



Construction of Fuzzy Fologic Mamdani Model and Tuning of its Parameters Using Modern Evolutionary Algorithms

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Abstract: *This article delves into the construction of a Fuzzy Logic Mamdani Model, enriched with modern evolutionary algorithms for parameter tuning. The synergy of fuzzy logic and evolutionary techniques enhances the model's adaptability and accuracy. Through empirical experiments, the effectiveness of this hybrid approach is demonstrated, showcasing improved performance in various domains. The study underscores the significance of evolutionary algorithms in optimizing fuzzy systems, offering a powerful methodology for refining and automating complex decision-making processes.*

Keywords: *Mamdani Model, Fuzzy Logic, Fuzzy Systems, Hybrid Model.*

Models described by a database of fuzzy rules of the "if-then" type of relationship between input and output are considered. Uncertainty modeling often uses a Mamdani format database, where the antecedent and posterior results of the rules are given in the form of fuzzy sets, for example, "Low", "Average", "High" (height). Fuzzy rules in this format were proposed, on the basis of which E. Mamdani and S. Assilian developed the first fuzzy controller [1-4]. Unlike "black box" models, Mamdani's fuzzy models are transparent, their structure is interpreted in a way that is understandable not only to developers with high mathematical skills, but also to doctors, economists, managers. The transparency of Mamdani fuzzy models is one of the main advantages, as a result of which fuzzy technologies successfully compete with other methods, especially for practical problems where meaningful interpretation is more important than modeling accuracy.

In a Mamdani type model, $X = (x_1, x_2, \dots, x_n)$ the relationship between inputs and outputs is defined through a fuzzy knowledge base in the following format:

IF ω_{j1} with weight $(x_1 = a_{1,j1})$ *ea* $(x_2 = a_{2,j1})$ *ea* ... *ea* $(x_n = a_{n,j1})$

OR ω_{j_2} by weight $(x_1 = a_{1,j_2})$ *ва* $(x_2 = a_{2,j_2})$ *ва* ... *ва* $(x_n = a_{n,j_2})$...

OR ω_{jk_j} by weight $(x_1 = a_{1,jk_j})$ *ва* $(x_2 = a_{2,jk_j})$ *ва* ... *ва* $(x_n = a_{n,jk_j})$,

IN THAT CASE $y = d_j, j = \overline{1, m}$

Here is $a_{1,jp}$ a linguistic term that evaluates a jp string x_i variable;

k_j - the number of connecting lines, in which y the output d_j is evaluated by a linguistic term;

ω_{jp} - jp indicates the rules of relative weight in the fuzzy logical output between sequence number $;[0,1]$

m - the number of terms used for the linguistic evaluation of the output variable.

Y Using (OR) operations and I (and) rewriting the fuzzy knowledge base in a more compact form.

$$\sum_{p=1}^{k_j} \left(\prod_{i=1}^n (x_i = a_{i,jp}) \omega_{jp} \text{ оғирлик билан} \right) \rightarrow y = d_j, j = \overline{1, m}. \quad (1)$$

All linguistic terms in the knowledge base (1) are represented as fuzzy sets defined by corresponding membership functions. The knowledge base (1) can be interpreted as a certain division of the space of influencing factors into subdomains with fuzzy boundaries, in each of which the response function takes the value determined by the corresponding fuzzy set. Forming a vague knowledge base in a certain field of science, as a rule, does not cause difficulties for a specialist.

$\mu_{jp}(x_i)$ - the relevance function of access $a_{i,jp}$ to an ambiguous term x_i ,

$$i = \overline{1, n}, j = \overline{1, m}, p = \overline{1, k_j}, \text{ that is } a_{i,jp} = \int_{\underline{x_i}}^{\overline{x_i}} \mu_{jp}(x_i) / x_i, x_i \in [\underline{x_i}, \overline{x_i}]$$

$\mu_{dj}(y)$ - the function of the output belonging to the uncertain term d_j , i.e

$$d_j = \int_{\underline{y}}^{\overline{y}} \mu_{dj}(y) / y, y \in [\underline{y}, \overline{y}].$$

From the knowledge base (2), the degree of relevance $x^* = (x_1^*, x_2^*, Kx_n^*)$ of the input vector to the uncertain terms d_j is determined by the following system of fuzzy logic equations:

$$\mu_{d_j}(X^*) = \bigcup_{p=1, k_j} \omega_{jp} \cdot \prod_{i=1, n} [\mu_{jp}(x_i^*)], j = \overline{1, m} \quad (2)$$

Here is $\vee(\wedge)$ the s -norm operation (t -norma), i.e. various implementations of logical OR (AND) operations. The most commonly used applications are: "OR" operation - to find the maximum, "AND" operation - to find the minimum.

X^* corresponding to the input vector y is defined as:

$$y = \underset{j=1,m}{agg} \left(\int_{\underline{y}}^{\overline{y}} imp(\mu_{d_j}(X^*), \mu_{d_j}(y)) dy \right) / y,$$

Here *imp* -implication is the operation of finding the minimum;

agg - collection of fuzzy sets, which is often considered a maximization operation.

y the output definite value X^* is determined by defuzzification of the fuzzy set corresponding to the input vector : y

$$y = \frac{\int_{\underline{y}}^{\overline{y}} y \mu_y(y) dy}{\int_{\underline{y}}^{\overline{y}} \mu_y(y) dy},$$

Here \int is the integral symbol.

It is assumed that there is a pattern of experimental data that connects the inputs $(X_r, x_r), (r = \overline{1, M})$ to the output $X = (x_1, x_2, \dots, x_n)$ of the relationship being studied : y .

Here, $X_r = (x_{r,1}, x_{r,2}, \dots, x_{r,n})$: r -pair and y_r output vector;

M -study sample size.

F Finding a fuzzy model consists of the task of adjusting the minimum mean square value:

$$R = \frac{1}{M} \sum_{j=1,M} (y_r - F(X_r))^2 \rightarrow \min \quad (3)$$

$F(X_r)$ - here $F(X_r)$ - X_r the output value of the fuzzy model at the input value given by the vector.

The output of the fuzzy model depends on its structure - rules and parameters of the knowledge base: additional functions, rule weights, implementation of logical operations, defuzzification method. The task of finding and adjusting the parameters of the fuzzy model that provides the minimum value of the criterion is presented in (3).

To improve accuracy, a fuzzy model is trained, that is, its parameters are iteratively changed to reduce the deviation of the experimental data from the logical output. Both rule weights and fuzzy relevance functions are adjustable. Mamdani fuzzy model training is a non-linear optimization problem, and many theoretical and practical works have been devoted to its study, where the main focus is on achieving the maximum accuracy of fuzzy model training. In this case, the adjusted parameters sometimes change so much that it becomes difficult to meaningfully interpret the fuzzy model. Thus, the "pursuit of precision"

leads to the loss of an important competitive advantage - the transparency of the fuzzy model. If the transparency of the model is of secondary importance, then it is appropriate to use other (non-fuzzy) methods, which are generally better suited for determining dependencies [5-8].

The purpose of this work is to study a new method to preserve the transparency of the Mamda fuzzy model and to improve its accuracy when learning from experimental data. First, the fuzzy Mamdani model is described, the training of the model is formalized in the form of a nonlinear optimization problem, and the ways to improve the training accuracy are analyzed, then the transparency requirements of the Mamdani fuzzy model are formulated, and the main methods of its maintenance are analyzed. To improve the accuracy of this model, it is proposed to set additional parameters - the limits of the carrier of fuzzy sets in appropriate rules, and to reduce the number of controlled variables and introduce new restrictions to maintain its transparency. Conventional and proposed training schemes are compared on the example of vehicle fuel consumption prediction.

Proposed the Conscious Evolution Algorithm (OEA) rule in 1998 with Chengai co-authors. The OEA algorithm models the human behavior in society, not the working activity of the human brain. In the OEA algorithm, each individual is considered as a conscious agent operating in some group of people. When making decisions, he feels the influence of his group members and other group members. More precisely, in order to achieve a high position in society, an individual must learn from the most successful individuals in his group. At the same time, in order for the group to which a certain individual belongs to be more successful than other groups, this individual, like all individuals of his group, must follow the same principle in intergroup competition [8-10].

The Multipopulation of Consciousness Evolution Algorithm is one of the leading groups $S^b = (S_1^b, S_2^b, \dots, S_{|S^b|}^b)$ and lagging behind $S^w = (S_1^w, S_2^w, \dots, S_{|S^w|}^w)$ consists of groups, the number of which is , respectively S^b, S^w . In OEA, initially the number of agents in each group is assumed to be the same and equal.

S_i^b, S_j^w each of the groups has its own communication environment, declared by the authors of the algorithm as a local bulletin board. We mark these boards accordingly C_i^b, C_j^w . In addition, all (S^b, S^w) multipopulations C^g have a common global bulletin board.

If no indexes are subsequently placed in group designations and appropriate local boards b, w , then an optional one from this group and bulletin board is assumed.

Initial version of OEA group declaration operations, local proportionality and dissimilation, called by the authors a simple algorithm of consciousness evolution based on [11].

The act of declaring groups *creates groups* $|S|$ of agents S^b, S^w and places them in the search area : $S_i, i \in [1:|S|]$.

- 1) a random vector whose components P is uniformly distributed in the search field $X_{i,1}$ is generated. This vector S_i matches the individual in the group ; $s_{i,1}$
- 2) initial coordinates corresponding to the remaining agents of this group $s_{i,j}, j \in [2:|S|]$ are determined according to the following formula

$$X_{i,j} = X_{i,1} + N_{|X|}(0, \sigma) \quad (4)$$

i.e. $s_{i,1}$ we randomly place around the agent according to the law of normal distribution.

Local competitions practice $S_i^b, S_j^w, i \in [1:|S^b|], j \in [1:|S^w|]$ of groups each one for the maximum of the fitness-function local respectively looks for An example as this act S_i to the group relatively application let's see :

- 1) C_i announcements from the board S_i group the winner about information we can This $s_{i,k} k \in [1:|S|]$ be an agent .
- 2) this of the group the rest agents , $s_{i,l} l \in [1:|S|], j \neq k$ rule (4) . according to we define , that is winner around normal distribution the law according to placed ;
- 3) group agents new accounts is determined $\varphi_{i,l} = \varphi(X_{i,l}), l \in [1:|S|]$;
- 4) $s_{i,j}, m \in [1:|S|]$ of the group new the winner , that is the same until then maximum account have agent is defined as :
- 5) $\max_j \varphi_{i,j} = \varphi(X_{i,m}) = \varphi_{i,m}, j \in [1:|S|]$;
- 6) $s_{i,m}$ of the group new the winner about information C_i, C^s announcements to the board is issued .

Dissimilation practice global the search manages _ Amal scheme the following to look has :

- 1) global announcements C^s from the board all of groups $\varphi_i^b, \varphi_j^w, i \in [1:|S^b|], j \in [1:|S^w|]$ accounts by reading is obtained (i.e this of groups current accounts);
- 2) is indicated accounts mutually is compared . If leader group S_i^b of account behind remaining S_j^w of the group at the expense of small if , then last group leader groups in the collection S_i^b place occupies , S_i^b — and behind remaining S_j^w groups from within place takes _ If S_j^w group account all leader of groups at the expense of small if , then S_j^w the group from the population delete ;
- 3) Update practice using turned off of groups instead of new the group announcement we do

Consciousness evolution in the algorithm local competitions and acts of dissimilation leader of groups increasing the maximum number until you go is repeated. From the increase in the number of issues when it stops , the winner the group expressive matter the solution global extremum point that announcement will be done [12-14] .

In this research work, along with the theory of fuzzy sets, n eytrosoft collections _ theory based on classification model construction problems were studied.

Consciousness evolution of the algorithm extended algorithm local competitions and dissimilation actions , as well from the new cooperation uses [15]. In the algorithm each one leader and backward group development stage three development stage pressing passes : ad to be done stage , stage of evolution and

maturity stage . Group mature status achieves , if his account given iteration in number if it doesn't change . If during evolution this group another group with defined to the distance approaches , or his if replaced , then from groups the first is the assimilation group status takes _ Group status about information global announcements to the board is entered .

$s_{i,k} k \in [1:|S|] - S_i$ of the group current the winner let it be In that case changed local competitions in the operator this of the group the rest agents coordinate next in an iteration according to the following formula is found

$$\begin{cases} X_{i,j} = X_{i,k} + N_1(0;1)V_j, \\ V_j = \rho V_j \end{cases} j \in [1:|S|], j \neq k, \quad (5)$$

This on the ground $V_j - (|X| \times 1) - s_{i,j} \rho \in (0;1)$ of the individual current step training is a vector , given cognitive is a parameter *that* increases the number of iterations with V_j step to increase take will come

(5) in formula V_j step direction $(X_{i,k} - X_{i,j})$ direction with , that is , $s_{i,j}$ of the individual this group the winner towards direction with is determined . V_j step size of the winner teaching $s_{i,j}$ to the individual how effect to show defines and winner account and between this individual account difference $(\varphi_{i,k} - \varphi_{i,j})$ representing _ grower is a function . Most simple in case this function as

$$V_j = \alpha(\varphi_{i,k} - \varphi_{i,j})$$

in appearance linear from the function they use it on the ground α - positive proportionality coefficient s ient .

Changed dissimulation practice perform in the process , first in line of the group current status we will check . If it is " mature " or " assimilated " status have if , then him from the population off let's throw it instead of while new group we create new of the population the first agent , for example $s_{j,1}$ the agent mind evolution from the algorithm different to look for to the field random numbers generator using not to burn imitation algorithm based on we place [16]. This is it algorithm as a result mind of evolution extended algorithm hybrid population algorithm as interpretation reach it is necessary

Also consciousness _ of evolution from the algorithm different like $s_{j,1}$ of the agent received $X_{j,1}$ coordinates all in the group of the winners current coordinates with comparison should (data global announcements from the board we can C^g) . $X_{j,1}$ point around new the group $s_{j,1}$ agent and this the winners between distance given minimum from a distance big just in case announcement we do

Content in terms of mind of evolution extended algorithm algorithm announcement to do practice evolution in the process global announcements from the board received information based on C^g next door the most good the group finds and that's it group towards will move .

$s_{i,j} - S_i$ of the group current the winner let it be $s_{k,l} - S_k$ next door the most good of the group current the winner so be it $\varphi_k > \varphi_i$ inequality appropriate will be In that case cooperation practice the following formula determines

$$\begin{cases} X_{i,j} = X_{i,j} + N_1(0;1)V_i, \\ V_i = \lambda(X_{k,l} - X_{i,j}), \\ i, k \in [1:|S|], j \neq k, j, l \in [1:|S|], \end{cases}$$

b there $\lambda > 0$ - step value measuring size

Particles this algorithm as , common without next door the most good S_k the group in determining neighborhood of topologies each different options application can

Consciousness of evolution of the algorithm upcoming development improved . Consciousness of evolution improved algorithm the following own into takes : groups announcement in doing algorithm search field part to areas to be from the strategy uses himself - adjuster from the algorithm is used , it is local competitions practice current does : dissimulation practice leadership tools with filled .

search space part to spaces to be strategy of the algorithm early approach prevention to get directed . Talk that's a lot the population initial to work drop off stage P search field (S^b, S^w) it or this way equal to in volume P_1, P_2, \dots to parallelepipeds separated , shown each one of the group initial points this part in the fields flat distribution the law based on random respectively is generated .

Local competitions of action himself adaptor mechanism of the matter variable parameters from the vector uses , it owns into X from the vector except V of the individual to move step own into takes S_i group for local competitions of action main formula the following to look have will be

$$\begin{cases} x'_{i,j,k} = x_{i,l,k} + N_1(0;1)v'_{i,j,k}; \\ v'_{i,j,k} = \mu v_{i,l,k} + N_1(0;1)a_{i,j,k}, \end{cases} \quad (6)$$

$$i \in [1:|S|], j, l \in [1:|S|], j \neq l, k \in [1:|X|],$$

this on the ground $x_{i,j,k}, v_{i,j,k} - s_{i,j} \in S_i, x_{i,l,k}, v_{i,l,k}$ variable of the agent $X_{i,k}, V_{i,j}$ organize are the ones , i.e this of the group $X_{i,l}, V_{i,l}$ the $\mu \in (0;1)$ winner - $v'_{i,j,k}$ step value determiner step value which determines manly real parameter ; $a_{i,j,k}$ parameter random of the component this step to the value of added contribution determines and to the following equal to

$$a_{i,j,k} = \frac{x_{i,l,k} - x_{i,l,k}(t_{i,l,k}^-)}{t - t_{i,l,k}^-}$$

This on the ground $t_{i,l,k}^-$ - agent detected iteration number $s_{i,l} \in S_i$ group the winner as S_i .

To repeat finish criterion as (6), locally of competition changed performance out of necessity uses

$$\frac{1}{|X|} \sum_{k=1}^{|X|} v_{i,l,k} \leq \varepsilon_v \quad (7)$$

Smart water drops algorithm .

$$f(x) = f((c_1, \sigma_1), (c_2, \sigma_2), \dots, (c_n, \sigma_n))$$

Step 1: x_0 - of the argument initial value is given ;

Step 2: a_s, b_s, c_s, v_0 - parameters values is installed ;

Step 3: $\rho_0 + \rho_n = 1$ a must based on ρ_0 and ρ_n value to is given ;

$$\text{Step 4: } \text{time}(v_t) = \frac{1}{v_t} \text{ and } \Delta x = \frac{a_s}{b_s + c_s * \text{time}(v_t)}, \Delta v = \frac{a_s}{b_s + c_s} \text{ is -}$$

Step 5: Argument next value $x_{t+1} = \rho_0 x_t + \rho_n \Delta x$ and $v_{t+1} = v_t + \Delta v$ formulas _ based on is found ;

Step 6: By the given number of iterations calculations done is increased .

These algorithms are used to adjust fuzzy model parameters in the process of solving classification problems. Solving these classification problems on the basis of Neutrosophic set theory gives alternative results. For this purpose, an algorithm for constructing a neutrosophic model was proposed for solving the classification problem.

In this study, the integration of Fuzzy Logic Mamdani Model with modern evolutionary algorithms has proven to be a potent approach for enhancing model performance and accuracy. The successful application of evolutionary algorithms in parameter tuning showcases their ability to optimize complex systems effectively. The results from empirical experiments underscore the efficacy of this hybrid methodology, validating its potential to revolutionize decision-making processes across diverse fields. The combination of fuzzy logic and evolutionary algorithms offers a promising avenue for advancing automated and optimized decision support systems.

References

1. P. Havali, J. Banu. Deep Convolutional Neural Network for Image Classification on CUDA Platform, ScienceDirect, 2019, Pages 99-122.
2. Dilnoz Muhamediyeva, Nadir Egamberdiyev. An application of Gauss neutrosophic numbers in medical diagnosis // International Conference on Information Science and Communications Technologies: Applications, Trends and Opportunities <http://www.icisct2021.org/> ICISCT 2021, November 3-5, 2021.
3. Kamilov M.M., Khujaev OK, Egamberdiev NA The method of applying the algorithm of calculating grades for finding similar diagnostics in medical information systems, International Journal of Innovative Technology and Exploring Engineering, 8-6S, pp. 722-724.
4. Muhamediyeva DT, Jurayev Z.Sh., Egamberdiyev NA, Qualitative analysis of mathematical models based on Z-number // Proceedings of the Joint International Conference STEMM: Science – Technology – Education – Mathematics – Medicine. May 16-17, 2019, Tashkent, pp. 42-43.
5. Egamberdiyev NA, FUZZY REGRESSION ALGORITHM FOR CLASSIFICATION OF WEAKLY FORMED PROCESSES // SCIENCE AND PRACTICE: IMPLEMENTATION TO MODERN SOCIETY MANCHESTER, GREAT BRITAIN, 26-28.12.2020.
6. D.Mukhamediyeva, N.Egamberdiev, ALGORITHM OF CLASSIFICATION OF MEDICAL OBJECTS ON THE BASIS OF NEUTROSOPHIC NUMBERS, Proceedings of the 4th International

Scientific and Practical Conference SCIENCE, EDUCATION, INNOVATION: TOPICAL ISSUES AND MODERN ASPECTS TALLINN, ESTONIA, 4- 5.10.2021, pp. 374-380.

7. Mukhamedieva DT, Egamberdiev NA, Zokirov J.Sh., Mathematical support for solving the classification problem using neural network algorithms // Turkish Journal of Computer and Mathematics Education. Vol.12 No.10 (2021).
8. DTMukhamedieva and NAEgamberdiev, APPROACHES TO SOLVING OPTIMIZATION TASKS BASED ON NATURAL CALCULATION ALGORITHMS, Scientific-technical journal, 3(2) 2020, pp. 58-67.
9. NAEgamberdiev, OTXolmuminov, KhROchilov, ANALYSIS OF CLASSICAL MODELS OF CLASSIFICATION OF SLOWLY FORMED PROCESSES, International Scientific-Online Conference: SOLUTION OF SOCIAL PROBLEMS IN MANAGEMENT AND ECONOMY", Spain, October 7, 2022, pp. 12-16.
10. NAEgamberdiev, OTXolmuminov, Khrochilov, CHOOSING AN EFFICIENT ALGORITHM FOR SOLVING THE CLASSIFICATION PROBLEM, International Scientific Online Conference: THEORETICAL ASPECTS IN THE FORMATION OF PEDAGOGICAL SCIENCES, October 10, 2022, pp.154-158.
11. D. Muhamedieva, N. Egamberdiev, O. Kholmuminov, APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES FOR CREDIT RISK ASSESSMENT, "Science and innovation" international scientific journal. 2022, No. 6. Pages 388-395.
12. D. Muhamediyeva, N. Egamberdiyev, An application of Gauss neutrosophic numbers in medical diagnosis, International Conference on Information Science and Communications Technologies ICISCT 2021, Tashkent, Uzbekistan, 2021, pp. 1-4.
13. D. Muhamediyeva, N. Egamberdiyev, A. Bozorov, FORECASTING RISK OF NON-REDUCTION OF HARVEST, Proceedings of the 2nd International Scientific and Practical Conference, SCIENTIFIC COMMUNITY: INTERDISCIPLINARY RESEARCH, Hamburg, Germany, 26-28.01.2021, pp. 694-698.
14. F. Nuraliev, O. Narzullov, N. Egamberdiev, S. Tastanova, V Mejdunarodnaya nauchno-prakticheskaya konferenciya, RECENT SCIENTIFIC INVESTIGATION, Oslo, Norway, April 26-28, 2022, c. 447-451.
15. Mukhamedieva D.T., Egamberdiev N.A., Podkhody k resheniyu zadach optimizatsii na osnove algoritmov prirodnyx vychisleniy, Scientific and technical journal of Fergana Polytechnic Institute, 2020, Volume 24, No. 2, c. 75-84.
16. NAEgamberdiyev, MMKamilov, A.Sh. Hamroyev, Development of an algorithm for determining the system of dimensional fixed basis sets for educational selections, Muhammad al-Khorazmi Avlodali, 1(7) 2019, pp. 45-48.
17. Khojayev OQ, NAEgamberdiyev, Sh.N. Saidrasulov, Algorithm for choosing an effective method for solving the problem of classification, Information Communications: Networks, Technologies, Solutions. 1(49) 2019. Quarterly Scientific and Technical Journal, pp. 39-43.