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EVOLUTIONARY ALGORITHM FOR INTELLIGENT HYBRID SYSTEM TRAINING

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ABSTRACT

Here we considered the evolutionary algorithm of the adaptive hybrid control system training. This algorithm differs by the application of combined operators of random changes and the possibility of dynamic correction of operators parameters based on information about solution population. We defined the types and parameters of operators of random changes: crossing-over, mutation, and re-initialization. The combination of operators is considered. Also we presented the algorithm of parameter adaptation for the combined operators of casual changes and developed the structure of parallel genetic algorithm.

Keywords: artificial intelligence, adaptive hybrid control system, uncertainty, neuro-fuzzy networks, genetic algorithms.

1. INTRODUCTION

The modern automatic control systems operating in the conditions of uncertainty are implemented with application of neural networks (NN), neuro-fuzzy networks (NFN) which parameters are received by preliminary training. The problem of training turns into to a problem of NN, NFN optimization [1]. Solution of this problem can be obtained on the basis of genetic algorithms (GA). Distinctive feature of GA is the taking into account their application specific by the modification of algorithm parameters [2-4]. The problem of choice of desired GA parameters is complicated by variety of different approaches [3, 5] and absence of standard methods. Analysis of papers [4, 13] allows the conclusion about the appropriateness of adaptive GA application in training tasks.

2. DEVELOPMENT OF EVOLUTIONAL TRAINING ALGORITHM

Design of GA consists of two tasks: choice of adapted parameters; choice of adaptation method. The solution of the first task consists in searching for the group of algorithm parameters correction of which values most strongly influences the effectiveness of algorithm. The majority of known approaches to adaptation of GA [4-12, 19] are similar in the using of expert experience for the definition of parameters changing degree. Experts form analytical dependences for recalculation of the adaptive GA parameters. There are also other approaches, for example, with the use of fuzzy logic [12, 15-18, 20].

We present the complex task of GA development in the form of successive stages [2, 4, 13, 14, 18] in Figure-1. Adjusted GA parameters are the probabilities of the combined operators of random changes application in different forms, the probability of the mutation operator application.

The combined operator of crossing (crossing-over) carries out a randomized exchange of a genetic material between chromosomes to receive more adapted posterity that allows surveying a solution space. Researchers refer to the high probability of solutions destruction before the beginning of solutions operation in the course of reproduction [21] as a shortcoming of this operator.

The conventional form of a crossing-over allows carrying out simultaneous crossing of only two chromosomes. There are no restrictions on a quantity of processed chromosomes, and the increase in quantity of chromosomes in the course of crossing is capable to accelerate the process of search for optimum solutions [22, 23].

Stage 1. Determination of solution representation form

Stage 2. Determination of form and parameters of operations of random changes

Stage 3. Determination reproduction operator representation

Stage 4. Determination of approach to chromosomes fitness assessment

Stage 5. Determination of algorithm stop condition

Stage 6. Determination of creation method for initial decisions

Stage 7. Determination of selection method for new population

Stage 8. Development of common GA block diagram

Figure-1. Stages of GA development.

We offer to combine three types of crossing operators. At the same time, we use implementation versions with two and three parental individuals, one and two points of a chromosome break. We set the equal probabilities of application of a certain crossing-over operator version with a subsequent correction. The average degree of solution fitness is calculated after each GA iteration. Then the probabilities of application of each crossing operator type are defined with a help of fuzzy controller. After that, the type of applied crossing operation is defined in a random way on the basis of a roulette method [2, 22].

The probability of crossing operation usually is a fixed value [22]. In this paper it is equal to 75%.

The combined operator of mutation allows restoring and adding new genetic material to the population of solutions. Probability of mutation application, as a rule is no more than 1% [22]. We suggest combining single-point and two-point mutations, re-initialization. Probability of application of each mutation operator form is calculated on the basis of fuzzy comptroller operation results and dynamically changes during GA operation. The form of used operator is determined randomly on the basis of roulette method [2, 22, 24]. Replacement of initial chromosome bits by opposite or random values is conducted according to the chosen operator form.

Algorithm for parametric adaptation of combined operators of random changes. The parameters of mutation and crossing operators are usually set as constant values at the GA development and determined on the basis of expert experience or experimentally. The basic parameters of operators is the form of operator (f_c, f_m are the forms of crossing-over and mutation operator accordingly); the probability of operator application (p_c, p_m is the probability of application of crossing-over, mutation accordingly).

Adaptive GAs are able to carry out self-tuning of parameters, have the best quality, and find global solutions with a greater probability and for a less time [4, 6].

There is an exchange of genetic information between the chromosomes of population during GA operation. The longer exchange lasts, the more alike solutions become. Their gradual degeneration occurs. If the chromosome satisfying to given quality requirements will be found, the condition of algorithm stop is fulfilled.

The development of algorithm impeding the phenomenon of population solutions degeneration is impossible without comparison indexes for the determination of distinction degree of chromosomes genetic information. The determination of chromosomes distinction degree can be carried out based on their fitness value, but it can appear not enough. It is necessary to have a criterion of population variety.

Most methods of homogeneity degree determination of chromosomes from population are related to the average value calculation of estimation parameter of their genetic variety [4 - 12]. It allows calculating average fitness of all population solutions.

The next parameters of operators of random changes vary during work of genetic algorithm: the probability degree of mutation operator application; the probability degree of application of each mutation operator form; the probability degree of application of each crossing (crossing-over) operator form. We showed the main ideas of offered approach in Figure-2.

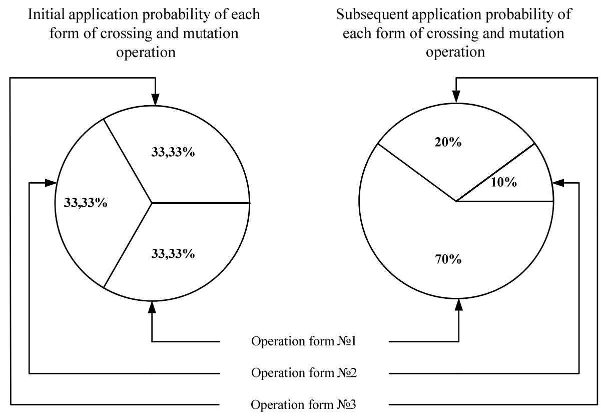

Figure-2. Correction of application probability of each mutation and crossing operator from.

Initially the application possibilities of each mutation and crossing operator form are equal, and then these possibilities are corrected proportionally to the average value of chromosome fitness functions in the process of GA operation. A fuzzy controller (FC) carries out the parameter correction of operators of random changes. The FC development process consists of the next steps.

Step-1. Determination of main control parameters: The input parameters of FC are the degree of genetic variety of chromosomes population; the degree $F(c_j)$ of successful application of j-th crossing operator form; the degree $F(m_j)$ of successful application of j-th mutation operator form. The output parameters of FC are the application probability (p_m) of the mutation operator; the application probabilities (pc_j, pm_j) of each crossing and mutation operator form. We calculated the degree GD of genetic variety of chromosomes population by formula

$$GD = F(ch_k)_{\max} - \frac{F(ch_1) + F(ch_2) + ... + F(ch_i)}{N}; \; i = \overline{1, N}, \qquad (1)$$

where $F(ch_k)_{max}$ is the maximum value of k-th chromosome fitness f unction; $F(ch_1)$, $F(ch_2)$, …, $F(ch_i)$ are the functions of fitness of population chromosomes; N is the population size.

The degree of successful application of the j-th crossing operator form is determined by formula

$$F(c_j) = \frac{F_{cp}(c_j)}{F_{cp}}; \;\; j = \overline{1, K}, \qquad (2)$$

where F_{cp} is the average fitness of chromosome population; $F_{cp}(c_j)$ is the average fitness of chromosomes developed with the use of i-th crossing-over operator form. We calculated the degree of successful application of j-th mutation operator form by formula

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$$F(m_j) = \frac{F_{cp}(m_j)}{F_{cp}}; \;\; j = \overline{1, K} \; , \tag{3}$$

where F_{cp} is the average fitness of chromosomes population; F_{cp} (m_j) is the average fitness of chromosomes developed with the use of j-th mutation operator form.

Step-2. Definition of membership functions and control rules: We mean the process of development of linguistic variables (LV) term sets, the selection of used fuzzy variables form when we talk about the definition of LV.

The term set of LV "degree of a genetic variety (GD)" has the form T(GD) = {PVS, PS, PM, PH, PVH}, where PVS is the very low GD; PS is the low GD; PM is the medium GD; PH is the high GD; PVH is the very high GD.

The term sets of LV "degree of successful application of j-th crossing operator $F(c_j)$ form", " degree of successful application of j-th mutation operator $F(m_j)$ form", "application probability p_m of mutation operator", "application probability p_{mj} of j-th mutation operator form" have a similar form with the term set of LP " degree of a genetic variety".

The rule base (RB) of FC allows establishing the logical interrelation between existing input and output LVs, defines operation procedures in different situations. We separated the FC of developed GA on three parts (see Table-1): FC_1 controlling the application probability (p_m) of mutation operator; FC_2 controlling the application probability (pc_j) of each crossing-over operator form; FC_2 controlling the application probability (pm_j) of each mutation operator form. If it is necessary, the execution of stages 3, 4 is possible after a checking of FC (FC_1, FC_2, FC_3) operation correctness.

FCs used for parametric correction of operators of random changes are simple, however, they can be changed in the case of need for the implementation of more complex non-linear dependences.

The reproduction operator sets a sequence of actions defining what chromosomes will participate in crossing and mutation operations, will give children, etc., and what chromosomes will not. We suggested using the methods of roulette and pank-mission in combination [2, 22].

Table-1. RBs for FC_1, FC_2, FC_3.

RB for FC₁	
GD	***p_m***
PVS	*PVH*
PS	*PH*
PM	*PM*
PH	*PS*
PVH	*PVS*
RB for FC_2	
$F(m_j)$	***p_{mj}***
PVS	*PVS*
PS	*PS*
PM	*PM*
PH	*PH*
PVH	*PVH*
RB for FC_3	
$F(c_j)$	***p_{cj}***
PVS	*PVS*
PS	*PS*
PM	*PM*
PH	*PH*
PVH	*PVH*

GA operation is based on a cyclic process of solutions generation, their comparison for the purpose of selection of the most adapted. When GAs are applied to a problem of NN, NFN training, required solutions are the sets of their parameters values providing the greatest accuracy of an output signal.

3. STRUCTURE OF PARALLEL GENETIC ALGORITHM

The block diagram of parallel genetic algorithm is given in Figure-3. We distinguish the following steps in this algorithm.

Step-1. Formation of initial population of chromosomes: Adjusted NN, NFN parameters are integrated and coded by Gray's method for the emergence of initial population chromosome ch_1. The random change of chromosome ch_1 sections generates a number of alternate solutions. The initial population of chromosomes has the form P = {ch1, ch_2, ch_3, …, ch_n }, where ch_1, ch_2, ch_3, … , ch_n are population chromosomes; n is a population size.

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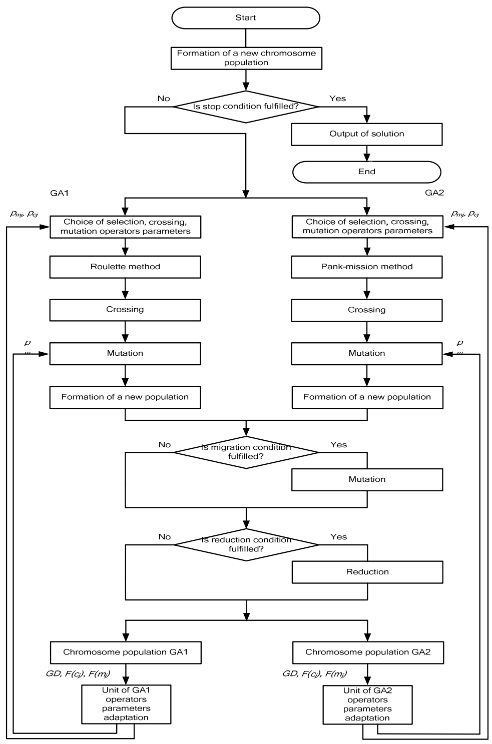

Figure-3. Parallel genetic algorithm.

Step-2. Occurs check: The degree of fitness of each population chromosome $F(ch_i)$ is calculated and the checking of accuracy of obtained solutions is made. If the condition of accuracy is not satisfied, there is a check of achievement of the run time or operations number limit by the GA. The algorithm continues operation only at the nonfulfilment of all listed stop conditions.

Step-3. Shaping of operators of random changes: The choice of form of these operators is carried out with the use of roulette method from their application probabilities pm_j. pc_j [2, 22]. Initially the values pm_j, pc_j for each operator form are set equal and then corrected according to application results.

Step-4. Selection of parental individuals: Two or three parent individuals are selected depending on a crossing operation type. The roulette method carries out directional selection of solutions based on their fitness degree, the pank-mission methods selects randomly.

Step-5. Execution of operators of random changes: The application probabilities of crossing and mutation operators have values less than 1. The checking of condition of these operators execution is necessary. If the crossing operator has been carried out, he executes transformation of the chosen quantity of chromosomes:

$$\{ch_5, ch_{17}\} \xrightarrow{cros\sin g-over} \{ch_5^c, ch_{17}^c\},$$

$$\{ch_3, ch_5, ch_{17}\} \xrightarrow{cros\sin g-over} \{ch_3^c, ch_5^c, ch_{17}^c\},$$

where ch_3, ch_5, ch_{17} are the chromosomes chosen for crossing-over operation; $ch_3^c, ch_5^c, ch_{17}^c$ are the chromosomes transformed by crossing-over.

When performing, the mutation operator also carries out transformation of genetic information of chromosomes:

$$\{ch_5, ch_{17}\} \xrightarrow{mutation} \{ch_5^{cm}, ch_{17}^c\},$$

$$\{ch_3, ch_5, ch_{17}\} \xrightarrow{mutation} \{ch_3^c, ch_5^{cm}, ch_{17}^c\},$$

where ch_5^{cm} is the chromosome submitted to crossing-over and mutation.

Step-6. Formation of new population: Creation of new populations of chromosomes realizes in two ways. The first is the conventional generation process of the necessary number of solutions, and the second includes the execution of migration and reduction operations.

The migration occurs each 30 iterations and carries out an exchange of 30% of a genetic material (20% of the best, 10% of the worst chromosomes) between populations. After carrying out operations of population crossing, mutation, and migration, GAs have the following form:

$$P_{GA1} = \{ch_1^c, ch_2^c, ch_3^c, ch_4^{cm}, ch_5^{cm}, ch_6^{\mathrm{m}}, \ldots, \overset{GA2}{ch_{n-3}^{\mathrm{cm}}}, \overset{GA2}{ch_{n-2}^{\mathrm{m}}}, \overset{GA2}{ch_{n-1}^{\mathrm{m}}}, \overset{Ga2}{ch_n^{\mathrm{m}}}\},$$

$$P_{GA2} = \{ch_1^c, ch_2^c, ch_3^c, \overset{GA1}{ch_4^{cm}}, \overset{GA1}{ch_5^{cm}}, \overset{GA1}{ch_6^{\mathrm{m}}}, \ldots, ch_{n-3}^{\mathrm{cm}}, ch_{n-2}^{\mathrm{m}}, ch_{n-1}^{\mathrm{m}}, ch_n^{\mathrm{m}}\},$$

where ch_i^{cm} are the chromosomes submitted to crossing and mutation; ch_i^c are the chromosomes submitted to crossing; ch_i^m are the chromosomes submitted to mutation; $\overset{GA1}{ch_i^{cm}}$ are the chromosomes migrating from GA1; $\overset{GA2}{ch_i^{cm}}$ are the chromosomes migrating from GA2; *i* is a chromosome number in population.

The reduction operator carries out compression of solution populations, returns their size to the value given at the development of GA. The execution of reduction is made in 15 iterations after migration. In such a way we provide the participation of migrating chromosomes in the reproduction process.

Step-7. Parametric adaptation of GA operators: The correction of parameters p_m, p_{mj}, p_{cj} of operators of random changes is executed on the basis of FC input signals GD, $F(c_j)$, $F(m_j)$.

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4. GA WITH TWO SELECTION OPERATORS

We presented the block diagram of GA with two simultaneously operating operators of selection in Figure-4. The algorithm is not parallel, but has some features of parallel GA.

Difference of this GA from GA shown in Figure-3 consists in the absence of two independently evolving populations of solutions. We distinguish the following steps in this algorithm.

Steps 1 - 3, 5, and 7 are carried out similarly with the step 1 of parallel GA.

Step-4. Selection of parental individuals. The roulette and pank-mission methods for the selection of parental individuals participate only in the generation of 85% and 15% of population chromosomes respectively. It means that the first part of parental individuals will be chosen based on their fitness functions $F(ch_i)$, and the second will be chosen completely randomly.

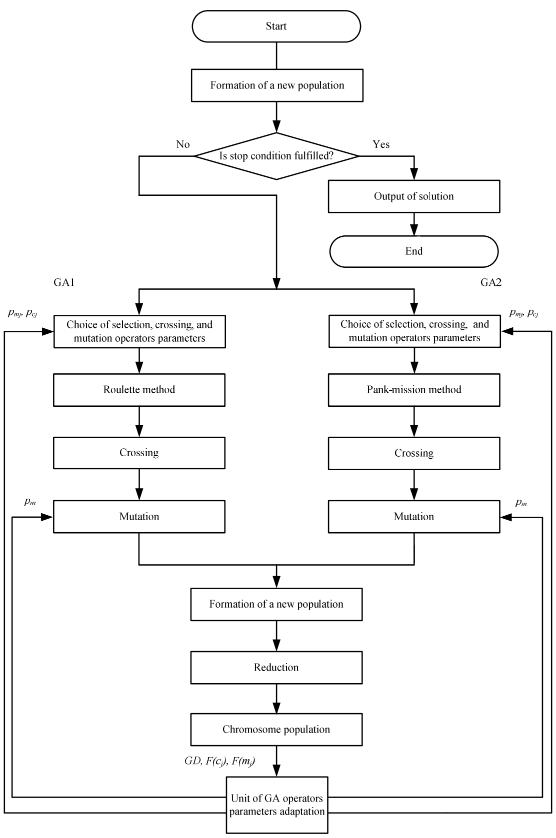

Figure-4. GA with two operators of selection.

Step-5. Formation of a new population of chromosomes. The quantity of generated chromosomes will be 20% higher than a given population size. Therefore, it is necessary to apply the reduction operator. The reduction operator selects 80% of the best and 20% of the worst chromosomes of a given solutions quantity.

5. CONCLUSIONS

We developed two evolutionary algorithms with the combined operators of random changes. The first algorithm is fuzzy, adaptive with integrated population, and the second algorithm is fuzzy, adaptive, and parallel. The combined operators of random changes were developed. Each of these operators includes three various types of mutation and crossing according to a variable application probability. Also we developed and presented the block diagrams of GAs allowing visual presentation the sequence of operator application and executed actions directed on searching for optimal solutions of intelligent control systems.

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