Chapter 9. Introduction to Soft Computing

Soft computing (**SC**) represents an innovative approach to building computationally intelligent systems. Nowadays complex real-world problems require intelligent systems that combine knowledge, techniques and methodologies from several sources. The intelligent systems are assumed to possess humanlike experience within specific domains, adapt themselves and learn to improve their actions in modifying environments, and explain how they make decision or take actions.

In coping with real-world computing problems it is frequently advantageous to use several computing techniques resulting in hybrid intelligent systems. The structure of this type of intelligent systems can be summarized as follows:

- neural networks recognize patterns and adapt themselves to cope with modifying environments,
- fuzzy inference systems incorporate human knowledge and perform inferencing and decision making,
- derivative-free and nature-inspired evolutionary-based optimization techniques contribute to optimizing the behaviour of intelligent systems.

This chapter will present a brief overview on relevant soft computing approaches focused on intelligent systems and intelligent control systems.

9.1. Soft computing constituents and conventional artificial intelligence

SC consists of several computing paradigms representing **constituent methodologies**, each of them having its own strength pointed out as follows (Jang et al., 1997):

- neural networks, with strength in learning and adaptation,
- fuzzy set theory, with strength in knowledge representation by means of IF-THEN rules,
- genetic algorithms and simulated annealing (recently, more general nature-inspired evolutionary-based optimization), with strength in systematic random search,
- conventional artificial intelligence (AI) with strength in symbolic calculation.

The integration of these methodologies makes the core of SC, and the synergism allows SC to incorporate human knowledge effectively, deal with imprecision and uncertainty, and learns to adapt to unknown or modifying environments aiming performance enhancement.

SC requires extensive computations for learning and adaptation. In this context, SC shares the same characteristics as computational intelligence. Generally speaking, SC does not perform much symbolic manipulation, so it can be viewed as complementary to conventional AI approaches and vice versa.

The schematic representation of an intelligent system that can sense its environment (perceive) and act on its perception (react) is illustrated in Fig. 9.1. This representation allows the implementation of several SC constituents in its blocks.

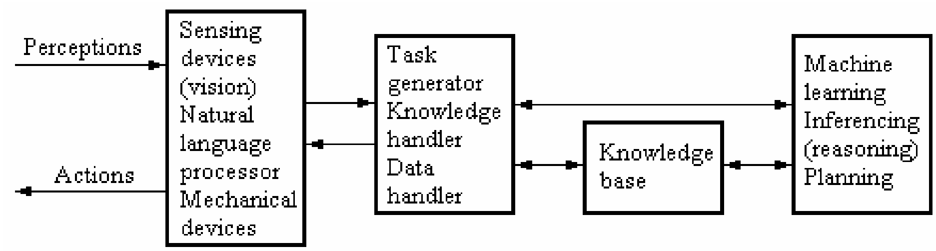

Fig. 9.1. Schematic representation of an intelligent system.

9.2. Soft computing characteristics

The characteristics of SC, can be summarized as follows taking into account the consideration of neuro-fuzzy modelling and control as its core:

1. **Human expertise**. SC uses human expertise expressed as fuzzy IF-THEN rules (fuzzy control rules or fuzzy modelling rules) for conventional knowledge representation in order to solve practical problems.

2. **Biologically inspired computing models**. Artificial neurons are inspired by biological neurons, and they are employed extensively in SC to deal with perception, patter recognition, nonlinear regression and classification.

3. **Innovative optimization methods**. SC applies new optimization methods arising from various sources: genetic algorithms (inspired by the evolution and selection process), simulated annealing (motivated by thermodynamics), random search method, downhill Simplex method. All these methods do not require the calculation of the gradient vector of the objective function in the optimization problems solved using SC methods. Therefore, these methods are more flexible in coping with complex optimization problems associated often with multiple extremum points.

4. **Numerical computation**. This characteristic makes a quite difference to symbolic AI because SC relies mainly on numerical computation. However, incorporation of symbolic techniques in SC plays also an important role.

5. **Model-free learning**. Neural networks and fuzzy systems have the ability to construct models using only input-output system data. Detailed information on the system to be identified enables setting up the initial model structure.

6. **Intensive computation**. SC relies heavily on high-speed computation in situations with less background knowledge of the problem being solved in order to find rules or regularity in data sets.

7. **Fault tolerance**. Neural networks and fuzzy inference systems permit fault tolerance. The deletion of a neuron in a neural network or a rule in a fuzzy inference system does not necessarily destroy the system behaviour. Instead, the system continues exhibiting acceptable performance because of its parallel and redundant architecture, although quality performance indices gradually deteriorate.

8. **Goal driven characteristics**. SC constituents are goal driven, i.e. the trajectory leading from the current state to the solution does not really matter as long as it is moving toward the goal. This is particularly true when used in combination with derivative-free

optimization techniques. Domain-specific knowledge contributes to reduce the amount of computation and search time, but this is not a prerequisite.

9. **Real-world applications**. Most real-world applications, beyond the applications of AI, are computationally expensive, belong to large-scale systems and inevitably incorporate built-in uncertainties. This makes problematic the use of conventional approaches that require detailed mathematical models of the problems being solved. SC is an integrated approach that can usually utilize specific techniques within subtasks to build generally satisfactory solutions to real-world problems.

9.3. Soft computing in intelligent control systems in the framework of intelligent systems

The presentation will be firstly focused on three of SC components, fuzzy set theory, neural networks and evolutionary computation.

Fuzzy set theory provides a systematic calculus to deal linguistically with information interpreted by the grain (imprecise and incomplete sensory information provided by perceptive organs), and it performs numerical computation using linguistic terms stipulated by the fuzzy sets and associated membership functions. In addition, a selection of fuzzy IF-THEN rules builds the rule base, a key component of a fuzzy inference system that can effectively model human experience in specific applications.

Although fuzzy inference systems, as general term referring not just the fuzzy controllers usually associated with industrial applications (although the applications areas of fuzzy controllers and fuzzy control systems are numerous), have structured knowledge representation in the form of fuzzy IF-THEN rules, they lack the adaptability to deal with modifying external environments. That is the reason to incorporate neural network abilities to fuzzy inference systems, resulting in **neuro-fuzzy modelling**.

Artificial **neural networks** are inspired by biological nervous systems and provide a nonalgorithmic approach to information processing. They model the human brain (source of natural intelligence and remarkable parallel computer) as continuous- or discrete-time dynamic systems in connectionist architectures that are expected to mimic brain mechanisms aiming the simulation of intelligent behaviours. Such connectionism replaces symbolically structured representations with distributed representations in the form of weights between a large set of interconnected neurons. These algorithms do not require critical decision flows.

Much attention is paid to **evolutionary computation** including genetic algorithms (GAs) because simulating complex biological evolutionary processes may lead to discovering how evolution pushes living systems towards higher-level intelligence. GAs are based on the evolutionary principle of natural selection. Heuristically informed search techniques are employed in a lot of AI applications. When the search space is too large for an exhaustive search and it is difficult to identify knowledge that can be applied to reduce this search space, it is necessary to use other efficient techniques to find the so-called **less-than-optimum solutions**. GAs represent candidate techniques with this respect offering the capacity for population-based systematic random searches. Simulated annealing and random search are other serious candidates that explore the search space in a stochastic manner.

Connecting SC to intelligent systems, it is necessary to highlight the control methodology as set of techniques and procedures used to construct and / or implement a controller for a dynamical system. A control methodology is an **intelligent control methodology** is it uses human / animal / biologically motivated techniques and procedures specific to SC to develop and / or implement a controller for a dynamical system (Antsaklis and Passino, 1993). The controller is referred to as **intelligent controller** if it is developed and / or implemented with:

- an intelligent control methodology or
- conventional control techniques

to emulate / perform control functions, that are normally performed by humans / animals / biological systems.

Modelling and representation aspects concerning the controlled plants are important in the development of intelligent control systems. Usually the trend is in trying to model an as wide as possible range of plant behaviour in order to expand as possible the operating range of the plant. However, several problems come with this approach:

- a mathematical model is never a perfect representation of a physical system, being an abstraction,
- everything that is done in theoretical analysis and development is based on the modelling assumption,
- if the plant model is chosen to be too complex, it will be harder to develop and utilize mathematical approaches for the analysis of the resulting closed-loop system.

On the other hand, there are several shortcomings in the opposite trend, the attempt to develop controllers without depending on the model:

- there are few assumptions (if any) to be violated by a control technique and the technique can be indiscriminately applied,
- heuristics are all that is available to perform controller development,
- ignoring a formal model (if available) leads to ignoring a serious amount of information about how to control the plant,
- standard control systems analysis techniques cannot be used to test the operation of the resulting control systems,
- it is difficult to characterize in clear manner the limitations of several SC techniques that enable the decision on which plants can be controlled best with different either intelligent or conventional controllers,
- it may not be possible to clearly connect the results of using the intelligent controllers to previous results in conventional control of the same plant and to highlight the control system performance indices.

Concluding, models are always necessary, and the model development task employing SC techniques must be appropriately approached with a cost / benefit analysis.

The **analysis of intelligent control systems** is of exquisite importance. In this framework, it is necessary to first state, from an engineering perspective, why it is important to perform nonlinear analysis of intelligent control systems. While current nonlinear analysis techniques do not always offer a complete testing approach for implemented controllers they do provide methods to help avoid problems such as instabilities and limit cycles. For a complete testing and certification, certainly simulation and experimental results also play a major role. In any case, careful engineering analysis must be employed as far all intelligent control system developments and evaluations are concerned. Ad hoc implementations of intelligent control systems must be avoided because:

- thet represent bad engineering practice,
- such implementations are likely to not being reliable,
- they will not be trusted.

When intending to perform mathematical analyses of intelligent control systems it is important to first recognize that there are some trade-offs with the type of modelling approach used. Generally speaking, a more complex model may offer the possibility to obtain a better representation of a system and may facilitate development, but it may not lend itself to straightforward analysis. Is a simpler model is used, one may ignore some of the dynamical behaviour of the plant and be able to get more analytical results but they may only be valid in an approximate way for the real system or for part of its operating points. Naturally here will be different analysis techniques that are appropriate for different models that are used.

References

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