Prioritized Multiobjective Optimization in WSN Redeployment Using Waterfall Selection

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Abstract. This paper proposes and evaluates a novel evolutionary selection called *waterfall selection* in a multi-objective optimization evolutionary algorithm for a priority-based wireless sensor nodes redeployment problem. Since, there are a variety of sensor node types in a target area. Each sensor node may have different objectives (E.g., network lifetime, data transmission, and success rate). Practically, the objectives of sensor nodes are prioritized after the deployment process. This paper focuses on the redeployment process of wireless sensor nodes to achieve their prioritized objectives simultaneously. Simulation results show that the proposed novel *waterfall selection* in multi-objective optimization evolutionary algorithm seeks to the solutions that conform to the prioritized objectives in timely manner and outperforms a *NSGA-II* evolutionary algorithm for multi-objective optimization.

Keywords: WSN, Redeployment, Multi-objective optimization, Prioritized Objective.

1 Introduction

A Wireless sensor network (WSN) contains a group of small sensor nodes. These sensor nodes can communicate and transmit sensing data to each other. Wireless sensor nodes can be deployed on a disaster risk area to serve as the intermediate nodes. Mostly, the initial deployment of sensor nodes is processed in random fashion. For example, into a disaster management application, a group of small sensor nodes can be dropped from a helicopter in the desired area [3]. After the deployment process, each sensor node starts exchanging some information with its neighbors and send its information to a base station (BS). The data transmission route can be generated by the BS using a routing protocol in the wireless sensor network (WSN) [1,2]. Then, the sensing data from the sensor node automatically transmit to the BS via intermediate nodes on the data transmission route.

However, the random fashion deployment leads to several problems such as short network lifetime and low data transmission success rate. A data transmission route may happen to be a bottleneck route; shortly, the intermediate nodes will run out of battery energy. The network lifetime is short [1]. Also; some sensor nodes may not be used and cannot transmit data to the base station because

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they are isolated in the unwanted area [10]. Moreover, in heterogeneous wireless sensor network, sensor nodes sense and transmit variety sensor data types. Each sensor node requires specific set of objectives. The set of objectives are different among sensor nodes. The objectives can be ordered by their priority due to the importance of their sensing data. Some of sensing data must be guaranteed to be arrived at the BS because it is a critical data. On the other hand, some of sensing data are delivered without haste. Thus, the prioritized multi-objective optimization problem will be considered. These problems can be solved by a redeployment process when some nodes are moved to the new locations in order to create more data transmission routes and eliminate the isolated networks. Finding the new optimal locations of redeployment process, this problem is proven to be an NP-complete problem [7]. To overcome this issue, an evolutionary algorithm(EA) with the redeployment process will be applied. An evolutionary algorithm is one of heuristic techniques that can be used to solve a NP-complete problem [11] and also can be used to seek a set of optimal solutions in the multi-objective problems [5].

This research proposes to apply a novel selection mechanism in an evolutionary algorithm to address the WSN priority-based redeployment problem. A novel selection mechanism , called *waterfall selection*, is proposed to apply in the wireless sensor node redeployment process. It heuristically seeks the Pareto optimal sensor node new locations. The *waterfall selection* is designed to improve the offspring creation process by considering objective priority of the sensor nodes. Its performance is evaluated through simulations. Simulation results show the comparison of the result from *waterfall selection* and the results from a well-known existing evolutionary algorithm for multi-objective optimization, NSGA-II [4].

2 The Problems in WSN Priority-Based Deployment

The objectives in this research are considered in three aspects: the network lifetime(NT), the data transmission success rate(SC) and the moving cost(MC). The network lifetime is a time that the sensor nodes can send their sensing data to the BS. The moving cost is a cost when some sensors move to new locations and the data transmission success rate is a ratio of send and receive sensing data. The sensor node stations (T_1, T_2, T_3) in the Fig 1 have the same for all three above objectives and each objective have different priority number. The objectives in this station are prioritized by the importance of their sensing data. For example, in flash flood monitoring WSN [8], the water level data is a critical data. This sensing water level data must be guaranteed to be arrived at the BS to investigate an occurrence of a flash flood. Thus, the highest priority of this water level sensor is the data transmission success rate; the network lifetime is considered as the second order priority. On the other hand, the weather monitoring sensor stations which sense temperature, humidity, and rain fall level can be deployed in the same WSN but in the different region. Normally, these weather monitoring stations are deployed in an area that are difficult to reach.

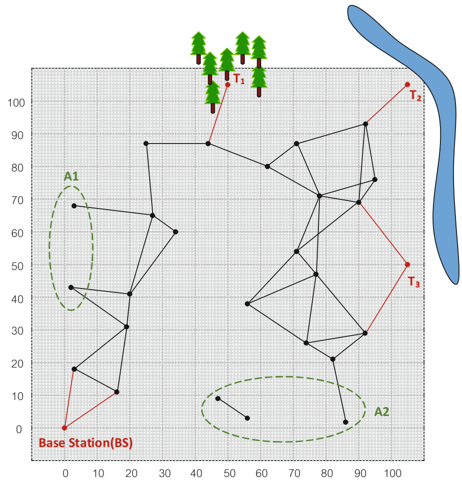

Fig. 1. An Example of WSN Priority-Based Deployment Problem

It is hard to replace the batteries. The weather sensing data is not critical. Thus, the highest priority of this weather monitoring station is the network lifetime; the data transmission success rate is considered as the second order priority. Thus, the priority number of objectives in sensor nodes are different. This research emphasize about priority-based in each objective.

In Fig 1, this is a normal WSN for environmental data sensing. Three sensor node stations(T_1, T_2, T_3) are considered to send the data to the BS. The other sensor nodes are the intermediate node. The sensor node stations (T_1) is a weather monitoring station, (T_2) and (T_3) are the flash flood monitoring station. The sensor node stations have the same objectives as network lifetime, the data transmission success rate and moving cost and each objective have different priority number as shown in the Table 1. After random deployment, the sensor nodes are crowded in the areas $A1$ and $A2$ and the sensor node stations used the same data transmission route in order to send their sensing data to the BS. An isolated problem and bottleneck route will be occurred. These problem can be solved by redeployment process. The redeployment process must improve not only the overall network performance but also the objective priority of each sensor node.

Table 1. Priority Number of Each Objective for Sensor Node Stations in Fig 1

	Sensor Node Station		
Priority Number	T_1	T_2	T_3
1 ($HighestPriority$)	NT	SC	MC
2	SC	MC	SC
3	MC	NT	NT

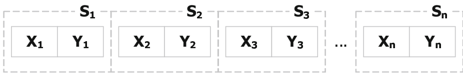

Fig. 2. The Structure of an Individual

However, an important issue of the redeployment process is the moving cost. If the goal of the redeployment process is only focus on minimizing the moving cost, all of the sensor nodes are not moved. Thus, the network lifetime is not lasting long. In contrast, if the objective of the redeployment process is only focus on maximizing the network lifetime, all sensor nodes will be moved to the new locations in order to increase the number of data transmission routes. In this case, the moving cost must be very high. Consequently, if the objective of the redeployment process is only focus on maximizing the network lifetime. All sensor node stations (T_1, T_2, T_3) will rarely sent their sensing data because this sensing node station want to save their energy. The data transmission success rate is very low. To overcome for all above issue, this research proposes an algorithm that considers the network lifetime, the data transmission success rate and the moving cost as the prioritized objectives simultaneously.

3 ***Waterfall Selection*** for WSN Priority-Based Redeployment

In order to improve the network lifetime, the data transmission success rate and minimize the moving cost as the prioritized objectives simultaneously, the multi-objective optimization approach is considered. For an example, assume that there are 10×10 grids represent as disaster area and there are 10 sensor nodes in the WSN. There are 100 positions which can be deployed for each sensor node. Therefore, the node placement combination is huge $(10 \times 10)^{10}$. So, the brute-force technique may not be suitable for node placement of a WSN. An evolutionary algorithm (EA) is one of heuristic techniques that can be used to solve a NP-complete problem [11] and also can be used to seek a set of optimal solutions in the multi-objective problems [5]. After EA is finished, the set of node properties (i.e., the set of solutions) are provided to the decision makers. The decision maker will select one of the solutions to develop the node redeployment process. This section describes the design of the study selection operators in a multi-objective optimization evolutionary algorithm.

3.1 Individuals

Each individual represents a set of nodes' positions in (x,y) coordinate. It consists of multiple segments, each of which represents a sensor node in the WSN. Therefore, the number of segments in each individual is equal to the total number of sensor nodes in the WSN. Fig 2 visualizes the structure of an individual. S_1 to S_n represent the first to n^{th} sensor nodes.

3.2 Optimization Objectives

This research considers prioritized multi-objective optimization in WSN redeployment problem. The objectives consist of three objectives as follow:

Network Lifetime (F_{nt}): The network lifetime(NT) in this research is defined as the time that each sensor node station starts to send their sensing data to the BS until the time that the sensing data cannot reach to the BS. This research seeks to maximize the network lifetime. The network lifetime can be calculated as Equation 1.

$$F_{nt} = Time_{last} - Time_{first} \tag{1}$$

Moving Cost (F_{mc}): The moving cost(MC) in this research is defined as the total cost when some of sensor nodes have to move to the new locations. This research seeks to minimize the moving cost. The total moving cost is a summation of each sensor node moving distances as described as Equation 2.

$$F_{mc} = \sum_{i=1}^{N} \sqrt{(x_{new} - x_{old})^2 + (y_{new} - y_{old})^2} \tag{2}$$

where N is the total number of sensor nodes, (x_{old}, y_{old}) is a current sensor node position and (x_{new}, y_{new}) is a new sensor node position.

Data Transmission Success Rate (F_{sc}): The data transmission success rate (SC) in this research is defined as the ratio of the number of received packets at the BS to the number of sent packets from each sensor node station. The data transmission success rate shows the WSN throughput performance. This throughput performance can be measured as Equation 3. This research seeks to maximize the data transmission success rate.

$$F_{sc} = \frac{\sum_i (P_{BS})_i}{\sum_i (P_{Total})_i} \tag{3}$$

where i is the number of sensor node stations, P_{BS} is the number of packets in each sensor node station received by the BS and P_{Total} is the total number of generate packet from each sensor node station in the target area.

3.3 Evolutionary Optimization Process

Waterfall Selection runs on the BS after random deployment. *Waterfall Selection* performs its evolutionary optimization process to adjust node properties. After *Waterfall Selection* is finished, the set of solutions are provided to the decision makers. The decision maker will select one of the solutions to develop the node redeployment process.

Algorithm 1 shows the algorithmic structure of evolutionary optimization in *Waterfall Selection*. The initial population (P^0) consists of μ individuals that

```
output: the set of solutions (Q)
parameter: g=number of each generation;
           μ=total number of individuals;
g ← 0;
P^0 ← Randomly generated μ individuals;
Q^0 ← Null;
while g != g_max do
    while |Q^g| != μ do
        p1 ← WaterfallTournament(P^g);
        p2 ← WaterfallTournament(P^g);
        q1, q2 ← Crossover(p1, p2);
        Q^g ← Q^g ∪ {q1, q2};
    end
    Q^g ← Mutation(Q^g);
    P^{g+1} ← WaterfallSelection(P^g ∪ Q^g);
    g ← g++;
end
```

Algorithm 1. Evolutionary Optimization in *Waterfall Selection*

contain randomly-generated node positions. In each generation (g), a pair of individuals, called parents (p_1 and p_2), are chosen from the current population P^g using a *waterfall tournament* operator (`WaterfallTournament()`). A *waterfall tournament* operator randomly takes two individuals from P^g, compares them based on their fitness values and order by the priority number, and chooses a superior one (i.e., the one whose fitness is higher) as a parent.

A pair of parents (p_1 and p_2) reproduce two offspring (q_1 and q_2) by using a crossover operator (`crossover()`). The offspring is mutated with a mutation operator (`mutation()`). The crossover and mutation operators change the node positions. The two offspring are created. These operators (`WaterfallTournament()`, `crossover()`, and `mutation()`) are repeated until the population of offspring ($|Q^g|$) reaches the population size (μ). Then, the *Waterfall Selection* is performed to select μ individuals for the next generation. The $|Q^g|$ offspring population is combined to the parent population P^g. Thus, the population size is 2μ (i.e., $P^g \cup Q^g$). Then, the (`WaterfallSelection()`) operator will be executed and selects the top μ individuals from $P^g \cup Q^g$ as the next generation population (P^{g+1}). This selection operator is performed by ordering of the fitness values and the priority number of each individual. The *Waterfall Selection* terminates its process when the number of the generations (g) reaches its predefined value (g_{max}).

3.4 Waterfall Selection Operation

The *waterfall selection* is designed to select a good parent or a good offspring with priority-based in multi-objectives optimization problem. The *waterfall selection* is divided into two procedures. First is called the *waterfall tounament* procedure. Algorithm 2 describes the pseudo code of the *waterfall tournament*

```
   input  : Population (Q)
   output: Parent individual (p)
1  parameter: i =number of sensing nodes station;
2             j^th=number of objectives priority;
3             n =total number of sensing node station;
4  r1, r2 ← random selection from Q;
5  j ← 1;     // Begin at First Priority
6  while p isNull do
7      for i ← 1 to n do
8          w1 ← PriorityValue(i, j, r1);
9          w2 ← PriorityValue(i, j, r2);
10         i++;
11     end
12     p = DominationRanking(w1, w2);
13     j++;
14 end
```

Algorithm 2. *Waterfall Tounament* Procedure

procedure. The input for this procedure is a population(Q). Two individuals (r_1, r_2) are selected by random technique from a population(Q). In each priority(j), the objective values(fitness value)(w_1, w_2) is calculated from each individual(r_1, r_2) by operator `PriorityValue()`. Then, a domination ranking operator (`DominationRanking()`) selects the winner (the highest fitness value). A domination ranking technique is described in [5]. The winner is become a parent in Algorithm 1. Second is called the *waterfall selection* procedure. The pseudo code of the *waterfall selection* procedure is quite similar to the *waterfall tournament*. A little difference between the *waterfall tournament* and the *waterfall selection* procedure is adding crowding distance procedure(`CrowdingDistance()`) after line number 12 in Algorithm 2. The crowding distance procedure is used for select the best individual in the same rank. The crowding distance procedure is described in [5].

4 Simulation Evaluation

This section shows simulation configurations and a set of simulation results to evaluate how *waterfall selection* contributes to search for appropriate node position that optimize the three objectives and three priority numbers of priority-based problem.

4.1 Simulation Configurations

The *waterfall selection* simulations were carried out on the modified jMetal[6]. The WSN simulator has been implemented and use the Gradient-based routing protocol(GBR)[12] as a WSN routing protocol. The simulator is combined with battery energy consumption of wireless sensor nodes and the media loss [13] in this simulation is set to be 5%. The sensing node station generate sensing data one packet per second.

The *waterfall selection* enter a group of individuals to the WSN simulation. Each individual compounds with a set of sensor node positions (x,y) . Then, the WSN simulator performs the WSN operations and returns the network lifetime, the data transmission success rate and the moving cost value to the jMetal. The simulation terminates its evolutionary optimization process when the number of the generations reaches its maximum predefined value.

It is assumed that the simulated wireless sensor network is initial randomly deployed sensor nodes in disaster risk area. The simulated wireless sensor network consists of 29 nodes in maximum. Sensor nodes are placed to the disaster area size 100×100 m^2. The physical properties of each wireless sensor node shows as Table 2, the priority table of the sensing node stations show as Table 1 and the simulation configurations in *EA* (*waterfall selection* and NSGA-II used the same config) show as Table 3

Table 2. Sensor Node Types

Type	#	Communication Range	Sensing Range
BS	1	50(m)	-
Sensor Node Station	3	25(m)	10(m)
Intermediate Node	25	25(m)	-

Table 3. The *EA* Simulation Configurations

Configuration	*EA*
# number of independent runs	16
μ	100
g_{max}	2,000
mutation rate	$1/n$
crossover rate	0.9
degree of SBX crossover	20
degree of polynomial mutation	20

4.2 Simulation Results

The simulation results are discussed in this section. The results from 16 independent runs of *waterfall selection* and *NSGA-II* are selected and compared in three metrics 1) The solution at last generations for all priority number of objectives 2) $\mathcal{C}$-metric which compared the obtained solutions of the algorithms, 3) The comparison of optimal solutions from each algorithm.

In jMetal[6], the default objectives is set to find minimum value. Thus, this research have to adjust the NT and the SC objectives. The NT and the SC objectives are re-formulated to $100 - NT$ and $1/SC$ respectively. Thus, if any algorithm which can find near the minimum value is better than the others.

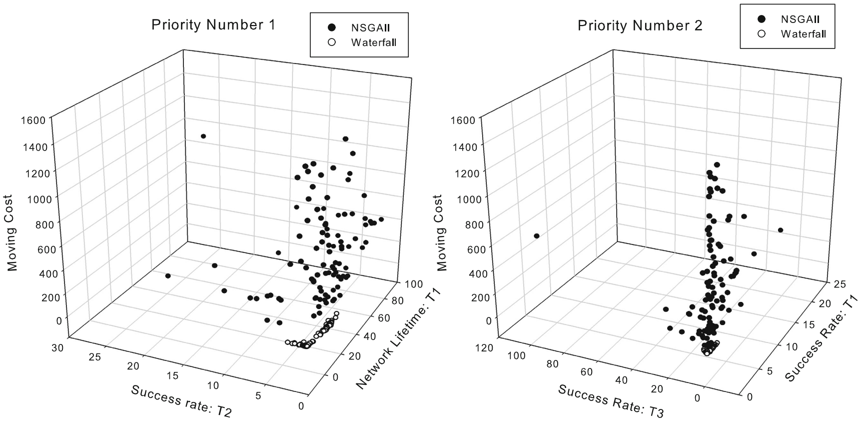

Fig. 3. *Waterfall Selection* versus NSGA-II in priority number 1 and 2

Fig 3 and Fig 4, the solutions from *waterfall selection* is near minimum value (the bottom right conner is a minimum value) than the solutions from *NSGA-II* for all priority number.

Table 4. $\mathcal{C}$-metric

Priority Number	$\mathcal{C}$(*Waterfall*,NSGA-II)	$\mathcal{C}$(NSGA-II, *Waterfall*)
1	0.98	0.00
2	0.47	0.00
3	0.78	0.00

$\mathcal{C}$-metric [14] represents how the individuals of an algorithm outperform the individuals of the other algorithm. Table 4 shows the $\mathcal{C}$(*Waterfall*,NSGA-II) and $\mathcal{C}$(NSGA-II, *Waterfall*) at generation 2,000. The result shows that at final generation $\mathcal{C}$(*Waterfall*,NSGA-II) is greater than $\mathcal{C}$(NSGA-II, *Waterfall*) for all priority number of objectives. This result means that the solutions from *Waterfall* dominate 98% of solutions from NSGA-II in priority number 1, 47% in priority number 2, 78% in priority number 3, and the solutions from NSGA-II cannot dominate any solutions of *Waterfall* in all priority number of objectives. Thus, the combination of genetic operations in *Waterfall* contribute to better solutions compared to the NSGA-II algorithm.

Table 4.2 shows average number of percentage which solutions from *waterfall selection* are superior than the solutions from *NSGA-II* and prioritized for all objectives. The priority number is the same as Table 1. The first order priority of sensor node station(T_1) is a NT. The solutions from *waterfall selection* can increase the NT to 52.8% from initial random deployment while the solutions from *NSGA-II* can increase the NT only 9.3%. The second order of sensor node station(T_1) is a SC. The *waterfall selection* can increase to 11.2% but the *NSGA-II* is decrease -6.5%. In sensor node station(T_1), the first order(NT) is increased

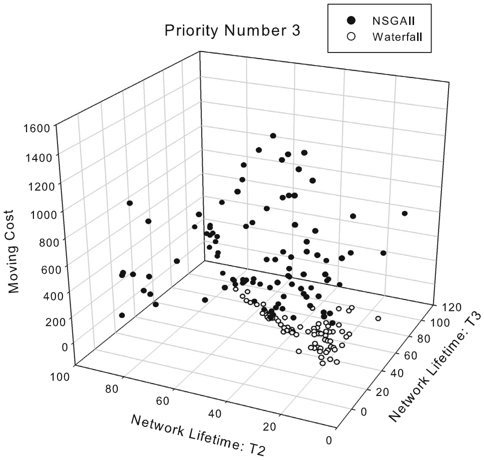

Fig. 4. *Waterfall Selection* versus NSGA-II in priority number 3

Table 5. Comparison of priorities

	T_1					T_2					T_3				
	Initial	*NSGA-II*		*waterfall*		Initial	*NSGA-II*		*waterfall*		Initial	*NSGA-II*		*waterfall*	
P_1	NT	NT	%	NT	%	SC	SC	%	SC	%	MC	MC	%	MC	%
	57	62.3	9.3	87.1	52.8	0.65	0.52	-20	0.75	15.3	0	503.8	-	18.3	-
P_2	SC	SC	%	SC	%	MC	MC	%	MC	%	SC	SC	%	SC	%
	0.62	0.58	-6.5	0.69	11.2	0	503.8	-	18.3	-	0.46	0.48	4.3	0.70	52.1
P_3	MC	MC	%	MC	%	NT	NT	%	NT	%	NT	NT	%	NT	%
	0	503.8	-	18.3	-	58	51.1	-11.9	65.9	13.6	58	57.5	-0.8	59.9	3.32

Note: T is a sensor nodes station, P is a priority number

up to 52.8% and the second order is increased up to 11.2%. This is ordered by priority number. It can be seen that the *waterfall selection* emphasize in order number of priority. Similarly with the sensor node stations(T_2, T_3), the *waterfall selection* can improve not only each of objectives versus initial random deployment but also achieve prioritized objective.

Fig 5 shows how the redeployment process improves the objectives of WSN. Fig 1 represents the initial nodes' positions from the random deployment process. Fig 5(left) represents one of the solutions after 2,000 generation evolution of *NSGA-II* and Fig 5(right) represents one of the solutions after 2,000 generation evolution of *waterfall selection*. Obviously, in Fig 5(right), there are more date transmission routes than that of the initial deployment and solution from *NSGA-II*. Since the data transmission load is distributed among the sensor nodes, the network lifetime of WSN is increased. Also, the data transmission rate is enlarged. However, only a few of the sensor nodes are moved to the new locations, which means the moving cost is small.

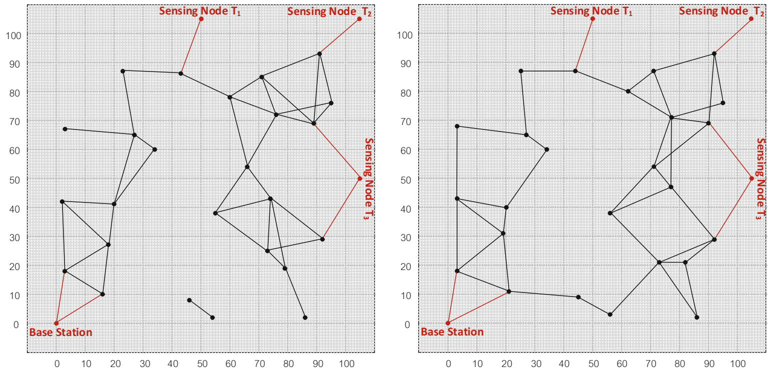

Fig. 5. An Example Solution from *NSGA-II*(Left) versus *Waterfall Selection*(Right)

5 Related Work

In [9], this paper investigates the proposed evolutionary algorithm to find appropriate sets of node locations for wireless sensor node redeployment. Simulation results show that the genetic operators in *FBEA* work properly and are able to find an appropriate set of node locations while handle the moving cost and data transmission success rate. The number of individuals that violate the constraints reduce faster than *NSGA-II* does. However, sensing node station in this research has only one station and does not take into account in prioritized multi-objective optimization problem.

6 Conclusion

This research investigates the proposed a novel *waterfall selection* operation in the evolutionary algorithm to find appropriate sets of node positions for prioritized multi-objective optimization problem. This selection mechanism selects a good offspring and evolve them via genetic operator in evolutionary algorithm. Simulation results show that the *waterfall selection* work properly and are able to find an appropriate set of node positions while corresponds with maximum the network lifetime, minimum the moving cost and maximum the data transmission success rate. The solutions from *waterfall selection* outperforms NSGA-II in all priority number of objectives while *waterfall selection* and NSGA-II take on the same execution time.

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