A Survey on Soft Computing Based Approaches for Fuzzy Model Identification

Neety Bansal, Parvinder Kaur

Abstract: ***The identification of an optimized fuzzy model is one of the key issues in the field of fuzzy system modeling. This can be formulated as a search and optimisation problem and many hard computing as well as soft computing approaches are available in the literature to solve this problem. In this paper we have made an attempt to present a survey on fuzzy model identification using some soft computing techniques like ACO, BBO, BB-BC, ABC, etc.***

Keywords: ***Fuzzy system, Fuzzy model identification, Soft computing, Nature inspired approaches.***

I. INTRODUCTION

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 [1, 2]. Fuzzy rule-based (FRB) models successfully overcome many problems related to real time applications. The main hindrance in designing an FRB model is the proper and adequate generation of their structure (the rule base, membership functions and linguistic labels) and parameters [3].

The task of fuzzy model identification can be formulated as a search and optimisation problem and hence optimisation techniques can be applied to this problem. This task can be performed through following steps [3]:

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.

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 execution of the process continues with Step 2.

The process of identification of a fuzzy model includes three major issues: structure identification (input selection, membership function specification and rule-base generation), parameter estimation and model validation as shown in figure 1 [4].

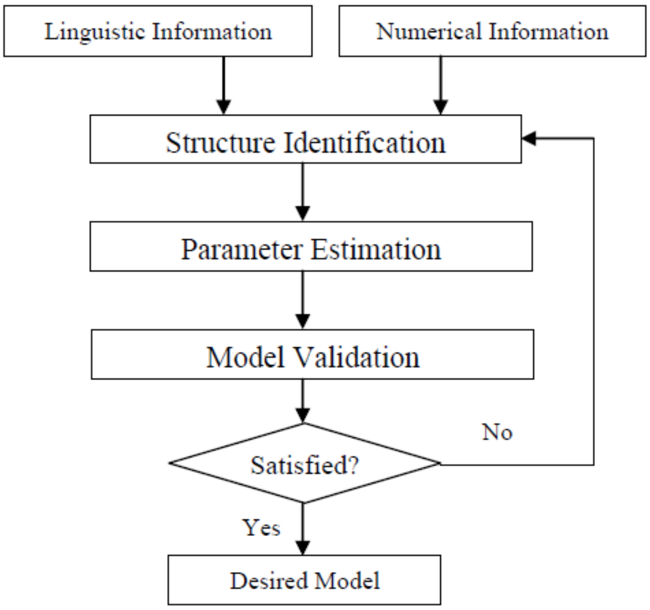

Figure 1: Fuzzy Model Identification Process

Structure identification involves finding the important input variables from all possible input variables, specifying membership functions and generation of a compact rule-base with only relevant elements.

Parameter estimation involves identifying the best values for a set of model parameters. There are two types of parameters in a fuzzy model: parameters of antecedent membership functions and parameters of consequent part of rules.

Model validation involves verifying the model based on some performance criterion.

The paper provides a survey on fuzzy model identification using soft computing techniques. Rest of the paper is divided into various sections: Section 2 gives a brief introduction about soft computing, Section 3 provides the survey of soft computing approaches used for fuzzy modeling and Section 4 draws the conclusion.

II. SOFT COMPUTING

The discipline of computing is the systematic study of algorithmic processes that describe and transform information. The conventional hard computing techniques are certain, precise and accurate but with a cost of delay. Hard computing approaches are not suitable for real life applications where we cannot provide a precise computing model because.

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of the changing non-ideal environment of real life scenarios. Unlike hard computing, soft computing is tolerant to imprecision, uncertainty and approximation. This makes the soft computing approaches suitable for real life scenarios. The challenge is to exploit the tolerance for imprecision and approximation by devising methods of computation that lead to acceptable solutions at low cost. This, in fact, is the guiding principle of soft computing [4, 5].

Basically soft computing is not a homogenous body of concepts and techniques. Rather, it is a partnership of distinct methods that in one or another confirm to its guiding principle. The principal constituents of soft computing are: Fuzzy logic (FL), Neural networks (NN), Evolutionary computation (EC) and Machine learning (ML). Soft computing provides flexibility in the computation of an imprecise problem by leading to an approximate low cost solution. We can use the soft computing tools for fuzzy model identification which includes membership function optimisation and rule base generation. A fuzzy system can be designed by using a multilayer neural network whose parameters can be determined through Genetic algorithms (GA's). Such systems can be termed as neuro-fuzzy-genetic [6]. So, all the soft computing tools can be used to design an intelligent system which is capable of remarkable human ability of making rational decisions in an uncertain and imprecise situation.

III. SOFT COMPUTING APPROACHES FOR FUZZY MODEL IDENTIFICATION

Fuzzy model identification is a complex problem which needs to be treated as a real time application. Soft computing techniques are the best suited solution for such problems. Some of these soft computing techniques that have already been used for fuzzy modeling are mentioned below:

A) 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 Charles L. Karr [7] 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 [8] 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 T. Pal and N.R. Pal [9] for FLC.

Andreas Bastian [10] identified fuzzy models using genetic programming and for this purpose, several new reproduction operators were introduced. M. Setnes and H. Roubos [11] 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. H. Sarimveis, G. Bafas [12] used genetic algorithm for fuzzy models predictive control of non-linear processes.

For the problems related to classification Eghbal G. Mansoori et al. [13] 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 Zhu et al. [14].

B) Neural Networks

There are many scholars who provided various methods of fuzzy modeling through neural networks. Ishikawa [15] demonstrated the training of a network using structural learning with forgetting. It leads to easy extraction of rules. This was modified by Duch et al. [16] who constrained the weights to 1, 1 or 0. Fu [17] 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.

A fast method for extraction of rules was developed by Setiono and Leow [18] from trained feedforward network. Extraction of rules corresponding to partition of space using hyperplanes was given by Setiono and Liu [19]. This resulted in extraction of compact rules with high accuracy from the trained network. Wen Yu and Xiaoou Li [20] suggested new learning laws for Mamdani and TSK type fuzzy neural networks based on input-to-state stability approach. Stable learning algorithms for the premise and the consequence parts of fuzzy rules are proposed.

G Leng et al. [21] proposed an approach for online extraction of fuzzy rules using a self-organising fuzzy neural network which lead to successful identification of fuzzy model. R.H. Abiyev and O Kaynak [22] proposed the integration of fuzzy set theory and wavelet neural networks (WNNs). This includes a wavelet function in the consequent part of the rule. The parameter update rules of the system are derived based on the gradient descent method. Neural networks and fuzzy systems both have their advantages and disadvantages. But if we combine them the result is a powerful approach to learn.

C) PSO

Particle swarm optimisation is inspired by social foraging behaviour of some animals such as flocking behaviour of birds and the schooling behaviour of fish. PSO [23] is a stochastic algorithm that is population based and it searches for an appropriate solution from its search space. The algorithm is executed like a simulation, advancing the position of each particle based on its velocity, the best known global position in the problem space and the best position known to a particle. The objective function is sampled after each position update. He Zhenya et al. [24] presented a four layer fuzzy neural network to realise knowledge acquisition from input-output samples.

The network parameters including the necessary membership functions of the input variables and the consequent parameters are tuned and identified using a modified particle swarm algorithm.

R. Marinke et al. [25] proposed PSO as a method for optimizing the premise part of production rules and least mean squares technique is employed for consequent part of production rules of a T-S fuzzy model. A.A.A. Esmin et al. [26] showed that PSO is able to generate an optimal set of parameters for fuzzy reasoning model based on either, their initial subjective selection, or on a random selection. PSO algorithm was used by Arun Khosla et al. [27] for optimised fuzzy model identification from given numerical data. Araujo and Coelho [28] proposed PSO approach intertwined with Lozi map chaotic sequences to obtain Takagi–Sugeno (TS) fuzzy model for representing dynamical behaviours.

D) ACO

Ant colony optimisation (ACO) is a metaheuristic technique that belongs to the group of swarm intelligence based techniques. ACO is motivated by the behaviour of real ants and the way they communicate to each other through pheromone tracks. This elementary ant's behaviour inspired the development of ant colony optimization algorithm by Marco Dorigo in 1992 [29].

ACO was first applied to fuzzy modeling by Casillas et al. [30]. Some applications of ACO in fuzzy model identification are given in [31, 32, 33]. Shakti Kumar et al. used ACO for automatic rule generation of a Sugeno type system. The problem of rule-base generation was converted into weighted graphs and path lengths are termed as error. ACO searches for minimal path representing minimal error. Juang and Chang [34] proposed the design of fuzzy-rule-based systems using continuous ant-colony optimization (RCACO). It uses an online-rule-generation method to determine the number of rules and identify suitable initial parameters for the rules and then optimizes all the free parameters using continuous ant-colony optimization (ACO). SM Vieira et al. [35] used to cooperative ant colonies for feature selection using fuzzy models.

E) BBO

Biogeography is the study of geographical distribution of biological organisms. Biogeography based optimisation (BBO) is a population based algorithm and in this algorithm problem solutions are grouped as islands and sharing of features between these islands are termed as emigration or immigration.

BBO was first implemented by Simon [36] and it showed the use of a natural process to solve general optimisation problem. Shakti Kumar et al. [37] used BBO for rule-base extraction problem and enumerate rules corresponding to each data set. The results indicate that BBO is a very promising optimisation algorithm for fuzzy model identification. Zheng et al. [38] developed an earthquake rescue system whose key component is a Takagi-Sugeno (T-S)-type neuro-fuzzy network. A novel differential biogeography-based optimization (DBBO) algorithm is developed for parameter optimization of the main network and the subnetwork.

F) BB-BC

The origin and evolution of universe is summarised in the big bang theory which is broadly accepted. Big bang-Big crunch optimisation algorithm is inspired by the big bang theory. Erol et al. [39] provided this optimisation method. As energy dissipation creates disorder from ordered particles, randomness is used as a transformation of totally new solution (disorder) from a converged solution (order). Creation of an initial population randomly is referred as big bang phase which is followed by big crunch phase. Big crunch is a convergence operator with many inputs and only one output. The successive disordering and ordering (convergence) is carried out repeatedly until a stopping criterion has been met.

P. Bhalla et al. [40] applied BB-BC algorithm to successfully extract rule-base from numerical data to form a fuzzy model. The simulation results show that the proposed method has a low number of incorrectly classified patterns and also BBBC appears to be most efficient in terms of computational complexity (high speed of convergence). T. Kumbasar [41] used BB-BC as an online model adaption scheme to compensate modeling errors and disturbances by internal model control. S. Kumar et al. [42] presented a modification to existing big bang big crunch optimization algorithm. The algorithm proposes the use of more than one population and is applied to identify a fuzzy model. Engin Yesil [43] proposed an Interval type-2 fuzzy PID load frequency controller using Big Bang–Big Crunch algorithm.

G) ABC

Artificial bee colony (ABC) algorithm simulates the foraging behaviour of a bee colony. It was proposed by Karaboga in 2005 [44]. The colony of artificial bees contains three groups: employees, onlookers and scouts. The scout bee carries out random search and finds the food sources. The onlooker bee decides the food source and the employee bee visits the food source that is previously visited by it.

Shakti Kumar et al. [45] implemented the ABC algorithm for fuzzy model identification. The behaviour of an artificial bee colony is used to find an optimal solution to the rules extraction problem. D. Karaboga and C. Ozturk [46] tested the performance of the Artificial Bee Colony Algorithm which is a recently proposed algorithm, on fuzzy clustering and applied the Artificial Bee Colony (ABC) Algorithm fuzzy clustering to classify different data sets.

Beloufa and Chikh [47] designed a fuzzy classifier for diabetes disease using modified ABC algorithm. They have proposed a novel Artificial Bee Colony (ABC) algorithm in which a mutation operator is added to an Artificial Bee Colony for improving its performance. Hacene Habbi [48] proposed an artificial bee colony (ABC) optimization based methodology for automatically extracting Takagi–Sugeno (TS) fuzzy systems with enhanced performance from data.

H) FA

Firefly algorithm is again a nature inspired optimisation algorithm. It is a metaheuristic approach based on the flashing behaviour of fireflies.

The flash emitted by the fireflies is to attract other fireflies. They are attracted to each other regardless to their sex because they are unisex and this attractiveness is proportional to their brightness. The attractiveness and brightness both decrease with the increasing distance between two fireflies.

Shakti Kumar et al. [49] applied firefly algorithm for fuzzy system identification. The brightness of firefly is determined by the landscape of the objective function to be optimised. A fuzzy logic based system for academic rating of institutions of higher learning is designed using firefly (FA) optimization approach. The problem is formulated as minimization problem and all the input parameters and their membership functions along with the consequents for the rules of the rule base are modified randomly to find the desired values for the system with minimum MSE.

N. Susila et al. [50] applied a fuzzy based firefly algorithm for dynamic load balancing in cloud computing environment. By applying this it is observed that, a better performance is achieved in terms of computational time, load arrived, task migration and the cost incurred. Nguyen Cong Long and P. Meesad [51] propose an optimal design for interval type-2 Takagi-Sugeno-Kang (TSK) fuzzy logic system. A hybrid between chaos firefly algorithm and genetic algorithms (CFGA) is developed, which is used to find the desirable parameters of membership functions and consequents parameters of the fuzzy logic system. K.M. Sundaram et al. [52] used a fuzzy logic and firefly algorithm based hybrid technique for performance improvement of A.C. voltage controller fed three phase induction motor drives.

Parvinder Kaur et al. [53] presented a comparative study for designing a complete fuzzy system from available data using the above mentioned nature inspired approaches: BBO, BB-BC, ACO, ABC and FA. Another soft computing technique called Hunting search algorithm [54] was applied to tune the TSK-type neuro-fuzzy model.

IV. CONCLUSION

In this paper, we have tried to survey as many soft computing techniques as possible for fuzzy model identification. Fuzzy model identification is a very complex problem related to real time scenarios. These kinds of problems are hard to solve using traditional hard computing approaches. So, we need to shift our attention towards the various soft computing approaches. We have attempted to integrate the soft computing techniques that have already been implemented in fuzzy modeling.

The identification of fuzzy model is based on determination of parameters of membership functions and the parameters of consequent part of the rules. Soft computing techniques have proven effective in realising a complete fuzzy system model with less computational time. These approaches, specifically nature inspired approaches result in reduction of input parameters, efficient specification of membership functions and a compact rule-base and in turn decrease the computational complexity of the system. Even after the amazing results achieved so far there is still scope for improvement. More soft computing techniques are needed to be explored and implemented to identify a robust fuzzy system.

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