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Technological aspects of creating helioenergic stratospheric platforms with adaptive neural control

A new approach to the structural-parametric synthesis of stratospheric unmanned aerial vehicles with adaptive neural control is proposed

Renewable energy is the key to a cleaner, brighter energy future. And solar energy is one of the world's most promising sources of renewable energy. It's cheaper (and possibly cleaner) than nuclear, coal or combined gas turbines – and that's why we're seeing an increasing number of solar projects of widespread use emerge around the world. This is especially important for the implementation of Unmanned Aerial Systems (UAS) long flight or High-altitude long endurance (HALE). Other names are Atmospheric satellite (United States usage, abbreviated atmosat), pseudo-satellite (British usage) or High-altitude platform station (HAPS) is a marketing term for an aircraft that operates in the atmosphere at high altitudes for extended periods of time, in order to provide services conventionally provided by an Artificial Satellite orbiting in space [1, 2].

When creating a HAPS-type UAS, a number of technological problems arise.

One of the main problems of Unmanned Aerial Systems (UAS) is endurance or flight time, since common domain aircraft use conventional fuel. Despite their use in various applications, they lack performance due to power constraints, and currently the ability to fly without the use of conventional fossil fuels is primarily focused on both the applied point of view and the scientific direction, since the main problems are an increase global warming and a decrease in natural resources. Since the beginning of the use of electric aircraft, there has been widespread use of batteries, but here the decisive problem is the need for their high capacity compared to the limited storage of their accumulated energy. Therefore, if either by increasing the size of the battery or by turning on more batteries will only lead to an increase in the weight of the aircraft, which directly affects the flight time of the UAS.

One possibility of increasing flight time is to use unlimited solar energy through transformative solar cells. Therefore, a possible solution to increase endurance is to use aircraft on solar films and batteries driven by power plants on an electrical basis, in which energy is continuously supplied throughout the day by solar energy, which can eliminate fuel, as well as solve the problem of limited energy storage.

Despite their widespread use in various applications, they lack performance due to power limitations. and at present, the possibility of flying without the use of conventional fossil fuels is primarily focused on both the applied point of view and the scientific direction, since the main problems are the increase in global warming and the reduction of natural resources. Since the beginning of the use of electric aircraft, there has been widespread use of batteries, but here the decisive problem is the need for their high capacity compared to the limited storage of their accumulated energy. Therefore, if either by increasing the size of the battery or by turning on more batteries will only lead to an increase in the weight of the aircraft, which directly affects the flight time of the UAV.

Increasing the flight time to solve a number of problems is associated with the use of unlimited solar energy and its conversion into electrical energy. Therefore, a possible solution to increase the endurance of flights is to use aircraft on solar films and batteries that drive power plants. In such electrically based installations, energy is continuously supplied during a sunny day, which eliminates the need to use traditional fuel and solves the problem of limited energy storage for flying at night. If we consider the performance of solar cells, then the photovoltaic system depends not only on its main characteristics, but also on environmental issues should be taken into account. One of these environmental problems is the ambient temperature, which plays an important role in the photovoltaic conversion process.

Other difficulties can be observed when solving specific problems of their application. Fig. 1 shows the main applications HAPS, which can use artificial intelligence to increase the efficiency of operations.

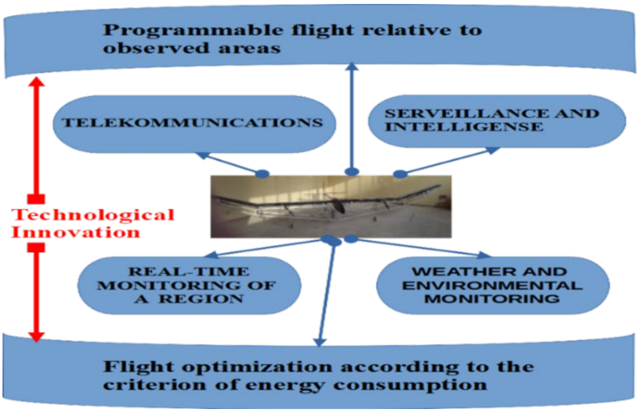

Fig. 1. Innovative stratospheric satellite technologies.

Structural and parametric synthesis of neural network models for stratospheric satellite based on evolutionary optimization methods. In the structural-parametric synthesis of neuromodels, optimal values of neural network weights (input layer and hidden layers), neuron shifts, and neuron activation functions are selected.

Therefore, it is suggested that the solution (chromosome) be composed of several parts (Fig. 2): in the first part, store information about the values of the input layer neuron weights, in the second – the values of the hidden layer neuron weight coefficients, in the third – values of shifts of neurons, in the fourth – activation functions for each neuron of the network.

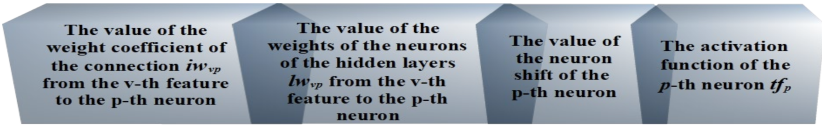

Fig. 2. Chromosome presentation with structural-parametric synthesis of neural networks.

In Fig. 2, the following designations are used:

iw_{vp} is the value of the weight coefficient of the connection from the v-th feature to the p -th neuron;

lw_{vp} is the value of the weight coefficient of the connection from the v-th neuron to the p-th neuron;

b_p is the shift value of the p-th neuron;

tf_p is the activation function of the p-th neuron.

As we can see from Fig. 2, the second part of the chromosome, which contains information about the values of the weight coefficients of the neurons of the hidden layers, is coded using a method similar to the parametric representation of a chromosome during structural synthesis [3, 4].

The size of the S chromosome is determined by the formula:

$$S = S_1 + S_2 + S_3 + S_4 = L \cdot A + \frac{A(A-1)}{2} + A + A = L \cdot A + \frac{A(A+3)}{2}, \qquad (1)$$

where

S_1, S_2, S_3, S_4 are the number of genes of the first, second, third and fourth parts of the chromosome, respectively.

In order to find neuromodels with the minimum number of synaptic connections in the proposed method of structural-parametric synthesis, special crossover and mutation operators were developed, which aim to reduce the number of connections in the network.

In order to increase the effectiveness of evolutionary optimization in the structural-parametric synthesis of neuromodels and to reduce the search time, it is suggested that at the stage of initialization of chromosomes corresponding to neural network models, the selection of the initial values of the weighting coefficients and shifts should be carried out in such a way as to evenly distribute the active area of the definition of the activation function of each neuron in the space of input variables, taking into account the individual informativeness of the signs.

The developed evolutionary method of structural-parametric synthesis of neural network models is proposed to be performed as the following sequence of steps.

Step 1. Form the initial generation of chromosomes that contain information about the structure of the network and its parameters.

Step 2. Perform chromosome estimation of the current population by calculating the value of the fitness function, which takes into account the error of the neural network and the complexity of its architecture (number of interneuron connections, neurons, layers). To calculate the error of the network corresponding to the estimated chromosome Hj, it is advisable to use the formula:

$$E(H_j)\sum_{p=1}^{m}(y_p - y(H_j, X_p))^2, \quad (2)$$

where

$y\ (H_j, X_p) = y_{Ap}$ is the value of the output of the neuromodel *NM*, built on the basis of the chromosome *Hj*, calculated for the set of values of *Xp*:

$$y_{Ap} = tf_A(b_A + \sum_{c=1}^{L} iw_{cA}x_{cp} + \sum_{c=1}^{A-1} lw_{cA}y_{cp}), \quad (3)$$

where

y_{Ap} is the value of the output of the *A*-th neuron of the network for the *p*-th instance;

y_{cp} is the value of the output of the *c*-th neuron of the network for the p-th instance, calculated according to the formula similar to the calculation of the value of y_{Ap}.

Step 3. Check the criteria for completing the search (achieving an acceptable value of the error of the model being synthesized, exceeding the maximum permissible number of iterations, exceeding the permissible operating time of the method). If at least one of these criteria is met, proceed to step 8.

Step 4. Select the most adapted chromosomes to perform evolutionary crossover and mutation operators on them.

Step 5. Execute the crossing operator, which reduces the number of synaptic connections in the network.

For parts of chromosomes that contain information about the values of the weight coefficients of the neurons of the input and hidden layers, the value of the *i*-th gene of the offspring is proposed to be determined by the formulas:

$$h_{i\text{п}1} = \begin{cases} 0, \text{if } h_{i1} \cdot h_{i2} < 0; \\ kh_{i1} + (1-k)h_{i2} \quad , \text{otherwise} \end{cases} \quad (4)$$

$$h_{i\text{п}2} = \begin{cases} 0, \text{if } h_{i1} \cdot h_{i2} > 0; \\ (1-k)h_{i1} + kh_{i2} \quad , \text{otherwise} \end{cases}$$

where

$h_{i\text{п}1}$ and $h_{i\text{п}2}$ are values of the *i*-th genes of the first and second offspring, respectively;

h_{i1} and h_{i2} – values of the *i*-th genes of the first and second parents, respectively;

k is a coefficient set by the user, $k \in (0; 1)$.

Values of genes corresponding to shifts in neurons can be determined by the following formulas:

$h_{i\Pi 1} = kh_{i1} + (1-k)h_{i2}$ та $h_{i\Pi 2} = kh_{i2} + (1-k)h_{i1}$.

The value of genes that determine the function of neuron activation is proposed to be determined as follows:

$$h_{i\Pi 1} = \begin{cases} h_{i1}, \text{if } h_{i1} = h_{i2} \text{ or } r > 0{,}5; \\ \text{rand[TF]}, \quad \text{otherwise}, \end{cases}$$

$$h_{i\Pi 2} = \begin{cases} h_{i2}, \text{if } h_{i1} = h_{i2} \text{ or } r \le 0{,}5; \\ \text{rand[TF]}, \quad \text{otherwise} \end{cases}, \quad (5)$$

where

r is a randomly generated number in the interval (0; 1);

rand [TF] is a randomly selected element of the TF set that contains the activation functions used to build the neural network.

Step 6. Execute the point mutation operator.

If a chromosome gene is selected for mutation, which contains information about the values of the weight coefficients of the neurons of the network, then the new value of the i-th gene is proposed to be calculated using the formula:

$$h_{i\text{п}} = \begin{cases} 0, & \text{if } |r| < 0{,}5h_i \,; \\ r, & \text{otherwise}, \end{cases} \tag{6}$$

where

h_i and $h_{iП}$ are the values of the i-th gene before and after the mutation, respectively;

r = rand [$-h_i$; h_i] is a randomly generated number in the interval [$-h_i$; h_i].

If a chromosome gene corresponding to the displacement of the neuron is chosen for the mutation, then the value of the i-th gene after the $h_{iП}$ mutation is proposed to be determined as follows: $h_{iП}$ = rand [$h_{i,min}$; $h_{i,max}$], where $h_{i,min}$ and $h_{i,max}$ are the minimum and maximum value of the i-th gene in the population.

In the case of choosing a chromosome gene for mutation, which contains information about the function of neuron activation, the new value of the gene is proposed to be determined by the formula: $h_{iП}$ = rand [TF].

Step 7. Create a new generation from the offspring chromosomes obtained in the previous step and the most adapted chromosomes of the current generation. Go to step 2.

Step 8. Stop. Using this approach, it is possible to build adaptive and robust control of a stratospheric unmanned aerial vehicle. We will describe the adaptive and robust neural control.

The developed evolutionary method of structural-parametric synthesis of neural networks makes it possible to build a neural network model HAPS, while using crossover and mutation operators that reduce the number of synaptic connections in the network.

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