An Intelligent Knowledge Management System from a Semantic Perspective

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Abstract. Knowledge Management Systems (KMS) are important tools by which organizations can better use information and, more importantly, manage knowledge. Unlike other strategies, knowledge management (KM) is difficult to define because it encompasses a range of concepts, management tasks, technologies, and organizational practices, all of which come under the umbrella of the information management. Semantic approaches allow easier and more efficient training, maintenance, and support knowledge. Current ICT markets are dominated by relational databases and document-centric information technologies, procedural algorithmic programming paradigms, and stack architecture. A key driver of global economic expansion in the coming decade is the build-out of broadband telecommunications and the deployment of intelligent services bundling. This paper introduces the main characteristics of an Intelligent Knowledge Management System as a multiagent system used in a Learning Control Problem (**IKMSLCP**), from a semantic perspective. We describe an intelligent KM framework, allowing the observer (a human agent) to learn from experience. This framework makes the system dynamic (flexible and adaptable) so it evolves, guaranteeing high levels of stability when performing his domain problem P. To capture by the agent who learn the control knowledge for solving a task-allocation problem, the control expert system uses at any time, an internal fuzzy knowledge model of the (business) process based on the last knowledge model.

Keywords: knowledge management, fuzzy control, semantic technologies, computational intelligence

1. Introduction

Today's organizations are continuously faced with the challenge of complexity and urgency in their core business activities. The business environment is very chaotic and organizations need to be able to cope with many different kinds of business, technological, social, and human requirements. There is an inherent need for organizations to improve their business activities. In order to be able to solve complex problems the individual (agent) and group problem-solving processes involved in computer-mediated communication systems need to be integrated. On the basis of their studies of Japanese companies, Nonaka and Takeuchi proposed their widely known model of the knowledge-creating company [11]. They argued that much of the innovation created and accumulated in a firm is actually based on tacit knowledge, i.e. arising out of experience, and cannot be easily communicated by workers within excessively formalized management procedures.

This paper presents in order the basic properties of KM (section 2), present and future intelligent technologies for KM (section 3), a case study based on a fuzzy intelligent control solution for a task-allocation problem (section 4) and conclusions (future researches). An example for task-allocation problem is a virtual organization (VO) or an electronic institution (EI). They are composed of a number of autonomous entities (representing different individuals, departments and organizations), each of which has a range of problem-solving

capabilities and resources at its disposal. The question is "*how a VO or an EI are to be dynamically composed and re-composed from individual agents, when different tasks and subtasks need to be performed*?". This would be done by allocating them to different agents who may each be capable of performing different subsets of those tasks [1].

2. The basic properties of KM

KM is an emerging, interdisciplinary business model dealing with all aspects of knowledge within the context of the firm, including knowledge creation, codification, sharing, and using these activities to promote learning and innovation. It encompasses both technological tools and organizational routines of which there are a number of components. These include generating new knowledge, acquiring valuable knowledge from outside sources, using this knowledge in decision making, embedding knowledge in processes, products, and/or services, coding information into documents, databases, and software, facilitating knowledge growth, transferring knowledge to other parts of the organization, and measuring the value of knowledge assets and/or the impact of knowledge management [10]. KM is becoming very important for many reasons. To serve customers well and to remain in business, companies must reduce their cycle times, operate with minimum fixed assets and overhead (people, inventory and facilities), shorten product development time, improve customer service, empower employees, innovate and deliver high quality products, enhance flexibility, capture information, create and share knowledge. Knowledge management draws from a wide range of disciplines and technologies. These include cognitive science, artificial intelligence and expert systems, groupware and collaborative systems, and various other areas and technologies [8,9]. In summary, we can describe knowledge management as an audit of *intellectual assets* [7,10,11].

KM is typically implemented through the performance of knowledge tasks, e.g. create, distribute, reuse and refers to the rational (re) allocation of knowledge assets by means of effective and efficient organizing, planning, leading, controlling, and coordination. KM goals are also described in terms of knowledge, such as knowledge sharing and leveraging. In fact, KM goes far beyond knowledge. It refers to a number of human abilities (referred as KM abilities) that allow them to interface with a dynamic world, learn, evolve, reason, adapt, and keep performing tasks they are intended to deliver. Recent interest in this field has shown that although humans are equipped with a series of KM abilities that allow them to adjust to the world's changing conditions; they lose these abilities when organized in systems. Such a fact represents one of the KM's biggest challenges, i.e. transferring individual KM abilities to organizational contexts. Not surprisingly, few strategies have resulted in success [3,4,5]. The problem is that systemic KM outside humans has to be artificially conceived, implemented and managed to succeed. One of the difficulties is in trying to incorporate KM processes into existing systems i.e. that were conceived without it. Better results can be obtained when KM processes are part of the original and integral design and development of systems. Although challenging to conquer, KM abilities allow systems to learn, evolve, adapt, and successfully perform in the context of a dynamic world. Similar challenges are faced by computer systems designed to deliver tasks in the context of the same dynamic world. Therefore, it is reasonable to assume that knowledge systems can also benefit from KM strategies. The needs and respective benefits are directly proportional to the complexity of the system's task and to the assurance levels a problem context requires. A reliable knowledge-based system should be able to learn, evolve, and adapt in order to guarantee its successful performance in the context of a dynamic world. The simplest form of KM in a computer system occurs when it is maintained. Reasons for maintenance may originate from flaws or changing conditions. When a computer system monitors its own performance and is able to learn from it, it can guarantee longer periods of response without the need for maintenance. This self-monitoring also gives the system the ability to recognize when it fails and cannot learn, flagging its need for

maintenance. Fast adaptation to changing conditions has the potential to increase assurance levels, justifying the incorporation of KM strategies into high assurance systems.

3. Technologies for Knowledge Management

The great majority of the KM and search tools on the market are server-based enterprise systems. As such, they are often designed top-down, centralized, inflexible and slow to respond to change. There has been numerous articles published on the role of IT and KM systems in organizations but there is a lack of research into KM tools for individuals and server-less KM tools/systems. By adopting a bottom-up approach, this research focuses on tools that assist the Individual Knowledge Worker (IKW) who, in today's competitive knowledge-based society, has a constant need to capture, categorize and locate/distribute knowledge on multiple devices and with multiple parties. Furthermore, knowledge sharing between IKWs often extends across organizational boundaries. As a result, personal KM tools have very different characteristics to the enterprise KM tools mentioned above. At the group level, the impact of Peer-to-Peer (P2P) computing on Knowledge Management has been specifically identified as file sharing, distributed content networks, collaboration, and search. Potential applications for P2PKM systems include, among others, E-Learning in higher and distance education, real-time collaborations and battle simulations in defense, collaborative product development, business process automation, and E-business payment systems, and many others.

From an organizational perspective, people, process and technology are commonly regarded as the three fundamental components underpinning the success of any KM program. People and cultural issues, in particular, are seen as the two crucial factors in determining the adoption and sustainability of any enterprise-wide KMS (whether technical or not). Cultural issues may include, but not limited to, the norms and values shared by individuals and groups, as well as trust between peers in an organization. Up to now, technology has been generally perceived as an enabler in supporting the various KM processes i.e. capturing, categorizing, storing, searching, and distributing. Business capability exploration focuses on reaching agreement about basic concepts and terms that different groups use. As a vehicle for reaching agreement between stakeholders, an ontology supports multiple points of view as well as different vocabularies. Developments in the field of Semantic Web Services show the opportunity of adding higher semantic levels to the existing frameworks, to improve their usage and ease scalability [9,12]. Semantic models are inherently multi-perspective and can generate controlled vocabularies and taxonomies as needed by different business problems, functional units, or communities of practice within the enterprise as well as across the supply chain. Building an *intelligence layer* allows delivery of capabilities and business value to users by building composite services. The knowledge plane models the essential business context, integration, relationships and business rules between applications, databases, and processes. Applications and data sources link to and interact with each other in real time and in context through the business ontology layer. Dynamic semantic models can be reasoned over. Connections can be inferred and ontologies can be consulted by different applications at execution time, make ongoing integration costs more linear rather than exponential.

Semantic technologies

Semantic technologies have emerged as a central theme across a broad array of ICT research and development initiatives. The four major development themes in the semantic wave are [2]: networking, content, services, and cognition.

- *Networking* — Semantics to enable computers to configure and manage dynamic, persistent, virtual systems-of-systems across web, grid & P2P.
- *Content* — Semantics to make information interoperable, improve search, enable content discovery, access, and understanding across organization and system boundaries, and improve information lifecycle economics.

§ *Services* — Semantics to enable computers to discover, compose, orchestrate, and manage services, and link information and applications in composite applications.
§ *Cognition* — Semantics to make knowledge executable by computer; augment capabilities of knowledge workers; enable robust adaptive, autonomic, autonomous behaviors.

Semantic technology functions are to create, discover, represent, organize, process, manage, reason, explain with, present, share, and utilize meanings and knowledge in order to accomplish business, personal, and societal purposes. Semantic technologies represent, organize, integrate and interoperate resources, content, knowledge and logic reasononig. Organization of meanings makes use of taxonomies, ontologies and knowledge-bases. These are relatively easy to modify for new concepts, relationships, properties, constraints and instances. Because semantic technologies integrate data, content, applications, and processes via a shared ontology, this minimizes development and maintenance costs. Semantic capabilities enhance value and improve the lifecycle economics of information and knowledge. Semantic enablement of information can enhance authoring, search, discovery, access (or sharing), aggregation, understanding, and communication of information. It imparts new capabilities for knowledge work automation and knowledge worker augmentation.

The *interoperability* and *logic reasoning* are the capabilities of semantic technologies, from search to knowing:
§ From bottom-to-top, the amount, kinds, and complexity of metadata, modeling, context, and knowledge representation increases.
§ From left-to-right, reasoning capabilities advance from (**a**) information recovery based on linguistic and statistical methods, to (**b**) discovery of unexpected relevant information and associations through mining, to (**c**) intelligence based on correlation of data sources, connecting the dots, and putting information into context; to (**d**) question answering ranging from simple factoids to complex decision-support, and (**e**) smart behaviors including robust adaptive and autonomous action.
§ Moving from lower right to upper left, the diagram depicts a spectrum of progressively more capable categories of knowledge representation together with standards and formalisms used to express metadata, associations, models, contexts, and modes of reasoning.

Information intelligence

Semantic capabilities enable information intelligence (information in context of need) through aggregation, integration, and interpretation of diverse data sources. The spectrum of requirements includes [2]:
§ *Sense-making* — Extract knowledge and tag metadata based on statistical, language-based, semantic, and knowledge-centered approaches. Enable sharing and interoperability at this level through data services that parse formats, match patterns, distinguish features (such as parts of speech), apply linguistic and statistical methods, etc. Intelligent adaptation services mine and extract knowledge and semantic from data sources, or otherwise add semantic metadata of various kinds to the data. Semantic integration services link information, metadata, and semantic models.
§ *Information sources* — discovery, access, and understanding of structured, semi-structured, unstructured information sources. Sources are federated and distributed.
§ *Information structure levels* — Signal, data, content, metadata, model, and semantic model; sharing and interoperability span a continuum of contexts.
§ *Search contexts* — Semantic query services access, navigate, and reason over semantically enabled content to be provisioned to various client applications. Retrieval, discovery, intelligence, question-answering, and decision-support reasoning, and thus a need to enable exploitation of content interoperability at increasing cognitive depths
§ *Sharing contexts* — encompasses: (a) general search, (b) task or context-based search and line of thought navigation, (c) composite applications providing, integration of structured and unstructured information in context of need, and interaction with information in user-

determined context involving processes, tracking; and (d) mission and time-critical situation awareness, reasoning and trade-off assessments, and decision-support, and (e) autonomic, adaptive, and autonomous system behavior.

Computational intelligence

Computational intelligence systems (CIS) use a variety of techniques, e.g. evolutionary computing, to derive solutions to real world problems. They make good candidates for a KM approach because they build new solutions at every execution. Intelligent systems in general only learn from experience when they are designed with this specific purpose. Some learning systems are designed to learn from inputs but not from their own executions. Computer systems that deliver tasks interfacing with a dynamic environment can only be considered reliable if they are prepared to learn, adapt, and evolve. The KM frameworks allow CIS to learn, adapt, and evolve; potentially resulting in continuous improvement and increased reliability because it is designed to enhance a system's capabilities. Managing knowledge in CIS means giving these systems the ability to learn from their own executions. The KM framework represents an additional effort to guarantee a system performs as required; therefore, reaching the core of high assurance. In addition, systems engineering pursues high assurance in systems interfacing with a dynamic world where task environments evolve. Consequently, enabling systems to respond to dynamic environments and behave in conformity with the context's changes is beneficial to high assurance systems engineering. A system that incorporates a KM framework evolves because it observes its executions and uses metrics to evaluate its performance. For example, in a CIS that trains an artificial neural network (ANN), its accuracy can be used as a measure of its performance. The resulting system can be configured to submit every new thing it learns to be validated by humans, so it will not act in unexpected ways. KM solutions are typically presented through KM processes that detail knowledge tasks.

An analysis of different KM processes described in the context of technological KM solutions resulted in the conceptual cycle; it consists of the tasks *create*, *understand*, *distribute* and *reuse*. The *create* task refers to applying different methods to collect or generate knowledge (and information) within the application's context. The *understand* task is responsible for performing all necessary steps (e.g. validate, represent, store) to make collected knowledge ready to be distributed. The *distribute* task matches stored knowledge to the knowledge needs of its proper recipients. The *reuse* task oversees that knowledge is properly reapplied back into the application's context.

Universal knowledge technology

Over the next decade, we can expect rapid progress towards a *universal knowledge technology* that can provide a full spectrum of information, metadata, semantic modeling, and advanced reasoning capabilities. Very large-scale knowledge-bases, complex forms of situation assessment, sophisticated formal logics and reasoning with uncertainty and fuzziness (for example case-based reasoning, fuzzy logic with generalized modus ponens, description logics, etc.), and autonomic and autonomous system behavior pose challenges that exceed the capabilities and performance capacity of current open standards approaches. Second, no good reason exists for settling for only a portion of the capability spectrum when we can just as easily have the whole thing.

For this we have: *Knowledge = Theory* $\copyright_1$ *Information*, *IKMS=Knowledge* $\copyright_2$ *Reasoning*, where $\copyright_1$, $\copyright_2$ are two metaoperators (where IKMS – Intelligent KMS)

§ *Theories* are the conditional constraints that give meaning to concepts, ideas and thought patterns. Theory asserts answers to "how", "why" and "what if" questions. For humans, *Theory* is learned through enculturation, education and life experience and represents 85% of knowledge content.

§ *Information,* or data, provides situation awareness — who, what, when, where and how-much facts of situations and circumstances. Information represents only 15% of knowledge and requires *theory* to define its meaning and purpose.

Case-based reasoning is a reasoning methodology inspired by the human process of reuse a previous similar episode to solve a new problem [6]. The act of being reminded of a previous episode is modeled in case-based reasoners by comparing a new problem with a collection of stored cases (the *case base*), often based on indexes describing the contents of the stored cases. The most similar cases are then retrieved, and can be used as references to classify the new case or the solutions from the retrieved similar case(s) can be adapted to fit the new problem. If the adaptation results successful, a new case has been created and is retained in the case base. However, adaptation is one way of acquiring cases. Other case bases consist exclusively of real experiences, where adapted cases are not learned. Cases can also describe prototypical situations or be artificially authored. What distinguishes universal knowledge technology is that it enables both machines and humans to understand and reason with any form of knowledge, of any degree of complexity, at any scale.

4. A case study

Problem solving can be seen as a process consisting of problem space search and knowledge search. Expert systems were introduced as an intelligent tool for diagnosis and it is now widely used in classification and control tasks in a variety of human activity fields. Fuzzy logic is an attempt to capture valid reasoning patterns about uncertainty. In addition to modeling the gradual nature of properties, fuzzy sets can be used to represent incomplete states of knowledge. In general, a more complex model may provide the capability to obtain a better representation of a system and may facilitate design, but it may not lend itself to straightforward analysis.

If a simpler model is used, one may ignore some of the dynamical behaviour of the plant (problem domain) and be able to get more analytical results, but such results may only be valid in an approximate way for the real system. There will be different analysis techniques that are appropriate for different models (conventional, discrete event models, distributed architectures etc.).

Our Intelligent Knowledge Management System is a multiagent system used in a Learning Control Problem (**IKMSLCP**).The **IKMSLCP** consists of [9]:

§ ***the controlled process agent*** (**CPA**) is defined by a class of discrete event system, with a precisely goal and represents the domain problem;

§ ***the control expert system agent*** (**CESA**) of the plant and learning process, which includes more fuzzy knowledge models M_i, i=1,k. The existence of a number of fuzzy knowledge models $M_0 \subset M_1 \subset \ldots \subset M_k$ means a gradual and incremental learning process [9]. The **CESA** agent of **IKMSLCP** has to be designed so that it can eliminate the undesirable system behaviours. There is a need to specify the initial state of the closed-loop system to reduce the combinations that may complicate the model. In analysis, the focus is on testing the closed-loop properties: reachability (firing a sequence of rules to derive a specific conclusion), cyclic behaviour of the fuzzy inference loop, stability (the ability to concentrate on the control problem).

§ ***the diagnosis agent*** (**DA**) used in the generation of plausible explanations. The **DA** activates a certain intern knowledge model of the **CPA** that will be used by the **CESA**. Based on the generated explanations, the observer learns the used knowledge model of the **CPA**. If these explanations are valid, then they represent the sum of knowledge that permit the observer advance in the learning process.

§ ***the observer*** or the human agent (**HA**).

To capture by the agent who learn the control knowledge for solving the problem P, the control expert system uses at any time, an internal knowledge model of the process $M_i|_{i=\overline{0,k}}$ based on the level of the last knowledge model. The output of the controlled process is compared with the reference (goal) and, if this output doesn't satisfy the required criteria, it will represent a fuzzy qualitative error (i.e. a set of manifestations). These k+1 qualitative errors represent the unique activated inputs in the **DA**, having the characteristics of a dynamic system [9].

The fuzzy logic inference refers to the problem of possibilistic and temporal reasoning in **IKMSLCP**. Let $s_0 \in U$ denote the unknown current state of process under consideration. U may be viewed as the cartesian product of domains $U^{(i)}$, attached to attributes $P^{(i)}$ that are chosen to characterize s_0. We suppose that s_0 is a n-tuple $(s^{(1),0},...,s^{(n),0})$ of attribute values $s^{(i),0} \in U^{(i)}$, i=1,...,n. The definition and application of fuzzy expert systems consists of four phases, which can be distinguished conceptually as follows: **i)** In the first phase the knowledge acquisition which leads to appointing the attributes $P^{(1)},...,P^{(n)}$, $n \in N$ and their domains $U^{(1)},...,U^{(n)}$. Fixing the universe $U = \prod U^{(i)}, i \in N_n, N_n \subset N$ provides the representation structure for the expert knowledge and forms the set of all states that are a priori possible. **ii)** In the second phase rules are formulated that express general dependencies between the domains of the involved attributes $P^{(1)},...,P^{(n)}$. The single rule $R_j, j = 1,...,m, m \in N$ do not concern all attributes normally but only a small number $P^{(i)}, i \in M_j$ which are identified by an index set $M_j \subseteq N_n$ of low cardinality.

The matching window is either a point or a rectangle depending on whether the matched fuzzy proposition holds at a time point or in a time interval. First we should determine the time domains of variables in the database or in other words determine the size of the matching window and its position by giving priority to the temporal matching. In the case that the event described by a fuzzy fact has appeared or is appearing we can continue to perform the numeric matching. The application of the fuzzy formulation is advantageous in cases when small violations of specific constraints may be tolerable for the decision maker with the goal to achieve a more reasonable objective.

Therefore there exist some unique problems in the fuzzy reasoning procedure the successful pattern matching of a fuzzy rule not only requires that all the fuzzy propositions in the rule's premise should match the data in the database in a fuzzy sense but also requires that the temporal relations among these fuzzy propositions should match the temporal relations implicitly formed by the corresponding dynamic situations in the database in a fuzzy sense.

A model associated with a possibilistic expert system and which is also based on a temporal reasoning should meet the following requirements as outlined in the following algorithm:

Context - *A fuzzy compiled rulebase, to which time descriptors have been associated*
-Fuzzy database reflecting the state of the controlled process in conjunction with fuzzy temporal relations

1. *Find* a time range associated with the time variable $X^{(i)}, i = 1,...,m$ from the database according to the fuzzy descriptor DT, where $\Delta T = \left(\int_T \frac{\mu_1(t)}{t} \int_T \frac{\mu_2(t)}{t} \right)$, the sentence P_i associated with variable $X^{(i)}$ is assumed to be within on interval DT formally described by $DT\left(P_i \int_T \frac{\mu_1(t)}{t} \int_T \frac{\mu_2(t)}{t} \right)$. In this way we can find the size and the position of the matching window priority been given to the temporal matching.

2. *Perform* the temporal pattern matching in compliance with the existing temporal attributes. **If** the temporal pattern matching is successful **then** compute its degree of confidence and proceede to step 3 **otherwise** rejected situation

3. *Perform* the numeric pattern matching by using the pair $(\cdot)$ and N. **If** the numeric pattern matching is successful **then** continue the fuzzy reasoning algorithm based on compiled fuzzy rulebase **otherwise** rejected fact. The numeric pattern matching calls for the synthesis of X^{DT} based on associated values x^{DT} of the DT into a single value.
4. *Complete* the global pattern matching with both new facts derived from the process and already with the inferred facts. More specifically finish the fuzzy reasoning process starting from a given fuzzy state up to its (finite) limit passing through a sequence of internal states of the possibilistic expert system.
5. *Defuzzify* outputs to obtain the the results for all output variables.

It is assumed that the **CPA** can be represented with the following model: $CPA = (X, E, f_e, \delta_e, g, E_v)$ that can represent certain class of discrete event systems, where X is the set of **CPA** states denoted by x. E is the set of all events. f_e are the state transition map: $f_e: X \to X$ $(e_k \in P(E), k \in T)$. δ_e are the output maps. g is the enable function: $g: X \to P(E)$, and E_v is the set of all valid event trajectories (that are physically possible).

Note that E is the union of the command input events (E_u), the disturbance input events (E_d) and the output events (E_o) of the plant. When discussing the states and events at time k ($k \in T$ or k is a fuzzy instant or a fuzzy time interval), $x_k \in X$ is the **CPA** state, $e_{uk} \in E_u$ is a command input event of the plant, $e_{dk} \in E_d$ is a disturbance input event of the plant, $e_{ok} \in E_o$ is an output event of the plant that is equal to input event $e_{pk} \in E_p$ for **CESA**. Each $e_k \subset g(x_k)$ is an event that is enabled at time k and it represents a set of command and disturbance input events of the plant. If an event $e_k \in E$ occurs at time k and the current state of **CPA** is x_k, then the next state is $x_{k+1} = f_{ek}(x_k)$ and the output is $e_{ok} = e_{pk} = \delta_{ek}(x_k)$. Any sequence (x_k) such that for all k, $x_{k+1} = f_{ek}(x_k)$, where $e_k \subset g(x_k)$ is called a *state trajectory*.

The **CESA** has two inputs: the reference input events $e_{rk} \in E^{CES}_r$ (user inputs) and the output events of the **CPA** $e_{ok} = e_{pk} = e_{rk} \in E^{CES}_p$. Based on its fuzzy state and these inputs, the **CESA** generates enable command input events to the **CPA** $e^{CES}_{0k} \in E^{CES}_0$. Hence the **CESA** models how the observer in the loop coordinate the use of feedback information from the **CPA**, reference and user inputs in modeling the current control fuzzy objectives, and information in its memory (the fuzzy **CESA** state). This inference loop constitutes the core of the **CESA** where the knowledge is interpreted by the inference engine, actions are taken, the fuzzy factbase is updated and the process repeats. Usually, the fuzzifier may transform the measured value (e_{pk}) of the measurement into a corresponding universe of discourse for each input variable, as an input fuzzy fact. Fuzzy rules $R_i \in R$ are used to express knowledge. Three kinds of variables are used: input, output and intermediate variables. The defuzzification process decides for each output variable a single value. The **CESA** is modeled by:

$$\mathbf{CESA} = (X^{CES}, E^{CES}, f^{CES}, e_0, g^{CES}, E^{CES}_v)$$

where $X^{CES} = X^b \times X^{int}$ is a set of fuzzy **CESA** states, $x^{CES}_k = X^b$ is the set of fuzzy factbase states and X^{int} is the set of possibilistic inference engine fuzzy states. E^{CES} is the set of events of the **CESA** (reference inputs E^{PES}_r, user inputs, output **CESA** events E^{CES}_0, the set of fuzzy rules R and the **CPA** output events E^{CES}_p), so that g^{CES} is the enable function: $f^{CES}(e_k \in P(E^{CES}), \emptyset)$ is the state transition map, δ^{CES} is the output map of **CESA** and E^{CES}_v is the set of all valid inference loop trajectories that are possible.

The input events inclusion in the fuzzy knowledge model (**FKB**) allows the **CESA** designer to incorporate the **CPA** feedback and the reference input variables directly as parts of the **FKB**. This is analogous to the use of variables in conventional rule-based expert systems. It is important to note here that the consequent formulas of the rules represent how the fuzzy state

x^b in the fuzzy factbase changes based on the occurrence of input events and they can be defined in a recursive manner.

The fuzzy decision-making capabilities of the **CESA** are more sophisticated than those of the standard fuzzy control systems. The **CESA** has to be designed so that it can eliminate the undesirable closed-loop system behaviors. There is a need to specify the initial state of the closed-loop system to reduce the insignificant state combinations that may unnecessarily complicate the model.

The operation of the **CESA** at the inference level proceeds by the following steps:

- *Acquiring the CPA outputs and reference input events at time k;*
- *Forming the conflict set in the fuzzy match phase from the compiled set of rules in the fuzzy knowledge-model M_{KF} based on e_{uk} , the current status of the truth of various fuzzy facts, and the current values of variables in the knowledge-base;*
- *Using conflict resolution strategies (refraction, recency, distinctiveness, priority, and arbitrary) in the select phase, find one rule r' to fire;*
- *Executing the actions characterized by the consequent of rule r' in the act phase.*

Although every occurrence of an input event of the **CPA** always affects the **CESA**, the occurrence of an input event of the **CESA** does not necessarily immediately affect the **CPA** state. In qualitative analysis of our **CESA**, we focus especially on testing if the closed-loop **CESA** satisfy certain properties as follows: reachability, cyclic properties and stability [9]. In our **IKMSLCP**, the learning process is supervised and the goal of this problem is that human agent **HA** can assimilate in a gradual way the fuzzy planning knowledge so that he becomes as far as possible autonomous in a restricted time I_T (the learning time).

The results for the learning problem shows that: (i) The most cases of unsolved problem is represented by disregarding the control strategy; (ii) The increasing or decreasing of the probability attached to the causes influence in the same direction the importance of an hypothesis in comparison with the others. Even if the probability of the hypotheses varies in the same direction, they can increase or decrease as importance according to their trend. The predictability of our **IKMSLCP**, from the practical point of view, simulates only the diagnosis component but include knowledge models of the considered planning problem in different stages of its development. The diagnosis model involve diagnostic entities (disorders, manifestations), causal associations relating these entities (the causal network), the notion of diagnostic explanation and the process of hypothesize reasoning. The algorithm works in a sequential and constructive manner. It takes one present manifestation for each time and than incorporates its causes into the existing hypotheses. The process continues until all present manifestations are processed and the learning time is less or equal with I_T. The **DA** accept as inputs a set of manifestations and supply outputs that represents explanation.

Conclusions

Tomorrow's organizations will need to be more mobile, agile, competitive and learning oriented than ever before. Increasing competition at home and abroad has created a sense of urgency for organizations to be mobile and innovate at a quick pace. Creating knowledge suggests the need for improved knowledge flows internally within the organization and externally to the customers and stakeholders. Leveraging knowledge through the connection and collaboration of others may lead to critical success factor in whether a mobile organization is successful. One technique that is gaining prominence for determining knowledge flows in organizations to facilitate the communication, collaboration and innovation of others is Social Network Analysis (SNA). SNA deals with mapping knowledge flows between actors, whether individuals, departments, companies, and so on. It is a powerful technique that has been used in many applications, ranging from education, business, international trade and government.

Semantic development will enable solutions with new capabilities, such as: i) virtual infrastructure, semantically modeled middleware; ii) netcentric services and operations that reduce integration costs; iii) linking multiple information sources through an ontology that allows users to search and access any source using their own business vocabulary; iv) real-time integration and system-of-systems interoperability (internally, across supply chains) to provide advanced capability; v) composite applications that enable knowledge workers to put information in context, interact with information and applications in the context of their business process; vi) business aligned, rapid tactical implementation of strategic capabilities such as: enterprise IT integration, consolidation, and modernization; knowledge-centered customer-facing process; business intelligence; exception management; case management; command and intelligent control.

Future research might include a more comprehensive study about what components make an impact to collective work and learning in Internet environments. Studies would combine multiple perspectives such as technological environments, organizational structure and external barriers. Organizations need to modify their recognition and reward systems as a part of their knowledge and learning strategies. The knowledge that is gained from the sharing process can then be leveraged and feed-back into the organization as a part of its knowledge and learning strategy.

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