The place of fuzzy logic in AI

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Abstract: Fuzzy logic is more than thirty years old and has a long-lasting misunderstanding with Artificial Intelligence (A.I.), although the formalization of some forms of commonsense reasoning has motivated the development of fuzzy logic. What fuzzy sets typically brings to AI is a mathematical framework for capturing gradedness in reasoning devices. Moveover gradedness can take various forms: similarity between propositions, levels of uncertainty, and degrees of preference. The paper provides a brief survey of the fuzzy set contribution to the modelling of various types of commonsense reasoning, and advocates the complementarity of fuzzy set methods, and more generally of soft computing techniques, with symbolic A.I.

1 Introduction

To-date, the term "fuzzy logic" often refers to a particular control engineering methodology, that exploits a numerical representation of commonsense control rules, in order to synthetize, via interpolation, a control law. This approach has many common features with neural networks. It is now mainly concerned with the efficient encoding and approximation of numerical functions, and has currently less and less relationships to knowledge representation issues. This is however a very narrow view of fuzzy logic that has little to do with AI. Scanning the fuzzy set literature, one realizes that fuzzy logic may also refer to two other AI-related topics: multiple-valued logics, and approximate reasoning. While the multiple-valued logic stream is very mathematically oriented, the notion of approximate reasoning as imagined by Zadeh is much more related to the mainstream program of AI research: he wrote in 1979 that "the theory of approximate reasoning is concerned with the deduction of possibly imprecise conclusions from a set of imprecise premises". In the following, we shall use the term "fuzzy logic" to refer to any kind of fuzzy set-based method intended to be used in reasoning machineries.

Fuzzy logic methods have not been considered as belonging to mainstream AI tools until now, although an important part of fuzzy logic research concentrates on approximate reasoning and reasoning under uncertainty issues (e.g., Ralescu, 1994; Martin and Ralescu, 1997). Some reasons for this situation may be found in the antagonism which had existed for a long time between purely symbolic methods advocated by AI and numerically-oriented approaches that were involved in fuzzy rule-based systems. Besides, fuzzy sets were a new emerging approach not yet firmly settled, but apparently challenging the monopoly of probability theory as being the unique proper framework for handling uncertainty. In spite of the fact that fuzzy sets have received a better recognition recently, there still exists a lack of appreciation of what fuzzy logic really is by AI researchers, as for instance recently exemplified by Elkan (1994).

In the mid-seventies, at a time when MYCIN was becoming a landmark among rule-based expert systems dealing with uncertainty, the first fuzzy rule-based system was designed by Mamdani's group at Queen Mary College in London following an idea suggested by Zadeh shortly before. This system is the direct ancestor of the most of the fuzzy control systems which have become so largely used in the early nineties. What is at work in rule-based fuzzy control is a simple device for interpolating between numerically-valued conclusions of parallel rules. This interpolation is made on the basis of degrees of matching of the current situation with respect to the fuzzy condition parts of the rules. These degrees estimate the similarity between the current situation and prototypical values which constitute the core of the fuzzy sets describing the firing conditions of the rules. Such coefficients obtained through a matching procedure were quite different from the certainty factors attached to facts and rules in MYCIN-like expert system. However, AI expert systems and fuzzy rule-based controllers did share the idea that the rules were encoding expert knowledge. This view has more or less disappeared in the recent neuro-fuzzy based methods where fuzzy rules are just a convenient format for synthesizing control laws from sets of inputs/outputs pairs and thus for approximating functions and tuning them locally. Then the knowledge representation and approximate reasoning aspects are no longer the main features of the approach in its present development. However, the basic notions of similarity and interpolation might be useful in other, more AI-oriented, applications such as case-based reasoning, for retrieving cases and extrapolating from them by means of gradual rules of the type "the more x is A, the more y is B" (Dubois and Prade, 1996a). Similarity reasoning should encode commonsense inferences of the form if "p is close to p' ", and "p implies q" then "q is not far from being true". Fuzzy set theory is a natural framework for modelling such inference patterns.

Apart from similarity, two other basic semantics can be addressed by fuzzy set-based methods, namely uncertainty and preference: uncertainty pervading available information in reasoning problems, preference among more or less acceptable values in a decision-oriented perspective (Dubois and Prade, 1997). Possibility theory (Zadeh, 1978) offers a framework for dealing with uncertainty when the available information is no longer precise and certain, but represented by means of fuzzy sets. Using fuzzy sets, uncertainty is estimated by means of two dual measures of possibility and necessity. This framework has merits for the representation of states of partial or total ignorance. Another interesting feature of possibility theory is that it only requires purely ordinal scales for the assessing of uncertainty. It provides a very qualitative approach and facilitates the elicitation of the uncertainty levels. Based on possibility theory, a possibilistic logic (which should not be confused with the fully compositional calculus of fuzzy set membership degrees) has been developed, both at the syntactic and semantic level. In this logic, classical logic formulas are associated with lower bounds of necessity measures expressing the level of certainty, or equivalently of epistemic entrenchment of the formulas. It has been established that rational nonmonotonic inference relation (in the sense of Lehmann) can be represented in possibilistic logic, where a default rule "if p then q generally" is understood as the constraint that the possibility measure of "p and q" is strictly greater than the possibility of "p and not q". Connections with other approaches to nonmonotonic reasoning including the one based on infinitesimal probabilities have been laid bare. Possibilistic logic is a genuine extension of classical logic that encodes an uncertainty calculus. Possibilistic assumption-based truth maintenance systems provides simple implementations of nonmonotonic reasoning. Possibilistic logic can be used as well for reasoning from multiple sources of information having different reliability levels. The corresponding data fusion tools have been developed.

When fuzzy sets model preference among values according to flexible constraints, rather than imprecise and uncertain information, possibility theory offers a natural framework for extending the constraint satisfaction problem paradigm to soft and prioritized constraints. Scheduling provides a good example of application of these techniques where, for instance, due dates are often somewhat elastic. Moreover, some parameters like the duration of operations (which are not under our control) may be pervaded with uncertainty. In this situation a trade-off has to be achieved between a high level of satisfaction of constraints and the necessity to cope with unlikely but potentially dangerous states of the world. Possibility theory can be used as the basis for a qualitative utility theory (Dubois and Prade, 1995a) that tackles such a decision problem (including computation with ill-known numerical quantities).

Finally, an important feature of fuzzy sets is to provide a framework for interfacing in a non-rigid way classes with numerical values. In classification problems the use of fuzzy classes obviates the need for arbitrarily classifying borderline cases at the beginning of a reasoning stage. Numerical data can be summarized by means of linguistically labelled fuzzy sets, so as to feed a symbolic reasoning machinery. These issues come close to learning, another subfield of AI where this aspect of fuzzy sets might be particularly interesting.

The contents of this paper largely borrow to the ones of three previous articles by the authors (Dubois and Prade, 1995b, 1996b, 1998). See Yager (1995, 1997) for a complementary point of view.

2 Fuzzy logic in commonsense and approximate reasoning

Fuzzy sets offer a powerful tool for the modelling of various kinds of commonsense reasoning, where membership functions are used for expressing graded notions such as uncertainty, preference and similarity, interfere. Such a theory of gradedness is not necessarily numerical, contrary to what many people tend to believe to-date, but can be purely ordinal (lattice-based). Let us review some of them, after a brief recall of some formal background.

2.1 Logical Embeddings

Very different extensions of classical logic that exploit the notion of a fuzzy set have been proposed. Some are truth-functional, while others are not. We may distinguish between:

- *many-valued logics* that were proposed before fuzzy set theory came to light. They are exclusively devoted to the handling of "vague" propositions `p, i.e., propositions which may be partially true (e.g., propositions involving properties whose satisfaction is a matter of degree). The underlying algebraic structure is then weaker than a Boolean algebra. Such logics can handle truth-values t(`p) that lie in the unit interval and remain truth-functional. There are two families of "fuzzy logics that cope with graded truth. A first family relies on residuated lattice-like structures, and their extensions such as MV-algebras. The syntax is based on related conjunction and implication connectives, and deduction is based on modus ponens in the settting of a Hilbert-like axiomatization. See, e.g., (Hajek, 1995) for an introduction and (Novak, 1996) for a discussion. A very different family of fuzzy logics uses only a clausal language based on a De Morgan algebra, typically the (max, min, 1 − .) triple for modeling disjunction, conjunction and negation. This trend, initiated by Lee (1972), has blossomed in the framework of logic programming. There are to-date a lot of such fuzzy programming language proposals (for instance Mukaidono et al., 1989; Li and Liu, 1990).
- *possibilistic logic* that is built on top of classical logic, and where each crisp proposition is attached a lower bound of a degree of necessity N(p) expressing the certainty of p given the available information. N(p) = 1 iff p is surely true and N(p) = 0 expresses the complete lack of certainty that p is true (either p is false when $N(\neg p) = 1$, or it is unknown if p is true or false and then $N(\neg p) = 0$). The degree N(p) is compositional *for conjunction only* $(N(p \wedge q) = \min(N(p),N(q))$, and $N(p \vee q) \geq \max(N(p),N(q))$ generally. For instance, if $q = \neg p$, $p \vee q$ is tautological,hence surely true $(N(p \vee q) = 1)$, but p may be unknown $(N(p) = N(\neg p) = 0)$. Moreover $N(\neg p) = 1 - \Pi(p)$ where $\Pi(p)$ is the degree of possibility of proposition p. Functions N and Π stem from the existence of a fuzzy set of more or less possible worlds, one of which is the actual one. It is described by means of a possibility distribution π on the interpretations of the language, and $N(p) = 1 - \sup \{\pi(\omega), \omega$ $. \neg p\} = 1 - \Pi(\neg p)$, i.e., N(p) is computed as the degree of impossibility of the proposition $\neg p$. A possibilistic logic formula (p,α) understood as $N(p) \geq \alpha$, is represented by a fuzzy set such that interpretations which makes p false have degree $1 - \alpha \geq \Pi(\neg p)$ (i.e., the possibility that p is false is upper bounded by $1 - \alpha$), while the interpretations which makes p true have degree 1. Then, the possibility distribution π representing a set of possibilistic formulas is obtained by the min-conjunction of the fuzzy sets representing the formulas (Dubois, Lang and Prade , 1994).

In possibilistic logic a fuzzy set describes incomplete knowledge about where the actual world is, and a weighted formula has a fuzzy set of models. In many-valued logics, fuzzy sets describe the extensions of vague predicates, and a weighted formula has a crisp extension (corresponding to a level cut). The truth-functionality is not compulsory however when dealing with vagueness. In *similarity logics* it is supposed that the vagueness of predicates stems from a closeness relation (Ruspini, 1991) that equips the set of interpretations of the language. Then a Boolean proposition p is actually understood as a fuzzy proposition `p whose models are *close* to models of p. Let [p] be the set of models of p and R(p) = [p] ô R the fuzzy set of models close (in the sense of fuzzy relation R) to models of p. Then generally, $R(p \wedge q) \subseteq R(p) \cap R(q)$, without equality, so that truth-values are not truth-functional with respect to conjunction.

In classical logic, a proposition p entails another proposition q whenever each situation where p is true is a situation where q is true. Entailment is denoted ., and p . q means $[p] \subseteq [q]$ where [p] is the set of models of p. In possiblitistic logic, the type of inference which is at work is plausible inference. The possibility distribution π on the set of interpretations encodes an ordering relation that ranks possible worlds ω in terms of plausibility. Then p plausibly entails q if and only if q is true in the most plausible situations where p is true, i.e., $\max[p] \subseteq [q]$, where $\max[p] = \{\omega \in [p], \pi(\omega) \text{ maximal}\}$. This type of inference is also called "preferential inference" in nonmonotonic reasoning. In contrast, inference in similarity logics is dual to preferential inference. The set of interpretations of the language is equipped with a similarity relation R. Then p entails approximately q in similarity logic if all the situations where p is true are close to situations where q is true, i.e., $[p] \subseteq \text{support}[R(q)]$. More generally, a degree of strength of the entailment can be computed as $I(q \mid p) = \inf_{\omega \in [p]} \sup_{\omega' \in [q]} \mu_R(\omega, \omega')$. It plays in similarity logic the same role as a degree of confirmation in inductive logic. In possibilistic logic the counterpart of $I(q \mid p)$ is the conditional necessity $N(q \mid p)$ computed from π, i.e., $N(q \mid p) = N(\neg p \vee q) > 0$ if $\Pi(q \wedge p) > \Pi(\neg q \wedge p)$, and $N(q \mid p) = 0$ otherwise.

These newly emerged notions of fuzzy set-based inference certainly deserve further developments, and lead to very different types of logic. Of interest is the study of their links to the usual entailment principle of Zadeh (defined as a fuzzy set inclusion), and various extensions of consequence relations in multiple-valued logic, as studied by Chakraborty (1988), Castro et al. (1994).

2.2 Fuzzy deductive inference

This type of approximate reasoning has been advocated by Zadeh in the mid-seventies, as a calculus of fuzzy restrictions (Zadeh, 1979; Dubois and Prade, 1991). The principles of this approach rely on the conjunctive combination of possibility distributions and their projection on suitable subspaces. A particular case of the combination/projection procedure, named "generalized modus ponens", has been emphasized, where from a fact of the form "X is A' " and a rule "if X is A then Y is B" (where X and Y are variables, A', A and B are fuzzy sets), a conclusion Y is B' is computed. The generalized modus ponens can be also understood in terms of fuzzy truth-values (Zadeh, 1979; Baldwin, 1979), where the truth-value of a proposition "X is A" is viewed as its compatibility with respect to what is actually known, say, "X is A' " (this compatibility is computed as the fuzzy set of possible values of the membership $\mu_A(u)$ when the fuzzy range of u is A').This conjunction/projection method is at work in the POSSINFER system of Kruse et al. (1994). This type of inference is also a generalization of constraint propagation to flexible constraints, provided that one interprets each statement as a requirement that some controllable variable must satisfy. Then the possibility distributions model preference, and inference come down to consistency analysis (such as arc-consistency, path-consistency, etc.) in the terminology of constraint-directed reasoning. The advantage of fuzzy deductive inference is to directly account for flexible constraints and prioritized constraints, where the priorities are modelled by means of necessity functions (see Dubois, Fargier and Prade, 1994).

2.3 Reasoning under uncertainty and inconsistency

A possibilistic knowledge base K is a set of pairs (p, s) where p is a classical logic formula and s is a lower bound of a degree of necessity ($N(p) \geq s$). It can be viewed as a stratified deductive data base where the higher s, the safer the piece of knowledge p. Reasoning from K means using the safest part of K to make inference, whenever possible. Denoting $K_\alpha = \{p, (p,s) \in K, s \geq \alpha\}$, the entailment K ; (p,α) means that K_α ; p. K can be inconsistent and its inconsistency degree is $inc(K) = \sup\{\alpha, K ; (\perp,\alpha)\}$ where $\perp$ denotes the contradiction. In contrast with classical logic, inference in the presence of inconsistency becomes non-trivial. This is the case when K ; (p,α) where $\alpha > inc(K)$. Then it means that p follows from a consistent and safe part of K (at least at level α). This kind of syntactic non-trivial inference is sound and complete with respect to the above defined preferential entailment. Moreover adding p to K and nontrivially entailing q from $K \cup \{p\}$ corresponds to revising K upon learning p, and having q as a consequence of the revised knowledge base. This notion of revision is exactly the one studied by Gärdenfors (1988) at the axiomatic level.

2.4 Nonmonotonic plausible inference using generic knowledge

Possibilistic logic does not allow for a direct encoding of pieces of generic knowledge such as "birds fly". However, it provides a target language in which plausible inference from generic knowledge can be achieved in the face of incomplete evidence. In possibility theory "p generally entails q" is understood as "$p \wedge q$ is a more plausible situation than $p \wedge \neg q$". It defines a constraintof the form $\Pi(p \wedge q) > \Pi(p \wedge \neg q)$ that restricts a set of possibility distributions. Given a set S of generic knowledge statements of the form "p_i generally entails q_i", a possibilistic base can be computed as follows. For each interpretation ω of the language, the maximal possibility degree $\pi(\omega)$ is computed, that obeys the set of contraints in S. This is done by virtue of the principle of minimal specificity (or commitment) that assumes each situation as a possible one insofar as it has not been ruled out. Then each generic statement is turned into a material implication $\neg p_i \vee q_i$, to which $N(\neg p_i \vee q_i)$ isattached. It comes down, as shown in Benferhat et al. (1992) to rank-order the generic rules giving priority to the most specific ones, as done in Pearl (1990)'s system Z. A very important property of this approach is that it is exception-tolerant. It offers a convenient framework for implementing a basic form of nonmonotonic system called "rational closure" (Lehmann and Magidor, 1992), and addresses a basic problem in the expert system literature, that is, handling exceptions in uncertain rules.

2.5 Hypothetical reasoning

The idea is to cope with incomplete information by explicitly handling assumptions under which conclusions can be derived. To this end some literals in the language are distinguished as being asssumptions. Possibilistic logic offers a tool for reasoning with assumptions. It is based on the fact that in possibilistic logic a clause $(\neg h \vee q, \alpha)$ is semantically equivalent to the formula with a symbolic weight $(q, \min(\alpha, t(h))$ where t(h) is the (possibly unknown) truth value of h. The set of environments in which a proposition p is true can thus be calculated by putting all assumptions in the weight slots, carrying out possibilistic inference so as to derive p. The subsets of assumptions under which p is true with more or less certainty can be retrieved from the weight attached to p. This technique can be used to detect minimal inconsistent subsets of a propositional knowledge base (see Benferhat et al., 1994).

2.6 Interpolative Reasoning

This type of reasoning is at work in fuzzy control applications, albeit without clear logical foundations. Klawonn and Kruse (1993) have shown that a set of fuzzy rules can be viewed as a set of crisp rules along with a set of similarity relations. Moreover an interpolation-dedicated fuzzy rule 'if is A then Y is B" can be understood as "the more x is A the more Y is B" and the corresponding inference means that if X = x and $\alpha = \mu_A(x)$ then Y lies in the level cut B_α. When two rules are at work, such that $\alpha_1 = \mu_{A_1}(x)$, $\alpha_2 = \mu_{A_2}(x)$, then the conclusion $Y \in (B_1)_{\alpha_1} \cap (B_2)_{\alpha_2}$ lies between the cores of B_1 and B_2, i.e., on ordered universes, an interpolation effect is obtained. It can be proved that Sugeno's fuzzy reasoning method for control can be cast in this framework (Dubois, Grabisch, Prade, 1994). More generally interpolation is clearly a kind of reasoning based on similarity (rather than uncertainty) and it should be related to current research on similarity logics (Dubois et al., 1997). More generally similarity relations and fuzzy interpolation methods should impact on current research in case-based reasoning.

2.7 Abductive reasoning

Abductive reasoning is viewed as the task of retrieving plausible explanations of available observations on the basis of causal knowledge. In fuzzy set theory causal knowledge has often been represented by means of fuzzy relations relating a set of causes C to a set of observations S. However the problem of the semantics of this relation has often been overlooked. $\mu_R(c,s)$ may be viewed either as a degree of intensity or a degree of uncertainty. Namely, when observations are not binary, $\mu_R(c,s)$ can be understood as the intensity of presence of observed symptom s when the cause c is present. This is the traditional view in fuzzy set theory. It leads to Sanchez (1977) approach to abduction, based on fuzzy relational equations. Another view has been recently proposed by the authors, where by $\mu_R(c,s)$ is understood as the degree of certainty that a binary symptom s is present when c is present. A dual causal matrix R' must be used where $\mu_{R'}(c,s)$ is the degree of certainty that a binary symptom s is absent when c is present. On such a basis the theory of parsimonious covering for causal diagnosis by Peng and Reggia (1990) can be extended to the case of uncertain causal knowledge and incomplete observations. This method is currently applied to satellite failure diagnosis (Cayrac et al., 1994).

3 Soft Computing should not be antagonistic to symbolic AI

Perhaps due to the intermediary, bridging position of fuzzy logic between symbolic and numerical processing, a significant deviation from original motivations and practice of fuzzy logic has been observed in the fuzzy set community in the last five years. Namely, fuzzy rule-based systems are more and more considered as standard, very powerful universal approximators of functions, and less and less as a means of building numerical function from heuristic knowledge, nor of linguistic summarization of data. This trend raises several questions for fuzzy logic. First, if fuzzy logic is to compete alternative methods in approximation theory, it faces a big challenge because approximation theory is a well-established field in which many results exist. Approximate representation of functions should be general enough to capture a large class of functions, should be simple enough (especially the primitive objects, here the fuzzy rules) to achieve efficient computation and economical storage, and should be amenable to capabilities of exploiting data. Are fuzzy rules capable of competing on its own with standard approximation methods on such grounds? the answer is far from clear. On the one hand the universal approximation results for fuzzy rule-based systems presuppose a large number of rules. This is good neither for the economy of representation nor for linguistic relevance. On the other hand the identification between fuzzy rule-based systems with neural nets or variants thereof (radial basis functions and the like, see Mendel, 1995) has created a lot of confusion as to the actual contribution of fuzzy logic. To some extent it is not clear that fuzzy logic-based approximations methods for modeling and control needs fuzzy set theory any longer (Bersini and Bontempi, 1997). Moreover the connection to knowledge representation, part of which relies on the "readability" of fuzzy rules as knowledge chunks, is lost. Actually, from the point of view of approximation capabilities, the good performance of a fuzzy rule-based system seems to be incompatible with the linguistic relevance of the rules. This incompatibility leads systems engineers into cutting off the links between fuzzy logic and Artificial Intelligence, hence with fuzzy set theory itself. This is very surprizing a posteriori since the incompatibility between high precision and linguistic meaningfulness in the description of complex systems behavior is exactly what prompted Zadeh (1973) into introducing fuzzy sets as a tool for exploiting human knowledge in controlling such systems.

It is questionable whether the present trend in fuzzy engineering, that immerses fuzzy logic inside the jungle of function approximation methods will produce path breaking results that puts fuzzy rule-based systems well over already existing tools. It is not clear either that it will accelerate the recognition of fuzzy set theory, since there is a clear trend to keep the name "fuzzy" and forget the contents of the theory.

The reason for this overfocus on fuzzy rules as numerical approximation methods is because control engineers are more concerned with modeling than explaining. Yet, it seems that system engineering practice and soft computing at large can benefit from the readability of fuzzy rule-based systems. Fuzzy rules are easier to modify, they can serve as tools for integrating heuristic, symbolic knowledge about systems, and numerical functions issued from mathematical modeling. Interestingly, the original motivation of fuzzy logic in control engineering (Mamdani and Assilian, 1975) was to represent expert knowledge in a rule-based style and to build a standard control law that faithfully reflects this knowledge. Fuzzy logic control was thus put from the start in the perspective of Artificial Intelligence (Assilian, 1994) because it did not use the classical control engineering paradigm of modeling a physical system and deriving the control law from the model. As such fuzzy logic control is viewed as an application of the approximate reasoning methodology proposed by Zadeh (1973), that exploits formal models of commonsense reasoning. Following this path might have sounded promising, even for control engineers, since they do employ heuristic knowledge in practice, be it when they specify objectives to attain. Supervision also involves a lot of know-how, despite the existing sophisticated control theory, and some interesting works have also been done in fuzzy rule-based tuning of PID controllers. More generally the ranges of applicability of fuzzy controllers and classical control theory are complementary (Verbruggen and Bruijn, 1997). Whenever mathematical modeling is possible, control theory offers a safer approach, although a lot of work is sometimes necessary to bridge the gap with practical problems. Fuzzy logic sounds reasonable when modeling is difficult or costly, but knowledge is available in order to derive fuzzy rules. This philosophy, which has led to successful applications in Europe before fuzzy logic become worldwide popular (for instance the cement kilns controllers of Holmblad and Østergaard (1997)), tends to disappear from the literature of fuzzy control, when one looks at the recent literature.

It must be noticed that while in the beginning of fuzzy control, fuzzy rule-based systems were construed as part of Artificial Intelligence, Artificial Intelligence had rejected fuzzy control as a non-orthodox approach that was not purely symbolic processing. To-date, some fuzzy logic advocates tend to reject symbolic Artificial Intelligence as not capable of dealing with real complex systems analysis tasks. Doing so there is a danger of cutting fuzzy logic from its roots and making fuzzy set theory obsolete as well. Zadeh (1996) himself recently advocated the idea of computing with words as being the ultimate purpose of fuzzy logic and he also insists on the role of fuzzy logic for information granulation (Zadeh, 1997a). In order to achieve this program that repositions fuzzy logic in the perspective of automated explanation tasks, it seems that part of fuzzy logic research should go back to Artificial Intelligence problems, and that fuzzy logic should again serve as a bridge between Systems Engineering and Artificial Intelligence research. Needless to say that in that perspective, control engineers should receive some education in logic, and Artificial Intelligence researchers interested in systems engineering should be aware of control theory. Such a shift in education and concerns would open the road to addressing, in a less ad hoc way, issues in the supervision of complex systems, a problem whose solution requires a blending between knowledge and control engineering, namely computerized tools for automatically explaining the current situation to human operators, and not only tools for approximating real functions, be they non-linear.

4 Conclusion

Reducing soft computing to the simultaneous use of neural nets, genetic algorithms and fuzzy rule-based systems seems to propose a very narrow and heterogeneous view of intelligent computers that may endanger the future of fuzzy set and Artificial Intelligence research. The merits of fuzzy set theory is to offer a bridge between symbolic and numerical processing, while neural nets, as of to-date, fully belong to the numerical processing area, and genetic algorithms are just one among other families of meta-heuristics for combinatorial approximation. What we propose is rather to consider soft computing as a field dedicated to problem-solving methods capable of simultaneously exploiting numerical data and human knowledge, using mathematical modelling and symbolic reasoning systems. A soft computing package is then one that could at the same time learn to solve a problem accurately (such as classification, control, diagnosis and the like) possibly via modeling and optimization techniques, and supply explanations about how it can be solved by moving up to a symbolic level. A fusion of methodologies, why not, but then, of symbolic AI and numerical methods at large, letting fuzzy set theory, neural nets and other fields develop their own paradigms, occasionally helping one another in specific applications where their complementarity is needed.

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