A Prospect-Theory-Based Operation Loop Decision-Making Method for Kill Web

Luyao Wang 1, Libin Chen 2, Zhiwei Yang 1,*, Minghao Li 1,*, Kewei Yang 1 and Mengjun Li 1

1 College of Systems Engineering, National University of Defense Technology, Changsha 410073, China
2 College of Intelligence Science and Technology, National University of Defense Technology, Changsha 410073, China
* Correspondence: zhwyang@nudt.edu.cn (Z.Y.); liminghao4869@nudt.edu.cn (M.L.)

Abstract: In the military field, decision making has become the core of the new operational concept, known as the “kill web”. Although the theory of kill web has been widely recognized by many countries, the decision-making methods for the kill web are still in the early stage. Therefore, there is a need for a new decision-making method for the kill web. Firstly, different from the traditional scheme decision, the kill web is a complex system. The method of complex network provides a new perspective on complex systems, so the kill web was modeled based on complex network. Secondly, the kill web relies on artificial intelligence to provide decision-makers with operation loop solutions, and then decision-makers rely on the experience to make a final decision. However, the current decision-making methods only consider one of the intelligent and human decision-making methods, while the kill web needs to consider both. Hence, we combined intelligent decision making with human decision making through multi-objective optimization and the prospect theory. Finally, we designed a nondominated sorting ant colony genetic algorithm-II (NSACGA-II) to solve large-scale problems, since the kill web is a large-scale system. In addition, an illustrative case was used to verify the feasibility and effectiveness of the proposed model. The results showed that, compared with other classical multi-objective optimization algorithms, the NSACGA-II is superior to other superior algorithms in terms of the hypervolume (HV) and spacing (SP), which verifies the effectiveness of the method and greatly improves the quality of commanders’ decision-making.

Keywords: operation loop; kill web; combat decision making; prospect theory; decision preference; multi-objective optimization; multi-criteria decision making; TODIM; TOPSIS; nondominated sorting genetic algorithm-II (NSGA-II); ant colony (AC) algorithm

MSC: 93A30

1. Introduction

The military field is gradually transitioning from information-based warfare to intelligent warfare. Intelligent warfare realizes highly complex, fast-paced, large-scale military confrontation through intelligent decision-making technology. Governments have put forward a series of new operational concepts to cope with the advent of intelligent warfare. Among them, the concept of kill web proposed by the Defense Advanced Research Projects Agency (DARPA) [1,2] has received substantial attention from scholars. In terms of force design, the kill web can rapidly and dynamically reorganize combat units and their roles by decomposing a single multi-tasking unit into smaller units with larger numbers, fewer functions, and more composability [3]. In terms of command and control, the kill web uses a machine control system to analyze the intentions of decision-makers and provide decision-makers with action schemes, which are a series of operation loops, namely the loop starting from the enemy target, passing through our equipment (sensor equipment, command and control equipment, and attack equipment), and then returning to the enemy target [4], and a final decision is made by the commander. In order to find the most effective action scheme to attack the intended target, the decision of operation loops often depends...
on the utility of the operation loops. In traditional research, the utility of operation loops is often calculated by building a mathematical model for the engagement process. However, these studies ignore the role of people, which is the main body of decision making in combat. People’s judgments on future gains and losses, as well as their preferences, have an important impact on the outcome of wars. So, this study focuses on a mathematical model building problem of people’s subjective factors by studying its impact patterns to support intelligent operational decision-making.

Intelligent decision-making has a wide range of applications in civilian and military. In terms of public transport management, a study proposed a multi-criteria decision-making algorithm to choose the best public transportation management in times of a pandemic [5]. The method with a fuzzy Einstein CoCoSo framework is a powerful tool for rational and objective decision-making. Another study proposed an integrated WISP method based on the combination of double normalization processes, the generalized Dombi AOs, and the combined weighting model with q-ROFSs for assessing and prioritizing sustainable public transportation in Metaverse [6]. In terms of weapon system portfolio selection and weapon equipment development planning, Jiang et al. proposed a unified framework called structure-oriented weapon system portfolio selection (SWSPS) to solve the weapon system portfolio selection problem based on the operation loop theory [7]. Wan et al. proposed a mathematical formulation, named the operation loop, to investigate the cooperative interactions between armaments, sequentially facilitating the description of the development plans’ performance [8]. Chi et al. proposed a tool offering the degree evaluation method for the weapon system-of-system combat network (WSOSCN) based on the operation loop [9]. Research on intelligent decision making in the operation loop has just begun. Xia has carried out a series of studies on the operation loop recommendation method for the kill web in mosaic warfare [10]. Chen et al. proposed a DQN-based operation loop recommendation model [11].

Expected utility theory establishes a framework for analyzing rational actor selection under uncertainty [12]. At present, it has been successfully applied to the purchasing optimization of electricity retailers [13], optimal option purchase decision [14] portfolio selection [15], etc. However, these problems assume that people are completely rational and do not consider the factors of decision preference. In fact, a lot of empirical evidence [16–18] has shown that the decision-maker’s preferences play an important role in the decision-making process. The emergence of the prospect theory solves this kind of problem very well. The prospect theory proposed by Kahneman and Tversky [19,20] is one of the most influential psychological behavior theories, and considers decision preference. More and more scholars are paying attention to the characteristics of preference in decision making, and are applying the prospect theory to problems such as transportation network optimization [21], path selection [22], and combat capability planning [23], etc.

However, the above studies have several shortcomings. On the one hand, in the “human–machine” system of the kill web, humans are still the core of decision making and creative intelligence, while machines provide assistance, support, and services for human decision-making processes [24]. Therefore, military decision making should also face up to the human factors. The above literature, however, indicates that intelligent decision making in the military field has not yet considered human factors, especially decision preferences. On the other hand, the prospect theory provides a new perspective for the study of human decision making. It is widely used in the field of civil decision making and can better simulate the decision-making process of decision-makers. With the motivations stated above, this study proposes a method of the operation loop decision-making for the kill web by applying the prospect theory, aiming to integrate intelligent decision making and human decision making for improving the level of decision making in combat. The main contributions of this study can be summarized as follows:

- In terms of intelligent decision-making, this study provided a multi-objective optimization model for determining the operational loop scheme, and designed a non-dominated sorting ant colony genetic algorithm-II (NSACGA-II) to determine the
optimal solutions for the multiple objectives. The compromise solution, based on the technique for order preference by similarity to an ideal solution (TOPSIS), was used to evaluate the Pareto solution set for the multiple objectives.

- In terms of human decision making, in the model of multi-objective optimization model, we considered the two conflicting objectives of operation loop damage capability and closed-loop time, and used the prospect theory to describe the preference degree of decision making for these two objectives.

- In addition, different from the traditional scheme decision, the operation loop schemes are produced by the kill web, while the kill web is a complex system. The method of complex network provides a new perspective on complex systems, so the kill web was modeled based on complex network in this study. The combination of network analysis methods and decision-making methods can enrich and improve the existing decision-making theories.

The remainder of this study is organized as follows. Section 2 constructs a multi-objective optimization model for the operation loop decision-making problem, based on the modeling and evaluation of the operation loop. Due to the huge number of solution spaces for the above multi-objective optimization problem, in order to solve this problem, Section 3 proposes an NSACGA-II algorithm to solve the operation loop decision-making problem, and evaluates the Pareto solution set generated by the algorithm through the TOPSIS. Section 4 uses a case to verify the feasibility and advantages of the proposed operation loop decision-making method. Finally, the work of the study is concluded and future work is discussed on the limitations of the study in Section 5.

2. Modeling the Operation Loop Decision-Making Problem

2.1. Modeling of the Operation Loop

The modern combat cycle theory states that the combat process is a cyclic process composed of observation, orientation, decision, and action (OODA) [25]. According to the combat cycle theory, Professor Tan put forward the concept of the operation loop—that is, the closed loop composed of a sensor, C2 (command and control), attack and other equipment entities, and the enemy target entity [4]. Among them, the sensor entity finds the enemy target and transmits the relevant information to the C2 entity, the C2 entity sends commands to the attack entity after analysis, and the attack entity attacks the enemy target after receiving the attack command [4]. Both warring sides build their own operation loops and regard the enemy’s nodes as targets in their own operation loops. A schematic diagram of the operation loops in engagement is shown in Figure 1, where red and blue are sides in combat. Generally, red represents our side, and blue represents the enemy side. According to the definition of the operation loop, it is necessary to model the nodes and edges between nodes.

![Figure 1. Schematic diagram of the operation loops in the engagement.](image-url)
2.1.1. Node Modeling

The evaluation the operation loop is the foundation, and on this basis, we analyze how to make operation loop decisions. Therefore, in the process of node modeling, the focus is on describing the attributes related to evaluating the operation loop. There are some node attributes that all nodes need to consider, such as node location attributes, which are called common attributes in this study. The following will first describe the common attributes of nodes, and then analyze the unique attributes of sensor nodes, C2 nodes, attack nodes, and target nodes.

- **Common attributes**

  According to the combat mission, the common attributes of the node mainly consider the side, type, location, closed-loop time, and number of channels of the equipment, which are expressed as:

  \[ v = (\text{side}, \text{type}, \text{location}, \text{time}, \text{channel}) \]  

  (1)

  (1) **Side:** \( \text{side} \in \{R, B\} \)

  This study only considers combat between two sides, and does not consider the situation of multiple sides participating in combat, so the side attribute of the equipment node only includes the red party \( R \) and the blue party \( B \).

  (2) **Type:** \( \text{type} \in \{S, C, A, T\} \)

  Equipment types are divided according to the functions of equipment nodes. According to the definition of the operation loop, equipment types include four basic types: sensor, C2, attack, and target equipment. Sensor equipment (\( S \)) mainly has the functions of acquiring, processing, and transmitting battlefield information, such as sensor drones and radars. The main function of C2 equipment (\( C \)) is to receive information from sensor equipment, process the information according to the battlefield situation, and make operational decisions. Since this study focuses on the impact of human factors in decision making, the C2 equipment refers specifically to decision-makers in this study. Attack equipment (\( A \)) mainly undertakes offensive and defensive tasks in the combat, such as fighter jets, missiles, and electromagnetic interference equipment. For one side, all equipment of the other side belongs to the target equipment (\( T \)). The unique attributes of different equipment types are described in detail in the subsequent sections.

  (3) **Location:** \( \text{location} = (x, y, z) \), \( x, y, z \in \mathbb{R} \)

  In the actual combat process, the position information of equipment nodes is represented by longitude, latitude, and height, but in order to facilitate subsequent calculations, this study uses Cartesian three-dimensional coordinates to represent the position attributes of equipment. \( x, y, \) and \( z \) represent the \( x \)-coordinate, \( y \)-coordinate, and \( z \)-coordinate of the equipment, respectively.

  (4) **Closed-loop time:** \( \text{time} \in \mathbb{R} \), in seconds

  The closed-loop time of equipment is the time it takes for equipment nodes to form an operation loop. For the sensor equipment node, it represents the time taken to detect the target and transmit the information to the C2 node; for the C2 equipment node, it represents the time taken to process battlefield information, form a decision, and issue combat orders to the attack equipment node; for the attack equipment node, it represents the time taken to receive the combat order from the C2 equipment node and complete the combat task.

  (5) **Number of channels:** \( \text{channel} = (\text{chan}_1, \text{chan}_2, \text{chan}_3, \text{chan}_4) \), \( \text{chan} \in \mathbb{R} \)

  The number of channels represents the number of equipment nodes that can be connected to other equipment nodes, which can be subdivided into four types: the number of sensor channels, C2 channels, attack channels, and communication channels. The number of sensor channels refers to the number of targets that sensor equipment nodes can detect at the same time; the number of C2 channels is the number of pieces of equipment that can be simultaneously commanded and controlled by the C2 equipment nodes—that is,
the number of pieces of attack equipment that can be connected at the same time; the number of attack channels is the number of targets that attack equipment nodes can attack at the same time; the communication channel is a channel for information sharing between sensor equipment nodes at the same time, a channel for cooperative command between C2 equipment nodes, and a channel for information feedback between sensor equipment nodes and C2 equipment nodes simultaneously.

- Sensor node attributes

  The unique attributes of the sensor node include the sensor distance and the scan path width, which are expressed as:

  \[ v = (d_s, \text{width}) \]  

(1) Sensor distance: \(d_s \in \mathbb{R}\), in kilometers

  The sensor distance is the most important attribute of sensor equipment—it indicates the effective distance that sensor equipment can detect targets. When the distance between the target and the sensor equipment is greater than the sensor distance, the sensor equipment cannot detect the enemy target.

(2) Scan path width: \(\text{width} \in \mathbb{R}\), in meters

  The scan path width is the path distance of each scan by the detector of the sensor equipment.

- C2 node attribute

  The unique attributes of the C2 node include preference, which is expressed as:

  \[ v = (\text{preference}) \]  

(1) Preference: \(\text{preference} = (\alpha, \beta, \xi, \lambda)\), \(\alpha, \beta, \xi, \lambda \in \mathbb{R}\)

  Preference refers to the decision preference attribute of the decision-maker. The decision part of OODA loop is emphasized in the decision-centric warfare, which corresponds to the C2 node in the operation loop. Its main function is to receive information from sensor nodes, analyze the battlefield situation, and make decisions based on the decision-maker’s own decision preferences. The prospect theory introduces decision preferences into the decision-making process, and quantifies such preferences through relevant parameters in the value function \(v(x) = \left\{ \begin{array}{ll} \xi (x-x_0)^\alpha, & x \geq x_0 \\ -\lambda(x_0-x)^\beta, & x < x_0 \end{array} \right.\), see Section 2.2.2 for details). Therefore, in this study, the decision preference attribute of the C2 node is expressed as \(\text{preference} = \{\alpha, \beta, \xi, \lambda\}\), including risk attitude coefficients \(\alpha\) and \(\beta\), as well as gain and loss sensitivity \(\xi\) and \(\lambda\). The prospect theory calculates prospect values by setting fixed decision preference attributes for decision-makers. However, in the course of combat, setting a fixed decision preference attribute cannot accurately reflect the flexibility of decision making. For different decision-makers, due to their different personalities and characteristics—for example, some people tend to take risks, and some people tend to be conservative—the above decision preference attributes will also be slightly different.

- Attack node attributes

  The unique attributes of the attack node include the range, accuracy of fire, and warhead effectiveness, which are expressed as:

  \[ v = (d_a, \text{CEP}, \text{effect}) \]  

(1) Range: \(d_a \in \mathbb{R}\), in kilometers

  The range is the effective attack distance of the attack node. When the distance between the target and the attack equipment is greater than the range, the attack equipment cannot attack the target.
(2) Accuracy of fire: \( CEP \in \mathbb{R} \), in meters

The accuracy of fire of the attack equipment is usually expressed by the circular error probable \( CEP \). Its definition involves drawing a circle with the target as the center. If the equipment has at least a 50% chance of hitting the circle, the radius of the circle is the circular error probable.

(3) Warhead effectiveness: \( effect \in [0, 1] \)

A warhead is the final damage unit of various ammunition and missile damage targets, mainly composed of shells, combat charges, detonating devices, and safety devices. The capability of the warhead to attack the target can be represented by the warhead effectiveness. In order to facilitate the calculation, this study normalizes the warhead effectiveness of the attack node, and its value ranges from 0 to 1.

• Target node attributes

The unique attributes of the target node include the cross-sectional area, hiding the coefficient, vulnerable area, display falsity survival probability, early warning time, and maneuvering speed, which are expressed as:

\[
v = (\text{area}, \text{hiding}, \text{v}_\text{area}, \text{falsity}, t, s)
\]

(1) Cross-sectional area: \( \text{area} \in \mathbb{R} \), in square meters

The total area of the target that can be sensed or attacked under normal conditions is an important factor affecting the sensor capability of the sensor node and the damage capability of the attack node.

(2) Hiding coefficient: \( \text{hiding} \in [1, \infty] \)

The hiding coefficient is an index of the hiding capability of the target node. In the actual combat process, the enemy target will take various measures to camouflage itself, so that the area to be detected is reduced or the sensor effect is weakened, so as to achieve the effect of hiding. The value of the hiding coefficient is greater than 1. When the hiding coefficient is equal to 1, it is considered that the target node has no hiding capability.

(3) Vulnerable area: \( \text{v}_\text{area} \), in square meters

The vulnerable area is the area where the target node is damaged by the attack of the attack node. Different attack nodes have different warhead effectiveness levels, and target nodes have different vulnerable areas when facing warheads with different powers. The larger the vulnerable area, the easier the target node is to be destroyed.

(4) Display falsity survival probability: \( \text{falsity} \in \{0, 1\} \)

Display falsity is a general term for the camouflage methods that cause enemy mistakes or negligence by simulating various exposed targets of the target and displaying false phenomena, such as setting false targets, spreading false information, and implementing feints. The survival probability of display falsity is the probability that the target node will not be discovered by sensor equipment by taking display falsity.

(5) Early warning time: \( t \in \mathbb{R} \), in seconds

The early warning time is the time required for the target node to escape before being discovered by the sensor equipment node or attacked by the attack equipment node, according to the previous summarized rules or observed precursors, and to avoid being discovered by the sensor equipment or attacked by the attack equipment. For static targets, the early warning time is 0.

(6) Maneuvering speed: \( s \in \mathbb{R} \), in kilometers/hour

The maneuvering speed is the speed at which the target node escapes during the early warning process. For static targets, the maneuvering speed is 0.
2.1.2. Edge Modeling

In the kill web, the edges between nodes are the relationships between equipment. The different types of nodes lead to the diversity of edge types between nodes. There are not only the edges between the same nodes, but also the edges between different nodes. However, there is not always an edge between any two nodes, and the edge based on the operation loop theory is directed. For example, there is an edge from the target node to the sensor node, while there is no edge from the sensor node to the target node. At the same time, each edge is supported by the corresponding capability. Therefore, the edge model can be expressed as:

\[ e_{ij} = (v_i, v_j, edgetype_{ij}, q_{ij}) \] (6)

where \( v_i \) is the starting point of an edge; \( v_j \) is the ending point of an edge; \( edgetype_{ij} \) is the edge type from node \( v_i \) to node \( v_j \) and \( q_{ij} \) is the edge capability corresponding to an edge from node \( v_i \) to node \( v_j \). The edge type is determined by the starting and ending node types. According to Section 2.1.1, there are four types of equipment (S, C, A, T) in the kill web, so there are sixteen types of potential edge in total, but nine types of logically nonexistent edge are excluded [26]. The other seven types of edge are shown in Table 1. By summarizing the edge types in Table 1, it can be found that there are four types of edge types: the sensor edge, the communication edge, the C2 edge, and the attack edge. Therefore, the corresponding edge capabilities include the sensor capability, the communication capability, the sensor capability, and the attack capability. A specific analysis of the four types of edge and four types of edge capabilities is provided below.

**Table 1. Types of edge between nodes.**

<table>
<thead>
<tr>
<th>Edge Type</th>
<th>S</th>
<th>C</th>
<th>A</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>Communication edge</td>
<td>Communication edge</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td>C</td>
<td>Communication edge</td>
<td>Communication edge</td>
<td>C2 edge</td>
<td>/</td>
</tr>
<tr>
<td>A</td>
<td>/</td>
<td>/</td>
<td>/</td>
<td>Attack edge</td>
</tr>
<tr>
<td>T</td>
<td>Sensor edge</td>
<td>/</td>
<td>/</td>
<td>/</td>
</tr>
</tbody>
</table>

"/" indicates that there is no directed edge between the equipment type in the row and the equipment type in the column.

- **Sensor edge**

  The sensor edge describes the sensor relation from the target node to the sensor node \((T \rightarrow S)\), which is the process of the sensor node acquiring, processing, and transmitting the information regarding the target.

  The sensor capability of the sensor edge refers to the capability of the sensor node to detect the target node, which is affected by the attributes of the sensor node and the target node. The sensor capability depends on the cross-sectional area and the hiding coefficient of the target node, the sensor distance and scan path width of the sensor node, and the distance between the target node and the sensor node [27,28]. The formula for calculating sensor capability is as follows:

\[
q_1(v_i, v_j) = \begin{cases} 
0, & d(v_i, v_j) + s_{vj} \cdot t_{vj} > d_s \\
(1 - falsity_{vj}) \cdot (1 - \exp \left(- \frac{K_1(v_i, v_j)}{d(v_i, v_j)} \arctg \left( \sqrt{\frac{d_s^2 - d(v_i, v_j)^2}{d(v_i, v_j)}} \right) \right)), & d(v_i, v_j) + s_{vj} \cdot t_{vj} \leq d_s 
\end{cases} 
\] (7)

\[
K_1(v_i, v_j) = \frac{2K_{vj} \cdot \text{area}_{vj}}{hiding_{vj} \cdot \text{width}_{vj}} 
\] (8)

where \( v_i \) and \( v_j \) represent the sensor node and the target node, respectively. \( q_1(v_i, v_j) \) represents the capability of the sensor node to detect the target node. \( d(v_i, v_j) \) is the initial distance between the sensor node and the target node, \( s_{vj} \) is the maneuvering speed of the target node, and \( t_{vj} \) is the early warning time of the target node, \( d(v_i, v_j) + s_{vj} \cdot t_{vj} \) represents
the distance that the target node may escape through the early warning maneuver. \(d_{sv_j}\) is the sensor distance of the sensor node. The parameter \(K_1(v_{ij}, v_{ij})\) is related to parameter \(K_v\), (related to the performance and the sensor principle of different sensor equipment), the cross-sectional area of the target node, the hiding coefficient of the target node, and the scan path width of the sensor node.

When \(d(v_{ij}, v_{ij}) + s_{v_j} - t_{v_j} > d_s\), the distance between the sensor node and the target node is greater than the sensor distance of the sensor node, and the sensor capability is 0. When \(d(v_{ij}, v_{ij}) + s_{v_j} - t_{v_j} \leq d_s\), the sensor capability is negatively correlated with the distance between the sensor node and the target node, the display falsity survival probability of the target node, the scan path width of the sensor node, and the hiding coefficient of the target node, and was positively correlated with the cross-sectional area of the target node.

In addition, the higher the display falsity survival probability of the target node, the lower the sensor capability. \(falsity_{v_j} = 1\) means that the display falsity capability of the target node is very strong, and the sensor capability is 0.

### Communication edge

The communication edge describes the information sharing relationship between sensor nodes (\(S \rightarrow S\)), the cooperative command relationship between C2 nodes (\(C \rightarrow C\)), and the information transfer relationship between sensor nodes and C2 nodes (\(S \rightarrow C, C \rightarrow S\)). It comprises the process of information communication between the sensor node and the C2 node.

The communication capability of the communication edge is the ability to perform information transmission between the sensor node and the C2 node. It mainly depends on the distance between the equipment nodes [10]. The calculation formula is as follows:

\[
q_2(v_i, v_j) = \begin{cases} 
0, & d(v_i, v_j) > d_m \\
\frac{d_m^2}{d(v_i, v_j)^2 + d_m^2}, & d(v_i, v_j) \leq d_m 
\end{cases}
\]  

(9)

where \(v_i\) and \(v_j\) represent the information sending equipment node and the information receiving equipment node, respectively. \(q_2(v_i, v_j)\) represents the communication capability between \(v_i\) and \(v_j\). \(d_m\) is the communication distance between \(v_i\) and \(v_j\). \(d(v_i, v_j)\) is the distance between \(v_i\) and \(v_j\). When the distance between two equipment nodes exceeds the communication distance, the communication capability is 0. When the distance between two equipment nodes is within the communication distance, the communication capability is inversely proportional to the distance between the equipment nodes.

### C2 edge

The C2 edge describes the command and control relationship between the C2 node and the attack node (\(C \rightarrow A\)), which is the process of the C2 node processing battlefield situation information, making operational decisions, and issuing operational mission orders to attack nodes.

The C2 capability of the C2 edge is the capability of the C2 node to issue combat orders to the attack node, and it is essentially the communication capability between equipment [10]. Therefore, the C2 capability and the communication capability have the same meaning. The calculation formula is as follows:

\[
q_3(v_i, v_j) = q_2(v_i, v_j)
\]  

(10)

where \(v_i\) and \(v_j\) represent the C2 node and the attack node, respectively. \(q_2(v_i, v_j)\) represents the communication capability between \(v_i\) and \(v_j\). It should be noted that when a piece of equipment does not have a C2 channel, the C2 capability is 0.

### Attack edge
The attack edge describes the attack relation from the attack node to the target node \((A \rightarrow T)\), which is the process of the attack node attacking the corresponding target according to the combat mission commands received from the C2 node.

The attack capability of the attack edge depends on the hit probability \(p(v_i, v_j)\) of the warhead of the attack node acting on the target and the damage degree \(q(v_i, v_j)\) exerted on the target under the condition that the warhead hits the target \([29]\). The formula for calculating attack capability is as follows:

\[
q_4(v_i, v_j) = p(v_i, v_j) \cdot q(v_i, v_j)
\]  

The hit probability is a measure of the possibility that the warhead of the attack node hits the target. It depends on the range and accuracy of fire of the attack node and the cross-sectional area of the target node. The calculation formula is as follows:

\[
p(v_i, v_j) = \begin{cases} 
0, & d(v_i, v_j) + s_{v_j} \cdot t_{v_j} > d_a \\
\min\left(\frac{\text{area}_{v_j}}{\pi(\text{CEP}_{v_j})^2}, 1\right), & d(v_i, v_j) + s_{v_j} \cdot t_{v_j} \leq d_a
\end{cases}
\]  

where \(v_i\) and \(v_j\) represent the attack node and the target node, respectively. \(p(v_i, v_j)\) represents the probability that the attack node successfully hits the target node. \(d(v_i, v_j)\) is the initial distance from the attack node to the target node, \(d_a\) is the range of the attack node, and \(d(v_i, v_j) + s_{v_j} \cdot t_{v_j}\) represents the possibility that the target node may escape the range of the attack node by means of early warning maneuvers.

When \(d(v_i, v_j) + v_{v_j} \cdot t_{v_j} > d_a\), the distance between the attack node and the target node is greater than the attack node’s range, and the hit probability is 0. When \(d(v_i, v_j) + v_{v_j} \cdot t_{v_j} \leq d_a\), the target node falls within the range of the attack node, and the hit probability is related to the cross-sectional area of the target node and the accuracy of fire of the attack node.

Under the condition of hitting the target, the damage degree of the warhead exerted on the target depends on the warhead effectiveness of the attack node and the vulnerability of the target node, where the vulnerability is measured by the vulnerable area, which is expressed by the following formula:

\[
q(v_i, v_j) = v_{\text{area}_{v_j}}[\text{effect}_{v_i}]
\]  

where \(\text{effect}_{v_i}\) represents the warhead effectiveness of the attack node, and \(v_{\text{area}_{v_j}}[\text{effect}_{v_i}]\) represents the vulnerable area of the target node with the warhead effectiveness of \(\text{effect}_{v_i}\) of the target node. It should be noted that, for the convenience of the research in this study, the conditional damage degree in this study only considers the attack node directly hitting the target to cause damage to it, and only considers the case where the single-shot warhead hits the target.

2.2. Evaluation of the Operation Loop

2.2.1. Evaluation of the Target Value

The target value includes both attribute values and system values \([30]\). Since the object of this study is the kill web, and the combination of kill web equipment varies, it is difficult to obtain the system value. This study only evaluates the target value from the perspective of attribute values. Target attribute value evaluation is a multi-criteria decision-making problem. Therefore, it is necessary to construct the index system first. Combined with the description of target node attributes in Section 2.1.1, the evaluation index system of the target value can be constructed, as shown in Figure 2, and the description of evaluation index is displayed in Table A1 in Appendix A.
The standardization methods of benefit-type and cost-type indexes are as follows: value max

indexes with different dimensions. First, the minimum value min

is satisfactory schemes” more effectively when faced with risky decisions. Therefore, this study

agglomerating the individual dominance degrees. It can help decision-makers to find “sat-

of pairwise comparisons of alternative plans according to the different preferences of

multi-criteria decision-making in English) that considers the psychological behavior of
decision making in recent years. Based on the prospect theory, Brazilian scholars Gomes and Lima proposed a multi-criteria decision-making method TODIM (acronym of the Por-
tuguese expression Tomada de Decisão Interativa e Multicritério, which means interactive multi-criteria decision-making in English) that considers the psychological behavior of decision-makers [31]. It is based on the prospect theory and constructs the dominance of pairwise comparisons of alternative plans according to the different preferences of decision-makers on gains and losses, and forms the overall dominance of each plan by agglomerating the individual dominance degrees. It can help decision-makers to find “satisfactory schemes” more effectively when faced with risky decisions. Therefore, this study adopts the TODIM method to evaluate the target value. The specific steps are as follows:

- **Step 1: Construction of the original decision matrix**
  The set of target nodes is \( T = \{ t_1, t_2, \cdots, t_n \} \), and the set of index is \( U = \{ u_1, u_2, \cdots, u_m \} \), while the original decision matrix is \( X = [x_{ij}]_{n \times m} \), where \( x_{ij} \) represents the index value of the target \( t_i \) corresponding to index \( u_j \).

- **Step 2: Standardization of index value**
  Range transformation is a method of index value standardization, in order to compare indexes with different dimensions. First, the minimum value \( \min x_{ij} \) and maximum value \( \max x_{ij} \) of the index value \( x_{ij} \) are obtained. Second, the range \( \max x_{ij} - \min x_{ij} \) is calculated. Third, the indexes are divided into two types: the benefit type and cost type. The standardization methods of benefit-type and cost-type indexes are as follows:

  For the benefit index:
  \[
  y_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{14}
  \]

  For the cost index:
  \[
  y_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{15}
  \]
where \( y_{ij} \) is the standardized index value \( x_{ij} \). The index value is mapped to \([0,1]\) and the original decision matrix \( X = [x_{ij}]_{n \times m} \) is converted into a standardized decision matrix \( Y = [y_{ij}]_{n \times m} \) by range transformation method.

- Step 3: Determination of the index weight

In this study, the entropy weight method is used to determine the index weight. The specific calculation steps are as follows:

1. The entropy \( e_j \) of the index \( u_j \) is calculated:

\[
e_j = \frac{1}{\ln n} \sum_{i=1}^{n} f_{ij} \ln f_{ij}
\]  

(16)

where \( f_{ij} = y_{ij} / \sum_{i=1}^{n} y_{ij} \). If \( f_{ij} = 0 \), then define \( \lim_{f_{ij} \rightarrow 0} f_{ij} \ln f_{ij} = 0 \).

2. The entropy weight \( \omega_j \) of the index \( u_j \) is determined:

\[
\omega_j = \frac{1 - e_j}{\sum_{j=1}^{m} (1 - e_j)}
\]  

(17)

The entropy weight of each index is calculated, and the weight vector of the index is obtained as \( \omega = (\omega_1, \omega_2, \ldots, \omega_m) \).

- Step 4: Calculation of the dominance of each index

1. The relative weight \( \omega_{jr} \) of the index \( u_j \) is calculated:

\[
\omega_{jr} = \frac{\omega_j}{\omega_r}
\]  

(18)

where \( \omega_{jr} \) is the relative weight of the index \( u_j \), \( \omega_j \) is the weight of the index \( u_j \), and \( \omega_r = \max\{\omega_1, \omega_2, \ldots, \omega_m\} \).

2. The dominance \( \varphi_j(t_i, t_k) \) of the target \( t_i \) relative to the target \( t_k \) under the index \( u_j, \forall t_k \in T = \{t_1, t_2, \ldots, t_n\} \), \( t_i \neq t_k \), \( i, k = 1, 2, \ldots, n \) is calculated using the following expression:

\[
\varphi_j(t_i, t_k) = \begin{cases} 
\frac{\omega_{jr}(y_{ij} - y_{kj})}{\sum_{j=1}^{m} \omega_{jr}} & y_{ij} - y_{kj} > 0 \\
0 & y_{ij} - y_{kj} = 0 \\
\frac{-1}{\beta} \frac{\sum_{j=1}^{m} \omega_{jr}(y_{ij} - y_{kj})}{\omega_{jr}} & y_{ij} - y_{kj} < 0
\end{cases}
\]  

(19)

where dominance \( \varphi_j(t_i, t_k) \) is consistent with the connotation of the value function of the prospect theory, and the square-root structure used in \( \varphi_j(t_i, t_k) \) can be regarded as a special case of the value function \( v(x) = \begin{cases} 
\xi(x - x_0)^\alpha & x \geq x_0 \\
-\lambda(x_0 - x)^\beta & x < x_0
\end{cases} \) (see Section 2.2.2 for details), namely \( \alpha = \beta = 0.5 \), \( \lambda \) is the loss sensitivity coefficient, and \( 0 < \theta < (\sum_{j=1}^{m} \omega_{jr}) / \omega_r \). The change in \( \theta \) causes the shape of the value function of the prospect theory in the negative quadrant to be different. The smaller the value of \( \theta \), the higher the degree of loss aversion of decision-makers. In Equation (19), there are usually three cases:

- If \( y_{ij} - y_{kj} > 0 \), then \( \varphi_j(t_i, t_k) \) represents “gain”;
- If \( y_{ij} - y_{kj} = 0 \), then \( \varphi_j(t_i, t_k) \) represents “break even”;
- If \( y_{ij} - y_{kj} < 0 \), then \( \varphi_j(t_i, t_k) \) represents “lose”.

In addition, \( \frac{\omega_{jr}(y_{ij} - y_{kj})}{\sum_{j=1}^{m} \omega_{jr}} \) represents that when the decision-maker is faced with the same gain and loss, they are more sensitive to loss, that is, the decision-maker is loss-averse.
• Step 5: Calculation of the dominance of all indexes Considering all of the indexes, the
dominance of the target $t_i$ is calculated over the target $t_k$:
\[
\delta_i(t_i, t_k) = \sum_{j=1}^{m} q_j(t_i, t_k)
\]
(20)

• Step 6: Calculation of the overall dominance In the case of comprehensively considering all targets, the overall dominance of the target $t_i$ over all other targets is calculated, and the target values are ranked according to the overall dominance. The greater the dominance, the greater the target value. The equation is as follows:
\[
v(t_i) = \frac{\sum_{k=1}^{n} \delta_i(t_i, t_k) - \min_{1 \leq k \leq n} \sum_{k=1}^{n} \delta_i(t_i, t_k)}{\max_{1 \leq k \leq n} \sum_{k=1}^{n} \delta_i(t_i, t_k) - \min_{1 \leq k \leq n} \sum_{k=1}^{n} \delta_i(t_i, t_k)}
\]
(21)

2.2.2. Evaluation of the Damage Capability Value

For an operation loop $ol = (v_1, v_2, v_3, v_4), v_1, v_2, v_3,$ and $v_4$ represent the target node, sensor node, C2 node, and attack node, respectively. Then, $q_1(v_1, v_2), q_2(v_2, v_3), q_3(v_3, v_4),$ and $q_4(v_4, v_1)$ represent the sensor capability, communication capability, C2 capability, and attack capability, respectively. For the entire operation loop, the damage capability is an objective evaluation of the combat capability of the operation loop itself. It is closely related to the edge capability. A reduction in the capability of an edge will lead to a decrease in the damage capability of the entire operation loop. Therefore, this study calculates the operation loop damage capability based on the multiplication rule [32], namely:
\[
Q(ol) = q_1(v_1, v_2) \cdot q_2(v_2, v_3) \cdot q_3(v_3, v_4) \cdot q_4(v_4, v_1)
\]
(22)

Although we quantitatively described the damage capability of the operation loop, the damage capability is an objective result, and its value varies from person to person. For example, an operation loop with a damage capability of 0.5 can satisfy the operational requirement for the risky decision-maker. However, for the conservative decision-maker, an operation loop with a damage capability of 0.8 may be required to meet the operational requirements. The value of the consequence is to be determined—that is, quantifying the value of the consequence is the final and most important part of the decision.

The main difference between the value of the consequence and the consequence is that people often need to rely on a reference to judge things—that is, reference dependence. When the damage capability of the operation loop to the target reaches the decision-maker’s psychological expectations (reference point), the decision-maker is risk-averse. When the damage capability of the operation loop to the target is lower than the decision-maker’s psychological expectations (reference point), the decision-maker is risk-averse. In addition, the lower the damage capacity is compared to the reference point, the more serious the consequence is.

The value of the consequence is used to determine the decision-maker’s preferences for the consequence. The prospect theory uses value function to reflect decision-makers’ preferences for the objective consequence. Kahneman and Tversky [20] gave the value function, and the specific form of the value function is as follows:
\[
v(x) = \begin{cases} 
(x - x_0)^\alpha, & x \geq x_0 \\
-\lambda(x_0 - x)^\beta, & x < x_0 
\end{cases}
\]
(23)

where $x$ represents the objective consequence; $x_0$ represents the reference point; and $x - x_0$ is the deviation of the consequence $x$ relative to the reference point $x_0$. $\alpha$ and $\beta$ are the risk attitude coefficients, $0 < \alpha, \beta < 1$. The larger $\alpha$ and $\beta$ are, the more likely the decision-maker is to take risks. $\lambda$ is the loss sensitivity. If $\lambda > 1$, it means that the decision-maker is more sensitive to the loss.
Ma et al. [33] proposed an improved prospect theory in combination with the utility function proposed by Bernoulli [34], in which the improved value function is expressed as follows:

$$v(x) = \begin{cases} \xi(x - x_0)^\alpha, & x \geq x_0 \\ -\lambda(x_0 - x)^\beta, & x < x_0 \end{cases}$$

(24)

where $\xi$ and $\lambda$ represent the gain and loss sensitivity, respectively. If the decision-maker is more sensitive to gains than losses, then $\xi > 1$, $\lambda = 1$; if the decision-maker is more sensitive to losses than gains, then $\xi = 1$, $\lambda > 1$. $\alpha$ and $\beta$ are the risk attitude coefficients.

If the decision-maker is an adventurous type, then $0 \leq \alpha, \beta \leq 1$; if the decision-maker is an intermediate type, then $\alpha = \beta = 1$; if the decision-maker is a conservative type, then $\alpha, \beta > 1$. The improved value function expands the value range of the types of decision-maker. In addition, the individual’s sensitivity to gain is incorporated into the value function. Therefore, this study calculates the value of the operation loop damage capability according to the improved value function. The calculation formula of the damage capability value is as follows:

$$v(Q) = \begin{cases} \xi(Q - Q_0)^\alpha, & Q_0 < Q \\ -\lambda(Q_0 - Q)^\beta, & Q_0 \geq Q \end{cases}$$

(25)

where $Q_0$ is the reference point of the damage capability—that is, the psychological expectation of the decision-maker for the damage capability. $Q - Q_0$ represents the gain or loss of the damage capability. For the operation loop, the stronger the damage capability is, the better. $Q - Q_0 > 0$ represents the gain of the damage capability—that is, the damage capability is higher than the decision-maker’s psychological expectations of the damage capability; $Q - Q_0 \leq 0$ represents the loss of the damage capability—that is, the damage capability is lower than the decision-maker’s psychological expectations of the damage capability. The damage capability value is a characterization of the decision-maker’s preference for the damage capability of the operation loop.

2.2.3. Evaluation of the Closed-Loop Time Value

In the process of combat, the formation of the operation loop takes a certain amount of time, and the duration from the start of the sensor mission (the start of the closed loop) to the end of the attack mission (the end of the closed loop) is defined as the closed-loop time of the operation loop [10]. For an operation loop $ol = (v_1, v_2, v_3, v_4, v_1, v_2, v_3, v_4)$, $v_1$, $v_2$, $v_3$, and $v_4$ represent the target node, sensor node, C2 node, and attack node, respectively. Then, $time_{v_1}$, $time_{v_2}$, and $time_{v_4}$ represent the time consumed by the sensor node, the C2 node, and the attack node to form a closed loop, respectively. For different types of node, the closed-loop time has different meanings. For the sensor node, it represents the time taken to detect the target and transmit the information to the C2 node; for the C2 node, it represents the time taken to process battlefield information, form a decision, and issue combat orders to the attack node; and for the attack node, it represents the time taken to receive combat orders from the C2 node and complete the attack task. The closed-loop time of the operation loop is expressed as follows:

$$TIME(ol) = time_{v_1} + time_{v_2} + time_{v_4}$$

(26)

Similar to damage capability, closed-loop time is also an objective consequence of operation loop execution. This study calculates the value of the closed-loop time of the operation loop based on the improved value function as the decision-maker’s evaluation of the closed-loop time of the operation loop. The calculation formula of the closed-loop time value is as follows:

$$v(TIME) = \begin{cases} \xi(TIME_0 - TIME)^\alpha, & TIME_0 > TIME \\ -\lambda(TIME - TIME_0)^\beta, & TIME_0 \leq TIME \end{cases}$$

(27)
where \( TIME_0 \) represents the reference point for the closed-loop time—that is, the decision-maker’s psychological expectation for the closed-loop time. \( TIME - TIME_0 \) represents the gain or loss of the closed-loop time. For the operation loop, the smaller the closed-loop time, the better. \( TIME_0 - TIME > 0 \) represents the gain of the closed-loop time—that is, the closed-loop time of the operation loop is shorter than the psychological expectations of the closed-loop time. \( TIME_0 - TIME \leq 0 \) represents the loss of closed-loop time—that is, the closed-loop time is longer than the psychological expectations of the closed-loop time. The closed-loop time value is a characterization of the decision-maker’s preference for the closed-loop time of the operation loop.

2.3. Definition of the Operation Loop Decision-Making Problem

Assuming that the kill web confronted by the red and blue sides contains \( n \) targets \( T = \{t_1, t_2, \ldots, t_n\} \), the red side hits the targets in turn, according to the target value. The red side selects a series of equipment according to the decision-maker’s preferences to form an operation loop, then a set of operation loops \( OL = \{ol_1, ol_2, \ldots, ol_n\} \) is formed for each target. The set of damage capability is \( Q = \{Q_1, Q_2, \ldots, Q_n\} \). The set of closed-loop time is \( TIME = \{TIME_1, TIME_2, \ldots, TIME_n\} \). \( Q_j \) and \( TIME_j \) are the damage capability and closed-loop time of the operation loop \( ol_j \) against the target \( t_j \), respectively.

The degree of preference for operation loops is characterized by the value function of the prospect theory. According to the value function, the damage capability value \( v(Q_j) \) and the closed-loop time value \( v(TIME_j) \) are also the decision-maker’s preferences for the operation loop \( ol_j \). Then, the objective of operational loop decision-making process is to maximize the value of damage capability and minimize the value of closed-loop time. Since it is impossible to achieve the two objectives of maximum damage capability value and minimum closed-loop time value, and the dimensions of damage capability and closed-loop time are inconsistent, they can only be regarded as two optimization objectives. This is a typical multi-objective optimization problem, so it is necessary to study related multi-objective optimization models and algorithms to solve the operation loop decision-making problem.

2.4. Multi-Objective Optimization Model for Operation Loop Decision-Making Problem

According to the description of the operation loop decision-making problem, this study constructs the following multi-objective optimization model for the operation loop decision-making problem:

\[
\begin{align*}
\max f_1 &= \sum_{l=1}^{n} v_{lj} \cdot v \left( \sum_{(i,j) \in A} z_{ij}, q_{ij} \right) \quad (28) \\
\min f_2 &= \sum_{l=1}^{n} v_{lj} \cdot v \left( \sum_{ij \in N, j \neq n} z_{ij}, \text{time}_l \right) \quad (29) \\
\text{s.t.} & \quad \sum_{j \in N^{R}} z_{nj}^{l} = 1 \quad (30) \\
& \quad \sum_{i \in N^{R}} z_{in}^{l} = 1 \quad (31) \\
& \quad \sum_{ij \in N} z_{ij}^{l} - \sum_{i,j \in N} z_{ij}^{l} = 0 \quad (32) \\
& \quad z_{ij}^{l} \in \{0, 1\}, \forall l = 1, 2, \ldots, n, i, j \in N \quad (33)
\end{align*}
\]

From the constraint condition (33), it can be seen that \( N \) is the set of equipment nodes in the kill web (\( N^{R} \) represents the red side equipment node in the kill web); the kill web contains \( n \) target nodes (represented by \( l \)); the decision variable is \( z_{ij}^{l} \); and the value range is 0 and 1, where taking 1 indicates that the operation loop for target \( l \) includes edges from
node $i$ to node $j$, and taking 0 means that the operation loop for target $l$ does not include edges from node $i$ to node $j$.

Equation (28) is the objective function 1, which indicates that the weighted total damage capability value of the operation loop for all targets is the largest. Among the components of this equation, the weight is the value $v_l$ of the target, and $q_{ij}$ indicates the quality of the edge between node $i$ and node $j$ (including the sensor capability, communication capability, C2 capability, and attack capability). Equation (29) is the objective function 2, which indicates that the weighted total closed-loop time value of the operation loop for all targets is the smallest. Among the components of this equation, the weight is the value $v_l$ of the target, and $time_j$ represents the time it takes for node $j$ to form an operation loop. The larger the objective function 1, the better, in order to improve the capability to complete the combat mission. The smaller the objective function 2, the better, in order to reduce the risk of target escape or operation loop failure. Equations (30)–(32) constrain each closed loop to start from the target $l$ and finally return to the target $l$ to form an operation loop.

3. Solving the Operational Loop Decision-Making Problem

3.1. NSACGA-II Algorithm

Combined with the characteristics of the operation loop decision-making problem, this study proposes an NSACGA-II algorithm, which combines NSGA-II [35] and the ant colony (AC) algorithm [36], to adapt it to the special collaborative constraints of the operation loop decision-making problem. This study makes the following two improvements to the NSGA-II algorithm:

1) Constructing the initial solution based on the ant colony algorithm. There are many constraints in the operation loop decision-making problem, especially the edge connection rules of equipment nodes in the operation loop, so the randomly generated initial solution is not conducive to the efficient search of the algorithm in the feasible region. This study proposes using the ant colony algorithm to construct the initial population, letting the algorithm search directly in the feasible region, reducing the cost of the search time, and greatly improving the efficiency of the algorithm.

2) Improving the crossover and mutation operations. The traditional crossover operation randomly selects two individuals from the population, and through the exchange and combination of two chromosomes, the excellent genes are passed on to the offspring; the main purpose of the traditional mutation operation is to maintain the diversity of the population. The mutation operation randomly selects an individual from the population and selects a point of the chromosome to mutate to produce a superior individual. However, in the operation loop decision-making problem, if the traditional crossover and mutation operations are directly adopted, the loop structure of the operational loop itself may be destroyed. Therefore, this study improves the traditional crossover and mutation operations to adapt to the operational loop decision-making problem. The algorithm framework of NSACGA-II is shown in Figure 3, and the pseudocode is shown in Algorithm A1 in Appendix B. Subsequent sections will introduce the improved algorithm in detail.

- Encoding rule

Since the NSACGA-II algorithm cannot directly deal with the parameters of the problem space, the feasible solution of the problem to be solved must be represented as a chromosome in the genetic space by encoding. The chromosome corresponding to each operation loop consists of five loci, which represents the operation loop consisting of “target → sensor → C2 → attack → target”. Assuming that the kill web contains $n$ targets, and each target selects an operation loop, the operation loops for all targets are connected together to form a chromosome of an operation loop scheme, which contains a total of $5n$ loci. The chromosome-encoding rule in the operation loop decision-making problem is shown in Figure 4.
with the ant colony algorithm, which greatly improves the efficiency of the algorithm. The main idea of the ant colony algorithm to construct the initial population is to use pheromones to find the path that satisfies the unique equipment coordination constraint rule (target → sensor → C2 → attack → target) of the operation loop. Therefore, the pseudocode for generating the initial population based on the ant colony algorithm is shown in Algorithm A2 in Appendix B.

- **Crossover and Mutation Operations**

  In this study, a genetic operator is designed which can ensure that the operation loop can still maintain the structure stability after crossover and mutation operations. According to the encoding rule of chromosomes, a chromosome of the operation loop scheme contains
In the crossover operation, the chromosomes of the two operation loop schemes are randomly selected from the population, and then $5np_{\text{crossover}}$ gene loci ($p_{\text{crossover}}$ for the crossover probability) are randomly selected, so that the two chromosomes are crossed in these selected gene loci. The operation mode of the gene loci can leave the equipment type on the gene loci unchanged, so as to ensure that the gene ordering on the chromosome still follows the edge connection rule of the operation loop. In the mutation operation, a chromosome of the operation loop scheme is randomly selected, and then $5np_{\text{mutation}}$ gene loci ($p_{\text{mutation}}$ for the crossover probability) are randomly selected, so that the chromosome is mutated on the selected gene loci, but it requires that the mutated gene loci correspond to the same type of equipment (randomly selecting equipment of the same type from our equipment collection for replacement), and the gene loci corresponding to the target will not be mutated. The above improvements to the crossover and mutation operations can avoid changes to the edge connection rule of the operation loop.

Figure 5. Crossover and mutation operations in the operation loop decision-making problem.
3.2. Evaluation Index

Each multi-objective optimization algorithm will eventually generate the Pareto solution set. It is impossible to evaluate the algorithm by directly comparing each Pareto solution set. In order to facilitate the quantitative comparison of algorithms, this study uses the following two popular evaluation indexes for multi-objective optimization algorithms.

- Hypervolume (HV)
  
  Hypervolume is the volume of the region in the target space bounded by the Pareto solution set obtained by the algorithm and the reference point. The larger the hypervolume value, the better the overall performance of the algorithm.

  \[ HV = \sum_{h=1}^{\mid P \mid} V_h \]  

  where \( \mid P \mid \) is the size of the solution set and \( V_h \) represents the hypervolume formed by the \( h \)th solution and the reference point.

- Spacing (SP)
  
  Spacing calculates the standard deviation of the minimum distance from each solution to other solutions, which is used to measure the uniformity of the Pareto solution set. The smaller the index value is, the more uniform the solution set is.

  \[ SP = \sqrt{\frac{1}{\mid P \mid-1} \sum_{h=1}^{\mid P \mid} (d - d_h)^2} \]  

  where \( \mid P \mid \) is the size of the solution set, \( d_h \) is the distance between consecutive solutions, and \( d \) is the average value of the distance.

3.3. TOPSIS

The NSACGA-II algorithm is used to optimize and solve the operation loop decision-making problem, and finally a Pareto solution set, namely the Pareto frontier, is obtained, which is a set of nondominated solutions. However, choosing a solution from the nondominated solution set is also a difficult problem. In this study, the technique for order preference by similarity to an ideal solution (TOPSIS) method is used to sort the Pareto optimal solutions, and an operation loop scheme that meets the actual combat needs is obtained. TOPSIS is one of the most popular multi-criteria decision-making (MCDM) methods. The most remarkable characteristic of TOPSIS is the identification of the best solution for the closest to the positive ideal and the furthest to the negative ideal. The distances being two-fold provides consideration of not only conditions to be maximized but also those to be minimized, and the best choice is selected accordingly [37]. According to Shih et al., TOPSIS has several advantages compared with other MCDM methods, including: (1) it conforms to the logic of people’s choices; (2) as a scalar, it can reflect both the best and worst choices; (3) the calculation process is simple and convenient; and (4) it is easy to visualize [38]. The steps of TOPSIS are as follows:

Step 1: The vector norm method is used to obtain the normative decision matrix;
Step 2: The weighted norm matrix is obtained;
Step 3: The ideal solution and negative ideal solution are determined;
Step 4: The distance from each scheme to the ideal solution and the negative ideal solution is calculated;
Step 5: The approximation degree of each scheme to the ideal solution is calculated;
Step 6: The solutions are arranged in descending order according to the approximation degree.
4. Case Study

4.1. Case Description

The red side contains seven types of equipment, and the total number of pieces of equipment is 60. The blue side contains seven types of equipment, and the total number of pieces of equipment is 37. The number of pieces of equipment on both the red and blue side, the closed-loop time, the number of channels, and other basic attributes are shown in Tables 2 and 3.

Table 2. Basic attributes of the red side’s equipment.

<table>
<thead>
<tr>
<th>Equipment Name</th>
<th>Number of Equipment</th>
<th>Equipment Type</th>
<th>Closed-Loop Time/s</th>
<th>Number of Sensor Channels</th>
<th>Number of Communication Channels</th>
<th>Number of C2 Channels</th>
<th>Number of Attack Channels</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>16</td>
<td>C/A</td>
<td>13</td>
<td>0</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>R2</td>
<td>1</td>
<td>S/C</td>
<td>9</td>
<td>15</td>
<td>12</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>R3</td>
<td>12</td>
<td>S/C/A</td>
<td>10</td>
<td>3</td>
<td>4</td>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>R4</td>
<td>2</td>
<td>S/C/A</td>
<td>12</td>
<td>9</td>
<td>12</td>
<td>12</td>
<td>36</td>
</tr>
<tr>
<td>R5</td>
<td>1</td>
<td>S</td>
<td>6</td>
<td>8</td>
<td>10</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>R6</td>
<td>3</td>
<td>S</td>
<td>5</td>
<td>8</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>R7</td>
<td>25</td>
<td>S</td>
<td>3</td>
<td>6</td>
<td>5</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 3. Basic attributes of the blue side’s equipment.

<table>
<thead>
<tr>
<th>Equipment Name</th>
<th>Number of Equipment</th>
<th>Equipment Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>8</td>
<td>T</td>
</tr>
<tr>
<td>B2</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>B3</td>
<td>20</td>
<td></td>
</tr>
<tr>
<td>B4</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>B5</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>B6</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>B7</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

In order to describe the nodes of the kill web, it is necessary to describe the attributes of the nodes, sensor nodes, C2 nodes, attack nodes, and target nodes through node attributes, as shown in Tables 4–8.

Table 4. Attributes of the red side’s sensor nodes.

<table>
<thead>
<tr>
<th>Equipment Name</th>
<th>Sensor Distance/km</th>
<th>Scan Path Width/m</th>
<th>K</th>
</tr>
</thead>
<tbody>
<tr>
<td>R2</td>
<td>200</td>
<td>200</td>
<td>20,000</td>
</tr>
<tr>
<td>R3</td>
<td>120</td>
<td>120</td>
<td>11,000</td>
</tr>
<tr>
<td>R4</td>
<td>220</td>
<td>220</td>
<td>19,000</td>
</tr>
<tr>
<td>R5</td>
<td>130</td>
<td>130</td>
<td>15,000</td>
</tr>
<tr>
<td>R6</td>
<td>250</td>
<td>250</td>
<td>15,000</td>
</tr>
<tr>
<td>R7</td>
<td>100</td>
<td>100</td>
<td>10,000</td>
</tr>
</tbody>
</table>

Table 5. Attributes of the red side’s C2 nodes.

<table>
<thead>
<tr>
<th>Equipment Name</th>
<th>Preference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>α</td>
</tr>
<tr>
<td>R1</td>
<td>0.88</td>
</tr>
<tr>
<td>R2</td>
<td>1.00</td>
</tr>
<tr>
<td>R3</td>
<td>1.21</td>
</tr>
<tr>
<td>R4</td>
<td>0.88</td>
</tr>
</tbody>
</table>
Table 6. Attributes of the red side’s attack nodes.

<table>
<thead>
<tr>
<th>Equipment Name</th>
<th>Range/km</th>
<th>CEP/m</th>
<th>Warhead Effectiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>400</td>
<td>8</td>
<td>0.6</td>
</tr>
<tr>
<td>R3</td>
<td>6000</td>
<td>5</td>
<td>0.8</td>
</tr>
<tr>
<td>R4</td>
<td>3000</td>
<td>6</td>
<td>0.7</td>
</tr>
</tbody>
</table>

Table 7. Attributes of the blue side’s target nodes.

<table>
<thead>
<tr>
<th>Equipment Name</th>
<th>Cross-Sectional Area/m²</th>
<th>Hiding Coefficient</th>
<th>Vulnerable Area</th>
<th>Display False Survival Probability</th>
<th>Early Warning Time/s</th>
<th>Maneuvering Speed/km/h</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>150</td>
<td>1.5</td>
<td>1.0 × F</td>
<td>0.3</td>
<td>24</td>
<td>200</td>
</tr>
<tr>
<td>B2</td>
<td>200</td>
<td>2</td>
<td>1.0 × F</td>
<td>0.45</td>
<td>25</td>
<td>300</td>
</tr>
<tr>
<td>B3</td>
<td>100</td>
<td>2</td>
<td>0.8 × F</td>
<td>0.68</td>
<td>35</td>
<td>220</td>
</tr>
<tr>
<td>B4</td>
<td>200</td>
<td>3</td>
<td>1.5 × F</td>
<td>0.55</td>
<td>22</td>
<td>50</td>
</tr>
<tr>
<td>B5</td>
<td>150</td>
<td>3</td>
<td>1.5 × F</td>
<td>0.4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B6</td>
<td>170</td>
<td>1</td>
<td>0.8 × F</td>
<td>0.7</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>B7</td>
<td>130</td>
<td>1.5</td>
<td>2.0 × F</td>
<td>0.42</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

F represents the warhead effectiveness of the attack node, and the vulnerable area is the linear function of the warhead effectiveness of the attack node. The larger the slope, the larger the easily damaged area, and the more vulnerable the target node is. Furthermore, since B5, B6, and B7 are static targets, the early warning time and the maneuvering speed is 0.

Table 8. Communication distance of the red side’s equipment.

<table>
<thead>
<tr>
<th>Communication Distance/km</th>
<th>R1</th>
<th>R2</th>
<th>R3</th>
<th>R4</th>
<th>R5</th>
<th>R6</th>
<th>R7</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>/</td>
<td>30</td>
<td>28</td>
<td>0</td>
<td>0</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>R2</td>
<td>45</td>
<td>/</td>
<td>40</td>
<td>50</td>
<td>50</td>
<td>30</td>
<td>35</td>
</tr>
<tr>
<td>R3</td>
<td>25</td>
<td>30</td>
<td>/</td>
<td>0</td>
<td>0</td>
<td>22</td>
<td>22</td>
</tr>
<tr>
<td>R4</td>
<td>0</td>
<td>40</td>
<td>0</td>
<td>/</td>
<td>0</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>R5</td>
<td>0</td>
<td>40</td>
<td>0</td>
<td>0</td>
<td>/</td>
<td>25</td>
<td>25</td>
</tr>
<tr>
<td>R6</td>
<td>23</td>
<td>25</td>
<td>22</td>
<td>25</td>
<td>25</td>
<td>/</td>
<td>20</td>
</tr>
<tr>
<td>R7</td>
<td>35</td>
<td>35</td>
<td>30</td>
<td>33</td>
<td>33</td>
<td>28</td>
<td>/</td>
</tr>
</tbody>
</table>

4.2. Result Analysis

The decision information is inputted into the multi-objective optimization model, and the NSACGA-II algorithm is used to solve it. The specific parameters are set as follows: the initial population size is 500, the crossover probability is 0.7, the mutation probability is 0.02, and the maximum evolutionary generation is 100. In addition, the reference points of the damage capability and the closed-loop time are set to 0.5 and 30, respectively. After the parameters are set, the NSACGA-II algorithm proposed in this study is used to optimize and solve the problem, and the Pareto front generated by the algorithm is shown in Figure 6.

Figure 6. Pareto front.
Then, we use the TOPSIS method to evaluate the Pareto solution set, and finally select the operation loop scheme that the decision-maker prefers. The weights of the two objectives are equal, at 0.5. The operation loops scheme is shown in Table 9.

<table>
<thead>
<tr>
<th>Number</th>
<th>Target</th>
<th>Operation Loop Scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>B104'</td>
<td>B104'/R602'/R104'/R105'/B104'</td>
</tr>
<tr>
<td>2</td>
<td>B103'</td>
<td>B103'/R111'/R310'/B103'</td>
</tr>
<tr>
<td>3</td>
<td>B108'</td>
<td>B108'/R602'/R102'/R104'/B108'</td>
</tr>
<tr>
<td>4</td>
<td>B107'</td>
<td>B107'/R602'/R101'/R105'/B107'</td>
</tr>
<tr>
<td>5</td>
<td>B105'</td>
<td>B105'/R603'/R109'/R312'/B105'</td>
</tr>
<tr>
<td>6</td>
<td>B106'</td>
<td>B106'/R109'/R312'/B106'</td>
</tr>
<tr>
<td>7</td>
<td>B201'</td>
<td>B201'/R201'/R304'/R104'/B201'</td>
</tr>
<tr>
<td>8</td>
<td>B307'</td>
<td>B307'/R309'/R308'/R307'</td>
</tr>
<tr>
<td>9</td>
<td>B101'</td>
<td>B101'/R201'/R304'/R101'</td>
</tr>
<tr>
<td>10</td>
<td>B102'</td>
<td>B102'/R301'/R301'/R102'</td>
</tr>
<tr>
<td>11</td>
<td>B306'</td>
<td>B306'/R305'/R305'/B306'</td>
</tr>
<tr>
<td>12</td>
<td>B702'</td>
<td>B702'/R302'/R301'/B702'</td>
</tr>
<tr>
<td>13</td>
<td>B309'</td>
<td>B309'/R302'/R301'/B309'</td>
</tr>
<tr>
<td>14</td>
<td>B308'</td>
<td>B308'/R309'/R310'/R312'/B308'</td>
</tr>
<tr>
<td>15</td>
<td>B310'</td>
<td>B310'/R308'/R109'/R312'/B310'</td>
</tr>
<tr>
<td>16</td>
<td>B311'</td>
<td>B311'/R309'/R308'/R308'/B311'</td>
</tr>
<tr>
<td>17</td>
<td>B303'</td>
<td>B303'/R603'/R109'/R111'/B303'</td>
</tr>
<tr>
<td>18</td>
<td>B315'</td>
<td>B315'/R309'/R309'/R309'/B315'</td>
</tr>
<tr>
<td>19</td>
<td>B313'</td>
<td>B313'/R201'/R302'/B313'</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number</th>
<th>Target</th>
<th>Operation Loop Scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>B314'</td>
<td>B314'/R310'/R308'/R309'/B314'</td>
</tr>
<tr>
<td>21</td>
<td>B312'</td>
<td>B312'/R312'/R312'/R312'/B312'</td>
</tr>
<tr>
<td>22</td>
<td>B316'</td>
<td>B316'/R309'/R308'/R308'/B316'</td>
</tr>
<tr>
<td>23</td>
<td>B319'</td>
<td>B319'/R309'/R310'/R310'/B319'</td>
</tr>
<tr>
<td>24</td>
<td>B304'</td>
<td>B304'/R302'/R302'/R301'/B304'</td>
</tr>
<tr>
<td>25</td>
<td>B320'</td>
<td>B320'/R302'/R301'/R302'/B320'</td>
</tr>
<tr>
<td>26</td>
<td>B305'</td>
<td>B305'/R303'/R303'/R302'/B305'</td>
</tr>
<tr>
<td>27</td>
<td>B301'</td>
<td>B301'/R603'/R109'/R114'/B301'</td>
</tr>
<tr>
<td>28</td>
<td>B317'</td>
<td>B317'/R302'/R301'/B317'</td>
</tr>
<tr>
<td>29</td>
<td>B701'</td>
<td>B701'/R301'/R301'/R301'/B701'</td>
</tr>
<tr>
<td>30</td>
<td>B318'</td>
<td>B318'/R603'/R308'/R312'/B318'</td>
</tr>
<tr>
<td>31</td>
<td>B302'</td>
<td>B302'/R603'/R114'/R110'/B302'</td>
</tr>
<tr>
<td>32</td>
<td>B601'</td>
<td>B601'/R304'/R303'/R303'/B601'</td>
</tr>
<tr>
<td>33</td>
<td>B502'</td>
<td>B502'/R201'/R305'/R305'/B502'</td>
</tr>
<tr>
<td>34</td>
<td>B401'</td>
<td>B401'/R305'/R305'/R304'/B401'</td>
</tr>
<tr>
<td>35</td>
<td>B602'</td>
<td>B602'/R603'/R110'/R114'/B602'</td>
</tr>
<tr>
<td>36</td>
<td>B603'</td>
<td>B603'/R302'/R303'/R303'/B603'</td>
</tr>
<tr>
<td>37</td>
<td>B501'</td>
<td>B501'/R303'/R201'/R304'/B501'</td>
</tr>
</tbody>
</table>

4.3. Algorithm Comparison

In order to further verify the effectiveness and feasibility of the NSACGA-II algorithm proposed in this study, using the same data, NSACGA-II is compared with the popular multi-objective optimization algorithms SPEA-II [39] and NSGA-III [40]. The multi-objective optimization algorithm generates the Pareto solution set. It is not convenient to compare the performance of the algorithm directly through the value of the objective function of the scheme. Therefore, the performance of the algorithm is analyzed according to the multi-objective evaluation indexes HV and SP. The boundaries of the Pareto front are taken into account when calculating HV to determine the reference point. The solution space is shown in Figure 7.

![Figure 7. Solution space.](image-url)

The larger the objective 1, the better. The smaller the objective 2, the better. So, the solution space boundary in the lower right corner is the Pareto front. It can be judged from...
Figure 7 that the abscissa of the Pareto front is not less than 2 and the ordinate is not more than 450, so the reference point of the Pareto front is set as [2, 450].

We run the NSACGA-II, SPEA-II, and NSGA-III 10 times independently; generate specific data of indexes HV and SP; and perform statistical analysis on HV and SP. The results are shown in Table 10.

Table 10. HV and SP comparison results.

<table>
<thead>
<tr>
<th>Index</th>
<th>Algorithm</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Average</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>HV</td>
<td>NSACGA-II</td>
<td>0.778</td>
<td>0.894</td>
<td>0.8453</td>
<td>0.001596</td>
</tr>
<tr>
<td></td>
<td>SPEA-II</td>
<td>0.781</td>
<td>0.873</td>
<td>0.8304</td>
<td>0.001086</td>
</tr>
<tr>
<td></td>
<td>NSGA-III</td>
<td>0.715</td>
<td>0.843</td>
<td>0.7769</td>
<td>0.002445</td>
</tr>
<tr>
<td>SP</td>
<td>NSACGA-II</td>
<td>0.93263</td>
<td>2.5092</td>
<td>1.496493</td>
<td>0.243332</td>
</tr>
<tr>
<td></td>
<td>SPEA-II</td>
<td>0.79896</td>
<td>3.1368</td>
<td>1.924286</td>
<td>0.480957</td>
</tr>
<tr>
<td></td>
<td>NSGA-III</td>
<td>1.7224</td>
<td>3.0746</td>
<td>2.34323</td>
<td>0.260036</td>
</tr>
</tbody>
</table>

In order to obtain a more intuitive understanding of the distribution of HV values of each algorithm, a histogram and boxplot are drawn in combination with the final HV value of the algorithm, as shown in Figure 8. Figure 8 (top) plots the HV histogram of 10 runs of the three algorithms, and Figure 8 (bottom) plots the HV boxplot of 10 runs of the three algorithms. Since the larger the HV value, the better, from Figure 8, the distribution of the NSACGA-II algorithm is better. This shows that the Pareto front generated by the NSACGA-II algorithm is closer to the real Pareto front.

Similarly, in order to have a more intuitive understanding of the distribution of SP values of each algorithm, a histogram and a boxplot are drawn in combination with the final SP values of the algorithm, as shown in Figure 9. Since the smaller the SP value, the better, from Figure 9, the distribution of the SP value of the NSACGA-II algorithm is the best. In terms of uniformity, the NSGA-II algorithm is still better than the SPEA-II algorithm, and even better than the NSGA-III algorithm.
Figure 9. SP of NSACGA-II, SPEA-II and NSGA-III.

However, from the convergence curves of the three algorithms, as shown in Figure 10, SPEA-II, NSACGA-II, and NAGA-III reach stability at the 198th, 234th, and 243rd iterations, respectively. It shows that NSACGA-II and NSGA-III are slightly inferior to SPEA-II in terms of convergence efficiency.

Figure 10. Convergence curves of NSACGA-II, SPEA-II and NSGA-III.

To sum up, the NSACGA-II algorithm performs better and is more stable when solving the operation loop decision problem, but its convergence efficiency needs to be further improved.

5. Conclusions and Future Directions

In this study, we proposed a operation loop decision-making method for the kill web. The preferences of decision-makers are fully taken into account based on the prospect theory. The operation loop is modeled by the nodes and edges. We evaluate the operation loop from three aspects: target value, the damage capability value, and the closed-loop time value. Based on this, we constructed a multi-objective optimization model for the operation loop decision-making problem, considering the damage capability value and the closed-loop time value, and designed the NSACGA-II algorithm based on NSGA-II and the
ant colony algorithm to solve the multi-objective optimization problem. In the NSACGA-II algorithm, the initial solution is based on the ant colony algorithm and the crossover and mutation operations are modified. Compared with other popular multi-objective optimization algorithms (SPEA-II, NSGA-III), NSACGA-II is better in terms of evaluation index of HV and SP, which indicates that the proposed algorithm is more comprehensive and uniform. We also evaluated the Pareto solution set generated by the algorithm through the TOPSIS. This study provides theoretical and algorithm guidance for improving the level of intelligent decision making in combat.

The proposed decision-making method is used for systems modeling on complex networks. The complex network in this paper is referred to the kill web which can also be generalized to other networks, but nodes and edges need to be redefined. For example, in the Twitter network, each node represents a user, and each edge represents “follow” relationship. Similarly, in traffic network, each node represents a crossing, and each edge represents a path. Therefore, the method proposed in this paper can be generalized to MCDM problems for other systems, such as the study of large-group consensus decision-making problem in Twitter network or the study of route selection in transportation network.

There are also two limitations to the study. (1) The mathematical model of the prospect theory is not flexible enough in the modeling process. By relaxing the assumption of “rational actor”, the prospect theory explains why people are risk-seeking when they “lose” and risk-averse when they “gain”. However, human decision-making behavior is complex. In addition to the assumption of rational actor, it is necessary to make complex assumptions on emotions, memory, attention, etc., and to repeatedly revise the model. Therefore, only mathematical models used to describe human risk decision-making is incomplete. In learning and imitating human decision making, deep learning has given us new insights into risk perception due to its flexibility. Therefore, in future research, deep learning models can be trained to predict human decision-making behavior, and the relevant assumptions of the prospect theory can be introduced to improve the prediction accuracy of the model. The interpretability of mathematical models and the flexibility of automatic modeling can be complemented by the combination of the prospect theory and deep learning. (2) The NSACGA-II algorithm needs to be further improved. Through the two indexes of HV and SP, it is verified that the NSACGA-II algorithm makes the generated Pareto frontier closer to the real Pareto frontier and makes the Pareto frontier more uniform, but the algorithm has low convergence efficiency. In future research, the hierarchical strategy can be improved to reduce the number of nondominated frontier layers to improve the convergence efficiency. In addition, the multi-objective optimization algorithm proposed in this study is only used for two objectives, but the objectives that need to be optimized in the actual combat process are more complex and diverse. Therefore, in future research, the operation loop decision-making method needs to be designed for more than two objectives.

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Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.
Appendix A

Table A1. Description of the target value evaluation index.

<table>
<thead>
<tr>
<th>Capability</th>
<th>Index</th>
<th>Unit</th>
<th>Value Range</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hiding capability</td>
<td>Hiding coefficient</td>
<td>/</td>
<td>$[1, \infty]$</td>
<td>The coefficient of the hiding capability of the target node</td>
</tr>
<tr>
<td>Display falsity capability</td>
<td>Display falsity survival probability</td>
<td>/</td>
<td>$[0, 1]$</td>
<td>The probability that the target node will not be discovered by sensor equipment by taking display falsity</td>
</tr>
<tr>
<td>Vulnerability</td>
<td>Vulnerable area</td>
<td>$m^2$</td>
<td>R</td>
<td>The area where the target node is damaged by the attack of the attack node</td>
</tr>
<tr>
<td>Early warning capability</td>
<td>Early warning time</td>
<td>s</td>
<td>R</td>
<td>The time required for the target node to escape before being discovered by the sensor equipment node or attacked by the attack equipment node</td>
</tr>
<tr>
<td>Maneuvering capability</td>
<td>Maneuvering speed</td>
<td>km/h</td>
<td>R</td>
<td>The speed at which the target node escapes during the early warning process</td>
</tr>
<tr>
<td>Threat level</td>
<td>Shortest distance</td>
<td>m</td>
<td>R</td>
<td>The shortest distance between the enemy target and our equipment</td>
</tr>
</tbody>
</table>

Appendix B

Algorithm A1. Pseudocode of NSACGA-II.

**Input:**
- $m$: population size
- $maxite$: the maximum number of iterations of the algorithm
- $crossover$: crossover probability
- $pmutation$: mutation probability
- $\alpha$: pheromone importance factor
- $\beta$: heuristic function importance factor
- $\eta$: heuristic function
- $\tau$: pheromone matrix
- $q$: sensor capability, communication capability, C2 capability, attack capability
- $TIME$: closed-loop time
- $\upsilon$: target value
- $F = (f_1(x), f_2(x), \ldots, f_m(x))$ corresponds to a multi-objective optimization problem, this study sets $m = 2$

**Output:** $ND = []$: used to store the Pareto solution set

1  //Step 1 Initialization
2  Step 1.1 Generate initial population based on ant colony algorithm
3     for $i=1$ to $m$ do
4     Ant $i$ forms an operation loop scheme for all targets
5     end for
6  Step 1.2 Fast nondominated sorting
7     $[pop, F] = NonDominatedSorting (pop)$
8  Step 1.3 Calculate crowding distance
9     $pop = CalcCrowdingDistance (pop, F)$
10 Step 1.4 Select the parent individuals
11     $[pop, F] = SortPopulation (pop)$
12  //Step 2 Iterative optimization
13  while $iter < maxiter$ do
14     Step 2.1 Population optimization based on genetic operator
15     for $i=1$ to $m/2$ do
16     Randomly select individuals, perform crossover and mutation operations,
17     get the offspring individuals $popc$ and $popm$
18     end for
19     Step 2.2 Merge individuals

19 pop = [pop popc popm]
20 Step 2.4 Fast nondominated sorting
21 [pop, F] = NonDominatedSorting (pop)
22 Step 2.5 Calculate crowding distance
23 pop = CalcCrowdingDistance (pop, F)
24 Step 2.6 Screening individuals to generate a new population
25 pop = SortPopulation (pop)
26 iter = iter+1
27 end while
28 Return ND

Algorithm A2. Pseudocode of generating an initial population.

1 for all ants do:
2 for all targets do:
3 allow 1 = [], allow 2 = [], allow 3 = [], allow = []
4 allow 1 = {red side’s equipment | sensor capability to target j > 0}
5 allow 2 = {red side’s equipment | sensor channel number > 0}
6 allow 3 = {red side’s equipment | communication channel number > 0}
7 allow = allow 1 ∩ allow 2 ∩ allow 3
8 Based on allow and pheromone to find sensor equipment x1
9 Sensor channel number of x1-1
10 Number of communication channels of x1-1

Find sensor equipment

11 allow 1 = [], allow 2 = [], allow = []
12 allow 1 = {red side’s equipment | communication capability with xj > 0}
13 allow 2 = {red side’s equipment | C2 channel number > 0}
14 allow = allow 1 ∩ allow 2
15 Based on allow and pheromone to find C2 equipment x2
16 Number of communication channels of x2-1

Find C2 equipment

17 allow = allow 1 ∩ allow 2 ∩ allow 3, allow = []
18 allow 1 = {red side’s equipment | C2 capability with x2 > 0}
19 allow 2 = {red side’s equipment | attack channel number > 0}
20 allow 3 = {red side’s equipment | attack capability to target j > 0}
21 allow = allow 1 ∩ allow 2 ∩ allow 3
22 Based on allow and pheromone to find attack equipment x3
23 Number of attack channels of x3-1

Find attack equipment

24 The operation loop formed by the current ant to attack the target is j → x1 → x2 → x3 → j
25 end for
26 A set of operation loops formed by the current ants against all targets
27 end for

References

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