3-D Multiobjective Deployment of an Industrial Wireless Sensor Network for Maritime Applications Utilizing a Distributed Parallel Algorithm

Bin Cao, *Member, IEEE*, Jianwei Zhao, Po Yang, *Member, IEEE*, Zhihan Lv, *Member, IEEE*, Xin Liu, and Geyong Min, *Member, IEEE*

***Abstract*—Effectively monitoring maritime environments has become a vital problem in maritime applications. Traditional methods are not only expensive and time consuming but also restricted in both time and space. More recently, the concept of an industrial wireless sensor network (IWSN) has become a promising alternative for monitoring next-generation intelligent maritime grids, because IWSNs are cost-effective and easy to deploy. This paper focuses on solving the issue of 3-D IWSN deployment in a 3-D engine room space of a very large crude-oil carrier and also considers numerous power facilities. To address this 3-D IWSN deployment problem for maritime applications, a 3-D uncertain coverage model is proposed that uses a modified 3-D sensing model and an uncertain fusion operator. The deployment problem is converted into a multiobjective optimization problem that simultaneously addresses three objectives: *coverage*, *lifetime,* and *reliability*. Our goal is to achieve extensive coverage, long network lifetime, and high reliability. We also propose a distributed parallel cooperative coevolutionary multiobjective large-scale evolutionary algorithm for maritime applications. We verify the effectiveness of this algorithm through experiments by comparing it with five state-of-the-art algorithms. Numerical results demonstrate that the proposed method performs most effectively both in optimization performance and in minimizing the computation time.**

***Index Terms*—3-D engine room, multiobjective evolutionary algorithm (MOEA), very large crude-oil carrier (VLCC), wireless sensor network deployment.**

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I. Introduction

Recently, due to such advantages, as automatic operation, simple deployment, real-time performance, and cost effectiveness, industrial wireless sensor networks (IWSNs) have become promising alternatives for next-generation intelligent maritime grid (IMG) applications. Numerous studies have been conducted on the use of IWSNs for monitoring maritime environments, including sensor designs and deployment [1], systems architecture and efficiency [2], [3], communication and optimization techniques [4], [5], and so on.

Among these issues, the IWSN deployment problem is a fundamental challenge in IMG security monitoring and operational management [6], [7]. However, thus far, most existing current research on IWSNs has assumed that these networks are deployed in terrestrial 2-D environments and can be optimized by applying a probabilistic fusion operator [8]–[11] using omnidirectional 2-D sensing models, such as the disk/Boolean sensing model [12], the Elfes sensing model [13], and the Li sensing model [14]. While the above-mentioned methods have achieved promising performances in addressing traditional coverage optimization problems in ideal 2-D IWSN environments, meeting the practical requirements of IWSN deployments in real-world 3-D situations are still difficult. Additionally, for many maritime applications, the environment is highly sensitive to the effects of human activities, etc. Therefore, developing new effective IWSN deployment solutions for maritime applications are important.

The goal of this paper lies in exploring the possibility of utilizing biologically inspired optimization algorithms to efficiently solve the deployment problem in 3-D IWSNs for maritime applications. Here, we study the 3-D deployment problem of an IWSN in a 3-D engine room space of a very large crude-oil carrier (VLCC), in which many power facilities exist. To better consider the coverage problem and improve the precision and practicability of deployment, we propose a 3-D directional coverage model that simultaneously considers not only sensing distance but also horizontal and vertical sensing angles in a nonprobabilistic measure fashion. In addition, our model includes support for heterogeneous directional sensor nodes [15] that offers improved practicability.

Inspired by the idea of [16], we consider balancing the energy consumed by relay nodes to maximize the lifetime. Additionally, the reliability is guaranteed by ensuring that each node is associated with multiple relay nodes. Rather than treating the reliability as a constraint, we transform it into an objective for optimization. Because our model considers the three above-mentioned objectives simultaneously, the deployment problem can be characterized as a multiobjective optimization problem (MOP). Finally, we investigate and utilize multiobjective evolutionary algorithms (MOEAs) to analyze and optimize this 3-D deployment problem in 3-D maritime applications. The main contributions of this paper are as follows.

1) For the operational management and security monitoring of IMGs, we present a novel IWSN coverage model for a 3-D engine room in a practical maritime application that uses a modified 3-D sensing model and an uncertain fusion operator.
2) We consider the deployment problem with heterogeneous sensors in a 3-D engine room space of a VLCC, in which many power facilities exist that are also considered. We transform the problem of deployment in 3-D IWSNs for maritime applications into a multiobjective deployment problem by simultaneously considering three factors: *coverage*, *lifetime,* and *reliability*.
3) We propose and evaluate a distributed parallel cooperative coevolutionary multiobjective large-scale evolutionary algorithm (DPCCMOLSEA) to tackle the above-mentioned problem. Additionally, to reduce the computation time, this algorithm employs message-passing interface (MPI) parallelism.

The remainder of this paper is organized as follows. Section II reviews the related literatures. Section III describes the 3-D engine room deployment problem and presents related preliminaries. We provide a detailed introduction to the novel 3-D uncertain coverage model in Section IV. Section V describes the three considered objective functions, details the lifetime and reliability objectives, and provides the representation of individuals in the population for the MOEAs. The proposed algorithm is presented in Section VI. We report our experimental results and analyses in Section VII, and the paper is concluded in Section VIII.

II. Literature Review

Over the past few years, IWSNs have been widely studied and utilized in many industrial applications related to forest monitoring [17], agricultural monitoring [18], and healthcare [19], [20]. Compared to the practical working environments of these applications, maritime environment systems are highly sensitive to the influence of human activities. In maritime environment research, IWSN-based approaches improve generation of real-time data covering long periods and large areas significantly [21]. Typically, an IWSN-based maritime system must measure various physical and chemical parameters. For instance, in the 3-D engine room space of a VLCC, an IWSN system should monitor mechanical and environment parameters in the 3-D space and also, potentially, some human activities. To achieve this goal, it requires embedding wireless network sensor nodes into the maritime application environment at a large scale. Hence, effectively optimizing the deployment of 3-D IWSNs in complex maritime application environments is a key research problem for designing and developing adaptive, scalable, and self-healing IWSN systems for maritime applications.

Traditionally, the real-world IWSN deployment problem has been considered as a 2-D single-objective task, which means that the core deployment target is to maximize a single goal, such as robustness, energy consumption, scalability, adaptability, self-healing, simplicity, and so on. The sensing models that have been considered in traditional maritime wireless sensor networks (MWSNs) [22]–[24] are quite simple and mostly deployed on a 2-D plane. While the above-mentioned methods have demonstrated promising performances in addressing the traditional coverage optimization problem in ideal 2-D IWSN environment, achieving the multiple practical requirements of IWSN deployment in real-world 3-D cases is still difficult.

To address the problem of extending the sensing model into 3-D space, some researches have attempted to extend the 2-D solution from a 2-D ideal plane region-of-interest (RoI) to a full 3-D space RoI. Brown *et al.* [25] provided a solution for the full 3-D-space coverage problem for wireless video sensor networks (WVSNs). Yang *et al.* [26] attempted to minimize the cost for the target coverage problem in a 3-D space above a 3-D terrain. However, the above-mentioned studies did not consider network lifetime or energy consumption [27]. In practical maritime environment applications, the sensor nodes in IWSNs have limited battery power. Thus, sensor node energy consumption is an important aspect of sensor networks.

Regarding the existing multitask sensing models, Wang *et al.* [28] simultaneously considered connectivity, cost, and lifetime. To prolong the lifetime, Kuila and Jana [16] utilized a heterogeneous structure involving both sensor and relay nodes simultaneously in which the energy consumptions of the different node types were considered simultaneously. The energy consumed by each relay node was comprehensively balanced with respect to the sensor nodes for relaying information, data aggregation, and extra energy consumed when acting as a hop node for other relay nodes.

In [27], Wang *et al.* guaranteed reliability by ensuring that each node was associated with multiple relay nodes. In this paper, we also consider the IWSN reliability; however, rather than treating the reliability objective as a constraint, we transform it into an objective to be optimized. So, the deployment problem of 3-D IWSNs in maritime applications is actually a 3-D

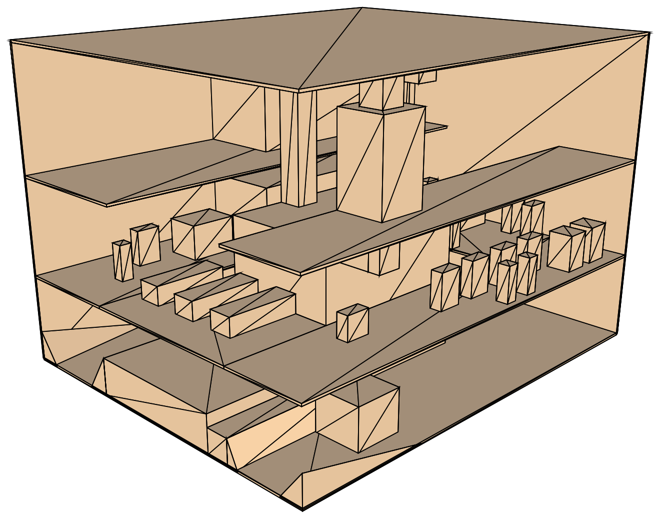

Fig. 1. Engine room model of a VLCC.

multiobjective problem, which requires effective optimization algorithms applying for 3-D sensing models to solve it. So far the practically efficient solutions for dealing with this issue are rare. In this paper, we aim at exploring the possibility of utilizing biologically inspired optimization algorithms with modified 3-D sensing model to efficiently solve the deployment problem in 3-D IWSNs for maritime application.

Regarding multiobjective algorithms, many studies have been conducted in other wireless sensor networks. Hacioglu *et al.* [29] considered multiple aspects of energy consumption and applied the nondominated sorting genetic algorithm II (NSGA-II) [30]. In [31], Jameii *et al.* simultaneously considered coverage, energy consumption, and the quantity of active sensors and also utilized the NSGA-II. Sengupta *et al.* [32] formulated the deployment problem with respect to three objectives: lifetime, coverage, and the connectivity constraint. To solve this MOP, they blended fuzzy Pareto dominance with a multiobjective evolutionary algorithm based on decomposition (MOEA/D) [33], and proposed MOEA/DFD, which outperformed both popular MOEAs and several single-objective evolutionary algorithms (EAs).

III. Preliminaries and Problem Simulation

For the maritime application, we regard the 3-D engine room space of a VLCC as a cuboid inside of which facilities are represented by smaller cuboids, as shown in Fig. 1. To perform the mathematical simulation, we discretize the engine room space, constructing a 3-D matrix in which a 0 represents free space and a 1 denotes obstacle (e.g., facilities, bulkheads, and upper decks).

A. Line of Sight (LOS) [34]

For a sensor s attempting to observe a target t in 3-D space, when no obstacle blocks the sight line joining them, then s and t can "see" each other, and we say that a LOS exists; otherwise, a non-LOS (NLOS) condition prevails between them. The LOS condition is a prerequisite for sensor s to be able to detect point t.

B. Deployment Positions

1) Sensor Nodes: The deployment positions of the wireless sensors are restricted, that is, directional wireless sensors can be deployed on the bulkheads and the upper decks of the engine room. However, not all position points are feasible deployment positions (e.g., obstacles exist). To restrict the coordinates of the deployment points, we utilize a penalty, p_S:

$$p_S = n_S^{\text{infeasible}} \times \text{penalty} \tag{1}$$

where $n_S^{\text{infeasible}}$ represents the number of infeasible sensor positions, and $penalty$ denotes the penalty parameter, which is assigned a huge value (e.g., 10^6).

2) Relay Nodes: Because the relay nodes collect messages from directional sensors, they are also deployed on the bulkheads and the upper decks. Thus, we also apply a penalty p_R for the relay nodes:

$$p_R = n_R^{\text{infeasible}} \times \text{penalty} \tag{2}$$

where $n_R^{\text{infeasible}}$ represents the number of infeasible points for relay node deployment.

IV. Uncertain Coverage Model

The coverage model consists of a sensing model and a fusion operator. The sensing model applies to an individual sensor, whereas the fusion operator describes the cooperation among multiple sensors. In the following sections, we describe the coverage model which we use in greater detail.

A. Sensing Model

In a 3-D space, the sensing intensity $P^S(s,t)$ that a sensor s can sense a target point t can be calculated as follows:

$$P^S(s,t) = P_{\text{LOS}}^S(s,t) \times P_D^S(s,t) \times P_P^S(s,t) \times P_T^S(s,t) \tag{3}$$

where $P_D^S(s,t)$, $P_P^S(s,t)$, and $P_T^S(s,t)$ are the sensing intensity associated with the sensing distance, the horizontal sensing angle, and the vertical sensing angle, respectively, and $P_{\text{LOS}}^S(s,t)$ is a two-valued function with the following form:

$$P_{\text{LOS}}^S(s,t) = \begin{cases} 1, & \text{if LOS} \\ 0, & \text{if NLOS.} \end{cases} \tag{4}$$

Below, we first describe the distance-based sensing model and then the angular sensing model.

1) Distance-Based Sensing Model: The Li sensing model [14] is used. Let the deterministic sensing distance be denoted by R_d, and let the fuzzy distance be R_f. The mathematical representation is as follows:

$$P_D^S(s,t) = \begin{cases} 1, & r(s,t) \in [0, R_d] \\ e^{\left(-\alpha_1 r_1^{\beta_1}/r_2^{\beta_2} + \alpha_2\right)}, & r(s,t) \in (R_d, R_d + R_f) \\ 0, & r(s,t) \in [R_d + R_f, +\infty) \end{cases} \tag{5}$$

where $r_1 = r(s,t) - R_d$; $r_2 = R_d + R_f - r(s,t)$; α_1, α_2, β_1, and β_2 are parameters; and sensors with various characteristics can be simulated by adjusting their values.

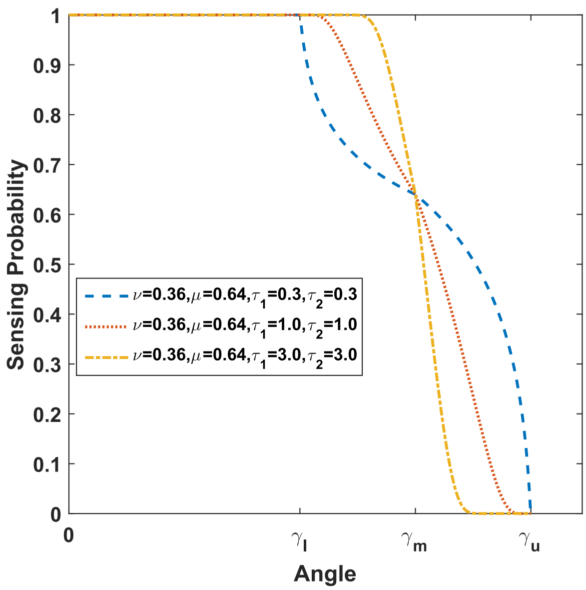

Fig. 2. Angular sensing model characteristics.

2) Angular Sensing Model: We consider two angular sensing dimensions: the horizontal angular range and the vertical angular range. By calculating the sensing intensity with respect to these two angles, we can then obtain the sensing intensity corresponding to any 3-D angle.

The sensing behaviors with respect to both angles are similar. We define three angle thresholds, γ_l^X, γ_m^X, and γ_u^X, where $\gamma_l^X \leq \gamma_m^X \leq \gamma_u^X$, and X denotes either P or T, referring to the horizontal or vertical direction, respectively. This model is

$$P_X^S(s,t) = \begin{cases} 1, & \delta_X(s,t) \in \left[0, \gamma_l^X\right] \\ 1 - \nu^X \times e^{1-\left(\frac{\gamma_m^X - \gamma_l^X}{\delta_X(s,t) - \gamma_l^X}\right)^{\tau_1^X}}, & \delta_X(s,t) \in \left(\gamma_l^X, \gamma_m^X\right] \\ 0 + \mu^X \times e^{1-\left(\frac{\gamma_u^X - \gamma_m^X}{\gamma_u^X - \delta_X(s,t)}\right)^{\tau_2^X}}, & \delta_X(s,t) \in \left(\gamma_m^X, \gamma_u^X\right) \\ 0, & \delta_X(s,t) \in \left[\gamma_u^X, +\infty\right) \end{cases}$$
$$\text{s.t. } \delta_X(s,t) = |rt_X \times \varepsilon_X(s,t)| \quad (6)$$

where $\varepsilon_X(s,t)$ is the deflection angle; $\delta_X(s,t)$ is its modified value; rt_X is the modification ratio; ν^X, μ^X, τ_1^X, and τ_2^X are parameters used to simulate different sensing characteristics; and $\nu^X + \mu^X = 1$, $\nu^X, \mu^X \in [0,1]$. The model characteristics for different parameter values are illustrated in Fig. 2.

B. Uncertain Fusion Operator

At a given point t in a 3-D space, the sensing regions of multiple sensors may overlap. The traditional method for addressing this situation is based on the additivity of probability. However, in a practical environment, various sources of interference may exist; consequently, the sensing intensity may not be additive. Therefore, we utilize the Sugeno measure [35], [36] to simulate the fused sensing behavior of multiple sensors. For the sensor set $S = \{s_1, s_2, \ldots, s_{N_S}\}$ (where N_S is the number of sensors), we can calculate the fused sensing intensity $P_S^F(t)$ for point t as follows [36]:

$$P_S^F(t) = \min\left(1, \frac{1}{\lambda} \times \left\{\prod_{k=1}^{N_S}\left[1 + \lambda \times P^S(s_k, t)\right] - 1\right\}\right) \quad (7)$$

where $-1 \leq \lambda < 0$ is an adjustable parameter used to simulate different environments. The Sugeno measure [35], [36] is a type of nonprobabilistic measure that possesses the characteristic of weak additivity; when $\lambda = -1$, the Sugeno measure operator becomes a probabilistic measure operator.

To determine whether t can be detected, we define a threshold P_{th}^F to convert the sensing intensity $P_S^F(t)$ into the two-valued sensing result $P_S^{\mathrm{BF}}(t)$:

$$P_S^{\mathrm{BF}}(t) = \begin{cases} 1, & P_S^F(t) \geq P_{th}^F \\ 0, & \text{otherwise.} \end{cases} \quad (8)$$

The quality-of-coverage (QoC) metric can be defined as the average coverage degree of the entire 3-D space:

$$\mathrm{QoC} = \frac{1}{N}\sum_{k=1}^{N} P_S^{\mathrm{BF}}(t_k) \quad (9)$$

where N denotes the considered quantity of discrete points inside the 3-D space.

V. Optimization Objectives and Representation of Individuals in the Population

The deployment problem is converted into an MOP by simultaneously considering the calculation of the QoC, the lifetime, and the reliability. MOEAs are utilized for such optimizations. In the following, we will discuss these issues in detail.

A. Coverage

We need to guarantee extensive coverage of the 3-D engine room space. Let f_{Coverage} denote the value of the objective function for *coverage*, which has the following form:

$$f_{\text{Coverage}} = 1.0 - \mathrm{QoC}. \quad (10)$$

B. Lifetime

According to the radio propagation model for energy consumption introduced in [37], we have

$$E^t\left(l^d, d\right) = \begin{cases} l^d E_0 + l^d \varepsilon_{fs} d^2, & d < d_{th} \\ l^d E_0 + l^d \varepsilon_{mp} d^4, & d \geq d_{th} \end{cases} \quad (11)$$

and

$$E^r\left(l^d\right) = l^d E_0 \quad (12)$$

where E^t and E^r are the energy used for transmitting and receiving messages, respectively, l^d is the quantity of a message; d denotes the distance between the transmitter and the receiver; d_{th} is a threshold that determines whether the freespace (fs) or the multipath (mp) model is adopted; E_0 represents the electronics energy; and ε_{fs} and ε_{mp} are the amplifier energy parameters for the freespace (fs) and multipath (mp) models, respectively.

The lifetime issue [16] mainly considers the relay nodes as described below.

The relay nodes gather messages from sensor nodes and transmit them to the sink node either directly or indirectly using other relay nodes as hop nodes. Thus, we should balance the nodes' energy consumption by comprehensively considering the number of messages and the transmission distances. Simply, among relay nodes nearer to the sink node, the nearest one is chosen as the next hop of the current relay node; otherwise, the current relay node is nearest to the sink node, and messages are directly transferred to the sink node.

Therefore, the *lifetime* objective function, f_{Lifetime}, has the following form:

$$f_{\text{Lifetime}} = \frac{v_L^{\text{scale}}}{L_{\text{min}}^{\text{RN}}} \tag{13}$$

where v_L^{scale} is a scale value used to guarantee that the value of f_{Lifetime} is within $[0, 1)$. Here, v_L^{scale} is set to 10^4, and $L_{\text{min}}^{\text{RN}}$ represents the minimum lifetime of all relay nodes.

C. Reliability

Based on the work of Wang *et al.* [27], we transform the reliability constraint into an optimizable objective. Assuming that each sensor or relay node is connected to N_R^{relia} relay nodes, the fitness value for the *reliability* objective is calculated in the following:

$$f_{\text{Reliability}} = \frac{\sum_{i=1}^{N_S} \overline{d^S}_i \;/\; N_S + \sum_{i=1}^{N_R} \overline{d^R}_i \;/\; N_R}{v_R^{\text{scale}}} \tag{14}$$

where $\overline{d^S}_i$ denotes the average distance of a sensor node i to its nearest N_R^{relia} relay nodes, $\overline{d^R}_i$ is the above-mentioned distance for relay node i, N_R denotes the quantity of relay nodes, and v_R^{scale} denotes a scale value.

D. Representation of Individuals in the Population

Because there are three rooms (see Fig. 1) in the target space and because nodes can be deployed on the bulkheads and upper decks of each room, an indicator is utilized to denote which plane (out of a total of 15 planes) is considered.

The directional sensor s_i^S can be represented by the five-tuple $(b_i^S, x_i^S, y_i^S, \theta_i^{\text{PAN}}, \theta_i^{\text{TILT}})$, where b_i^S indicates the deployment plane, (x_i^S, y_i^S) denotes the position, and θ_i^{PAN} and θ_i^{TILT} are the horizontal and vertical sensing angles, respectively. Each relay node s_k^R is represented by a three-tuple (b_k^R, x_k^R, y_k^R), where b_k^R indicates the deployment plane, and (x_k^R, y_k^R) denotes the deployment position. Therefore, in the optimization algorithm, the set of all individuals in the population can be represented by $(s_1^S, \ldots, s_{N_S}^S, s_1^R, \ldots, s_{N_R}^R)$, whose dimension $nDim$ is $(N_S \times 5 + N_R \times 3)$.

VI. Proposed Algorithm

To address the 3-D multiobjective deployment problem of an IWSN for the maritime application, we propose an algorithm

Algorithm 1: DPCCMOLSEA.

Separate large numbers of variables into several groups;
Uniformly distribute all MPI resources to all groups;
Form a species in the master CPU for each group;
while *The number of fitness evaluations is below a maximum* **do**
  /* Evolution */
  Evolve the variables in the group in each master CPU serially while processing all groups in parallel;
  /* Crossover */
  The remaining variables are generated through crossover;
  /* Evaluation */
  Master CPUs allocate the generated offspring; then, the fitness evaluations are performed in parallel in all CPUs, and the fitness values are collected by the master CPUs;
  /* Updating species */
  In the master CPUs, based on the fitness values of the generated offspring, update the species;
  /* Synchronizing species */
  All the master CPUs communicate with each other;
Gather the individuals in all species, and generate the final population by selecting the best individuals;

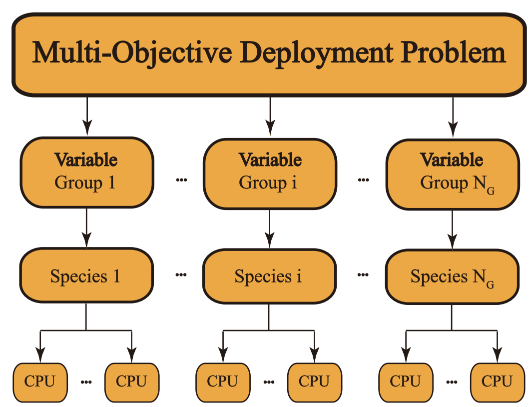

Fig. 3. Organization of DPCCMOLSEA for the considered problem.

called the distributed parallel cooperative coevolutionary multi-objective large-scale evolutionary algorithm (DPCCMOLSEA), which is implemented in the MPI parallel environment. DPCCMOLSEA is based on decomposition. For an MOP, we first separate all the variables into several groups, each of which forms a species. The computational burden of each species is allocated to CPU resources.

A. Overall Structure

The pseudocode of DPCCMOLSEA is provided in Algorithm 1, and its overall structure is illustrated in Fig. 3. Similar to our previously proposed Distributed Parallel Cooperative Coevolutionary Multi-objective Evolutionary Algorithm (DPCCMOEA) [38], the variables are separated into several groups and each group is optimized by a species. However, for the

TABLE I
PARAMETER SETTINGS FOR THE COVERAGE MODEL

Symbol	Attribute	Quantity
N_S	Number of directional sensors	17
N_R	Number of relay nodes	9
(α_1, α_2)	Distance sensing model parameters	(1.0, 0.0) [14]
(β_1, β_2)		(1.5, 1.0) [14]
R_d	Deterministic sensing distance	$[15, 24] \times 2$ m [15]
R_f	Fuzzy sensing distance	$1.0 \times R_d$
γ_l^X [1]	Lower bound on fuzzy sensing angle	$[\pi/6, 2\pi/9]$ [15]
γ_m^X	Middle bound on fuzzy sensing angle	$1.5 \times \gamma_l^X$
γ_u^X	Upper bound on fuzzy sensing angle	$2.0 \times \gamma_l^X$
(τ_1^X, τ_2^X)	Angle sensing model parameters	(3.6, 3.6)
(ν^X, μ^X)	Angle sensing model parameters	(0.5, 0.5)
rt_{PAN}	Modification ratio	1.0
rt_{TILT}		1.3
λ	Fusion parameter	-0.5 [36]
P_{th}^F	sensing intensity threshold	0.9 [36]

[1] X denotes PAN or TILT.

TABLE II
PARAMETER SETTINGS FOR ALGORITHMS

Symbol	Attribute	Quantity
F	Scale factor in DE	0.5
CR	Crossover rate in DE	1.0
p_c	*SBX* crossover probability	1.0
p_m	*Polynomial mutation* probability	$1/nDim$
η_c	Distribution index of *SBX*	20
η_m	Distribution index of *polynomial mutation*	20
niche	Neighborhood size	$0.1 \times NP$
limit	Replace limit	$0.01 \times NP$
P_{slct}	parent selection probability	0.9
N_{Contr}	Number of control property analyses	20
N_{Depen}	Number of interdependence analyses	6 (MOEA/DVA) 1 (others)

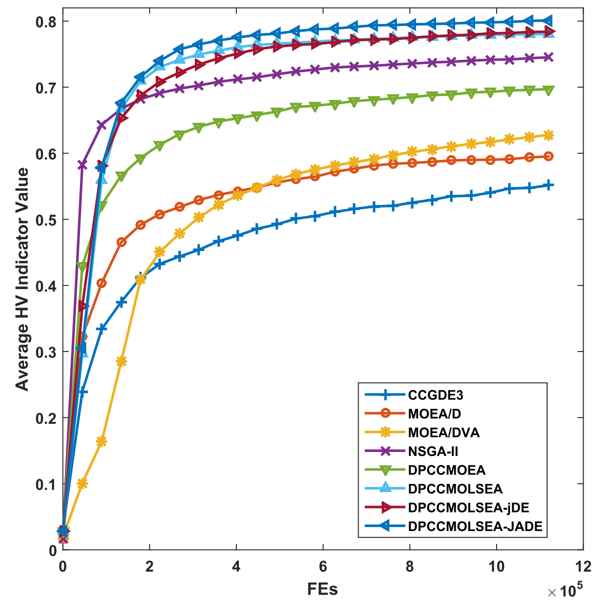

Fig. 4. Evolutionary curves of the average HV indicator values obtained by all algorithms.

TABLE III
AVERAGE RANKINGS OF ALGORITHMS (FRIEDMAN) AND THE WILCOXON TEST RESULTS FOR DPCCMOLSEA-JADE

Algorithm	Ranking	R^+	R^-	P-value
DPCCMOLSEA-JADE	1.700	/	/	/
DPCCMOLSEA-jDE	2.250	162	48	$3.2760E-2$
DPCCMOLSEA	2.500	158	52	$4.8440E-2$
NSGA-II	3.700	209	01	$3.8140E-6$
DPCCMOEA	5.050	210	00	$1.9074E-6$
MOEA/DVA	6.100	210	00	$1.9074E-6$
MOEA/D	7.100	210	00	$1.9074E-6$
CCGDE3	7.600	210	00	$1.9074E-6$

second layer, in DPCCMOEA, individuals are further allocated to the CPUs owned by each species, and each CPU is in charge of the evolution and fitness evaluations (FEs) of individuals. In contrast, in the proposed DPCCMOLSEA, a master CPU is responsible for the evolution of the individuals in each species, while the computational burden of FEs is shared by all the CPUs. The difference is in the lower layer—whether the evolution of individuals is conducted by a single master CPU or delegated to all CPUs.

B. Optimization

DPCCMOLSEA inherits the evolution pattern of DPCC-MOEA, which was borrowed from MOEA/D [33]. Thus, each individual relies on its neighborhood for evolution. In DPCC-MOEA, as individuals in each species are separated into several sets, the neighborhood relationship is gradually cut off; the updating process also involves these disrupted neighborhoods. In contrast, DPCCMOLSEA evolves all individuals of a species in a single master CPU (see Line 5), which is the same process that occurs in serial algorithms; thus, it comprehensively capitalizes on the mutual relations among the individuals in an entire species.

C. Crossover

Each species optimizes a group of variables using differential evolution (DE) [39]; specifically, *DE/rand/1* is the form applied in DPCCMOEA, while in DPCCMOLSEA, we also experiment with jDE [40] and JADE [41] (denoted as DPCCMOLSEA-jDE and DPCCMOLSEA-JADE, respectively).

For convenience, each species stores the other variables as well as the optimized variables. To form a complete solution, these remaining variables should be integrated. For this, we use crossover (see Line 6); that is, all the evolved variables in the current optimized group are reserved in the generated offspring, while the stored parent and other selected stored solutions are utilized to generate the remaining variables through crossover. In DPCCMOEA, half the remaining variables come from the stored parent, whereas in DPCCMOLSEA, we use a fixed value of 0.5 for *DE/rand/1* and the corresponding adaptive strategies for jDE and JADE.

VII. EXPERIMENTAL RESULTS AND ANALYSES

We conduct experiments to validate the optimization effectiveness and efficiency of the proposed algorithm for the

TABLE IV
AVERAGE COMPUTATION TIMES OF ALL ALGORITHMS AND THE SPEEDUP RATIOS OF DPCCMOLSEA WITH RESPECT TO OTHER ALGORITHMS

TIME	CCGDE3	MOEA/D	MOEA/DVA	NSGA-II	DPCCMOEA	DPCCMOLSEA	DPCCMOLSEA-jDE	DPCCMOLSEA-JADE
MEAN ($\hat{T}2$)	4.84E+03	4.70E+03	4.42E+03	4.60E+03	**7.07E+01**	**7.72E+01**	**8.08E+01**	**8.30E+01**
Speedup Ratio	6.27E+01	6.10E+01	5.73E+01	5.97E+01	**9.16E-01**	**/**	**1.05E+00**	**1.08E+00**
$T1$	3.25E+03	3.25E+03	3.25E+03	3.25E+03	4.51E+01	4.51E+01	4.51E+01	4.51E+01
$\hat{T}2 - T1$	1.59E+03	1.45E+03	1.17E+03	1.35E+03	2.56E+01 (1.84E+03)	3.21E+01 (2.31E+03)	3.57E+01 (2.57E+03)	3.79E+01 (2.73E+03)

maritime application involving 3-D multiobjective deployment of an IWSN.

A. Experimental Setup

The parameter settings for the coverage model are listed in Table I. The proposed algorithm is compared with five MOEAs: Cooperative coevolutionary generalized differential evolution 3 (CCGDE3) [42], MOEA/D [33], multiobjective evolutionary algorithm based on decision variable analyses (MOEA/DVA) [43], NSGA-II [30], and DPCCMOEA [38]. Each algorithm is executed 20 times, and the quantity of FEs for each run is set to $[(N_S \times 5 + N_R \times 3) \times 10^4]$. All the algorithms are implemented in C++, and the experimental platform used for the simulations is the TianHe-2 supercomputer.

To ensure a fair comparison, the population size (NP) for all algorithms is set to 120. The quantity of species in CCGDE3 is set to 2, and the species size is 60.

The following list summarizes the components of all the algorithms.

1) DE is used in CCGDE3, MOEA/D, MOEA/DVA, DPCCMOEA, and DPCCMOLSEA.
2) *SBX* and *polynomial mutation* are used in NSGA-II; *polynomial mutation* is used in MOEA/D, MOEA/DVA, DPCCMOEA, and DPCCMOLSEAs.
3) MOEA/DVA, DPCCMOEA, and DPCCMOLSEAs are based on the decomposition framework of MOEA/D.
4) Variable analysis and grouping are performed in MOEA/DVA, DPCCMOEA, and DPCCMOLSEAs.

Correspondingly, the detailed parameter settings are summarized in Table II.

B. Results and Analysis

We utilize the hypervolume (HV) indicator [44] for the performance evaluation of the algorithms. A higher HV indicator value indicates a better optimization performance. In addition, the nondominated solution sets are visualized.

The evolutionary curves of the average HV indicator values are illustrated in Fig. 4, from which we can spot that DPCCMOLSEAs perform the best; specifically, DPCCMOLSEA-JADE outperforms the other algorithms. By comparing DPCCMOEA and DPCCMOLSEAs, we can deduce that the parallel structure modification is quite beneficial. Therefore, we can conclude that the comprehensive utilization of the mutual relations among all individuals of the species contributes significantly to the performance improvement. This is because DPCCMOEA and DPCCMOLSEAs are based on the optimization framework of MOEA/D, in which each individual utilizes individuals in the neighborhood as well as the whole species for evolution. In DPCCMOEA, the evolution of individuals is distributed as several parts, breaking the relations among individuals, whereas DPCCMOLSEAs conduct the evolution of all individuals in a species on a single master CPU, thus preserving all the interactions among individuals. Table III lists the statistical test [45], [46] results, including the rankings from the Friedman test and the Wilcoxon test with respect to the best algorithm, DPCCMOLSEA-JADE, from which we can see that DPCCMOLSEA-JADE is significantly better than the other algorithms (with p-values less than 0.05). The performance of DPCCMOLSEAs with different DE optimizers varies greatly: JADE is highly effective, while jDE is not particularly powerful, and is indistinguishable from *DE/rand/1*. Visualizations of all the nondominated solutions generated from the 20 runs by each algorithm are provided in the supplementary material and show that DPCCMOLSEAs optimize all the objectives.

C. Time and Space Complexities

Table IV lists the computation time of all algorithms. Because DPCCMOEA and DPCCMOLSEAs are parallel algorithms, they require much less computation time. The speedup ratio values are approximately 79.6%–87.1% of the ideal speedup (i.e., 72, which is the number of CPUs). DPCCMOLSEAs performed slightly more slowly than DPCCMOEA, a result that can be ascribed to the parallel structure modification. $T1$ represents the time consumed by FEs of the objective function, and $\hat{T}2$–$T1$ provides the time consumptions of the algorithms without the FEs (viz., the time complexity of each algorithm). Note that there are two time values for each parallel algorithm; the first denotes the time consumption for one MPI process, whereas the second (in parentheses) is the sum of the time consumed by all the MPI processes. Regarding the operation time, the time complexities of the parallel algorithms are significantly lower than those of the serial algorithms; however, if the time taken by all CPUs is considered, the serial ones perform better, which can be attributed to the communication load in parallel algorithms.

Considering the space complexity, the population is the most important factor. MOEA/D, MOEA/DVA, and NSGA-II are similar. In CCGDE3, the variables are separated to two groups; correspondingly, there are two subpopulations, each of which stores the variable group and also the complete individuals with all variables, which requires more space. For all the parallel algorithms, analogous to CCGDE3, corresponding to each group of variables, there is a species in the master CPU, while for the evaluation, extra space is needed for the remaining CPUs.

Therefore, in total, the space is doubled. Overall, the space complexity is summarized as follows: parallel algorithms > CCGDE3 > other algorithms.

VIII. Conclusion

In this paper, for the operational management and security monitoring of IMGs, we study the deployment of an IWSN in a 3-D engine room space of a VLCC with many power facilities. A novel 3-D uncertain coverage model consisting of a sensing model and an uncertain fusion operator is proposed. This approach allows the *coverage* to be calculated, and by simultaneously considering the *lifetime* and *reliability* objectives, we solve the deployment problem as a MOP. To address this MOP, we propose a novel method. Compared with several state-of-the-art algorithms, the proposed method performs the best with respect to both optimization performance and computation time (compared to serial algorithms). In future work, other objectives can also be considered. The parallelism of the proposed algorithm can be further improved through implementation on GPUs or MICs.

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