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A novel system optimal design approach using artificial fish swarm algorithm

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ABSTRACT

The research to system optimal design problems plays an important role in both the theoretical and practical significance. In this paper, an artificial fish swarm algorithm is proposed to the system optimal design problem. Experimental results suggest that this approach outperforms other existing approaches.

Key words: System Optimal Design, Artificial Fish Swarm, Neural Network

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INTRODUCTION

Recently, various systems become more and more complex and the corresponding influence factors also enjoy a great increase. Therefore, it becomes a very difficult job to make an overall system optimal design. For example, the design of weapon system is the feedback and iteration process of technical information between the whole system and equipment. Usually many conflicts exist among different performances of the weapon system and in the performance between the whole system and equipment. They should be coordinated constantly to improve the performance of the whole system [1-3]. Therefore, most of the countries in the world have shifted their focus to the integrity of combat ability, survival ability, rapidity, maneuverability and compatibility when designing weapon systems [4-6] during recent years.

PROBLEM DESCRIPTION

The problem to be studied in this paper can be concluded as: employing simulation optimization approaches to study system optimal design problems and attempting to make the system to be studied output satisfactory results through fewer times of system simulation. The corresponding target function is described as

$$\begin{cases} \max \{P_1, P_2, \cdots, P_s\} \\ \min \{T, Q_1, Q_2, \cdots, Q_r\} \end{cases}$$

Here, $P_1, P_2, \cdots, P_s$ denote some indicators that need to be maximized in the system to be studied, $Q_1, Q_2, \cdots, Q_r$ denote ones that need to be minimized, and T denotes the total time cost by the system simulation during the optimization process. Constraint conditions of the problem are described as:

$$\begin{cases} P_i = Sim(S_1 S_2, \cdots, S_n), i = 1, 2, \cdots, s \\ Q_i = Sim(S_1 S_2, \cdots, S_n), i = 1, 2, \cdots, r \\ T = \sum_{i=1}^{n+1} t_i c_i \\ S_i = Sim(x_{i1} x_{i2}, \cdots, x_{i(k_i)}), i = 1, 2, \cdots, n \\ x_{ij} \in \left[x_{ij}^{low}, x_{ij}^{up} \right], i = 1, 2, \cdots, n, j = 1, 2 \cdots, k_i \end{cases}$$

In the first constraint condition and the second one, take simulation outputs of all the subsystems as the input of the whole system and then make simulations to obtain the output value of all the indicators of the system to be studied. $S_i(1 \le i \le n)$ denotes the simulation output of the i^{th} subsystem, either a single value or a vector. The third constraint condition denotes the total time cost by simulations during the optimization process. $t_i\left(1 \le i \le n\right)$ denotes the average time spent by the i^{th} subsystem on a single simulation. t_{n+1} denotes the average time spent by the system on the overall simulation. $c_i\left(1 \le i \le n\right)$ denotes the number of simulations implemented by the i^{th} subsystem during the optimization process, and c_{n+1} denotes the total number of overall simulations. The fourth constraint condition denotes that simulation outputs of subsystems can be obtained solely through subsystem simulations. $k_i\left(1 \le i \le n\right)$ denotes the number of input variables of the i^{th} subsystem. The fifth constraint condition defines the feasible region of input variables of the system to be studied.

ARTIFICIAL FISH SWARM ALGORITHM

Fishes can always find out places with high food concentration by following other fishes. Therefore, the place with the largest number of fishes is always the place with the most sufficient foods in water. In the artificial fish swarm algorithm, fish schools in the natural world are observed for a long time to structure artificial fishes to imitate foraging, swarming, rear-end and random behavior of fishes, making local optimum to highlight in groups through local optimization of individual fish in the fish school, so as to reach global optimum and realize the optimization process.

(1) Foraging behavior: fishes select tendency through visual or olfactory perception of concentration of foods in water.
(2) Swarming behavior: a kind of survival mode of fishes; considerable or a small quantity of fishes can gather into swarms for collective foraging and damage avoidance.
(3) Rear-end behavior: when a certain fish or several fishes find foods, fishes around them will tail after them and rapidly come, thus leading fishes in the further distance to come.
(4) Random behavior: fishes move about freely and leisurely in water. Basically, it is random. In fact, they are aimed at foraging or finding companions in a larger range.

DEFINATION OF PARAMETERS

When the artificial fish swarm algorithm is used to train BP neural network, each artificial fish represents a neural network. The concentration C of foods at the current position of artificial fish is

$$C = \frac{1}{E}$$

Wherein, E stands for the error between actual output and expected output of neural network. With three layers (input layer, hidden layer and output layer) of BP neural network as an example, suppose the number of nerve cells in the input layer as n , that of the hidden layer as h and that of the output layer as m . Two artificial fishes are defined as F_p and F_q respectively. The sum $\left(F_p + F_q\right)$ of two artificial fish individuals or the difference $\left(F_p - F_q\right)$ of two artificial fish individuals still represents a neural network. The distance $d_{p,q}$ between two artificial fish individuals is

$$d_{p,q} = \sum_{i=1}^{h}\sum_{j=1}^{n}[w_{ij}(p) - w_{ij}(q)]^2 + \sum_{k=1}^{m}\sum_{i=1}^{h}[v_{ki}(p) - v_{ki}(q)]^2 + \sum_{i=1}^{h}[w_{i0}(p) - w_{i0}(q)]^2 + \sum_{k=1}^{m}[v_{k0}(p) - v_{k0}(q)]^2$$

Wherein, w_{ij} stands for the connection weight between input layer and hidden layer, v_{ki} stands for the connection weight between hidden layer and output layer, w_{i0} stands for the threshold value of nerve cell in hidden layer and v_{k0} stands for the threshold value of nerve cell in output layer.

BEHAVIOR DESCRIPTION

(1) Foraging behavior and random behavior. The current state of artificial fish is F_p. Within its sight range, another state F_q is randomly selected. If the food concentration C_q of F_q is higher than the food concentration C_p of F_p (i.e. $C_q > C_p$), then make a step forward in the direction of F_q; on the contrary, execute random behavior. In other words, randomly select a state in the sight range, and then move towards this direction. The change process of artificial fish training $w_{ij}(p)$ is shown in the following Formula. Changes of $v_{ki}(p)$, $w_{i0}(p)$ and $v_{k0}(p)$ are similar to it.

$$\begin{cases} w_{ij}(p+1) = w_{ij}(p) + \mathrm{Rand}(T)\dfrac{w_{ij}(q) - w_{ij}(p)}{d_{p,q}} & C_q > C_p \\ w_{ij}(p+1) = w_{ij}(p) + \mathrm{Rand}(T) & C_q \le C_p \end{cases}$$

Wherein, T stands for the maximum value of artificial fish movement step length and $Rand(T)$ stands for a random number between $[0, T]$. Foraging behavior and random behavior of fishes in the natural world are uniformly summarized as foraging behavior in the algorithm and as default behavior of swarming behavior and rear-end behavior.

(2) Swarming behavior. In the sight of artificial fish F_p, suppose

$$Y_p = \left\{ F_q \,\middle|\, d_{p,q} \le V \right\}$$

Wherein, Y_p stands for the collection formed by other artificial fish individuals and V stands for the sight range of artificial fish F_p. If $Y_p \neq \phi$, search its central position F_c according to the following Formula.

$$\begin{cases} w_{ij}(c) = w_{ij}(c) + w_{ij}(q) \\ v_{ki}(c) = v_{ki}(c) + v_{ki}(q) \\ w_{i0}(c) = w_{i0}(c) + w_{i0}(q) \\ v_{k0}(c) = v_{k0}(c) + v_{k0}(q) \end{cases}$$

Wherein, $w_{ij}(q)$, $v_{ki}(q)$, $w_{i0}(q)$ and $v_{k0}(q)$ are parameters of artificial fish F_q.

After scanning all artificial fish individuals in the sight range, parameters of central position F_c of artificial fish partners in the sight F_p should be calculated according to the following Formula.

$$\begin{cases} w_{ij}(c) = w_{ij}(c) / f \\ v_{ki}(c) = v_{ki}(c) / f \\ w_{i0}(c) = w_{i0}(c) / f \\ v_{k0}(c) = v_{k0}(c) / f \end{cases}$$

Wherein, f stands for the number of other artificial fish partners in the sight F_p. Suppose C_c as the food concentration at the central position; if it meets the following Formula, it indicates that the central position is relatively optimal and not too crowded, then the change process of artificial fish parameters $w_{ij}(p)$ is shown as follows, or artificial fish will execute foraging behavior.

$$\frac{C_c}{f} > \delta C_p$$

Wherein s stands for the crowding degree factor.

$$w_{ij}(p+1) = w_{ij}(p) + \mathrm{Rand}(T)\frac{w_{ij}(c) - w_{ij}(p)}{d_{p,c}}$$

If $Y_p = f$, artificial fish will execute foraging behavior. Change processes of $v_{ki}(p)$, $w_{i0}(p)$ and $v_{k0}(p)$ are similar to $w_{ij}(p)$.

REAR-END BEHAVIOR

Suppose artificial fish with the maximum foods in all partners in the artificial fish sight as $F_{\max}$; if its food concentration $C_{\max}$ meets the following Formula, then it indicates that the food concentration of artificial fish $F_{\max}$ is high and it is not too crowded around. The change process of artificial fish parameter $w_{ij}(p)$ is shown as the following Formula; or artificial fish will execute foraging behavior.

$$C_{\max} > \delta C_p$$

$$w_{ij}(p+1) = w_{ij}(p) + \mathrm{Rand}(T)\frac{w_{ij}(\max) - w_{ij}(p)}{d_{p,\max}}$$

Wherein, $w_{ij}(\max)$ stands for the parameter of artificial fish $F_{\max}$. If $Y_p = f$, artificial fish will execute foraging behavior. Change processes of $v_{ki}(p)$, $w_{i0}(p)$ and $v_{k0}(p)$ are similar to $w_{ij}(p)$.

RESULTS

XX system exerts its damage on the target through target search, target identification and target attack. The system owns multiple factors and its exertion process is complicated, so we can make full use of its high cost-effectiveness only by optimizing structure parameters and performance parameters and coordinating their relationships. Performance factors selected in this paper for the system mainly include: the fall velocity V_y, rotating speed ω, scanning angle θ_s, operating distance H, position error of sensors and dispersion error of warhead E, ambient wind velocity F. The hit probability is selected as the target function.

According to the practical simulation model of XX system, the obtained simulation hit probability corresponding to the above-mentioned optimization parameters is 0.812. Compare the optimal hit probability with the simulation hit probability and we can find that the simulation model based on the performance factors of neural network is feasible and accurate. The author has made a comparative analysis between the result obtained in this paper and that in literatures. It shows that the two are in close proximity to each other, which further indicates that it is totally feasible to employ genetic neural networks for optimal design.

CONCLUSION

The contribution of this paper can be summarized as follows: an artificial fish swarm algorithm is proposed to the system optimal design problem. Experimental results suggest that this approach outperforms other existing approaches.

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