Optimization of Shipborne Equipment System Reliability Based on Artificial Immune PSO Algorithm

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Abstract: According to fuzzy optimum selection theroy, the Euclidean distance from feasible projects to the ideal project and the minus-ideal project is regarded as evaluation criterion for establishing the fuzzy multi-targets optimization model. It can be known that particle swarm optimization(PSO) algorithm is easy to get in local extremum and the particles lack diversity through the analysis of its constringency. The particles’ velocity is controlled to improve the deficiencies of this algorithm. The theory of artificial immune system(AIS) and the improved particle swarm optimization algorithm are combined to put forward a new algorithm, artificial immune particle swarm optimization(AI-PSO). This method is applied to the solution of system reliability optimization, and the simulation result show that this algorithm has better capability of entire range search and the optimization result is more reasonable compared to other algorithms.

1. Introduction
Reliability is an important target of application performance for shipborne weapon equipment system. Under the circumstance of existing manufacturing craft and technical level, how to make the reliability of whole system to be optimal through reasonable allocation of system units’ reliability is the problem need to be solved for equipment system optimization. At the beginning of system design, an important work is to determine the reliability target of every component elements based on the system reliability[1]. If the component units’ reliability is unable to reach the required level, another method of improve system reliability is to add redundancy equipment, the purpose of which is make the comprehensive targets(targets of benefit and cost as well as the targets of other aspects) of the whole system to be optimal, the process of which is structural optimization of system reliability. According to the analysis above, the system reliability optimization is a problem of mixed nonlinear multi-targets optimization. At present, many optimization methods have been successfully applied to solve this problem. For example, the genetic algorithm is used on the solution of system reliability optimization in references[2], but the optimization model is established under the circumstance of resources restriction to make the system reliability to be optimal, the resources restriction in the model is greatly influenced by man-made subjective factors, therefore, the optimization result got from the model is actually not optimal in most cases. Multi-objective decision-making method with discrete variables is present in references[3] to select the optimal reliability value of units in large and complex system, however, the process of solution is complicated and the result is not precise. The redundancy optimization model for three-state system and its calculation method is given in references[4], in which the system redundancy is optimized based on the case that the reliability of system component units is known, which is not consistent with the fact.
In this paper, the fuzzy multi-targets optimization model of shipborne equipment system’ reliability allocation is set up. According to fuzzy optimum selection theory. The artificial immune system (AIS)\(^5\) and the improved particle swarm optimization (PSO)\(^6\) are combined to put forward a new algorithm of improved artificial immune particle swarm optimization (AI-PSO). In the calculation process of this algorithm, the velocity of the particles is controlled to make particles have better capability of entire range search. This new algorithm is applied to the solution of shipborne equipment system reliability optimization, the fuzzy multi-targets optimization model of system’ reliability allocation is regarded as the adaptability function of this algorithm, from which the result got is more accurate and reasonable.

2. Multi-targets optimization model of shipborne equipment system reliability

If only consider the target of reliability in the phase of system design, the problem of system optimization is easy to solve, but this case is not exist in the actual engineering. In the process of system reliability optimization, understanding the relationship between every optimization targets is the basis for system reliability optimization. In different optimization targets, the most ordinary targets are system reliability, cost and expense, weight and volume.

Suppose a shipborne equipment system is composed of \( N \) units, the reliability and the redundancy of every unit are \( R_i \) and \( N_i \) respectively, so the design variables of this system is: \( X=[R_1,R_2,\ldots,R_n,N_1,N_2,\ldots,N_n] \).

1) System reliability: the system shown in fig.1 can be equivalent to \( N \) serial units, the calculation formula of system reliability is as follow:

\[
R(X) = \prod_{i=1}^{N} \left[1 - (1 - R_i)^{N_i}\right]
\]

(1)

2) Cost and expense: the cost of the whole system is the sum cost of every component units and joint and switch equipment, however, the cost of the system units is closely related with its reliability. The higher of the reliability, the larger of the cost, the two targets show their direct proportion relationship. Therefore, we can get that \( c_i = \alpha_i \cdot [-t / \ln(R_i)]^{-\beta} \), \( t \) is the non-disabled runtime of the \( i^{th} \) accessory, the calculation formula of the cost and expense is:

\[
C(X) = \sum_{i=1}^{N} c_i \left( -t / \ln(R_i) \right)^{-\beta} (N_i + K(N_i))
\]

(2)

3) Volume: the volume of the whole system is the sum volume of every component units, considering the interspace between different units, the volume calculation formula should be multiplied with revision factor \( \Gamma (\Gamma > 1) \), the concrete value of which depend on actual case, so the calculation formula of volume is:

\[
V(X) = \Gamma \cdot \sum_{i=1}^{N} v_i \cdot N_i^2
\]

(3)

4) Weight: Like the volume, the weight of the whole system is also the sum weight of every component units, considering the weight of redundancy units and the joint switch equipment, it should be multiplied with revision factor \( \kappa (\kappa > 1) \), which is the function of \( N_i \). So the calculation formula of system weight is as follow:
Form the formula above: 
\[ W(X) = \sum_{i=1}^{n} \omega_i \cdot N_i \cdot K(N_i) \]  

(4)

The system optimization project is a better project with higher reliability and fewer cost and expense. In addition, considering the volume and the carrying capacity of the warship are limited, therefore, the volume and the weight should be small and light possible in the phase of shipborne equipment system design. According to the analysis above, the multi-targets optimization model of shipborne equipment system’ reliability allocation is:

\[
\begin{align*}
\max R &= \prod_{i=1}^{n} \left[ 1 - (1 - R_i)^{v_i} \right] \\
\min C &= \sum_{i=1}^{n} \alpha_i \left( -\frac{1}{\ln R_i} \right)^{N_i} (N_i + \exp(N_i / 4)) \\
\min V &= \Gamma \cdot \sum_{i=1}^{n} v_i \cdot N_i^2 \\
\min W &= \sum_{i=1}^{n} \omega_i \cdot N_i \cdot \exp(N_i / 4)
\end{align*}
\]  

(5)

3. The fuzzy multi-targets optimization model

3.1 Method of ideal project

The ideal project is a supposed optimal project, and the minus ideal project is a supposed worst project, which could be got through choosing the optimal or the worst target. These two projects are not existed in practice, only considered as the optimal or the worst project in ideality. The purpose of system reliability optimization allocation is to find the optimal project among different feasible allocation projects, the optimal project is closest to the ideal project and farthest to the minus ideal project[7].

In order to measure the approach degree between feasible project and the ideal or minus ideal project, suppose the optimization targets of the project are \( m \), the ideal project is \( x^*_0 \), the minus ideal project is \( x^0 \).

\[
\begin{align*}
X^*_0 &= [x^*_0(1), x^*_0(2), \ldots, x^*_0(m)] \\
X^0 &= [x^0(1), x^0(2), \ldots, x^0(m)]
\end{align*}
\]  

(6)

3.2 The Euclidean distance between feasible project and the ideal or minus ideal project

Different targets have different dimension, non dimension and standardization need to be done for the projects’ synthesis value matrix \( X = [x_{ij}]_{m \times n} \) so as to make sure the same factors of every target can be compared with each other. There are many means of standardization, the method adopted in this paper is as follows[8]

\[ r^*_j(i) = \begin{cases} 
\frac{x^*_j(i) - \min x^*_j(i)}{\max x^*_j(i)}, & \text{target of benefit} \\
\frac{\max x^*_j(i) - x^*_j(i)}{\max x^*_j(i)}, & \text{target of cost} 
\end{cases} \]  

(7)

The targets synthesis value \( x_{ij} \) can be transformed into the corresponding degree \( r^*_j(i) \) related to the optimal project through the formula(7). \( r^*_0 = [r^*_0(i)]' \) is recorded as the corresponding degree
vector related to the ideal project \( x_0^* \), and the \( x_0^- = [x_0^* (j)]^\top \) is recorded as the corresponding degree vector related to the minus ideal project \( x_0^- \). Therefore, the Euclidean distance between the feasible project \( X \) and the ideal project \( x_0^* \) as well as the minus ideal project \( x_0^- \) are showed below:

\[
d(X, X_0^*) = \sum_{j=1}^n \| w_j [r_0^* (i) - r_j (i)] \|^2 \tag{8}
\]

\[
d(X, X_0^-) = \sum_{j=1}^n \| w_j [r_j (i) - r_0^- (i)] \|^2 \tag{9}
\]

As the formula showed above, \( w_i \) is the weight of the \( i^{th} \) target.

3.3 The fuzzy optimum selection model

**Theorem:** the fuzzy optimum selection model of system reliability target allocation is

\[
u_j = \left\{ \frac{\sum_{j=1}^n (w_j [x_0^* (i) - r_j (i)]^2)^{-1}}{\sum_{j=1}^n (w_j [r_j (i) - x_0^- (i)]^2)^{-1}} \right\} \tag{10}
\]

**Proof:** according to multi-targets fuzzy optimization theory, the targets function is established as bellow:

\[
\theta_j (u_j, \overline{w}) = d (X, x_0^*) + d (X, x_0^-) = \sum_{j=1}^n \{ u_j \cdot \| w_j [x_0^* (i) - r_j (i)] \|^2 \}
\]

\[
+ \sum_{j=1}^n \{ u_j' \cdot \| w_j [r_j (i) - x_0^- (i)] \|^2 \}
\]

The formula (11) can be transformed into the nonlinear programming problem with the form of

\[
\min F(u, \sigma) = \frac{\sum_{j=1}^n \theta_j (u_j, \sigma)}{n} \quad \text{under the restriction that } \sum_{j=1}^n w_j = 1, \quad w_j \geq 0, \quad 0 \leq u_j \leq 1.
\]

In order to decrease the number of unknown factors and the equations so as to make the problem easy to solve, the restrictions of \( w_j \) and \( u_j \) are not considered. The Lagrange function established is as bellow:

\[
L(\overline{w}, \lambda) = \sum_{j=1}^n \theta_j (u_j, \overline{w}) / n + \lambda \cdot (\sum_{j=1}^n w_j - 1)
\]

Calculating the differential coefficients of formula above for \( w_j \), \( u_j \) and \( \lambda \) and making them to zero, then the formula(10) could be got. Proof is over.

4. Improved artificial immune particle swarm optimization algorithm

4.1 Theory of artificial immune system

Artificial immune system(AIS) is an intelligent which combines the information processing technique with calculation Method. It draws on and use of biological immune system mechanism for the development of technical methods to solve engineering and scientific problems. Biological immune system is also a highly evolitional biological system, which is designed to distinguish between outside harmful antigens and their own organs to remove pathogenic organisms and thereby maintain the stability of organisms. Inspired from biological immune system mechanism, an application-oriented
computation model of the immune system - Artificial Immune System (AIS) is developed. Clonal selection theory (CS), put forward by the Jerne firstly, the main characteristics of which is that the immune cells will do the cloning proliferation under the stimulation of antigens, subsequently diversity effector cells (such as antibodies) and memory cells are generated through genetic mutation. Clonal selection counterparts an affinity maturing process, that is, the process of antigen individuals with low affinity gradually raising their affinity and "maturing" after experiencing the operation of replication proliferation and mutation based on the clonal selection mechanism. So the affinity maturing is essentially a Darwinian selection and mutation process. Clonal selection is realized through the use of genetic operator such as cross, mutation and the corresponding control mechanism for the colony.

4.2 Elementary particle swarm optimization algorithm
The particle swarm optimization algorithm (PSO) is put forward firstly by Kenney et al in 1995, which is a evolution algorithm that simulate the bird and fish swarm’s migration and gathering action in the process of seeking for food.

Suppose there is a colony which is composed of \( N \) particles in a targets searching space with \( n \) dimensions, the \( i^{th} \) particle is expressed as a \( n \) dimensions vector \( X_i = (x_{i1}, x_{i2}, \ldots, x_{in}) \), \( i = 1, 2, \ldots, N \), the place of every particle is a potential result. The flight speed of the \( i^{th} \) particle is also a \( n \) dimensions vector, which is recorded as \( V_i = (v_{i1}, v_{i2}, \ldots, v_{in}) \). Suppose the optimal place that being searched by the \( i^{th} \) particle so far is \( p_i = (p_{i1}, p_{i2}, \ldots, p_{in}) \), and the optimal place that being searched by particle swarm so far is \( p_g = (p_{g1}, p_{g2}, \ldots, p_{gn}) \), \( w \) is inertial weight. Formula (12) and formula (13) are called as the standard equation of PSO.

\[
v_i^{(t+1)} = wv_i^{(t)} + c_1r_1(p_i^{(t)} - x_i^{(t)}) + c_2r_2(p_g^{(t)} - x_i^{(t)})
\]

\[
x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)}
\]

Clerc et al’s Research find that compressed factors can help to make sure particle swarm optimization algorithm converge with more rapid speed, and the renewal speed equation is shown by formula (14).

\[
v_i^{(t+1)} = \chi(wv_i^{(t)} + c_1r_1(p_i^{(t)} - x_i^{(t)})) + c_2r_2(p_g^{(t)} - x_i^{(t)})
\]

In the formula (14), \( \chi = 2 / (2 - \phi - \sqrt{\phi^2 - 4\phi}) \), \( \phi = c_1 + c_2 \), \( \phi > 4 \), \( c_1, c_2 \in [0,2] \), \( r_1, r_2 \) is random number from zero to one.

4.3 Convergence analysis of elementary particle swarm optimization algorithm
The PSO algorithm’s capability of searching for optimal particle mainly depend on the mutual effect and impact between particles, if such mutual effect and impact is removed from the algorithm, the PSO algorithm’s searching capability will become quite limited[9]. The searching capability of elementary PSO algorithm depend on the competition and cooperation between particle swarm, so the particles itself lack mutation mechanism, once the single particle get into the local extremum, the particles itself are difficult to leap out of the restriction. At the beginning of calculation, this algorithm’s convergent speed is rapid and its motion locus wiggled with the form of sine wave[10], however, the speed of particles begin to become slow or even stagnant after calculating some time. The particle swarm lose the capability of further evolution when the speed of all particles in colony is nearly to zero, then it could consider that the algorithm has converged. But in many cases, the algorithm has not converged to entire range extremum or even got the local extremum, which is called the phenomenon of prematurity or stagnation[11,12]. The particle swarm is high-congregated and
seriously lack diversity when this phenomenon is taking place, and the particle swarm will not leap out of the rallying point for long time or forever. Therefore, many methods for improving particle swarm optimization algorithm are mainly centralized in boosting the diversity of particle swarm, which can make particle swarm maintain the capability of further evolution in the process of iterative circulation.

4.4 Artificial immune particle swarm optimization and its realization steps

According to analysis of the elementary PSO algorithm’s convergence, it can be known that there are two main factors that make PSO algorithm to get into local extremum or prematurity. One is the particle swarm’s diversity, the other is the particle swarm’s flight speed. Experiment analysis tells us the effective method for avoiding PSO algorithm to get into prematurity is to boost particle swarm’s diversity and keep its durative flight during calculation or circulation process, that is, the particle swarm’s flight speed is not equal to or close to zero, which make particles to search adequately in shrink state and fly out of the gathering place in dispersing state. Therefore, particles can search in a bigger space and has better capability of entire range search.

Elementary PSO algorithm is improved through the operation of cross and mutation in artificial immune system or the control to particles’ flight speed, the basic method is as follows. In the process of calculation or circulation, if the comparability $\xi$ of the $t^{th}$ generation particle swarm which is made up of $N$ particles exceeds the initialized setting value, the cross and mutation operation is done to every particles of the $t^{th}$ generation. $\xi = n(\text{affinity}) / N$, $n(\text{affinity})$ is the number of particles with the same adaptability in colony. If the particles’ speed $v$ of the $t^{th}$ generation colony is less than a certain value(this value can be set according to the actual case), speed control operation is done to make particles renew its flight speed for flying out of convergence point, specific operation is $v_i = a \cdot \text{rand}()$, if $v_i \leq v_{\text{min}}$. $a$ is speed control parameter, $\text{rand}()$ is random number from zero to one.

The realization steps of AI-PSO algorithm are:

Step1: determine the parameters of learning factors, the maximum circulation steps $T$ and the colony scale, and the learning factors $c_1, c_2 \in [0,2]$, with the restriction $c_1 + c_2 > 4$.

Step2: generate the initialized colony randomly, and initialize the particles’ speed and position, set the circulation counter $t = 1$.

Step3: calculate the particles’ optimal position $P_i^t$ and the whole particle swarm’s optimal position $P^t$.

Step: using formula (13) and formula (14) to renew particles’ position and speed and calculating every particle’s adaptability $\text{aff}_i^t$, the adaptability calculation method is shown by formula (15).

\[
\text{aff}_i^t = \frac{\sum_{j=1}^{m} (w_i x_i^t(i) - r_j(i))^2}{1 + \sum_{j=1}^{m} (w_j x_j^t(i) - r_j(i))^2}^{-1}
\]  \hspace{1cm} (15)

Step5: calculate particles’ comparability $\xi$ in the colony, the particles in colony are carried out the cross or mutation operation with some probability if $\xi \geq \xi_{\text{max}}$. Take the algorithm’s code of this paper as example, the transformation of cross and mutation operators are shown below.

**Cross operators**

Before cross:

| 0.3 | 0.4 | 0.4 | 0.1 | 0.2 | 0.5 | 0.5 | 0.4 | 3 | ... | ... | ... | 2 | 3 |
| 0.5 | 0.1 | 0.2 | 0.2 | 0.3 | 0.3 | 0.4 | 0.2 | 4 | ... | ... | ... | 1 | 5 |

After cross:
0.2 0.3 0.3 0.1 0.2 0.5 0.5 0.4 3 ⋯ ⋯ ⋯ 2 3

0.5 0.1 0.2 0.3 0.4 0.4 0.2 4 ⋯ ⋯ ⋯ 1 5

**Mutation operators**

Before mutation:

0.5 0.1 0.2 0.1 0.3 0.4 0.4 0.2 4 ⋯ ⋯ ⋯ 1 5

After mutation:

0.3 0.2 0.3 0.1 0.3 0.4 0.4 0.2 4 ⋯ ⋯ ⋯ 1 5

Step6: calculate the speed $v'^i_j$ of every particle in the colony, if $v'^i_j$ is less than the setting value, operation is carried out to control the particle’s speed.

Step7: Determine whether the termination conditions are satisfied, if not, transfer to step 3 and continues, otherwise, to end the calculation.

**5. Simulation result and its conclusion**

Suppose a shipborne equipment system is made up of five series units, and the initialized parameters of the system are shown below.

$$\alpha = (2.33 \times 10^{-5}, 1.45 \times 10^{-5}, 5.41 \times 10^{-5}, 8.05 \times 10^{-1}, 1.95 \times 10^{-4})$$

$$\beta = (1.52, 1.56, 1.63, 1.48, 1.51)$$

$$\omega = (7, 8, 8, 6, 9), \quad v = (2, 3, 4, 5, 4), \quad t = 2000$$

$$0.1 \leq R_i \leq 0.9, \quad 1 \leq N_i \leq 5$$

The weight of the optimization targets is $w$, and the $w = (0.55, 0.3, 0.1, 0.05)$, the ideal project and the minus-ideal project of system reliability optimization can be gained according to the initialized parameters. The ideal project is the project with maximum reliability target and at the same time, with minimum cost, volume and weight. Opposed to the ideal project, the minus-ideal project is the project with minimum reliability target and maximum cost, volume and weight. Thus the ideal project and the minus-ideal project is shown below.

$$X^*_0 = (0.99995, 8.9254, 18, 48.793)$$

$$X^*_0 = (0.00001, 3589.55, 450, 663.17)$$

The algorithm’s initialized parameters in simulation are as follows: the scale of particle swarm $N_a = 40$, learning factors $c_1 = 2.678$, $c_2 = 2.762$, cross probability $P_c = 0.5$, mutation probability $P_m = 0.1$, the maximum circulation steps $T = 200$. The particles’ adaptability of the first and the last generation is shown in figure2.

![Fig.2 Distribution of particles’ adaptability](image)

The algorithm is simulated with ten times, the best particle searched in the process of ten times optimization is $R = (0.7069, 0.7797, 0.7942, 0.7304, 0.7885)$, $N = (4, 3, 3, 3, 3)$. The
corresponding system reliability $R_s = 0.9454$, cost and expense $C_s = 506.03$, volume $V_s = 176$, and the weight $W_s = 272.993$.

In order to explain the validity of artificial immune particle swarm optimization algorithm, the algorithm’s performance is compared with other algorithm’s, which include elementary particle swarm optimization (PSO) and artificial immune algorithm (AIA). Different algorithms’ maximum adaptability of every generation is shown in fig.3, after circulation several tens of steps, the optimal result searched by the colony of particle swarm optimization and artificial immune algorithm has tended to be stable, in other words, the colony’s adaptability is not improved as the circulation steps increase. Because of colony’s diversity and the control for particles’ speed, AI-PSO algorithm’s particles will go down slightly form the current optimal local extremum when the algorithm tend to get into the premature state during the whole circulation process, and then leap out of the local extremum and search again. The holistic change trend of colony’s adaptability is improved as the circulation step continues.

Different algorithms’ optimal calculation results during ten times simulation are shown in Tab.1 below, data in Tab.1 show that AI-PSO algorithm’s particles can search in a bigger solution space and have a better entire range search capability compared to other two optimization algorithms, and the optimization project has a better adaptability and its result is more reasonable.

| Optimization targets | Algorithms | PSO | AIA | AI-PSO |
|----------------------|------------|-----|-----|--------|
| $N$                  | (4, 3, 3, 4, 2) | (3, 3, 3, 5, 3) | (4, 3, 3, 3) |
| $R_1$                | 0.702979   | 0.789969 | 0.706921 |
| $R_2$                | 0.781289   | 0.774742 | 0.779721 |
| $R_3$                | 0.743838   | 0.798672 | 0.794211 |
| $R_4$                | 0.667529   | 0.525390 | 0.730449 |
| $R_5$                | 0.788542   | 0.785099 | 0.788542 |
| $R_s$                | 0.945365   | 0.938616 | 0.945365 |
| $C_s$                | 584.9748   | 458.4094 | 506.0276 |
| $V_s$                | 191        | 242   | 176   |
| $W_s$                | 272.6436   | 307.9423 | 272.9929 |
6. Conclusion

In this paper, the shipborne equipment system’s reliability multi-target allocation model is established based on fuzzy optimum selection, artificial immune system mechanism is introduced to PSO algorithm. Simulation result and the algorithm’s performance analysis show that AI-PSO algorithm has better entire range search capability compared to PSO and AIA, and the optimization project has a better adaptability and its result is more reasonable.

However, the AI-PSO algorithm has also its deficiencies compared to other heuristic algorithms. For example, sometimes it can not get stable result. The occurrence probability of this case is very low, which occurs once in every 20 calculations. Sometimes the adaptability of optimization project obtained from AI-PSO algorithm is only 0.967~0.971, however, after several simulations to PSO and AIA, all of the optimization projects’ adaptability are hold from 0.981 to 0.985, which show that AI-PSO algorithm is not stable enough. This deficiency can be avoided through calculation for several times in the problem of equipment reliability optimization design, but in some cases, for example, the operational project decision making in battle, occurrence of this case is fatal. Because of the instantaneous change of situation in battlefield, commander has not enough time to operate the program repeatedly for the optimization of combat project. Therefore, in order to make the algorithm has more extensive application area, the next research is mainly on the aspect of algorithm’s stability.

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