

A multi objective optimization in wireless sensor network using enhanced NSGA-3 algorithm

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Abstract

Wireless sensor network (WSN) is one of the most challenging study areas in the field of information technology. Among the many challenges posed by WSN, optimization in the presence of multiple conflicting objectives is one of the most major challenges. This paper discusses the previous research work in the field of MOO WSN. This research proposes a new algorithm, Enhanced NSGA-III which is a reference based with new dynamic weight-based cluster scheduling algorithm. ENSGA uses multi-parent order crossover (MPOX) to enhance fresh child to produce the best Pareto Fronts (PF). Total number of sensor nodes, network coverage and energy consumption are considered as the three conflicting objectives

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for the optimization study. ENSGA exhibits promising results in comparison to the NSGA-II and NSGA-III. The possible future work is also discussed in the paper.

Subject Classification: 68M18, 68M10.

Keywords: WSN, Cluster, Coverage, Connectivity.

1. Introduction

A wireless sensor network, sometimes known as a WSN, is an open wireless network with the capacity to observe and manage physical environments. It has numerous tiny, autonomous nodes that are spatially distributed. These widespread deployment of autonomous devices in the WSN are designed to collect data on the state of the environment or physical objects. The desired attributes of sensing nodes include low power consumption, versatility, self-adaptation, configuration. The latency, coverage, and impartiality among the competing sensor nodes comprise the quality of service (QoS). Maintaining QoS on the WSN node is challenging specially with the constraint of limited battery life [25-26].

The optimal deployment of the sensor nodes in WSN is obtained by optimization study. A simpler optimization study is solving a single optimization problem with one objective in focus with other objectives considered as constraints¹. This is not an effective study as it overemphasizes the objective in focus on the cost of other objectives². A simultaneous multi-objective optimization (MOO) gives equal emphasis on all the objectives. Thus, it is more realistic approach for optimal deployment of nodes in WSN³. The classical method of finding multi-objective optimization results was by solving a single-objective optimization problem with the single objective as a weighted sum of all the different objectives⁴. The challenge with such population-based algorithms is that we cannot get one single best deployment. The result of MOO study is a set of non-dominated points as solutions⁵. These sets of non-dominated solutions are known as Pareto set. Every point in this Pareto set represents one optimal deployment of the sensors. The multi-objective algorithms for solving WSN problems are population-based methods. Thus, the result gives the user a choice to choose any of the solution based on the user's priority of the various objectives⁶. In such cases the priority for different objectives can be represented in the form of weights. Fei et al.⁴ have reviewed of various MOO algorithms for optimization of WSN. The lifetime of the WSN and the energy efficiency are the major performance

metrics. Significant work has been done in the field of MOO study of WSN in the last two decades. To consider energy efficiency in WSN a lossy compression technique⁷ is proposed for the constrained resources available (nodes) is used. MOGA is used to create a collection of factors controlling the information loss with compression performance for ideal trade-offs. Maximizing reliability of WSN and with minimum deployment cost are recently studied using competitive multi-objective marine predator's algorithm (CMOMPA)⁸.

The result of MOO problem makes it difficult for the user to utilize the results as one optimal deployment of nodes. Bouzid et al.⁹ have proposed MOO algorithm MOONGA for the application in WSN. Based on the preferences of the network and the specifications of different applications, this algorithm gives an optimal deployment of sensor nodes according to the topology, the environment, and the designer users. A comparative study¹⁰ of Multi Objective Ant Colony Optimization (MOACO) against NSGA-II, SPEA-II is studied on maximizing coverage area and lifetime of the network based on coverage and a method of minimizing potential cost. The numerous machine learning algorithms for clustering to create a two-tier network architecture are discussed in detail¹¹. Yetgin et al.¹² studied the best paths between sources and destinations when competing goals, such as end-to-end delay, dissipated energy, and arbitrary multi-hop networks. The NSGA-II and MODE (Multi-Objective Differential Evolution) algorithms were compared by the authors. A performance comparison⁶ between the resulting algorithm MOEA/DFD and MOEA dubbed NSGA-II has shown a trade-off solution has been contrasted with node deployment schemes (single objective) based on DE (original), JADE, and Comprehensive Learning PSO. MOEA/DFD was reported to perform better than all test cases. The other study focusing on congestion control in WSN proposed a congestion control technique called PSOGSA¹³ algorithm. The waiting for queue size, level of congestion, data transmission rate, total packet loss, and delay are considered as performance measures. It is suggested that subsequent research look at load balancing and security issues [27-30].

NSGA-II has been the most widely used MOO algorithm due to its simplicity and robustness. The MOO study considering coverage and connectivity¹⁴ and the MOO study considering lifetime, coverage, and connectivity¹⁵ have shown that NSGA-II is a robust algorithm for obtaining optimal solutions in WSN too. Many application-based modifications have also been studied for WSN applications. An adaptive NSGA-II with learning automata termed as MOOCTC¹⁶ is studied for coverage and

topology control. The algorithm of NSGA-II has been modified to NSGA-III^{17,18} by considering a reference plane in place of crowding distance to maintain the diversity of the Pareto solution. This reference-based algorithm has also shown promising results in WSN applications¹⁹. The reference plane in NSGA-III is defined in such a manner to make the MOO algorithm robust for various applications. An application-based modifications²⁰ in the reference plane of NSGA-III has shown a better result in other fields. Such a study suggests possible modified reference plane work for WSN applications. We have proposed an enhanced algorithm ENSGA by modifying the reference plane in NSGA-III in this work.

2. Problem Description and Objective function

This research addresses three objectives MOP. Those three objectives are: minimizing the number of sensor nodes, increasing network coverage, and consuming the least amount of energy possible.

2.1 Minimization of number of sensor nodes

Each sensor increases the overall system cost and maintenance cost²¹. Minimization of number of sensors depends on the maximization of number of active sensors.

$$f_{active\ sensor(x)} = \sum_{i=1}^N Status_i \quad (1)$$

N: Total number of sensor nodes x_i, y_j

$F_{1(x)}$: Minimum Number of Senser in WSN

2.2 Maximization of network coverage

Coverage corelated to the sensing range²². The coverage objective is to ensure that the finite set of points in the target region are covered or monitored by at least one sensor node. Here we take maximum segregation is used to maximize the coverage.

$$f_{coverage}(x) = \frac{\sum_{x'=0}^x \sum_{y'=0}^y g(x', y')}{xy} \quad (2)$$

$$g(x', y') = \begin{cases} 1, & \text{if } \exists j \in \{1, \dots, N\}, d_{(x_j, y_j), (x', y')} \leq R_s \\ 0, & \text{otherwise} \end{cases}$$

R_s : Sensing range, the same for all sensors.

2.3 Minimization of energy consumption

Sensor nodes have limited battery power because of that total energy consumption is a crucial issue²³. Reducing intersection area between two or more sensors will decrease the energy consumption [31-32].

$$f_{\text{energy consumption}}(q) \sum_{i=1}^N \sum_{j=1}^N RS_i \cap RS_j \quad (3)$$

3. Network model and Proposed work

A clustering and scheduling based technique are applied. This algorithm helps to solve the multi objective problem by providing better convergence [33-34]. The new multi objective fitness function is proposed for achieving the multi objectives that is network coverage, active sensor, and energy consumption. this method based on node connectivity and clustering. The radius is taken as constraint which ensures the path reliability. We choose the new cluster heads (CH), based on the communication range, sensing range and total node energy consumption. The node scheduling techniques is used for enhancing the objective.

3.1 Clustering

The clustering techniques is used for dividing the large amount of sensor into a similar group or collection of objects based on resemblance and difference between them. In WSN the clustering [30-32] is used to ease the scalability to the large number of nodes and prolong the network lifetime by maintain the energy efficiency while communicating with neighbour sensor. in this work clusters are formed based on the active and inactive status of the sensor node. Let NS in the parameter for Node Status which can be active or nonactive node and CW is the weighted cluster value.

3.2 Novel Multi parent order crossover (MPOX)

A crossover operator called multi-parent order crossover (MPOX) [24] is adopted to resolve metaheuristic issue. MPOX enhances GA's performance by extending the order crossover (OX) into a multi-parent crossover. The primary driver for using a successful MPOX for order-based representation is to produce legal offspring with no duplicate numbers. MPOX uses a three-step process: first is substring selection, second step is substring copy, and third step is elements selections. In the MPOX substring selection phase an n-parent MPOX, n1 crossover points

are created at random. to split each parent into its child strings. The chosen substrings in this instance are n . Each parent is divided into four substrings by the chosen crossover points. The second chosen substring is copied into the newly formed offspring during the substring copy phase at the same absolute position as the first, in between the primary and secondary crossover points. The MPOX only produces one child from n parents since it is stated to pass the substring from the original parent to the new offspring. MPOX starts at the second crossover point of the second parent and then chooses the missing components to add to the child in the element selection phase to create a viable offspring from more than two parents. Following that, the filling phase will begin at the second crossing point that is the third substring. Up until the completion of the offspring of the third substring, the process is repeated. The MPOX proceeds until the fourth crossing point of the succeeding parent, at which time it chooses the elements missing from the progeny and begins to add them. Up until the next crossing point or the end of the offspring, this cycle is repeated. When MPOX reaches the final parent, it begins at the beginning of the parent, picks the components that the offspring is missing, and copies those components until the second crossover point is achieved, into the progeny commencing at the starting point. As a result, the offspring is complete and is full of all the necessary components.

3.3 Enhance Non-dominated Sorting Genetic Algorithm III (ENSGA).

The NSGA, NSGA-II, and NSGA-III algorithms are all evolutionary algorithms for MOO problems that use non-dominated sorting to achieve convergence. A group of non-dominated solutions constitute a MOO problem's solution. As a result, the MOO problem also aims to achieve a well-diversified solution set in addition to convergence. Both NSGA and NSGA-II use the principle of crowding distance to achieve this. The crowding distance is determined by NSGA using decision variable space and NSGA-II using function space. NSGA-III uses the concept of association of a reference plane to obtain a well-diversified solution. In Figure 1 shows the framework of evolutionary Algorithm. This research suggests an improved clustering and scheduling based multi objective method called Enhance NSGA-III (ENSGA), which is based on, to address performance issues in QoS for WSNs. Previous multi-objective algorithm issues including premature early convergence and the adverse impact of similar repeated redundant solutions can be avoided with this method. In comparison to other algorithms, ENSGA also produces more convergent

global solutions by using MPOX operation and adjusted dynamic weighted clustered scheduled reference points (RP), the NSGA-III algorithm is improved.

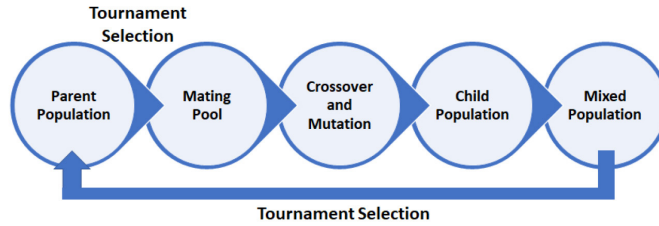


Figure 1

Framework of Evolutionary Algorithm

3.4 Calculation of Weight Value in ENSGA

The ENSGA algorithm is designed to accelerate the convergence of the NSGA-III algorithm. It is based on weighted clustered scheduled with vector adjustment. By using novel differential evolution techniques, ENSGA improves ability for evolution while dynamically modifying the weight vector. Cluster densities are too low if they are lower.

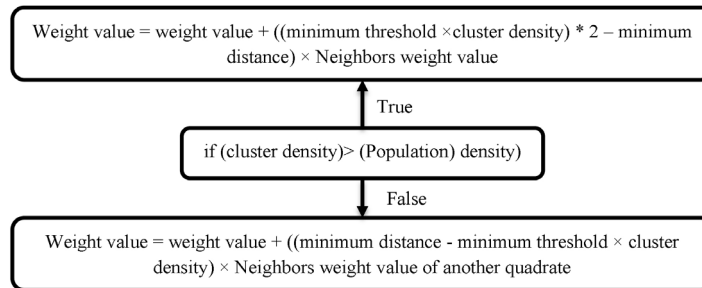


Figure 2

The distribution of weighted vectors

than the minimal population density. If the weighted clustered scheduled vector is not removed in this situation, the two nearest weighted clustered scheduled vectors are modified. If the cluster density (CD) is higher than the MPD (maximum population density), it is said to be excessive. The weighted clustered vector (WCV) should be considered in this situation; otherwise, the vectors of the two closest neighbors must be modified.

Figure 2 shows the how modifications done in the weight value base on cluster density and population density.

4. Result and Analysis

We simulate the proposed method (ENSGA) using MATLAB 2018a to determine how effectiveness of algorithm. MATLAB is widespread used for mathematical Calculation and simulation. In this simulation we assume that the network is free from packet collision and wormhole attack problem also assume that the network environment is dynamic in nature.

$$DRW = \sum_{\text{iteration } 25}^{100} \sum_{\text{objective}=1}^4 (PEC + NAS + NC + NCT) \quad (4)$$

here

DRW = Dynamic Random Weight

PEC = Percentage of Energy Consumption

NAS = Number of Active Sensors

NCT = Normalized Computation Time

NC = Network coverage

The algorithm configuration entails the utilization of 20 N division values along with crossover and mutation values of 1, and a mutation rate of 0.2. The total number of iterations ranges from a minimum of min 25 (+25) max 100 iterations. The population size ranges from a minimum of 10 (+10) maximum of 100 size. Ten different configurations were tested in the experiment. Table 1 shows the parameters of simulation of WSN. The Dynamic Random Weight (DRW) is calculated shown in equation 4. the normal as well as dynamic both value is taken under consideration. Figure 2 shows the result that the computed outcomes demonstrate that the

Table 1
Parameters of WSN (simulation)

WSN size	100*100 m ²
Total sensor nodes (n)	min100 (addition 100)max 500
Sensing Radius (RS)	Min 1 to max 300cm
Communication Radius (R _c)	Min1 to max 300cm
No of Objective	3

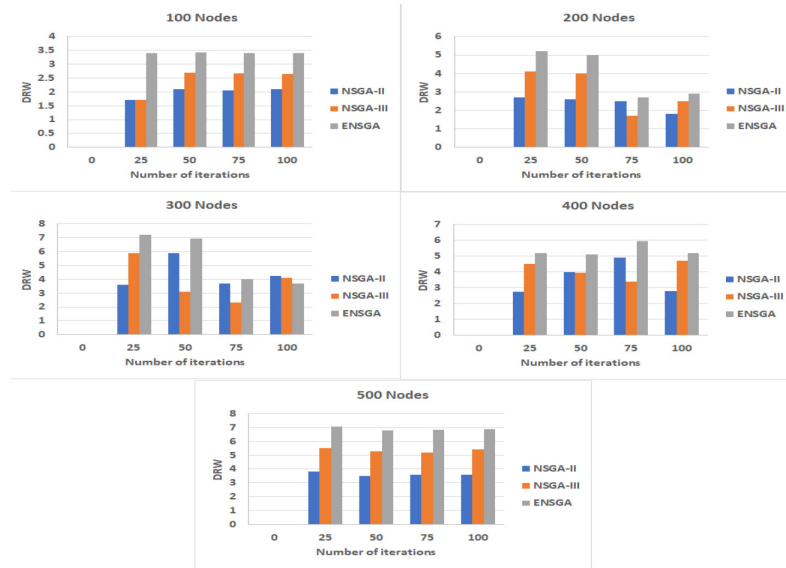


Figure 2

The MOO Resultant by Dynamic Random Weight Vs Number of Iteration for different number of Nodes.

suggested ENSGRA algorithm is superior to the other techniques and has been assigned the highest value would be next followed by other two algorithms. This result shows that, even when the combination model considers computation time, ENSGRA is still capable of outperforming the other techniques of MOO.

5. Conclusion and future work

The current research focuses primarily on enhancing two or more objectives and solving the Multi Objective Problem (MOP) is an NP-hard issue. finding solutions for conflicting multi-objectives by using meta-heuristic MOO algorithms. The most widely used algorithms in this field for providing Pareto Fronts (PF) solutions, which help the decision-making choose the optimum course of action, are NSGA-II and NSGA-III. For improving the performance of WSN, we proposed a ENSGA which is based on NSGA-3. Result shows the improved optimize result by using new algorithm. To evaluate the suggested method, we therefore want to

consider more objectives in the future, investigate their performance, and add more indications.

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Received February 2023