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Non-Preference Bi-Objective Compound Event Barrier Coverage Algorithm in 3-D Sensor Networks

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ABSTRACT With the increase of complexity of monitoring tasks in wireless sensor networks, using a single kind of sensor can no longer fit the strict monitoring requirements. Nowadays, event coverage is widely applied to detect events accurately by utilizing diverse kinds of sensors. The traditional 2-D event model cannot meet the actual monitoring requirements, and there will be many kinds of complicated constraints in the environment. Therefore, a compound event model with multiple constraints is put forward to 3-D sensor networks. Simultaneously, a compound event barrier coverage algorithm on the basis of non-preference bi-objective evolution (NPBO) strategy is presented in multiple constraints sensor networks. The proposed algorithm introduces a non-preference α-dominance mechanism to solve the low efficiency problem of multi-objective evolutionary under multiple constraints. A large number of experimental results indicate that the NPBO mechanism is more high-efficient than the latest algorithm in allocating sensor resources.

INDEX TERMS Compound event barrier coverage, non-preference bi-objective evolution strategy, multiple constraints, α-dominance, 3-D sensor networks.

I. INTRODUCTION

Event coverage is a brand new research area in wireless sensor networks [1]. The purpose of the event coverage application is to apply a variety of different types of sensor resources reasonably. It is not possible for a single type of sensor to complete the network monitoring perfectly. For instance, in the intrusion detection, it cannot confirm the occurrence of invasion event even if the data of infrared sensors exceeds the threshold. This is due to the data might be influenced by the disturbance of wind or animal passing. Therefore, other perceptual information from vibration sensors, ultrasonic sensors and camera sensors should also be analyzed to improve the accuracy of the result.

The traditional research of event coverage only focuses on two-dimensional plane coverage. While the existing two-dimensional unconstrained event coverage model is unable to meet the needs of practical applications anymore [2], [3]. In practical applications, in order to achieve the best monitoring performance, the sensors are deployed in three-dimensional space according to the requirements of monitoring, instead of in the two-dimensional plane. Event coverage is subject to three-dimensional space constraints. For example, in the application of environmental monitoring, there will be a large number of sensors deployed in trees or on the top of hills to get more accurate monitoring results. On the other hand, the event barrier coverage works more often in complex environments. For example, in border surveillance, the sensors cannot be deployed across the border; in the battlefield front monitoring, the height of the sensor deployment cannot be too low or too high, otherwise it will affect the detection performance or be found by the enemy.

A variety of constraints in complex scenarios have be analyzed, for instance, energy constraints, space constraints, noise constraints, confidence constraints and so on [4]–[7]. Energy constraints indicate that the energy of sensors is constrained by extreme environments where replenishing is impossible to accomplish [8]–[11]; space constraints mean that the locations and paths of the deployment of sensors are constrained; noise constraints denote that sensors might be affected by noise interference in complex environments when the performance of sensors would be constrained by excessive noise; and confidence constraints can be defined as the minimum credibility factor for forest fire event in the application of forest fire monitoring. It is necessary to put forward a set of model and algorithm to solve the issue of CEBC, so as to enhance the detection ability of barrier coverage in multiple constraints sensor networks.

As mentioned above, it is necessary to put forward an effective algorithm for CEBC problem so as to allocate the sensor resources efficiently. The following is our contributions:

- For the first time, the three-dimensional CEBC problem is put forward. And three-dimensional event model and space constraints are considered. In real world, most of application scenarios are three-dimensional space. Therefore, two-dimensional event model has been unable to meet the needs of practical application.
- A non-preference bi-objective model is proposed, which solves the low efficiency problem of multi-objective evolutionary under multiple constraints. When the constrained optimization issue is transformed into a bi-objective issue, the bi-objective optimization issue is with preference. If the multi-objective evolutionary algorithm on the basis of Pareto domination relation is used to figure out the bi-objective issue, the algorithm is not efficient. Because the Pareto dominance relationship believe all the objectives are equally important when individuals are compared. In order to figure out the bi-objective issue effectively, it is not feasible to search entire corresponding area of the Pareto frontier. On the other hand, adding additional preference mechanism to accelerate the search of the algorithm in the target region will make the algorithm more complicated. The additional preference mechanism cannot guarantee the optimum solution of constrained optimization issue. In order to overcome this shortcoming, the constrained optimization issue is transformed into a non-preference bi-objective model. Meanwhile, a non-preference bi-objective evolution strategy is proposed.
- A CEBC algorithm based on non-preference bi-objective evolution strategy is put forward to allocate the sensor resources effectively in multiple constraints sensor networks. The proposed CEBC algorithm is more reasonable and more efficient than the latest algorithm verified by many simulation experiments. The experimental results show that the proposed method is more efficiently, especially in complex networks.

The rest of this paper is organized as follows. Related works are described in Section II. The three-dimensional compound event model is proposed based on joint probability density in Section III. The bi-objective evolution problem is analyzed and an α-dominance bi-objective evolution model is described in Section IV. In the next Section V, a CEBC algorithm on the basis of non-preference bi-objective evolution strategy is proposed to figure out CEBC problem under multiple constraints in 3-D sensor networks. In Section VI, the simulation experiments and analysis of the results are set forth. Meanwhile, the experimental results are compared with the performance of the latest event coverage method. Finally, the conclusion and future work are illustrated in Section VII.

II. RELATED WORKS

The barrier coverage can monitor the intruder in the target area effectively. Barrier coverage can be classified as k-barrier coverage, strong barrier coverage and weak barrier coverage, etc [12]–[16]. In [17], an efficient method is proposed to form barrier coverage by leveraging multiple types of mobile sensors to fill in gaps between pre-deployed stationary sensors in heterogeneous WSNs. In [18], Gong *et al.* characterize the optimal placement order and the optimal placement spacing of BRs for barrier coverage. In [19], a deterministic sensor deployment scheme is proposed under a general setting for barrier coverage in wireless sensor networks.

With in-depth research of barrier coverage, the traditional barrier coverage can no longer meet the requirement of practical application scenarios. Yang *et al.* [20] put forward the concept of event monitoring model for the first time. Based on the event monitoring model, Gao *et al.* [21] illustrated the compound event issue under a single cost restriction. The above method only applies to the ideal environment. While in practical application scenarios, people are more likely to pay attention to the detection performance after deployment, not merely to the coverage performance in the initial situation.

The barrier coverage often works in complex environments, where subject to many kinds of constraints. Gao *et al.* [21] only considered a single cost constraint. While in practical application scenarios, there are still energy constraints, spatial constraints, path constraints and so on [22], [23].

The current research on event coverage mostly stays in the two-dimensional plane [20], [21]. While the practical application scenarios are usually in three-dimensional space. Currently, there are a lot of blanks in the research of CEBC in three-dimensional space.

For the bi-objective problem [24], the traditional algorithm is not efficient because the Pareto dominance relationship believe that all the objectives are equally important when individuals are compared. In order to solve the bi-objective problem effectively, searching the entire corresponding area of the Pareto frontier is infeasible [25], and adding additional preference mechanism will make the algorithm more complicated. In addition, the additional preference mechanism cannot guarantee the optimum solution.

The related research of barrier coverage, CEBC, multiple constrained conditions, three-dimensional coverage and bi-objective problem are analyzed separately. There are some gaps in the research of CEBC in 3-D sensor networks under multiple constraints. Therefore, a CEBC algorithm based on non-preference bi-objective evolution strategy is put forward to figure out the integrating confidence of compound event accurately and allocate the sensor resource optimally.

III. THE EVENT MODEL

The study of event barrier coverage is more concerned about providing effective coverage for the event monitoring area. On the premise of ensuring the confidence of event monitoring, the coverage quality of the monitoring area should be improved as much as possible. The event barrier coverage is mostly applied in complex and dangerous scenarios. Therefore, the research of event barrier coverage is to study the rational application of various types of sensors to improve network coverage quality under a variety of complex constraints.

The existing two-dimensional unconstrained event barrier coverage model cannot meet the needs of practical application scenarios. A three-dimensional event barrier coverage model is proposed as follows.

In the barrier coverage, an event is denoted as an occurrence of the earthquake in the period of monitoring. Events can be divided into sub-events and compound events. The compound event is synthesized by a plenty of sub-events which satisfy specified temporal or spatial constraints in a target area. The occurrence of a compound event indicates every individual sub-event has taken place. However, the occurrence of individual sub-events could not ensure that a compound event occurs. The increasing possibility of relevant sub-events indicates an increasing tendency of a compound event taking place in the target area. To our knowledge, this is the first time to propose the issue of event barrier coverage in 3-D sensor networks.

The sub-event denotes a phenomenon of the physical world or the cognition of an objective derived from a single sensing index, such as a slice of meaningful video stream which captured by camera sensors or a monitoring indicator which exceeds the threshold. The occurrence of many sub-events leads to the occurrence of compound event which meets multiple constraints, such as temporal and spatial constraints. This indicates the occurrence of a complex phenomenon. The occurrence of a compound event indicates that all of the relevant sub-events have happened. More specifically, in seismic monitoring system, geoelectric sensors, geomagnetism sensors, inductive sensors, gravity sensors, infrasound sensors and ionospheric sensors are applied in the monitoring region to detect the occurrence of the earthquake. When the seism occurs in the monitoring area, the aberrant perception data is generated and the related perception data can be detected by six different kinds of sensors. By means of analyzing all the perception data comprehensively, a "seism" event can be verified.

The traditional event barrier coverage model is only in the two-dimensional plane. Its event model coordinates are two-dimensional coordinates (x, y). As shown in Fig. 1, the 2-D event barrier model is two overlapping circular regions whose position coordinates are defined as (x_1, y_1) and (x_2, y_2), respectively. The 3-D event barrier model is two

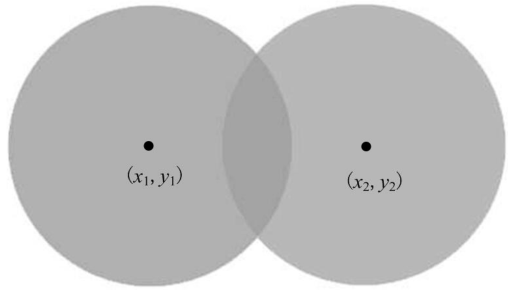


FIGURE 1. Two-dimensional event barrier coverage model schematic.

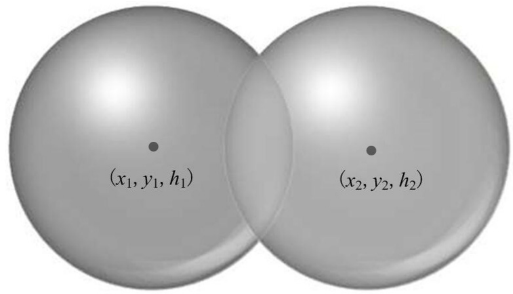


FIGURE 2. Three-dimensional event barrier coverage model schematic.

overlapping spherical areas whose position coordinates are defined as (x_1, y_1, h_1) and (x_2, y_2, h_2) respectively in Fig. 2. When two types of sensors detect abnormalities at the same time period and in the same area, it can be determined that the compound event E occurs in the overlapping area which is monitored by two different types of sensors. Similarly, when six types of sensors detect abnormalities at the same time period and in the same area, it can be determined that the compound event E occurs in the overlapping area monitored by six different types of sensors. The greater the number of sensors in the networks, the more accurate the monitoring performance will be. For example, in indoor fire monitoring, temperature sensors and SO_2 sensors cannot be deployed on a two-dimensional plane in practical applications. When the temperature sensors and the SO_2 sensors detect a fire event, the two-dimensional model can only determine the plane position of the fire but cannot know the floor where the fire occurs. Therefore, the three-dimensional coordinates (x, y, h) are proposed in the three-dimensional event model. And three-dimensional space constraints are proposed for the three-dimensional event model, including horizontal, vertical and height constraints which more in line with the needs of practical applications.

A sub-event can be defined as a monitoring index triggers a single type of sensor in the object area [22]. For example, in indoor fire monitoring, when the temperature sensors detect a fire event, the two-dimensional model can only determine the plane position of the fire but cannot know the floor where the fire occurs. This is unable to meet the actual requirements of fire monitoring. Therefore, the three-dimensional coordinates (x, y, h) are proposed in the three-dimensional event model. $s(t, l, e)$ can be defined as a sub-event. t is the time of the event which can be a time point or time period. l is the location of the sub-event which can be represented by a three-dimensional coordinate (x, y, h). e represents the threshold of the event which can be denoted by a logical expression. For instance, sub-event $s(t, l, e)$=(11/6/2017/15:26, (x, y, h), $Temp > 87°C$), indicates the temperature at location (x, y, h) on 11/6/2017/15:26 is higher than $87°C$.

Compared to traditional area coverage, there is no need for barrier coverage to cover the entire area. It is sufficient for barrier coverage to ensure effective detection to the targets which crossing through the target region. The barrier coverage is more concerned about the Region of Interest (ROI).

The confidence of compound event is synthesized by lots of sub-events. The confidence of compound event is generally defined as the detection indicator of compound event which exceeds the predetermined index. In this paper, an event model on the basis of joint probability is proposed to calculate the synthesized confidence of sub-events effectively.

The coverage mechanism $\alpha = \{\alpha_1, \alpha_3\}$ represents the synthesized confidence of sub-events which derived from category 1 and category 3, namely, $f(\alpha) = f(\alpha_1 \Theta \alpha_3) = g(\alpha_1, \alpha_3)$. The composition operator Θ denotes that the operation of synthesizing the joint probability. By that analogy, the coverage performance of $\alpha = \{\alpha_1, \alpha_2, \alpha_3, \alpha_4\}$ can be denoted as $f(\alpha) = f(\alpha_1 \Theta \alpha_2 \Theta \alpha_3 \Theta \alpha_4) = g(\alpha_1, \alpha_2, \alpha_3, \alpha_4)$. In the above formula, α represents the confidence of different types of sub-events, that is, the confidence coefficient of different kinds of sensors; $f(\alpha)$ denotes the compound event which can be defined as $f(\alpha) = f(\alpha_1 \Theta \alpha_2 \Theta \alpha_3 \Theta \alpha_4)$.

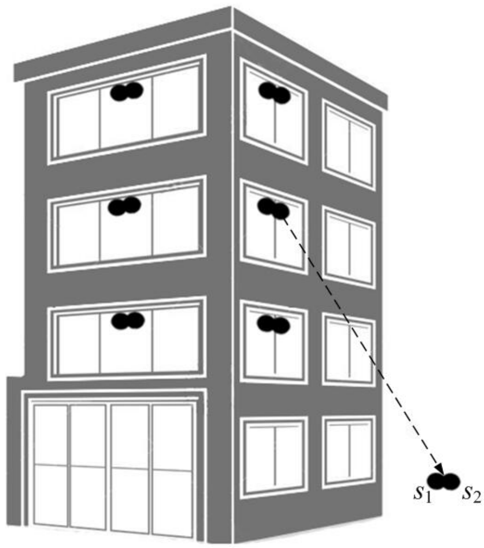
Definition 1 (Joint Probability): p_i represents the confidence of sub-event α_i. Where P denotes the confidence of the compound event after synthesizing. The confidence expression can be defined.

$$P = 1 - \prod_{i=1}^{n} (1 - p_i) \tag{1}$$

On the basis of the nature of the joint probability, it can be concluded.

$$P \geq MIN(p_i) \tag{2}$$

For example, in Fig. 3, many temperature sensors and SO_2 sensors are deployed in the building. When a fire occurs in the building, the burning flame and released SO_2 gas will trigger temperature sensors and SO_2 sensors in nearby locations. The trigger temperature sensor is defined as sub-event s_1, and the trigger SO_2 sensor is defined as sub-event s_2. $s_1(t_1, l_1, e_1) = (t_1, (x_1, y_1, h_1), Temp > 87°C)$ denotes that the sub-event of the temperature at t_1 in location l_1 (x_1, y_1, h_1) is greater than $87°C$. $s_2(t_2, l_2, e_2) = (t_2, (x_2, y_2, h_2), SO_2 > 121.5\mu g/m^3)$ denotes that the sub-event of the SO_2 concentration at t_2 in location l_2 (x_2, y_2, h_2) is more than $121.5\mu g/m^3$. T is the time of the compound event which can be a time point or time period. L is the position of the compound event which can be a location point or an area. The compound event that the fire occurs can be forecasted by sub-event s_1 and s_2. Specifically, the confidence of the temperature sensor is 0.3, and the confidence of the SO_2 sensor is 0.7. Both sensors are triggered at time 11/6/2017/15:26. The location of the two sensors is (25, 6, 15), which can determine the location of the fire. Each floor of the building is 5 meters high. From the monitoring results, it can be determined that there is a fire on the 3rd floor in the building. The confidence of the fire is $E[(s_1, 0.3)(s_2, 0.7), t_1, l_1, t_2, l_2]=(Temp > 87°C \cap SO_2 > 121.5\mu g/m^3 \cap (t_1, t_2 \in T) \cap (l_1, l_2 \in L))$=0.79. It represents that the confidence of the fire event is 0.79 when two sub-events happen at the same time period and in the same area. It is the first time to calculate the confidence of compound event coverage precisely, while the traditional method is based on historic information and experience [21].



$s_1 (t_1, l_1, e_1)= (t_1, (x_1, y_1, h_1), Temp>87\ ^oC)$

$s_2 (t_2, l_2, e_2)= (t_2, (x_2, y_2, h_2), SO_2>121.5\ \mu g/m^3)$

FIGURE 3. **The fire application scenario of the 3-D event model.**

IV. BI-OBJECTIVE EVOLUTION MODEL

A. MAIN IDEA

In the area of barrier coverage, a compound event is detected by monitoring each sub-event by n diverse types of sensors. The occurrence of a compound event E represents the accumulation of the results of the sub-events e. If there is no energy, space and minimum confidence constraints, it is very easy to deploy sufficient sensors to guarantee better monitoring performance in the event barrier coverage. Different from traditional coverage scenarioes, the barrier coverage is subject to multiple constraints due to the hostile and intricate application scenarios.

B. PROBLEM FORMULATION

Without losing generality, an event barrier coverage model with multiple constraints is established as follows.

$$\begin{aligned}&\max\ f(\alpha)=f(\alpha_1,\alpha_2,\ldots,\alpha_n)\\&s.t.\ g_i(\alpha_1,\alpha_2,\ldots,\alpha_n)\le 0\quad(i=1,2,\ldots,p)\\&\qquad h_j(\alpha_1,\alpha_2,\ldots,\alpha_m)=0\quad(j=1,2,\ldots,q)\end{aligned}\tag{3}$$

$f(\alpha)$ is the optimization objective function of the event barrier coverage. $\alpha=(\alpha_1,\alpha_2,\ldots,\alpha_n)$ represents different types of sensors, where $\alpha=(\alpha_1,\alpha_2,\ldots,\alpha_n)\in T\subset R^n$ is the n-dimensional decision vector. $T=\{\alpha\in R^n|d_i\le\alpha\le u_i, i=1,2,\ldots,n\}$ is the target space, where $d_i\in R$ and $u_i\in R$ denote the lower bound and upper bound of α respectively. $g_i(\alpha)$ represents inequality constraint function and $h_j(\alpha)$ denotes equality constraint function. For example, $s.t.\ \{g_1(\alpha)\le 0, g_2(\alpha)\le 0, h_1(\alpha)=0\}$ indicates that the objective function is subject to two inequality constraints and one equality constraint. $\Omega=\{\alpha|\alpha\in S, g_i(\alpha)\le 0, h_j(\alpha)=0, i=1,\ldots,p, j=p+1,\ldots,m\}$ is the feasible domain and the points in the feasible domain are feasible solutions.

The traditional penalty function is a common method to solve the constrained optimization issue. The penalty parameter affects the performance of the algorithm directly, and the selection of the penalty parameters is difficult. In addition, in the processing method based on penalty function, the feasible solution is always better than the infeasible solution in the individual comparison. For the optimization problem of the global optimal solution near the boundary of the feasible domain, it is easier to find the optimal solution from the infeasible solution which is near the optimal solution than from the feasible solution which is away from the optimal solution. If these infeasible solutions are ignored, the efficiency of the algorithm will be reduced. Therefore, the constrained optimization issue is transformed into a bi-objective optimization issue to eliminate the impact of penalty parameters on the algorithm. Constraint violation degree is denoted as:

$$V_i(\alpha)=\begin{cases}\max\{0,g_i(\alpha)\}, & 1\le i\le p;\\ \max\{0,|h_i(\alpha)|-\varepsilon\}, & p+1\le i\le m.\end{cases}\tag{4}$$

In the formula (4), ε is the tolerance value of the equation constraint which generally takes a smaller positive number. Obviously, $V_i(\alpha)\ge 0$. If $V_i(\alpha)=0$, then α satisfies the i-th constraint; If $V_i(\alpha)>0$, then $V_i(\alpha)$ represents the constraint violation degree of i-th sub-event α. The constraint violation function can be defined as $V(\alpha)=\sum_{i=1}^{m}V_i(\alpha)$, which indicates the degree of constraint violation and reflects the distance between sub-event α and feasible domain.

By using the coverage optimization objective function $f(\alpha)$ as an objective and using constraint violation function $V(\alpha)$ as another objective, the problem (3) is transformed into a bi-objective optimization problem:

$$\begin{cases}\max\{f(\alpha)\};\\ \min\{V(\alpha)\};\\ s.t.\ \alpha\in T.\end{cases}\tag{5}$$

In the formula (5), $\alpha\in T\subset R^n$ is a decision vector; T is a decision space, and the image space of $\alpha\in T$ is defined as target space. For convenience, the two objectives of formula (5) are denoted as $f_1(\alpha)=f(\alpha), f_2(\alpha)=V(\alpha)$.

The significance of the multi-constrained compound event barrier coverage problem is to apply various types of sensors reasonably to achieve the best coverage performance in the network under a variety of complex constraints. With limited network resources, the increasing number of one type of sensors will inevitably lead to the declining number of other types of sensors. The Pareto theory is the basis for measuring the distribution of resources. The Pareto optimal solution is defined as an ideal state of resource allocation. For example, there is a group of people and limited resources that can be allocated, from a state of distribution to another state, to make at least one person better without making anyone worse off. The Pareto optimal state is no more room for Pareto improvement. That is, the optimal coverage performance. Therefore, the Pareto theory is introduced to deal with CEBC problem in order to achieve the best coverage performance and the most reasonable distribution of sensor resources.

Definition 2 (Pareto Domination): Vector $n=(n_1,n_2)$, n Pareto dominate vector m, $m=(m_1,m_2)$, can be defined as $n\prec m$, if and only if $n_1\le m_1$, $n_2<m_2$ or $n_1<m_1$, $n_2\le m_2$.

Definition 3 (Pareto Optimal Solution): The vector $\alpha_n\in T$ denotes the Pareto optimal solution of the bi-objective issue (5), if and only if $\neg\alpha_n\in T$ makes $m\prec n$, where $n=(f_1(\alpha_n),f_2(\alpha_n))$, $m=(f_1(\alpha_m),f_2(\alpha_m))$.

Definition 4 (Pareto Optimal Solution Set): For the bi-objective optimization issue (5), the Pareto optimal solution set is defined as:

$$P_{Best}=\{\alpha_n\in T|\neg\alpha_m\in T, m\prec n\}\tag{6}$$

Definition 5 (Pareto Frontier): For the bi-objective optimization issue (5), the Pareto optimal solution set P_{Best} in the target space is defined as Pareto front P_F.

$$P_F=\{n=(f_1(\alpha_n),f_2(\alpha_n))|\alpha_n\in P_{Best}\}\tag{7}$$

C. α-DOMINANCE BI-OBJECTIVE EVOLUTION STRATEGY

The general Pareto domination relationship is no preference. When individuals are compared and selected, it is usually believed that all objectives are equally important, and does not take into account the preference of the problem. The algorithm based on general Pareto domination is not efficient. While, adding additional mechanism to satisfy the preference of the algorithm will increase the complexity of the algorithm.

Based on the above analysis, aiming at the characteristics of the bi-objective issue, a CEBC algorithm on the basis of non-preference bi-objective evolution strategy is proposed to solve the constrained bi-objective optimization problem.

Definition 6 (α-Domination): For the bi-objective optimization problem (5),

$$\begin{cases} \Psi_1(f_1(\alpha), f_2(\alpha)) = f_1(\alpha) + \alpha_{12} f_2(\alpha)\Gamma_1(\alpha) \\ \Psi_2(f_1(\alpha), f_2(\alpha)) = \alpha_{21} f_1(\alpha) + f_2(\alpha)\Gamma_2(\alpha) \end{cases} \quad (8)$$

In the formula (8), $\alpha_{12}, \alpha_{21} \geq 0$. Suppose α and β are two decision vectors, if $\forall i \in \{1, 2\}$, $\Gamma_i(\alpha) \leq \Gamma_i(\beta)$, meanwhile $\exists j \in \{1, 2\}$, $\Gamma_j(\alpha) < \Gamma_j(\beta)$, then $\alpha\alpha$-dominate β which can be defines as $\alpha \prec_\alpha \beta$.

According to α-dominance relationship, a CEBC algorithm on the basis of non-preference bi-objective evolution strategy is proposed to solve the constrained bi-objective optimization problem.

V. COMPOUND EVENT BARRIER COVERAGE ALGORITHM BASED ON NON-PREFERENCE BI-OBJECTIVE EVOLUTION STRATEGY

A. MAIN IDEA

When the constrained optimization problem is transformed into a bi-objective problem, the bi-objective optimization problem is with preference. If the multi-objective evolutionary algorithm based on Pareto domination relation is used to figure out the bi-objective problem, the algorithm is not efficient. Because the Pareto dominance relationship believe all the objectives are equally important when individuals are compared. In order to solve the bi-objective problem effectively, it is not feasible to search entire corresponding area of the Pareto frontier. However, adding additional preference mechanism to accelerate the search of the algorithm in the target region will make the algorithm more complicated. Also, the additional preference mechanism cannot guarantee that the final solution converges to the optimum solution of constrained optimization problem. Therefore, in order to overcome this shortcoming, the constrained optimization problem is transformed into a non-preference bi-objective model. Also, a non-preference bi-objective evolution algorithm is proposed.

B. NON-PREFERENCE BI-OBJECTIVE MODEL

Three-dimensional CEBC needs to meet the condition of multiple constraints and achieve the best coverage performance as much as possible. Therefore, satisfying a variety of constraints is the primary condition. The solution should be preference to constraint satisfaction, namely, $V(\alpha) = 0$. Since the model is no preference, it is necessary to control the constraint violation function by introducing parameter λ. The non-preference bi-objective model (10) is as follows.

$$\begin{cases} \max(\Psi_1(\alpha)) \\ \min(\Psi_2(\alpha)) \\ s.t.\ \alpha \in T \end{cases} \quad (10)$$

In the formula (10), $\Psi_1(\alpha) = f(\alpha) + \lambda V(\alpha)$, $\Psi_2(\alpha) = V(\alpha)$, λ is a control parameter. λ reflects the control degree of the constraint. The greater the λ, the stronger control of the constraint, so the constraint violation degree can be controlled by control parameter λ.

Obviously, the bi-objective model (5) is the special case of the non-preference model (10). The non-preference model $\Psi_2(\alpha) = V(\alpha)$ indicates the constraint violation degree of α. The greater the value of $\Psi_2(\alpha)$, the farther away from the feasible domain, and vice versa. $\Psi_1(\alpha) = f(\alpha) + \lambda V(\alpha)$ is the linear combination of the individual objective function and its

Mechanism α-Dominance Bi-Objective Evolution Strategy

1: Initialization: In the search space T, NP individuals are randomly generated to form the initial population $P^{(0)} = \{\alpha_1^0, \alpha_2^0, \ldots, \alpha_N^0\}$, and $k = 0$;

2: Mutation: For each individual $\alpha_i^k = \{\alpha_{i,1}^k, \alpha_{i,2}^k, \ldots, \alpha_{i,n}^k\}$, $(i = 1, 2, \ldots, NP)$ in $P^{(k)}$, the "rand / 1" mutation is applied to produce the mutation of descendants $V_i^k = (V_{i,1}^k, V_{i,2}^k, \ldots, V_{i,n}^k)$, where $V_i^k = \alpha_{r1}^k + F(\alpha_{r2}^k - \alpha_{r3}^k)$;

3: Crossover: For each variation of the descendant in step 2, they are crossed with the target vector for binary "bin" to generate the test vector $E\alpha_i^k = (E\alpha_{i,1}^k, E\alpha_{i,2}^k, \ldots, E\alpha_{i,n}^k)$,

$$E\alpha_i^k = \begin{cases} V_{i,j}^k, \textit{ if } \ \textit{rand} < \textit{Cr or } j = j_{rand}; \\ \qquad (j = 1, 2, \ldots n) \\ \alpha_{i,j}^k, \quad \textit{else} \end{cases} \quad (9)$$

$Cr \in [0, 1]$ is the crossover probability. $j_{rand} \in \{1, 2, \ldots, n\}$ chooses arbitrarily to ensure that the test vector $E\alpha_i^k$ is different from the target vector α_i^k in at least one gene bit. The descendant set of all test vectors is: $Q^{(k)} = (E\alpha_1^k, E\alpha_2^k, \ldots, E\alpha_{NP}^k)$;

4: Selection: Instead of the greedy selection operator of standard DE algorithm, the non-preference α-dominance hierarchical ranking method is applied to select the individuals into the next generation population. An α-dominance relationship is applied to make non-dominated hierarchy $H^{(k)}$ which can be defined as $H^{(k)} = P^{(k)} \cup Q^{(k)}$. Then select the α-non-dominated individuals one by one. The α-non-dominated individuals are saved into $P^{(k+1)}$ and removed from $H^{(k)}$; If $P^{(k+1)}$ does not reach a predetermined size, then find α-non-dominated individuals in $H^{(k)}$ and save it into $P^{(k+1)}$. Repeat the above process until $P^{(k+1)}$ reaches the predetermined size. If a certain non-dominated individual of $H^{(k)}$ is added into $P^{(k+1)}$, so that it exceeds the predetermined size, then these individuals will be sorted by the constraint violation degree from small to large and selected into $P^{(k+1)}$ according to the sequence;

5: Termination condition: If the termination condition is satisfied, the optimal solution is output; Otherwise, $t = t + 1$, skip back to step 2.

constraint violation function. The constraint violation degree punishes its objective function value. In particular, when α is a feasible solution, that is $V(\alpha) = 0$, the penalty value for the objective function is 0; when α is a non-feasible solution, that is $V(\alpha) > 0$, the penalty value for the objective function is $\lambda V(\alpha)$. Moreover, the farther α away from the feasible domain, the greater the penalty for its objective function value, otherwise the smaller. Thus, λ is the penalty parameter, the larger the penalty parameter, the greater the penalty for the objective function value of the infeasible solution. At this time, the comparison and selection of the individual is preference to the feasible solution or the solution with small constraint violation degree.

When multi-constraint CEBC problem is transformed into bi-objective model, the control of the constraint satisfaction has been in the first place. The control degree of the constraint satisfaction can be adjusted by penalty parameter λ. Therefore, the problem (3) is transformed into a non-preference bi-objective problem.

C. COMPOUND EVENT BARRIER COVERAGE ALGORITHM ON THE BASIS OF NON-PREFERENCE BI-OBJECTIVE EVOLUTION STRATEGY

In this paper, the non-dominance hierarchical relationship based on Pareto domination is used to replace greed selection of *DE* as the selection criterion in the non-preference bi-objective evolution strategy. The primary task of constrained optimization problem is to satisfy the constraint condition. Therefore, when two individuals are not dominated each other, the individual which has small constraint violation degree is better.

On the other hand, in order to ensure the diversity of the evolutionary population and avoid the solution of the algorithm falling into local optima, λ should not be too large.

$$\lambda(k+1) = \eta\lambda(k) \tag{11}$$

In formula (11), k represents the evolutionary generation. $\eta(\eta > 1)$ is the scale factor which controls the growth rate of λ. λ is a control parameter. λ reflects the control degree of the constraint. The greater the λ, the stronger control of the constraint, so the constraint violation degree can be controlled by control parameter λ.

The flow diagram of CEBC algorithm on the basis of non-preference bi-objective evolution strategy is presented in Fig.4 for more clarity.

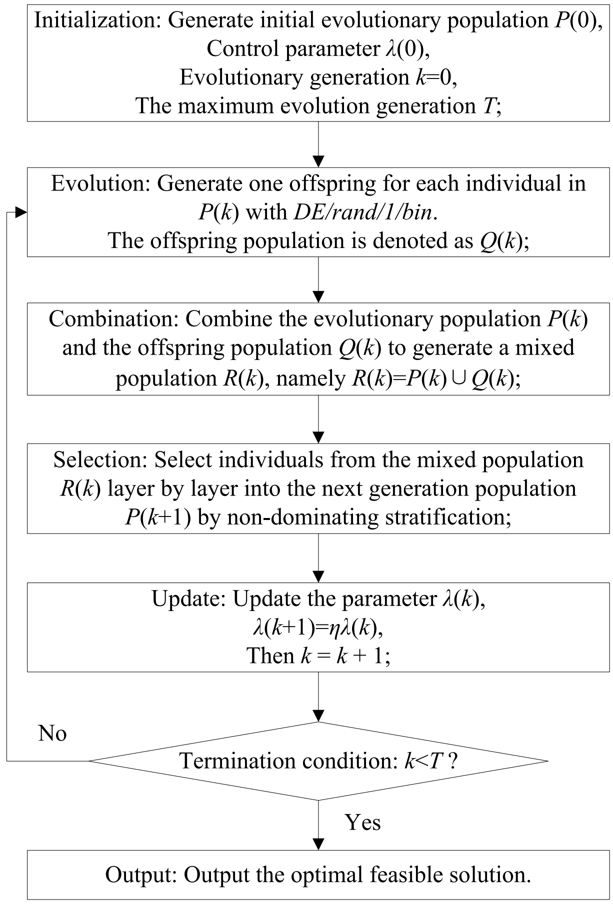


FIGURE 4. The flow diagram of CEBC algorithm on the basis of non-preference bi-objective evolution strategy.

D. THE COMPLEXITY ANALYSIS OF THE ALGORITHM

First, generated by *DE*, the parent population (scale *NP*) and the offspring population (scale *NP*) are 2*NP*, meaning that there are 2*NP* individuals need to be saved. Thus memory space is required for $O(n \times NP)$. In addition, the computational complexity of NPBO algorithm is mainly reflected in the generation of progeny populations and selection operations. In the generation of descendants with *DE/rand/1/bin*, the amount of computations required by NPBO algorithm (eg, $+$, $-$, $*$, / and so on) are $O(n \times NP)$; in the selection operation, the non-dominated hierarchical ranking based on α-dominance relationship for 2*NP* population requires $O(2(2NP)^2 + NP) = O(NP^2)$ comparisons in the worst case. So the total computational complexity of NPBO algorithm is $O(NP^2)$, where $n < NP$. Therefore, the problem studied is a P problem.

E. THE ACCURACY ANALYSES OF THE ALGORITHM

Firstly, the uniqueness of the Pareto optimal solution is proven. Then the accuracy of the algorithm is analyzed.

Theorem 1: In compound event non-preference bi-objective model (10), when $\lambda \to \infty$, the Pareto optimal target vector is unique.

Proof: Proof by contradiction. Suppose that when $\lambda \to \infty$, the Pareto optimal target vector of the problem is not unique. Then there are at least two Pareto optimal solutions α and β correspond to different Pareto optimal target vectors, that is $(f(\alpha) + \lambda V(\alpha), V(\alpha)) \neq (f(\beta) + \lambda V(\beta), V(\beta))$. When $\lambda \to \infty$, α and β are both Pareto optimal solutions. So α and β are not dominated by each other. Without loss of

Algorithm 1 CEBC Algorithm on the Basis of Non-Preference Bi-Objective Evolution Strategy

Begin
$k = 0$;
Generate the initial population $P(k) = \{\alpha_1^k, \alpha_1^k, \ldots, \alpha_{NP}^k\}$ randomly;
Evaluate $(\Psi_1(\alpha_i^k), \Psi_1(\alpha_i^k)), \forall i = 1, 2, \ldots, NP$;
 For $k = 1$ to T Do
  For $k = 1$ to NP Do
   Select $r1, r2, r3 \in \{1, 2, \ldots, NP\}$ randomly, Meantime $r1 \neq r2 \neq r3 \neq i$
   $j_{rand} = rand\ int(1, n)$
   For $j = 1$ to n Do
    If $(rand_j[0, 1] < Cr \text{ or } j = j_{rand})$ Then
     $E\alpha_{i,j}^k = \alpha_{r1,j}^k + F(\alpha_{r2}^k - \alpha_{r3}^k)$
    Else
     $E\alpha_{i,j}^k = \alpha_{i,j}^k$
    End If
   End For
  End For
 Evaluate $(\Psi_1(E\alpha_i^k), \Psi_2(E\alpha_i^k)), \forall i = 1, 2, \ldots, NP$
 $P(k+1) =$ Non-dominated stratification $(P(k) \cup Q(k))$, $Q(k) = \{E\alpha_1^k, E\alpha_2^k, \ldots, E\alpha_{NP}^k\}$
 Update λ: $\lambda(k+1) = \eta\lambda(k)$
 $k = k + 1$
 End For
End

generality, suppose the following holds:

$$\begin{cases} f(\alpha) + \lambda V(\alpha) > f(\beta) + \lambda V(\beta); \\ V(\alpha) < V(\beta). \end{cases} \tag{12}$$

Due to $V(\alpha) < V(\beta)$, if $f(\alpha) \leq f(\beta)$, then $\forall\lambda > 0$, $f(\alpha) + \lambda V(\alpha) < f(\beta) + \lambda V(\beta)$ holds; If $f(\alpha) > f(\beta)$, when $\lambda > (f(\alpha) - f(\beta)/(V(\beta) - V(\alpha))$, $f(\alpha) + \lambda V(\alpha) < f(\beta) + \lambda V(\beta)$ also holds. Both of them are contradictory to the first expression of (12). Thus, when $\lambda \to \infty$, the Pareto optimal target vector of non-preference bi-objective model is unique.

For the CEBC problem under multiple constraints, the constraint satisfaction is the primary condition. So it should be $\lambda \to \infty$ to ensure that the solution of non-preference bi-objective model satisfies the constraint condition. The relationship between the non-preference bi-objective model and the optimal solution of CEBC problem under multiple constraints is as follows.

Theorem 2: α^* is the optimal solution for CEBC problem. $\Leftrightarrow$ $(\Psi_1(\alpha^*), \Psi_2(\alpha^*))$ is a unique Pareto optimal target vector when $\lambda \to \infty$ for non-preference bi-objective model.

Proof: First proof of necessity. Suppose α^* is the optimal solution of CEBC problem, then its constraint violation function value is 0, that is $V(\alpha^*) = 0$. The following two cases indicate that α^* is a Pareto optimal solution of non-preference bi-objective model when $\lambda \to \infty$. That is to say $\forall\alpha \in D$, α is not dominated α^*.

Case 1: If α is a feasible solution, but not the optimal solution of CEBC problem (3), then $V(\alpha) = 0$ and $f(\alpha^*) < f(\alpha)$. So $\forall\lambda > 0, f(\alpha^*) + \lambda V(\alpha^*) < f(\alpha) + \lambda V(\alpha)$, that is $\Psi_1(\alpha^*) < \Psi_1(\alpha)$. Meanwhile, $\Psi_2(\alpha^*) = \Psi_2(\alpha) = 0$, therefore $\alpha^*\alpha$. If α is the optimal solution of CEBC problem (3), then $f(\alpha^*) = f(\alpha)$ and $V(\alpha^*) = V(\alpha) = 0$, that is to say, α and α^* has the same target vector. So α^* is not dominated by α. It can be concluded: α^* is not dominated by any feasible solution α.

Case 2: If α is not a feasible solution, then $V(\alpha) > 0$, thus $\Psi_2(\alpha^*) < \Psi_2(\alpha)$. Further, if $f(\alpha^*) \leq f(\alpha)$, then $\forall\lambda > 0, f(\alpha^*) + \lambda V(\alpha^*) \leq f(\alpha) + \lambda V(\alpha)$, that is to say, $\Psi_1(\alpha^*) < \Psi_1(\alpha)$, so $\alpha^*\alpha$. If $f(\alpha^*) \leq f(\alpha)$, let $\lambda > (f(\alpha^*) - f(\alpha))/(V(\alpha) - V(\alpha^*))$, then $f(\alpha^*) + \lambda V(\alpha^*) < f(\alpha) + \lambda V(\alpha)$, that is to say, $\Psi_1(\alpha^*) < \Psi_1(\alpha)$. So $\alpha^*\alpha$, namely, α^* is not dominated by α. It can be concluded that when λ is large enough, α^* is not dominated by any infeasible solution α.

Based on the Above Analysis: When $\lambda \to +\infty$, α^* is the Pareto optimal solution of the non-preference bi-objective model (10). According to Theorem 1, the non-preference bi-objective model (10) has a unique Pareto optimal target value when $\lambda \to +\infty$. Therefore, $(\Psi_1(\alpha^*), \Psi_2(\alpha^*)$ is the unique Pareto optimal target value of non-preference bi-objective model (10) when $\lambda \to +\infty$.

Then prove sufficiency condition. Suppose $(\Psi_1(\alpha^*), \Psi_2(\alpha^*))$ is the unique Pareto optimal target value of non-preference bi-objective model (10) when $\lambda \to +\infty$. Then α^* is the Pareto optimal solution, so $\neg\exists\alpha \in D$, so that the following holds:

$$\begin{cases} \Psi_1(\alpha) \leq \Psi_1(\alpha^*); \\ \Psi_2(\alpha) \leq \Psi_2(\alpha^*). \end{cases} \tag{13}$$

In formula (13), at least one inequality sign is strictly true. The formula (13) can also be expressed as:

$$\begin{cases} f(\alpha) + \lambda V(\alpha) \leq f(\alpha^*) + \lambda V(\alpha^*); \\ V(\alpha) \leq V(\alpha^*). \end{cases} \tag{14}$$

In formula (14), at least one inequality sign is strictly true.

Suppose α^* is not the optimal solution of CEBC problem (3), then α^* is either an infeasible solution or a feasible solution. But the objective function value $f(\alpha^*)$ is not optimal. Suppose α' is the optimal solution for CEBC problem (3), then $f(\alpha')$ is minimized within the feasible domain Ω, that is to say, $V(\alpha') = 0$.

If $V(\alpha^*) > 0$, then $V(\alpha') < V(\alpha^*)$. Further, if $f(\alpha') < f(\alpha^*)$, then $\forall\lambda > 0$, $\Psi_1(\alpha') < \Psi_1(\alpha^*)$ holds; If $f(\alpha') \geq f(\alpha^*)$, then when $\lambda > (f(\alpha') - f(\alpha^*))/(V(\alpha^*) - V(\alpha'))$, $\Psi_1(\alpha') < \Psi_1(\alpha^*)$ holds. Both of them are contradictory to formula (13).

If $V(\alpha^*) = 0$, then $f(\alpha') < f(\alpha^*)$, and $V(\alpha') = V(\alpha^*) = 0$, so $\Psi_1(\alpha') < \Psi_1(\alpha^*)$ holds. This is also contradictory to formula (13).

On the basis of the above discussion, α^* is the optimal solution for CEBC problem (3).

Proof finished.

VI. PERFORMANCE EVALUATION

In this part, the NPBO algorithm is evaluated by a series of experiments in multiple constraints sensor networks and compared with Active Set Multiplier Policy (ASMP) and OCQ-Series mechanism in the same experimental condition.

A. ENVIRONMENT SETTINGS

Matlab2014a is used to perform the experiments. In the experiments, there are six types of sensors. The confidence coefficient of the six different types of sensors is 0.30, 0.15, 0.20, 0.10, 0.45 and 0.25, respectively. Every type of sensors has different energy consumption, perceived radius, deployment height and confidence according to their own properties. The parameters of these sensors are presented in Table 1 and the experimental parameters are listed in Table 2. The monitoring area sets up in a 1000m∗100m long and narrow area. Experiments are performed for five different cases in order to verify the performance under different situations.

TABLE 1. Parameters of sensors.

Symbol	Meaning	E/w	R/m	H/m	Conf
α_1	Geoelectric Sensor	5	35	45	0.30
α_2	Geomagnetism Sensor	2	15	20	0.15
α_3	Inductive Sensor	4	45	35	0.20
α_4	Gravity Sensor	6	20	25	0.10
α_5	Infrasound Sensor	2	30	30	0.45
α_6	Ionospheric Sensor	3	25	15	0.25

In Table 1, the meaning of abbreviations is as follows.
E: Energy consumption (E/w);
R:Perceived radius (R/m);
H:Height (H/m);
Conf: Confidence.

B. EXPERIMENTAL EVALUATION

The experiments are performed to analyze the efficiency of the NPBO mechanism which is based on non-preference bi-objective evolution strategy in multiple constraints sensor networks. The energy, horizontal, vertical, height and minimum confidence constraints are listed in Table 2 for five different cases. The experimental results and analysis are as follows.

Case 1 is subject to hard energy constraint. So the geomagnetism sensors and infrasound sensors which consume less energy are applied more than other kinds of sensors.

Compared to case 1, case 2 is required to have a higher minimum confidence. Moreover, the horizontal, vertical and height constraint increase substantially. The monitoring space that needs to be covered has increased by more than 3 times compared to case 1. However, the energy constraint only increases by 2 times to put forward a higher request to the coverage performance. So the geoelectric sensors and inductive sensors with higher minimum confidence and bigger perceived range are more used under severe space constraints.

TABLE 2. Parameters of experiments.

CASE	ENER	X	Y	H	MIN	RATIO	RUN
1	164	1440	1695	1705	0.69	59.2%	$<$1s
2	353	2100	2775	2445	0.76	73.6%	$<$1s
3	545	3220	3500	3880	0.84	81.5%	$<$1s
4	607	3640	4845	4215	0.93	88.3%	$<$1s
5	832	6825	7710	7930	0.99	95.2%	$<$1s

In Table 2, the meaning of abbreviations is as follows.
Ener: Energy Constraints;
X:Horizontal Constraints;
Y:Vertical Constraints;
H:Height Constraints;
Min: Minimum Confidence Constraints;
Ratio: Coverage Ratio;
Run: Running Time.

In comparison to case 2, the minimum confidence has a further rise in case 3 and its energy constraints continue growing, which puts forward a stricter request to the coverage performance. Case 3 and case 4 are restrained by energy constraints. Thus low-energy inductive sensors are applied for 66 and 42. Meanwhile, taking into account the requests of high confidence, the ionospheric sensors are also applied for 28 and 34.

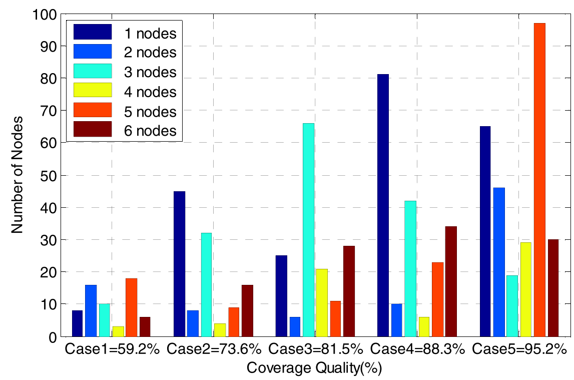


FIGURE 5. Sensor resource distribution for CEBC in multiple constraints 3-D sensor networks.

Case 5 is limited by a strict minimum confidence constraint. So, the infrasound sensors and geoelectric sensors with higher confidence have been widely used, comparing with the previous four cases. However, under the energy and space constraint, the quantity of infrasound sensors is limited to 96.

Fig.5 shows the sensor resource allocation of these five cases and the network coverage performance. It indicates that, with the increasing of the number of sensors, the network coverage performance is enhanced gradually. Each of the five cases is bound by energy, horizontal, vertical, height and minimum confidence constraints. However, these five cases have diverse characteristics. Specifically, case 1 needs to meet the other four constraints under the precondition of strict energy constraints; case 2,3,4 have to meet the other four constraints based on the precondition of severe horizontal, vertical and height constraints respectively in 3-D space; case 5 have to meet the other four constraints under the precondition of rigorous minimum confidence constraints. The experimental results show that the NPBO algorithm is efficient to allocate sensor resources in multiple constraints 3-D sensor networks.

The significance of the above experiments is to test and verify whether the NPBO algorithm is effective and efficient in multiple constraints 3-D sensor networks. In order to test the performance of the algorithm, the NPBO algorithm is compared with the latest event coverage algorithm in the following experiments.

C. COMPARISON WITH OCQ-SERIES AND ASMP ALGORITHMS

This section shows the comparison of CEBC algorithm which is based on non-preference bi-objective evolution strategy (NPBO), ASMP algorithm and OCQ-Series mechanisms. As mentioned above, the proposed algorithm which introduced NPBO strategy is much better than OCQ-Series mechanisms.

In this paper, ASMP, OCQ-Naïve, OCQ-Greedy and OCQ-Max-fit algorithms are compared to NPBO with onefold energy constraint. Since there is no relevant works on event barrier coverage in multiple constraints 3-D sensor networks so far. It can be seen from the experimental results that the NPBO algorithm is superior to the latest algorithm in terms of energy saving, large area barrier coverage and operational efficiency.

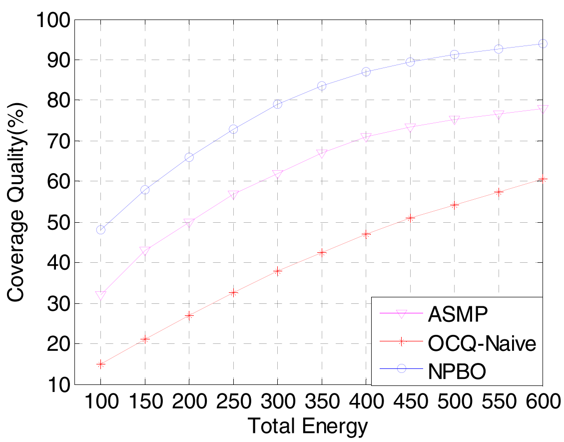


FIGURE 6. The NPBO algorithm is compared with ASMP and OCQ-Naïve algorithm on coverage quality with diverse total energy.

Fig.6 shows that the coverage quality has been significantly enhanced with the increasing of the total energy. As the available energy increases, more and more sensors can be put into use. Furthermore, the NPBO algorithm is more superior to OCQ-Naïve and ASMP mechanism in terms of coverage quality under different total energy constraints. That is because the greater the total energy, the greater the number of sensors will be, the greater the complexity of the networks will be. OCQ-Naïve algorithm is based on greedy algorithm, which only chooses the current optimal solution rather than global optimal solution. Whereas, the non-preference bi-objective evolution strategy is more suitable for the optimization issue whose global optimal solution near the boundary of the feasible domain. So it is more effectively to find out the global optima.

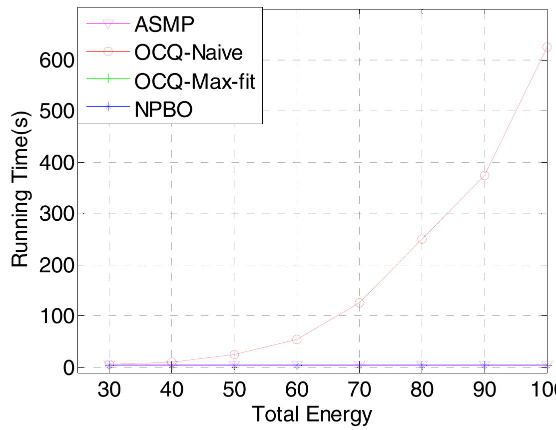


FIGURE 7. The NPBO algorithm is compared with ASMP, OCQ-Naïve and OCQ-Max-fit algorithm on running time with diverse total energy.

Fig.7 shows that as the total energy increases, the running time of four algorithms continues to increase. It can be seen from Fig.7, the running time of NPBO, ASMP and OCQ-Max-fit algorithm is much shorter than OCQ-Naïve algorithm, especially in the case of sufficient total energy. This is due to the fact that when the total energy increases, the OCQ-Naïve algorithm does not adapt to the complex network environment. While, the running time of OCQ-Max-fit and ASMP algorithm only increases slightly. The increase of the running time of NPBO algorithm is almost negligible when compared with OCQ-Naïve algorithm. As the non-preference bi-objective evolution strategy transforms a variety of complex constraints into another objective function to solve, which reduce the expenditure of computing effectively and make the algorithm more efficient.

Fig.8 elaborates that the coverage quality is significantly deteriorated with the increasing of deployment area. The coverage quality of NPBO is more superior to ASMP and OCQ-Max-fit algorithm, especially in the case of large deployment area. As the increasing of the deployment area, the quality of coverage gets worse due to limited total energy. The NPBO algorithm can adapt to complex network environment and large area deployment. So, the deployment area can still maintain high quality coverage even though the deployment area has grown significantly.

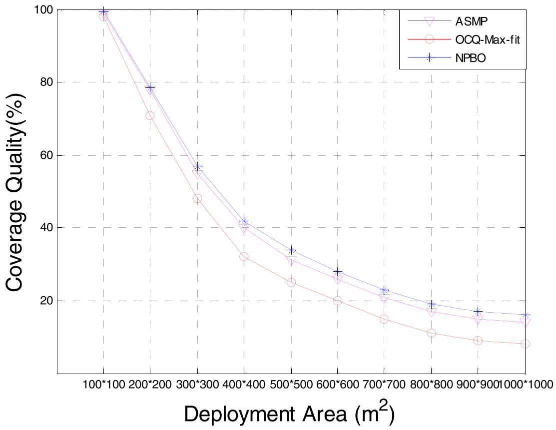


FIGURE 8. The NPBO algorithm is compared with ASMP and OCQ-Max-fit algorithm on coverage quality in diverse deployment region.

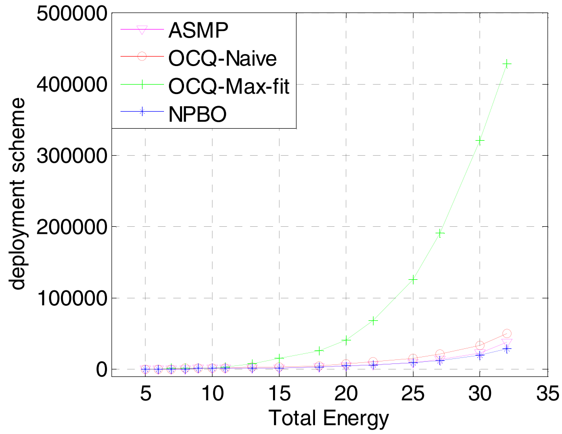


FIGURE 10. The NPBO algorithm is compared with ASMP, OCQ-Naïve and OCQ-Max-fit algorithm on deployment schemes with diverse total energy.

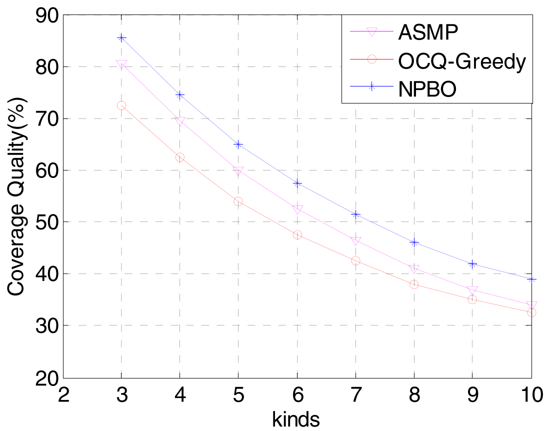


FIGURE 9. The NPBO algorithm is compared with ASMP and OCQ-Greedy algorithm on coverage quality with different kinds of sensors.

Fig.9 demonstrates that the coverage quality gets worse with the increase of the sensor types. Fig.9 indicates that the coverage quality of NPBO is more superior to ASMP and OCQ-Greedy algorithm, especially in the case of a large variety of sensors. As the compound event is composed by many sub-events, when the total energy is fixed, the coverage quality will get worse with the increase of the sensor types. The NPBO algorithm can adapt to complex network environment. Therefore, the quality of coverage is better than OCQ-Greedy and ASMP algorithm with the increase of the sensor types.

Fig.10 shows that as the total energy increases, the amount of deployment schemes generated by four algorithms continues to increase. It can be seen from Fig.10, the growth of the deployment schemes generated by NPBO algorithm is slower than ASMP, OCQ-Naïve and OCQ-Max-fit algorithm, especially in the case of sufficient total energy. The deployment schemes can be defined as there are diverse methods to apply different kinds and numbers of sensors with the same energy constraint. There are many types of sensors in the network, and each type of sensor contains a different number of sensors. If the network is not constrained by energy, the deployment methods of the network are infinite. In the energy constrained network, there are many deployment methods that meet the energy constraints of the network. Each of method can be defined as a deployment scheme. With the increase of the total energy, there will be more methods to apply diverse kinds and number of sensors, namely, there will be more deployment schemes. Once the number of deployment schemes increases, the computation and network load will increase dramatically. As a result, the total energy in the network will be consumed rapidly. So, the fewer deployment schemes the algorithm generates, the faster the network transmits; the fewer deployment schemes the algorithm generates, the lower energy the network consumes; the fewer deployment schemes generated by the algorithm, the higher operational efficiency of network.

With the increase of the total energy, each algorithm will generate more deployment schemes. It can be seen from Fig.10, the growth rate of deployment mechanism generated by NPBO algorithm is much slower than that generated by the other three algorithms. That is to say, the NPBO algorithm has higher operational efficiency than the other three algorithms. As the non-preference bi-objective evolution strategy is more suitable for the optimization problem whose global optimal solution near the boundary of the feasible domain. So the NPBO algorithm produces less invalid solutions. And the NPBO algorithm is more effective to find out the global optima.

VII. CONCLUSION AND FUTURE WORK

In the sections above, a CEBC mechanism on the basis of non-preference bi-objective evolution strategy is proposed aiming at 3-D space constraints. Aiming at the application of multiple constraints barrier coverage, the non-preference bi-objective evolution strategy transforms a variety of complicated constraints into another objective function to solve, which decreases computing costs effectively. Finally, the experimental results demonstrate the performance of the NPBO algorithm in 3-D sensor networks.

The event coverage with multiple constraints has many practical applications, such as air quality monitoring, public safety monitoring and water pollution control. At the meantime, camera sensors will be applied for better monitoring performance which may cause the privacy issues. In the future, we will put more effort on privacy issues in the event coverage.

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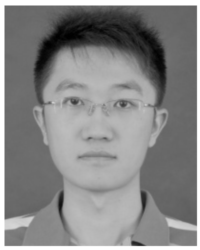

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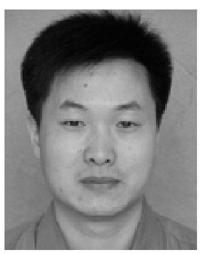

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