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Research Article

ACO for Fact Gathering of a Fuzzy System

Shikha Sharma[Ȧ*], Praveen Kumar[Ȧ] and Ruchika Manchanda[Ḃ]

[Ȧ]IST,Kalwad, Haryana, India
[Ḃ]GNI, Mullana, Haryana, India

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Abstract

Fact Gathering means generating rule base from available numerical data. The intelligence of a fuzzy system lies in its rule base. Number of rule base generation methods are used for fuzzy system such as neural networks, as Hybrid Learning, genetic algorithms, Wang & Mendel Approach, biogeography based optimization approach and particle swarm optimization found in the literature. Designing fuzzy systems is an optimization problem. This paper presents a recent nature-inspired algorithm named Ant Colony optimization (ACO) approach for automatic generation of optimized fuzzy rule base from available numerical data i.e. Fact Gathering. The ACO is inspired by real ant colony observations. It is a multi-agent approach. In the ACO, artificial ant colonies cooperate in finding good solutions for difficult discrete optimization problems. Here, Ant paths help to determine the consequent parameters of generated rules. Extracted rules are printed and then system performance is evaluated using MSE value. This approach is applied on well-known fuzzy control problem of battery charger. The proposed approach provides fuzzy models described with reduced number of rules as compared to initial fuzzy models. Also, this approach is much more efficient in terms of computational time and MSE as compare to other approaches.

Keywords: *Ant colony optimization, designing fuzzy systems, Fact Gathering, pheromone, rule base, system performance.*

1. Introduction

Fuzzy systems provide a scheme to represent the knowledge in a way that resembles human communication and reasoning. Design of fuzzy model is the task of finding the parameters of fuzzy model so as to get the desired behavior of the system. Two different approaches are used for the design of fuzzy models: Knowledge driven and Data driven models. In the Knowledge driven approach, the design is constructed from the knowledge acquired from the expert. While in Data driven models; the input-output data called numerical data is used for building fuzzy model. The design of fuzzy systems can be regarded as an optimization problem. Many intelligent optimization techniques such as neural networks, genetic algorithms, swarm intelligence, biogeography based optimization etc. have been proposed to automatically generate fuzzy rules from numerical data.

This paper discusses a new approach for Fact gathering of a fuzzy system making use of Ant colonies called ant colony optimization technique. ACO, inspired by real ant colony observations is a multi-agent approach to solve difficult combinatorial optimization problems. In the ACO meta-heuristic, artificial ant colonies cooperate in finding good solutions for difficult discrete optimization problems. Here, Ant paths help to determine the consequent parameters of generated rules.

*Corresponding author **Shikha Sharma** is a M.Tech Student; **Praveen Kumar** and **Ruchika** Manchanda are working as Lecturers

2. Structure of Fuzzy rule base system

It consists of four major modules: fuzzification, inference engine, knowledge base and defuzzification module. The fuzzification module transforms the crisp input(s) into fuzzy values. These values are then processed by inference engine based on the knowledge base supplied by the domain expert(s). The knowledge base is composed of Rule Base (RB) and Data Base (DB). Finally, the processed output is transformed from fuzzy domain to crisp domain by defuzzification module. The structure of a Fuzzy rule-based system is shown in Figure 1.

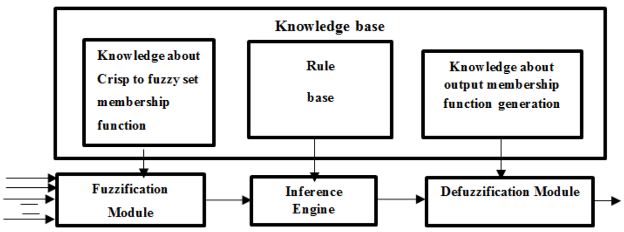

Figure 1: Structure of fuzzy rule base system

3. Structure of fuzzy Rules

A fuzzy rule is the basic unit for capturing knowledge for a fuzzy system. A fuzzy rule has two components: an if-part also referred as antecedent and a then-part also referred as consequent.

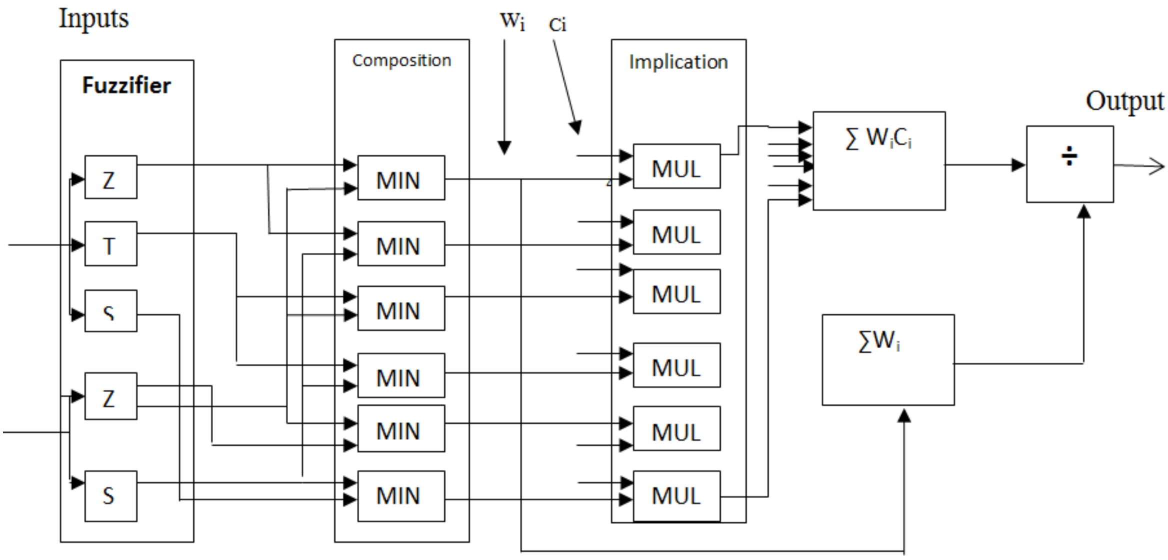

Figure 2: Sugeno type fuzzy system

Fuzzy rule: IF< antecedent > THEN < consequent >
The antecedent describes a condition and consequent describes a conclusion that can be drawn when the condition holds.

4. Problem formulation

The aim of this is to develop an optimized Rule-base for a fuzzy system. In order to determine the optimal Rule-base consider a Sugeno type fuzzy system shown in figure 2.
It consists of four main modules, *i.e.*, fuzzifier, rule composition module (fuzzy 'MIN' operators in this case), implication module (fuzzy 'MUL' operators in this case), and defuzzification module.

The overall computed output can be written as:

$$\text{Computed output} = \sum_i (Wi * Ci) / \sum Wi \quad (1)$$

The number of fuzzy rules can be defined as: $R = \sum_{i=1}^{n} \text{mi}$
But these R rules are due to combination of membership functions of various inputs and these are incomplete as we could have knowledge only about antecedent part and consequents are yet unknown. Because for any set of inputs W_i are easily computed by fuzzifier and rule composing modules, the right hand side of output expression (1) can be evaluated if we could choose the proper values for C_i's.

We compare this computed output with actual output as given in data set and find error. Let the error be defined as follows:

Error E = Actual output (as given in the data set) – computed output (as given in equation 1).

The appropriate values of C_i can be find such that the difference between the computed output and the actual output is minimum. Now the main problem of rule base generation is minimization of error. We apply S-ACO (simple-ant colony optimization) algorithm to evaluate rule base.

5. Simple- Ant colony optimization (S-ACO) algorithm

One of the most successful examples of ant algorithms is known as "Ant Colony Optimization "or ACO. It has four steps based on the behavior of real ant colonies.

Nomenclature: L^k = Length of ant K's path, ρ= evaporation constant, ρϵ (0,1] , α = a constant = 2
$\Delta\tau^k$ = increment in pheromone quantity = 1/ L^k , N_i^k = neighborhood of ant k when at node i.

Step 1 Ant's Path-Searching Behavior: This step is used for finding the next node. For this, At each node, a constant amount of pheromone is assigned to all the arcs. When located at the node i an ant k use the pheromone trails τ_{ij} to compute the probability of choosing j as next node:

$$P_{ij}^k = \begin{cases} \tau_{ij}^{\alpha} / \sum_{l\epsilon N_i^k} \tau_{ij}^{\alpha}, & \text{if } j\epsilon N_i^k; \\ 0, & \text{if j } j\epsilon N_i^k \end{cases}$$

Step 2 Path Retracing and Pheromone Update: When ant K reaches the destination node, then ant retraces step by step the same path back to source node. During its return travel to the source the ant K deposits an amount $\Delta\tau^k$ of pheromone on arcs it has visited. In particular, if ant k is in the backward mode and it traverses the arc (i, j), it changes the pheromone value τ_{ij} as follows:

$$\tau_{ij} \leftarrow \tau_{ij} + \Delta\tau^k \quad (2)$$

Step 3 Pheromone Trail Evaporation: Pheromone trails evaporates with exponential speed. Pheromone trails are evaporated by applying the following equation to all the arcs:

$$\tau_{ij} \leftarrow (1-\rho)\, \tau_{ij}$$

Step 4:Termination Condition: The program stops if at least one termination condition applies: 1. A maximum number of algorithm iteration has been reached.

2. If end of edge is the terminal node.

6. Simulation Results

Problem: Battery charger: The ACO has been applied for Fact gathering of fuzzy model for the rapid Nickel-Cadmium (Ni-Cd) battery charger. The main objective of development of this charger was to charge the batteries as quickly as possible but without doing any damage to them. Input-output data consisting of 561 points, obtained through experimentation. For this charger the two input variables used to control the charging rate (ct) are absolute temperature of the batteries (T) and its temperature gradient (dT/dt). Charging rates are expressed as multiple of rated capacity of the battery. The input-output variables identified for rapid Ni-Cd battery charger along with their universes of discourse are listed in table 6.1.

Table 1: Input and Output variables for rapid Ni-Cd battery charger along with their Universe of discourse

Input Variables	Minimum Value	Maximum Value
Temperature (T)[0C]	0	50
Temperature Gradient (dT/dt)[0C/sec]	0	1
Output Variable		
Charging Rate (Ct) [A]	0	4

The block diagram for the system used to gather fact is given below. Consider sugeno type model for battery charger with two inputs and single output variable. The input variable temperature with the universe of discourse ranging from 0-50 degree centigrade is partitioned into three fuzzy sets namely low, medium and high. The input variable temperature gradient with the universe of discourse ranging from 0-4 degree centigrade per second is partitioned into two fuzzy sets namely low and high.

After fuzzification of the inputs, 6 combinations of input membership functions (3*2=6) representing 6 antecedents of rules are obtained. The rule base is yet incomplete as for each rule the consequent is need to be found out. From the given data set there are only 5 consequents that from where to choose one particular element as the consequent for a particular rule. The specified set of consequents in this case are C1 = trickle=0.1A, C2=Low=1A, C3= Medium=2A, C4= high=3A, C5= ultrafast=4A. Choose parameters of antecedent and consequent in such a way as to satisfy the condition given by expression: Error E=O $_{\text{Actual}}$ – O $_{\text{Computed}}$. In order to solve the minimization problem using ACO the problem is converted into a weighted graph. Since there are six rules the number of nodes has to be 7 (i.e. n+1, where n=number of rules). Since for each rule select one appropriate consequent from the available 5 choices, the graph has 5 parallel paths between each pair of nodes. An edge between the two adjacent nodes represents a length equal to (Wi*Ci)/2. Further this weighted graph is normalized by dividing all the distances by minimum distance of all the edges. This normalization helps convert the distances into integers in terms of minimum distance. This step has been carried out purely for computational ease. The consequent has to be chosen in such a way as to minimize error as given in the condition.

The methodology presented above has been implemented as a Matlab m-file. Set of operating parameters as listed in Table 6.2, were used for the above model.

Table 2: ACO algorithm parameters for battery charger problem

Parameter	Value
Number of ants	40
α (constant)	2
Number of Iterations	2000
ρ (evaporation constant)	0.4
$\Delta\tau^k$ (Pheromone deposit factor)	0.1

Generated Rules are shown in figure. 3.

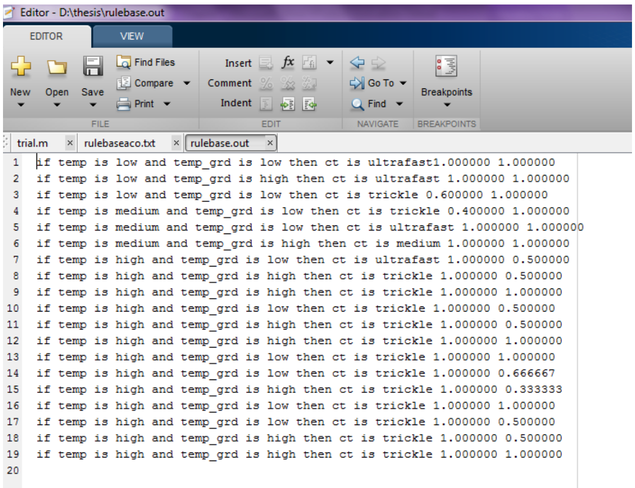

Figure 3: Generated Rules

Extracted rule base: With tuning of membership functions and application of rule reduction algorithm. ACO leads to the following set of rules.

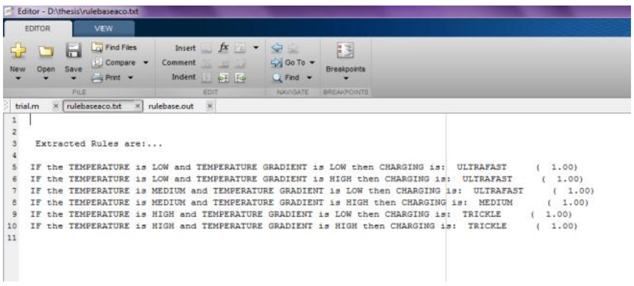

Figure 4: Final Extracted Rules

Results and comparison

The Mean Square Error (MSE) for the battery charger control system using proposed approachis 0.030.
The comparison of proposed approach with other methods is shown in table.

Table.3. Comparison of different methods with proposed approach

Approach	Mean Square Error (MSE)
Hybrid Learning	0.132
Genetic Algorithm	0.13
Particle Swarm Optimization	0.112
Wang & Mendel Approach	0.06
Proposed Approach (ACO)	0.03

Future scope and Conclusion

The proposed algorithm successfully generated optimized fuzzy models from training data. The proposed approach was successfully validated on battery charger problem. For battery charger problem, ACO appears to be more efficient in terms of computational time and MSE as compare to other approaches. Simulation results show that ACO generated a fuzzy model with average MSE of 0.03. Proposed approach provides optimized membership functions and generation of rules that produce minimum error. The proposed S-ACO algorithm provides fuzzy models described with reduced number of rules as compared to initial fuzzy models. This approach can be applied to other data sets such as for iris data classification problem.

Appendix

Training Data Set for Battery Charger

Data Point	Input 1	Input 2	Actual Output
1	0	0.1	4.0
2	5	1.0	4.0
3	10	0.5	4.0
4	20	0.2	4.0
5	30	0.9	4.0
6	37	0.8	4.0
7	37	1.0	4.0
8	38	0.4	3.0
9	38	1.0	3.0
10	40	0.8	3.0
11	41	0.7	2.0
12	42	0.5	2.0
13	42	0.6	2.0
14	43	0.4	2.0
15	44	0.2	0.1
16	44	1.0	0.1
17	45	0.8	0.1
18	48	0.1	0.1
19	50	0.1	0.1
20	50	1.0	0.1

Input 1 – Temperature
Input 2 – Temperature Gradient
Actual Output - Charging Current

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