

Increasing the Decision Making Capacities Based on an Inference-Event Algorithm for Artificial Agents

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The aim of this paper is to present an inference-event algorithm for a Knowledge Management System based on Fuzzy Logical Events (KMSFLE), a real-time intelligent agent to meet the challenges of the dynamic environment. The main feature of our integrated shell KMSFLE is that it models and integrates the temporal relationships between the dynamic of the evolution of an external process with some fuzzy inferential methods, using a knowledge model for control, embedded within the intelligent agent operational knowledge base.

Keywords: inference-event algorithm, fuzzy control, artificial agents

1. Introduction

The objective of an artificial Knowledge Management System (KMS) is to support knowledge capturing, categorizing, storing, searching, distributing and application within organizations [2,5,10,15,17,29]. An agent-based model is a computerized simulation of a number of decision-makers (agents) and institutions, which interact through prescribed (logical inference) rules. Technical advances in processing and storage capacity, together with linking these computers into networks of distributed nodes, have greatly increased the capability of organizations to deliver goods and services [30]. Along with these capabilities we need quality, accuracy, responsiveness and capacity. Particular topics of interest on KMSs include among others: organizational knowledge management approaches, online learning environments, service oriented architecture (SOA), financial markets, cognitive reasoning systems, analysis of information, hypothesis refinement, semantic web, fuzzy evaluation, abductive models, information modeling and ontologies, intelligent software tools and services, automation and robotics, games theory [8,9,12,16,20,22,34]. There are some successful agent based models of small portions of the economy. The models of the financial market built by Blake LeBaron of Brandeis University in Waltham, Massachusetts, for example, provide a plausible explanation for bubbles and crashes, reproducing liquidity crises and crashes that never appear in equilibrium models. Rob Axtell of George Mason University in Fairfax, Virginia, has devised firm dynamics models that simulate how companies grow and decline as workers move between them. These replicate the power-law distribution of company size that one sees in real life: a very few large firms, and a vast number of very small ones with only one or two employees. The economies need agent-based modelling [33]. At any given time, each agent acts according the state of the world around it. Exploiting the growing capabilities of computers, Agent-Based Models analyze economic processes as dynamical systems of heterogeneous interacting agents. Repeated interactions among agents over time induce continuously changing microeconomic patterns, the aggregation of which generates a dynamics for the macroeconomic variable of interest. This special issue gathers contributions of leading scholars in Agent-Based and computational economics and shows the applicability of this methodology to several issues both in micro- and in macroeconomics. Agent-based Computational Economics (ACE) investigates how aggregate outcomes arise from the micro-processes of interactions among many agents.

As important contributions of this work, we have integrated some elements of control theory, fuzzy and temporal logics and discrete event systems to increase the decision making capabilities [21]. We also focused particularly on time, in its many facets (real-time, algorithmic complexity and reasoning over time), by using a time meta-equation [21]. The closed-loop of our KMSFLE starts from an initial state and allows planning a number of states to achieve a desired final state. At the end of its operation, the control expert system provides the human decider the possible actions, under specific conditions of the problem [23,26]. All references are important, because each of the mentioned authors has used a series of concepts that we have integrated in KMSFLE conception. Section 2 refers a model

of a generic architecture of a KMSFLE in a distributed control structure, section 3 presents exactly the decision making capabilities based on a fuzzy-event inference algorithm. We used logical discrete events. Section 4 undertakes the conclusions of our research.

2. KMSFLE in a distributed control structure

KMSFLE, as a control agent, is an expert system that integrates imprecise knowledge. The reasoning specific to this agent is performed by the inference engine based on fuzzy logic. This agent's architecture follows the general characteristics of any agent like in [11,31,32]. However, there are several new elements emphasized in figure 1. It is noted that planning and coordination module (PC_{io}) comprises three levels: the level of evaluation of the global situation, the meta-planning level and the level of coordination of cooperation. Its main functions are dedicated to monitoring the activity of other agents, choosing the communication protocol, analyzing whether to respond to other agents and detecting global conflicts. The major difference between the monitoring function of PC_{io} and the monitor is that the monitor supervises the activity of its own system based on fuzzy knowledge.

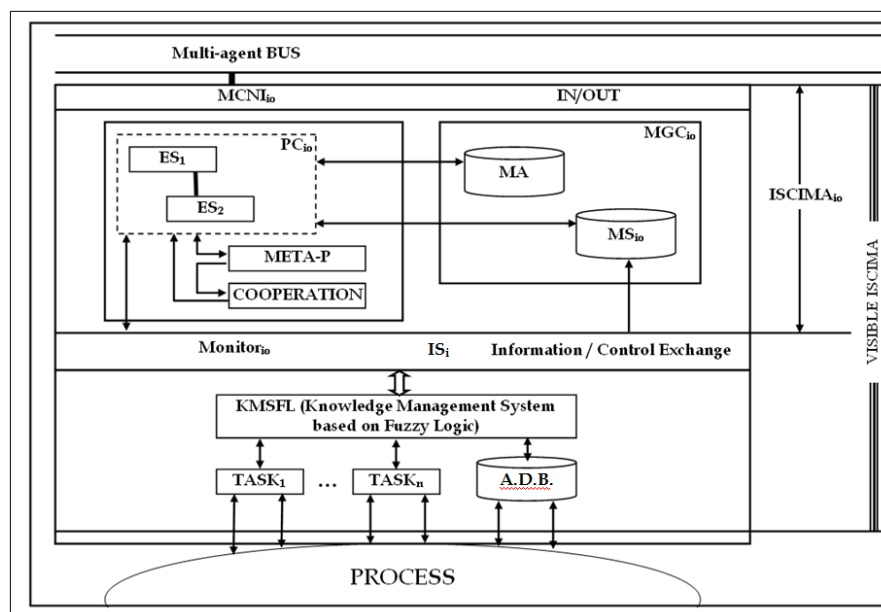


Figure 1. KMSFLE in a multi-agent structure

The monitor is the only link between the system based on imprecise knowledge and the $ISICMA_{io}$ interface, and implicitly between the system based on imprecise knowledge and the whole multi-agent control system. Its basic role is of remote control of its own system based on fuzzy logic, meaning that the monitor will communicate through messages, because it is not a part of the Artificial Intelligent (AI) system based on imprecise knowledge. Decisions concerning the control of the intelligent control system based on fuzzy knowledge are made at the level of $Monitor_{io}$, whose main functions are: retrieving information from various sources, granting access to MS_{io} , evaluating the local situation, updating the local information, describing high-level goals, planning the decisions and actions. In order to eliminate the possible conflicts between these functions and the ones of the AI system based on imprecise knowledge, $Monitor_{io}$ invokes the low-level behaviors stored in MS_{io} .

Fuzzy logic is a generalization of bivalent logic, replacing the discreet nature of the latter with one of continuous nature. While in bivalent logic, in order to demonstrate the validity of formulas, are used methods that use up all the possibilities of evaluation according to the interpretation function, in fuzzy logic this is no longer possible. A special feature of human reasoning is the effective use of natural language, even in the logical reasoning. According to this observation, we may conclude that the mathematical model of how a man thinks during a control process and at a certain level of decision synthesis may be based on fuzzy logic combined with modal temporal attributes [1,7,14,18].

Approximate reasoning theory, as a methodology for exploiting imprecise knowledge relative to the control expert system's state (denoted $x^{CES} \in X^{CES}$ and represented in the form of possibility distributions), allows, by means of logical inferences, to obtain rigorous characterizations of the values of linguistic variables within the structure of state x^{CES} , according to the control goal [3,4,6,24]. The set

X^{CES} can be defined as a Cartesian product $X^b \times X^{int} \times X$, where $\mathbf{x}^b = [x_1^b, x_2^b, \dots, x_{k_1}^b]^t \in X^b$. For example, the component x_1^b indicates, through its values, the potential command events for the process, $x_i^b \in U^{(i)}$, $i=2, \dots, k_1$, where $U^{(i)}$ are the universes of discourse attached to linguistic variables $x^{(i)}$ (chosen to characterize the state $\mathbf{x}^{ES} \in X^b \times X^{int}$), X^{int} is the set of internal states of the inference engine and X is the set of states of the process. Thus, we can model KMSFL and the corresponding reasoning as a possibilistic expert system, that allows us to characterize a state $\mathbf{x}^{CES} \in X^{CES}$ based on imprecise information relative to the state $\mathbf{x}^{CES}$, i.e. with a subset $E \subseteq X^{CES}$, for which $\mathbf{x}^{CES} \in E$. We assume that there may be components of state $\mathbf{x}^{CES}$, defined as predicates that have firm truth values. Moreover, in this case is met the condition of membership of truth values to the interval $[0,1]$ and thus we can work only with interval $[0,1]$.

The control expert system manages knowledge specific to a state of the closed-loop system $\mathbf{x}^{CES} \in X^{CES}$, characterized at time k by $\mathbf{x}_k^{CES} = (x_k, x_k^{ES})$. The class of possibilistic expert systems [7] can encompass also temporal reasoning [6,13]. In this case, the rules base consists no longer of relationships, but of multi-dimensional possibility distributions to which are attached temporal descriptors, modeled in turn by means of possibility distributions, in order to attach the fuzzy statements to temporal features. Attaching the fuzzy temporal descriptors is specific to AI techniques, while in terms of control, this corresponds to fuzzifying the moments of time in the theory of discrete event systems.

3. Case study

For the synthesis of fuzzy knowledge control model for the flexible production system, we considered the loads as fuzzy T-numbers, expressed linguistically as "around" or "approximately", and we introduced intermediate variables in the knowledge model's structure, such as: global balance degree bd (for the whole flexible manufacturing system) with the fuzzy values *satisfactory* and *unsatisfactory*, partial balance degrees pbd_i , $i = 1, \dots, 5$ (per groups of subsystems), corresponding to certain situations unresolved in the crisp model, and fuzzy variables $d_{56}, d_{42}, d_{13}, d_{21}, d_{43}$ and d_{35} , whose values can be the fuzzy T-numbers *small*, *large* or *zero*. The currently used partial balance degrees have as imprecise characteristics the linguistic values *good* and *unsatisfactory* (*unsatisfactory* value, in this case, is similar, in fuzzy number, to the one associated with the linguistic value *unsatisfactory* of the global balance degree). It was also useful to introduce knowledge in the form of imprecise facts of type $(X1 \ X2 \ X3 \ X4 \ ?v_q)$, $(X1 \ X2 \ X4 \ ?v_q)$, $(X3 \ X4 \ X5 \ X6 \ ?v_q)$, $(X1 \ X3 \ X4 \ X5 \ X6 \ ?v_q)$, $(X2 \ X4 \ X5 \ X6 \ ?v_q)$, ensuring that the balancing is continuously accomplished, partially and gradually, and a number of *meta-rules* in which these facts are present. They will be activated chained, as (R13, R14) (R13, R15) (R16, R17) (R16, R24) (R18, R19) (R18, R25) (R20, R21) (R22, R23)) and support the synthesis of fuzzy decision. We may notice that, for this control model, we followed the stages for the synthesis of a linguistic model, in terms of knowledge acquisition process [27], and the knowledge and meta-knowledge are represented according to KMSFLE formalism.

Exploiting this model requires calculating the fuzzy unification and the partial conclusion inferred through the GMP scheme, the call of procedures in rules' consequent and of a control module, dynamically updating the priorities of the rules according to the current imprecision of all knowledge involved at some point in the decision synthesis, chaining the fuzzy meta-rules and demonstrating the global asymptotically stable behavior of the closed-loop system [19,25]. Intermediate fuzzy variables $pbd_1, pbd_2, pbd_3, pbd_4$ and pbd_5 are degrees of partial balance between groups of subsystems (1, 2, 3, 4), (1, 2, 4), (3, 4, 5, 6), (1, 3, 4, 5, 6) and (2, 4, 5, 6). These variables were used to eliminate the unbalance situations obtained in the crisp case, these being the control meta-knowledge of the expert in the field. They depend essentially on the structure of flexible manufacturing system and are actually imprecise knowledge used in decision synthesis. For each inference cycle it must calculate all the corresponding fuzzy values and generate the updated facts, thus, the current state of the control system.

The fuzzy control model has the following properties: *i*) variable pbd_1 appears in rules 14 and 15, and its value is recalculated after the pattern-matching between its current fuzzy value and the motive $(pbd_1 * b)$ by applying the GMP inference scheme. The same calculation method is applied to other partial balance degrees; *ii*) for meta-rules 14, 16, 18, 20 and 22 fuzzy unification is applied differently, requiring the calculation of the resulting fuzzy value for the variable $?v_q$ from the consequent; *iii*) variable $?v_q$, together with variables $pbd_1, pbd_2, pbd_3, pbd_4$ and pbd_5 , allow chaining the fuzzy rules while the control model is used by the KMSFL inference engine; *iv*) within the structure

of meta-rules 13-25 are present fuzzy variables $d_{56}, d_{35}, d_{13}, d_{21}, d_{43}, d_{42}$, representing the fuzzy instant differences between machine loads, referenced by the corresponding indexes, in the appropriate order. The values of these variables are fuzzy numbers $tp * ma(2 \text{ pbd}_j \ 1 \ 1)$, $j=1 \dots 5$ and $tp * mi(0 \ 1 \ 0 \ 1)$. Fuzzy value $*b$ is generated similarly. To clarify how the fuzzy model for flexible production system is initialized and exploited, follow the *KMSFLE algorithm*, in which are also presented some functional aspects of the control intelligent system.

This algorithm associated with the inference subsystem within the KMSFL was developed in close relation with fuzzy knowledge representation formalism. In addition, we tested the knowledge model using the generator G2 (only for the crisp case) to highlight some of the advantages and limitations of the knowledge management model and of the inference engine. However, fuzzy processing is specific to the intelligent developed system, this being our major objective.

KMSFLE Algorithm

- 1) Enter the initial fuzzy loads $\mu_{x_{i_0}}$;
- 2) Calculate the expected average value $\mu_{c_0} = \frac{\sum_{i=1}^6 x_{i_0}}{6}$, the fuzzy distances $\mu_{d_{i_0}} = \mu_{x_{i_0}} - \mu_{c_0}$ and the initial balance degree $bd_0 = \max_{i=1, \dots, 6} \{\mu_{d_{i_0}}\}$;
- 3) Generate sets $*s$ (the characteristics of fuzzy sets $*s$ are checked in tests, in relation to the initial loads), $*n = tp(3 \text{ bd}_0 \ 2 \ 2)$ (d and δ are checked in tests in relation to the initial loads) and the facts $(bd * n)$ and $(bd * s)$;
- 4) Initialize $x^b = (x^{b1}, x^{b2})$ where $x^{b1} = \mathbf{0}$ and $\dim(x^{b1}) = 12$, x^{b2} contains the initial facts attached to all linguistic variables involved in the control model, such as: $((X1 \ ?x), (X2 \ ?y), (X3 \ ?z), (X4 \ ?v), (X5 \ ?w), (X6 \ ?\xi), (X1 \ X2 \ X3 \ X4 \ ?v_q), (X1 \ X2 \ X4 \ ?v_q), (X3 \ X4 \ X5 \ X6 \ ?v_q), (X1 \ X3 \ X4 \ X5 \ X6 \ ?v_q), (X2 \ X4 \ X5 \ X6 \ ?v_q), (X1 \ X2 \ X4 \ ?v_q), (X12b \ 1), (bd * n), (CFS * zero), (pbd_1 * b), (d_{56} * ma), (d_{35} * ma), (pbd_2 * b), (d_{13} * ma), (pbd_3 * b), (d_{21} * ma), (pbd_4 * b), (d_{42} * ma), (pbd_5 * b), (d_{43} * ma)$, to evaluate the effect of all fuzzy variables that appear in structure of this state component of KMSFLE. As initial fact attached to the reason $(bd * n)$, is launched the fact $(bd * v_0)$, where $*v_0$ is generated as a fuzzy set around the value of bd_0 , of the form $(constfaz * v_0(tp \ bd_0 - 1 \ bd_0 + 1 \ 2 \ 2))$. Is also initialized $x^{int} = \mathbf{0}$.
- 5) In the consequent of rules R1-R10, along with the deduction of fact $(xib \ i)$, corresponding to a procedure call, is attached the calculation of the balance degree bd with its new fuzzy value, i.e. is generated the new fact $(bd * v_k)$, $k \geq 1$. Value $*v_k$ can filter or not $*n$ or $*s$, and properly the fuzzy values of partial balance degrees and the fuzzy distances between the physically interconnected subsystems;
- 6) If the inference engine stops on a different event than on the one corresponding to the activation and execution of rule 11, then are recalculated the fuzzy differences $\mu_{d_{i_k}} = \mu_{x_{i_k}} - \mu_{c_0}$, along with determining the subsystem ($i = 1, \dots, 6$) and the corresponding rule j ($j = 1, \dots, 25$) to be activated, to satisfy the balancing goal at the current time, by using meta-rules (R13-R25) or by launching the *control module*.

For each inference cycle must calculate all the corresponding fuzzy values, and generate the updated facts and thus the current state of the control system.

Implementation results for KMSFLE

Test A. This test aims to prove the functioning of the KMSFLE prototype for a first set of knowledge. Fuzzy values involved in testing the control model by using the corresponding inference engine are: $(constfaz * s(tp \ 0 \ 1 \ 0 \ 1))$, $(constfaz * n(tp \ 2 \ \infty \ 1 \ 1))$, $(constfaz * ma(tp \ 2 \ \infty \ 1 \ 1))$, $(constfaz * mi(tp \ 0 \ 1 \ 0 \ 1))$, $(constfaz * b(tp \ 0 \ 1 \ 0 \ 1))$, $\epsilon=1$, $\eta=0$, $\mu_{x_1} = \mu_{x_2} = \mu_{x_3} = (199.5 \ 200.5 \ 1 \ 1)$, $\mu_{x_4} = \mu_{x_5} = \mu_{x_6} = (-0.5 \ 0.5 \ 1 \ 1)$, "around x_0 " $= (x_0 - 0.5 \ x_0 + 0.5 \ x_0 - 1.5 \ x_0 + 1.5) = "x_0"$, $x^{b1} = \mathbf{0}$.

We get the following results: the first complete execution of the inference engine implies a number of 118 inferences and the values of subsystems' loads and of the global balance degree are: $\mu_{x_1} = "101.33" = (100.83 \ 101.83 \ 0.5 \ 0.5)$, $\mu_{x_2} = "102.60" = (101.56 \ 102.56 \ 0.5 \ 0.5)$, $\mu_{x_3} = "101.33" = (100.83 \ 101.83 \ 0.5 \ 0.5)$, $\mu_{x_4} = "102.04" = (101.54 \ 102.54 \ 0.5 \ 0.5)$, $\mu_{x_5} = "100.61" = (100.11 \ 101.11 \ 0.5 \ 0.5)$, $\mu_{x_6} = "92.627" = (92.127 \ 93.127 \ 0.5 \ 0.5)$, $bd = (6.87 \ 7.87 \ 0.5 \ 0.5)$. In this case, the balance degree $bd = "7.3731"$ is an unsatisfactory value, which means that the balancing problem is not completely solved. For inferences 42, 43, 54, 55, 58, 59, 70, 71, 82, 83, 86, 87, 95, 96, 100, 101, 103, 104, 105, 106

are activated meta-rules 16, 17, 13, 14, 13, 15, 16, 17, 13, 14.13, 15, 16, 17, 16, 17, 13, 14, 13, 15 respectively, the rest of the inferences activating the basic rules R1-R10.

After resetting the inference engine with the values previously obtained, we get a total of 18 inferences, whose result is presented in Table 1 (SC=Set of Conflicts, ER=Executed rule):

No.	μ_{x1}	μ_{x2}	μ_{x3}	μ_{x4}	μ_{x5}	μ_{x6}	x_{b1}	x^{b1}	SC _k	ER	Event	bd
0	101.33	102.01	101.33	102.00	100.61	92.627	0	000000000000	7	7	e ₄₃	7.3575
1	101.33	102.01	101.67	101.67	100.61	92.627	7	000000100000	4	4	e ₃₅	7.3575
2	101.33	102.01	101.14	101.67	101.14	92.627	4	000100100000	8	8	e ₅₆	7.3575
3	101.33	102.01	101.14	101.67	96.883	96.883	8	000000110000	4	4	e ₃₅	3.1018
4	101.33	102.01	99.011	101.67	99.011	96.883	4	000100100000	2	2	e ₁₃	3.1018
5	100.17	102.01	100.17	101.67	99.011	96.883	2	010100100000	3	3	e ₂₁	3.1018
6	101.09	101.09	100.17	101.67	99.011	96.883	3	001000100000	13	13		3.1018
7	101.09	101.09	100.17	101.67	99.011	96.883	3	001000100000	13,14	14	[e ₅₆]	3.1018
8	101.09	101.09	100.17	101.67	97.947	97.947	8	000000110000	13	13		2.0378
9	101.09	101.09	100.17	101.67	97.947	97.947	8	000000110000	13,15	15	[e ₃₅]	2.0378
10	101.09	101.09	99.058	101.67	99.058	97.947	4	000100100000	2	2	e ₁₃	2.0378
11	100.07	101.09	100.07	101.67	99.058	97.947	2	010100100000	3	3	e ₂₁	2.0378
12	100.58	100.58	100.07	101.67	99.058	97.947	3	001000100000	6	6	e ₄₂	2.0378
13	100.58	101.12	100.07	101.12	99.058	97.947	6	000001000000	7	7	e ₄₃	2.0378
14	100.58	101.12	100.60	100.60	99.058	97.947	7	000000100000	4	4	e ₃₅	2.0378
15	100.58	101.12	99.829	100.60	99.829	97.947	4	000100100000	13	13		2.0378
16	100.58	101.12	99.829	100.60	99.829	97.947	4	000100100000	13,14	14	[e ₅₆]	2.0378
17	100.58	101.12	99.829	100.60	98.888	98.888	8	000000110000		0	e _{≠e₀₀}	1.1394

Table 1. Inference process results for test A

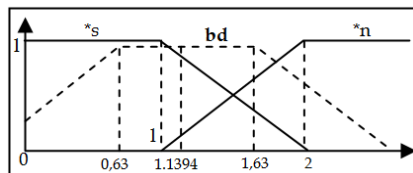


Figure 2. The fuzzy final balance degree

We notice that, at the end of inference engine execution, in accordance with the reset, the balance degree is $bd = "1.1394"$, which corresponds to linguistic value *satisfactory* (figure 2) because $\Pi(*s, "bd") = 1$ and $N(*s, "bd") = 0.246 > 0$. The balance degree is satisfactory but the fuzzy differences between the final values of subsystems' loads and the expected average value are not similar (i.e. they are not all around zero). This is proved by the inference engine stop after the execution of meta-rule 14 (after which it cannot infer anything) and not of rule 11, as is conceived the control model. This is due to improper choice of the fuzzy set for the linguistic value *unsatisfactory*.

Test B. The purpose of this test is to highlight that, for other initial subsystems' loads, the control model achieves its intended objective, in terms of balance degree (which must be satisfactory at the end of the execution), and that the final loads are similar to the expected average value, given by $\mu_{\bar{x}} = (constfz * \mu_{\bar{x}} (tp \ 32.83 \ 33.83 \ 1 \ 1))$, according to the similarity criteria adopted within the KMSFL. In this case $\mu_{x_1} = "200"$, $\mu_{x_2} = \dots = \mu_{x_6} = "0"$, $x^{b1} = 0$, and the other fuzzy values of the knowledge model are initialized and are similar to those in the test A. After the first execution, the inference engine performs 67 inferences and the values of fuzzy loads are: $\mu_{x_1} = "33.419"$, $\mu_{x_2} = "34.289"$, $\mu_{x_3} = "33.419"$, $\mu_{x_4} = "34.961"$, $\mu_{x_5} = "32.55"$, $\mu_{x_6} = "31.361"$. The last rule activated is meta-rule 13, and the balance degree at this stage is $bd = "1.9725"$. It is noted that the balance degree is satisfactory ($\Pi(*s, "0.967") = 1$ and $N(*s, "0.967") = 0.266 > 0$), the fuzzy differences between the final loads and the expected average value are approximately zero, but the loads of the subsystems analyzed in pairs, according to the reasons within antecedent of rule 11, are not all similar to each other, because the execution does not end with rule

11. The observation above is based on the following calculations: for $\mu_{\bar{x}} = (32.83 \ 33.83 \ 1 \ 1)$, $\mu_{x_1} = (32.919 \ 33.919 \ 1 \ 1)$, $\mu_{x_2} = (33.789 \ 34.789 \ 1 \ 1)$, $\mu_{x_3} = (32.87 \ 33.87 \ 1 \ 1)$, $\mu_{x_4} = (33.69 \ 34.69 \ 1 \ 1)$, $\mu_{x_5} = \mu_{x_6} = (31.865 \ 32.865 \ 1 \ 1)$ we get respectively the following pairs: $\Pi(\mu_{x_1}, \mu_{\bar{x}}) = 1$, $N(\mu_{x_1}, \mu_{\bar{x}}) = 0.455$, $\Pi(\mu_{x_2}, \mu_{\bar{x}}) = 1$, $N(\mu_{x_2}, \mu_{\bar{x}}) = 0.02$, $\Pi(\mu_{x_3}, \mu_{\bar{x}}) = 1$, $N(\mu_{x_3}, \mu_{\bar{x}}) = 0.48$, $\Pi(\mu_{x_4}, \mu_{\bar{x}}) = 1$, $N(\mu_{x_4}, \mu_{\bar{x}}) = 0.07$, $\Pi(\mu_{x_5}, \mu_{\bar{x}}) = 1$, $N(\mu_{x_5}, \mu_{\bar{x}}) = 0.01$ that satisfy the condition of similarity between any of the final states of the loads and the expected average value.

Test C. This test emphasizes the *dynamic circularity* [28]. All subsystems are loaded with fuzzy values different from "0", and the characteristics of the associated fuzzy numbers are closer to the case of natural perception, i.e. have been increased the cores and the imprecision areas of fuzzy values, as follows: $*s = *b = *mi = (-1 \ 1 \ 2 \ 2)$, $*n = *ma = (3 \ \infty \ 3 \ 3)$, "around x_0 " = $(x_0 - 1 \ x_0 + 1 \ x_0 - 3 \ x_0 + 3)$, $\epsilon = 1$, $\eta = 0$, $\mu_{x_1} = (1222 \ 1224 \ 2 \ 2) = "1223"$, $\mu_{x_2} = (309 \ 311 \ 2 \ 2) = "310"$, $\mu_{x_3} = (444 \ 446 \ 2 \ 2) = "445"$, $\mu_{x_5} = (37 \ 39 \ 2 \ 2) = "38"$, $\mu_{x_6} = (741 \ 743 \ 2 \ 2) = "742"$, $x^{b1} = 0$. We may notice the intensive use of meta-rules in the second part of the execution and the correct ending of the balancing problem, in terms of final state. The expected average fuzzy value is $\mu_{\bar{x}} = "610.8(3)"$. After the first execution of the inference engine of KMSFLE, starting from inference 39, the system goes in a cyclical operation (dynamic circularity), since all inferences starting from inference 40 do not change the KMSFLE state so that to achieve the intended objective correctly. This is justified by the value of $bd = "3.7213"$, with $\Pi(*n, "3.7213") = 1$ and $N(*n, "3.7213") = 0.54426$. In this example is not activated the control module from rule 12 consequent, whose purpose is to eliminate the cycles from inference engine operation. To solve this problem, which is not allowed in the operation of an expert system, in the next we will highlight the behavior of inference engine when activating the control module. Solving the above listed deficiencies is founded on resetting the inference engine operation, based on user inputs UI, in order to achieve the goal. Reset is done by positioning the vector $x^{b1} = 0$, the subsystems' loads and the other fuzzy values being equal to the last values previously used. After the reset, are used the meta-rules from the structure of knowledge management model to achieve the goal state. We get the following final fuzzy values of subsystems' loads: $\mu_{x_1} = (609.87 \ 611.87 \ 2 \ 2)$, $\mu_{x_2} = (611.76 \ 613.76 \ 2 \ 2)$, $\mu_{x_3} = (609.34 \ 611.34 \ 2 \ 2)$, $\mu_{x_4} = (611.71 \ 613.71 \ 2 \ 2)$, $\mu_{x_5} = \mu_{x_6} = (608.16 \ 610.16 \ 2 \ 2)$. The final balance degree is satisfactory because $\Pi((-1 \ 1 \ 2 \ 2), (0.9311 \ 2.9311 \ 2 \ 2)) = 1$ and $N((-1 \ 1 \ 2 \ 2), (0.9311 \ 2.9311 \ 2 \ 2)) = 0.017225 > 0$. Final loads above are similar to each other because: $\Pi(\mu_{x_1}, \mu_{x_2}) = 1$, $N(\mu_{x_1}, \mu_{x_2}) = 0.275 > 0$, $\theta(\mu_{x_1}, \mu_{x_2}) = 0.945$, $K(\mu_{x_1}, \mu_{x_2}) = 0.055$, $\Pi(\mu_{x_1}, \mu_{x_3}) = 1$, $N(\mu_{x_1}, \mu_{x_3}) = 0.367 > 0$, $\theta(\mu_{x_1}, \mu_{x_3}) = 0.265$, $K(\mu_{x_1}, \mu_{x_3}) = 0.75$, $\Pi(\mu_{x_1}, \mu_{x_4}) = 1$, $N(\mu_{x_1}, \mu_{x_4}) = 0.04 > 0$, $\theta(\mu_{x_1}, \mu_{x_4}) = 0.92$, $K(\mu_{x_1}, \mu_{x_4}) = 0.145$, $\Pi(\mu_{x_1}, \mu_{x_5}) = \Pi(\mu_{x_1}, \mu_{x_6}) = 1$, $N(\mu_{x_1}, \mu_{x_5}) = N(\mu_{x_1}, \mu_{x_6}) = 0.725 > 0$, $\theta(\mu_{x_1}, \mu_{x_5}) = \theta(\mu_{x_1}, \mu_{x_6}) = 0.855$, $K(\mu_{x_1}, \mu_{x_5}) = K(\mu_{x_1}, \mu_{x_6}) = 0.145$.

It is noted that all criteria regarding the correct stop off the inference engine are met, thus obtaining the solution, whose value must be calculated through unification according to rule 11 antecedent. Thus, is revealed the inference engine behavior in order to avoid dynamic circularity presented in this example. The KMSFLE can effectively predict a number of states that characterize the process, for a finite time horizon, as a result of its own inferences and of its knowledge management model.

4. Conclusions and future work

The importance of this paper consists of demonstrating the possibility of employing an expert KMS in problems of process control and planning, using imprecise knowledge. It was necessary to continuously adapt known models (e.g. theory of possibilities, discrete event systems) to synthesize a control structure based on fuzzy knowledge. We also tried to conceptually develop a multi-agent real control structure, which is a solution to meet a series of demands on the complexity of the control process. Such systems, especially those based on communication between agents by sharing memory, bring up features well suited for real-time applications, such as: integration of heterogeneous agents, interaction between activities of acquisition, reasoning and action on the external environment, fusion of data coming from sensors of different nature and operation, flexibility and efficiency in the integration of new data needed for reasoning, by simply writing them in the common memory. Real-time applications require the cooperation of elaborate reasoning processes. The essential point in integrating the cognitive/reactive aspects is the modeling of the relations between the process evolution and certain inferential methods, to allow the closed-loop system to achieve a range of required performances. Temporal aspects are an important dimension of any KMS embedded in the new semantic technologies. There is a distinction between real-time reasoning and reasoning over

time, the latter being a feature of the knowledge-based systems. For this reason, it was absolutely necessary to explain the significance of time in the design and implementation of KMSFLE, emphasizing its implications in the specific case of the developed application. Following the tests presented and the knowledge representation and exploitation structures within KMSFLE, we may outline the following conclusions:

i) the formalism chosen for knowledge representation is strong enough to support the representation of some types of knowledge underlying the synthesis of control decisions. It has the advantage of factorizing the knowledge, which substantially reduced the size of fuzzy rules base [9]. Also, this knowledge representation method is more appropriate to express some types of knowledge similar to those commonly used in the decision synthesis through natural language;

ii) the knowledge fuzzy model for the problem presented was developed incrementally, as was embedded in the model sufficient domain knowledge, resulting from the limitations observed in the crisp case. Is it possible to constantly adapt the fuzzy model through hard simulations;

iii) an inferential subsystem based on fuzzy logic solves the control situations correctly, both from the computational point of view and in terms of the semantics of the conclusions inferred through the chosen inference scheme;

iv) modelling the process and the expert system as systems with logical events allowed the qualitative analysis of KMSFLE;

v) the control module integrated into the inferential subsystem automatically adapts the problem-solving process, being equivalent to closed-loop system input, denoted UI (user input). In this way, through the control meta-rule 12, we can simulate practically the activation of the relation between output Hypotheses/Conclusions and user inputs. This component is not activated in every case (initial loads). This justifies a major feature of the designed control expert system: its ability to correctly solve the problem, under the conditions specified for each case;

vi) The case when $c_k \in \mathbf{N}^+$ is not a particular case for $\mu_{ck} \in \mathbf{R}^+$ due to certain restrictions on the events trajectories and to system's lack of flexibility in achieving the balance, thus leading to partial balance. For the discrete case, there is a tolerated unbalance value, denoted ψ and for which $|x_i - x_j| \leq \psi$, which defines the invariant set. For the fuzzy case, is achieved a good balancing solution, regardless of the initial subsystems' loads. In this case the system is broadly asymptotically stable relative to event trajectories.

We also summarize possible further development, which inherently can be obtained starting from KMSFLE: identifying stronger planning characteristics, the logical specification of the real-time systems so that to describe how the statements change their truth values, depending on time or in order to meet some strong real-time restrictions, knowledge acquisition, as well as the correct choice of the inference operators that lead to consistent results with regard to the well-defined knowledge semantics, integrating a control expert system like the one developed (agent) into a multi-agent system structure, identifying real problems in different application areas that can be solved using the expert system developed.

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