Computational Intelligence in Prognostics and Health Management (PHM)

Plenary Talk

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Prognostics and Health Management (PHM) is a multi-discipline field, as it includes facets of Electrical Engineering (reliability, design, service), Computer Science and Decision Sciences (Computational Intelligence, Artificial Intelligence, Soft Computing, Machine Learning, Statistics, OR), Mechanical Engineering (geometric models for fault propagation), Material Sciences, etc.

Within this talk we will focus on the role that Computational Intelligence (CI) plays in PHM for assets such as locomotives, medical scanners, aircraft engines, etc. functionalities. The main goal of PHM is to maintain these assets' operational performance over time, improving their utilization while minimizing their maintenance cost. This tradeoff is typical of long-term service agreements offered by OEM's to their valued customers. The main goal of PHM for assets such as locomotives, medical scanners, and aircraft engines is to maintain these assets' operational performance over time, improving their utilization while minimizing their maintenance cost. This tradeoff is critical for the proper execution of Contractual Service Agreements (CSA) offered by OEM's to their valued customers.

When addressing real-world PHM problems, we usually deal with systems that are difficult to model and possess large solution spaces. So we augment available physics-based models, which are usually more precise but difficult to construct, customize, and adapt, with approximate solutions derived from Computational Intelligence methodologies. In this process we leverage two types of resources: problem domain knowledge of the process (or product) and field data that characterize the system's behavior. The relevant available domain knowledge is typically a combination of first principles and empirical knowledge. This knowledge is often incomplete and sometimes erroneous. The available data are typically a collection of input-output measurements, representing instances of the system's behavior, and are generally incomplete and noisy. Computational Intelligence is a flexible framework in which we can find a broad spectrum of design choices to perform the integration of knowledge and data in the construction of approximate models.

To better understand PHM requirements, we introduce a decision-making framework in which we analyze PHM decisional tasks. This framework is the cross product of the decision's *time horizon* and the *domain knowledge* used by CI models. Within such a framework, we analyze the progression from simple to annotated lexicon, morphology, syntax, semantics, and pragmatics. We use this metaphor to monitor the leverage of domain knowledge in CI to perform anomaly detection, anomaly identification, failure mode analysis (diagnostics), estimation of remaining useful life (prognostics), on-board control, and off board logistics actions. This is shown in the following figure.

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<tr><th></th><th>One Shoot</th><th>Tactical</th><th>Operational</th><th>Strategic</th><th>Lifecycle</th></tr>
<tr><td>Lexicon</td><td></td><td>Anomaly Detection</td><td></td><td></td><td></td></tr>
<tr><td>Morphology</td><td></td><td rowspan="2">Anomaly Detection
Anomaly Identification</td><td></td><td></td><td></td></tr>
<tr><td>Marked-up Lexicon</td><td></td><td></td><td></td><td></td></tr>
<tr><td>Syntax</td><td></td><td>Anomaly Id. Diagnostics</td><td>Scheduling</td><td></td><td></td></tr>
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Diagnostics
Prognostics
Control</td><td rowspan="2">Scheduling
Planning
Readiness Assessment
Asset Allocation
Optimization
DM</td><td rowspan="2">Long-Term Planning
Contingency Planning
Asset Management
MOO, Tradeoffs, MCMD</td><td></td></tr>
<tr><td>Pragmatics</td><td>Model Update & Maintenance</td></tr>
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Time Horizon

Domain Knowledge

We will illustrate this concept with a case study in anomaly detection, which is solved by the construction and fusion of an ensemble of diverse detectors, each of which is based on different CI technologies.

Evolutionary Multi-Objective Optimization: Current and Future Research Trends

Plenary Talk

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During the last few years, there has been an increasing interest in using heuristic search algorithms based on natural selection (the so-called “evolutionary algorithms”) for solving a wide variety of problems. As in any other discipline, research on evolutionary algorithms has become more specialized over the years, giving rise to a number of sub-disciplines. This talk deals with one of these emerging sub-disciplines that has become very popular due to its wide applicability: evolutionary multi-objective optimization (EMOO).

EMOO refers to the use of evolutionary algorithms (or even other biologically-inspired metaheuristics) to solve problems with two or more (often conflicting) objectives. Unlike traditional (single-objective) problems, multi-objective optimization problems normally have more than one possible solution (the so-called Pareto optimal set, whose vectors are called nondominated and whose image is called the Pareto front). Even the notion of optimum is different in this case, since the main aim is not to find one globally optimum solution, but the best possible trade-offs or compromise solutions (i.e., solutions in which it is not possible to improve one objective without worsening another one). This is called Pareto optimality, which is the most popular definition of *optimum* currently adopted in multi-objective optimization. Thus, traditional evolutionary algorithms (e.g., genetic algorithms or evolution strategies) need to be modified in order to deal with such problems, since in their original form they will tend to converge to a single solution (i.e., the fittest in the population) after a sufficiently large number of iterations. The main change required involves modifying the selection process, which must be blocked such that several solutions can be retained in the population during a run. This has as its goal to be able to generate, after a single run, several elements of the Pareto optimal set, rather than only one.

This talk will provide a general overview of the EMOO field, from a historical view, focused, mainly, around the major algorithmic achievements in the field. Thus, at the beginning, the first generation multi-objective evolutionary algorithms (MOEAs) will be discussed. Such algorithms were relatively simple, normally not too efficient, were non-elitist and remained in use during about 10 years. Elitism refers to retaining the best solutions found in one iteration into the next population. Such a concept is more complicated in EMOO, since all the nondominated solutions are equally good and, in theory, all of them must be retained. In practice, however, elitist mechanisms are normally bounded, limiting the number of nondominated solutions that are maintained, and giving rise to the another key mechanism of modern MOEAs: diversity estimators. A diversity estimator tries to promote the search towards little explored regions of the search space, by penalizing solutions that are in very crowded regions, and rewarding those lying in isolated regions. The use of elitism is important, since it has been proved that such mechanism is required in order to guarantee convergence of a MOEA. Nowadays, elitism is normally implemented through the use of an external archive that stores the (globally) nondominated solutions generated by a MOEA. However, other elitist mechanisms are also possible.

Towards the end of the 1990s, elitist MOEAs started to become popular, and new, more elaborate, efficient and effective MOEAs were developed. The most representative approaches from these two groups (non-elitist and elitist MOEAs) will be briefly described in this talk, emphasizing their key components.

In the final part of the talk, some of the current applications of MOEAs will be mentioned. Then, the main current challenges faced by EMOO researchers will be briefly discussed (e.g., problems having many objectives, mechanisms to deal with very expensive objective functions, etc.), aiming to motivate practitioners, researchers and students to get interested in this exciting field that has already attracted the interest of a wide number of people from diverse disciplines around the world.

From Interval to General Type-2 Fuzzy Logic Controllers- Towards FLCs that can Better Handle Uncertainties in Real World Applications

Plenary Talk

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Most real world applications face high levels of uncertainties that can affect the operations of such applications. Hence, there is a need to develop different approaches that can handle the available uncertainties and reduce their effects on the given application. To date, Type-1 Fuzzy Logic Controllers (FLCs) have been applied with great success to many different real world applications. The traditional type-1 FLC which uses crisp type-1 fuzzy sets cannot handle high levels of uncertainties appropriately. Nevertheless it has been shown that higher order Fuzzy Logic Controllers (FLCs) such as interval type-2 FLCs using interval type-2 fuzzy sets can handle such uncertainties better and thus produce a better performance. Through the review of the various interval type-2 FLC applications, it has been shown that as the level of imprecision and uncertainty increases, the interval type-2 FLC will provide a powerful paradigm to handle the high level of uncertainties present in real-world environments. It has been also shown in various applications that the interval type-2 FLCs have given very good and smooth responses that have outperformed their type-1 counterparts. Thus, using interval type-2 FLC in real-world applications can be a better choice since the amount of uncertainty in real systems most of the time is difficult to estimate.

General type-2 FLCs are expected to further extend the interval type-2 FLC capability. However, the immense computational complexities associated with general type-2 FLCs have until recently prevented their application to real world control problems.

This speech will explain the concepts of interval and general type-2 FLCs and will present a new framework to design general type-2 FLC based on the theory of interval type-2 FLC. The proposed approach will lead to a significant reduction in both the complexity and the computational requirements for general type-2 FLCs while offering the capability of representing complex general type-2 fuzzy sets. This speech will explain how the proposed approach can present a way forward for fuzzy systems in real world environments and applications that face high levels of uncertainties. The talk will present different ways to design interval and general type-2 FLCs. The talk will also present the successful application of type-2 FLCs to many real world settings including industrial environments, mobile robots, ambient intelligent environments video congestion control and intelligent decision support systems. The talk will conclude with an overview on the future directions of type-2 FLCs.

Multiobjective Genetic Fuzzy Systems
- Accurate and Interpretable Fuzzy Rule-Based Classifier Design -

Plenary Talk

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Fuzzy rule-based systems are universal approximators of non-linear functions [1] as multilayer feedforward neural networks [2]. That is, they have a high approximation ability of non-linear functions. A large number of neural and genetic learning methods have been proposed since the early 1990s [3, 4] in order to fully utilize their approximation ability. Traditionally, fuzzy rule-based systems have been mainly applied to control problems with a few input variables. Recently, they have also been applied to approximation and classification problems with many input variables.

The main advantage of fuzzy rule-based systems over black-box non-linear models such as neural networks is their linguistic interpretability. Fuzzy rules are often written in the if-then form with linguistic terms such as "If x_1 is *small* and x_2 is *small* then y is *large*" and "If x_1 is *large* and x_2 is *large* then Class 1". In this case, it is easy for human users to understand fuzzy rule-based systems since each fuzzy rule is linguistically interpretable.

As we have already explained, fuzzy rule-based systems have two advantages: high approximation ability and high interpretability. These advantages, however, often conflict with each other as shown in Fig. 1. For example, accuracy maximization (i.e., error minimization in Fig. 1) often leads to accurate but complicated fuzzy rule-based systems with low interpretability. On the other hand, interpretability maximization (i.e., complexity minimization in Fig. 1) often leads to interpretable but inaccurate fuzzy rule-based systems.

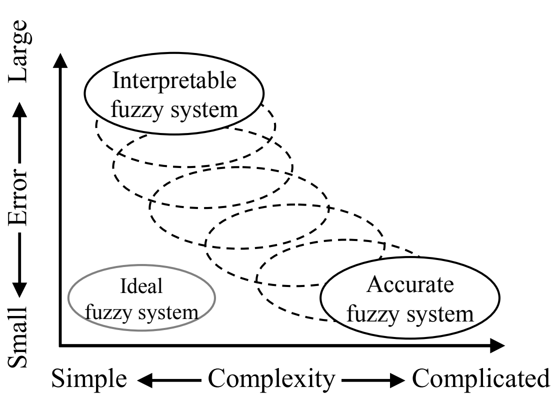

Fig. 1. Tradeoff between accuracy and complexity.

These discussions mean that we usually do not have an ideal fuzzy rule-based system with high accuracy and high interpretability. Thus the design of fuzzy rule-based systems can be viewed as finding a good compromise (i.e., tradeoff) between accuracy and interpretability [5, 6]. One approach to this problem is to integrate accuracy and interpretability into a single objective function. Another approach is the use of constraint conditions on fuzzy rule-based systems in order to maintain their interpretability. A large number of genetic algorithm-based techniques have been proposed under the name of genetic fuzzy systems [7] to find a single fuzzy rule-based system on the accuracy-interpretability tradeoff curve.

Recently the design of fuzzy rule-based systems has been handled as multi-objective optimization problems [8] as

$$\text{Maximize } Accuracy(S) \text{ and } Interpretability(S), \qquad (1)$$

where $Accuracy(S)$ and $Interpretability(S)$ measure the accuracy and the interpretability of a fuzzy rule-based system S. Multiobjective genetic algorithms are used to search for a large number of non-dominated fuzzy rule-based systems on the accuracy-complexity tradeoff curve of (1).

In this talk, first we explain some fuzzy rule generation methods for classification problems. Next we explain single-objective and multi-objective approaches to the design of accurate and interpretable fuzzy rule-based classifiers. Then we discuss the interpretability of fuzzy rule-based classifiers.

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Algorithmic Facets of Human Centricity in Computing with Fuzzy Sets

Plenary Talk

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In information processing we are faced with new challenges and opportunities that can lead to the enhancements of the ways in which the technology of fuzzy sets becomes utilized. More often than before we encounter systems that are distributed and hierarchical in their nature in which there is a significant level of knowledge generation and knowledge sharing. As a matter of fact, knowledge generation is inherently associated with the mechanisms of collaboration and knowledge sharing being realized between participating systems. The aspects of distributed intelligence and agent systems stress the facet of human centricity and human–centric computing (HC^2). In numerous ways of forming efficient conceptual and algorithmic vehicles of human-system interaction fuzzy sets, and Granular Computing, in general, have been playing an important role in the HC^2 domain. We show how this feature gives rise to the paradigm shift.

The intent of this talk to bring into attention several ideas being of interest in the context of the challenges identified above. The feature of human centricity of fuzzy set-based constructs is the underlying leitmotiv of our considerations.

New directions of knowledge elicitation and knowledge quantification realized in the setting of fuzzy sets In the past there have been a number of ways of designing fuzzy sets. The two main directions, that is (a) expert – based, and (b) data – based elicitation of membership functions have formed quite distinct avenues that are visible in the theory and practice of fuzzy sets. We must note here that fuzzy sets- information granules as being reflective of domain knowledge underpinning the essence of abstraction, dwell on numeric, data-oriented experimental evidence as well as perception of the humans who use such information granules. This stresses a hybrid nature of fuzzy sets, which has to be reflected in the foundations fuzzy sets are to be dwelled upon. We elaborate on an idea of knowledge-based clustering, which aims at the seamless realization of the data-expertise design of information granules. We emphasize the need for this unified treatment in the context of knowledge sharing where fuzzy sets are developed not only on the basis of numeric evidence available locally but in their construction we also actively engage the domain knowledge being shared by others. It is also emphasized that collaboration and reconciliation of locally available knowledge give rise to the concept of higher type fuzzy sets along with the principle of justifiable granularity supporting their construction. This principle helps capture the diversity of numeric entities and encapsulate them in the form of information granules where the level of granularity is adjusted to quantify the level of existing diversity. Likewise when dealing with a diversity of information granules of type-1, the concept of justifiable granularity supports a realization of information granules of type-2.

Non-numeric quantification of fuzzy sets and their processing To enhance human centricity of computing with fuzzy sets, it becomes beneficial to establish a conceptual and algorithmic setup in which the predominantly numeric values of membership functions could be interpreted at the qualitative level of membership characterization such as *high*, *medium* or *low* membership, *low* relationship between concepts, etc. We discuss a suite of algorithms facilitating such qualitative assessment of fuzzy sets, formulate a series of optimization tasks guided by well-formulated performance indexes and discuss the essence of the resulting solutions. It will be demonstrated that type-2 fuzzy sets emerge in this setting as a viable conceptual entity with sound algorithmic underpinnings. The concepts of three–valued logic quantification of membership functions are also elaborated in the context of the linguistic quantification of fuzzy sets. Proceeding with fuzzy models, we show how to endow fuzzy modeling with an additional interpretation layer of type-2 fuzzy sets, which enhances the functionality of the existing fuzzy models and their human-centricity. It will allow us to view fuzzy models in a broader context of system modeling and introduce a concept of linguistic equivalence, linguistic stability and other descriptors. We also revisit a plethora of logic operators available in the theory of fuzzy sets vis-à-vis their qualitative interpretation.