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Optimal topology planning of electromagnetic waves communication network for underwater sensors using multi-objective optimization algorithms (MOOAs)

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ABSTRACT

"Extremely High Frequency (EHF)" and "Very high frequency (VHF)" bands are mainly utilized with "Underwater Wireless Sensor Networks (UWSNs)" for communication purposes. However, due to the mobility of underwater sensors in water because of the water tide, the EHF/VHF signals may attenuate, lose or fade depending on the condition of the water. Therefore, it is a challenging stint of finding the optimal parameters of UWSN topology planning. In this paper, three "Multi-Objective Optimization Algorithms (MOOAs)" have been utilized to mitigate this problem, namely MOSFP, SPEA2 and NSGA-II. This work also intends to minimize path loss. On the other hand, it intends to maximize the power density of the network. Various network configurations, such as distance between sender and receiver, water conductivity and water permeability, are considered to evaluate the proposed objective models. Qualitative and quantitative tests have been conducted to analyze the results. From the analysis of the intersection point of Pareto-front of the objective functions, it is shown that all the algorithms find the optimal distance between transmitter and receiver, which balances the aforementioned maximization and minimization objective functions. This value is 36 m.

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1. Introduction

"Wireless Sensor Network (WSN)" is a set of sensors used to detect physical and environmental events or phenomena, such as vibration, humidity, sound, temperature, motion or pressure. In addition, it uses its frequency band to cooperatively transmit the data through the network to the final destination [1]. Due to the functionality of monitoring, wireless sensors can be allocated in different environments that are unconventional for electromagnetic signalling [2].

Examples of these applications of WSN are "Underwater Wireless Sensor Networks (UWSNs)", which are used with a wide set of scientific applications, such as marine life monitoring, disaster monitoring of water flood, military surveillance, coastline protection and environmental monitoring [3,4].

The wireless communications in UWSNs rely on sonic transducers because of the high attenuation of "Electromagnetic Wave (EMW)" in the water. The functionality of UWSNs is based on communication inside the water. This makes it an extremely challenging tool, which is vulnerable to facing many odds, such as severe energy limitation, limited available bandwidth, high error probability and large propagation delay. These challenges make the design of communication mechanisms rather awkward. Deploying more nodes or sonic transceivers is used to overcome these challenges, but the network cost will be significantly high. For this reason, electromagnetic waves instead of sound ones are used. This is because EMW has a faster propagation to reduce the latency. Moreover, electromagnetic wave has a high frequency of the wave to give a high data rate of transmission [5,6].

In addition, the speed of EMW is extremely higher than that of sonic ones and it essentially depends on volume charge density (ρ), conductivity (σ), permittivity (ε) and permeability (μ) [6]. These parameters are changed based on the kind of water, including, pure water or seawater; therefore, the speed of wave propagation may be changed. The researchers in this area should take into their consideration that the water dielectric constant may be changed with variations in water temperature, the salinity of the water and frequency of the transmission [6,7].

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The main problem of electromagnetic wave communications inside water is the signal fade and loss because of the water conductivity. Moreover, if the frequency of electromagnetic waves increases, the attenuation and path loss will be increased. In this paper, three "Multi-Objective Optimization Algorithms (MOOAs)" known as "Non-Dominated Sorting Genetic Algorithm (NSGA-II)", "Strength Pareto Evolutionary Algorithm 2 (SPEA2)" and "Multi-Objective Optimization Algorithm Based on Sperm Fertilization Procedure (MOSFP)" are utilized. They will be utilized to study the effect of distance between sender and receiver on the "Quality of Service (QoS)" of the network and determining the optimal setting for certain parameters. This work will be utilized to create a real architecture of UWSN in future. The input criteria include water conductivity, water permeability and the distance between the sender and receiver. Minimization and maximization models of path loss and power density that are affected by the aforementioned criteria are put forward. The analysis of the "Pareto-optimal" is set to find the optimal location of the Bow-Tie antenna based on the distance between the sender and receiver that maximizes the power density of the network. On the other hand, the other "Pareto-optimal" set is analyzed to minimize path loss based on the same input settings. This is followed by an evaluation of the three MOOAs to find the most efficient one. This paper is organized as follows: Section 2 shows the literature review. Section 3 presents "Multi-Objective Optimization Algorithms (MOOAs)". Section 4 shows network modelling. Section 5 presents a case study. Section 6 shows the experimental set-up and results. Section 7 shows the discussion. We conclude the findings in Section 8.

2. Literature review

There are many wireless communication applications, such as applications that need long-range transitions and other applications that need short-range transmission. Based on that many frequency ranges have been established to fulfill this matter. "Very High Frequency and Ultra High Frequency (VHF/UHF)" are two examples of these frequencies. VHF/UHF can be used with applications of communication, monitoring and broadcasting. These frequencies have the features of the ability of long-distance transmission, which the users can easily access their devices from far places. UHF can support the frequency from 300 MHz to 3 GHz, while VHF can support the frequency from 30 MHz to 300 MHz [8,9]. Figure 1 shows the electromagnetic spectrum ranges for different bands.

Antenna plays a significant role in any communication system, which is used to spread the signals in the topology area. Under-water sensors need a very efficient antenna for communicating through a "Wireless Sensor Network (WSN)". The scenario in underwater is different, in which the antenna must meet a set of requirements required to overcome many issues such as path loss, attenuation, etc. These requirements are divided into two : requirements for operation and requirements for design. The requirements for operation can be summarized as antenna gain, which should be equal to or over 10 dB. On the other hand, the requirements for design can be summarized by antenna dimension, which should be small in dimension to achieve the sensor balance while the antenna is fixed on the sensor surfaces. The most popular antenna that is used with inside water communications is the Bow-Tie antenna, which is used to broadcast the aforementioned types of electromagnetic signals [6].

This antenna can operate on different frequency ranges, including, "Ultra High Frequency (UHF)" and "Extremely High Frequency (EHF)" which operate from 300 MHz to 3 GHz, and from 30 GHz to 300 GHz, respectively. The performances of Bow-Tie antennas are not affected by the variations of small parameters, which are created to improve robustness to manufacturing tolerances. The wide range of frequencies bands supported by Bow-Tie antennas do not mean high antenna performance in which many demanding

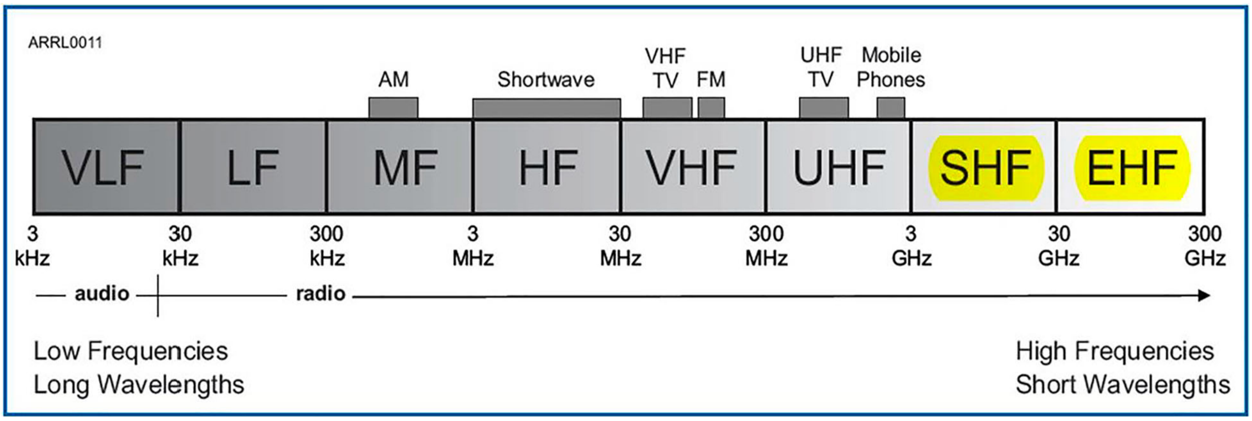

Figure 1. The electromagnetic spectrum ranges [10].

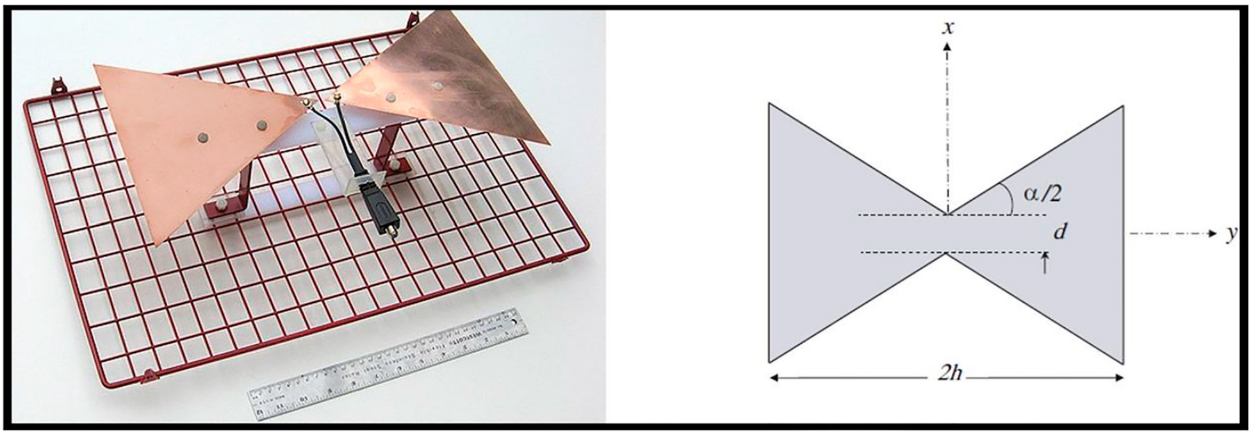

Figure 2. Bow-Tie antenna and its geometry [12].

applications may require more complex designs. The pulse radiation may have happened with the resistively loaded bow-tie antenna [11,12].

The Bow-Tie antenna has many physical characteristics, such as being easy to construct and its very robust body. However, in the case of low-frequency transmission, the physical shape becomes restrictively large. This antenna is mostly constructed using suspended metal cut-outs or supported by a dielectric substrate. While using a substrate, the body should be thin, and low-permittivity substrates are encouraged to use to avoid the degradation of antenna performance. The Bow-Tie antenna and its geometry with a feeding neck width (d), flare Angle (α) and half-height (h) are depicted in (Figure 2) [12].

Indeed, many problems are related to this antenna and its applications. Many of these problems have been simulated as a form of mathematical functions (models). Optimization algorithms have been created to solve these problems by giving optimal or near-form optimal solutions for them [10]. These algorithms use different techniques and strategies to solve problems. For example, some of them operate based on a metaphor of some man-made or natural process. Examples of these algorithms are "Non-dominated Sorting Genetic Algorithm II (NSGA-II)" [13], "Strength Pareto Evolutionary Algorithm 2 (SPEA2)" [14] and our algorithm, namely "Multi-Objective Optimization Algorithm Based on Sperm Fertilization Procedure (MOSFP)" [15,16].

These algorithms are used to optimize many problems in different areas, especially in the Wireless Sensor Network (WSN) field. We can summarize a few of the works as follows.

Gunjan et al. [17] discussed the optimal number of clusters in WSN using "Non-Dominated Sorting Genetic Algorithm-II (NSGA-II)". They tried to optimize a set of conflict objective functions, such as network lifetime, energy conservation, load balancing and coverage. The proposed algorithm is compared against the "Low-Energy Adaptive Clustering Hierarchy (LEACH)" protocol using the "Network Simulator (NS2)". The results showed that the NSGA-II algorithm outperformed the LEACH protocol.

Tam et al. [18] looked to further detail by discussing a "Multi-Objective Optimization Problem (MOOP)", namely "Optimal Relay Node Placement Problem (ORP3D)" which consists of two objective functions, such as energy consumption and the number of relay nodes. They used "Multi-Objective Evolutionary Algorithm Based on Decomposition (MOEA/D)" to minimize the aforementioned objective functions. The experimental results proved the MOEA/D is a valuable alternative to solve this problem in a good manner. This study is lacking in studying network coverage. Shehadeh et al. [10] have the advantages of optimizing a set of problems of near-ground communication network. They tried to minimize signal attenuation and path loss. On the other hand, they tried to maximize signal propagation and electromagnetic fields. They used a set of algorithms to optimize this problem, such that NSGA-II, SPEA2 and "Optimized multi-Objective Particle Swarm Optimization (OMOPSO)". The results showed the Pareto front of the aforementioned objective functions depends on the distance between the transmitter and receiver and foliage depth.

In a different view, Shehadeh et al. [19] used a new optimization algorithm, namely "Multi-Objective Optimization Algorithm Based on Sperm Fertilization Procedure (MOSFP)" to solve test suites of WSN problems. They tried to use this algorithm with another three methods: SPEA2, OMOPSO and NSGA-II to solve a set of problems related to WSN. They tried to minimize end-to-end delay and end-to-end latency. On the other hand, they used the same algorithms to maximize energy efficiency and network throughput. The outcomes presented that MOSFP outperformed the other methods in solving the problems. This study is lacking in studying the interference in WSN. For this reason, Hamdan et al. [20] used a set of algorithms, such as SPEA2, OMOPSO and NSGA-II to maximize both network throughput and energy efficiency. On the other hand, they tried to minimize the interference of WSNs. The results showed the Pareto front of the aforementioned objective functions for the different network topology sizes and different distances between the transmitter and receiver.

Miranda et al. [21] had the advantage of using a set of "Multi-Objective Optimization Algorithms (MOOAs)" to prolong the lifetime of clusters in WSN. In each cluster in WSN, the cluster head has a problem with faster battery depletion. Based on that, it is challenging stint to reassign an optimal cluster head. Based on that, Miranda et al. used three algorithms to choose an optimal cluster head: MOEA/D, SPEA-II and "S-Metric Selection Evolutionary Multi-objective Optimization Algorithm (SMS-EMOA)". Meena et al. [22] proposed coverage, end-to-end delay and energy consumption problems of WSN as MOOP problems. The researchers used the NSGA-II algorithm to maximize the coverage and minimize both end-to-end delay and the energy consumption of the network. The results showed the previous models based on the number of hops in the network.

Previous studies have addressed various issues related to WSN, such as network coverage, network lifetime, cluster head selection and task allocation but are lacking in studying the external influences on these networks, such as studying the electromagnetic signal speed, signal propagation and signal path loss in water. So, we are going to study some issues that affect WSN in different mediums, such as water and air. In addition, these issues (network models) are planned to be optimized based on three well-known MOOAs, one of which is our algorithm, namely MOSFP.

3. Multi-objective optimization algorithms (MOOAs)

There are many problems related to "Wireless Sensor Network (WSN)" and UWSNs in specific. Many researchers have simulated and represented these problems as mathematical modelling (optimization model). Based on that, a wide variety of optimization algorithms have been created to solve these models and to find the optimal solutions for them. The procedure of modelling optimization and evaluation is depicted in Figure 3 [19].

Algorithms are an essential part of modelling optimization and evaluation procedure, which are responsible for giving the final results of the optimization model. We can summarize some of them as follows:

- *Non-dominated Sorting Genetic Algorithm (NSGA-II)*:

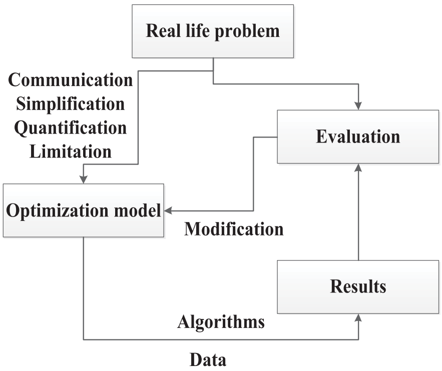

Figure 3. The process of modelling optimization [19].

Table 1. Pseudocode of NSGA-II [10].

Algorithm 1: Non-dominated Sorting Genetic Algorithm (NSGA-II)

```
Begin
Initialize Population
    Population production randomly – size M
    Evaluate Fitness
    Sort solutions depends on Pareto Dominance
    production of offspring population
        "Binary Tournament Selection (BTS)"
        Mutation and Recombination
For i = 1 to the end criterion Do
    With offspring and parent population
        Sort solutions depends on Pareto Dominance
        produce sets based on Pareto fronts
        Add solutions to the next generation by looping
        Calculated distance between each front
    Based on the lower rank choose elitist
    produce next generation
        Apply BTS
        Recombination and Mutation
    Increment the index of generation
End of Loop
End
```

NSGA-II is an MOOA, which is an extended version of the "Single Objective Optimization Algorithm (SOOA)", called "Genetic Algorithm (GA)" [23]. Table 1 presents the Pseudocode of NSGA-II [10].

- *The Strength Pareto Evolutionary Algorithm 2 (SPEA2)*:

Zitzler et al. [24] proposed an MOOA, namely SPEA2 as an improved version of the SPEA method. This approach utilizes the closest neighbour technique to lead the procedure of exploring the problem domain. In addition, this algorithm used the truncation method. The pseudo-code of this algorithm is summarized as follows [10] (Table 2).

- *Multi-Objective Optimization Algorithm Based on the Sperm Fertilization Procedure (MOSFP)*:

This method is proposed by Shehadeh et al. [15,19]. This algorithm is an extended version of SOOA, namely "Sperm Swarm Optimization (SSO)" [25–27]. The pseudocode of this algorithm is summarized in Table 3.

Table 2. The pseudocode of SPEA2 [10].

Algorithm 2: Strength Pareto Evolutionary Algorithm 2 (SPEA2)

```
Begin
Initialize Population P
  Assess objective model
  Apply Archive X
  For i = 1 to the end criterion Do
    Assess the population fitness in X and P
    Find Non-Dominated populations from X and P
    If load of X is Exceed Then
      Use Truncation operator to remove Individuals from X
    End If
    Create Mating Pool by Appling Binary Selection
    Apply crossover
    Apply Mutation
  End For
End
```

Table 3. The pseudocode of MOSFP [25–27].

Algorithm 3: Multi-Objective Optimization Algorithm Based on the Sperm Fertilization Procedure (MOSFP):

```
Begin
Initialize population and winners. Put winners to ε archive
crowding (winners), count = 0
While count < max
    For every sperm DO
        Choose winner. Swim. Mutation. Evaluation. Update sbest.
    End For
    Update Winners put Winners in ε -archive
    crowd winners, count++
End While
Report results in ε -archive
End
```

4. Objective models

In this part, we explain vital mathematical models that are used to evaluate the communication link of underwater sensors. These functions (objective models) are potentially influenced by crucial factors, such as frequency range and some parameters. We organize these models as follows.

4.1. Power density (ρ)

The received power density (ρ) between sensor nodes can be calculated using the following formula [28].

$$\rho = \left[\frac{P_T}{4\pi R^2}\right] \ [\mathrm{W/m^2}] \tag{1}$$

where

- P_T is the total transmit power;
- R is the distance between sensor nodes.

4.2. Signal propagation inside the water

The accurate channel characterization plays a significant role in the proper deployment of UWSNs. Path loss is one of the most important factors that is used to test the QoS of any communication channel, which is represented as the variation between the transmitted and the received signal powers. The signal propagation in water is affected by a set of factors, such as path loss factor, received power and gains of the antenna. This model can be described by Friis equation as follows [29]:

$$P_{\mathrm{rec}}(\mathrm{dBm}) = P_t(\mathrm{dBm}) + G_t(\mathrm{dB}) + G_r(\mathrm{dB}) - L_{\mathrm{pathloss}}(\mathrm{dB}) \tag{2}$$

where

- Pt is the transmit power;
- Gr and Gt are the gains of the receiver and transmitter antennas, respectively;
- L_{Pathloss} is the path loss in water.

The path loss can be expressed in Equation (3) [29].

$$L_{\mathrm{pathloss}}(\mathrm{dB}) = L_0(\mathrm{dB}) + L_w(\mathrm{dB}) + L_{att}(\mathrm{dB}) \tag{3}$$

L_0 is the path loss in air. It can be calculated as follows:

$$L_0(\mathrm{dB}) = 20 \cdot \log\left(\frac{4\pi df}{c}\right) \tag{4}$$

where

- d is the distance between the sender and receiver in metres;
- f is the operating frequency in Hertz;
- c is the velocity of light in the air in the unit of metres per second.

L_w(dB) is the path loss based on changes in a medium. It can be calculated as follows [29]:

$$L_w(\mathrm{dB}) = 20 \cdot \log\left(\frac{\lambda_o}{\lambda}\right) \tag{5}$$

where

- λ_o is the wavelength of the signal in air and can be calculated by Equation (6).

$$\lambda_o = \left(\frac{c}{f}\right) \tag{6}$$

- λ is the wave factor that can be calculated by the following formula.

$$\lambda = \left(\frac{2\pi}{\beta}\right) \tag{7}$$

- β is the constant of phase shifting that can be calculated by

$$\beta = \omega\sqrt{\frac{\mu\varepsilon'}{2}\left(1 + \sqrt{1 + \left(\frac{\varepsilon''}{\varepsilon'}\right)^2}\right)} \tag{8}$$

where ω is the angular frequency, which can be measured by ($\omega = 2\pi f$). The unit of μ is (H/m), which can be changed based on the medium. For example, in the water, it is $\mu = 1.256627 \times 10^{-6}$. ε' and

ε'' are the complex dielectrics of real and imaginary constant values, respectively, which can be given by $(\varepsilon = \varepsilon' - j \cdot \varepsilon'')$, where ε is the permittivity factor, and $j = \sqrt{-1}$.

L_{att}(dB) is the path loss based on attenuation in a medium. It can be expressed as follows [29]:

$$L_{att}(\mathrm{dB}) = 10\log(e^{-2ad}) \tag{9}$$

where α is the attenuation constant. We calculate it using Equation (10):

$$a = \omega\sqrt{\frac{\mu\varepsilon'}{2}\left(-1+\sqrt{1+\left(\frac{\varepsilon''}{\varepsilon'}\right)^2}\right)} \tag{10}$$

4.3. The speed of EMW inside water

The communication in underwater by establishing a communication link between the sensor node inside the water and the buoy node at the surface. In some cases, there is an intermediate node (relay) in between the sensor node and the buoy node. The signal attenuation of the electromagnetic wave at the sea-water–air boundary is affected by frequency ranges, and, if the frequency range is between 100 kHz and 1 GHz, the reflection loss will be decreased dramatically. On the other hand, if the frequency is higher than 2 GHz, the reflection loss remains almost constant at 4 dB. The speed of the electromagnetic wave underwater can be calculated by Equation (11) [6].

$$\upsilon_{RF} = \sqrt{\frac{2\cdot\omega}{\mu\cdot\sigma}} \tag{11}$$

where ω is the angular frequency and can be measured by $(\omega = 2\pi f)$, μ is the function of permeability and σ is the medium conductivity factor.

4.4. Conductivity

The medium conductivity (σ) factor is changed based on the medium type, such as salty water, pure water, etc., which affects the transmission of an electromagnetic wave. In the case of increasing the conductivity of the medium, the broadcasted signal will face more attenuation. The conductivity average changes based on the type of water, which is based on the physical and salinity properties of the water. For example, in pure water, the conductivity value can be changed in the ranges between 0.005 and 0.01 S/m [6], but in seawater, it is settled to be around 4 S/m [6]. The conductivity of seawater in relation to salinity (S) and temperature (T) can be measured by the following formula in which the salinity takes a range of 20 ppt $< S <$ 40 ppt. The medium conductivity (σ) can be calculated by Equation (12) [6].

$$\sigma = \sigma_o.S\cdot\frac{37.5+5.4\cdot S+0.015\cdot S^2}{1004.8+182.3\cdot S+S^2}\cdot \times\left(1+\frac{\frac{6.9+3.3\cdot S-0.1\cdot S^2}{84.6+69\cdot S+S^2}\cdot(T-15)}{49.8-0.23\cdot S+0.2\cdot S^{2+T}}\right) \tag{12}$$

where

- σ_o is the Siemens per meter, whose unit of s is in parts per thousand;
- T is in degrees centigrade.

In the case of $S = 35$ ppt, the conductivity can be measured in dependence on temperature using Equation (13) [6].

$$\sigma_o = 2.9 + 8.6\cdot\text{‘}10^{-2}\cdot T + 4.7\cdot 10^{-4}\cdot T^2 - 3.10^{-6}\cdot T^3 + 4.3\cdot 10^{-9}\cdot T^4 \tag{13}$$

4.5. Reflection from water interfaces

The reflection coefficient is used to calculate the reflection from the surface and bottom of the water, such as the interface between water and sand and also between water and air. Equation (14) summarizes the reflection coefficient [29].

$$\Gamma = \frac{p_2v_2 - p_1v_1}{p_2v_2 + p_1v_1} \tag{14}$$

where

p_1 and p_2 are the density of the first and second mediums, respectively, while v_1 and v_2 are the velocities of the wave in both mediums.

The reflection loss can be calculated as in Equation (15).

$$L_{\mathrm{ref}} = -V(\mathrm{dB}) = -10\log(V) \tag{15}$$

where V can be calculated by

$$V^2 = 1 + (|\Gamma|e^{-a\Delta(r)})^2 - 2|\Gamma|\mathrm{e}^{-\mathrm{a}\Delta(\mathrm{r})}\times\cos\left(\pi-\left(\Phi-\frac{2\pi}{\lambda}\Delta(r)\right)\right) \tag{16}$$

where

- $|\Gamma|$ is the reflection coefficient;
- Φ is the wave amplitude;
- r is the reflected path length;
- $\Delta(r)$ is the difference between d and r, where r can be measured by Equation (17) [29].

$$r = 2\sqrt{H^2 + \left(\frac{d}{2}\right)^2} \tag{17}$$

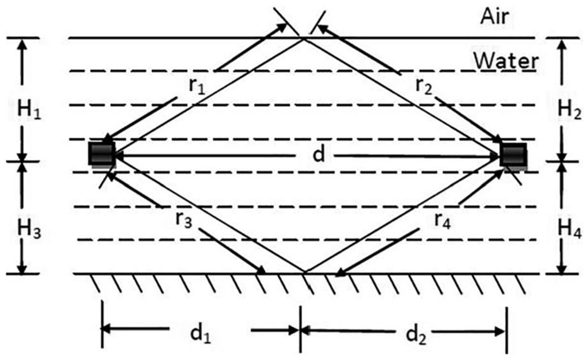

Figure 4. Three-path channel model.

Figure 5. Deepwater for rice cultivation in Thailand [30].

The tree path channel model is depicted in Figure 4. The distance between the transmitter and receiver is denoted by d. The distance between sensors and the surface is denoted by H. The distance between sensors and the reflection point is denoted by r.

5. Case study

Rice is one of the most important crops in the world, which is used to prepare many main meals in all countries. However, rice needs intensive care along with its cultivation time. Rice is different from other crops, which is cultivated in wide areas in water depths of more than 50 cm for one month or more during the growing season [30]. That is all proving that rice crops need intensive care during their cultivation period. If the farmers need to monitor their rice crops, they should use special types of sensors called underwater sensors. These sensors have special characteristics, which are able to operate underwater in harsh environments. Deepwater rice in Thailand is depicted in Figure 5 [30].

(Figure 6) shows our proposed network. In the figure, we can notice that there are underwater sensors deployed inside the water between rice crops. These sensors are responsible to measure some important parameters, which are used to monitor rice crop cultivation, such as pH value, water level and water temperature. These sensors transmit these parameters to the base station that is floating on the surface of the water. These sensors use Bow-Tie atenna to communicate with each other using radio wave frequencies, such as UHF/EHF. The floating base station is responsible to transmit this information to control the server [31].

Table 4. Test environment and simulation parameters.

#	Parameter	Values
1	Test environment	Windows 10
2	Simulation tool	jMetal tool
3	Type of CPU and RAM size	Intel core i7/6 GB RAM
4	P_t is the transmit power	40 dBm
5	G_r and G_t are the gains of the receiver and transmitter antennas	2.2 dB
6	f is the frequency	2.4 GHz
7	c is the velocity of light in air	3×10^8 m/s
8	Speed of light underwater	33.3×10^6 m/s
9	ε'' is the tangent loss in pure water	0.924
10	ε' is the dielectric constant of pure water	79
11	μ is the permeability factor of pure water	1.256627×10^{-6}
12	σ is the conductivity of pure water	0.01 s/m
13	P_1 is the density of water	1000 kg/m^3
14	P_2 is the density of air at 20°C	1.204 kg/m^3
15	d is the distance between the transmitter and the receiver	From 1 to 200 m
16	H is the distance between the sensors and surface	50 cm

Table 5. Parameters of algorithms.

#	Parameters	MOSFP	NSGA-II	SPEA2
1	Size of population	20	20	20
2	Size of archive	(winners)20	(Elite)20	20
3	Size of mating pool	–	–	20
4	Maximum iteration	250	250	250
5	Probability of crossover	–	0.9	0.9
6	Probability of mutation	1/n where n is the variable code size		

6. Experimental set-up and results

The aforementioned algorithms are coded based on "Java programming language" in the "jMetal tool" and run on Intel core i7 CPU, 6 GB RAM utilizing Windows 10. The path loss calculation is affected by the water types, such as seawater or pure water. The tangent loss ε'' in pure water is 0.924. The conductivity ε' in pure water is 79. The density is 1000 kg/m^3 at 2.4 GHz [29]. The test environment and parameters required in our simulation are presented in Table 4. The parameters of methods are presented in Table 5, one of which is our method, called MOSFP. As mentioned previously, this method is a multi-objective optimization version of "Sperm Swarm Optimization (SSO)" [32,33].

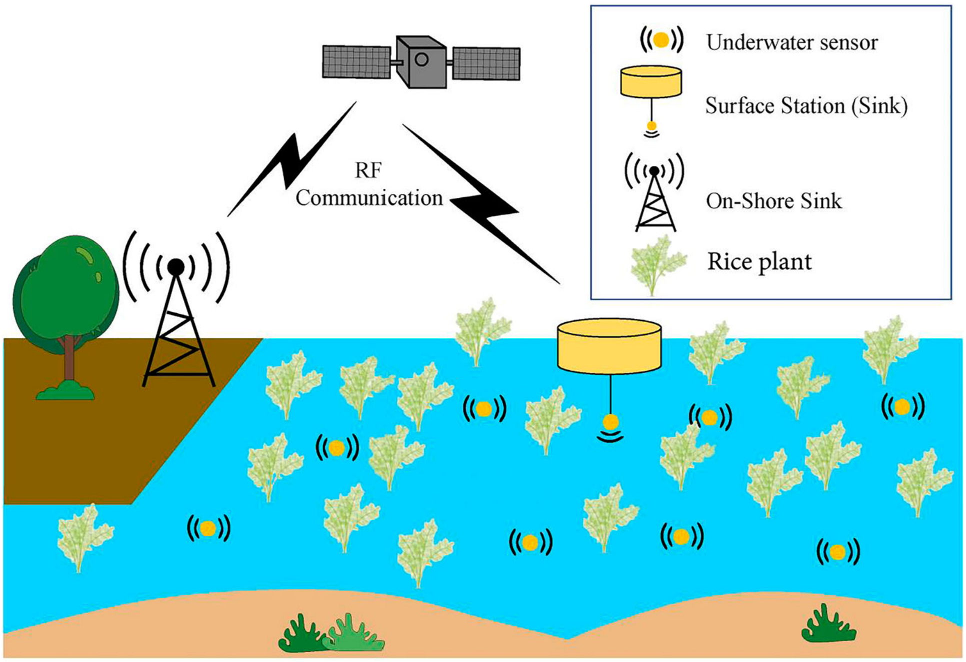

Figure 6. The geometry of our proposed underwater wireless sensor network.

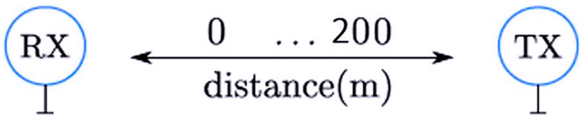

Figure 7. Point to point setting geometry between sensor nodes of our proposed network.

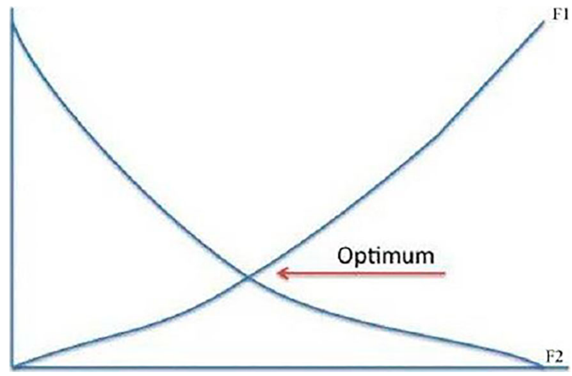

Figure 8. The optimal value based on the intersection point of the Pareto front, which is the intersection point.

6.1. Scenario of test and evaluation of Pareto-front of three algorithms

In this test, we study the network with two nodes as point-to-point settings, one of which transmits the data and the other sensor launches a listener to receive data. (Figure 7) shows the transmitter and receiver. We assume that the transmitter is mobilized, and the distance d between the transmitter and receiver varies between 0 and 200 m.

The "Multi-Objective Optimization Problems (MOOP)" are based on a set of conflict models that consist of maximization and minimization objective models. The optimality concept based on "Vilfredo Pareto" is used to balance the trade-offs between these models. This concept is utilized based on the Pareto front set of models. Pareto optimality works majorly depends on the set of Pareto fronts, which is utilized to balance the conflict models. Depending on the Pareto front of each model, the intersection point between objective models is utilized. This point can be considered an optimum value [19]. The optimality concept based on the intersection point can be summarized in Figure 8.

The prior figures present a sample of optimizing two objective models denoted by minimizing path loss and also maximizing power density using three MOOAs: SPEA2, MOSFP and NSGA-II. From the outcomes, the parameter of path loss decreased sharply until the value of distance attains 36 m, after that, it stabilizes above 0.0 when the distance is beyond 36 m. On the other hand, the power density increases dramatically until the value of distance attains 36 m, after that, it rises slightly until the value of distance attains 200 m. Based on the prior figures, the optimum value is the intersection point that balance objective models. This point is marked by black circles, which are created when the distance between sensor nodes is 36 m.

Table 6 presents the objective models, namely, power density and path loss, from ten runs for each approach. The statistical analysis using "one-way ANOVA (Tukey's test)" outlined in Table 7 presents that MOSFP significantly outperforms NSGA-II in which MOSFP substantially decreased the path loss ($-1.43\text{E}{-}03$, $p \leq .004$). These mean variances also show that MOSFP outperforms NSGA-II by 48.2% and 33.9% in terms of power density and path loss, respectively. Nevertheless, no significant mean variance is noticed between MOSFP and SPEA2 algorithms for all

Table 6. Comparisons between NSGA-II, MOSFP and SPEA2 based on mean and standard deviation.

Algorithm	Objective functions	Mean	Std.
SPEA2	Maximization function: Power density (W/m^2)	3.97E−03	6.66E−03
	Minimization function: Path loss (dB)	0.003371	0.001523
NSGA-II	Maximization function: Power density (W/m^2)	3.19E−03	8.56E−03
	Minimization function: Path loss (dB)	0.004213	0.001787
MOSFP	Maximization function: Power density (W/m^2)	**4.73E−03**	5.89E−03
	Minimization function: Path loss (dB)	**0.002781**	0.001187

Bold values show the best mean for the respective objective model.

Table 7. Analysis of "one-way ANOVA (Tukey's)" between NSGA-II, MOSFP and SPEA2 for the minimization and maximization objective models.

							95% Confidence interval	
Objective models	Method (*X*)	Method (*Y*)	*F*-value	*p*-Value	Mean difference (*X*-*Y*)	Margin of error	Lower bound	Upper bound
Power density (W/m^2)	SPEA2	NSGA-II	0.008155	.928518	−2.19E-04	0.004467	−4.69E−03	4.25E−03
		MOSFP	0.008155	.928518	−1.75E-03	0.003360	−5.11E−03	1.61E−03
Path loss (dB)	SPEA2	NSGA-II	2.572291	.117031	−9.49E-04	0.001130	−2.08E−03	1.81E−04
		MOSFP	1.867448	.17980	4.84E-04	0.000851	−3.68E−04	1.33E−03
Power density (W/m^2)	NSGA-II	MOSFP	0.008155	.928518	2.19E-04	0.004467	−4.25E−03	4.69E−03
		SPEA2	0.008155	.928518	2.19E−04	0.004467	−4.25E−03	4.69E−03
Path loss (dB)	NSGA-II	MOSFP	2.572290	.117030	8.42E−04	0.001086	−2.45E−04	1.93E−03
		SPEA2	8.909436	< .004*	1.43E−03	0.000993	4.39E−04	2.43E−03
Power density (W/m^2)	MOSFP	SPEA2	0.776997	.383603	1.75E−03	0.003360	−1.61E−03	5.11E−03
		NSGA-II	0.435638	.513217	1.53E−03	0.005208	−3.68E−03	6.74E−03
Path loss (dB)	MOSFP	SPEA2	1.867448	.17980	−5.90E−04	0.000949	−1.54E−03	3.59E−04
		NSGA-II	8.909436	< .004*	−1.43E−03	0.000993	−2.43E−03	−4.39E−04

*The mean difference is critical at the .05 level.

objective models. This shows that MOSFP outperforms SPEA2 with a small mean variance between them from 15% to 19%.

The consistency of the algorithm can be highlighted along with prior statistical analysis, which gives a good intention of the efficiency of the algorithm and its performance between runs. A more stable approach will result in a smaller standard deviation of the objective function. From the results for the respective objective models, MOSFP has resulted in a more consistent and efficient performance among the other algorithms.

The standard deviations of MOSFP are approximately 11.5%, 31.1%, 22% and 33.5% much smaller than others for power density and path loss models. Overall, the MOSFP approach achieved the best mean of all objective models, while the SPEA2 approach is in second, followed by NSGA-II. In terms of efficiency and consistency of performance, the MOSFP results are presented to be more stable and consistent in power density and path loss.

7. Discussion

"Underwater Wireless Sensor Networks (UWSNs)" have been utilized by modern sensors that can be deployed inside water. These sensors can be floated on the water services or be set inside the water. Mainly, these sensors operate over UHF/EHF bands. These sensors can be mobilized in water in which the distance between sensor nodes can be varied with time. Previous studies have addressed various issues related to WSN, such as network coverage, network lifetime, cluster head selection and task allocation but lack in studying the external influences on these networks, such as studying the electromagnetic signal speed, signal propagation and path loss in water. So, in this paper, we study some issues that affect WSN in different mediums, such as water and air. To achieve this, we represent our network in underwater sensors that are deployed inside the water between rice crops in which the distance between sensor nodes plays a significant role in determining the "Quality of Services (QoS)" of the network. In addition, these issues (network models) are optimized based on three well-known MOOAs, one of which is our algorithm, namely MOSFP.

Our findings prove that there is the main relationship between the distance between sensor nodes and the quality of the communication channel. The outcomes prove that if the distance between sensor nodes increased by 36 m, the path loss will be decreased dramatically. On the other hand, if the distance between sensor nodes increased more than the aforementioned value, the power density will be increased slightly. These two parameters of the network play a significant role in the estimation of the overall network "Quality of Services (QoS)". Statistical results show that the MOSFP algorithm has the best mean of all objective models, while the SPEA2 approach is in second, followed by NSGA-II. In terms of consistency based on standard deviation, the results of MOSFP are more consistent than the other algorithms in solving the respective objective functions. On the other hand, the results of the "one-way ANOVA (Tukey's) test" show that the

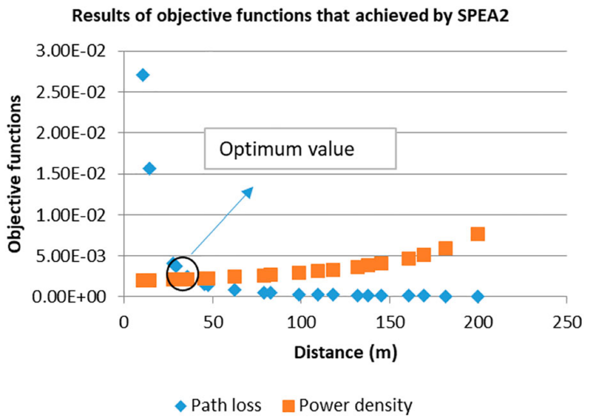

Figure 9. Maximizing power density and minimizing path loss based distance between sensor nodes achieved by the SPEA2 algorithm.

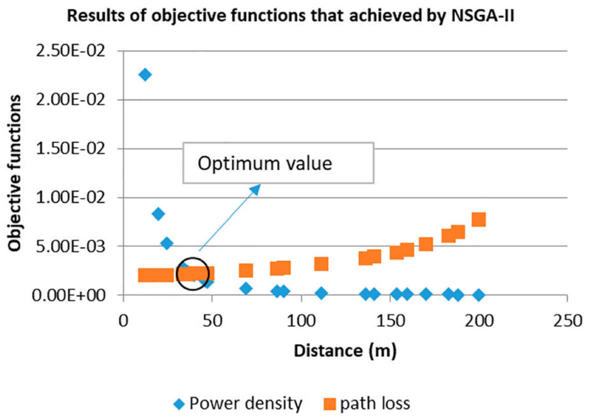

Figure 10. Maximizing power density and minimizing path loss based distance between sensor nodes achieved by the NSGA-II algorithm.

MOSFP algorithm significantly outperforms NSGA-II in solving the respective objective functions.

8. Conclusion

This paper has modelled the issues of "Underwater Wireless Sensor Networks (UWSNs)" as "Multi-Objective Optimization Problems (MOOPs)" with anticipation of the impacts that may affect it. These types of networks are vulnerable to signal loss and depletion of sensor battery based on the external influences on it. The experimental outcomes have been reported using two various scenarios. In the first scenario, the Pareto-optimal set of each approach has been drawn and analyzed using the intersection point concepts. In the second scenario, a statistical test, namely the "one-way ANOVA (Tukey's test)" between the approaches is calculated for every objective model depending on ten samples of results.

The mean-variance from the experimental results illiterates that our algorithm (MOSFP) significantly outperformed NSGA-II in optimizing the features, while no significant mean variance is indicated between

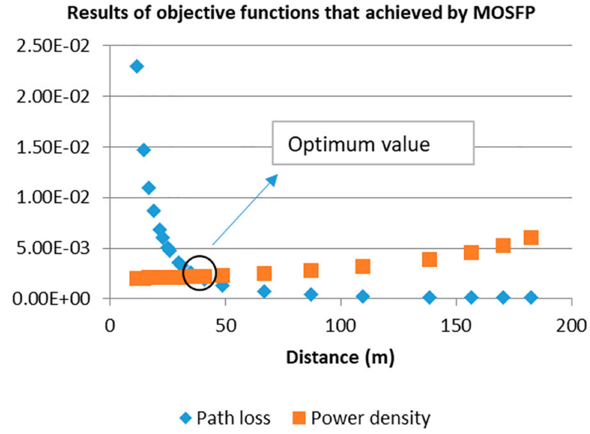

Figure 11. Maximizing power density and minimizing path loss based distance between sensor nodes achieved by the MOSFP algorithm.

MOSFP and SPEA2. However, the overall performance of MOSFP outperformed NSGA-II and SPEA2 by 48.2% and 15%, respectively. On the other hand, the Pareto front results indicated that the MOSFP algorithm has a good approximation and spread of the Pareto front points of the proposed models, while the SPEA2 algorithm is in second, followed by NSGA-II. This is clear in Figures 9–11. Overall, all the algorithms find the optimal value of the distance between sensor nodes, which balances path loss and power density. This value is 36 m, which is indicated by the intersection point of all the Pareto-optimal sets.

The objective models in this research may have restrictions. Other parameters may occur in a real environment that may change the outcome of this research. Therefore, the parameters of the topology planning of UWSNs should be evaluated in a real site in future to guarantee the efficiency of the QoS of the proposed network. In addition, future works should study the effectiveness of various environments on these applications, such as ocean, sea and river, as the topology of deployment can affect the overall QoS of the network. On the other hand, the types of water can affect the speed of EMW, which there are many parameters of the network that can be changed based on the type of water between salty and pure water, such as volume charge density (ρ), conductivity (σ), permittivity (ε) and permeability (μ).

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Disclosure statement

No potential conflict of interest was reported by the author(s).

Consent and data availability statement

We give our consent for the publication of identifiable details, which can include photograph(s) and/or videos and/or case history and/or details within the text ("Material") to be published in the above Journal and Article. We confirm that we have seen and been given the opportunity to read both the Material and the Article (as attached) to be published by your journal. In addition, a sample of data from this paper will be available upon request. The code of our algorithm, namely, MOSFP is available via the following link: https://github.com/sh7adeh1990/MOSFP.

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