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Hybrid Based Selective Genetic Algorithm

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ABSTRACT

Wireless Sensor Network WSN deployment is an active research area. Its goal is to deploy sensors in certain environment efficiently to optimize some evaluation measures. Meta heuristic searching optimization approaches have been proven to be effective in solving WSN deployment problem. They have strong power in exploring the solution space and converging toward the optimal region. One key factor in achieving more exploring power in the meta-heuristic searching is the selection criteria of the elite solutions from one iteration to another. Two common selection criteria are roulette wheel and pairwise tournament. In this article, a hybrid based selection is applied under genetic algorithm for solving the problem of WSND. The hybrid based selection selects between roulette wheel and pairwise tournament in order to maintain good exploration and fast convergence toward the best solutions.

Keywords*:* Meta-heuristic searching optimization, Genetic algorithms, Roulette wheel, Pairwise tournament.

1. INTRODUCTION

Wireless sensor network (WSN) consists of set of wireless sensors, low-cost, multi-functional communicating with each other using wireless signal to transfer data related to their environment. Typically, in WSN, data are transmitted through multi-hop to the sink node which is responsible of converting the data to higher level protocol. The deployment problem of WSN indicates to finding the best locations or distribution of the nodes in the environment in order to maintain certain level of performance measures such as: lifetime, coverage, latency, balance of distribution of energy, and quality of service QoS. However, these measures are implicitly conflicting with each other. For example: increasing coverage zone implies more energy consumption, which leads to a decrease in the lifetime of the network. Therefore, WSN deployment (WSND) is treated as multi-objective optimization (MOO). This treatment is superior over classical treatment where only one measure is taken as an objective and other measures are taken as constraints. The disadvantage of classical treatment is its over-emphasizing on the importance of one objective over the others. Contrary, treating the problem as MOO is more efficient to satisfy all objectives and to provide freedom of selecting the best balance of the objectives according to the specific nature of the application. MOO does not provide one optimal solution to the problem; instead, it provides set of non-dominated solutions named as Pareto set in which one solution cannot be dominated by others with respect to all objectives.

Literature contains various approaches to solve MOO some of them are classified under meta-heuristic searching optimization.
(Keskin, Altinel, Aras, & Ersoy, 2014) have provided a mathematical model to give decisions of sensor deployment integrated with activity schedules, data routes, and trajectory of the mobile sinks. Their work has demonstrated the effectiveness of heuristic deployment over randomly generated solutions.

(Sengupta, Das, Nasir, & Panigrahi, 2013) have studied WSND as MOO to maximize the coverage, minimize the energy consumption, maximize the network lifetime, maintaining the connectivity between the nodes and the sink with minimizing the number of the deployed nodes. For this purpose, they employed multi-objective evolutionary algorithm MOEA using differential evolution with a decomposition approach for converting the problem of Pareto fronts into a number of single objective optimization problem as an approximation.

(Jameii, Faez, & Dehghan, 2016) have performed an integration between non-dominated sorting genetic algorithm II (NSGA-II) and learning automata (LA). Their approach is named as multi-objective optimization coverage and topology control (MOOCTC).

LA has been used for automatically adapting the crossover and mutation rates without external control to improve the behavior of the optimization.

An integer linear programming formulation was performed by (Xu & Sahni, 2007) for WSND and was solved using greedy optimization. For coverage zone calculation, the authors have proposed an asymptotic approximation algorithms and a polynomial- time approximation scheme.

(Hashim, Ayinde, & Abido, 2016) have proposed an enhanced deployment algorithm based on Artificial Bees Colony (ABC). The goal of this algorithm is to optimize the network parameters in addition to the life time. Also, a constraint for the number of nodes has been incorporated. Their results have shown significant improve over classical approach of shortest path 3D.
The literature contains wide range of WSND approaches based on heuristic optimization. All of them work under the concept of generating random solutions and evaluating their fitness. More fitting solutions will be selected from one generation to another. The selection has to maintain two considerations: covering adequate areas in the searching space (exploration power), converging toward the optimum solution (convergence behavior). However, these two considerations are taken in different ways according to the selection process of fitting solutions. There are two main approaches of selection: roulette wheel RW, pairwise tournament PT. Roulette wheel favor solutions according to their fitness values, and adds them to the meeting pool which create a risk of convergence toward local minima. K-tournament selects randomly k-solution from one generation and favor the one with the best fitness value to add it to the mating pool. This can avoid the problem of local minima that appear in the roulette wheel. However, there is a risk of slow convergence when using k-tournament. In this article, a new approach of selection is developed. It is based on both approaches: the algorithm uses k-tournament in the early stage of the searching. Next, then the algorithm switches to roulette wheel in order to convergence and obtain the best solution.

2. METHODOLGY

The benchmark that has been used in this article is the work of (Khalesian & Delavar, 2016) which aims at performing wireless sensor deployment for 2D environment and homogenous type of sensors. The authors have developed genetic searching optimization for this purpose. In order to generate an off-spring from one generation, two operators: mutation and crossover were developed. The parents were selected based on two approaches: roulette wheels RW, and K-tournament. Results were generated based on different settings for the searching algorithm. In this article, our goal is to develop a new selection approach based on combination of RW and pairwise PT.

The selection approach will be based on two considerations: first one is that in the early iterations of the algorithm, it is important to explore more areas in the searching space by reducing the impact of one generation on the next. However, in order for the algorithm to converge, it is important reduce the exploration power and to rely more on the genetic characteristics of one generation to generate the next one. As it has been mentioned before, PT can serve for satisfying the first consideration while RW serve in satisfying the second consideration. The new criterion that is developed for this purpose is presented in the condition -1-.

$if(Rand > 1 - \frac{current\ iteration}{total\ numebr\ of\ iterations})$ ---------- (1)

perform roulette wheel

else

perform k-tournament

end

WSND is a multi-objective optimization problem, which requires using set of evaluation measures for multi-objective optimization.
The first measure to use is set coverage metric or C-metric. This measure takes the input as two optimal sets and gives the set coverage metric as output.

$C(P_{s1}, P_{s2}) = \frac{|\{y \in P_{s2} | \exists x \in P_{s1} : x > y\}|}{|P_{s2}|}$ ---------- (2)

C equals the ratio of non-dominated solutions in $Ps2$ dominated by non-dominated solutions in $Ps1$, to the number of solutions in $Ps2$. Thus, when evaluating a set PS, it is important to minimize the value of $C(x, PS)$ given that x is another pareto set.

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The second measure is the delta measure or the diversity metric Δ which indicates to extent of spread achieved among the obtained solutions. Mathematically, to calculate the delta measure, the function receives the non-dominated set of solutions and provides the result according to the equation

$$\Delta = \frac{d_f + d_l + \sum_{i=1}^{N-1} |d_i - \bar{d}|}{d_f + d_l + (N-1)\bar{d}}$$

This measure is preferred to be as small as possible which indicates to uniform distribution which provides a variety of choices to the decision maker.
This is done according to the procedure described in table --.

Table -1- **algorithm of calculating the diversity metric Δ**

Input: PS set of non-dominated solutions, PS_t set of true Pareto solutions
Output: Δ the extent of spread achieved

1- Sort the Pareto set according to each objective function in ascending order of magnitude.
2- Calculate the Euclidean distance d_i between consecutive solutions.
3- Calculate the average $\bar{d}$ of these distances
4- Fit a curve for PS_t and calculate the two extreme solutions
5- Calculate d_f , d_l the Euclidean distances between the extreme solutions and the boundary solutions.
6- Apply the equation --

The third measure is the hyper-volume metric (HV-metric or S-metric) which has been used widely in evolutionary multi-objective optimization to evaluate the performance of search algorithms. It computes the volume of the dominated portion of the objective space relative to a reference point. Higher values of this performance indicator imply more desirable solutions. The hyper volume indicator measures both the convergence to the true Pareto front and diversity of the obtained solutions (Sarker Liang & Newton 2002). It can be given by the following equation
The hyper-volume indicator $I_H^*(A) = \int_{(0,0,..0)}^{(1,1,...1)} \alpha_A(z)dz$ where

$$\alpha_A(z) = \begin{cases} 1 & if\ A \succcurlyeq \{z\} \\ 0 & else \end{cases} \text{----------} \quad (3)$$

Another measure that has been used in the generational distance metric or GD-metric, which is calculated by the equation

$$GD(P_S, P_T) = \frac{(\sum_{i=1}^{|P_S|} d_i^2)^{1/2}}{|P_S|} \text{----------} \quad (4)$$

where P_S is the number of solutions in the Pareto set,
P_T is the true Pareto front
d_i is the Euclidean distance between the solutions in P_S and the nearest solutions in P_T
Obviously, it is preferred to have the smallest values of GD.
Computational time is also considered as an important measure in multi-objective optimization algorithms considering that searching is highly complex computational problem.

3. RESULTS AND DISCUSSION

In order to evaluate the developed approach, we built three variant of the benchmark based on roulette wheel selection, pairwise k-tournament selection, and hybrid selection. The application is wireless sensor network deployment WSND with the parameters depicted in table-2-.

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Table -2- setting of simulation evaluation

Variable name	Value	Unit or explaining
Region of Interest	1000 X 1000	$meter^2$
Initial Energy	5	$joul$
Sensing Range	300	$meter$
Communication Range	$\frac{200}{\sqrt{2}}$	$meter$
Number Of Grid Points	500	points
Alpha	2	The path loss exponent
Beta	1	The transmission quality parameter
Amp	100*10^-12	
Number Of Sensors	20	Sensors
Number Of Solutions	40	elements
Number Of Iterations	50	Iteration
Dimension of Solution	2*number Of Sensors	Element
Crossover Rate	1	
Mutation Rate	0.5	
Selection Probability	0.5	Selection Probability to Determine how different the two solutions in Crossover is

The benchmark has been implemented in MATLAB environment version 2017a. Three variant of the model were implemented: the first one with roulette wheel selection (RW), the second one with pairwise tournament selection (PW), and the third one a hybrid selection HSBG. As it can be seen from figure-1-, the hybrid approach has achieved better Pareto front comparing with pw and rw. The solutions achieve higher coverage and more lifetime.

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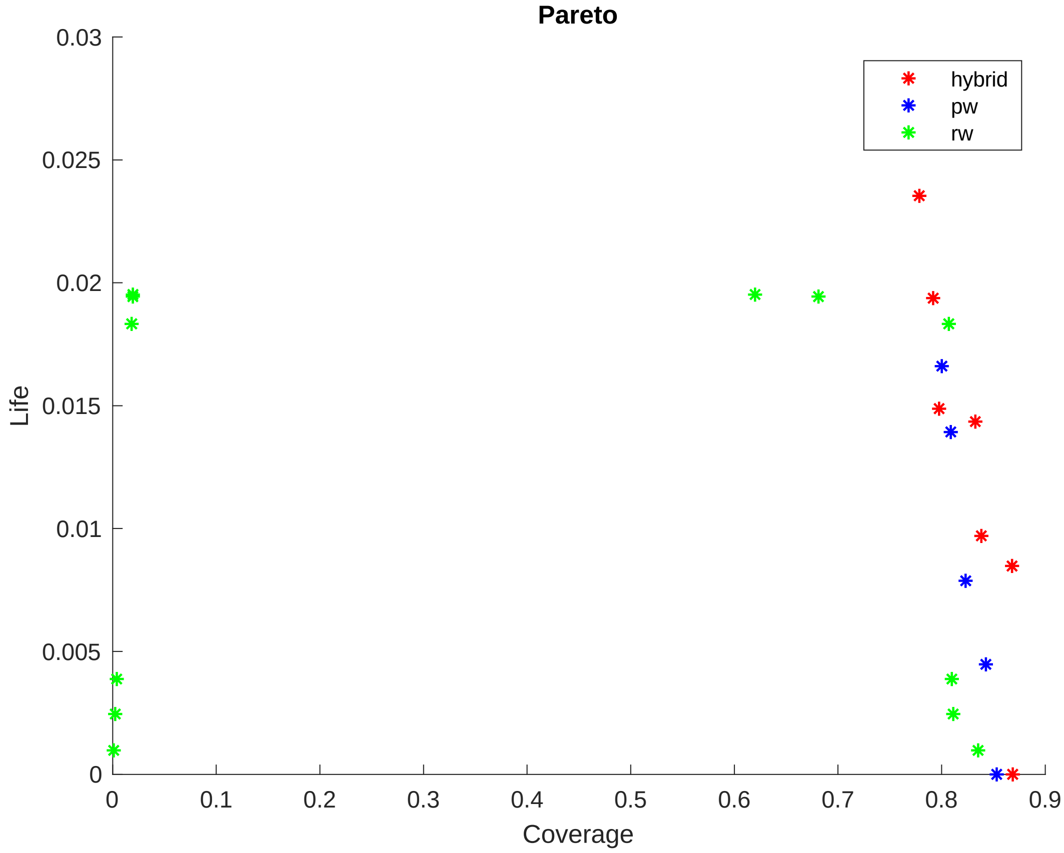

Figure -1-Pareto front comparison between three approaches

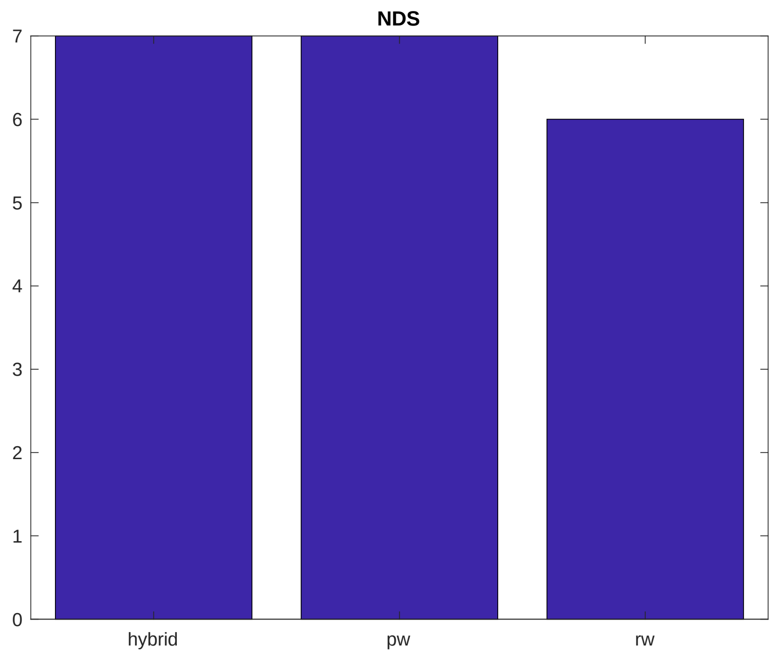

Figure -2-number of non-dominated solutions for the three approaches

For further comparison, we compare the hybrid approach with pw and rw in terms of hypervolume measure. As it is shown in figure-3- hybrid approach has achieved higher hypervolume comparing with the other measures.

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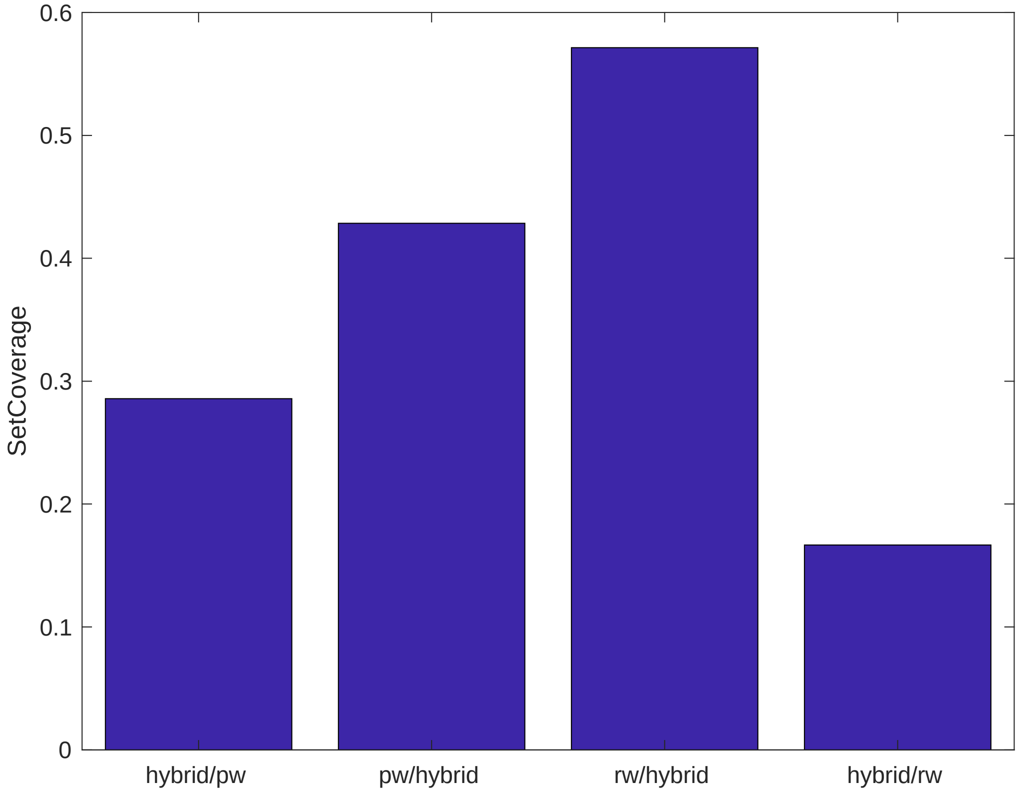

Figure-3-set coverage comparison of the hybrid with rw and pw

4. CONCLUSION

In this article, a hybrid selection based genetic based optimization has been proposed for the purpose of WSN deployment. Two mechanisms were considered, pairwise k-tournament and roulette wheel. Criterion function is used to determine which selection mechanism to use. The criterion is based on the iteration index, when the iteration index is low the algorithm will favor pairwise k-tournament in order to increase the exploration power while when the iterations increase the algorithm will favor roulette wheel over pairwise k-tournament in order to speed convergence.

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