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Neutral network application in the problem of determining the optimized flight for helicopter

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Abstract: *The problem of finding the optimal flight path for helicopters through a given number of points is a complex and practical problem in the aviation industry. There have been many methods to find the optimal flight path for transport vehicles, but there is almost no work for helicopters because of the complexity when taking into account the altitude of the helicopter. The article refers to the application of neural networks to solve the problem of optimizing fuel for helicopters..*

Keywords
Helicopter, artificial neuron , flying flat, fuel optimization .

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I. INTRODUCTION

Helicopter or helicopter is a type of motorized flying vehicle, operating on propellers, can take off, land vertically, can fly vertically in the air and even fly backward. Helicopters have many functions both in daily life, in the national economy and in the military. The reality is that a helicopter can go anywhere, as long as the landing pad is one and a half times the diameter of the propeller, it can land and take off.

Because of the special technical characteristics that fixed-wing aircraft cannot have, helicopters are increasingly developed, along with conventional fixed-wing aircraft and have increasingly diverse applications: ambulance, rescue, police, traffic control, security, sports, journalism and many other applications. Helicopters can take on the task of flying over the given benchmarks to do special tasks such as landing in the air, dropping relief goods ... We consider the problem that the helicopter must fly through n given flight reference points, starting from the point with coordinates x1, y1, h1 and ending at the point xn, yn, hn with the assumption $x_1<x_i<x_n$. We have to choose the flight path between n points so that the total fuel cost is minimized.

II. THEORETICAL BASIS

For helicopters when changing flight altitude will consume different fuel than when flying, so we go to determine fuel consumption when changing flight altitude. In the general case, the energy consumed is calculated based on kinetic and potential energy as follows:

$$N=N_{пр}+N_{ин}+N_{вр}+N_g+N_{кин} \tag{1}$$

The consumption component of the motor is calculated as follows:

$N_{пр}$: Energy consumed per wing profile.
$N_{ин}$: Energy consumption due to drag component
$N_{вр}$: Energy consumption due to the drag component of the helicopter blade
N_g : Potential energy
$N_{кин}$: Kinetic energy

According to[1] ta có:

$$N_{ин}=\frac{1}{3300\xi}\frac{T^2}{D^2V\Delta},\quad N_{вр}=\frac{\sum C_x S}{1200\xi}V^3\Delta,\quad N_g=\frac{1}{75\xi}GV_{yg},\quad N_{кин}=\frac{1}{75\xi}V^3\Delta$$

$$N_{пр}=m_{пр}\frac{1}{1200\xi}\Delta(\omega R)^3F,\qquad где\quad m_{пр}=\frac{1}{4}C_{xp0}\sigma\left(1+5\bar{V}^2\right)$$

while $V_г$, $V_в$ velocities in the horizontal and vertical planes, respectively. It can be calculated that $V_Г=V_{Г.П}$, $V_В=V_{yg}$ (while $V_{г.п}$ – airspeed in vertical plane, V_B- airspeed in the horizontal plane). Therefore, the power consumption of the engine when flying at altitude needs to be increased K times compared to flying equal to:

$$K = \frac{N_{\text{ПОД}}}{N_{\text{Г.П}}} = 1 + \frac{N_g}{N_{\text{пр}} + N_{\text{ин}} + N_{\text{вр}} + N_{\text{кин}}} = 1 + k$$

(2)

Consider a helicopter from point A with altitude H to point B with altitude H_1 ($H_1 > H$). The distance between 2 points is X. We can divide the helicopter's trajectory into two stages as follows: Stage 1, the helicopter can fly X_1 and get the altitude H_1, stage 2 helicopter flying equal to the distance ($X-X_1$) with

$$X_1 = \frac{H_1 - H}{\frac{V_{ygЭ}}{V_{ГЭ}}} = \frac{\Delta H V_{ГЭ}}{V_{ygЭ}}$$

(3)

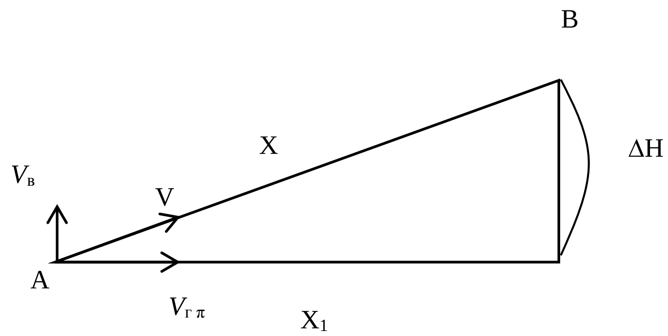


Figure 1. **Diagram illustrating the flight process from point A to point B**

Fuel consumption per kilometer is $q_{km} = \frac{NC_e}{3,6V\eta}$

Where: N is the fuel that can be carried by the helicopter

C_e – energy consumption factor

V- speed of helicopter

η – The coefficient depends on the type of helicopter.

From (4) it is clear that the amount of fuel consumed when flying in the horizontal plane and when in the vertical plane is the same.

So, the fuel consumption for the helicopter to fly in phase 1 is $Q_1 = X_1 q_{km} K$, and phase 2 is $Q_2 = (X - X_1) q_{km}$

Thus, we can get the coefficient corresponding to the total energy consumed when flying from point A to point B as follows:

$$Q=Q_1+Q_2=X_1q_{km}K+(X-X_1)q_{km}=q_{km}X+q_{km}(K-1)X_1=q_{km}X+q_{km}(K-1).\frac{\Delta H V_Г}{V_B}=q_{km}X+K_{th}.\Delta H$$

(4)

while: $K_{th} = \frac{(K-1)V_Г}{V_B}$ can be considered as constant for each type of helicopter.

So the energy consumed when flying from point i of height H_i to point j of altitude H_j is:

$$Q_{ij} = q_{km}.L_{ij} + qK_{th}.\Delta H_{ij} \quad (5)$$

Thus, according to formula (5) when the helicopter ascends (that is, $H_{ij}>0$), the fuel consumption will be higher than that of the level flight and vice versa when the helicopter descends (ie $\Delta H_{ij}< 0$) then the fuel consumption will be smaller when flying flat. We use the coefficient Q_{ij} to calculate the total fuel in the flight between the given points of flight. We can use the bound branching algorithm to solve the fuel optimization problem based on formula 5. The coefficient Q_{ij} is included in the cost matrix of the bounded branching algorithm as follows::

$$Q=\begin{bmatrix} \infty & Q_{12} & Q_{13} \dots & Q_{1n} \\ Q_{21} & \infty & Q_{23} \dots & Q_{2n} \\ \dots\dots\dots & & & \\ Q_{n1} & Q_{n2} & Q_{n3} \dots\dots & \infty \end{bmatrix}$$

The branching will be performed based on a certain Heuristic rule that allows us to shorten the process of finding the optimal solution. After branching, we will calculate the lower bound of the objective function value on each of the two subsets mentioned above. The search will be continued on the subset with the smaller lower bound. This procedure will be continued until a full journey is obtained.

Obviously the total cost of a helicopter cruise will contain exactly one element per row and exactly one element per column in the cost matrix Q. Hence if we subtract from each element of a row (or column) of the matrix Q with the same number α, the cost of all the journeys will decrease by α, so the optimal journey will also remain the same. So if we proceed to subtract the elements of each row and each of its columns by the smallest non-zero element, we get a matrix of non-negative elements that in each row and each of its columns have at least at least one zero, then the sum of the subtracting constants will give us the lower bound of all paths. After reducing on each row, each column of the matrix contains at least one 0, for each of these 0 elements, we calculate its index as the sum of the non-zero elements being considered and the smallest corresponding to the row. and that column. Select the element 0 with the largest index, corresponding to the arc to be selected for branching, and place the element symmetrical to it across the diagonal of ∞. After performing the lower bound and branching calculation, divide the journeys into two subsets, the set T1 includes the journeys containing arcs (p, q) and the set T2 includes the journeys not containing arcs (p, q). For the set T_1 the corresponding cost matrix Q_1 is obtained from the matrix Q by removing row p column q, i.e. the size of the matrix is reduced by one order. For the set T_2 the corresponding cost matrix Q_2 is obtained from the matrix Q by setting $Q_{pq} = \infty$, that is, in the next steps, the arc (p, q) will not be selected again.

Then we have split the journeys into two branches, on each of these branches the cost matrix is changed, so in each branch, the problem is returned to its original form, smaller in size with T_1 and is kept with T_2 with the number of other elements ∞ reduced by one. The next steps to solve the problem we perform the above procedures in turn for each branch. To limit the options to consider, we will choose the branch with the lower cost of the lower bound. In the end we will have the journey with the smallest cost. With different Q matrices we have different flight path. Then we have the standard data set to train the network.

III. ARTIFICIAL NEURAL NETWORK

An artificial neuron is a unit of computation that has many inputs and one output. Each input comes from a link. Its feature is a nonlinear activation function that converts the linear combination of all input signals into output signals. This activation function ensures the nonlinearity of the neural network computation.

An artificial neural network is a system consisting of many simple processing elements (also known as neurons) like neurons of the human brain. These elements work in parallel and are connected by neural connections. Each link is associated with a certain weight, which characterizes the activation or inhibition between neurons[2].

The weights are the means for long-term information storage in the neural network. The task of training the network is to update the weights as more information about the learning pattern becomes available. In other words, the weights are all adjusted so that the network's input-output relationship will perfectly match the environment under consideration.

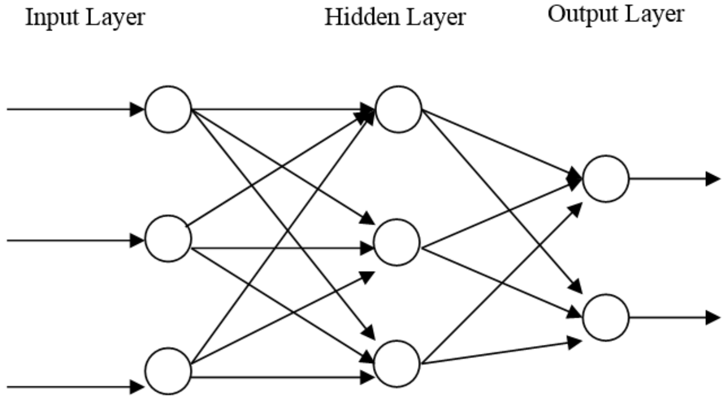


***Figure 2*. Simple diagram of an artificial neural network**

The above neural network model consists of 3 layers: input layer, hidden layer and output layer. Each node in the input layer receives the value of an independent variable and passes it on to the network. The data from all the nodes in the input layer is integrated ¬ (we call it the weight sum) and the results are passed to the nodes in the hidden layer. That layer is called a "hidden layer" because nodes in this layer communicate only with nodes in the input and output layers. The nodes in the output layer receive the weighted sum signals from the nodes in the hidden layer. Each node in the output layer corresponds to a dependent variable.

In order for the network to work, we must practice network training. "Network training" is a process in which the free parameters of a neural network are adjusted accordingly through a process stimulated by the environment. In order to train the network, it is necessary to have input and output data sets. A neural network is trained so that given a set of input vectors X, the network is capable of generating its desired set of output vectors T. The set X used to train the network is called the training set. The elements x belonging to X are called training samples. The training process is essentially changing the link weights of the network. During this process, the weights of the network will gradually converge to such values that for each input vector x from the training set, the network will produce the desired output vector T. Thus, in order to use neural networks for the fuel optimization problem of helicopters, we must have the input sample data set X and output T. The sample data set can be obtained from the branching algorithm that we use analyzed above.

IV. NEURAL NETWORK APPLICATION TO SOLVE THE PROBLEM OF AIR TRANSPORT

Suppose the helicopter needs to fly through n points. Each point has 3 coordinates, so the input of the neural network needs 3n inputs. Here we calculate that the network consists of only 2 layers, so the hidden layer and the input layer are 1 layer. Our output requirement is the stroke order of the points. Thus, our network will consist of n outputs in the order marked from 1 to n. At each output will receive values from 1 to n.

The network is selected as follows:

+ Layer 1: 3n neurons using the activation function tansig

+ Layer 2: n neurons use the activation function purelin

The neural network model is as follows:

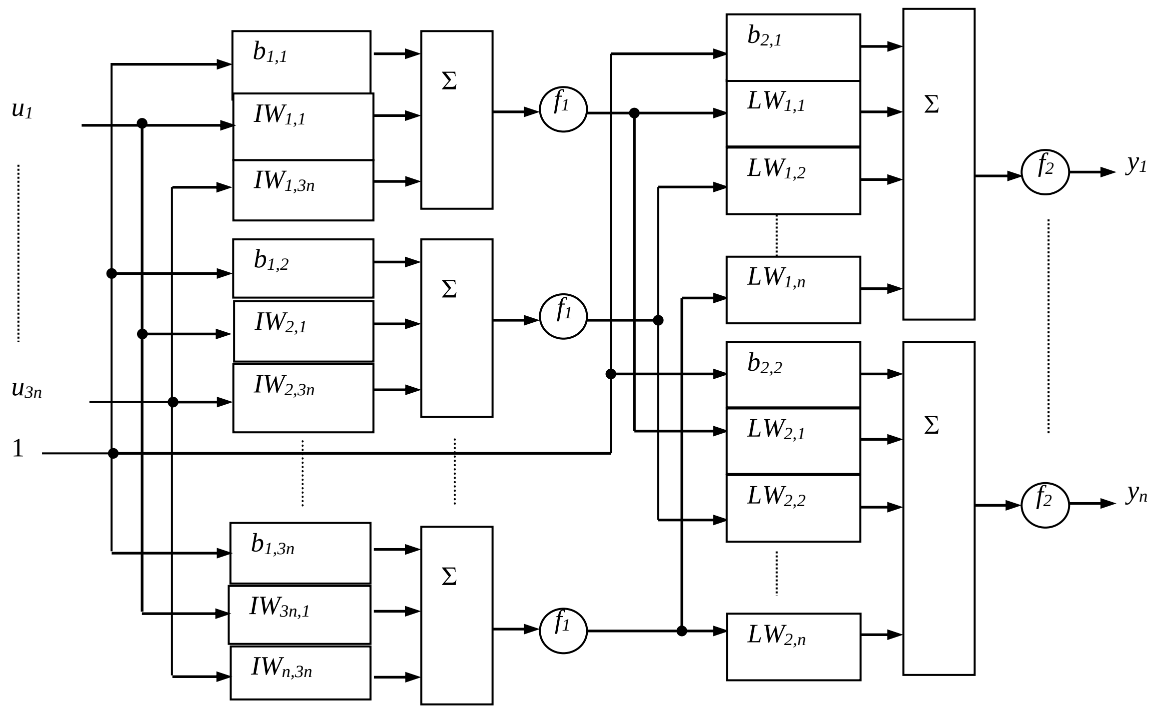


***Figure 3*. Structure diagram of the network**

Illustrated with 10 points given. With the above analysis, we build the network on Matlab-Simulink.

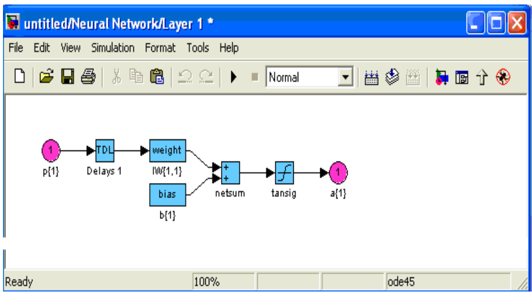


Figure 4. **Network 1st floor diagram**

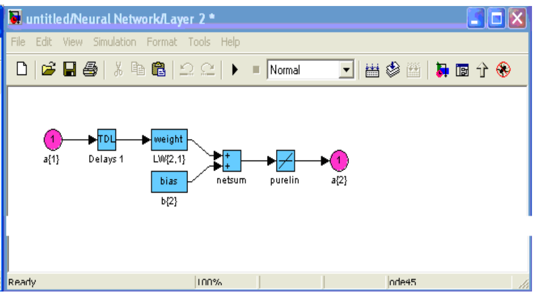
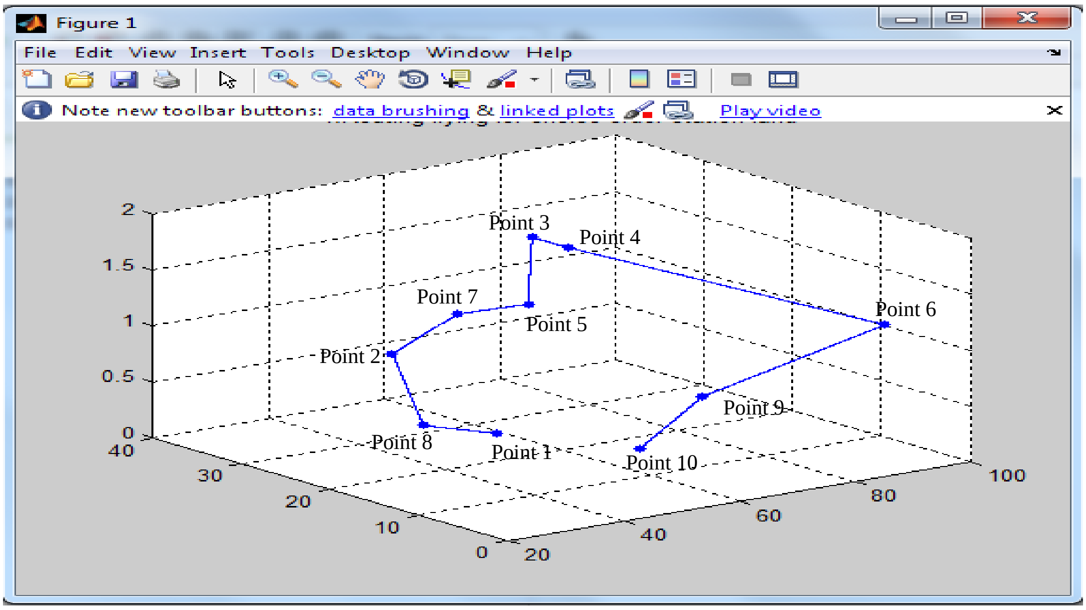


Figure 5. **Network 2nd floor diagram**

After training the network with the data set received from the branching algorithm, we can use the network to solve the problem of finding the flight path of the helicopter to optimize fuel. The test results with the data set of coordinates of the points are as follows:

```
x=[52 96 48 45 61 23 78 66 33 55];
y=[6 7 16 22 24 15 31 8 18 24];
z=[0.4 1.1 1.5 1.3 1.8 1.3 1.4 0.7 0.5 0.1];
```

We get the flight path as follows: 1→8→2→7→5→3→4→6→9→10



V. CONCLUSION

The application of neural networks to problem solving depends a lot on the structure of the neural network and the sample data set. Using the branching algorithm to create a training dataset will help the network work correctly. The article mentioned a direction of using neural networks to solve the combination problem of helicopter control.

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