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Investigation of resource allocation efficiency in optimization of fuzzy control system

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Abstract. The article investigates the efficiency of various computational resource allocation schemes for automated configuration of an output of a collective fuzzy control system. To configure such a system, two main tasks are required: optimization of the rule base (RB) and optimization of the terms. Each of the tasks requires its own computational resources and may occupy a different position in the general optimization scheme of a fuzzy logical system. The article compares alternative tuning schemes for a fuzzy collective-output control system and offers recommendations for the efficient allocation of computational resources.

1. Introduction

Fuzzy logic systems (FLS) are widely used in various fields, for example, image processing [1], energy systems [2], industrial control [3] and so on. For example, in the industry FLS are actively used because they allow to solve complex problems of nonlinear control or give the opportunity to work without building a model of a controlled object.

One of the tasks in designing FLS is to optimize the rule base (RB) and term-sets for linguistic variables (LV). The structure of a term-set of LV is characterized by the number and type of membership functions, which corresponds to its number of parameters. RB is a set of production rules that link LV, which consist of antecedents and conclusions. The number of antecedents in each rule can change, in which case they are combined by means of logical connectives "AND" or "OR." The problem of fuzzy model parameters identification is solved by methods of nonlinear functions optimization.

Evolutionary algorithms are a universal optimization method that simulates genetic adaptation in natural evolution [4, 5]. Unlike specialized methods developed for certain types of optimization problems, they do not require special knowledge about the structure of the problem, except for the objective function itself. The population of possible solutions develops over time with the help of genetic operators, such as mutation, crossing and selection.

Different approaches, such as genetic algorithms (GA), evolutionary strategies (ES), evolutionary programming (EP), differential evolution (DE) and genetic programming (GP) differ in genetic structures that are adapted and have specific genetic operators to generate new variants.



In the 1990s, evolutionary algorithms were proposed to automate the stage of fuzzy systems design [6] - [9]. These methods are described by the general term genetic fuzzy systems (GFS). Analysis of the literature shows that the most outstanding types of GFS are genetic fuzzy rule based system (GFRBS) [6], whose genetic process adjusts various components of the fuzzy rule based system (FRBS).

When constructing GFRBS, the process of forming both RB and LV requires large computational costs due to the use of optimization algorithms. In turn, it is necessary to solve the problem of effective resources allocation for each of these stages of designing a fuzzy model. At the same time, it is also necessary to determine the execution sequence of optimization stages RB and LV.

In this study, FRBS is a system described in [10], which is used as a special approach to the formation of ensemble for collective making solution, called «FRBS + Wmean» (or «FLS + Wmean»). FRBS is formed in such a way as to effectively combine algorithms (agents) into an ensemble.

In the process of the RB and LV «FRBS + Wmean» system optimization, a comparative analysis of the effectiveness of the fuzzy systems design for collective decision-making with different sequences of the stages implementation for automatic generation of the RB and LV is carried out. In this article, the rule base optimization was performed using GA, single-objective unconditional optimization, and LV using DE.

The rest of the paper is organized as follows: Section II describes the proposed genetic algorithm for the RB optimization and the DE for the LV optimization; Section IV contains the descriptions of numerical experiments and discussed results; Section V concludes this paper and discussed further research.

2. Proposed approach

In this work, the design of a fuzzy system is proposed to be considered as follows: at the first step, the initial RB and the initial set of LV are generated. Then the RB is formed using the GA for single-criteria optimization. In the second step, the optimization of the LV is also performed for each generated RB using the GA. Evaluation of the RB and the LV is carried out using the fuzzy collective inference procedure. The RB or the LV are installed in the GFRBS system and checked on a test set.

We considered two fundamentally different schemes. In the first scheme, as shown in figure 1, the LV optimization stage was performed after the RB optimization.

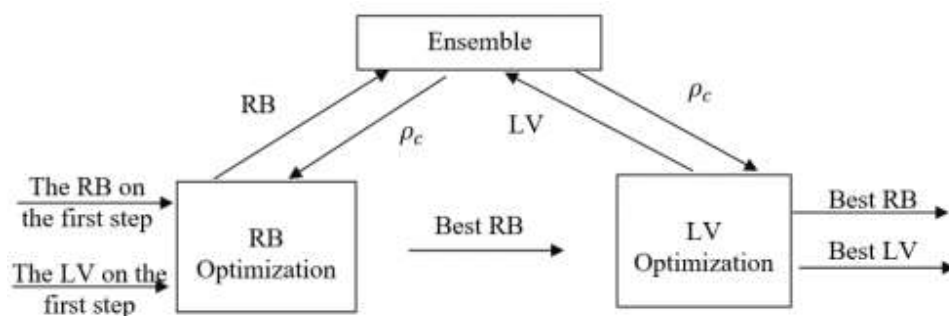


Figure 1. Example of a scheme in which first the RB optimized at step 1, and then the LV is optimized for the design of the fuzzy logic system for collective decision-making.

In the second scheme, the design of a fuzzy system is inverted, where the stage of the RB optimization was performed after the LV optimization.

The evaluation of the individual's efficiency is made using the Concordance Correlation Coefficient ρ_c - the quality criterion of the formed RB and LV in equation (1):

$$\rho_c = \frac{2\rho\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2 + (\mu_x - \mu_y)^2} \quad (1)$$

where μ_x and μ_y are the average values of the two variables, and σ_x^2 and σ_y^2 are the corresponding variance, ρ is correlation coefficient between two variables.

Figure 2 shows the coding of the GA chromosome (RB) for binary optimization, in which each rule consists of the antecedents and conclusions. The first line indicates the possible combinations of the fuzzy variable linkage by operators "AND" or "OR", and the second line shows the binary representation, where the values 0 mean the "AND" operator, and values 1 mean "OR". This binding applies to each rule in its own way.

Also, the first line indicates the number of terms for each LV, one bit is assigned to each of them, respectively, in the second line this is reflected in such a way that a value of 0 means the exclusion of the term from the rule, and 1 means inclusion.

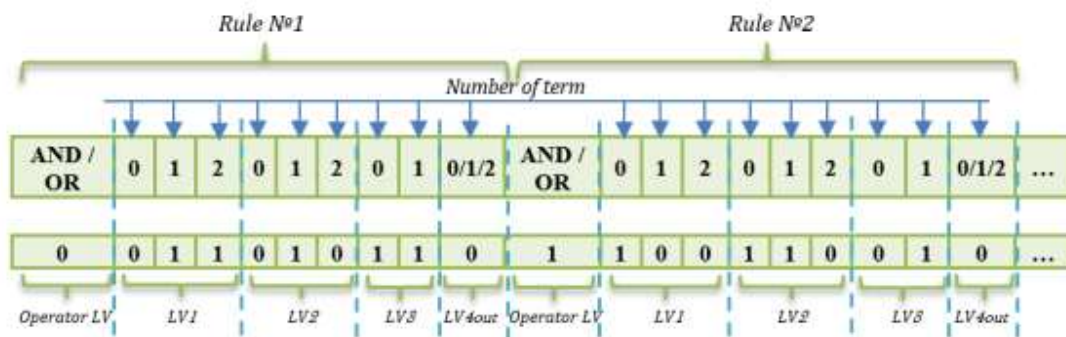


Figure 2. Chromosome coding structure, which is the RB for the GA single-objective optimization.

The LV input "Distance" (LV1) and "Error" (LV2) are described by 3 terms, and "Weight_agent" (LV3) has 2 terms. The LV output of "Confidence" (LV4out), which has 3 terms, has 2 bits, that is, this variable can take the following values: 00 – term 0, 01 – term 1, 10 – term 1, 11 – term 2.

The number of bits required to represent 1 rule equals 11. Accordingly, the chromosome (individual), which is the rule base, has a dimension ($m \times 11$) bits, where m is the number of rules. In this paper m equals 3.

The coding of the differential evolution chromosome (LV) is presented in figure 3 (real parameter optimization problem), which contains the parameters of the triangular membership function (a , b , c) for each LV term. The first line indicates the term number for each LV, and the second line shows the real-valued representation of the term parameters.

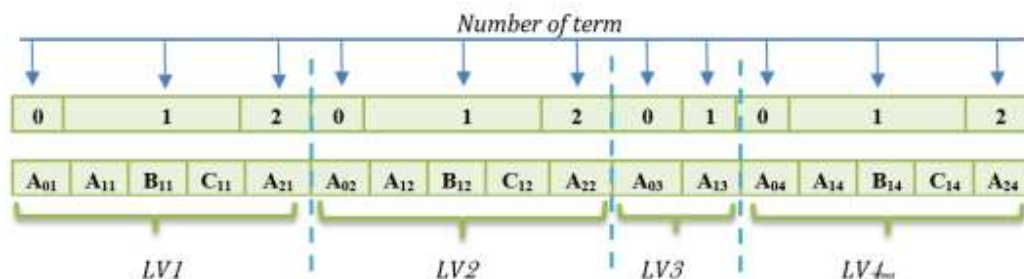


Figure 3. Structure of coding a chromosome, which is a LV for DE.

Thus, the consistent application of the genetic algorithm for the RB optimization and the DE for the LV optimization allows adjusting fuzzy collective inference system as a whole.

3. Dataset and features

The investigation of the efficiency of the direct (first RB, then LP) and inverse schemes for the formation of a collective inference with different sequence of stages of fuzzy system design was carried out using well-known sets of test problems: “House-16H”, “MV” and “Elevators”.

The “Elevators” dataset is obtained from the task of controlling a F16 aircraft, although the target variable and attributes are different. In this case the goal variable is related to an action taken on the elevators of the aircraft. The characteristics of the “Elevators” are: 16559 cases, 18 attributes (0 nominal, 18 continuous).

The “MV” dataset is an artificial dataset with dependencies between attribute values. The target values of the output variable are formed using logical rules of the “IF-THEN” type. The main characteristics of the “MV” dataset and its attributes: 10 features, 40768 sample instances.

The “House-16H” dataset is a task of predicting the average price of a house in the region based on demographic indicators and the state of the housing market. The number in the name indicates the number of attributes of the datasets. The next letter denotes some approximation to the complexity of the problem. The main characteristics of the “House-16H” dataset and its attributes: 16 attributes, described by continuous variables, 22784 sample instances. Each initial sample was divided into 3 parts: training, control and test, in the ratio of 65, 20 and 15 percent.

4. Experiments results

The genetic algorithm for the RB and the LV was tested with the distribution of resources (the number of function evaluations, NFE) in different ratios: 50/250, 100/200, 150/150, 200/100 and 250/50 for two variants of the system design sequences based on fuzzy logic for collective decision-making (Table 1).

Table 1. Benchmark dataset results in the optimization RB and LV in GFRBS.

DataSet	NFE for LV optimization	NFE for RB optimization	RB->LV ($P_{\text{test}}/P_{\text{valid}}$)		LV->RB ($P_{\text{test}}/P_{\text{valid}}$)	
			RB (first stage)	LV (second stage)	LV (first stage)	RB (second stage)
Houses	50	250	0.7407/0.7157	0.741/0.7156	0.7396/0.7105	0.7405/0.7154
	100	200	0.745/0.7163	0.7511/0.7273	0.7432/0.7142	0.7453/0.71535
	150	150	0.744/0.716	0.7455/0.716	0.7497/0.7174	0.7497/0.7118
	200	100	0.7438/0.7121	0.7512/0.7216	0.7509/0.7242	0.7509/0.7242
	250	50	0.738/0.7079	0.753/0.727	0.7496/0.7169	0.7563/0.7291
Elevators	50	250	0.9147/0.908	0.9148/0.9079	0.9147/0.9075	0.9147/0.9078
	100	200	0.9156/0.9065	0.9158/0.908	0.916/0.9055	0.9149/0.9086
	150	150	0.9147/0.908	0.9147/0.908	0.9143/0.9036	0.9147/0.908
	200	100	0.9156/0.9005	0.9238/0.9183	0.916/0.9082	0.9239/0.9185
	250	50	0.9144/0.9078	0.9249/0.9178	0.9185/0.9085	0.9247/0.9178
MV	50	250	0.9652/0.9616	0.9741/0.9765	0.9535/0.9634	0.976/0.9757
	100	200	0.9635/0.961	0.9762/0.976	0.9653/0.9654	0.9761/0.9718
	150	150	0.9602/0.966	0.9759/0.976	0.9637/0.9714	0.9759/0.9754
	200	100	0.9638/0.9643	0.9756/0.9722	0.9704/0.97123	0.977/0.975
	250	50	0.9697/0.969	0.9752/0.9762	0.9684/0.9705	0.9761/0.9758

On the basis of the results obtained for “House16” dataset, it can be concluded that the optimization order (LV-> RB or RB-> LV) is of no particular importance. The terms optimization required more computational resources than for rules optimization. This is primarily due to the difference in the types of the tasks. The RB optimization is a structural optimization and the search space is limited. The optimization of terms is the parametric optimization so that the search space has infinite number of values. Therefore, the

schemes in which more computational resources are allocated for optimization of terms turn out to be more efficient.

For the “Elevators” dataset, sufficiently high accuracy values were obtained for both optimization schemes. As can be seen from Table 1, the accuracy of the final solution weakly depends on the order of optimization (LV-> RB or RB-> LV). However, those schemes in which more computational resources are allocated for optimization of linguistic variables are more successful.

The “MV” dataset is a fairly simple task for the ensemble, so with any scheme and with any distribution of resources, a high enough level of accuracy is obtained. It is impossible to select any obvious dependencies of the resulting accuracy on the optimization scheme or the resource allocation scheme.

5. Conclusions

In this study, two alternative optimization schemes for a fuzzy collective inference control system were proposed and investigated. As a result of the study, it was shown that the order of the sequential usage of RB and LV optimization operator does not matter. However, the allocation of the resources in the RB structural optimization and LV parametric optimization is important. On two problems out of three, the schemes in which more computational resources were allocated for the optimization of the LV had won. This effect is primarily due to the differences in the structure and the dimension of the search spaces in these problems. On the third problem there was no significant difference in the schemes of designing the fuzzy system of collective inference. This may be due to the fact that the data for this problem were synthetic and the nature of the relationship between inputs and outputs is not complex.

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