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UMA ABORDAGEM EVOLUTIVA HÍBRIDA PARA O PROBLEMA DE M-CONECTIVIDADE E K-COBERTURA EM REDES DE SENSORES SEM FIO

TIMÓTEO HOLANDA DA SILVA SOUSA

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Trabalho de Conclusão de Curso II apresentado a Universidade Federal do Tocantins para obtenção do título de Bacharel em Ciência da Computação, sob a orientação do(a) Prof.(a) Dr. Rafael Lima de Carvalho.

Orientador: Dr. Rafael Lima de Carvalho

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RESUMO

Encontrar uma disposicao otima para sensores de uma Rede de sensores sem o (RSSF), enquanto procura-se maximizar tanto a cobertura e a conectividade e minimizando os custos pode se tornar uma tarefa nao trivial. No cenario apresentado, cobertura e conectividade sao medidas da Qualidade de Servico (QoS) para a rede de sensores. Neste caso, o problema foi abordado de uma maneira multi objetiva. Este trabalho propoe uma algoritmo de otimizacao h brido (AG-BPSO) baseado em um algoritmo genetico (AG) e um Algoritmo de Enxame de Part culas Binario (BPSO). A proposta deste trabalho apresenta resultados ate 27% melhores em comparacao a algoritmos presentes na literatura com a mesma nalidade.

Palavra-chave: Rede de sensores sem o. Otimizacao. Algoritmo Genetico. Otimizacao de enxame de part culas.

ABSTRACT

Finding optimal node deployment for a Wireless Sensor Network (WSN), while maximizing both coverage and connectivity as well as minimizing costs is a challenging task. In the considered scenario, coverage and connectivity are used as QoS (Quality of Service) measures for the desired wireless sensor network. In this case, the problem was handled as a multi-objective optimization problem. In this paper, we propose a hybrid optimization algorithm (GA-BPSO) based on Genetic Algorithm (GA) and Binary Particle Swarm Optimization (BPSO). The proposal of this work presents results up to 27% better in comparison to current algorithms in the literature with the same purpose.

Keywords: Wireless sensor networks. Otimizacao. Genetic Algorithm. Particle Swarm Optimization.

SUMÁRIO

1 INTRODUÇÃO

O Avanco tecnologico trouxe ao longo dos anos diversos benef cios no campo de comunicacao. A combinacao de elementos de comunicacao sem o e microcontroladores contribu ram para o desenvolvimento de sensores com capacidades de comunicacao e sensoriamento. Apesar dos avancos tecnologicos, os sensores ainda possuem certas limitacoes tais como: consumo de energia, faixa de cobertura e sensoriamento e portanto novos desa os foram criados. A estes sistemas de sensores interconectados da-se o nome de Rede de Sensores Sem Fio (RSSF). Existem tarefas cooperativas que requerem que uma RSSF forme uma componente conexa, permitindo que dados possam ser transmitidos por multiplos sensores.

O projeto de implantacao de uma RSSF pode receber restricoes mais rigorosas como redundância de conectividade e cobertura, ser mais tolerante a falhas. Uma RSSF e dita m-conexa, quando cada sensor da rede esta em estado de conexao com pelo menos m outros sensores. Em relacao a restricao de cobertura, diz-se que uma RSSF e k-coberta se existe pelo menos k sensores cobrindo cada ponto alvo da regiao que se deseja monitorar(GHOSH; DAS, 2008). Um exemplo de uma RSSF pode ser observado na Figura 1.

Este problema foi considerado por Liu (2017), onde na ocasiao foi proposto um algoritmo h brido evolutivo, unindo os benef cios do algoritmo *Particle Swarm Optimization - PSO* com alguns operadores geneticos, buscando descobrir a posicao otima de sensores a m de maximizar a m-conectividade de uma RSSF. Resultados de simulacoes reportados pelos autores demonstram que este metodo pode nao apenas melhorar o posicionamento dos sensores na rede, mas tambem reduzir o tempo de resposta entre sensores.

Alem disso, Sharma G. S TOMAR (2015) utilizou de um algoritmo baseado no LEACH (*Low Energy Adaptive Clustering Hierarchy Protocol*), combinado a um Algoritmo Genetico, com a nalidade de melhorar a e ciência do uso de energia em uma RSSF. O algoritmo genetico foi utilizado para selecionar e criar *clusters* de transmissao de dados. Resultados indicam que a utilizacao do algoritmo h brido resultou em uma prolongada vida util de sensores dentro da RSSF, assim como a otimizacao do gasto de energia pela mesma.

Por outro lado, Gupta Pratyay Kuila (2015) propoe um metodo para minimizar o numero de sensores de uma RSSF, buscando, ao mesmo tempo, maximizar a m-conectividade e a k-cobertura da rede. Para alcancar tal meta, os autores utilizam de um algoritmo genetico cuja funcao de aptidao e calculada baseada em uma funcao multi-objetiva dividida em três sub-objetivos. O primeiro objetivo busca minimizar a quantidade de sensores utilizados pela RSSF, enquanto ambos objetivos restantes buscam, respectivamente, maximizar tanto a m-conectividade quanto a k-cobertura.

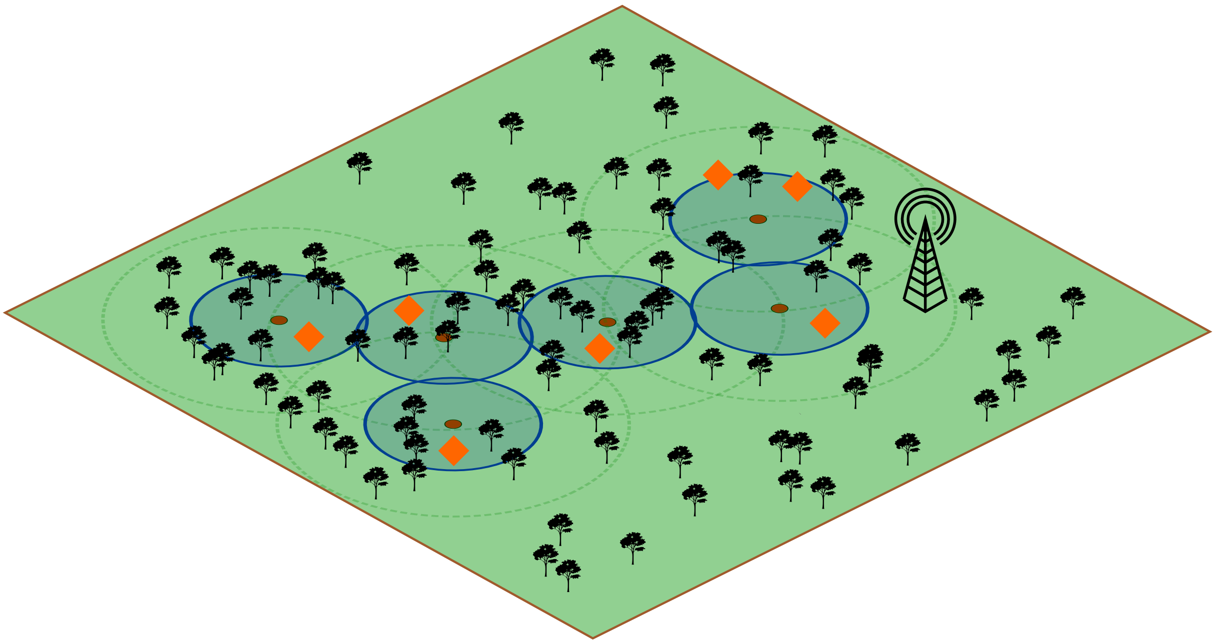

Figura 1 { Exemplo de uma RSSF 1-conectada e 1-coberta

Neste sentido, o presente trabalho apresenta um algoritmo h brido, composto de um Algoritmo Genetico e um algoritmo *Particle Swarm Optimization*, com a nalidade de descobrir uma posicao otima de sensores, bem como maximizando sua cobertura e conectividade, utilizando-se portanto da mesma modelagem e casos de teste propostos por Gupta Pratyay Kuila (2015).

A metodologia utilizada na hibridizacao do presente algoritmo e baseada em Rodrigues (2012). No caso proposto, uma populacao inicial e criada, entao a aptidao de seus indiv duos e calculada; A partir desta informacao, os indiv duos sao divididos em duas subpopulacoes, os melhores indiv duos sao enviados a um algoritmo genetico, enquanto os piores sao enviados a um algoritmo *Particle Swarm Optimization*. O algoritmo sempre busca minimizar a quantidade de sensores utilizados pela RSSF, respeitando as restricoes de m-conectividade e k-cobertura.

Para ns de comparacao, a metodologia de testes seguiu a mesma proposta por Gupta Pratyay Kuila (2015). No *Case Study I* os pontos potenciais formavam uma malha uniforme com intervalos de 25 metros entre si, tanto no eixo horizontal quanto vertical, enquanto no *Case Suty II* os pontos potenciais assumiam posicoes aleatorias. Neste sentido os resultados demonstraram que para os experimentos apresentados, a utilizacao do algoritmo proposto otimizou a solucao encontrada por Gupta Pratyay Kuila (2015) em ate 27% em sua melhor con guracao (k=1, m=3) do *Case Study I*, no entanto, em sua pior con guracao, o algoritmo apresentou resultados ate 6% (k=3, m=1) piores no *Case Study II*. Conclui-se que o modelo proposto e avaliado pelo presente trabalho obteve sucesso em sua proposicao. Mais detalhes do metodo apresentado podem ser encontrados no artigo anexado a este trabalho.

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A hybrid Algorithm for Deployment of Sensors with Coverage and Connectivity Constraints

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Abstract— *Finding optimal node deployment for a Wireless Sensor Network (WSN), while maximizing both coverage and connectivity as well as minimizing costs is a challenging task. In the considered scenario, coverage and connectivity are used as QoS (Quality of Service) measures for the desired wireless sensor network. In this case, the problem was handled as a multi-objective optimization problem. In this paper, we propose a hybrid optimization algorithm (GA-BPSO) based on Genetic Algorithm (GA) and Binary Particle Swarm Optimization (BPSO). In order to show the effectiveness of the proposed algorithm, we present some simulations and comparisons with existing methods in the literature.*
Keywords— ***Genetic Algorithms, Particle Swarm Optimization, Wireless sensor networks.***

I. INTRODUCTION

Technological advances brought several benefits in the communication field in the past few years. The combination of wireless communication elements and microcontrollers enabled the development of nodes with sensing capabilities. The joining of multiple nodes allowed the creation of comprehensive low-cost monitoring systems. While each node has restrictions such as power consumption, limited coverage, sensing capabilities and signal processing [1]–[3]; new challenges have been created. These systems of interconnected nodes are denominated in Wireless Sensor Networks (WSN).

Aiming an efficient operation, regardless of the used criteria, its nodes need to form a connected component. This way, it is possible that data can be transmitted by multiple sensors. However, maintaining connectivity coverage across the entire network is of utmost importance. Nodes have limited scope and power source or can be damaged, extinguishing their use in the network.

At the organizational level, each sensor can connect with neighboring sensors in order to reduce the assigned power consumption in its communication, minimizing external interference, and forming a connection network. By its nature, a WSN may run the risk of losing a partition of its network by some possible obstacle blocking the signals sent between sensors, whether by the existence of natural (mountains, trees, valleys, etc.) or artificial (buildings, monuments, walls, etc.) reasons. In this way, we must prevent such occurrence by requiring that each sensor has a defined range in order to have a finite number of neighboring sensors at any instant of time. Taking care in fulfilling this critical requirement may ensure that the sensor mesh remains connected [2], [4].

In order to avoid loss of connection, a network can make use of a restriction called m-connectivity. A WSN is said to be m-connected if, and only if, each sensor is connected to at least m other sensors. Thus, each sensor can hold up to m-1 faulty neighboring sensors [1]. Another QoS measure is related to the number of nodes covering a target. This constraint is given by the k-coverage restriction, i. e., each target must be covered by at least k different sensors [1, 2]. Fig 1 shows a WSN with $k=1$ and $m=1$.

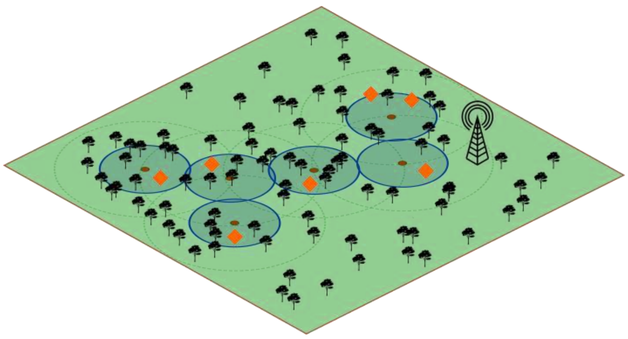

Fig. 1: Example of a one-connected and one-covered WSN.

In [5], the author proposes a hybrid evolutionary algorithm, mixing the benefits of the Particle Swarm Optimization (PSO) algorithm followed by evolutionary operators, in the discovery of the optimal position of sensors in a WSN network. Simulation results show that such a method can not only improve the location accuracy but also reduce its location response time.

Authors in [6] used a LEACH (Low Energy Adaptive Clustering Hierarchy Protocol) based algorithm, mixed

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with genetic algorithms to achieve increased lifetime and energy efficiency in WSN. The genetic algorithm is used to select cluster heads and create efficient clusters for data transmission. Simulations results show that the proposed hybrid protocol results in prolonged network lifetime and optimal energy consumption for sensor nodes inside a wireless sensor network.

In this sense, this work has as its main objective the proposition of a hybrid algorithm, composed of a Genetic Algorithm and a Particle Swarm Optimization algorithm, similar to the work done by [5], however, discovering an optimal position of sensors, as well as maximizing their coverage and connectivity.

The remainder of this paper is organized as follows.

Section 2 cites the background of Multi-objective Optimization, GAs, PSO and BPSO. Section 3 defines the problem formulation. Section 4 presents GA-BPSO. Section 5 presents results in two case studies. Finally, Section 6 concludes this paper.

II. BACKGROUND

2.1 Multi-objective Optimization

Multi-objective optimization (MOO) aims to find the Pareto optimal solution, forming the *Pareto-front* in the objective space [7]. It can be defined as:

$$f(x) = [f_1(x), f_2(x), \cdots, f_n(x)] \quad (1)$$

where Ὠ ẇ is the *i*th objective, ẇis the decision vector for ὲ ρ objectives.

Pareto optimal solutions for a multi-objective problem are virtually infinite. Thus, it is necessary to incorporate various objectives in order to determine a single suitable solution. Methods such *a priori articulation* depends on user indicated preferences before running the optimization, allowing the algorithm to determine a single solution that reflects what the optimal solution should represent, alternatively, *posteriori articulation* requires the user to manually select a single solution from the Pareto optimal set [8].

2.2 Genetic Algorithms

Genetic Algorithms (GAs) are simulated biological evolutions used to solve the optimization of nonlinear problems[9]. Vectors are encoded as possible solutions, which are representations of individuals, and they are made up of binary, real or integer elements, which represents their individual genes. A group of individuals is denoted as a population[10]. A fitness function is used as a means of measuring how close a given individual is to the optimal solution.

A GA starts by generating a random initial population, and a fitness value is calculated to each individual. The higher an individual's fitness, the higher its likelihood of reproduction. Evolution takes place by means of *crossover* and *mutation* operations, producing offspring that replace part of the population. This is repeated until the convergence criteria are met, the fittest individual of the last population is assumed to be the optimal solution found.

2.3 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a simulation based on the behavior of bird flocks and fish schools, also used as a means of finding optimal solutions for nonlinear problems. Individuals are represented by particles in a swarm and act according to self-acquired knowledge but also with the collective knowledge obtained by the swarm [11].

All particles move in a multidimensional space, where each particle has a position *x* and a speed vector *v* in relation to the time *t*. For each step of time, the velocity of each particle is updated according to the equation (2):

$$v_i^{t+1} = w \cdot \alpha_1 \cdot (p_i^b - x_i) + \alpha_2 \cdot (p_i^{gb} - x_i) \quad (2)$$

where ύ is the inertia factor, ἠ is the best local solution found by the particle so far, ἠ is the global best position found by all particles of the swarm, ȁ ȁ are coefficients of local and global learning, respectively.

With the new velocity, each particle *i* has its position updated by equation (3):

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (3)$$

3.2 Binary Particle Swarm Optimization (BPSO)

The BPSO modifies the original PSO algorithm, by using a similar methodology in a discrete binary search model. Therefore, since the position vector is binary, the speed is used as the probability of a bit to change. This way, the speed factor is limited to πἰρ using a Sigmoid function.

Thus, the speed is still obtained using equation (2), but the position is updated using the equation (4):

$$x_i^{t+1} = \begin{Bmatrix} 0 & if\ rand() \geq S(v_i^{t+1}) \\ 1 & if\ rand() < S(v_i^{t+1}) \end{Bmatrix} \quad (4)$$

where ὶώὲΩ ᴺ πἰρ and Ὑ ὐ is given by equation (5):

$$S(v_i^{t+1}) = \frac{1}{1 + e^{v_i^{t+1}}} \quad (5)$$

III. OPTIMIZATION PROBLEM

This work approaches the problem of given a set of targets Ὑ Ӧ ᴘ and a set of potential positions Ů Ӧ ᴘ, the *k*-coverage and *m*-connectivity deployment sensors

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problem is defined as selecting a subset Ὕ Ṗ Ữ such that each target in *T* is covered by at least *k* sensors and each sensor in *S* connected with at least *m* other sensors. In this context, a target is covered by a sensor, when within sensing range of that sensor. In addition, a sensor is said to be connected with another sensor whenever they are in each other connectivity range.

A solution Ὕ is said to be optimized if it minimizes the number of sensors while respecting the constraints. In addition, Ὕis considered the global optimum if, for every solution Ὕᾀ Ṗ Ữ, the number of sensors in Ὕis less or equal to the number of sensors in Ὕᾀ.

This work uses the same mathematical model as [12]. In this way, this problem is modeled as an integer decision problem. The decision variables are stated in equations (6) to (8).

$$b_{ij} = \begin{Bmatrix} 1, & \text{if target } T_i \text{ is covered by } S_i \\ 0, & \text{otherwise.} \end{Bmatrix} \quad (6)$$

$$c_{ij} = \begin{Bmatrix} 1, & \text{if a sensor } S_i \text{ is connected} \\ & \text{to another sensor } S_j \\ 0, & \text{otherwise.} \end{Bmatrix} \quad (7)$$

$$q_i = \begin{Bmatrix} 1, & \text{if a potential position } P_i \\ & \text{is selected for node placement} \\ & 1 \leq i \leq |P| \\ 0, & \text{otherwise.} \end{Bmatrix} \quad (8)$$

where Ὕᾷ is the *i*th element of Ὕ, and Ὕᾷ is the *i*th element of Ὕ. Thus, the problem can be formulated as follows:

$$Minimize \sum_{i=1}^{|P|} q_i \quad (8)$$

subject to:

$$\sum_{j=1}^{|P|} b_{ij} \geq k, \ \forall i, \ 1 \leq i \leq |T| \quad (9)$$

$$\sum_{j=1}^{|P|} c_{ij} \geq m, \ \forall i, \ i \neq j, 1 \leq i \leq |P| \quad (10)$$

Constraint (9) ensures that every target is covered by at least ὗsensor nodes, while constraint (10) states that each sensor should be connected with at least ά other ones.

IV. THE PROPOSED SOLUTION: GA-BPSO

In order to approach the considered problem, it is proposed a hybrid evolutionary algorithm combining the Genetic Algorithm and the Binary Particle Swarm Optimization (GA-BPSO).

4.1 Encoding

A sequence of potential positions Ὕ is encoded as a binary vector. Whether a position ὶ of S has the value 1, it means that the ith potential position is selected to deploy a sensor. Fig 2 shows an example of such encoding.

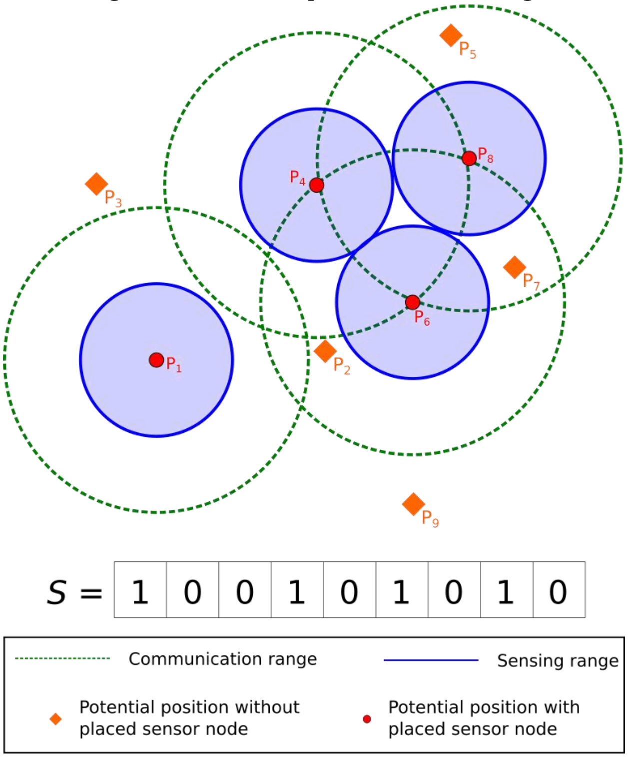

Fig 2: Example of encoding based on the potential position of sensor nodes.

4.2 Fitness

The fitness function is divided into three other objectives: F1, F2, and F3. F1 stands to minimize the number of potential positions selected by the algorithm. This quantity is related to the number of employed sensors of the network. F2 and F3 handle the *k*-coverage and *m*-connectivity restrictions, respectively.

Let Ὗ ȿὟȿ be the total of potential positions of Ữthat have been selected for placing sensor nodes, the first objective function is given by equation (11):

$$Minimize \ F_1 = \frac{N}{|P|} \quad (11)$$

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Let őἑὺ "Ỵ be the set of sensors nodes within sensing range of target "Ỵ, the second objective is then described by equation (12):

$$Maximize\ F_2 = \frac{1}{N \cdot k} \sum_{i=1}^{N} FCov(T_i) \tag{12}$$

where "Ōőἑὺ "Ỵ defines the full coverage by sensor nodes based on the set of sensors covering every target. Function "Ōőἑὺ "Ỵ is given by equation (13):

$$FCov(T_i) = \begin{cases} k, & \text{If } |Cov(T_i)| \geq k \\ |Cov(T_i)| - k, & \text{otherwise.} \end{cases} \tag{13}$$

Let őἑά Ũ be the set of sensors nodes within coverage range of Ũ, the third objective can be described as follows:

$$Maximize\ F_3 = \frac{1}{N \cdot m} \sum_{i=1}^{N} FCom(P_i) \tag{14}$$

where "Ōőἑά Ũ defines the full communication by sensor nodes based on the set of sensors covering every active sensor node. Function "Ōőἑά Ũ is defined in equation (15):

$$FCom(P_i) = \begin{cases} m, & \text{If } |Com(P_i)| \geq m \\ |Com(P_i)| - m, & \text{otherwise.} \end{cases} \tag{15}$$

It is important to note that both "Ō and "Ō conflict with "Ō, this happens because the objective aims to maximize the *k*-coverage and *m*-connectivity, this may be obtained by placing a substantial quantity of sensor nodes, shadowing the first objective. This way, the multiobjective is then modeled as a weighted sum. These weights can be applied without any transformation of the objective functions, as they merely represent the relative importance of the objectives [8].

Let ώ be a weight value applied to each objective, and all objectives are summed up into a single scalar objective function generating the following model:

$$\text{Maximize Fitness} = W_1 \times (1.0 - F_1) + W_2 \times F_2 + W_3 \times F_3 \tag{15}$$

Subject to:

$$0 \leq W_1, W_2, W_3 < 1 \tag{16}$$

where

$$W_1 + W_2 + W_3 = 1 \tag{17}$$

4.3 Description of GA-BPSO

The proposed approach is a combination of a Binary Particle Swarm Optimization (BPSO) algorithm and a Genetic Algorithm (GA). Following the logic presented by [13] and [14], this hybrid method is divided into two phases. In the first phase, the fitness of the generated population of size Ũ is calculated, then the population is divided into two parts of equal size. The best individuals are used as input for the GA, while the worst ones are used as input for the BPSO algorithm. In this way, the approach takes the benefits of GA, which GAs has genetic operators, so the individuals can evolve and find better offspring. While PSO does not provide such operators, it can perform exploration of solutions, which hopefully can guide the particles to possibly finding global optimal solutions.

In the second phase, a new population is generated by GA operators using the fittest individuals, while the worst individuals are enhanced by the BPSO evolution. These new and evolved individuals are merged back into a single population of size Ũ and sent back to phase 1 until the termination criteria are met.

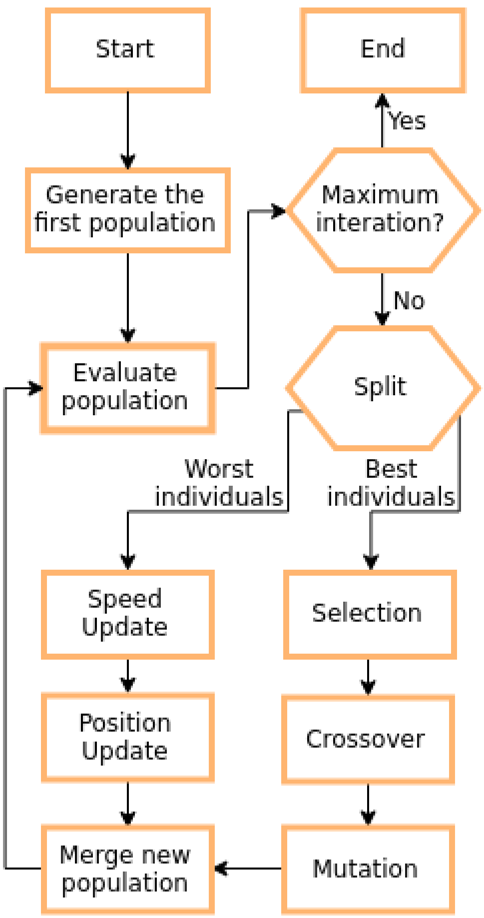

Fig 3: GA-BPSO diagram

4.4 Advantages of GA-BPSO

PSO shares many common points with GA. Both algorithms start with a group of a randomly generated population. Both use fitness values to evaluate the population. Both update the population and search for the optimum using stochastic algorithms. But, PSO is distinctly different from other evolutionary type methods in a way that it does not use the filtering operation and the members of the entire population are maintained through the search procedure so that information is socially shared among individuals to guide the search towards the best position in the search space [15], [16].

One of the advantages of GAs is the ability to finding local optima, by means of genetic operators that gradually improve the fitness of its individuals throughout generations. However, GAs can do less exploration for global search when compared to PSO solutions [17]. One disadvantage of PSOs is premature convergence. In order to avoid this effect, the PSO can be used to find better solutions from individuals with smaller fitness values in the population. On a PSO solution, every individual shares information among themselves, this way, such individuals converges to a better solution faster than GA [18]. Therefore, the proposed algorithm (GA-BPSO) combines the advantages of both GAs and PSO.

V. RESULTS

The evaluation of the GA-BPSO algorithm is done using the same two case studies as used by [12]. In both cases it is assumed an sensing field of σππ ά ό. Case Study I considered that each potential position could be positioned only on cross-points over a grid pattern with steps of ςυ ά. In the other hand, Case Study II assumed random potential positions inside the given sensing field.

Table.1: Presents all the simulation parameters.

Table 1: Simulation parameters.

Parameter	**Value**
Max iterations	100
Number of target points	100
No. of potential positions	100-500
Communication range	100 m
Sensing range	50 m
Initial population size	60
Mutation rate	3%
Elitism rate	50%
ώ ώ ώ	0.4, 0.3, 0.3
ǒ Ǖ Ύ Ǘ ώ ώ	[-6,6]
ǒ Ǖ Ύ Ǘ	.	2
ǒ Ǖ Ύ Ǘ ύ	[0.6-0.2]

Fig. 4 and Fig. 6 depict results in terms of the number of selected potential positions by varying the number of given potential positions, ranging from 100 to 500, with steps of 100. In both scenarios, a total of ρππ target points were given and Ώ ά values vary from ρ ρ to σ ς .

It should be noted that the number of given potential positions does not affect the quality of generated solutions. This is due to the fact that the optimal solution for any objective function is not mutable by the search parameters. It can also be observed the difference of selected potential positions varying *k* values, this is explained by a rise in complexity of the network mesh, when trying to adjust itself aiming to met its objective. The GA-BPSO results are compared with [12]. Fig. 5 shows the comparison results of Study Case I, as well as Fig 7, shows the comparisons results of Study Case II.

Comparing Fig 4 and Fig 6, there is a difference generated by the initial distribution of the network mesh. As depicted by Fig 4, on a grid-like pattern, GA-BPSO performs better. This is expected due to a guaranteed consistent distribution of sensor nodes on the field. This does not happen when using random potential positions instead. It is important to note the lack of substantial improvement when considering scenarios (k=2, m=1) and (k=2, m=2). A large communication range is responsible for keeping the sensors from disconnecting from each other while the algorithm evolves its population. This would not happen on a larger field though.

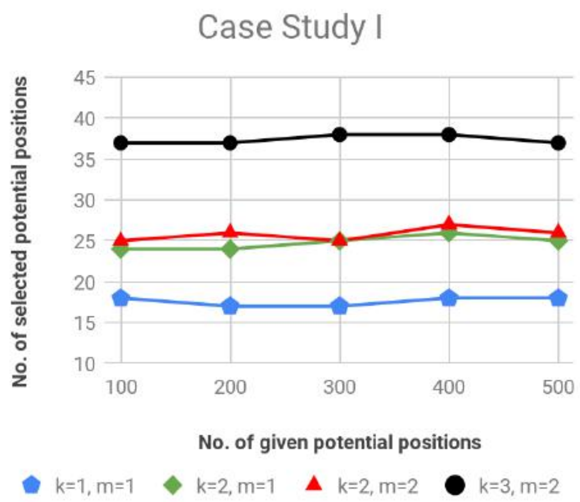

Fig 4: Comparison in terms of the number of selected sensor nodes for Case Study I.

Observing Fig 7, with instance (k=3, m=1) and Fig 6 with instance (k=4, m=1), it can be seen that GA-BPSO performed worse than the algorithm proposed by [12]. An investigation should be carried out in order to determine the sensitivity of GA-BPSO using (k > 4) scenarios as well as on larger sensing fields.

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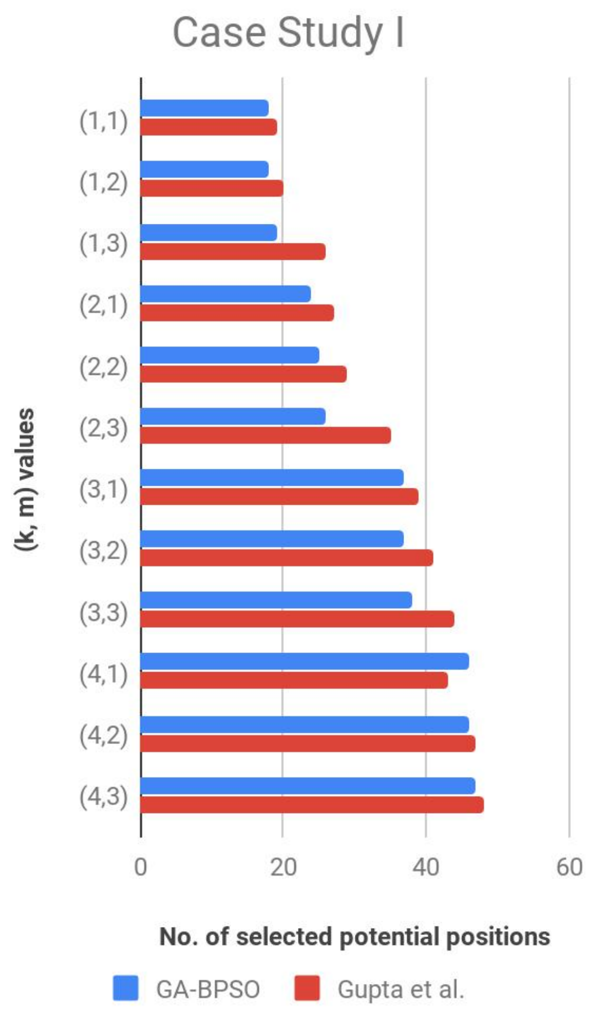

Fig 5: Comparison in terms of selected sensor nodes for Case Study I

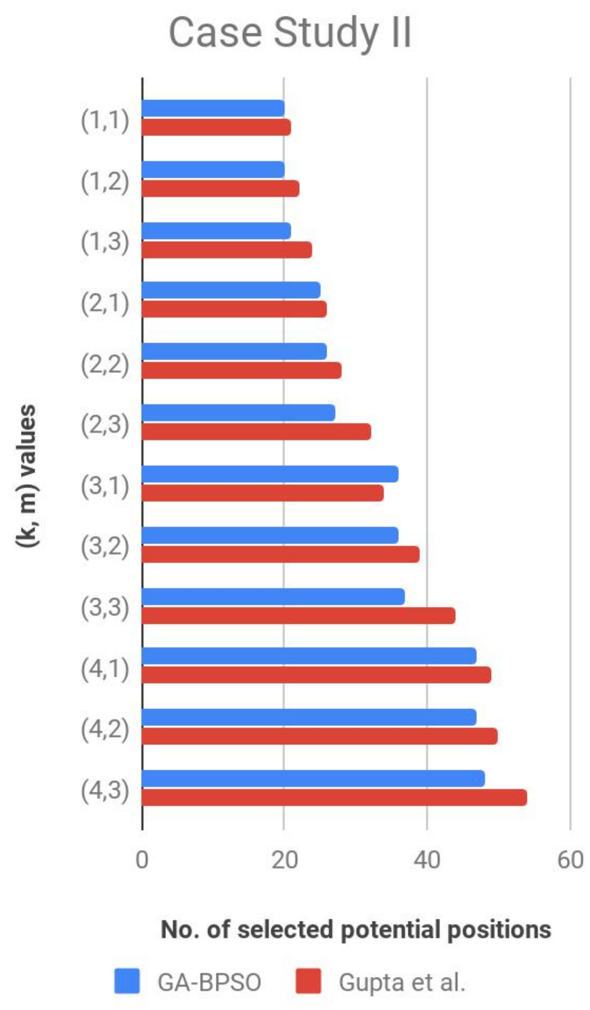

Fig 7: Comparison in terms of selected sensor nodes for Case Study II

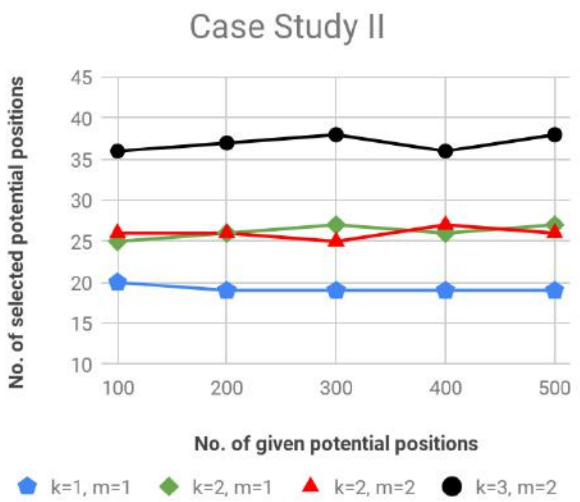

Fig 6: Comparison in terms of the number of selected sensor nodes for Case Study II.

VI. CONCLUSION

This paper proposed an alternative method, called GA-DPSO, for finding optimized solutions to the problem of sensor deployment, with *k*-coverage and *m*-connectivity restrictions. The GA-DPSO uses a combination of PSO algorithm and GA, mixing up the global search feature provided by the PSO algorithm (exploration) while using the local search with a GA (exploitation).

Results suggest that a large connectivity field can, in fact, make the network rely on the *k*-coverage for any further optimization. In some cases such as Case Study I instance (k=2, m=3), this algorithm found a solution at least 27% better than the results reported in [12]. The comparison results between both methods conclude that GA-BPSO performs better than the proposed in [12]. It improved, not only on finding reasonable less active sensors solutions, but also balancing the contradiction between the number of active sensors, coverage, and connectivity, improving on the WSN localization efficiency.

As future work, some more experimental studies with larger requirement parameters should be conducted. A clustering algorithm can be implemented utilizing AG-BPSO internally, intending to improve its processing power. In addition, mobile sensor nodes should also be considered on experiments.

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