Improving the quality of service in wireless sensor networks using an enhanced routing genetic protocol for four objectives

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Article Info

Article history:

Received Mar 15, 2021
Revised Feb 7, 2022
Accepted Mar 16, 2022

Keywords:

Clustering
Multi-objective algorithms
Nodes load balance
Pareto front
Quality of service
Scheduling
Wireless sensor networks

ABSTRACT

Multi-objective algorithms are used to achieve high performance for quality of service (QoS) in wireless sensor networks (WSNs) is an important field for researchers because these algorithms improve two or more conflicting objectives and present the best trade-off between the conflicting objectives to solve multi-objective problems (MOPs). Previous research proposed an algorithm that relies on non-dominated sorting genetic algorithm 3 (NSGA-III), namely enhanced non-dominated sorting genetic routing algorithm (ENSGRA). This algorithm is used to optimise three objectives, which include number of worked sensors, energy consuming and node covering area. The fourth objective, which is node load balancing, is added in the current research. Such an addition aims to improve node distribution around cluster heads and decrease network congestion, thus decreasing energy consumption and increasing network lifetime. The ENSGRA algorithm is compared with multi-objective multi-step particle swarm optimisation (MOMSPSO), non-dominated sorting genetic algorithm 2 (NSGA-II), and NSGA-III. The proposed algorithm ENSGRA exceed to MOMSPSO, NSGA-II, and NSGA-III in the proposed QoS model in the final outcomes, as the proposed approach achieved (38%) average combination (optimisation) percentage. Which is the highest percentage over other methods.

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1. INTRODUCTION

Wireless sensor networks (WSNs) need multi-hop communication to send data between two nodes due to their limited energy and transmission range [1]. Forward messages from the source node to the neighbour nodes until the messages reach the destination my be occure directly or indirectly. However, such a process causes energy consumption and reduces network lifetime. From this viewpoint, the importance of improving quality of service (QoS) in WSNs using multi-objective algorithms emerged as a popular research field to consider WSNs as a backbone of internet of things (IoT). To solving multi-objective problems (MOPs), several multi-objective methods are proposed as an efficient approach. In MOPs, multiple and conflicting parameters are traded off to find an optimal solution using pareto front (PF) operation to help the decision maker in selecting the appropriate solution.

Clustering is crucial to achieve energy efficiency by improving the QoS along with load balancing in coverage areas [2]. The energy efficiency and network coverage can be enhanced by clustering to improve optimisation operation. Clustering is classified into five types based on objectives: clustring based on dominated set, clustring based on low maintenance, clustring based on mobility consideration, clustering based on energy-efficient and clustering that based on load balance [3]. The standard deviation of communication radius from sink node without or with clustering based on optimal cluster heads (CHs) is used to measure the load balancing amongst sensor nodes. Low standard deviations lead to high load balancing and vice versa [4], [5].

Optimising multiple parameters using multi-objective optimisation algorithms to improve the performance of WSNs has been studied since 2004 until present. Moshref *et al*. [6] conducted some statistical analysis of the articles related to multi-objective algorithms for WSNs. Then, they considered a new approach to represent most of the previous studies in the domain of using algorithms based on more than one objective to improving the WSNs performance. Considering their study, non-dominated sorting genetic algorithm 2 (NSGA-II), which was introduced by [7], is the most frequently used algorithm in this field. Meanwhile, non-dominated sorting genetic algorithm 3 (NSGA-III) has minimal use in this field.

The current research focuses on using load balancing clustering considering distributing nodes between clusters concerning load balancing. Moshref *et al*. [6] found that 3% of research in the field utilise multi-objective algorithms in WSNs through load balancing with clustering. Singh and Kumar [2] proposed a clustering protocol based on coverage-aware load-balanced, which focuses on area coverage and node load balancing around cluster heads (CHs), allowing equalisation of load between CHs. Randhawa and Jain [8] proposed a novel technique by utilising multi-objective particle swarm optimisation (MOPSO), which based on multi-objective load-balanced clustering. The load balancing is implemted in each iteration by mixing up the roles of next hop nodes and cluster heads. Edla *et al*. [9] addressed the problem of heavily loaded gateways (cluster heads), which die in early stages and cause changes in network topology. By desining new fitness function for the proposed particle swarm optimization (PSO)-based routing protocol by considering the number of relay nodes, the distance between the gateway (cluster heads) to base station and relay load factor.

The optimal method to election of CHs is considered an NP-hard problem. Gunjan *et al*. [5] proposed a multi-objective optimisation algorithm, non-dominated sorting genetic algorithm-II (NSGA-II), based on clustering in WSNs. This algorithm obtains trade-off solutions amongst conflicting objectives, such as network lifetime energy consuming, network coverage and node load balance, around cluster heads (CHs). Hence, the authors of this paper will use enhanced non-dominated sorting genetic routing algorithm (ENSGRA), an algorithm that based on multi-objective, to improving QoS in WSNs using the following four objectives: the number of nodes that are active, energy consumption, coverage for nodes, and node load balance. This research aims to solve problems with more than one object to enhance QoS in WSNs using multi-objective algorithm based on four objective functions: to minimise the number of active sensors, to minimise sensor nodes intersection to reduce energy consumption, to maximise sensor nodes separation to increase network coverage, and to minimise the standard deviation of communication radius to achive high load balancing.

The research is organised as shown in: The introduction is presented in section 1. The proposed algorithm, framwork, and research methods, explained in section 2, and 3 respectivly. The results and discussion are displayed in section 4 in additional to results evaluations. Finally, section 5 represent the conclusion and future works.

2. THE PROPOSED ALGORITHM

2.1. Load balancing for sensor nodes

The network coverage, latency, computing divices capacity, security, energy consumption and lifetime, consider as shortcomings that affect WSNs; these factors are also important in maintaining many real-time applications for QoS, which is very crucial [10]. High WSN density due to a large number of deployed nodes in small areas, so it will increase the difficulty of problems and introduces challenges, such as load imbalancing, and covering area will have hole reduction problem [11]. Network lifetime is increased by minimising power consumption and realising high load balancing amongst the sensor nodes because despite some networks have ideal load balancing, it can die very quickly [2], [4].

Gunjan *et al*. [5] argued that the solution protocol for load balancing and energy-efficient communication is clustering. In clustering, the nodes organise themselves into clusters, and each cluster has CHs, which communicate their data to local base stations, further transmitting data to the global base station. The current research aims to optimise node load balancing using clustering as in the ENSGRA algorithm or without clustering as in other algorithms. Managing load balancing of CHs, which is an NP-hard problem, is necessary. If the goal further becomes complex, then the scheduling between active and inactive node based on coverage-aware must also be considered.

2.2. Sensor nodes clustering

Nodes clustering consider as an most effective topology to control approach and achieve long-term operations of WSNs. So it is most effective method to constructions networks that depend on clustering considering power utilisation [12], [13]. Clustering techniques can be classified into homogeneous or heterogeneous considering initial energy based on the type of WSN. Therefore, an efficient clustering allows load equalisation between CHs [2]. Dhumane and Prasad [14] classified clustering techniques into partitioned (fuzzy-based), optimised-based and low energy adaptive clustering hierarchy (LEACH)-based clustering. Finding the best possible CH is considered to be a critical issue in clustering methods. Selecting nodes using the optimisation algorithm and K-means can create clusters in the nodes because the selection of appropriate CHs with the largest energy will increase energy efficiency and prolong network lifetime [15], [16].

CHs are treated as gateways, which perform multiple activations, such as data gathering, aggregation and transmission. This mechanism are built on decreasing the distance between cluster heads (CHs) and base stations [9]. Sensor nodes correspond to the selected CH. Moreover, sensor nodes communicate with their CHs or other sensors in the same cluster, whilst CHs communicate with the sink node or base station, as shown in Figure 1 [17].

Figure 1. WSN using cluster heads (gateway) [9]

2.3. The framwork for new approach

Figure 2 shows the framework block diagram of the WSN architecture with the proposed ENSGRA. It represents the approach that are used to enhance the performance of QoS in WSNs based on four objectives. Sensor nodes are randomly deployed in the area of interest, then routing is achieved by clustering and scheduling operations. Initially, the algorithm deploys nodes and randomly selects a cluster head (the algorithm initialises the population). After using NSGA-III and updating genetic operations recombination (crossover), two parents' crossover are integrated with multi-parent crossover (MPX). Then reference points are updated by the adjusted weighted clustered scheduled reference points to enhance non-dominated PF solutions. The fitness of each node is calculated based on the proposed multi-objective fitness function to achieve enhanced objectives, which include the number of active sensors, energy consumption, network coverage, and node load balancing.

The decision maker takes the final WSN routing solutions (non-dominated PF solutions). In these solutions, the node energy, node sensing radius and node communication radius are used to select the new cluster heads. In addition, several deployed nodes turn off (become inactive) based on node scheduling, whereas in the final solutions, this will balance the deployed node around each cluster head, and increase and network lifetime by maximize energy efficiency, and network coverage. Figure 3 shows the format of the original individual, which contains (k) as the amount of active sensor nodes and (s) as the number of genes. These two must be equal given that each sensor is considered as a gene that contains four parameters: x coordination, y coordination, sensing radius and communication radius for each sensor. In this case, sensors have two types of status, active or non-active node, as shown in (1).

In the binary method [5], an individual (chromosome) is represented as a string of 0s and 1s, where 0 indicates that the node is a non-cluster head/member and a 1 indicates that the node is a cluster head. Figure 4 shows the format of an updated individual, which contains (k) as the amount of sensor nodes and (s) as the number of genes. The two must be equal given that each sensor is considered as a gene that contains four parameters: x coordination, y coordination, sensing radius, and communication radius for each sensor (as in Section 3.2). In addition, this format considers clustering by adding a number of cluster heads, with (m) PF and each PF solution has a number of cluster heads ci, then $i = \{1, \ldots, m\}$ and ci is $2 \leq c_i \leq \frac{k}{10}$. For example, for (100) sensors, the minimal number of cluster heads is (2) and the maximum number of cluster heads is (10). In clustering, two additional parameters (*Wc*) are the sensor node in any cluster and node status (*Ns*) that is a natural active or non-active node or cluster head.

$$\text{Node ststus} = \begin{cases} 0, \text{if node non active} \\ 1, \text{if node active} \end{cases} \quad (1)$$

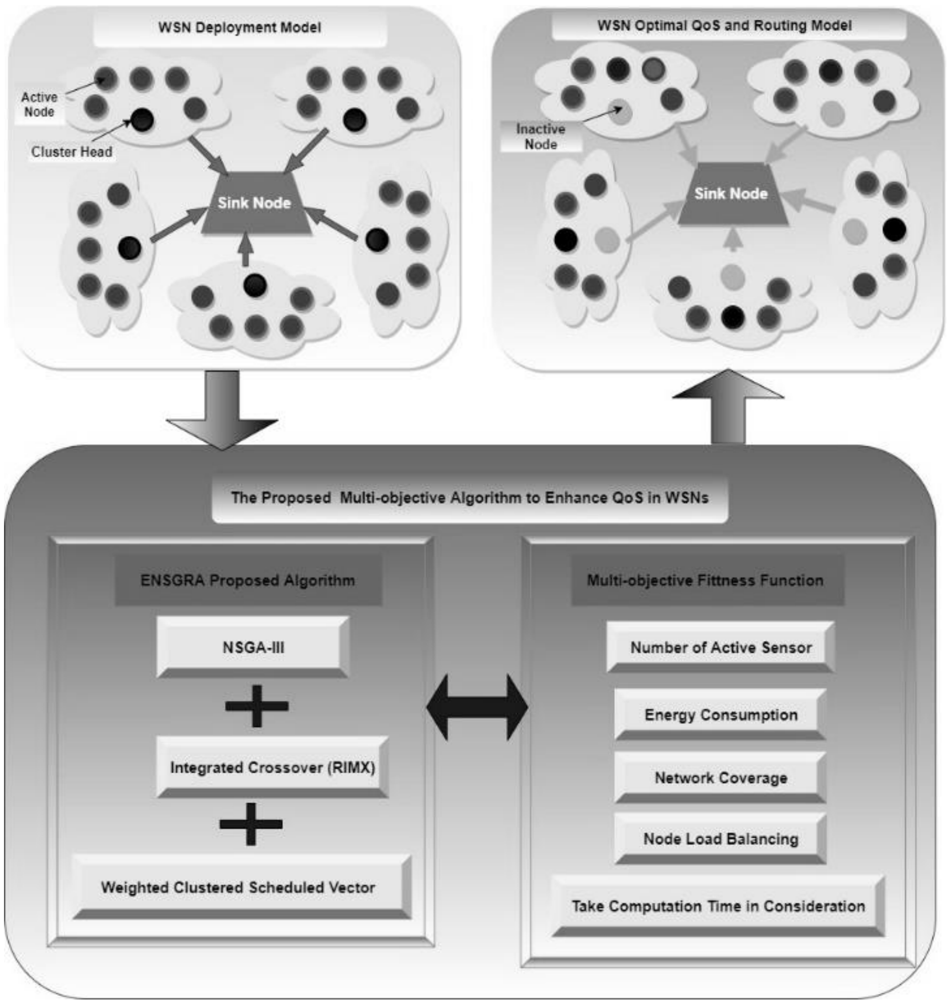

Figure 2. Framework block diagram using ENSGRA algorithm [18]

WSN Individual (Chromosome)

s_1				… …. …				s_k			
x_1	y_1	Rs_1	Rc_1	…	…	…	…	x_k	y_k	Rs_1	Rc_1

First Gene

Figure 3. Format of original individual

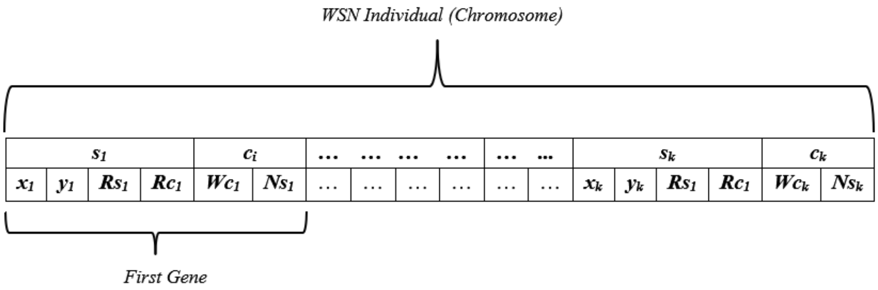

Figure 4. Format of updated individual

2.4. Network assumptions

In MOPs, several objective functions simultaneously need optimisation (minimised or maximised). For example, *m* objective functions require minimise or maximise expressed as (2).

$$F(x) = (F_1\,(x), \ldots, F_m(x)) \tag{2}$$

2.4.1. Number of active sensor nodes model

The function that finds the sum of the status of active sensors will be used to minimise the number of active sensors. Jameii *et al*. [19] used (3).

$$f_1(x) = \sum_{i \in N} Status_i \tag{3}$$

Where N is the number of sensors, and $\mathrm{f_1(x)}$ provides the minimum number of active sensors in WSNs that randomly deployed in the area of interest.

2.4.2. Energy consumption model

The function that minimises the intersection between sensors in its sensing area will be used in the current research to conserve energy. Kareem *et al*. [20] used (4).

$$f_2(x) = \sum_{i=1}^{N} \sum_{j=1}^{N} Rs_i \cap Rs_j \tag{4}$$

Where *N* is the number of sensors, and $f_2(x)$ must be as minimum as possible.

2.4.3. Coverage model

The function that maximises the separation between nodes will be used to maximise network coverage. Gunjan *et al*. [5] used (5) and (6).

$$f_3(x) = \max(sep) \tag{5}$$

$$sep = \sum_{i=1}^{N} \sum_{j=1}^{N} d_{ij} \tag{6}$$

Where *dij* is the distance between any two nodes and should be maximised as much as possible.

2.4.4. Load balancing model

The fourth objective function aims to add load balancing. That is, load balancing of deployed nodes in the area of interest should be maximised but heavy load (network congestion) should be minimised. The standard deviation of communication radius *Rc* from sink node is used to measure load balancing amongst sensor nodes. A low standard deviation indicates a high load balancing and vice versa [4]. Kareem *et al*. [20] used (7) and (8).

$$f_4(x) = \sum_{i=1}^{N} mean\left(\frac{Rc_i}{d_i}\right) + SD\left(\frac{Rc_i}{d_i}\right) \tag{7}$$

$$d_i = \sqrt{(x_i - x_{sink})^2 + (y_i - y_{sink})^2} \tag{8}$$

Where d_i is the distance between sink and node, and then find mean and standard deviation (SD) for communication radius Rc_i, divided by d_i, the result should be as minimum as possible.

3. METHOD

A directed graph is assumed *G = (V, E)*, where *V* represents the set of sensor nodes, and $E \subset V \times V$ represents the links between a pair of nodes (a communication radius), can be used to implement WSNs, whilst network performance depends on the transmission range of sensor nodes [5], [21]. The following assumptions must consider representing a WSN: i) All the nodes and the base station are static (stationary); ii) Sensor nodes have a uniform random deployment (distributed) in the network flat area; iii) Batteries in sensor nodes are not interchangeable (couldn't be change) and have a specific lifetime, whilst the base station (sink node) has an infinite reserve of power; iv) All the nodes are homogeneous (have similar initial power); and v) Two nodes can communicate directly to forward messages from the source node to the neighbour nodes until the messages reach the destination nodes. Therefore, the nodes act as host or router simultaneously.

Other assumptions must consider the method to build the WSN using multi-objective algorithms.

- Let $\mathcal{A}$ be the region of interest
- The sink node with coordination (x_{mid}, y_{mid}) is in the middle of the region of interest
- $\mathcal{S}_{\Theta s} = \{s_1, \dots, s_k\}$ is a set of k sensor nodes with set Θ_s of parameters, such as *x* coordinate, *y* coordinate, *Rs* sensing radius (for coverage) and *Rc* communication radius (for connectivity). $\Theta_s = \{(x_{s1}, y_{s1}, Rs_{s1}, Rc_{s1}), \dots, (x_{sk}, y_{sk}, Rs_{sk}, Rc_{sk})\}$, These parameters are considered similar to the original individual used with MOMSPSO, NSGA-II, and NSGA-II algorithms. However, with ENSGRA, $\mathcal{C}_{\Theta c} = \{c_1, \dots, c_m\}$, which is a set of m CHs with Θ_{sc} of parameters. These parameters are similar to previous parameters *x*, *y*, *Rs* and *Rc* with additional *Wc* means (which cluster the sensor node followed) and *Ns* means (node status: cluster head, active node non-cluster head or inactive node), as represented (9).

$$\Theta_{sc} = \begin{Bmatrix} (x_{s1c1}, y_{s1c1}, Rs_{s1c1}, Rc_{s1c1}, WC_{s1c1}, NS_{s1c1}), \dots, \\ (x_{skcm}, y_{skcm}, Rs_{skcm}, Rc_{skcm}, WC_{skcm}, NS_{skcm}) \end{Bmatrix} \tag{9}$$

- Let NSGA-II, NSGA-III, and ENSGRA have 8-tuples as (10).

$$Algorithm\ tuples = (\ I\ , \Phi, \Omega\ , \Psi, l\ , N\ , EP, \varphi\ ) \tag{10}$$

Where:

- I: is individual or chromosome, which is encoded as a complete solution. Each individual has a set of *k* solution containing sensors, and each sensor has *x*, *y* coordination and *Rs*, *Rc* radius. Clustering has additional parameters, such as *WC* and *NS*.

  I, without clustering as (11).

$$I = \{(x'_{s1}, y'_{s1}, Rs'_{s1}, Rc'_{s1}), \dots, (x'_{sk}, y'_{sk}, Rs'_{sk}, Rc'_{sk})\} \tag{11}$$

And *I*, with clustering as (12).

$$I = \begin{Bmatrix} (x'_{s1c1}, y'_{s1c1}, Rs'_{s1c1}, Rc'_{s1c1}, WC'_{s1c1}, NS'_{s1c1}), \dots, \\ (x'_{skcm}, y'_{skcm}, Rs'_{skcm}, Rc'_{skcm}, WC'_{skcm}, NS'_{skcm}) \end{Bmatrix} \tag{12}$$

IP represents the initial population, which is conducted randomly as (13).

$$IP = \{\ I_1, \dots, I_N\ \} \in\ I^N \tag{13}$$

- $\Phi = \mathrm{I} \longrightarrow \mathbb{R}^3$ is the fitness (objective) functions for individuals $\forall\ i: 1 \leq i \leq k$ as (14).

$$\Phi_i = \{NoS_i, EC_i, NC_i\} \tag{14}$$

Where: $NoS\ (I)$ is the number of active sensors, $EC(I)$ is used for energy consumption and $NC(I)$ is used for network coverage. Meanwhile, if using four objective functions, then expressed as (15) and $LB(I)$ is used for node load balancing as a representing objective function in section (4.4) a set of operations such as selection, crossover, and mutation in ENSGRA, which cosider as genetic opration used two parents and MPX operation, expressed as (16).

$$\Phi_i = \{NoS_i, EC_i, NC_i, LB_i\} \tag{15}$$

$$\Omega = \left\{ S_{\Theta_s}, C_{\Theta_c}, M_{\Theta_m} \middle| S_{\Theta_s}, C_{\Theta_c}, M_{\Theta_m}: I^N \rightarrow I^N \right\} \tag{16}$$

- EP : updated generation using the updated function.
- $\Psi: EP \rightarrow EP'$ is the updated function used to remove and/or add dominated and/or non-dominated solutions. The NSGA-II algorithm based on crowding distance, whilst the reference point, association, and niching considered when using NSGA-III algorithm. Meanwhile, the proposed algorithm ENSGRA uses weighted, clustered, scheduled and adjusted reference points.
- $l : I^N \rightarrow \{true, false\}$: is a termination criterion for algorithms.
- φ : EP $\rightarrow$ I^*: is one individual (solution) selected by the decision maker.

4. RESULTS AND DISCUSSION

Two types of parameters, namely WSN and multi-objective algorithm parameters (Tables 1 and 2, respectively), are assumed to perform the experiment on the proposed algorithm based on the synthetic dataset taken [10], [22]–[26]. Table 2 represents the parameters used to perform experiments through MOMSPSO, NSGA-II, NSGA-III, and ENSGRA. Some common parameters are used for all algorithms, whilst other parameters are solely for evolutionary algorithms, such as genetic algorithm. Other parameters are used for particle swarm algorithms.

Table 1. Settings for WSNs

Parameters	Amount
# Of sensors	200 and 500
Region of interest	1200x1200 m^2 and 1800x1800 m^2 respectively.
Sensing radius (*Rs*)	[1-300] cm
Communication radius (*Rc*)	[1-300] cm
# Of object	4

Table 2. Settings for four algorithms

Parameters	Amount
Common parameters	
# Of scenarios (configurations)	10
# Of populations (solutions)	10, 20, 30, 40, 50, 60, 70, 80, 90, and 100
Number of iteration	25, 50, 75, and 100
NSGA-II, NSGA-III, and ENSGRA parameters	
nDivision (for NSGA-III, and ENSGRA)	10
$P_{Crossover}$	0.5
$P_{Mutation}$	0.5
MutationRate	0.1
MOMSPSO parameters	
C_1	0.55
C_2	0.75 to 0.99
TimeLag	0 or 1

4.1. Optimization results for algorithms

After the experiments using three objectives are conducted in the previous resreach using MATLAB 2014 [18], those using four objectives are then performed. Therefore, the nodes load balancing object (factor) is added to the number of sensor nodes, energy consumption, and coverage objectives. Ten scenarios (configurations) are used, in each scenario, the number of solutions is changed to 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100. The same is applied for the different number of iterations, using 25, 50, 75, and 100 iterations. These experiments are repeated with different numbers of sensor nodes, including 200 and 500 sensor nodes.

4.1.1. The assumptions to QoS proposed model

The resultant of the four used objectives for each algorithm is calculated using dynamic weights (based on the ranking for each objective, the ranking ranged from 1 to 4, with 1 as the lowest ranking and 4 as the highestranking. Then, this ranking is converted to their respective weights (0.1–0.4), which must be dynamic, based on an objective ranking value. Table 3 shows that, if energy consumption in MOMSPSO algorithm has the lowest value, then it takes a 0.4 weight value. If ENSGRA has the second rank value, then it takes a 0.3 weight and so on. Computation times are also used as a factor that affects the results for each algorithm. Therefore, computation time is added and given a weight as other parameters to avoid time complexity for the proposed algorithm. This ranking is illustrated in Table 3 for 500 sensor nodes.

Table 3. Results and dynamic weights for algorithms using 500 nodes under four objectives

Iter.	MOM SPSO	NSGA -II	NSGA -III	ENSG RA	MOM SPSO	NSG A-II	NSGA -III	ENS GRA	MOMSPS O	NSGA-II	NSGA-III	ENS GRA
	Energy consumption results (EC)				Energy dynamic weight (EDW)				Energy weight x En. Cons. Dynamic weight (EW x EDW)			
25	0.6958	0.8930	0.8955	0.8854	0.4	0.2	0.1	0.3	0.092	0.046	0.023	0.069
50	0.6852	0.8961	0.8968	0.8924	0.4	0.2	0.1	0.3	0.092	0.046	0.023	0.069
75	0.6874	0.8950	0.8970	0.8932	0.4	0.1	0.2	0.3	0.092	0.023	0.046	0.069
100	0.6877	0.8944	0.8958	0.8925	0.4	0.2	0.1	0.3	0.092	0.046	0.023	0.069
	Number of active sensors results (*NS*)				# Sensors dynamic weight (*SDW*)				Sensors weight x synsor dynamic weight (*SW x SDW*)			
25	58	151	167	142	0.4	0.2	0.1	0.3	0.06	0.0`3	0.015	0.045
50	53	167	171	166	0.4	0.2	0.1	0.3	0.06	0.03	0.015	0.045
75	53	165	171	165	0.4	0.2	0.1	0.3	0.06	0.03	0.015	0.045
100	50	170	183	164	0.4	0.2	0.1	0.3	0.06	0.03	0.015	0.045
	Network coverage results (*NC*)				Coverage dynamic weight (*CDW*)				Coverage weight x coverage dynamic weight (*CW x CDW*)			
25	4.6	9.7	9.9	9.3	0.1	0.3	0.4	0.2	0.023	0.069	0.092	0.046
50	4.6	10.0	10.1	9.7	0.1	0.3	0.4	0.2	0.023	0.069	0.092	0.046
75	4.6	9.9	10.1	9.8	0.1	0.3	0.4	0.2	0.023	0.069	0.092	0.046
100	4.5	10.0	10.1	10.1	0.1	0.2	0.3	0.4	0.023	0.046	0.069	0.092
	Network congestion result, load balance (*LB*)				Load dynamic weight (*LDW*)				Load weight x load dynamic weight (*LW x LDW*)			
25	0.6605	0.5532	0.5416	0.4888	0.1	0.2	0.3	0.4	0.023	0.046	0.069	0.092
50	0.6656	0.5181	0.5139	0.4690	0.1	0.2	0.3	0.4	0.023	0.046	0.069	0.092
75	0.6691	0.5237	0.4959	0.4534	0.1	0.2	0.3	0.4	0.023	0.046	0.069	0.092
100	0.6717	0.5062	0.4958	0.4559	0.1	0.2	0.3	0.4	0.023	0.046	0.069	0.092
	Computation time results (*CT*)				Time dynamic weight (*TDW*)				Time weight x time dynamic weight (*TW x TDW*)			
25	1.11	2.75	2.37	22.06	0.4	0.2	0.3	0.1	0.06	0.03	0.045	0.015
50	7.93	9.99	9.34	73.77	0.4	0.2	0.3	0.1	0.06	0.03	0.045	0.015
75	6.96	7.88	10.87	77.66	0.4	0.3	0.2	0.1	0.06	0.045	0.03	0.015
100	9.71	13.58	9.84	79.65	0.4	0.2	0.3	0.1	0.06	0.03	0.045	0.015

Afterwards, the resultant of multi-objectives by using dynamic weights resultant of algorithms by using dynamic weights (RMDW) equations is created for each algorithm. This equation is used for the proposed QoS model.

- (*EC*) reflect energy consumption percentage
- (*NS*) reflect number of active sensors
- (*NC*) reflect network coverage
- (*LB*) reflect node load balance (network congestion percentage)
- (*CT*) reflect normalised computation time (considered time in hours)
- (*EW, SW, CW, LW, and TW*) reflect weights for energy consumption, number of active sensors, network coverage, load balance and computation time, respectively
- (*EDW, SDW, CDW, LDW, and TDW*) reflect dynamic weights for energy consumption, number of active sensors, network coverage and computation time, respectively
- Then, let (*i*) indicate the iteration number, which may be 25, 50, 75, and 100, and increases by 25 steps each time. Let (*j*) range from 1 to 4, indicating four algorithms

Therefore, the RMDW equation for any algorithm will be presented as (17).

$$RMDW = \sum_{i=25}^{100} \sum_{j=1}^{4} EC_{ij} \times EW_j \times EDW_{ij} + NS_{ij} \times SW_j \times SDW_{ij} + NC_{ij} \times CW_j \times CDW_{ij} + LB_{ij} \times LW_j \times LDW_{ij} + CT_{ij} \times TW_j \times TDW_{ij} \quad (17)$$

Where the objectives weights are assumed as: *EW=0.23*, *CW=0.23*, *LW=0.23*, *SW=0.15*, and *TW=0.15*.

4.1.2. The QoS proposed model for four objectives

Table 4 represents the RMDW for 200 and 500 nodes. The results that are computed for RMDW show that ENSGRA superior over other algorithms, which are represented in Figures 5 and 6 is illustrate that the proposed algorithm ENSGRA superior over other algorithms after the resultants are calculated and provided the highest value. NSGA-II, NSGA-III, and MOMSPSO respectively ranked second, third and fourth. This result indicates that ENSGRA overcomes other algorithms despite the additional computation time to the combination model (QoS model).

Table 4. The RMDW using four objectives

Algorithm	RMDW for 200				RMDW for 200			
	25	50	75	100	25	50	75	100
ENSGRA	4.43	3.80	4.11	4.19	7.25	9.12	9.14	9.61
NSGA-III	2.68	2.19	2.02	3.51	3.59	3.97	3.89	3.93
MOMSPSO	1.61	1.52	1.55	1.49	3.71	3.86	3.75	3.79
NSGA-II	4.04	2.92	3.47	2.45	5.35	6.05	6.03	6.03

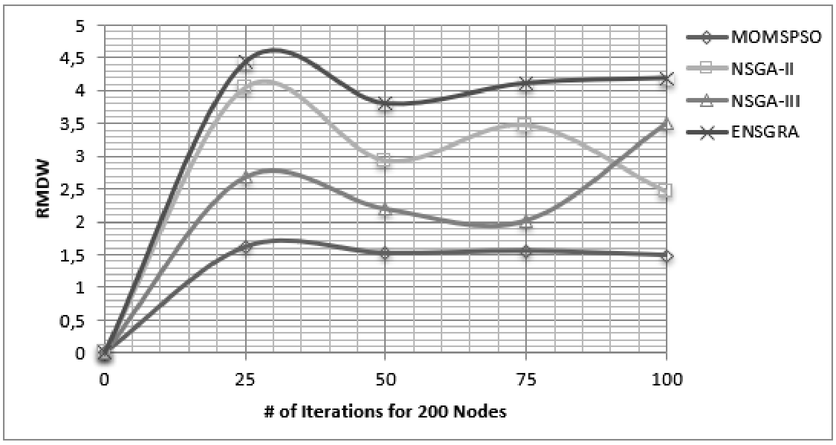

Figure 5. Average RMDW Vs number of iterations for 200 Sensors (using 4 objectives)

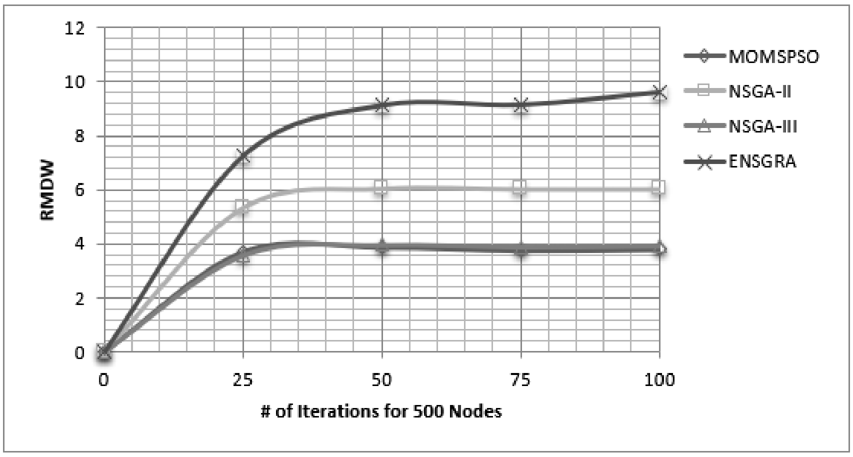

Figure 6. Average RMDW Vs number of iterations for 500 sensors (using 4 objectives)

4.2. Evaluation results for algorithms

Multi-objective optimisation problems (MOPs) defined as two or more conflicting objective functions that affect each other, emerge when developing new algorithms. To measure the quality and quantity of pareto front (PF) approximations produced by multi-objectives algorithms, several performance indicators (metrics) have been introduced [27]. Riquelme *et al*. [28] represent that many performance indicators mainly based on the following three points to find the solution set: i) Convergence (accuracy metrics): that is, the proximity to the notional Pareto optimal front; ii) Diversity: which are used to measure distribution and spread; and iii) Solutions number (cardinality and capacity metrics). The current research investigates the most important and used metrics, such as hypervolume (HV), delta (△), and number of non-dominated solutions (NDS) indicators.

4.2.1. Hypervolume (HV) indicator

The HV consider as the volume of the space that found in the objective space which dominated by the PF approximation, and restricted from above by a reference point. Thus, a bounded space must be established by the PF and a user-defined reference point [29], [30]. Figures 7 and 8 show the average evaluation of the HV indicator for the used algorithms in these experiments. Figures 7 and 8 respectively show the HV indicator for 200 and 500 sensor nodes using 25, 50, 75, and 100 iterations.

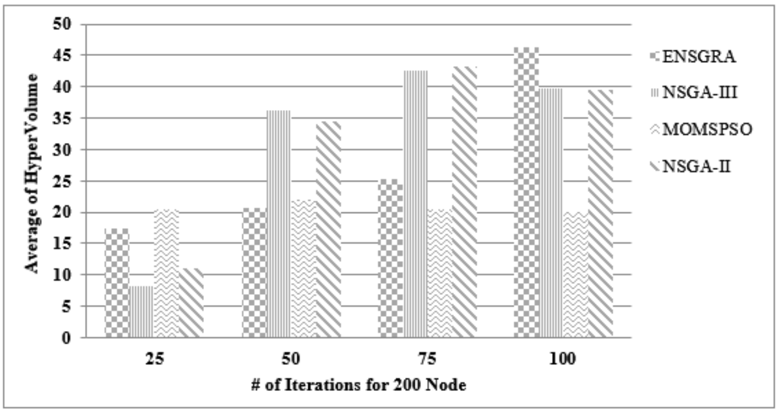

Figure 7. Average HV for algorithms for 200 sensor nodes using 25, 50, 75, and 100 iteration

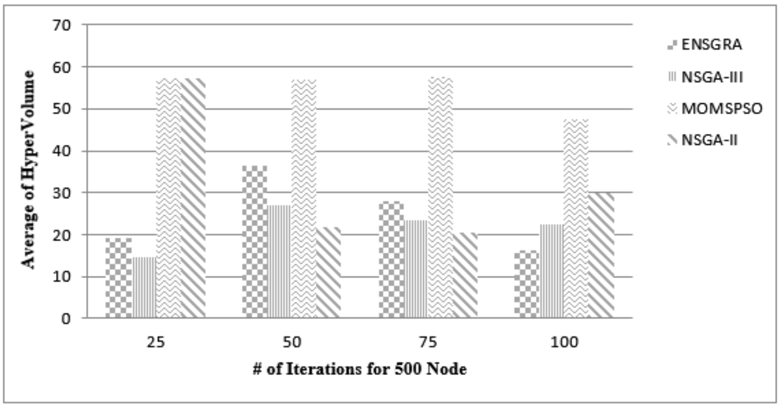

Figure 8. Average HV for algorithms for 500 sensor nodes using 25, 50, 75, and 100 iteration

4.2.2. Number of non-dominated solutions (NDS) indicator

This indicator considers capacity metric, which finds the number of optimal solution sets obtained by the optimisation algorithm. Another name for this indicator is overall non-dominated vector generation; this indicator is easy to use when it has low computational complexity [27]. Figures 9 and 10 represent the average evaluation for the NDS indicator for 200 and 500 sensor nodes using 25, 50, 75, and 100 iterations. In these figures, the same colour system is followed as in previous sections to indicate the various algorithms.

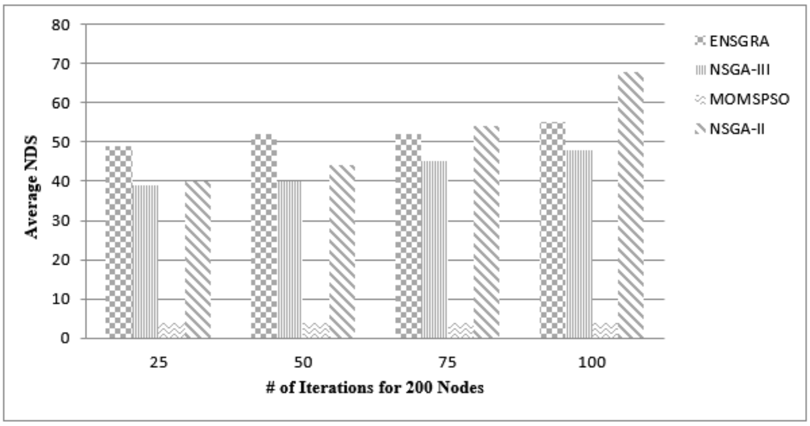

Figure 9. Average NDS for algorithms for 200 sensor nodes using 25, 50, 75, and 100 iteration

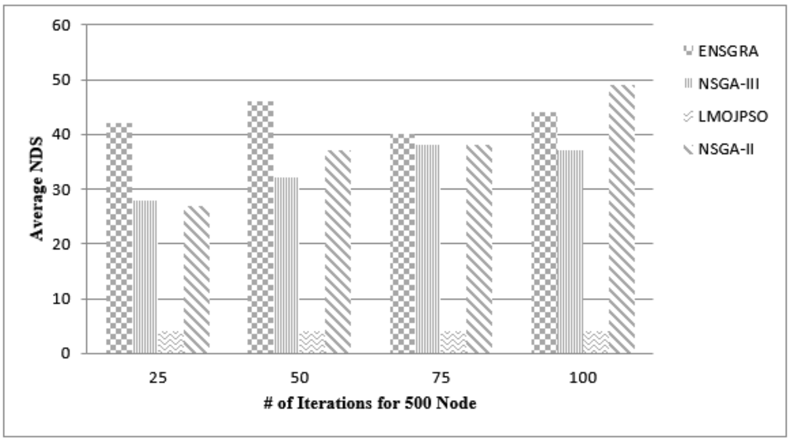

Figure 10. Average NDS for algorithms for 500 sensor nodes using 25, 50, 75, and 100 iteration

4.2.3. Delta (△) indicator

This indicator is used to calculate diversity by measuring the distribution and spread of solutions. This indicator also takes the number of PF solutions. The Pareto solutions are then sorted in accordance with the first fitness values. Afterwards, the Euclidean distance between consecutive solutions is computed, and the average of the consecutive distances is obtained. Other calculations, such as the Euclidean distance between the extreme and boundary solutions, must be calculated to find the diversity metric [27]. Finally, Figures 11 and 12 represent the average evaluation of the delta indicator for 200 and 500 sensor nodes, respectively.

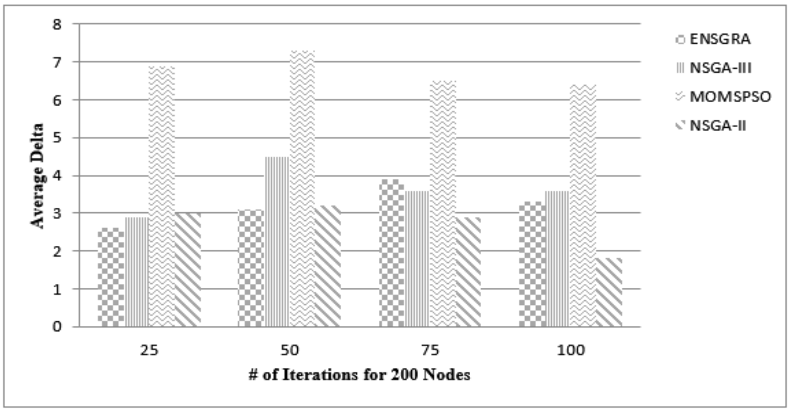

Figure 11. Average delta for algorithms for 200 sensor nodes using 25, 50, 75, and 100 iteration

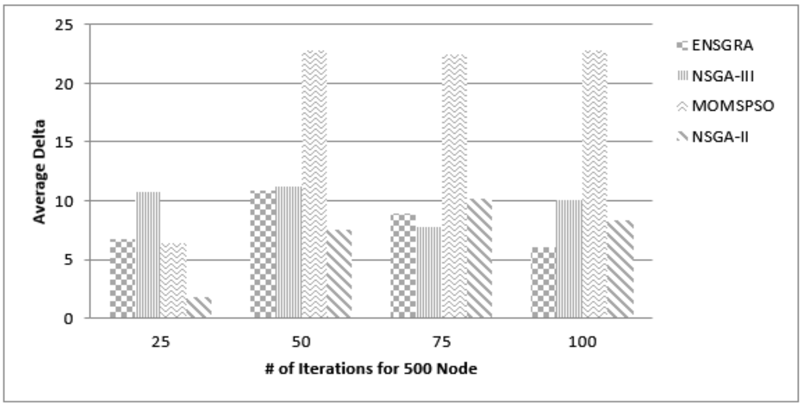

Figure 12. Average delta for algorithms for 500 sensor nodes using 25, 50, 75, and 100 iteration

4.2.4. Overall evaluation

Table 5 represents the average value for HV, NDS, and delta for 200 and 500 sensor nodes using 25, 50, 75, and 100 iterationsfor ENSGRA, NSGA-III, MOMSPSO, and NSGA-II algorithms. The table reveals that the iteration average is calculated for HV, NDS, and delta when using 200 and 500 sensor nodes. The overall average is then calculated for the three indicators. Previous figures reveal that the MOMSPSO algorithm is superior over NSGA-II and NSGA-III and the proposed algorithm ENSGRA considering HV when using 500 sensor nodes. By contrast, NSGA-II outperforms MOMSPSO considering HV when using 200 sensor nodes. The overall results show that MOMSPSO outperforms other algorithms. Therefore, the proposed algorithm ENSGRA failed in providing additional convergence but outperformed the other algorithms considering NDS when using 200 or 500 sensor nodes, indicating a high capacity, as represented by the definition of NDS. Lastly, the ENSGRA algorithm has lower delta in most cases than MOMSPS and NSGA-III. By contrast, NSGA-II overcomes ENSGRA considering low delta. Thus, NSGA-II yields the lowest distributed solutions. The second in lowest diversity (distribution spread) is ENSGRA because diverse solutions are necessary to prevent premature convergence and achieve a well-distributed PF trade-off. This finding is represented in Table 5, in which MOMSPSO, ENSGR, and NGA-II respectively ranked first considering HV, NDS, and delta, as illustrated in bold font in the overall results.

Table 5 shows that the HV indicator tends to settle down with the increase in the number of sensors when using the MOMSPSO algorithm. However, the proposed algorithm failed in HV using four objectives. This disadvantagein which the complexity of indicators (such as HV) increases as the objectives number rise, is usually encountered by any researcher. Meanwhile, other indicators achieved their objectives, in which ENSGRA outperformed others in NDS and ranked second considering Delta. Also, the optimization combination percentages for the proposed scenarios by using four objectives are shown in Table 6. It clearly indicated that the average combination optimisation percentage for the proposed scenarios proved that ENSGRA outperformed other algorithms for four objectives.

Table 5. Average value for hypervolume (HV), NDS, and delta for four objectives

Algorithm	25	50	75	100	25	50	75	100	Iterations Avg. for 200	Iterations Avg. for 500	Iterations Avg. for overall
	Avg. Hypervolume for 200				Avg. Hypervolume for 500				Avg. Hypervolume overall		
ENSGRA	17.3	20.6	25.3	**46.3**	19.3	26.3	28.1	16.4	27.4	22.5	25.0
NSGA-III	8.1	**36.2**	42.5	39.7	14.7	27.1	23.3	22.5	31.6	21.9	26.8
MOMSPSO	**20.5**	22.0	20.5	20.0	**57.3**	**56.8**	**57.6**	**47.6**	20.8	**54.9**	**37.8**
NSGA-II	11.1	34.5	**43.2**	39.6	**57.3**	21.8	20.6	29.8	**32.1**	32.4	32.3
	Avg. NDS for 200				Avg. NDS for 500				Avg. NDS overall		
ENSGRA	**49**	**52**	52	55	**42**	**46**	**40**	44	**52**	**43**	**47**
NSGA-III	39	40	45	48	28	32	38	37	43	33	38
MOMSPSO	4	4	4	4	4	4	4	4	4	4	4
NSGA-II	40	44	**54**	**68**	27	37	38	**49**	51	38	45
	Avg. Delta for 200				Avg. Delta for 500				Avg. Delta overall		
ENSGRA	**2.6**	**3.1**	3.9	3.3	**6.7**	10.9	8.9	**6.1**	3.2	**8.15**	5.7
NSGA-III	2.9	4.5	3.6	3.6	10.7	11.2	**7.8**	10.1	3.6	10.0	6.8
MOMSPSO	6.9	7.3	6.5	6.4	22.8	22.5	22.8	18.7	6.8	21.7	14.2
NSGA-II	3.0	3.2	**2.9**	**1.8**	7.5	**10.2**	8.3	7.0	**2.7**	8.2	**5.5**

Table 6. QoS model, combination (optimization) percentage for the proposed scenarios using four objectives

# of nodes	MOMSPSO	NSGA-II	NSGA-III	ENSGRA
200	13%	28%	23%	36%
500	17%	26%	17%	39%
Average	15%	27%	20%	38%

5. CONCLUSION AND FUTURE WORKS

This research attempted to optimise multi-objectives by using the proposed algorithm ENSGRA thess objectives namely active sensors number, power consumption, coverage of network and node load balancing, to avoid network congestion. The proposed algorithm relies on NSGA-III and was named ENSGRA. The reference points of this algorithm were adjusted by weighted, clustered, scheduled and adjusted vectors. The recombination operation was implemented by integrating two-parent crossovers with multi-parent crossover (MPX) using new algorithm which named RIMX.

The new algorithm is illustrated by the framework block diagram using a new individual format, depend on sensor clustering and scheduling. In this framework, the WSN transforms from random deployment model to optimal QoS and routing models because routing is crucial in maintaining and improving the QoS. Afterwards, a new QoS model is proposed to find the resultant of multi-objectives dynamic weights (RMDW) by combining the results of multi-objectives when using four objectives. The computation times are added to this combination to avoid time complexity for the proposed algorithm. The proposed algorithm superior over other algorithms as the experimental results show when considering RMDW, and the average combination optimisation percentage for the proposed scenarios proved that ENSGRA outperformed other algorithms for four objectives.

The evaluation metrics for ENSGRA with four objectives showed that lightweight MOPSO (LMOPSO) outperformed the other algorithms considering HV when calculating the overall results. Meanwhile, the proposed approach exceeds the other approaches when considering NDS during the calculation of the overall results. However, the proposed algorithm ranks in second place after NSGA-II considering delta. These results conclude the proposed algorithm yields high capacity and balanced diversity but failed in solving convergency. This failure is related to complexity, which increases when the number of objectives rises.

The future work will tend to increase the efficiency of the proposed approach (ENSGRA) as the work will go to improving its results considering three or four objectives to achieve improved QoS for WSNs. The computation time for the proposed algorithm will also be decreased by updating the algorithm operation in parallel processing. Moreover, the proposed algorithm will be examined with other objectives, such as connectivity, reliability, security and low delay. Other evaluation metrics, such as set coverage, general distance and overall Pareto spread, will be used to evaluate multi-objective algorithm.

ACKNOWLEDGEMENTS

The authors would like to thank Dr. Maher Alndiwee assistant professor at Damascus University, for his efforts and help in this research.

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