

Chapter 3.16

Soft Computing Paradigms and Regression Trees in Decision Support Systems

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ABSTRACT

Decision-making is a process of choosing among alternative courses of action for solving complicated problems where multi-criteria objectives are involved. The past few years have witnessed a growing recognition of soft computing (SC) (Zadeh, 1998) technologies that underlie the conception, design, and utilization of intelligent systems. In this chapter, we present different SC paradigms involving an artificial neural network (Zurada, 1992) trained by using the scaled conjugate gradient algorithm (Moller, 1993), two different fuzzy inference methods (Abraham, 2001) optimised by using neural network learning/evolutionary algorithms (Fogel, 1999), and regression trees (Breiman, Friedman, Olshen, & Stone, 1984) for developing intelligent decision support systems

(Tran, Abraham, & Jain, 2004). We demonstrate the efficiency of the different algorithms by developing a decision support system for a tactical air combat environment (TACE) (Tran & Zahid, 2000). Some empirical comparisons between the different algorithms are also provided.

INTRODUCTION

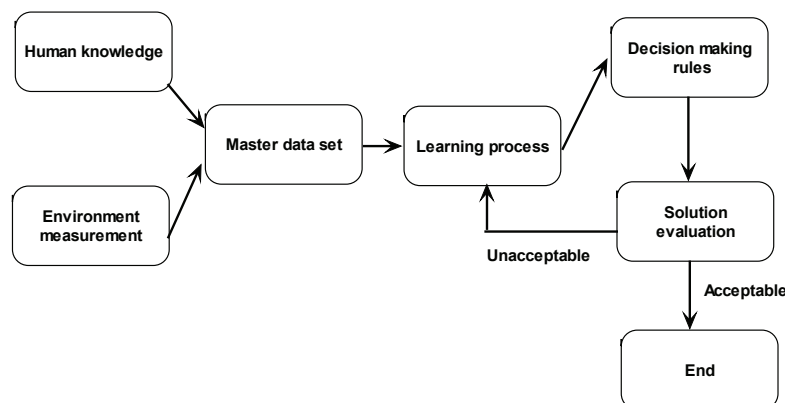
Several decision support systems have been developed in various fields including medical diagnosis (Adibi, Ghoreishi, Fahimi, & Maleki, 1993), business management, control system (Takagi & Sugeno, 1983), command and control of defence and air traffic control (Chappel, 1992), and so on. Usually previous experience or expert

knowledge is often used to design decision support systems. The task becomes interesting when no prior knowledge is available. The need for an intelligent mechanism for decision support comes from the well-known limits of human knowledge processing. It has been noticed that the need for support for human decision-makers is due to four kinds of limits: cognitive, economic, time, and competitive demands (Holsapple & Whinston, 1996). Several artificial intelligence techniques have been explored to construct adaptive decision support systems. A framework that could capture imprecision, uncertainty, learn from the data/information, and continuously optimise the solution by providing interpretable decision rules, would be the ideal technique. Several adaptive learning frameworks for constructing intelligent decision support systems have been proposed (Catral, Oppacher, & Deogo, 1999; Hung, 1993; Jagielska, 1998; Tran, Jain, & Abraham, 2002b). Figure 1 summarizes the basic functional aspects of a decision support system. A database is created from the available data and human knowledge. The learning process then builds up the decision rules. The developed rules are further fine-tuned, depending upon the quality of the solution, using a supervised learning process.

To develop an intelligent decision support system, we need a holistic view on the various tasks to be carried out including data management and knowledge management (reasoning techniques). The focus of this chapter is knowledge management (Tran & Zahid, 2000), which consists of facts and inference rules used for reasoning (Abraham, 2000).

Fuzzy logic (Zadeh, 1973), when applied to decision support systems, provides formal methodology to capture valid patterns of reasoning about uncertainty. Artificial neural networks (ANNs) are popularly known as black-box function approximators. Recent research work shows the capabilities of rule extraction from a trained network positions neuro-computing as a good decision support tool (Setiono, 2000; Setiono, Leow, & Zurada, 2002). Recently evolutionary computation (EC) (Fogel, 1999) has been successful as a powerful global optimisation tool due to the success in several problem domains (Abraham, 2002; Cortes, Larrañeta, Onieva, García, & Caraballo, 2001; Ponnuswamy, Amin, Jha, & Castañón, 1997; Tan & Li, 2001; Tan, Yu, Heng, & Lee, 2003). EC works by simulating evolution on a computer by iterative generation and alteration processes, operating on a set of

Figure 1. Database learning framework for decision support system



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