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

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Abstract—Effective monitoring marine environment has become a vital problem in the marine applications. Traditionally, marine application mostly utilizes oceanographic research vessel methods to monitor the environment and human parameters. But these methods are usually expensive and time-consuming, also limited resolution in time and space. Due to easy deployment and cost-effective, WSNs have recently been considered as a promising alternative for next generation IMGs. This paper focuses on solving the issue of 3D WSN deployment in a 3D engine room space of a very large crude-oil carrier (VLCC), in which many power devices are also considered. To address this 3D WSN deployment problem for maritime applications, a 3D uncertain coverage model is proposed with a new 3D sensing model and an uncertain fusion operator, is presented. The deployment problem is converted into a multi-objective problems (MOP) in which three objectives are simultaneously considered: Coverage, Lifetime and Reliability. Our aim is to achieve extensive Coverage, long Lifetime and high Reliability. We also propose a distributed parallel cooperative co-evolutionary multi-objective large-scale evolutionary algorithm (DPCCMOLSEA) for maritime applications. In the simulation experiments, the effectiveness of this algorithm is verified in comparing with five state-of-the-art algorithms. The numerical outputs demonstrate that the proposed method performs the best with respect to both optimization performance and computation time.

Index Terms—wireless sensor network deployment, 3D engine room, Very large crude-oil carrier (VLCC), Coverage, Lifetime, Reliability, Parallel, Multi-objective evolutionary algorithm.

I. INTRODUCTION

AS the increasing human activities being undertaken in the marine environment, effective and efficient monitoring marine environment has become a vital problem in the industrial applications. Traditionally, marine application mostly utilizes oceanographic research vessel methods [1-2] to monitor the environment and human parameters. But these methods are usually expensive and time-consuming, also limited resolution in time and space. Recently, due to the advantages of automatic operation, easy-deployment, real-time mode and cost-effective, industrial wireless sensor network (WSNs) have recently been considered as promising alternative for next generation intelligent maritime grid (IMG) applications. Many studies have been conducted on industrial WSNs for marine environment monitoring, including sensors design and deployments [3], systems architecture and efficiency [4-5], communication and optimisation techniques [6-7], etc.

Among these issues, the deployment problem of WSNs is a foundamental challenge for operational management and security monitoring of Intelligent Maritime Grids (IMGs). But so far most existing current research in WSNs assumes that these networks are deployed in a terrestrial 2D environment, and can be optimised by applying probabilistic fusion operator [11-14] with omni-directional 2D sensing models, like the disk/Boolean sensing model [8], the Elfes sensing model [9] and the Li sensing model [10]. While above methods have demonstrated promising performances on dealing with the traditional coverage optimisation problem in ideal 2D WSN environment, it is still difficult to achieve practical needs of WSN deployment in real word 3D cases. Especially, for many maritime application,

This paper aims at exploring the possibility of utilising biological inspired optimisation algorithms to efficiently solve the coverage problem in 3D WSNs for maritime application. In this paper, we study the 3D deployment problem of an IWSN in a 3D engine room space of a very large crudeoil carrier (VLCC), in which there are many power devices. To better consider the coverage problem, we propose a 3D directional sensing model by simultaneously considering the sensing distance and horizontal and vertical sensing angles, which is probabilistic to improve precision and practicability. Also, our model has considered supporting heterogeneous directional sensor nodes [21] with improved practicability.

In this paper, we inspired from the idea of particle swarm optimisation [22] and simultaneously deploy sensor nodes and relay nodes. Consequently, the energy consumptions of relay nodes are balanced to maximize the lifetime. For an IWSN, reliability is also crucial. In the work of [23], Wang et al. guaranteed reliability by ensuring the associations of each node to multiple relay nodes. In this paper, we also consider the reliability of the IWSN. Instead of making the reliability objective a constraint, we transform it into an objective to be optimized. Due to the fact that this model has considered three above objectives simultaneously, the deployment problem can

be characterized as a multi-objective optimization problem (MOP). Thus, we use multi-objective evolutionary algorithms (MOEAs) to address the deployment problem. Hacioglu et al. [24] considered multiple aspects of energy consumption, and Non-dominated Sorting Genetic Algorithm II (NSGA-II) [25] was applied. In the work of [24], Jameii et al. simultaneously considered coverage, energy consumption and the number of active sensors, and NSGA-II was also utilized. Sengupta et al. [26] formulated the deployment problem with respect to three aspects: lifetime objective, coverage objective and the connectivity constraint; to solve this MOP, they blended fuzzy Pareto dominance with Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D) [27], therein proposing MOEA/DFD, which outperformed popular MOEAs and several single-objective evolutionary algorithms (EAs). However, the above works only considered the 2D scenario; to our knowledge, studies having utilized MOEAs to solve the 3D engine room space deployment problem for maritime applications are rare. The main contributions of this paper are:

1. For the operational management and security monitoring of Intelligent Maritime Grids (IMGs), a novel WSN coverage model with a 3D sensing model and an uncertain fusion operator is proposed for 3D engine room in practical maritime applications.
2. We consider the deployment problem with heterogeneous sensors in a 3D engine room space of a VLCC, in which many power devices are also considered. The deployment in 3D WSN for maritime applications is transformed into a multi-objective deployment problem with simultaneous consideration of Coverage, Lifetime and Reliability.
3. An evolutionary optimization algorithm is proposed and evaluated for solving above problem. A modified MOEA, distributed parallel cooperative co-evolutionary multi-objective large-scale evolutionary algorithm (DPCCMOLSEA), is proposed; in addition to reduce the computation time, MPI (message passing interface) parallelism is utilized.

The remainder of this paper is organized as follows. Section II describes the 3D engine room deployment problem and related preliminaries. We provide a detailed introduction to the proposed novel 3D uncertain coverage model in Section III. Section IV describes the three objective functions considered, 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 V. We report our experimental simulations and analyses in Section VI, and the paper is concluded in Section VII.

II. Literature Review

During the last few years, WSNs (wireless sensor network) have been widely studied and utilised in many industrial applications, related to forest monitoring [28], agriculture monitoring [29], and healthcare [30-31]. Compared to the practical working environment of above applications, marine environment systems are quite sensitive to the effects of human activities. Traditionally, marine application mostly utilizes oceanographic research vessel methods [1-2] to monitor the environment and human parameters. But these methods are usually expensive and time-consuming, also limited resolution in time and space. For marine environment research, a WSN-based approach can dramatically improve the access to real-time data covering long periods and large geographical areas [32]. According to Tateson et al. [33], a WSN-based approach is at least one order of magnitude cheaper than a conventional oceanographic research vessel.

Typically, a WSN-based marine system needs to measure different physical and chemical parameters. While the development and deployment of an adaptive, scalable and self-healing WSN system need to address a number of critical challenges such as autonomy, scalability, adaptability, self-healing and simplicity [34], the design and deployment of a lasting and scalable WSN for marine environment monitoring should take into account the following challenges different from those on land [35]: stronger robustness, higher energy consumption, and sensor coverage problem, maintenance of sensor nodes.

There are many concerns relevant to the deployment problem, one of which is coverage [36-37]. The authors of [38] simultaneously considered connectivity, cost and lifetime. Similarly, in the present paper, in addition to the 3D space coverage, we also consider the lifetime of the IWSN. To prolong the lifetime, Kuila et al. [39] utilized a heterogeneous structure that contained both sensor nodes and relay nodes simultaneously. The energy consumptions of different types of nodes were considered simultaneously. The energy consumed by each relay node was comprehensively balanced with respect to the sensor nodes that it was in charge of, data aggregation, and extra energy consumption by acting as a hop node for other relay nodes. Consequently, the overall lifetime could be prolonged to a large extent.

Among these studies, the deployment problem of WSNs is a key issue for operational management and security monitoring of Intelligent Maritime Grids (IMGs). Traditional sensing models for 2-D sensor nodes are omni-directional and include the disk/Boolean sensing model [8], the Elfes sensing model [9] and the Li sensing model [10]. The most common fusion operator is the probabilistic fusion operator [11-12]. The traditional coverage models of WSNs are based on probability measures such as those in the problems of certain coverage discussed in [13-14]. While above studies have demonstrated promising performances on dealing with the coverage optimisation in ideal 2D WSN environment, it is still difficult to achieve practical needs of WSN deployment in real word 3D cases. However, most existing deployment strategies in WSNs focus on ideal 2D WSN environment, which are hardly to be applied in real maritime application environments. The sensing models considered in traditional maritime wireless sensor networks (MWSNs) [15-17] are very simple, mostly with the deployment on a 2D plane.

In light of coverage problem of the 3D space, the most common ways are to extend the 2D solution from 2D ideal plane region of interests (RoI) to 3D full space RoI. Brown et al. [18] provided solutions for the 3D full-space coverage problem for wireless video sensor networks (WVSNs). Yang et al. [19] attempted to minimize the cost for the target coverage problem in a 3D space

above a 3D terrain. However, the above studies did not consider network lifetime or energy consumption [20]. In real-world marine environment application, sensor nodes in WSNs have limited battery power. The energy consumption of sensor nodes is important for sensor networks. The lifetime is a result of energy consumption in WSNs. Consequently, so far there are no existing practically efficient solutions in literature for dealing with coverage and deployment problems in complex 3D surface of WSNs in marine environment application.

This paper aims at exploring the possibility of utilising biological inspired optimisation algorithms to efficiently solve the coverage problem in 3D WSNs for maritime application. In this paper, we study the 3D deployment problem of an IWSN in a 3D engine room space of a very large crudeoil carrier (VLCC), in which there are many power devices. To better consider the coverage problem, we propose a 3D directional sensing model by simultaneously considering the sensing distance and horizontal and vertical sensing angles, which is probabilistic to improve precision and practicability. Also, our model has considered supporting heterogeneous directional sensor nodes [21] with improved practicability.

In this paper, we inspired from the idea of particle swarm optimisation [22] and simultaneously deploy sensor nodes and relay nodes. Consequently, the energy consumptions of relay nodes are balanced to maximize the lifetime. For an IWSN, reliability is also crucial. In the work of [23], Wang et al. guaranteed reliability by ensuring the associations of each node to multiple relay nodes. In this paper, we also consider the reliability of the IWSN. Instead of making the reliability objective a constraint, we transform it into an objective to be optimized. Due to the fact that this model has considered three above objectives simultaneously, the deployment problem can be characterized as a multi-objective optimization problem (MOP). Thus, we use multi-objective evolutionary algorithms (MOEAs) to address the deployment problem. Hacioglu et al. [24] considered multiple aspects of energy consumption, and Non-dominated Sorting Genetic Algorithm II (NSGA-II) [25] was applied. In the work of [24], Jameii et al. simultaneously considered coverage, energy consumption and the number of active sensors, and NSGA-II was also utilized. Sengupta et al. [26] formulated the deployment problem with respect to three aspects: lifetime objective, coverage objective and the connectivity constraint; to solve this MOP, they blended fuzzy Pareto dominance with Multi-objective Evolutionary Algorithm Based on Decomposition (MOEA/D) [27], therein proposing MOEA/DFD, which outperformed popular MOEAs and several single-objective evolutionary algorithms (EAs). However, the above works only considered the 2D scenario; to our knowledge, studies having utilized MOEAs to solve the 3D engine room space deployment problem for maritime applications are rare.

III. Preliminaries and Problem Simulation

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

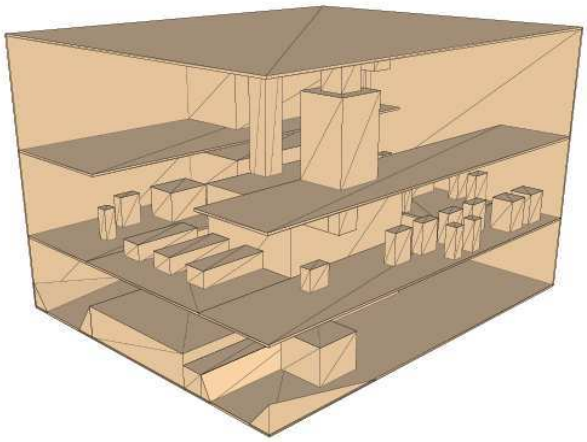

Fig. 1 Engine room model of a VLCC

A. Line of Sight (LOS)

For a sensor s attempting to observe a target point t in 3D space, if no obstacle blocks the sight line joining them, then s and t can "see" each other, and we say that there exists a Line of Sight (LOS); otherwise, the No Line of Sight (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: We restrict the deployment positions of the wireless sensors, that is, directional wireless sensors are deployed at the bulkheads and the upper decks of the engine room. However, not all position points are feasible (e.g., obstacles exist). To restrict the coordinates of the points, we utilize a penalty ps:

$$ps = n_S^{infeasible} \times penalty \quad (1)$$

Where $n_S^{infeasible}$ is 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: For the relay nodes, because they collect messages from directional sensors, they are also deployed at the bulkheads and the upper decks. Similarly, we also have a penalty pR for the relay nodes:

$$pR = n_R^{infeasible} \times penalty \quad (2)$$

Where $n_R^{infeasible}$ is the number of infeasible points of the relay node deployment.

IV. Uncertain Coverage Model

The coverage model consists of a sensing model and a fusion operator. The sensing model refers to an individual sensor, while the fusion operator describes the cooperation among multiple sensors. In the following, we describe our proposed coverage model in detail.

A. Sensing Model

In a 3D space, the sensing probability $P^S(s,t)$ of a sensor s to a target point t can be calculated as given by the equation below:

$$P^S(s,t) = P^S_{LOS}(s,t) \times P^S_D(s,t) \times P^S_P(s,t) \times P^S_T(s,t) \quad (3)$$

Where $P^S_D(s,t)$, $P^S_P(s,t)$ and $P^S_T(s,t)$ are the sensing probabilities associated with the sensing distance, horizontal sensing angle and vertical sensing angle, respectively, and $P^S_{LOS}(s,t)$ is a two-valued function with the following form:

$$P^S_{LOS}(s,t) = \begin{cases} 1, & \text{if LOS} \\ 0, & \text{if NLOS} \end{cases} \quad (4)$$

Below, we first describe the distance sensing model and then the angle sensing model.

1) Distance-based Sensing Model: The Li sensing model [10] 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

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

Where $r_1 = r(s,t) - R_d$; $r_2 = R_d + R_f - r(s,t)$; $\alpha_1, \alpha_2, \beta_1$ and β_2 are parameters; and sensors with various characteristics can be simulated by adjusting their values.

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

The sensing behaviours with respect to both angles are similar. We define three angle thresholds, γ_l^X , γ_m^X and γ_u^X , where $\gamma_l^X \le \gamma_m^X \le \gamma_u^X$, and X denotes PAN or TILT, referring to horizontal or vertical directions, respectively. This model can be described as follows:

$$P^S_X(s,t) = \begin{cases} 1, & \delta_X(s,t) \in [0, \gamma_l^X] \\ 1 - v^X \times e^{1-\left(\frac{\gamma_m^X - \gamma_l^X}{\delta_X(s,t) - \gamma_l^X}\right)^{\tau_1^X}}, & \delta_X(s,t) \in [\gamma_l^X, \gamma_m^X] \\ 0 + \mu^X \times e^{1-\left(\frac{\gamma_m^X - \gamma_l^X}{\delta_X(s,t) - \gamma_l^X}\right)^{\tau_1^X}}, & \delta_X(s,t) \in [\gamma_m^X, \gamma_u^X] \\ 0, & \delta_X(s,t) \in [\gamma_u^X, +\infty] \end{cases} \quad (6)$$

$$\text{s.t.} \delta_X(s,t) = \left| rt_X \times \varepsilon_X(s,t) \right|$$

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 $v^X + \mu^X = 1$, $v^X, \mu^X \in [0,1]$. For different parameter values, the characteristics of the model are shown in Fig.2.

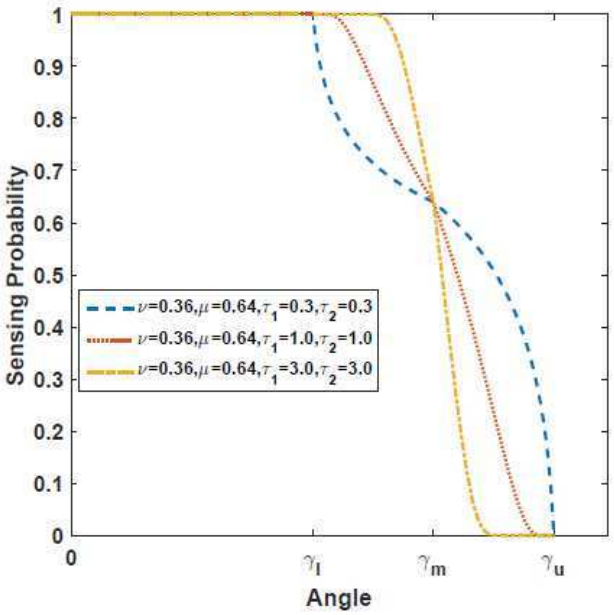

Fig. 2 Characteristics of the angular sensing model

B. Uncertain Fusion Operator

At a given point t in 3D 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, and consequently, the sensing probability may not be additive. Therefore, we utilize the Sugeno measure [40] to simulate the fused sensing behavior of multiple sensors. For the sensor set $S = \{s_1, s_2, ..., s_{Ns}\}$ (where N_S is the number of sensors), we can calculate their fused sensing probability $P^F_S(t)$ for point t as follows:

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

Where $-1 \le \lambda \le 0$ is an adjustable parameter that is used to simulate different environment. The Sugeno measure is a type of non-probabilistic measure that possesses the characteristic of weak additivity, and when $\lambda = -1$, the Sugeno measure becomes a probabilistic measure.

To determine whether t can be detected, we define a threshold P^F_{th} to convert the sensing probability $P^F_S(t)$ into the two-valued sensing result $P^{BF}_S(t)$:

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

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

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

Where N is the number of considered discrete points in the 3D 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. For the optimization, MOEAs are utilized. In the following, we will discuss these issues in detail.

A. Coverage

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

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

B. Lifetime

According to the radio model for energy consumption introduced in [29], we have

$$E^t(l^d,d)=\begin{cases}l^dE_0+l^d\varepsilon_{fs}d^2, & d<d_{th}\\ l^dE_0+l^d\varepsilon_{mp}d^4, & d\geq d_{th}\end{cases} \quad (11)$$

And

$$E^r(l^d)=l^dE_0 \quad (12)$$

Where E_t and E_r are the energy used for transmitting and receiving messages, respectively; l^d is the length of a message; d is the distance between the transmitter and the receiver; d_{th} is the threshold determining the adoption of the freespace model (fs) or the multipath model (mp); E_0 represents the electronics energy; and ε_{fs} and ε_{mp} are the amplifier energy parameters for the above two models, respectively.

The lifetime issue [38] mainly considers the relay nodes, which is detailed as follows:

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

Therefore, the objective function for the Lifetime objective, $f_{Lifetime}$, has the following form:

$$f_{Lifetime}=\frac{\upsilon_L^{scale}}{L_{min}^{RN}} \quad (13)$$

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

C. Reliability

Based on the work of [21], we transform the reliability constraint into an objective that can be optimized. Assuming that each sensor or relay node is connected to N_R^{relia} relay nodes, the fitness of the Reliability objective is as follows:

$$f_{Reliability}=\frac{\sum_{i=1}^{Ns}\overline{d_i^S}/Ns+\sum_{i=1}^{N_R}\overline{d_i^R}/N_R}{\upsilon_R^{scale}} \quad (14)$$

where $\overline{d_i^S}$ denotes the average distance of sensor node i to its nearest N_R^{relia} relay nodes, $\overline{d_i^R}$ is that distance with respect to relay node i, N_R is the number of relay node, and υ_R^{scale} is a scale value.

D. Representation of Individuals in the Population

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

The directional sensor s_i^S can be represented by the five tuple $(b_i^S, x_i^S, y_i^S, \theta_i^{PAN}, \theta_i^{TILT})$. Here, 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). Here, 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 $(s_1^S,...,s_{Ns}^S,s_1^R,...,s_{NR}^R)$, whose dimension nDim is $Ns\times 5+N_R\times 3$.

VI. Proposed Algorithm

To address the 3D multi-objective deployment problem of an industrial wireless sensor network for the maritime application, we propose an algorithm called the distributed parallel cooperative co-evolutionary 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 variables into several groups, for each of which we form a

species. Moreover, the computational burden of each species is allocated to the CPU resources.

A. Overall Structure

The pseudocode of DPCCMOLSEA is provided in Alg.1, and the overall structure is illustrated in Fig. 3. Similar to our previous proposed algorithm Distributed Parallel Cooperative Coevolutionary Multi-objective Evolutionary Algorithm (DPCCMOEA) [41], variables are separated into several groups, where each group is optimized by a species. However, for the 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 of individuals. For the proposed DPCCMOLSEA, in each species, a master CPU is responsible for the evolution of the individuals, while the computational burden of fitness evaluations is shared by all the CPUs. The difference is in, in the lower layer, whether the evolution of individuals is conducted by a single master CPU or delegated to all CPUs.

Algorithm 1: DPCCMOLSEA

1. Separate large numbers of variables to several groups:
2. **Uniformly distribute all MPI resources to all groups;**
3. **From a species in the master CPU for each group;**
4. **While** The number of fitness evaluations is not exhausted **Do**
   /* Evolution */
5. **Evolve the variables in the group in each master CPU in serial for all groups in parallel;**
   /* Crossover */
6. **Remaining variables are generated through crossover;**
   /* Evaluation */
7. **Master CPUs allocate the generated offsprings, the fitness evaluations are performed in parallel in all CPUs, and the fitness values are collected to the master CPUs;**
   /* Updating subpopulations */
8. **In the master CPUs, based on the fitness values of the generated offsprings, update the species;**
   /* Synchronizing subpopulations */
9. **All master CPUs communicate with each other;**
10. **Gather individuals in all species, and generate the final population by selecting the best individuals**

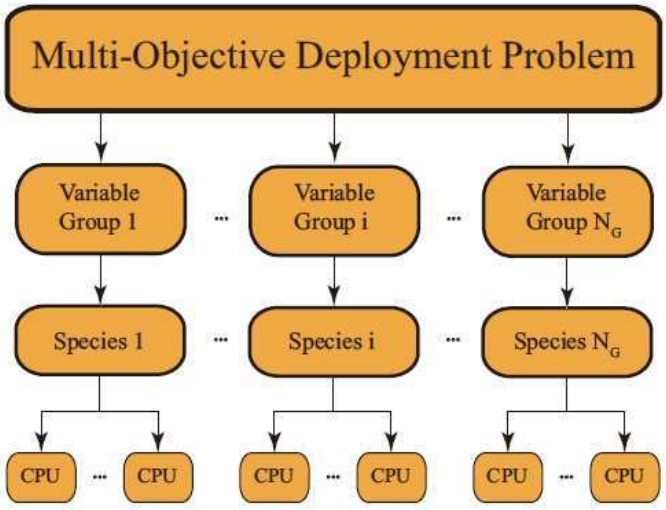

Fig. 3 Organisation of DPCCMOLSEA for the considered problem

B. Optimisation

The evolution pattern of DPCCMOEA, borrowed from MOEA/D [42], is inherited by DPCCMOLSEA. Thus, each individual refers its neighbourhood for evolution. In DPCCMOEA,as individuals in each species are separated into several sets, the neighbourhood relationship is cut off; the updating process also concerns the neighbourhood, which is also disrupted. In contrast, DPCCMOLSEA performs the evolution of all individuals of a species in a single master CPU, which is the same as in serial algorithms, thus comprehensively taking advantage of mutual relations among individuals for the whole species.

C. Crossover

Each species optimizes a group of variables, and differential evolution (DE) [43] is the optimizer used; specifically, DE/rand/1 is the detailed form in DPCCMOEA, while in DPCCMOLSEA, we also experiment with jDE [44] and JADE [45], denoted as DPCCMOLSEA-jDE and DPCCMOLSEAJADE, respectively.

For convenience, each species stores the other variables as well as the optimized variables. To form a complete solution, the remaining variables should be integrated. For this, we use crossover, 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 of the remaining variables come from the stored parent. 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 Simulation and Analysis

We conduct experiments to verify the effectiveness of the proposed algorithm for the maritime application of 3D multi-objective deployment of an industrial wireless sensor network.

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) [46], MOEA/D [42], Multi-Objective Evolutionary Algorithm Based on Decision Variable Analyses (MOEA/DVA) [47], NSGA-II [25] and DPCCMOEA [41]. Each algorithm runs 20 times, and the number of fitness evaluations (FEs) for each run is set to (N_D x 5 + N_R x 3) x 10^4. All algorithms are implemented in C++, and the simulation experiment platform is the TianHe-2 supercomputer.

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

For the components of all algorithms, we summarize:

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.

TABLE I: Parameter Settings for the Coverage Model

Symbol	Attribute	Quantity
N_D	number of directional sensors	17
N_R	number of relay nodes	9
(α_1, α_2)	distance sensing model parameters	$(1.0, 0.0)$ [8]
(β_1, β_2)		$(1.5, 1.0)$ [8]
R_d	deterministic sensing distance	$[15, 24] \times 2m$ [16]
R_f	fuzzy sensing distance	$1.0 \times R_d$
γ_l^X[1]	lower bound on fuzzy sensing angle	$[\pi/6, 2\pi/9]$ [16]
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 [28]
P_{th}^F	sensing probability threshold	0.9 [28]

[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)

B. Results and Analysis

We use the hypervolume (HV) indicator [48] to evaluate the performance of the algorithms. A higher HV indicator value indicates a better optimization performance. In addition, the non-dominated solution sets are visualized.

The evolutionary curves of the average HV indicator values are shown in Fig. 4, from which we can observe that DPCCMOLSEAs perform the best; specifically, DPCCMOLSEAJADE outperforms all other algorithms. By comparing DPCCMOEA and DPCCMOLSEAs, we can deduce that the parallel structure modification is quite beneficial. Therefore, we can find that the comprehensive utilization of the mutual relations among all individuals of the species significantly contributes 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, and the relations among individuals are broken; in DPCCMOLSEAs, the evolution of all individuals of a species is conducted on a single master CPU, thus preserving all the interactions among individuals.

Table III lists the statistical test 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 all other algorithms (with p-values less than 0:05). When adopting different DE optimizers, the performance of DPCCMOLSEAs varies greatly: JADE is quite effective, while jDE is not very powerful, indistinguishable from DE/rand/1. The visualizations of all the non-dominated solutions generated from the 20 runs by each algorithm are provided in the supplementary material. We can see that DPCCMOLSEAs can comprehensively optimize all objectives.

Table IV lists the computation times of all the algorithms. We can see that because DPCCMOEA and DPCCMOLSEAs are parallel algorithms, their computation times are much lower. The speedup ratios are also calculated. The ratio values are approximately 79:6% s 87:1% of the ideal speedup (i.e., 72, which is the number of CPUs). DPCCMOLSEAs are slightly slower than DPCCMOEA, which can be ascribed to the parallel structure modification.

C. Time and Space Complexities

Table IV lists the computation time of all algorithms. As DPCCMOEA and DPCCMOLSEAs are parallel algorithms, their computation time is much lower. The speedup ratio values are approximately 79:6% s 87:1% of the ideal speedup (i.e., 72, which is the number of CPUs). DPCCMOLSEAs are slightly slower than DPCCMOEA, which can be ascribed to the parallel structure modification. T1 is the time consumption of fitness evaluations of the objective function, and T2-T1 provides the time consumptions of the algorithms without the fitness evaluations, viz., the time complexity of each algorithm.

And for each parallel algorithm, there are two values: the first one denotes the time consumption for one MPI process, while the second one between parentheses is the sum of time consumed by all MPI processes. As to the operation time, the time complexities of parallel algorithms are significantly lower than serial ones; however, if the time taken by all CPUs is considered, the serial ones are better, which can be attributed to the communication load in parallel algorithms.

For the space complexity, the population matters the most. MOEA/D, MOEA/DVA and NSGA-II are similar; in CCGDE3, 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, so there will be more space required; for all parallel algorithms, analogous to CCGDE3, corresponding to each group of variables, there is a species in the master CPU, while for the evaluation, there is extra space needed for the remaining CPUs, therefore, in total, the space is doubled. All in all, the space complexity is summarized as: parallel algorithms > CCGDE3 > other algorithms.

VIII. Discussion

While the proposed novel 3D WSN coverage model with evolutionary optimisation algorithm has demonstrated a good performance in targeted objectives Coverage, Lifetime and Reliability for environment monitoring of Intelligent Maritime applications, there are still other issues requiring further investigation.

The first issue is about the oceanographic sensor protection. Typical marine environments contains over thousands organisms related to fouling problems. When oceanographic sensors are immersed in seawater, they are susceptible to bio-fouling problems which often lead to the long-term accuracy issues of marine environmental sensor measurements. So our model should also consider this issue in our WSN coverage model.

The second issue is about the limited energy of batteries of WSN in maritime system applications. In marine environment monitoring systems, wireless sensor nodes are often deployed in unapproachable sea surface areas, and they are mostly planned

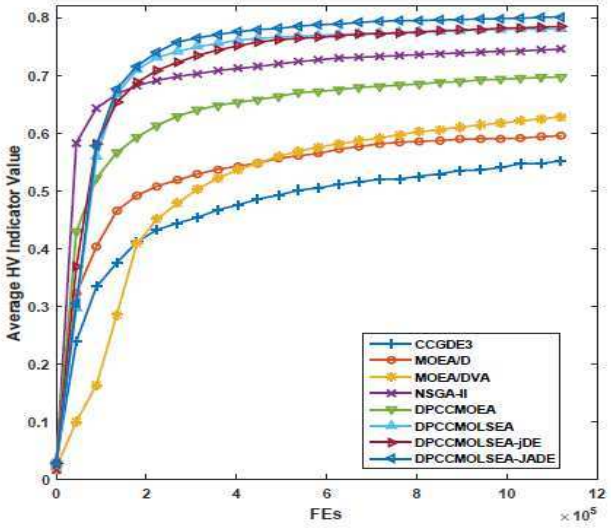

Fig. 4 Evolutionary curves of average HV indicator values obtained by all algorithms

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	149.5	40.5	$2.7380E-2$
DPCCMOLSEA	2.475	158.0	52.0	$4.8440E-2$
NSGA-II	3.725	190.0	00.0	$3.8140E-6$
DPCCMOEA	5.025	210.0	00.0	$1.9074E-6$
MOEA/DVA	6.100	210.0	00.0	$1.9074E-6$
MOEA/D	7.125	210.0	00.0	$1.9074E-6$
CCGDE3	7.600	210.0	00.0	$1.9074E-6$

for long-time operation, therefore, it is not convenient to replace the sensor batteries. So our model should consider the following three aspects: energy harvesting devices, power management system, and energy storage devices.

Lastly, the system stability and reliability problem of wireless sensor networks has been widely studied in order to measure physical parameters correctly and effectively, as well as to prolong the lifetime of the system dramatically. Considering the aggressive and complex environment, it is very important to analyze the system reliability in a marine environmental monitoring system using wireless sensor networks.

TABLE IV: Average Computation Times of All Algorithms and the Speedup Ratios of Other Algorithms with Respect to DPCCMOLSEA

TIME	CCGDE3	MOEA/D	MOEA/DVA	NSGA-II	DPCCMOEA	DPCCMOLSEA	DPCCMOLSEA-jDE	DPCCMOLSEA-JADE
MEAN	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

IX. CONCLUSION

In this paper, for the operational management and security monitoring of Intelligent Maritime Grids (IMGs), we study the deployment of an IWSN in a 3D engine room space of a VLCC with many power devices. A novel 3D uncertain coverage model that consists 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 an MOP. To address this MODP, 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 only). In future work, other objectives can also be considered. Larger scale deployment problems can be tested, and the parallelism of the proposed algorithm can be further improved through implementation on GPUs or MICs.

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