputation values following the approach proposed in chapter 3 and stores that information in a map structure.

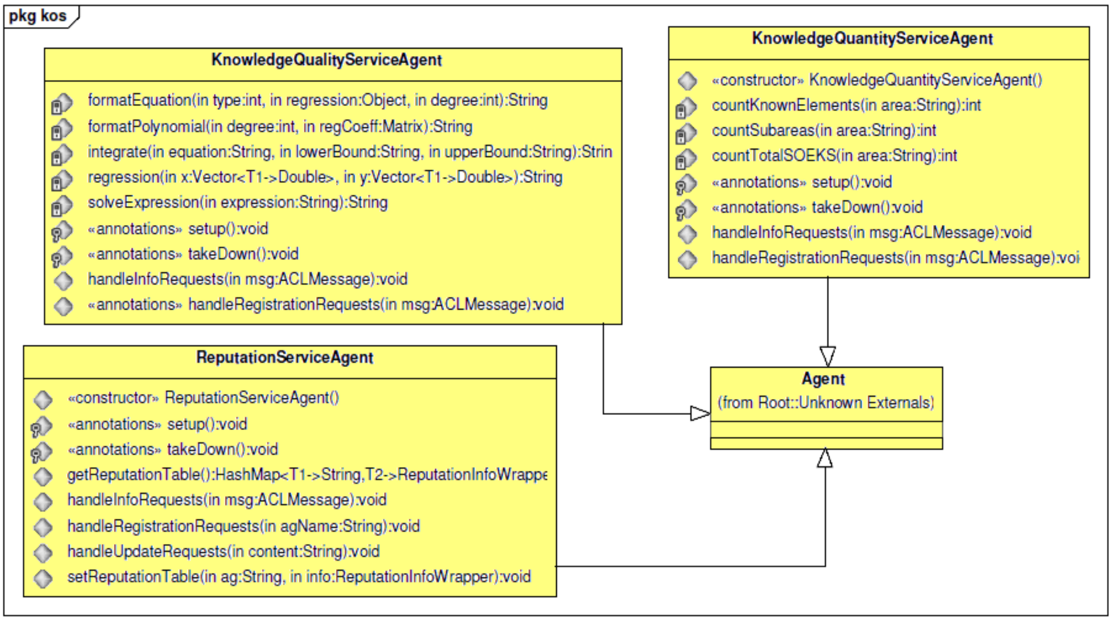

Figure 17. Class diagram for the KOS package in prototype 3.0

The current prototype is limited by its ability to compare the similarity of all of the SOEKS' comprising elements. The current SOEKS API version supports the comparison of variables and functions, which allows the agent platform to identify duplicates of these two elements; thus, an accurate count can be provided in order to measure quantity. Still, the same functionality is not yet provided for rules and constraints, affecting the final quantity assessment. As a consequence, obtaining a similarity measure for two or more SOEKS is not fully possible at this time; therefore, the quantity measures obtained by the agent prototype are somehow inaccurate because duplicate SOEKS, or duplicate constraints and rules, might be taken into account by the system.

5.3.3. Experiment Configuration

The different SOEKS used in the experiments are based on the data cubes of the NSW State and Regional Indicators (Dec 2009) made available online by the Australian Bureau of Statistics (Statistics 2011). The subareas covered by the indicators are: environment; work; health; education and training; housing; transport; family and community; household economic resources; crime and justice; economic activity. Each one of these data cubes is comprised of several tables, but due to the nature of the initial experiments, only one table of each subarea was converted into SOEKS. Each entry in a table is assumed to be a decision, which means that every table encompasses several decisional events. For instance, the first environment table presents thirty variables measured between 2001 and 2008; therefore, a total of eight SOEKS about the environment were obtained, one for each year in the table.

The conversion process produced a total of 93 SOEKS for the areas described by the indicators, and every SOEKS was comprised only by variables because of the data used for the test and the current SOEKS API limitations. In order to properly validate the presented approach, the set of SOEKS was distributed randomly amongst the agents in the system to simulate different degrees of expertise. In addition, the values of reputation and the remaining quality attributes were generated randomly in controlled groups. In other words, it was decided which agents received good feedback and bad feedback, allowing for a more precise evaluation of the possible scenarios. Table 6 shows the SOEKS assignment and the feedback control groups.

Table 6. SOEKS assignment and feedback configuration for the experiments

AGENT	KNOWN SUBAREAS	% FROM TOTAL	# SOEKS	% FROM TOTAL	REPUTATION FEEDBACK	QUALITY FEEDBACK
Agent 1	11	100	93	100	Positive	Positive
Agent 2	8	73	68	73	Random	Random
Agent 3	8	73	68	73	Positive	Positive
Agent 4	8	73	69	74	Negative	Negative
Agent 5	6	55	52	56	Random	Random
Agent 6	6	55	50	54	Positive	Positive
Agent 7	6	55	52	56	Negative	Negative
Agent 8	2	18	17	18	Positive	Positive
Agent 9	3	27	26	28	Negative	Negative
Agent 10	4	36	33	35	Random	Random

The experiments consisted on an agent issuing a request for a group creation, which is equivalent to requesting knowledge in a certain area and subarea of knowledge. A list of the agents with the highest knowledge quality is returned as a result of the process. This list is obtained from the knowledge quality agent. The experiments capture the values required for quality and quantity assessment from the moment the agents become active in the system, and throughout the entire process of group requests. The experiments were executed a total of fifty times for each subarea of knowledge, for a total of 550 independent trials.

5.3.4. Experimental Results

Figure 18 shows the behaviour of the knowledge quantity measurement for each one of the agents during the experiments. Knowledge quantity was measured when the agents entered the system, and each time a group creation request was issued. It can be seen how quantity measures are updated for all the entities when new knowledge is registered. For instance, quantity for Agent 1 decreases slightly when other agents register their measures, and when this process ends it reaches its expected maximum value, based on the configuration presented in Table 6. This is the desired behaviour of the system, because the addition/subtraction of knowledge alters the entire knowledge ecosystem, and after several iterations, knowledge quantity measures must stabilize in the absence of new elements.

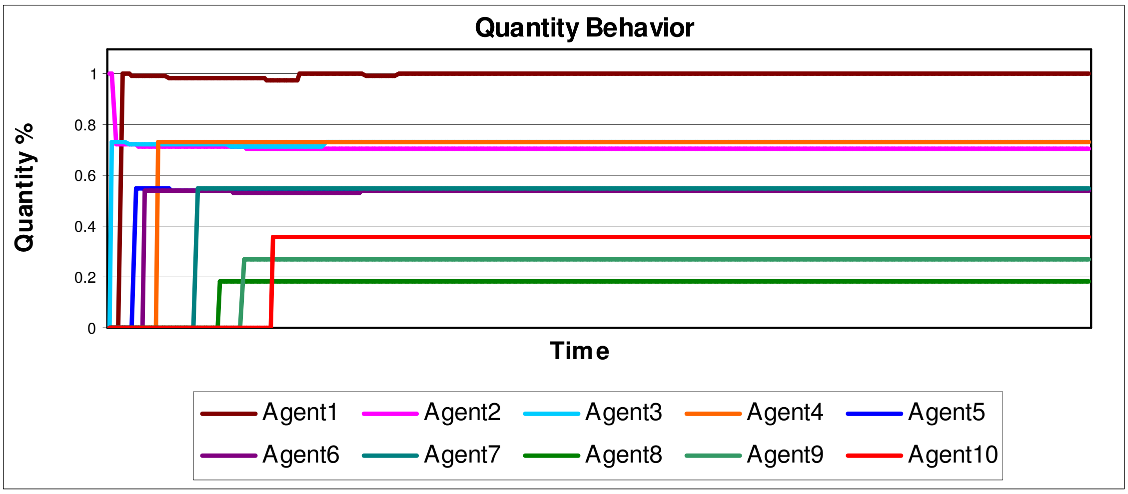

Figure 18. Knowledge quantity behaviour throughout the experiments

Figure 19, Figure 20, and Figure 21, show the measures of overall knowledge quality, reputation, and final knowledge quality for agents 1, 4, and 5, in the topic of Education and Training. Due to the control groups that were established, it is easier to validate the different behaviours that might be present, and determine whether the platform behaves as anticipated.

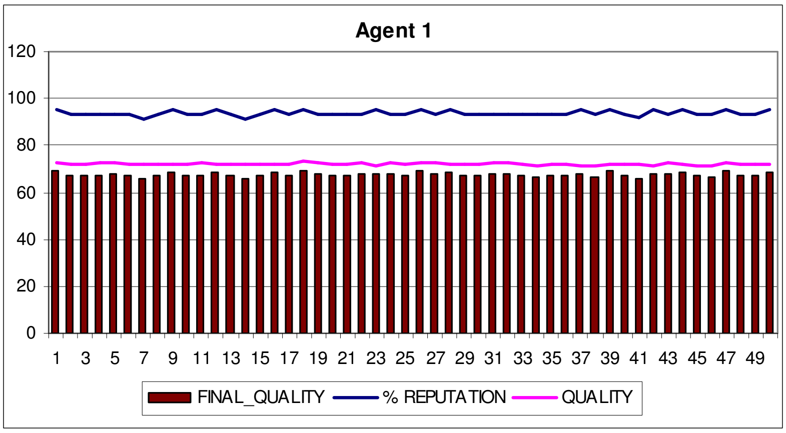

Figure 19. Overall Quality, reputation and final knowledge quantity estimate for Agent 1

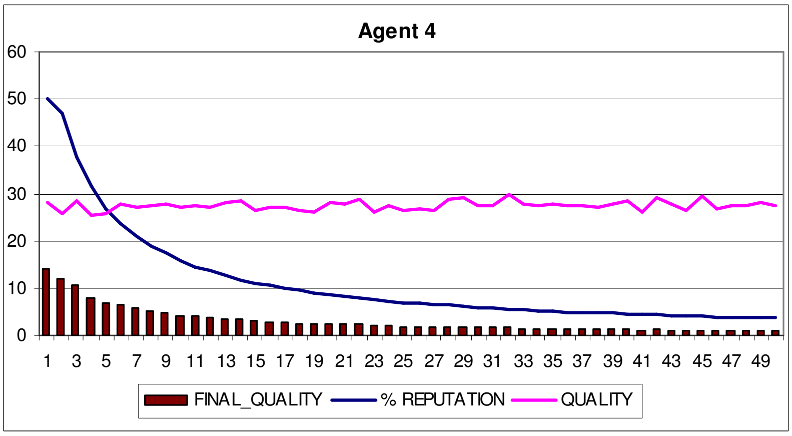

Figure 20. Overall Quality, reputation and final knowledge quantity estimate for Agent 4

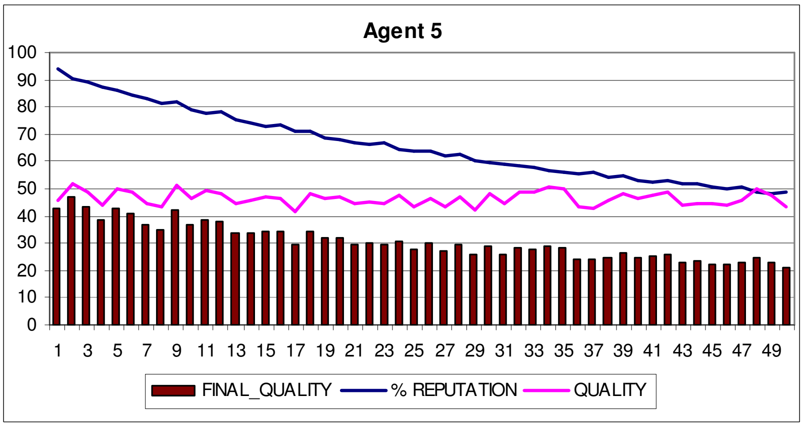

Figure 21. Overall Quality, reputation and final knowledge quantity estimate for Agent 5

The graphics confirm that final knowledge quality behaves as expected in the presence of reputation, and also that the proposed approach is useful when choosing between peers with similar quality. Reputation and quality enhance the system with the ability to resemble social human behaviour, because individuals usually ask for advice from others who can provide superior knowledge and are highly regarded inside a group. In other words, the probability of being selected for cooperation in the future depends on previous actions; after all, reputation is something that is earned inside the system by means of successful interactions, and in order to increase it, an entity should constantly provide high quality, and deliver successful results to the entire community.

5.4. SUMMARY

The mechanism described throughout this chapter represents a new way of estimating the quantity of knowledge held by individuals and agents in organizations. It takes advantage of the inherent features of the SOEKS for representing explicit knowledge; for instance, every experience is stored as a SOEKS, and every SOEKS is comprised by a set of elements that represent decisions made in the past. These characteristics provide the means to quantify experience, which represents a user's knowledge in a specific topic. It can be argued that the current proposal is not sufficient in order to evaluate external or subjective factors that may influence decisions; however, every approach aimed at assessing knowledge has similar limitations. The SOEKS is able to deal with one of these shortcomings by classifying variables as internal or external, which means that the SOEKS is able to differentiate between variables that are controlled by the users or organizations, and variables that are beyond their control but still play an important role in decision-making processes (e.g. inflation). Additionally, based on quality and quantity measures the system should be able to make decisions for pre-defined topics. The main idea of this approach is that the users can maintain control of the decisions they make in crucial areas, whilst leaving less vital or purely operational decisions to be made by the system.

The implementation of knowledge quantity measures is also a contribution for the development of a knowledge market, which is described in the following chapter. Customers have an increasing range of needs that should be satisfied by different products and services, and they demand more quality for their money. When quantity is used as part of quality measures, the e-Decisional Community is able to supply users with the best available solutions for their tasks. This yields major benefits for the final customers and the organizations themselves, because response times and costs are reduced thanks to the constant reuse of accurate experiences.

CHAPTER 6: MARKET ENVIRONMENT FOR THE e-DECISIONAL COMMUNITY

Knowledge sharing practices have evolved from simple document archiving and retrieval, into more complex service-based environments supported by advances in Information Technology. As a result of this trend, market-based mechanisms have been proposed with the objective of fostering knowledge sharing, by setting reward mechanisms and motivate employees to share their know-how at a deeper level. Many of the reward schemes presented in literature consider quality as an attribute that gives value to knowledge, but do not provide details on how to measure it. In addition, experience is a valuable asset for every individual and every organization, and like any other asset, it must have a cost associated to it. This ensures that contributors are rewarded for their efforts, and reduces the chance of free riding. Moreover, organizations should be able to determine how much their know-how is worth, and use this measure to define the terms of agreements with other enterprises.

The elements for trust, reputation, quality, and quantity assessment presented in the previous chapters are integrated in this chapter, which presents the proposed market environment required to exchange experiential knowledge in the platform. This chapter starts by presenting the motivation of the market proposal. Then, the formal model for the market environment is presented. Afterwards, agent roles, interaction, and pricing mechanisms for the proposed marketplace are discussed. Finally, the experimental prototype and results are presented and analysed.

6.1. BACKGROUND AND MOTIVATION

Researchers have explored automated negotiation in virtual market environments for quite a long time, with the intention of reducing the effort and time required to maximize profits and satisfaction. In fact, well-know organizations such as IBM envisioned an information economy in which millions of software agents will exchange information, goods, and services on behalf of their users (Kephart, Hanson, and Greenwald 2000). This idea has been extended more recently to include knowledge as one of the assets that can be exchanged in virtual market environments.

As a result, different proposals for knowledge exchange in market environments have been developed, such as the ones described in (Desouza, Awazu, Yamakawa, and Umezawa 2005; Zacharia, Moukas, Boufounos, and Maes 2000; Zhuge and Guo 2007; Dignum and Dignum 2003). The motivation behind knowledge marketplaces is that traditional solutions for knowledge sharing are incomplete. According to Desouza, Awazu, Yamakawa, and Umezawa (2005), the implementation of a knowledge marketplace will provide economic incentives, foster social interactions, as well as reduce free-riding. In addition, Dignum and Dignum (2003) say that knowledge markets provide ways for users to find each other and agree on the terms of the knowledge exchange.

One of the issues that should be considered when exchanging knowledge in a marketplace is that of price. Knowledge cannot be priced using traditional methods, given its intangible nature and other factors (Dignum and Dignum 2003). It is possible to find in literature pricing mechanisms for knowledge based on reputation or knowledge quality as the ones presented in (Desouza, Awazu, Yamakawa, and Umezawa 2005; Zacharia, Moukas, Boufounos, and Maes 2000; Zhuge and Guo 2007). However, proposals that take quality as part of pricing method for knowledge, do not describe a way of assessing knowledge quality. Furthermore, knowledge quantity in some cases is measured only as the number of documents inside the organization, or the number of posts contributed by users in organizational forums.

Based on the previous ideas, a market environment that improves existing marketplace and pricing proposals by using a formal mechanism for knowledge quantification and quality assessment is introduced. The main goal of the market environment for the e-Decisional Community is to provide to means to support the Knowledge as a Service (KaaS) approach.

6.2. A MARKET MODEL FOR THE E-DECISIONAL COMMUNITY

The main objective of the proposed market approach is to provide the means to foster experiential knowledge exchange between users. The knowledge market model for the e-Decisional Community is based on the principle of rewarding high quality knowledge that can be used to solve a problem. The market environment consists of several sellers and buyers, and every agent in the community can act as a knowledge provider or requester at any given time, because knowledge in the community is distributed amongst all of its members. The following sections present the details of the proposed market environment for the e-Decisional Community.

6.2.1. Using Knowledge Quantity and Quality in a Market Environment

One of the main contributions of this thesis is the establishment of a formal mechanism to evaluate quality and quantity of experiential knowledge, and use these attributes for pricing knowledge. This is considered to be a major step forward in the field of KM research, mainly because many other authors have considered quality and quantity as an important elements of their market environments, but it seems that existing work in the area of knowledge markets has not provided enough details about the mechanisms for quantity and quality assessment; such is the case of the proposal described in (Desouza, Awazu, Yamakawa, and Umezawa 2005).

As described in chapters 4 and 5, in the e-Decisional Community knowledge quantity and quality are calculated in a semi-automatic way taking into account user feedback, hence reducing the impact of biased decisions in the organization. Knowledge quality is calculated by evaluating a set of nine attributes for each individual decision captured by the system, and represented as SOEKS. These attributes are: accuracy, timeliness, completeness, relevance, understandability, reputation, believability, objectivity and quantity. Once each individual decision is scored with a quality value, the agent system will perform a regression on the quality values of several decisions, find the equation that best fits the data, and give a final quality estimate by calculating the area under the best fitting curve. On the other hand, knowledge quantity measurement is based on three dimensions: subareas of knowledge, experiences (i.e. number of SOEKS), and "depth" of knowledge. These dimensions are used to create a quantity vector, and its magnitude divided by the magnitude of the ideal case (i.e. all dimensions are 1) represents an agent's estimated quantity of knowledge, i.e. a normalized quantity of knowledge.

The values obtained from the processes of quantity and quality assessment are used as comparison criteria in the new market environment. Quantity and quality are not only useful for pricing knowledge as mentioned before, but also have an important role in the process of peer evaluation for engaging in KS activities, as presented in chapter 3.

6.2.2. Agent Role Description

The market proposal for the e-Decisional Community is based on a decentralized buyer/seller model. There is not a central entity in charge of controlling the negotiation process between agents. This vision is believed to improve the efficiency of the system because bottle necks are avoided, and agents are able to communicate freely with each other; thus, the time required to obtain a query's solution is reduced. The latter is an important feature when hundreds, or even thousands or users are exchanging experiential knowledge on a frequent basis for their daily activities.

Agents in the community can take any role in the market negotiation process. The two main roles defined in the marketplace are buyers and sellers of knowledge. Buyers are characterized as entities that seek to obtain a maximum utility in each transaction, and will not engage in any contract if their expected utility is zero or less than zero. An important feature of buyers is that they are sensitive to the quality and price of the offered knowledge. Consequently, there are three different types of buyer agents in the system: price sensitive, quality sensitive and indifferent. This behaviour is based on the approach proposed by Sairamesh and Kephart (2000), which has been incorporated into the e-Decisional Community. This proposal also models the utility function of the buyers as follows:

$$u_b = \left(\gamma_b\left(q - \overline{q}_b\right) + \left(1 - \gamma_b\right)\left(\overline{p}_b - p\right)\right) \times \Theta\left(\overline{p}_b - p\right)\Theta\left(q - \overline{q}_b\right)$$

Equation 12. Utility function for buyers in the e-Decisional Community

According to Equation 12, buyers have a price ceiling, i.e. the maximum price they are willing to pay $\overline{p}_b$, which is a uniformly distributed number in the interval (0,1). In addition, the minimum quality expected from the sellers is defined as $\overline{q}_b$ in the interval [0,1]. In order to evaluate the final utility, a step function $\Theta(x)$ in the range [0,1] is defined to validate that the quality floor and the price ceiling are within the specified range when compared to the offered quality and price. Finally, γ_b in the range of [0,1] defines the sensitivity of an agent towards price or quality. The closer γ_b is to 0, the highest the sensitivity to the offered price. If γ_b is close to 1, an agent is more sensitive to knowledge quality.

Sellers in the e-Decisional Community are also looking to maximize their benefits for each transaction, meaning that they are always trying to maximize their profits. Therefore, a key condition for sellers in order to participate in any knowledge transaction is that their profit must be always greater than zero. It is considered that as knowledge becomes more widespread in the e-Decisional Community, agents will make a smaller profit when exchanging commonly accepted solutions and they will only be able to increase their gains by providing highly specialized solutions to other peers.

Contrary to the buyers, sellers are not sensitive to any additional parameters; therefore, the profit function Π_s is defined as follows:

$$\Pi_s = p - C(q)$$

Equation 13. Sellers' utility function in the e-Decisional Community

In Equation 13 $C(q)$ is the cost of producing knowledge of quality *q*. At this stage, it is assumed that $C(q) \to 0$ because the agents in the system do not have to perform the process of converting decisions into SOEKS. This task is done by the SKMS (Sanin and Szczerbicki 2008a), and as a result of this process, agents can directly retrieve experience from their knowledge repositories. Also, the cost of reusing and sharing experience is assumed to be close to zero.

6.2.3. Pricing Mechanism

There are several pricing strategies for software agents that have been widely studied in literature (Dasgupta and Das 2000; Sairamesh and Kephart 2000; Zacharia, Moukas, Boufounos, and Maes 2000; Kephart, Hanson, and Greenwald 2000; Pourebrahimi, Bertels, Vassiliadisl, and Alima 2010). These strategies are suitable for different purposes and scenarios, depending on their computational complexity, and knowledge about the market environment that is required by each of them. Some of the most popular pricing strategies for software agents include, but are not limited to, game theory (GT), myoptimal (MY), derivative-follower (DF), and trial and error.

As part of the many proposals for improvement of existing pricing strategies, Zacharia, Moukas, Boufounos, and Maes have developed the concept of Reputation

Follower strategy (RF) (Zacharia, Moukas, Boufounos, and Maes 2000). This approach is based on the DF strategy in which agents set the price for transaction *t* based on the result of transaction *t-1*. In other words, sellers base their current bid depending on the success of the previous one. The RF approach improves the DF vision by presenting a way of pricing while dealing with changes in a seller's reputation.

The RF approach is used by sellers in the e-Decisional Community because reputation is defined as a key element for dynamic creation of knowledge groups, and knowledge quality evaluation, as described in chapter 3; therefore, it is considered that RF will improve the process of peer selection and will allow agents to rapidly respond to changes in their reputation. In addition, given that in the e-Decisional Community's environment sellers do not have complete information about the market, the implementation of GT or MY strategies would not be possible for two reasons: firstly, they require almost perfect knowledge about the entire market; secondly, they are informationally and computationally intensive (Kephart, Hanson, and Greenwald 2000). The latter would mean higher processing times for knowledge tasks, and higher complexity when deployed in a large-scale knowledge sharing environment like the e-Decisional Community.

Consequently, based on the concepts introduced in (Zacharia, Moukas, Boufounos, and Maes 2000), the pricing formula for sellers in the e-Decisional Community is given by:

$$P_s = R_s \cdot P_{Shadow}$$

Equation 14. Pricing formula for sellers in the e-Decisional Community

With R_s defined as the reputation of the seller agent. This value is calculated automatically by the e-Decisional Community based on the feedback of other agents. The details about trust and reputation in were introduced in chapter 3 of this thesis. On the other hand, P_{Shadow} is defined in (Zacharia, Moukas, Boufounos, and

Maes 2000) as a shadow price, which is the price a seller would offer if it has a perfect reputation. The shadow price follows the DF approach, and is the one that is increased or decreased according to the result of each transaction. Formally, the shadow price is defined as:

$$P_{Shadow} = LastContracted\Pr ice + S_{up} \cdot random_1 - S_{down} \cdot random_2 \cdot idle$$

Equation 15. Shadow price

In Equation 15, S_{up} and S_{down} are fixed steps for increasing and decreasing the price. The *idle* variable represents the number of iterations in which the agent has not gained a contract. Finally, the two random variables are uniformly distributed numbers picked for the next bidding iteration. Sellers in the e-Decisional Community can adjust their prices in three different ways: fixed price, aggressive, and conservative. Aggressive sellers will modify the price of their knowledge by using higher S_{up} and S_{down} values. On the other hand, conservative sellers will use small steps to set their price, and fixed price sellers will use $S_{up} = 0$ and $S_{down} = 0$. The values for the increasing/decreasing steps are set by the users, depending on what strategy they think is better in order to sell more knowledge and increase their reputation.

6.2.4. Interaction Mechanism

Agents in the proposed market environment use the Contract Net protocol (FIPA 2002b) in order to distribute the execution of knowledge intensive tasks. This protocol was chosen because it offers adequate support the market-oriented vision of the e-Decisional Community for several reasons. Firstly, Contract Net is a well known protocol that can be applied in distributed problem solving scenarios; therefore, it provides the means to locate the most suitable agents in order to distribute tasks, based on their reputation, and the quality and quantity of their knowledge. Secondly, by using Contract Net agents are able to recognize that they need help to complete a given job, resembling human behaviour as proposed for the e-Decisional Community in chapter 3. For instance, when an agent advertises a task it is able to specify the desired features for the knowledge it is expecting in terms of quality, quantity, and price, similarly to what people do when requesting services from others. Finally, by using the proposed interaction mechanism, agents are able to create sub-nets, meaning that if a knowledge activity is extremely complex, agents are able to sub-contract with others in order to get the job done in less time.

The interaction process for contracting and executing a knowledge transaction in the e-Decisional Community defines six steps as follows:

1. An agent issues a call for proposal (CFP), i.e. a query. The CFP defines the initiator agent's valuation of knowledge (price that it is willing to pay), the minimum quality expected in the response, and a deadline to receive the proposals from the participants.

2. The e-Decisional Community platform searches for other agents that may possess knowledge related to the initial query. The possible participants are ranked according to the quality of their overall knowledge in the required topic.

3. The CFP is forwarded to the agents selected by the system. These agents will then evaluate the proposal and determine if the profit is suitable for them, and they will respond to the initiator agent with a REFUSE or PROPOSE message. The PROPOSE message contains the quality and price of the knowledge provided by the participant.

4. The initiator evaluates the proposals and assigns the contract to the agent that provides a higher utility. If no agent meets the selection criteria the process is finished.

5. Once the contract has been assigned, the participant will execute the query, and return a response.

6. The initiator will evaluate the response that was obtained, and will provide the specified payment (reputation feedback) depending on how useful the knowledge was. If the knowledge was not suitable to solve the problem at hand, the initiator will give a negative reputation feedback.

It is worth noting that in step six, even when an agent has paid for knowledge that might not be enough to solve a given problem the platform "penalizes" the seller by forcing it to reduce its price P_s, using the negative feedback to recalculate its reputation inside the community. Consequently, future bids from the seller will have a lower price calculated as defined in Equation 14 and Equation 15. On the contrary, if the provided solution was satisfactory, positive feedback will allow for higher knowledge prices in the market.

6.3. CASE STUDY AND EXPERIMENTS

This section presents the final set of experiments performed for the validation of the concepts that support the e-Decisional Community. One of the major modifications for the last prototype was the use of a database to store the different SOEKS files for each agent in the system. The goal behind this was to provide a more scalable setting, similar to the one that would be found in a production environment. For this reason, eXist (Solutions 2012) was added to the prototype as the default XML database system. In addition, a transaction history agent was introduced to keep track of the different knowledge transactions executed by the system. The remaining of this section will focus on the test environment configuration and experimental results. Annexes 1-8 provide the architecture diagram for the e-Decisional Community, as well as the class diagrams for the different packages that were implemented in the final version of the prototype. The CD included with this document includes a more detailed documentation, including sequence diagrams, Java documentation, and source code.

6.3.1. Test Configuration

The test prototype is comprised by four service agents to handle reputation, quality and quantity of knowledge, and one agent to keep track of the entire knowledge transactions in the system. Also, nine working agents were developed: three agents representing each type of buyer, two aggressive sellers, two conservative sellers, and two fixed price sellers. Out of the fixed price sellers, one offered a low knowledge price and the other one a high price. Additionally, sub-contracting of knowledge is not considered in this series of experiments, because the main goal of the current tests is to validate the initial market proposal at its simplest configuration; therefore, all agents have the required knowledge to answer to any query. Later versions of the experimental prototype should consider larger scenarios and incomplete knowledge.

Similarly to the set of experiments presented in chapter 5, the different SOEKS used in the experiments are based on the data cubes of the NSW State and Regional Indicators (Dec 2009) made available online by the Australian Bureau of Statistics(Statistics 2011). The subareas covered by the indicators are: environment; work; health; education and training; housing; transport; family and community; household economic resources; crime and justice; economic activity. A total of 93 SOEKS were obtained, representing knowledge between 2001 and 2008.

Previous experiments have explored the behaviour of quality, quantity, and reputation in the system, and were presented in chapters 2 to 5. In the current set of experiments, the main goal is to explore price behaviour and what type of seller agent is able to obtain the most contracts under different scenarios. In general, the experiments were run for two major scenarios. The first one considers major differences in knowledge quality for the agents, and the second one uses similar knowledge quality. Each scenario was executed 400 times, with one of the buyer agents issuing a request to the community, receiving the list of prospective agents, and then performing the Contract Net negotiation and assigning contracts. For every scenario the quality values were not altered during the experiments, feedback was randomly simulated for each transaction, and cost functions were simulated with values close to 0. Table 7 summarizes the configuration of the latest experiments.

Table 7. Configuration scenario for the market environment tests

AGENT	BUYER TYPE	SELLER TYPE	QUALITY SCENARIO 1	QUALITY SCENARIO 2
Agent 1	Indifferent	N/A	N/A	N/A
Agent 2	Price Sensitive	N/A	N/A	N/A
Agent 3	Quality Sensitive	N/A	N/A	N/A
Agent 4	N/A	Fixed price (0.2)	31.5%	53%
Agent 5	N/A	Fixed price (0.5)	77.3%	58.5%
Agent 6	N/A	Aggressive	72.5%	65.5%
Agent 7	N/A	Aggressive	30.12%	53.4%
Agent 8	N/A	Conservative	73.5%	65.4%
Agent 9	N/A	Conservative	32.5%	54.7%

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For the first scenario with an indifferent buyer issuing knowledge requests, the results showed that agent 6 was able to outperform the other agents in the system, by rapidly adapting its price and offering a better utility to the buyer. The average shadow price offered in this case was 0.215, a standard deviation of 0.104, and average reputation of 0.85. Agent 8 was second in this series of tests with an average shadow price of 0.048, standard deviation of 0.409 reputation average of 0.753. These results show that even when an agent is able to adapt its prices quicker that others, reputation and quality are still key elements in the system for determining prices and collaborating peers. Figure 22 presents the price behaviour during the first testing scenario for an insensitive buyer.

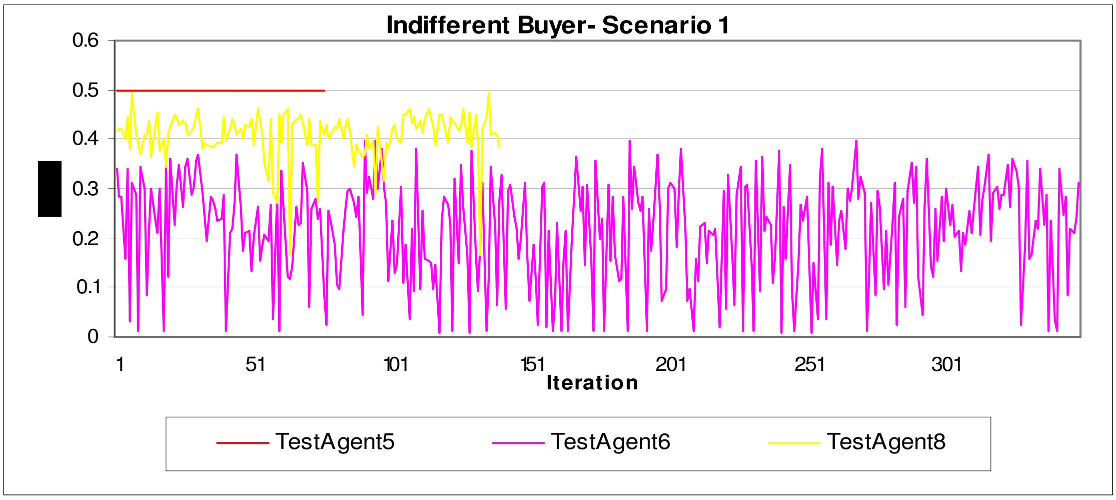


Figure 22. Prices with an indifferent buyer in scenario 1

Under the same scenario, but with a price sensitive buyer, the market proved to be more competitive. The buyer agent was configured using $\bar{q}_b = 0.2$ and $\gamma_b = 0.05$ to simulate almost total disregard for quality. Whilst in the previous series of tests, the main competitors were agents 5, 6 and 8, in the price-based environment agents 4, 6, 7, 8 and 9 got contracts at some stage; nevertheless, agent 5 was the only one not able to compete properly and did not get any contracts. Figure 23 presents the behaviour of prices throughout this series of experiments. It is clear how all agents in the system start to lower their prices in order to get more contracts. Once again, agent 6 outperformed the others with a total of 152 contracts, followed closely by agent 7 with 112 contracts. Agents 8 and 9 both got 52 and 53 contracts respectively, while agent 4 only got 2.

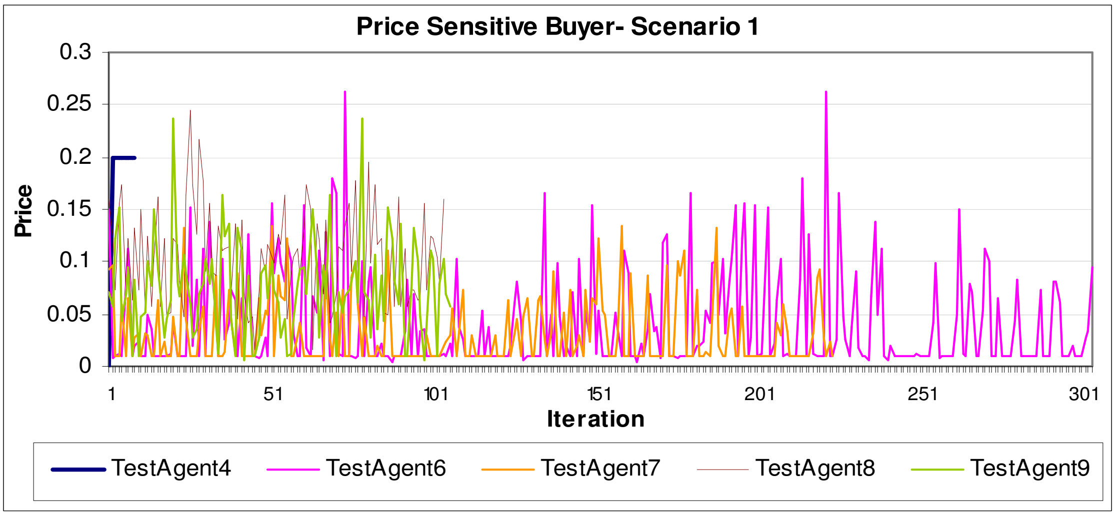


Figure 23. Prices with a price-sensitive buyer in scenario 1

In the experiments agent 7 had an average shadow price of 0.03, a deviation of 0.031, and a reputation average of 0.829, and agent 6 had an average shadow price of 0.04, deviation of 0.047 and reputation of 0.78. In spite of the similar values, an interesting behaviour can be noticed: during the tests, the agent who won the most contracts was not the one with the lowest average price, but the one who provided higher utility as a whole, based on their knowledge quality and reputation. The e-Decisional Community is able to prioritize agents that have a higher knowledge quality over those who only offer a lower price, by incorporating equation 1 into its design. Finally, the results obtained for the quality-driven buyer in the first testing scenario were as expected. Agent 5 was the one awarded with the most contracts by providing the highest quality in the system, even when its knowledge price is not the lowest when compared to agents 6 and 8, who also have very high quality values. These results are illustrated in Figure 24.

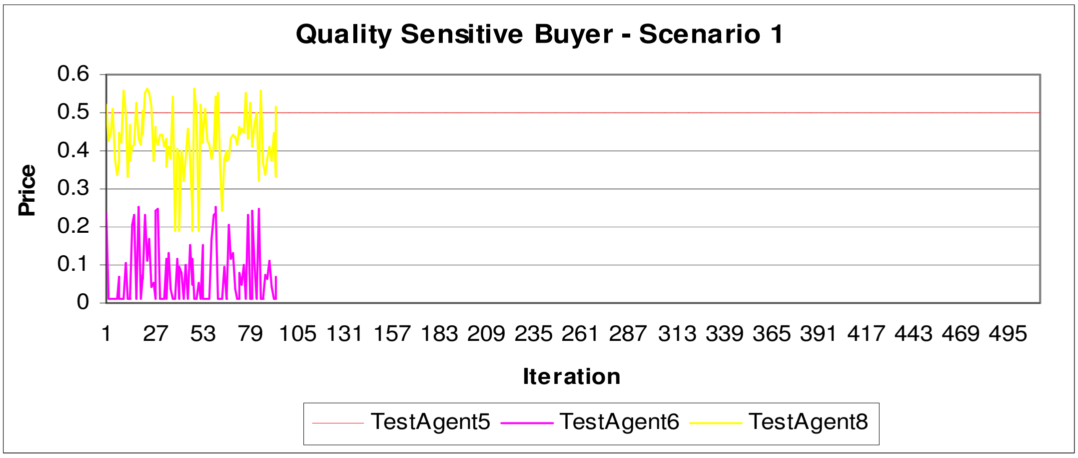


Figure 24. Prices with a Quality-sensitive buyer in scenario 1

The results of the second testing scenario, with all agents having relatively similar quality values and an insensitive buyer, showed that in spite of the market being more competitive and more agents getting contracts throughout time, aggressive sellers have the advantage. Once more, agent 6 (172 contracts) was the most effective, followed by agent 7 (102 contracts). Agents 8 and 9 were last with a similar number of contracts, 55 and 53 respectively. The behaviour of price in this testing setting is presented in Figure 25.

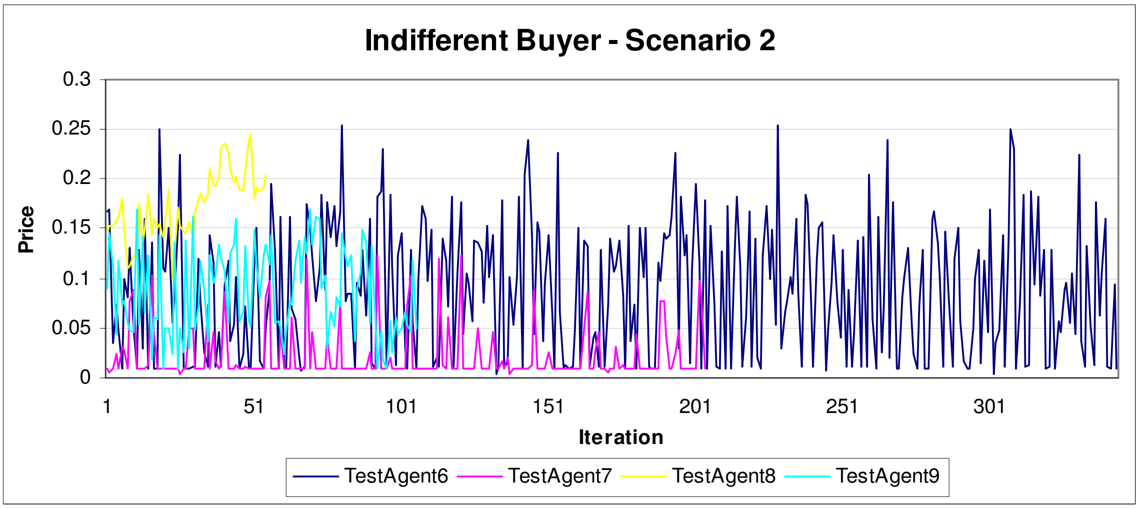


Figure 25. Prices with an indifferent buyer in scenario 2

When the price sensitive buyer was used in this new scenario, the results in terms of agents who got contracts were similar to the previous scenario: all agents but agent 5 gained a contract during the experiments. However, the price behaviour was not as clear as in the first scenario. Given the similar quality values, the agents engaged in a price war by reducing their prices to the minimum admissible by the platform (i.e. 0.01), and then increasing them until a negotiation was lost. This behaviour repeated itself throughout the entire 400 iterations. Figure 26 presents the price comparison for this test.

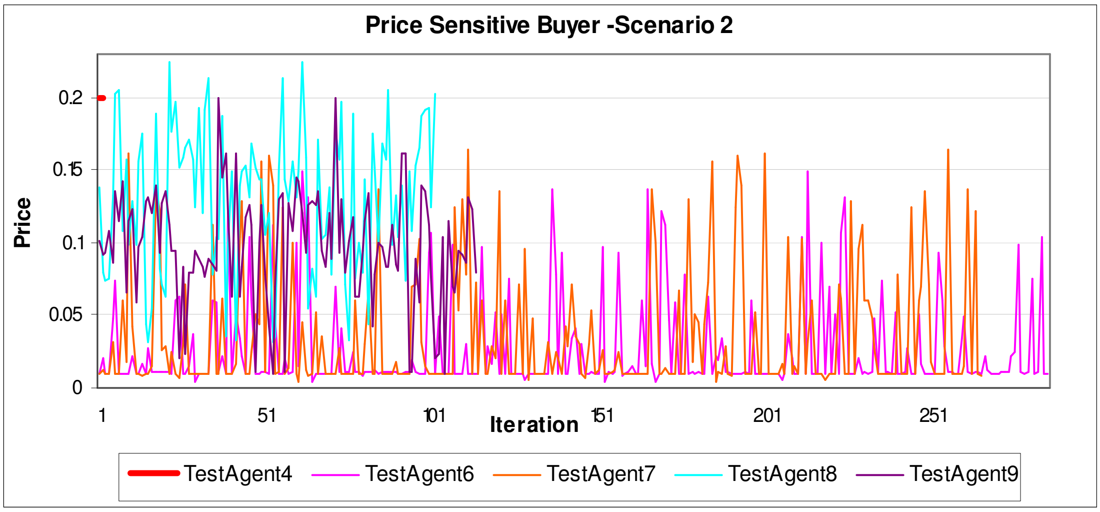


Figure 26. Prices with a price-sensitive buyer in scenario 2

The results shown in Figure 26 are comparable to those of the previous scenario, and agent 6 was again the most effective entity; nonetheless, the difference in the number of contracts with agent 7, who was again in second place, was smaller than in the first scenario. Agent 6 got 143 contracts and agent 7 got 133, showing how similar quality affects the process of negotiation, and how the platform is still able to reward agents even when the difference in their knowledge quality is small.

For the third type of buyer in the second scenario, results once again showed that the agents with the highest quality were the preferred ones as expected. Agents 6, 8 and 5 got the most contracts in that order. Also, price in this series of experiments behaved in a similar way to that depicted in Figure 26 with agent 6 being the most aggressive and reducing its price to a minimum. Agent 8 on the other hand kept its price range between 0.3 and 0.7. The ability to adapt their prices made agent 6 and 8 more efficient that agent 5; thus, this behaviour earned them the most contracts. The results of the final experiments with a quality sensitive buyer are presented in Figure 27.

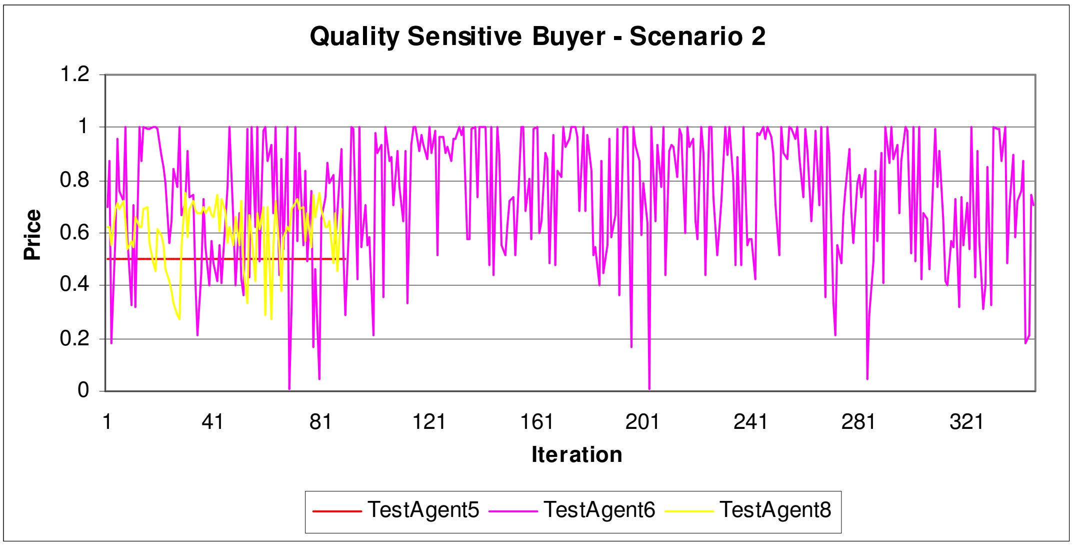


Figure 27. Prices with a quality-sensitive buyer in scenario 2

In conclusion, the results obtained in the experiments show that the e-Decisional Community is able to reward those agents with a higher knowledge quality. Also, the ability to change prices rapidly proved to increase the efficiency of negotiating agents; however, this behaviour can lead to a price war when agents try to obtain a contract.

6.4. SUMMARY

Existing research on knowledge markets have proposed different pricing and utility mechanisms based on quality of knowledge. However, most of them do not provide any details on how to measure knowledge quality and quantity, or are highly dependant on expert opinions. The main contribution of the work presented throughout this chapter is the formal definition of mechanisms to assess quality and quantity semi-automatically, and integrating these elements with existing proposals for pricing and negotiation in knowledge markets and multi-agent systems; thus, this thesis improves existing research on knowledge markets and knowledge sharing.

By using the formal mechanism defined for the e-Decisional Community, organizations will be able to have a more accurate price scheme for their experiential knowledge. In addition, given that every decision that is captured and converted into SOEKS and DDNA is an explicit representation of tacit knowledge, enterprises will also be able to have estimated measures and prices for the knowledge that resides in workers and processes. Finally, the proposed semi-automatic approach for quality and quantity assessment used by the e-Decisional Community is different from traditional document-based approaches or forums. The e-Decisional Community captures decisions, and measures their quality in a way that requires minimal user intervention. Therefore, the impact of biased judgments for the organization is reduced, achieving a more objective view of knowledge.

CHAPTER 7: CONCLUDING REMARKS AND THE ROAD AHEAD

Throughout this thesis the importance of knowledge as a major organizational asset has been highlighted. Adequate knowledge management allows for improved performance, cost-reductions, and more accurate and effective decisions to be made. In spite of all the different theoretical and technical elements provided by researchers, knowledge management techniques for day-to-day operations still lack the flexibility that is required to support today's generation of knowledge workers. As mentioned in chapters 1 and 2, previous proposals on organizational memories, document mining, or expert forums rely heavily on human labour for knowledge classification and contribution, either as documentation or posts. Examples of these approaches can be found in Wikipedia[1], Experts Exchange[2], or Salesforce.com[3]. In addition, traditional document-centric approaches require additional maintenance efforts in order to cope with the increasing speed in communications and large amounts of data/information/knowledge that is handled nowadays thanks to the Internet. Therefore, a new solution is required to improve existing solutions and support knowledge management activities in rapidly changing environments. The e-

[1] http://www.wikipedia.com
[2] http://www.experts-exchange.com/
[3] http://www.salesforce.com/crm/customer-service-support/knowledge-base-system/

Decisional Community was proposed as a new alternative to support knowledge management activities in organizations, especially knowledge sharing. This is achieved by incorporating the elements proposed by the SKMS (Sanin and Szczerbicki 2008a), as well as elements from software agent technology, grid and Cloud computing.

7.1. CONTRIBUTION OVERVIEW

In order make a contribution to the fields of KM and KS, a series of objectives were proposed in chapter 1 of this document. The main goal of the e-Decisional Community was to provide the guidelines for the development of a large-scale environment to share knowledge and experience represented as SOEKS and DDNA in order to support decision-making processes in organizations. As presented in chapter 2 of this thesis, the e-Decisional Community considers a variety of elements that should be taken into account to foster KS in organizations.

The main idea behind the platform is that knowledge and experience are not extracted only from documents or forum posts, but also from the constant interaction between users and organizations and from the software applications that they use on a daily basis. A key difference with traditional approaches is that shared knowledge in the e-Decisional Community is based on formal decision events. This follows the idea presented by Sanin & Szczerbicki (Sanin and Szczerbicki 2008a), and implies that every experience follows a formal procedure that can be reproduced in the future under similar conditions. Therefore, the KS environment provided by the e-Decisional Community addresses the issues mentioned earlier in this chapter, by providing the means to evolve knowledge and capture experience from different sources to support decision making in a scalable and flexible way.

But, what about support for capturing, storing, and evolving individual and collective experience? The agent-based approach of the e-Decisional Community is supported on the macro-processes defined by the SKMS (Sanin and Szczerbicki 2008a) to extract knowledge and experience from different sources. Moreover, the existing API for the e-Decisional Community allows integration with a variety of desktop and mobile applications to provide an additional way for capturing knowledge from daily operations and integrating it into the system. All the experiences are stored in the respective knowledge bases, as shown by the experimental prototype description in chapters 3 through 6.

Another contribution made by the research presented in this thesis is the conceptual integration of human inspired behaviour to promote KS. As presented in section 3.1 of chapter 3, existing approaches for KS have identified several elements in human behaviour and group interactions that affect the outcome of knowledge-based work; therefore, a people-oriented platform such as the e-Decisional Community must take those elements into consideration and provide a suitable way of dealing with them. By identifying the key elements defined in literature and by providing an actual implementation of some of them, i.e. trust, reputation, knowledge quantity, and knowledge quality, the e-Decisional Community makes a valuable contribution to research in the field of KM, because most of the conceptual elements presented in other publications are dealt with either from the social point of view, or the technical point of view. The e-Decisional Community deals with such issues from a socio-technical perspective following the trends depicted in section 3.2 of chapter 3, by capturing the final decisions made by the users and also through the use of semi-automatic knowledge assessment mechanisms and feedback from users and agents.

The inclusion of social elements in the e-Decisional Community was the starting point for the development of what is considered to be the most important contribution of this research: a semi-automatic way of assessing quantity and quality of knowledge. As described in chapters 4 and 5, many researchers have tackled the problem of measuring knowledge; however, existing work on this topic is highly coupled with the context in which knowledge is used, making it difficult to define indicators that can be used in any situation. In addition, some researchers have considered that the intangible nature of knowledge and the lack on a solid conceptual background represent a barrier towards the definition of standard indicators for knowledge quality (Steedman 2003). Thanks to the domain independence provided by the SOEKS and DDNA structures (Sanin, Mancilla-Amaya, Szczerbicki, and CayfordHowell 2009), the e-Decisional Community is able to provide estimated measures of quantity and quality of knowledge, via a set of indicators adapted from existing data and information quality literature. This approach was selected in accordance with the data-information-quality hierarchy defined by Davenport (Davenport and Prusak 1998), and extends existing research on this topic. The previous estimates can be used by organizations to asses the knowledge that resides in their workers and processes alike. Moreover, an immediate application of quantity and quality measures is presented in the market mechanisms proposed in chapter 6.

The market mechanism for the e-Decisional Community is not a contribution per se, but the inclusion of quality and quantity measures as part of the market environment is. Several knowledge-based market environments exist in literature, as presented in section 6.1 of chapter 6. Some of the existing markets for knowledge mention quality as an important part of their operation, but do not provide any details on how to measure it. Consequently, it can be assumed that this task is assigned to an expert who is in charge of evaluating every contribution that is made. In the market environment proposed for the e-Decisional Community, there is no need for a set of experts to evaluate knowledge; thus, workload and response times are reduced, and overall efficiency is increased because people can concentrate on their core tasks without worrying about additional system management duties.

7.2. *WHAT'S MISSING?*

Throughout chapter 3, a set of social elements that affect group interactions were defined as crucial for the concept of KVBOs. This thesis developed four of those elements, namely trust, reputation, knowledge quality, and knowledge quantity. The reasons for focusing on the previous elements are as follows:

- Trust and reputation had the highest degree of relationship with the other concepts, meaning that trust and reputation are elements that are taken into account by several proposals on KM and social theories.

- Figure 4 in section 3.3.1 of chapter 3, presented the conceptual relations between the KVBO requirements. Knowledge quality and quantity are elements that directly related to others such as community participation or rewards/punishment, and indirectly related to others via trust and reputation; for instance contracts, quality of KS processes, or conflict resolution. In order to provide a solid foundation for the implementation of the other components, knowledge quantity and quality needed to be addressed first. Otherwise, there would be a conceptual gap similar to the one described in section 6.1 for the role of quality in market environments.

- Knowledge quality and quantity are topics that have attracted the attention of several researchers, but no consensus has been reached in literature regarding a cardinal measure of knowledge, and no semi-automated solution for it has been proposed so far. In order to make a valuable contribution to research this thesis was focused on providing a new way of assessing knowledge represented as SOEKS and DDNA.

Consequently, the remaining elements for KVBO formation remain to be explored. This also means that the KVBO technical implementation provided in this thesis is not complete; however, as mentioned previously, by developing ways of assessing the quality and quantity of knowledge, the process of developing the other requirements should be facilitated.

Additionally, due to the extent of the research presented in this thesis and technical limitations, it was not possible to implement the e-Decisional Community in an actual CC environment. As a consequence, the validation of the platform's behaviour and performance in a highly distributed environment is still pending. However, the e-Decisional Community's design has taken the service oriented vision of the cloud into account, as mentioned throughout this thesis, and future validation of the platform on a CC setting is possible. The reasons that support the previous statement are as follows:

- The e-Decisional Community is based on an aggregation of services (i.e. service agents and personal agents) that can work in different containers distributed across several locations. Consequently, the platform can be deployed in a distributed environment, whether it is virtualized or physical. Previous work on the integration of SOA multi-agent systems and CC has been presented in CISM@ (Rodríguez et al. 2010). CISM@ is an architecture that sits on top of the different agent platforms and frameworks, including JADE, and allows for the integration of multi-agent systems with CC environments, providing support for SaaS and IaaS. The proposal described in (Rodríguez et al. 2010) provides a suitable solution for the deployment of the e-Decisional Community in a CC setting.

- Many of the existing proposals that integrate knowledge as a service in the Cloud are able to do so by adding an extra layer at the top of the CC stack (Ju and Shen 2011; Cao, Li, and Xia 2009; Cerri et al. 2008); therefore, a knowledge-oriented Cloud environment will have four layers as follows: IaaS, PaaS, SaaS, and KaaS. The e-Decisional Community can sit on the last stack layer without significant modifications to its conceptual model, and its operation will be supported by the other three layers.

- Other proposals that integrate agent-based KM platforms in the cloud are based on the principle of aggregation, i.e. add a layer of software agent functionality to improve or support new CC features. Examples of this approach can be found in (Gaoyun, Jun, Jian, and Zexu 2010; Chen and Yeh 2010; Rodríguez et al. 2010; Cao, Li, and Xia 2009; Sim 2011; Talia 2011). As a result, the service-oriented design approach followed by the e-Decisional Community proves to be suitable for deployment on CC environments as a way to add new knowledge-based functionality.

Finally, finding appropriate knowledge examples for the experiments was a complex process. Ideally, knowledge samples should contain all of the four SOEKS' elements for the validation experiments to be more significative, because knowledge requests and agent behaviour would be more accurate. However, finding such knowledge examples was a complex process, and it was not possible to find any knowledge example that was even close to the ideal. The Web is full of several datasets for research; however, most of them only contain variables and some functions. Similarly, the knowledge samples that could be gathered from other research centres at the University of Newcastle did not encompass all of the required elements for an adequate validation. As a result, the experiments were performed using SOEKS comprised of variables, as described in the experimental prototype sections in chapters 3 to 6.

In addition, the current prototype is limited by its ability to compare the similarity of all of the SOEKS' comprising elements. This becomes an issue when the measures of quality and quantity are calculated. The current SOEKS API supports comparison of variables and functions, which allows the agent platform to identify duplicates of these elements; thus, an accurate count can be provided in order to measure quantity. Still, the same functionality is not yet provided for rules and constraints, affecting the final quantity assessment; therefore, obtaining a similarity measure for two or more SOEKS is not possible at this time. As a result, the quantity measures obtained by the agent prototype are somehow inaccurate because duplicate SOEKS, or duplicate constraints and rules, might be taken into account by the system.

It is considered that the conceptual validation of the platform is not affected by the previous issues regarding the experiments, because current knowledge samples are adequate given the API's limitations. However, the problems described above have an impact on the technical implementation of the prototype, and need to be solved before the e-Decisional Community can be fully deployed in a real-life production environment.

7.3. FUTURE WORK

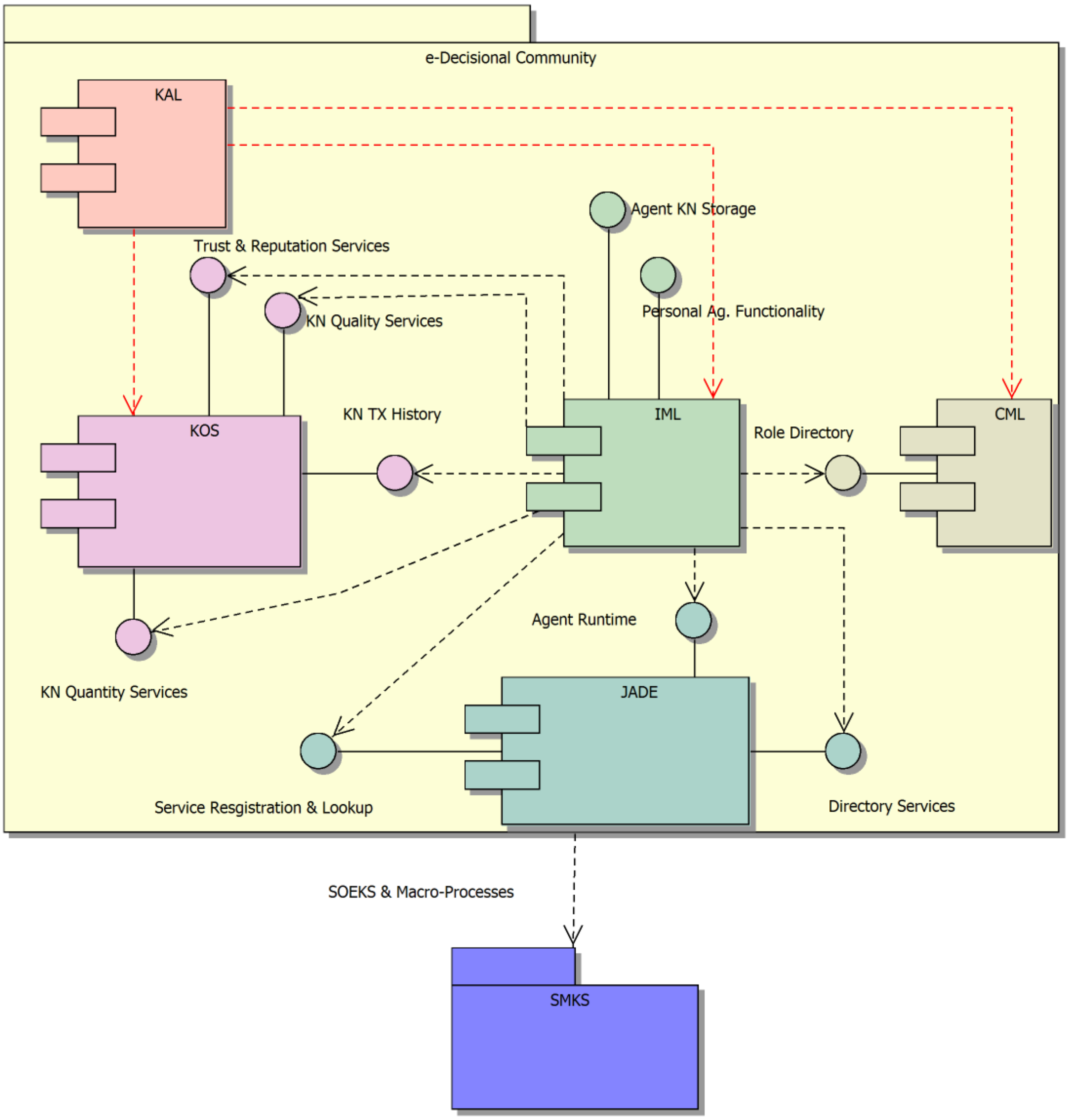
Throughout this section the guidelines for future work have been sketched by analysing the platform's contributions and missing elements. Consequently, the first step towards the improvement of the e-Decisional Community is the development of the remaining indicators for KBVOs, which will allow a complete deployment of such organizations in production environments. Also, the deployment of the e-Decisional Community in a CC environment will allow for further development of the KAL, and will allow users to access the platform's functionality anywhere and anytime.

Additionally, given the proliferation of mobile devices and embedded systems, another idea for future work is the integration of the e-Decisional Community with agents that run on portable devices or embedded systems. This will enrich the platform by guaranteeing that knowledge is gathered from every possible source. For instance, a mobile sales force could contribute to an organization's knowledge base by supplying decisions made on the field, which then can be used by customer support agents or managers to make decisions regarding specific sales strategies. Furthermore, the web is full of websites that contain information representing past decisions or that can be used to make forecasts. This is another valuable source of knowledge that can be exploited using smart web-mining techniques. By mining the web for knowledge, users and organizations could delegate mining tasks topics of interest to the agents of the e-Decisional Community. Then, the results of the mining process can be added to the collective knowledge base with the intention of increasing organizational experience from external sources. Work on the topics of embedded systems and web-mining is currently being developed at the University of Newcastle (Zhang, Sanin, and Szczerbicki 2010; Wang, Sanin, and Szczerbicki 2011; Zhang, Sanin, and Szczerbicki 2011b, 2011a), and the integration of such approaches with the e-Decisional Community will make a greater contribution for the development of decision-support systems.

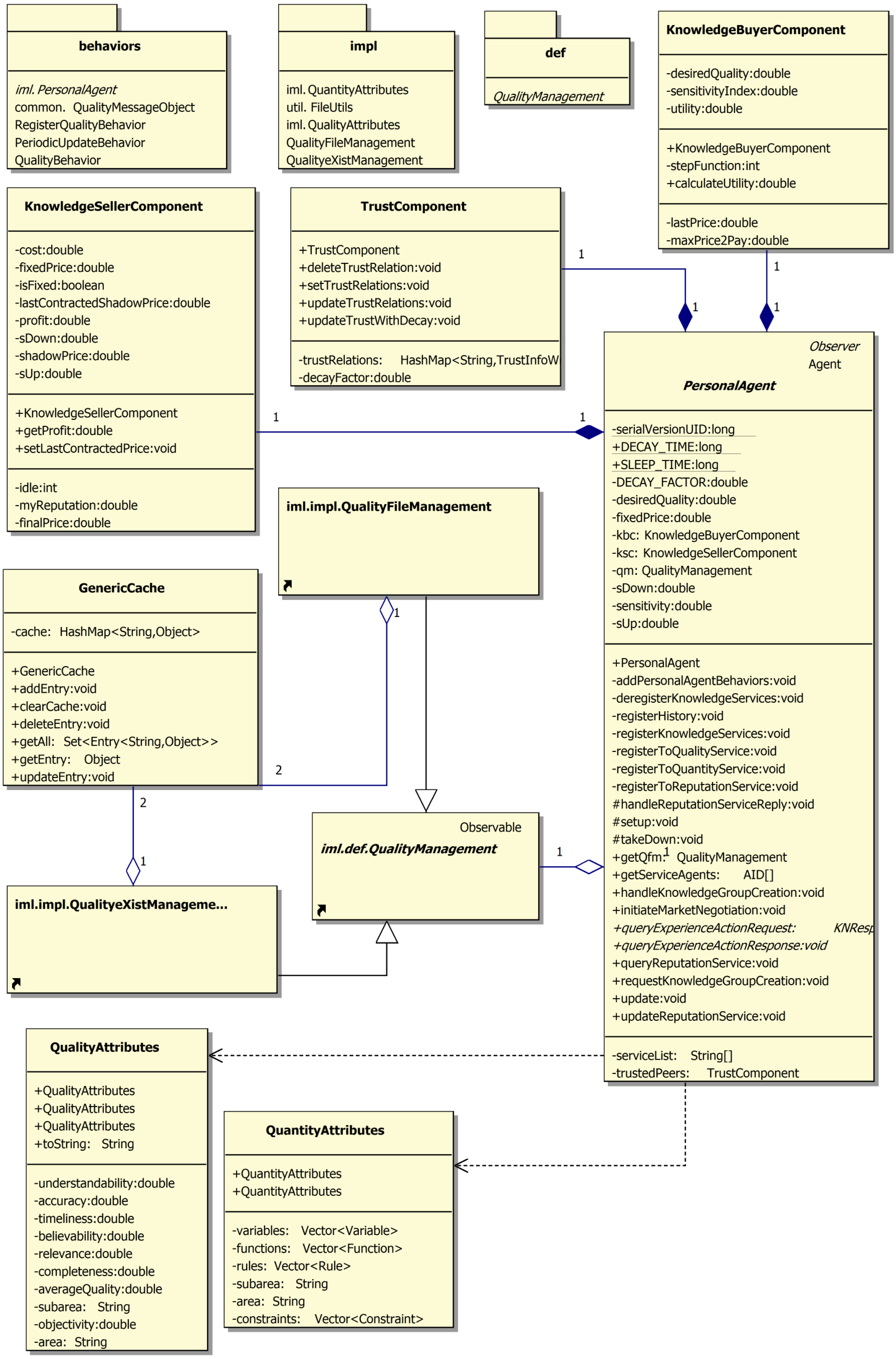
The previously presented ideas are just a guideline for the future development of the e-Decisional Community, and are not intended to restrict the development of the platform. Hopefully, researchers will find more opportunities and challenges for future work other than the ones mentioned in this thesis.

ANNEXES

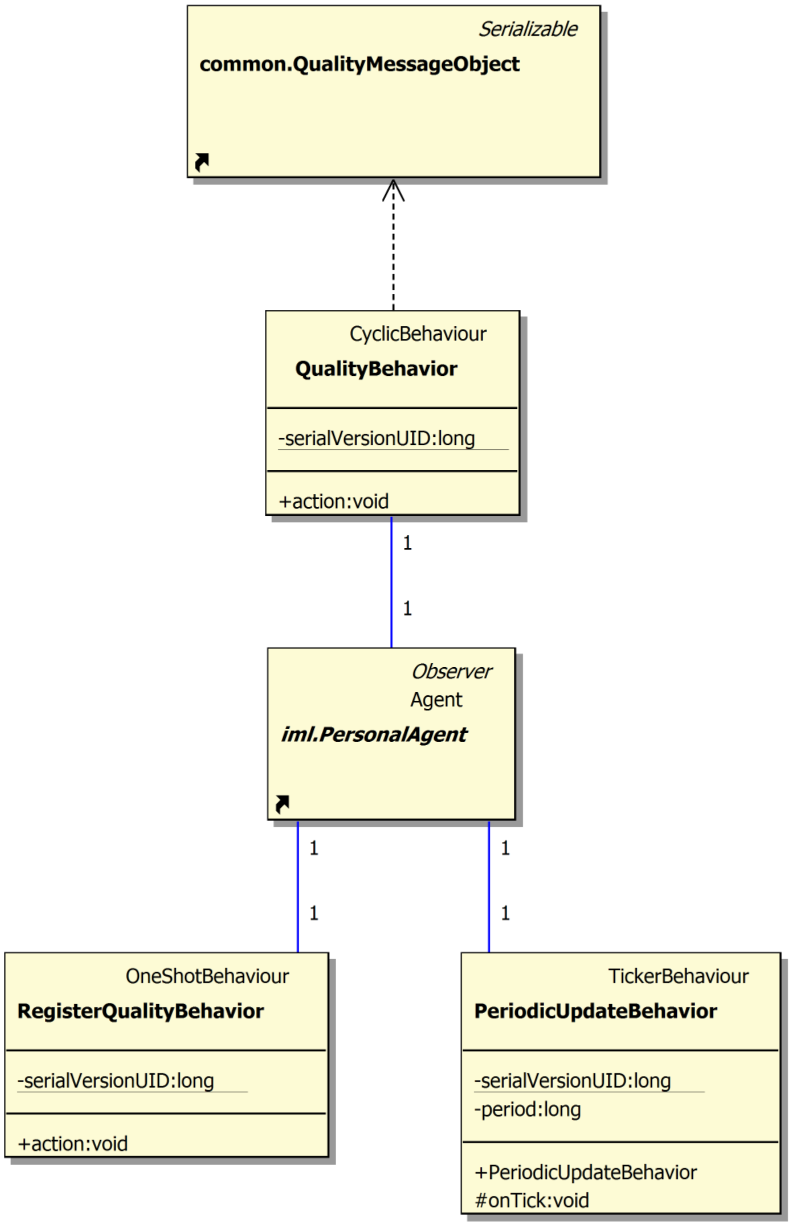
Annex 1. Architecture Diagram



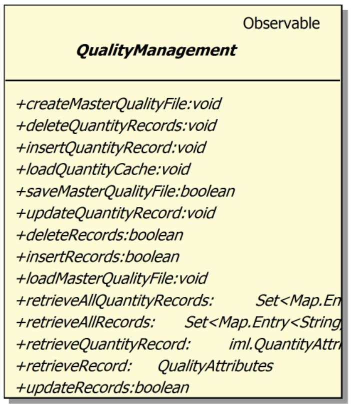
Annex 2. IML Class & Package Diagram



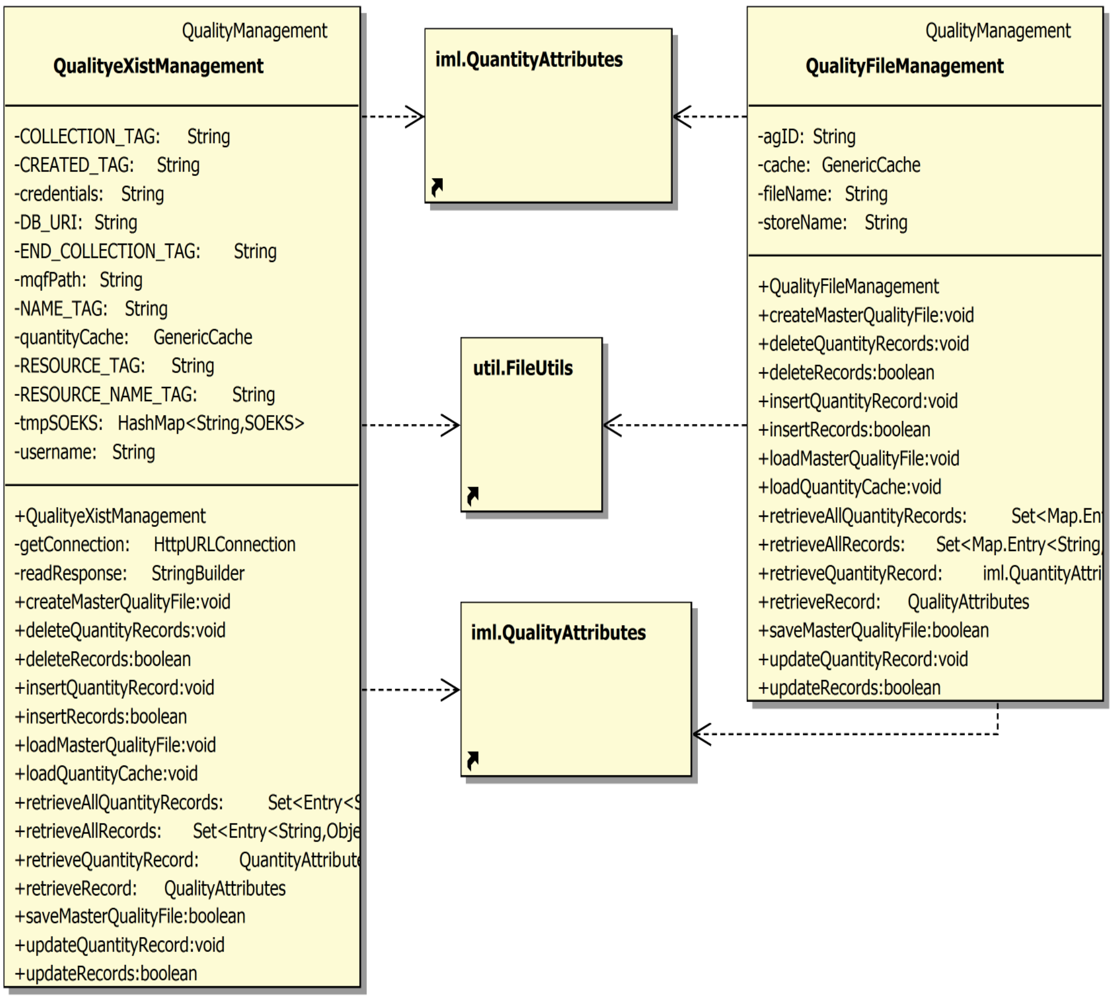
Annex 3. IML Behaviours Class Diagram



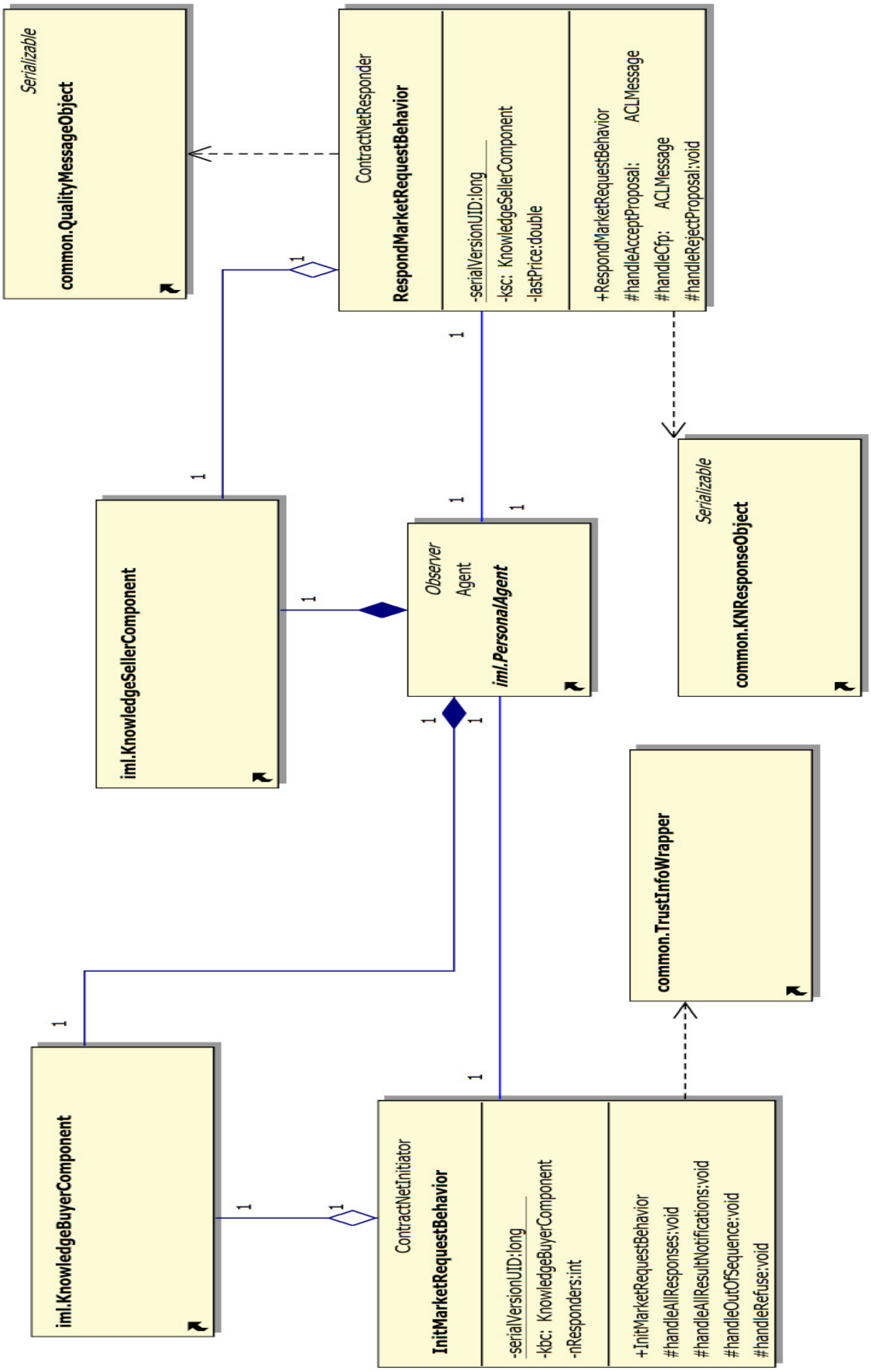
Annex 4. IML Definition Class Diagram



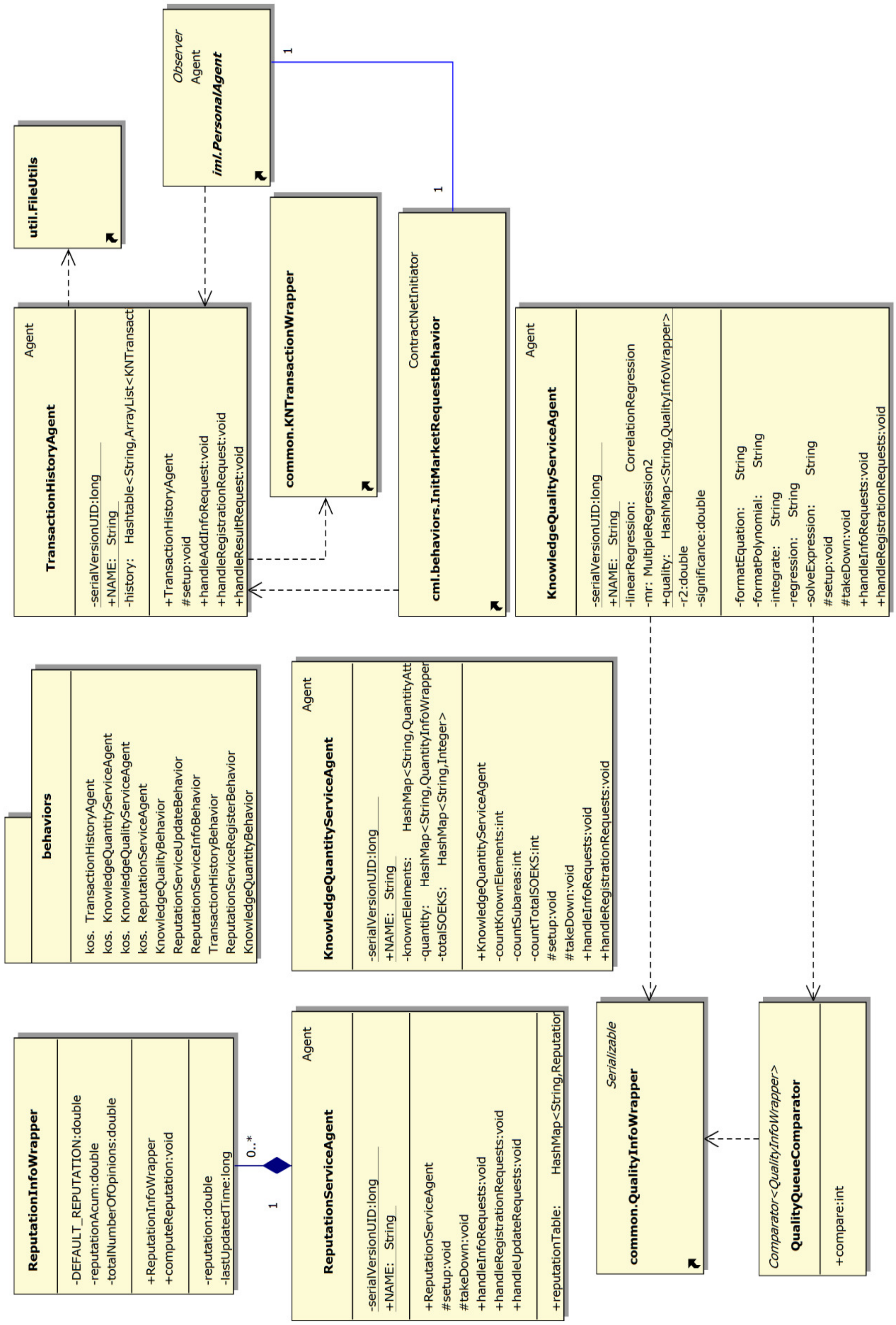
Annex 5. IML Implementation Class Diagram



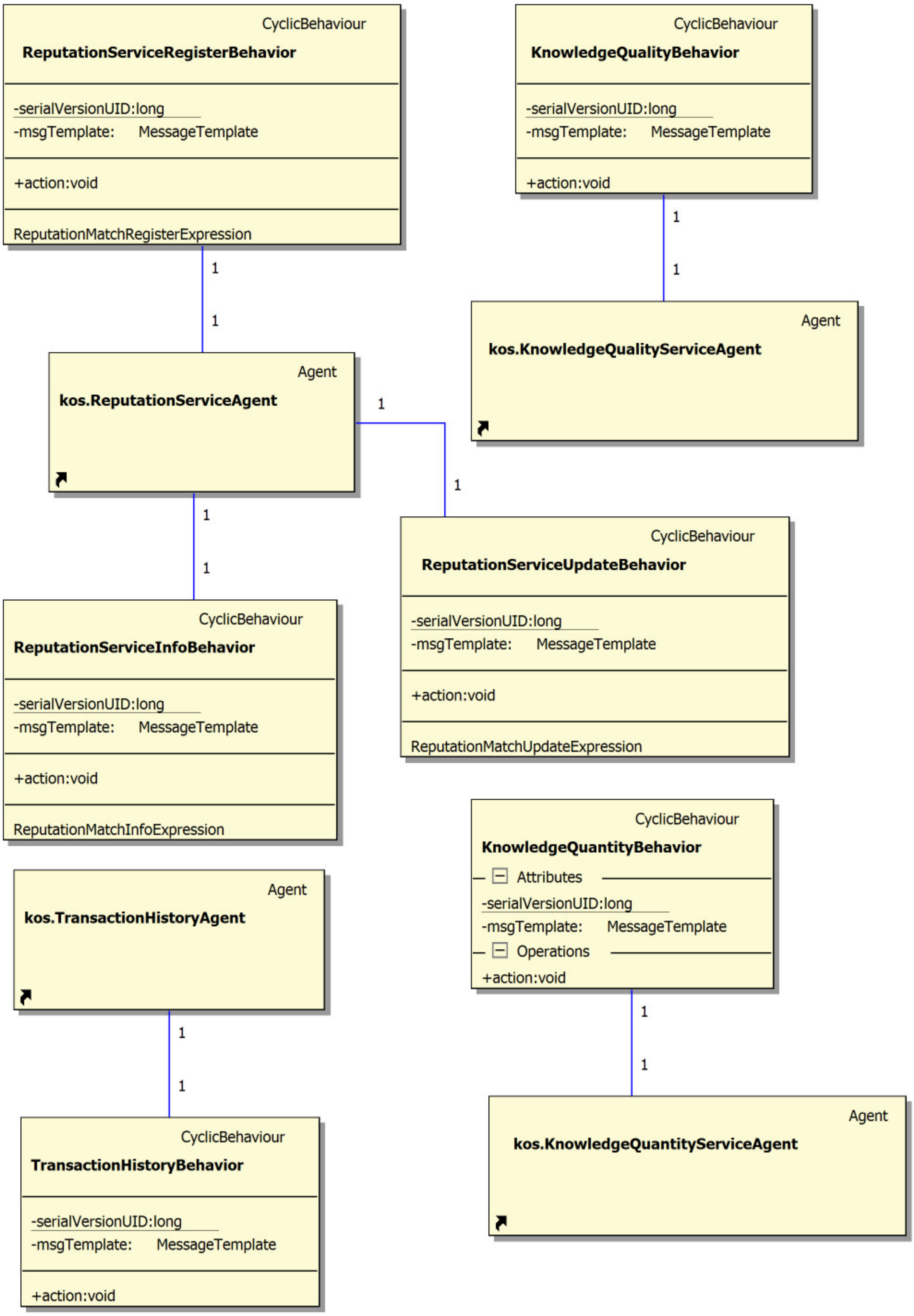
Annex 6. CML Class Diagram



Annex 7. KOS Class Diagram



Annex 8. KOS Behaviour Class Diagram



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