A Novel Approach to Fuzzy Model Identification Based on Bat Algorithm

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ABSTRACT

The identification of a fuzzy model is a complex and nonlinear problem. This can be formulated as a search and optimisation problem and many computing approaches are available in the literature to solve this problem. This research paper is focused on using a new nature inspired approach for fuzzy modeling based on Bat Algorithm which is derived from the behaviour of micro-bats to search for their prey. The bat algorithm approach has been implemented and validated successfully on a rapid battery charger fuzzy controller problem. Currently, the key requirement is real-time solutions to complex problems at a blazing speed. Bat algorithm evolved the optimised fuzzy model within a few seconds as compared to other approaches.

KEYWORDS


INTRODUCTION

Zadeh’s proposal of modeling the mechanism of human thinking with linguistic values rather than ordinary (crisp) numbers led to the introduction of fuzziness into statistical and dynamical modelling and to the development of a new class of systems called fuzzy models. Fuzzy models are capable of incorporating linguistic information naturally and conveniently. The ability to deal simultaneously both with linguistic information and numerical information in a systematic and efficient manner is one of the most important advantages of fuzzy models (Zadeh, 1965; Yen & Langari, 1999).

In fuzzy modeling, one of the most important problems is the identification of a predictive model from a set of numerical data. It is the task of identifying the parameters of a fuzzy inference system so that a desired behaviour is attained (Yager & Filev, 1994). The task of fuzzy model identification is basically based on proper generation of their structure which includes membership functions, input and output parameters and rule-base (Angelov & Buswell, 2002). This task can be performed by following the steps given below (Kumar, Bhalla & Singh, 2009):

Step 1: Initialization of the rule-base structure (antecedent part of the rules).
Step 2: Estimation of the parameters of the consequent part.
Step 3: Prediction of the output of fuzzy model through standard data sets.
Step 4: Reading of the next data sample at the next time step.
Step 5: Recursive calculation of the potential of each new data sample to influence the structure of the rule-base.

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Step 6: Recursive up-date of the potentials of old centres taking into account the influence of the new data sample.

Step 7: The new data sample competes with the existing rules’ centres. Decision to modify or update the rule-base structure is taken.

The problem of fuzzy model identification can be formulated as a search and optimisation problem and it becomes very difficult to realise when the available knowledge is incomplete, and the search space is very large. The survey related to this field reveals that many hard computing as well as soft computing techniques are available in the literature to solve such problems. But the best suited way to tackle this problem is proved to be the use of soft computing approaches like Genetic algorithms, Neural networks and other Nature inspired approaches. Unlike hard computing techniques, soft computing techniques do not rely on preciseness and accuracy. They provide good enough solutions with high probability and low cost.

Literature Survey

Some of the soft computing techniques that have already been used for fuzzy modeling are mentioned below:

Genetic Algorithms

The use of genetic algorithms (GAs) and other evolutionary optimization methods to design fuzzy rules for systems modeling and data classification have received much attention in literature. Genetic algorithms are adaptive heuristic search algorithms that are based on the idea of natural selection and genetics. The problem of fuzzy models having large sets of input variables and a rule-base with some unwanted elements that increase computational complexity of system can be solved by GAs. Genetic algorithms have the ability of exhaustive search to solve the above-mentioned problem.

An adaptive GA fuzzy controller was designed by Karr and Gentry (1993) for a laboratory acid-base system. It proved that the combination of GAs with fuzzy systems provide powerful control techniques in nonlinear environment like that of changing pH systems. An automatic fuzzy system was designed using GAs (Liska & Melsheimer, 1994) for three stages: membership function specification, number of fuzzy rules and the consequent parameters, all at the same time. A self-organised genetic algorithm-based rule generation method was presented by Pal and Pal (2003) for FLC.

Bastian (2000) identified fuzzy models using genetic programming and for this purpose, several new reproduction operators were introduced. Setnes and Roubos (2000) applied fuzzy clustering to obtain a compact initial rule-based model. Then this model is optimized by a real-coded GA subjected to constraints that maintain the semantic properties of the rules. Sarimveis and Bafas (2002) used genetic algorithm for fuzzy models predictive control of non-linear processes.

For the problems related to classification Mansoori, Zolghadri & Katebi (2008) designed a novel steady-state genetic algorithm for the extraction of a compact rule set. This method has many advantages including generation of few rules, saving memory, fast, etc. Memetic algorithm based fuzzy modeling was proposed by Ning, Ong, Wong and Seow (2003).

Neural Networks

There are many scholars who provided various methods of fuzzy modeling through neural networks. Ishikawa (1996) demonstrated the training of a network using structural learning with forgetting. It leads to easy extraction of rules. This was modified by Duch, Adamczak and Grabczewski (1998) who constrained the weights to 1, 1 or 0. Fu (1994) developed KT algorithm in order to extract rules from a trained network that searches subsets of connections to a network’s unit with summed weight exceeding the bias of that unit.
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