Hybrid Computational Intelligence Schemes in Complex Domains: An Extended Review

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Abstract. The increased popularity of hybrid intelligent systems in recent times lies to the extensive success of these systems in many real-world complex problems. The main reason for this success seems to be the synergy derived by the computational intelligent components, such as machine learning, fuzzy logic, neural networks and genetic algorithms. Each of these methodologies provides hybrid systems with complementary reasoning and searching methods that allow the use of domain knowledge and empirical data to solve complex problems. In this paper, we briefly present most of those computational intelligent combinations focusing in the development of intelligent systems for the handling of problems in real-world applications. We emphasize the appropriateness of hybrid computational intelligence techniques for dealing with specific problems, we try to point particularly suitable areas of application for different combinations of intelligent techniques and we briefly state advantages and disadvantages of the “hybrid” idea, seen as the next theoretical step in the evolving impact and success of artificial intelligence tools and techniques.

1 Computational intelligent components

Hybrid computational intelligence is defined as any effective combination of intelligent techniques that performs superior or in a competitive way to simple standard intelligent techniques. A very thorough analysis of what is meant by computational intelligence and what the trends of modern AI are, can be found in [1] and [2]. Lately more and more researchers recognize and define as main components of computational intelligence, four areas of research that dominate the area of AI, namely, (1) fuzzy sets and soft computing, (2) neural networks, (3) genetic algorithms and evolutionary computing and (4) machine learning and data mining. A collection of research work on computational intelligence and learning techniques in the sense presented above can also be found in [3]. Advantages and disadvantages of each individual approach, as well as reasons that make hybrid schemes attractive in modern AI research, are given in brief at the end of this paper, together with a description of the main clusters of application areas that hybrid appears particularly capable to be applied. Below we attempt a reference to the basic concepts of the most popular intelligent components of hybrid intelligent architectures, and then a review of more than 100 related research papers found in recent literature, is made.

Fuzzy logic [4] is a language, which uses syntax and local semantics where we can imprint any qualitative knowledge about the problem to be solved. The main attribute of fuzzy logic is the robustness of its interpolative reasoning mechanism. Neural networks were introduced by [5] and [6]. They are computational structures that can be trained to learn by examples. Using a supervised learning algorithm, such as the back-propagation [7], and a training set that samples the relation between input and output, we can perform fine local optimization. Genetic algorithms [8] give us a method to perform randomized global search in a solution space. Usually a population of candidate solutions, encoded internally as chromosomes, is evaluated by a fitness function in terms of its accuracy. The best chromosomes are combined and reproduced in subsequent generations. Genetic programming, proposed by [9] is an extension to the original concept of genetic algorithms. The population in genetic programming is composed by variable length tree-like candidate solutions. Each of these individual candidates, called program, may have functional nodes, enabling the solution to perform arbitrarily large actions. Machine Learning [10], [11], [12], [13], was conceived four decades ago for the development of computational methods that could implement various forms of learning, in particular mechanisms capable of inducing knowledge from examples or data [14, p.3]. Knowledge induction seems particularly desirable in problems that lack algorithmic solutions, are ill-defined, or only informally stated. Most research in machine learning has been devoted to developing effective methods for building learning systems that will acquire high-level concepts and/or problem solving strategies through examples in a way analogical to human learning. Most of the complex domain problems are ill-defined, difficult to model and they have large solution spaces. Any relevant information about these problems is the prior domain knowledge, usually incomplete, and input-output instances of the system's behavior, which is also incomplete. Therefore, in many cases, hybrid combinations are capable of describing an approximate reasoning for these domains. These hybrid systems are proved superior to each of their underlying computational intelligent components, thus providing us with better problem solving tools.

Table 1. Publications related to hybrid schemes in this paper, summarized by subject and date published

	<= '91	'92-'93	'94-'95	'96-'97	'98-'99	'00-'01	Total
Neural Networks and Fuzzy Logic (NN+FL)	5	6	3	7	-	10	*31*
Fuzzy Logic and Evolutionary Algorithms (FL+EA)	5	7	9	19	1	4	*45*
Neural Nets and Evolutionary Algorithms (NN+EA)	2	3	2	1	2	2	*12*
Machine Learning and Evol. Algorithms (ML+EA)	1	1	-	-	2	4	*8*
Other Hybrid Schemes (HS)	1	-	1	3	1	6	*12*
Total	*14*	*17*	*15*	*30*	*6*	*26*	

Table 1 summarizes those publications related to hybrid systems, that are presented in this paper, based on a classification by subject and date published, while *Table 2* is a digest of the hybrid application papers shown in this work classified by subject and task.

Table 2. Publications related to hybrid applications presented in this work, summarized by subject and task

	NN+FL	FL+EA	NN+EA	ML+EA	Other HS	Total
Fuzzy control	4	6	-	-	-	*10*
Function approximation	2	1	1	1	-	*5*
Forecasting	6	-	2	-	-	*8*
Knowledge discovery	1	-	-	-	-	*1*
Decision making	2	1	-	-	-	*3*
Scheduling	-	1	-	-	1	*2*
Feature selection	-	-	-	2	1	*3*
System design	-	1	-	-	-	*1*
Data classification	1	1	-	1	-	*3*
Image processing	2	-	-	-	-	*2*
Financial, medical, industrial appl.	5	2	1	2	-	*10*
Other / benchmarking	-	1	1	-	-	*2*
Total	*22*	*14*	*5*	*6*	*2*	

As observed from the above tables, combinations of machine learning and evolutionary algorithms are relatively few as compared e.g., with the fuzzy-neural systems. The main reason may be that these two domains (i.e. machine learning and evolutionary algorithms) were evolved separately, and only recently the number of this kind publications increases. Regarding the combination of neural networks and evolutionary algorithms, although there exists a sufficient number of (most theoretical) publications, the number of real-world applications remains relatively small as compared to the fuzzy-neural systems. This may be a result of the particular success of the fuzzy-neural approach in real-world complex domains, a fact that leads researchers to substitute neural-evolutionary approaches with the fuzzy-neural ones, although those two competitive hybrid schemes address mostly common domains. Similar observations exist for the comparison between fuzzy-evolutionary systems and fuzzy-neural ones. Fuzzy-evolutionary systems are commonly used -but not always- in the same complex domains as with the fuzzy-neural systems. However, the uniqueness in some of the fuzzy-evolutionary systems, which is the incorporation of fuzzy logic into an evolutionary algorithm (and not for example, the fuzzy rule-base construction using an evolutionary approach, which can also be done by fuzzy-neural systems) lets these hybrid schemes to work effectively in a larger scale of application domains. The literature presented above, is by no means exhaustive, though it can be considered as representative. The collection of these papers was mainly done from IEEE publications, edited books, research monographs, as well as from web databases such as the ScienceDirect and the Citeseer. No specific strategy was used for

performing keyword-search, as a "hybrid" system is not always defined under this term in literature. The paper is organized as follows:
Next section describes different major categories of hybrid systems and attempts to classify and analyze them, while section 3 presents some brief conclusions drawn from the comparison of the performance of all the alternative hybrid approaches into various domains of application.

2 Hybrid systems and combinations

Below we approach the concept of hybrid computational intelligence by presenting evidence found in literature, concerning effective combinations of two, either competitive or, complementary intelligent approaches to specific domains of application. Later in this text we also refer to more complex hybrid schemes that usually combine more than two techniques at the same time, in a more complicated manner.

2.1 Neural Networks and Fuzzy logic

Neural networks and fuzzy logic is maybe proved to be the most successful combination of intelligent techniques in modern literature around AI, also called as neuro-fuzzy systems and techniques[1]. Neuro-fuzzy systems have shown a high rate of success when applied in complex domains of application, either when fuzzy set theory is the heart of such a system, or when the neural mechanism is the dominant component in the architecture. The main principle of this combination, as seen by a neural network expert, can be roughly described as the adoption of fuzzy functions in (mostly consisted of 3-layers) neural networks' nodes. On the other hand, a fuzzy systems' expert may realize a neural-like training (such as back-propagation) for the membership functions of a fuzzy system. However, combinations and approaches in these hybrid systems can be less obvious and descriptive, concerning different NN or FS structures, such as self-organizing maps or radial basis functions.

Neural networks controlled by fuzzy logic. Some basic theoretical aspects, detailed description of the characteristics of the methodological components, as well as the early adoptions of neural networks controlled by fuzzy logic, can be found in a series of publications [15], [16], [17], [18], [19], [20], [21] and [22]. In [23], is addressed the concept of a fuzzy neural network to implement syllogistic fuzzy reasoning. In syllogistic fuzzy reasoning, the consequence of a rule in one reasoning stage is passed to the next stage as a fact. The approach is shown to be essential to effectively build up large-scale systems, with high-level intelligence, when applied in two benchmark problems from the fuzzy control and nonlinear function approximation domains. In [24], the problem of adaptive regularization in image restoration is addressed, by adopting a neural network learning approach. Instead of explicitly specifying the local regularization parameter values, the authors regard them as network weights, which are then modified through the supply of appropriate training examples. In addition,

[1] See for example the Neuro–Fuzzy International Conference NF-2002, La Habana, Cuba, January 2002, http://www.icsc-naiso.org/conferences/nf2002/.

they consider the separate regularization of edges and textures due to different noise masking capabilities and they propose a new edge-texture characterization measure, which is incorporated in a fuzzified form to the neural network. In [25], is proposed the fuzzy neural network for tuning the proportional-integral-derivative controller for plants with under-damped step responses. Several simulation examples demonstrate the effectiveness and robustness of the obtained fuzzy neural network. In [26], is proposed a supervisory control system using a recurrent fuzzy neural network to control the mover of a permanent magnet linear synchronous motor servo drive for the tracking of periodic reference inputs. The system combines a supervisory control subsystem and an intelligent control subsystem. The overall approach is shown to be effective to track various periodic reference inputs with robust control performance.

Fuzzy logic controllers tuned by neural networks. The early adoptions of fuzzy logic controllers tuned by neural networks can be found again in [27], [28], [29], [30], [31], and [32]. Since then, the term neuro-fuzzy has covered both previous areas.

Neuro-fuzzy systems. In [33], a distributed approach to genetic-neuro-fuzzy learning is presented, for a class of low-cost form of personal computers, built at the University of Messina. The performance of the serial version is significantly enhanced with the parallelization scheme described in the paper. In [34], the authors propose a neuro-fuzzy function approximator combining the reasoning method with stochastic reinforcement learning. The model is proved in the examples superior to back-propagation in simple non-linear approximation tasks. In [35], the authors show which elements have to be extracted from a chaotic time series in order to define the architecture of a forecasting neuro-fuzzy system. They test the model on Mac Key - Glass time series, concluding that the system is promising. In [36], the author presents a fuzzy-neural approach to the prediction of nonlinear time-series. The underlying mechanism governing the time series is expressed in the form of If-Then rules and is discovered by a modified self-organizing counter-propagation network. Tests over three different time-series demonstrate the efficiency and the effectiveness of this approach, over other network approaches. In [37], is presented a neuro-fuzzy system combining neural computation and heuristics fuzzy rule generation. The system is proved very efficient and effective in various complex domains in other publications [38]. In [39], the authors propose a combination of chaos analysis, neuro-fuzzy systems and evolutionary training for stock exchange daily trading. The system is demonstrated to be efficient in various test cases and superior to buy and hold strategies. In [40], the modeling of the German stock index DAX is attempted with a neuro-fuzzy approach.

2.2 Neural networks and Evolutionary algorithms

Fundamental implementations of neural networks generated and tuned by genetic algorithms can be found in a series of publications [41], [42], [43], [44], [45], [46]. The idea behind the implementation of such a hybrid system is the adoption of an evolutionary algorithm for the determination of neural network's weights or the neural network's architecture, or both. In the first case, neural networks are tuned by evolutionary algorithm, rather than generated by, which is the case in the second approach. The third approach may contain both generation and tuning. A special case of tree-like neural networks may also be served by genetic programming training.

Neural networks generated by genetic algorithms. In [47], the authors use a hybrid scheme combining neural networks and genetic training to forecast the three-month spot rate of exchange for four currencies. The forecasts are compared to the predictions made by the forward and futures rates and are evaluated based on their degree of accuracy and their ability to correctly forecast the direction of the change in the exchange rate movement. In [48], is proposed a more comprehensive evolution of network design, enabling all aspects of the network to evolve and all varieties of networks to be discovered. In their chromosome, they represented various neural network properties, intended to permit all possible connectivity. The system has been tested effectively in various benchmarking problems, such as the XOR and the parity problem, and a potential has been shown in this model.

Neural networks tuned by genetic algorithms. The work presented in [49], has proposed the neural networks weight selection by encoding these parameters in real-valued chromosomes. The authors of [49] applied this methodology in both feed-forward neural networks and to a new, at that time, topology, the weighted probabilistic neural networks. In [50], the authors compare the genetic algorithm training with the back-propagation for neural networks for five chaotic time series, showing that the genetic algorithms training is superior to back-propagation in terms of effectiveness, ease-of-use and efficiency.

Neural networks and genetic programming. In [51], the authors present the development of a hybrid system of neural networks and genetic programming trees for problem domains where a complete input space can be decomposed into several different sub-regions, and these are well represented in the form of oblique decision tree. The overall architecture of this system is called federated agents and consists of a facilitator, local agents, and boundary agents. Neural networks are used as local agents, each of which is expert at different sub-regions. Genetic programming trees serve as boundary agents.

2.3 Fuzzy Logic and Evolutionary algorithms

Genetic algorithms and fuzzy logic have been used in the past collaboratively for various control engineering applications and complex optimization problems. Both, fuzzy logic driven genetic approaches and genetic driven fuzzy logic based schemes have been proved effective in modern AI literature, as described in the following paragraphs. The fuzzy logic driven genetic approaches primarily concern the use of fuzzy logic, either for genetic parameters' tuning, or for fuzzy encoding of the chromosomes. The genetic driven fuzzy logic based schemes usually are consisted by fuzzy rule-based systems, using a genetic approach for the determination of the rule base. On the other hand, the prime theoretical aspects of implementing complex structures such as the fuzzy systems into genetic programming trees, is developed in a series of publications [52], [53], [54], [55] and [56], where the main concept, the grammar-driven or strongly-typed genetic programming is proved capable of describing arbitrarily large structure hierarchies. As it is shown in the following paragraphs, the fuzzy-genetic-programming approach, goes beyond a simple cooperation between two intelligent domains, while such a system may be seen as a single component that includes the attributes of both sub-components, such as fuzzy inference and genetic-based self-training.

Genetic algorithms controlled by fuzzy logic. Applications of genetic algorithms controlled by fuzzy logic can be found in a series of publications [57], [58], [59], [60], [61], [62], [63] and [64]. In [65], the authors use fuzzy coding for genetic optimization. This approach enables to establish a relevant level of information granularity and to provide with some search guidance. In [66], fuzzy logic controllers are used for the adaptation of genetic algorithms parameters. In [67], is proposed a bi-directional scheme, where fuzzy logic controllers are used for the tuning of a genetic algorithm and another genetic algorithm is used simultaneously for the tuning of these fuzzy logic controllers. The empirical study of this model has shown that it adapts the parameter settings according to the particularities of the search space allowing significant performance to a variety of problems.

Fuzzy logic controllers tuned by genetic algorithms. Some fundamentals of theory and description of individual components, as well as the early implementations of fuzzy logic controllers tuned by genetic algorithms can be found in a series of publications [57], [68], [69], [70], [71], [72], [61], [22], [73], [74] and [75].

Fuzzy logic controllers' learning by genetic algorithms. In [76], two different approaches to apply genetic algorithms to fuzzy logic controllers are described. The first approach uses the knowledge base as the individual of the genetic system, while the second uses the knowledge base as the population of the genetic system. Both systems are applied to complex control problem and their efficiency is demonstrated. In [77], hybrid fuzzy-genetic approaches are explored to intelligent systems design. The paper contains demonstrations of techniques on robotics control and biomedical diagnosis applications. The work in [78], proposes the training of fuzzy rule systems using messy genetic algorithms. The method is applied to a control problem in robotics. The control behavior proves robust enough, in order to compensate differences of sensory perception between simulation and reality. In [79], the authors describe a fuzzy rule learning system, developed for working with noise-affected systems. The system is proved capable of obtaining a reasonable small set of rules as compared with other algorithms. The paper described in [80], presents an evolutionary process based on genetic algorithms and evolution strategies for learning the fuzzy logic controller knowledge base from examples. Tests demonstrate the effectiveness of the proposed model and the results are compared with other methods. In [81], is proposed an algorithm for generating the rule-base of fuzzy systems via symbiotic evolution. In symbiotic evolution each chromosome in the population represents only one fuzzy rule and not the whole rule base. The authors have applied successfully this methodology for the design of an active control suspension system.

Fuzzy logic controllers' optimization by genetic algorithms. The work presented in [82], presents a genetic algorithm optimization method for fuzzy control and decision systems. The method extends traditional fuzzy systems by a learning ability without changing the fuzzy rule framework. The author uses the entropy of the fuzzy rule set in the fitness function together with a genetic optimization with different concurrent fuzzy systems in the population. A test case for charging high-power NiCd batteries, demonstrate the effectiveness of the proposed method. In [83], the cart-centering problem is addressed using a new controller concept called analytical influence controller, which is based on a general control surface structure. This concept is suited for optimization by a genetic algorithm. Tests show that with proper tuning, the results can have high accuracy. In [84], is proposed a self-tuning fuzzy controller with virus-evolutionary genetic algorithm. This algorithm realizes a horizontal propagation and a vertical inheritance of genetic information in a population. The effectiveness of the proposed method is shown through the simulations of the cart-centering problem. In [85], is proposed a hybrid method combining an evolutionary computation technique for input membership function parameters and a stochastic gradient descent, for rule conclusion parameters, for constrained optimization of fuzzy inference systems. The optimization process is shown to be able to find the optimal size of fuzzy inference systems for a given problem.

Fuzzy-Evolutionary systems. Early work in this domain can be found in [86], [87], and [88]. In [89], is proposed the evolutionary fuzzy modeling for various aerospace applications. Various test are conducted to analyze the stability and performance robustness of the methodology, demonstrating the feasibility of the model in non-linear control of the space station. In [90], it is addressed the problem of multi-objective job-shop scheduling using fuzzy processing time and fuzzy due-date. They formulate the multi-objective fuzzy job-shop scheduling as three-objective ones which not only maximize the minimum agreement index but they also maximize the average agreement index and minimize the maximum fuzzy completion time. With two examples, they demonstrate the feasibility and effectiveness of the proposed method by comparing with the simulated annealing method.

Fuzzy logic controllers generated by genetic programming. In [91] and [92], the authors present an evolutionary approach for the design of fuzzy logic controllers. They apply the genetic programming paradigm to evolve fuzzy rule-bases, internally represented as type-constrained syntactic trees. The obtained results from an application to the cart-centering problem, show that a good parameterization of the algorithm and an appropriate evaluation function can lead to near-optimal solutions. In [93], a model for the construction of fuzzy rule-based systems incorporating the fuzzy mechanism into the genetic programming functional nodes is proposed. The model has been tested effectively in the medical domain, showing the potential of its future use.

2.4 Machine Learning and Fuzzy Logic

Fuzzy logic is used for the modeling of ambiguity contained in decision attributes, before these attributes are subjected to further process using machine learning for classification and diagnosis tasks. The process followed for the definition of boundaries of the examined attributes, are defined by methods often called “fuzzy or soft thresholds”. On the other hand, machine learning can assist the formation of fuzzy membership functions by defining successfully the fuzzy boundaries among neighboring linguistic areas. In [94], a comparison between three different learning methods for fuzzy decision trees is presented. An early hybrid approach consisting of fuzzy rule based systems and inductive machine learning was presented in [95] where the cut-off points of different linguistic areas of the fuzzy membership functions used, where obtained by rules induced from experimental data, with the aid of entropy based inductive learning algorithms [96], [97]. In [98], fuzzy machine learning is introduced, through the application of a fuzzy machine learning technique in the knowledge acquisition process. Fuzzy logic support for the application of automated knowledge acquisition is presented by [99] with the construction of Fuzzy-ID3, an inductive decision tree generator. A very interesting study on heuristic algorithms for generating fuzzy decision trees is also presented by [100]. Fuzzy sets and machine learning are also working together in [101], where a fuzzy inference system learning by reinforcement methods is presented. Finally, another similar attempt for combining fuzzy set theory and inductive machine learning is given in [102].

2.5 Machine Learning and Evolutionary algorithms

Machine learning often works as feature selection or feature extraction methodology applied in large collections of data, prior to the application of evolutionary approaches for generalization from data. In this way, machine learning works as a mechanism for reducing complexity, a task which is necessary for time consuming approaches such as evolutionary computation. Genetic-based machine learning approaches are also described in literature, see [103]. The goal of this study is the automatic development of a rule set for an industrial production process. The problem is solved successfully, by applying a largely modified Learning Classifier System (a class of genetic based Machine Learning methods), called Fuzzy Efficiency-based Classifier System. On the other hand, machine learning and genetic programming form another very effective hybrid scheme for handling various applications in literature. In [9], was primarily introduced a genetic based approach for decision tree generation in a way that a result equivalent to that of pure machine learning [96] was obtained. In [104], a regularization approach to inductive genetic programming tuned for learning polynomials is presented. The presented experimental results within that work show that the suggested regularization approach outperforms traditional genetic programming on benchmark data mining and practical time-series prediction tasks. Credit scoring problems can also be handled with the combined use of inductive machine learning and genetic programming [105]. Inductive machine learning is used in first step as feature selector technique and then the reduced feature set serves as input of reduced complexity to a genetic programming approach for generalization purposes. The attempt to perform feature selection with the aid of inductive learning has proved effective in past literature [106], [107].

Decision trees generated by genetic programming. In [108], is proposed a study of inductive genetic programming with decision trees. The paper presents the development of fitness functions for improving the search guidance, where it is demonstrated that with careful design of the fitness function the global search space becomes smoother, thus facilitating the search. The overall method is shown to guarantee maintenance of decision trees with low syntactic complexity and high predictive accuracy. As stated above, in [9] was primarily introduced a genetic based approach for decision tree generation in a way that a result equivalent to that of pure machine learning [96] was obtained.

2.6 Other hybrid intelligent schemes

Before closing this brief review to effective hybrid schemes of well-known intelligent techniques, it should be added that a number of other techniques are also combined in real world applications. This paper will not attempt any extensive reference to those methods as part of hybrid architectures, but it should be noted that rough sets, Petri nets and wavelets are very often found useful and intelligent enough to be included in hybrid methodologies. Specially wavelets that are particularly capable of de-noising signal data, have been used in collaboration to neural networks for separation between order and disorder in stock index [109], as well as with fuzzy sets for function learning [110], and for real time tool condition monitoring [111]. The following paragraphs show a classification among hybrid systems not belonging clearly to one of the presented hybrid classes.

Hybrid Neural Network Systems. In [112], a hybrid neural network scheme for face recognition is proposed. The model combines local image sampling, a self-organizing map neural network and a convolutional neural network. The system provides a measure of confidence in its output and classification error approaches zero when rejecting as few as 10% of examples from a database of 400 images of 40 individuals which contains quite a high degree of variability in expression, pose and facial details. In [113], the authors use three alternative methods to empirically select predictors for neural networks in bankruptcy prediction. Among these methods -linear discriminant analysis, logit analysis and genetic algorithms- the best prediction results are achieved from the neural network when the prediction variables are selected using genetic algorithms. In [114], is proposed a structured model with multiple stages combining case-based forecasting, neural networks and discriminant analysis for bankruptcy prediction. This integrated approach produced higher prediction accuracy than the individual components. In [115], is proposed an integrated thresholding design of the optimal or near-optimal wavelet transformation by genetic algorithms to represent a significant signal most suitable for neural networks. The approach is applied to Korean won / US-dollar exchange rate forecasting. The results show that the proposed system has better performance than three other wavelet thresholding algorithms (cross-validation, best basis selection and best level tree). In [116] and [117], the authors propose a multistage hybrid system combining wavelet thresholding, neural networks and neuro-fuzzy systems for stock exchange daily trading. The system is proved to be superior to individual components performance and to buy and hold strategies. In [118] knowledge discovery is attempted by an inductive neural network scheme.

Hybrid genetic algorithms. Early findings and studies on hybrid genetic algorithms can be found in [119] and [120]. In [121], a hybrid genetic algorithm model is suggested for scheduling storage tanks. The proposed approach integrates genetic algorithms and heuristic rule-based techniques, decomposing the complex mixed-integer optimization problem into integer and real number sub-problems. The model is applied to three scenarios of a water treatment facility to a port and is found to be robust and to give a significantly better schedule as compared to heuristic or random search. In [122] is proposed a hybrid genetic scheme using genetic and micro-genetic algorithms (genetic algorithms with small population and short evolution), which has enhanced search capabilities. The suggested model, over a significant number of tests, has shown better performance in terms of solution accuracy, feasibility percentage of the attained solutions, and robustness. In [123], is proposed a parallel hybrid method that combines cellular genetic algorithms and the random walk strategy for solving the "satisfiability" problem. This method uses a cellular genetic algorithm to perform a global search and specializes this search in local search by adopting the random walk strategy. The aim of this work is to deal with large-sized problems and it is realized on a parallel machine with satisfactory results. In [124], is addressed the uncertainty of the estimated fitness of the solution in genetic algorithms. This uncertainty is either due to environmental changes (process noise), or due to noisy evaluations (observation noise). The Kalman formulation provides a well-developed formal mechanism for treating uncertainty within the genetic algorithms framework. In the paper, is developed a Kalman-extended genetic algorithm to determine when to generate a new individual, when to re-evaluate an existing individual and which one to re-evaluate. The overall approach shows efficient discovery of better-adapted solutions in examples with several levels of process and observation noise.

Hybrid genetic programming. In [125], the genetic programming is used to enhance the simulated annealing search by replacing the simulating annealing key parameter search (called the *simulated annealing schedule*), usually searched manually, by a genetic programming search. Two new algorithms are presented that are proved to be superior to existing simulated annealing algorithms. In [126], the authors apply a two-stage procedure for the identification of crack profiles using genetic programming and fuzzy inference. The genetic programming is used for feature extraction and a fuzzy inference system detects presence, position and size of a defect using the extracted features. The effectiveness of the proposed method is demonstrated through simulation studies.

3 Conclusions

For many years, in most applications of intelligent methodologies, the trend has been to use the most proper approach for each field of study. Usually, a successful application of the selected intelligent technique corresponds to the comparison of the performance of some competitive intelligence techniques in contrast to the proposed one. Superiority of the latter over the other techniques proves the correctness of the selection. After a large collection of such real-world applications of intelligent techniques within the past decade, scientists of today should attempt to draw general conclusions on the advantages and disadvantages of each category of intelligent methods (i.e. machine learning, neural nets, soft computing, genetic algorithms, etc.).

In this sense, machine learning seems more capable of handling large databases consisting of incomplete and/or nominal data by taking advantage of mathematical logic, induction and elements of information theory. Neural networks can perform

ideally in domains of purely numerical nature, as well as in making effective predictions in time series data. Genetic algorithms could competitively perform optimization tasks in a very large search space, identifying sub-optimal solutions of high quality, becoming thus the methods of choice for domains suffering from combinatorial explosion phenomena such as operations research, manufacturing etc. Soft computing and fuzzy rule-based systems have been proved ideal for handling approximate concepts, human characterizations and domains having unclear boundaries. Moreover, it has been observed that the highly increasing computing power and technology, could make possible the use of more complex intelligent architectures, taking advantage of more than one intelligent techniques, not in a competitive, but rather in a collaborative sense. This last fact corresponds to what is called a hybrid computational intelligence methodology throughout this paper.
Application areas for computational intelligence can be seen as almost any complex domain with the need for diagnosis, decision-making, supervision, modeling and analysis. Most of computational intelligence techniques seem to focus on (1) control engineering, data analysis and function approximation, (2) monitoring and diagnosis of complex dynamic systems, chaotic domains and time-series data, with a special emphasis on economic/financial problems and electromechanical devices and systems, (3) numerous medical diagnosis problems and, (4) managerial decisions and strategic decision-making. The need for the design of a generalized hybrid architecture combining both, theoretical intelligent components and suitable areas of application is currently under construction by the authors. More details are to be provided and discussed during the presentation of this work, together with evidence that authors have gained during their work on more than 15 different domains of real-world applications in the last decade.

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