# A Trapezoidal Fuzzy Membership Genetic Algorithm (TFMGA) for Energy and Network Lifetime Maximization under Coverage Constrained Problems in Heterogeneous Wireless Sensor Networks

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***Abstract***— Network lifetime maximization of Wireless Heterogeneous Wireless Sensor Networks (HWSNs) is a difficult problem. Though many methods have been introduced and developed in the recent works to solve network lifetime maximization. However, in HWSNs, the energy efficiency of sensor nodes becomes also a very difficult issue. On the other hand target coverage problem have been also becoming most important and difficult problem. In this paper, new Markov Chain Monte Carlo (MCMC) is introduced which solves the energy efficiency of sensor nodes in HWSN. At initially graph model is modeled to represent HWSNs with each vertex representing the assignment of a sensor nodes in a subset. At the same time, Trapezoidal Fuzzy Membership Genetic Algorithm (TFMGA) is proposed to maximize the number of Disjoint Connected Covers (DCC) and K-Coverage (KC) known as TFMGA-MDCCKC. Based on gene and chromosome information from the TFMGA, the gene seeks an optimal path on the construction graph model that maximizes the MDCCKC. In TFMGA gene thus focuses on finding one more connected covers and avoids creating subsets particularly. A local search procedure is designed to TFMGA thus increases the search efficiency. The proposed TFMGA-MDCCKC approach has been applied to a variety of HWSNs. The results show that the TFMGA-MDCCKC approach is efficient and successful in finding optimal results for maximizing the lifetime of HWSNs. Experimental results show that proposed TFMGA-MDCCKC approach performs better than Bacteria Foraging Optimization (BFO) based approach, Ant Colony Optimization (ACO) method and the performance of the TFMGA-MDCCKC approach is closer to the energy-conserving strategy.

***Keywords-*** *Heterogeneous Wireless Sensor Networks (HWSN), K coverage problem, Trapezoidal Fuzzy Membership Genetic Algorithm (TFMGA), Markov Chain Monte Carlo (MCMC), Disjoint Connected Coverage (DCC) and K Coverage (KC) nodes, network lifetime maximization.*

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## I. INTRODUCTION

Wireless Sensor Network (WSN) is a self-organized network which includes of many sensors nodes are deployed in a sensing field in an arranged manner. With the development of wireless communication technologies , real-time monitoring applications such as battlefield surveillance [1], environment supervision [2], and traffic control [3], has turn into more important in the recent work. Applying these applications to general WSN have been becomes difficult task. So Heterogeneous Wireless Sensor Network (HWSN) have been focused and used in many applications.

However HWSN is a sub-type of WSNs in which each sensor might have diverse abilities such as different transmission ability, varied number of sensing units, varied battery life etc [4-5]. HWSN is worked based on the multiple sensing units and each sensor in the network might be operational by means of more than one sensing unit, and the attribute with the purpose of each sensing unit can sense also be different. Since, sensors are operational by means of multiple sensing units are extremely frequent in various commercial products. For example, every MICA2 mote [6] is equipped with many sensing units used for temperature, humidity, brightness, noise, vibration, etc.

However HWSN with multiple sensing units is cost-efficient and power-efficient. Alternatively, if many sensing units are equipped in a sensor, thus increases the energy consumption. In the research study target coverage problem have been becomes also most important and difficult problem in HWSN. The target coverage problem is stated as the discovering an optimal scheduling for sensors to increase network lifetime. Though, the target coverage problem has been demonstrated to be NP complete [7] problem.

In general these problems have been classified into two major types: 1) field coverage, where the entire network field is covered with all sensors and no coverage hole is able to be standard at any time, and 2) target coverage, where each target is continuously monitored with as a minimum of one sensor [8]. Commonly, coverage problems additionally organize sensors in the direction of cover the sensing area entirely [9], or assure with the purpose of the entire sensing area is covered by 1-coverage and k-coverage [10-11] which is strongly position sensor networks within the cover of entire sensing area [12–13].

There have been many of works have been introduced and developed in the recent work for solving target coverage problem for WSN, however most of the works focused on homogeneous WSN with single sensing unit relying on centralized strategy. Subsequently energy efficient based scheduling is proposed for solving k-coverage problem in homogeneous WSN [14]. Cardei proposed a heuristic algorithm which solves the target problem and maximal set cover problem in homogeneous WSN with single sensing unit relying on centralized strategy [15]. As presented in [16], solves a flexible range set cover problem to maximize network lifetime in the flexible sensing ranges WSN. However they introduce and developed a new method which doesn't focus on the multiple sensing units for range set cover problem. The estimate algorithm for solving K-coverage problem was introduced and developed in [17-18] without consideration of multiple sensing units.

To increase the system performance, the Disjoint Connected Coverage (DCC) and K Coverage (KC) [19] problem is focused and solved in this research paper. K-coverage problem means with the purpose of each target must be covered by as minimum of k sensors, and a property known as k-coverage, wherever the highest value of k is known as the coverage degree. In this research paper we focus on resolving target coverage problem under MDCCKC in HWSNs with the purpose of network lifetime maximization and energy efficiency [20]. The main principle behind TFMGA is to introduce the concept of sensor priority, which is obtained by integrating three parameters together, which are the Coverage**,** Routing constraint, and the remaining energy. The present framework of TFMGA-MDCCKC is able to be devoted toward solving discrete point coverage with suitable objective function. It is expected with the purpose of the implicit procedure of the TFMGA framework is able to be used for decreasing the computational time of TFMGA-MDCCKC when beginning with large-scale HWSN.

## II. RELATED WORK

The problems of preserving sensing coverage and connectivity by maintaining a lesser number of sensor nodes in the dynamic manner in WSNs are introduced and solved in the recent work [21]. This work studies the connection among sensing coverage area and connectivity by solving two major sub-problems which is discussed as follows. At initially prove with the purpose of the radio range is as a minimum twice the sensing range, absolute coverage of a convex area involves connectivity between the functioning set of nodes. Second derive an Optimal Geographical Density Control (OGDC) for densities manage in large scale HWSNs with radio range and the sensing range. From the network simulator (Ns-2) results, it demonstrated that OGDC performs better than that of existing density control algorithms in terms of network lifetime, coverage problem.

Another research work also introduced in the recent work [22] to find the relationship among sensing coverage and network connectivity. This introduces a novel Stand Guard Algorithm (StanGA) for solving treating coverage and connectivity problem that promises network connectivity and sensing coverage.

Battery-powered sensor nodes are functional providing they are able to communicate captured information to a processing node. This process consumes energy, so sufficient power management and scheduling is able to successfully expand network lifetime. To solve this problem in the recent work propose an energy efficient method [23] that enhances the network lifetime in WSNs. In WSN sensors into a maximal number of disjoint set covers with the purpose are activated consecutively. Simply the sensors from the existing active set are dependable for monitoring each and every one targets and for transmitting the collected information, at the same time as nodes from each and every one other set are in a low-energy sleep mode.

Zhao and Gurusamy [24] proposed a Maximum Cover Tree (MCT) problem with the aim of increasing the network lifetime by means of scheduling sensors into multiple sets. This is able to keep together target coverage and connectivity among all the active sensors and the sink. Introduces and develops a new Communication Weighted Greedy Cover (CWGC) in a distributed manner. Simulation results shows that the proposed CWGC algorithm works better when compared to approximation algorithm in terms of the network lifetime and energy efficiency parameters respectively.

Chamam and Pierre [25] solves energy efficiency problem by considering optimal scheduling of sensors states in cluster-based WSNs. This design considers two major steps: At initially energy efficient problem is formulated as Integer Linear Programming model with the purpose of proves NP-Complete problem. Then Tabu search heuristic algorithm is introduced to solve computation time problem. Simulation results demonstrate that the proposed algorithm provides maximized network lifetime and less computation time this algorithm is appropriate for large-sized WSNs.

Mini et al [26] designed toward observe phase-transition behavior of enhancing network lifetime to solve target coverage problem in WSNs. To help the hardness examination, they introduced a new and efficient phase-transition algorithm to solve coverage problem in the target area. This phase-transition algorithm has the different capability of differentiating hard problem instances.

Zorbas et al [27] solves the problem of the smallest sampling value, where a result should be adequately distinguished by the greatest possible amount of time. The proposed localized algorithm gives up a measurement of the energy of the sensors through moving them to a new location in order to assure the preferred detection accurateness. It separates the monitoring procedure in rounds towards maximize the network lifetime, at the same time as it make sure network connectivity with the base station, but the closely covered areas with the purpose of are unsuccessfully covered.

Deng et al [28] introduces a new energy-efficient and target K-coverage algorithm which solves coverage area problem. This algorithm converts the coverage area problem into the target coverage issue, and then attains full area coverage through covering each and every one the targets. This algorithm is able to increase the security and efficiency of the WSNs.

Zhao et al [29] focus on the issue of scheduling sensors behavior towards network lifetime maximization at the same time as preserving both K-target coverage and network connectivity. In K-target coverage, it is important with the purpose of each target be supposed to be concurrently experimental by as a minimum of K sensors. The information collected by the sensors will be broadcasting to the sink node using multiple hop communications.

Li et al [30] examine the sensor scheduling for solving k-coverage problem .They need to capably schedule the sensors, such with the purpose of the observed area be able to be k-covered during the network lifetime thus enhancing the network lifetime. Yang et al [31] examine the critical situation for connected-k-coverage with the percolation theorem and show their efficiency using simulation results. From the results it concludes that the connected-k-coverage has been accepted as a successful concept for maximizing the network lifetime.

## III. PROBLEM FORMULATION AND SYSTME MODEL

In [32] the performance of Ant Colony Optimization (ACO) approach is introduced and used to increase network lifetime of HWSNs. This ACO approach is entirely used to discover the Maximum number of Disjoint Connected Covers (MDCC) that should satisfy both coverage areas of sensors and network connectivity. A construction graph model is formulated that has vertices which denote the assignment of a device inside a

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WSN. The pheromone and heuristic information of the ants is helpful in the direction of finding an optimal path from construction graph which used to maximize the connected cover's count. The heuristic information of ants is used to reproduce the magnetism of device assignments. The search effectiveness is enhanced by proposing a local search procedure. But still the major drawback of this schema is the computation time and coverage problems are also not solved by this approach. Consequently, energy efficiency becomes an important problem in HWSNs. To solve this problem new Markov Chain Monte Carlo (MCMC) is introduced in this research work which solves the energy efficiency and coverage problem in HWSN. These problems are solved by using Trapezoidal Fuzzy Membership Genetic Algorithm (TFMGA) in order to Maximize the number of Disjoint Connected Covers (DCC) and K Coverage (KC)(TFMGA-MDCCKC). This proposed TFMGA-MDCCKC algorithm converts the coverage problem into a construction graph model. The major objective of this paper is to solving target coverage problem which maximizing the network lifetime and reducing energy constraints.

### A. Network Model and Problem Formulation

The problem of discovering the MDCCKC nodes is discussed in this section. In addition this section also introduces a TFMGA method for approximating an upper bound of MDCCKC, covers in a HWSN.

**Problem formulation for target coverage:** Let us consider number of sensors as $\mathrm{SEN} = \{\mathrm{SEN}_1, \ldots, \mathrm{SEN}_{|SE|}\}$ and a number of sinks $\mathrm{SIN} = \{\mathrm{SIN}_1, \ldots, \mathrm{SIN}_{|SI|}\}$ in a region area $L \times W$ area ($|.|$denotes the size of a set). Let us consider that the sensing range of sensor as $r_s$ , a transmission range of sensor as $r_t$ , sinks have a transmission range $R_t$ higher than $r_t$ . Properly we need to discover a set of nodes, $SEN = \{SEN_1, \ldots SEN_{|SE|}\}$, and each number of sinks works for $T_i$ rounds. A routing is accordingly represented by a set of tuples, $\{\langle \mathrm{SIN}_1, \mathrm{SEN}_1, E_1^r \rangle, \ldots, \langle \mathrm{SIN}_{|SE|}, \mathrm{SEN}_{|SI|}, E_{|SE|}^r \rangle\}$ with the purpose that should satisfy the following constraints:

**Energy constraints:** The amount of energy consumed by any sensor node in the HWSN at the end of the network lifetime couldn't exceed by its initial energy value. Let us consider that the $\sigma$ be the energy level of sensor nodes $|SE|$ in the HWSN with $E_{|SE|}^r$ units of residual energy. Problem formulation of number of DCC and KC has been stated as maximization of DCC and KC constraints, between each connected cover $CS_i$ ($CS_i \subseteq SEN \cup SIN, i = 1, \ldots, DKC$) .

**Coverage constraint:** The coverage constraint, which require the sensors in $CS_i$ toward fully cover a target area TC. In other words, for any given point $P \in TC$, at least one sensor $SEN_j \in CS_i$ assures

$$\left\|\mathrm{SEN}_j - P\right\| \leq r_s \tag{1}$$

where $\left\|\mathrm{SEN}_j - P\right\|$ denoted as the distance between the sensors, $SEN_j$ and any known point $P \in TC$. The collection constraints must need to gather information of number of sinks (SIN) and their monitoring results are achieved by the sensor in the different subset. For each sensor $N_j \in CS_i$ , at least one sink $SIN_k \in CS_i$has

$$\left\|\mathrm{SEN}_j - \mathrm{SIN}_k\right\| \leq r_t \tag{2}$$

**Routing constraint:** The routing constraints which need the number of sinks SIN in $CS_i$to form a new DCC by transmitting data from source to destination. Accurately, this routing constraint is capable to be described as follows, among the two sinks $SIN_j, SIN_y \in CS_i$, there is a path ꝑt must satisfying

$$\max_{(\mathrm{SIN}_x - \mathrm{SIN}_y) \in ꝑt} \left\|\mathrm{SIN}_x - \mathrm{SIN}_y\right\| \leq R_t \geq KC \tag{3}$$

**K Coverage constraint:** Known an integer KC , and the condition KC < 0 is satisfied. The major objective of this proposed problem is to compute a subset of sensors $U_i$ sensors , $V_i$ sinks, and then it must need to assure the following conditions:

i. All sensor node in the subset of sensors $U_i$ must be enclosed by as a minimum of $K$ different wireless sensors in coverage set $CS$ .
ii. The number of SEN in $CS$ is reduced.
iii. The wireless sensors in $CS$ are DCC and targeted by each other.

Moreover, target KC problem is transformed to an integer programming model is discussed detail in the following sections. Assume that the this work deploy a number of sensors as $= \{\mathrm{SEN}_1, \mathrm{SEN}_2, \ldots, \mathrm{SEN}_{|SE|}\}$ , number of sinks as $\mathrm{SIN} = \{\mathrm{SIN}_1, \mathrm{SIN}_2, \ldots, \mathrm{SIN}_{|SI|}\}$ and $\alpha_{ij}$ is the coefficients which denotes K coverage relationship between different sensors , which is calculated as follows.

$$\alpha_{ij} = \begin{cases} 1 \text{ } if\ the\ sensor\ node\ SEN_i\ can\ be\ sensed\ by\ SE \\ 0\ otherwise \end{cases} \tag{4}$$

The selected sensor nodes under the $\alpha_{ij}$ is denoted as $\chi_i$ in boolean values, $j \in \{1, \ldots n\}$.

$$\chi_j = \begin{cases} 1 \text{ } if\ the\ sensor\ node\ SEN_i\ can\ be\ covered\ by\ C \\ 0\ otherwise \end{cases} \tag{5}$$

$$\text{Minimize } \sum_{i=1}^{n} \chi_i \tag{6}$$

$$\text{S.T. } \sum_{j=1}^{n} \alpha_{ij}, \chi_j \geq k, i \in \{1,2 \ldots, n\}, \chi_j \in \{0,1\} \tag{7}$$

To maximize the network lifetime in target Disjoint Connected Coverage (DCC) and K Coverage (KC) nodes process, the energy efficiency of the sensors $(SEN)$ must be measured. To calculate sensing range of sensor $r_s$ first need to compute the sensor priority. So the sensor priority of sensors should be calculated as follows:

$$\mathrm{Pr}_i = \frac{1}{2}(r_{si} + \gamma_i) \times [(r_{si} - 1 - \gamma_i) \times \tau + 2E_i^r - 2] + r_{si} \tag{8}$$

Here the parameter $\gamma_i$ is used to change the sensing range of sensor $r_s$ based on the computed sensor priority. This parameter $\gamma_i$ is computed as follows:

$$\gamma_i = \left\lceil \frac{E_i^r - 2}{\tau} \right\rceil \tag{9}$$

**Homogeneous and Heterogeneous WSNs:** A WSN is homogeneous if each and every one of sensors and its nodes have the equal sensing range $r_s$, the equal transmission range of sensor as $r_t$and the equal initial energy $E_i^r$ .Elsewhere the WSN is Heterogeneous. It should be simulated from the above mentioned four constraints that also address the sensing coverage and network connectivity.

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***Upper Bound of C:*** In a HWSN, the maximum number of connected covers shouldn't exceed the maximum number of full cover subsets that should satisfy the coverage constraint under DCC and KC. So, the maximum number of full cover subsets should b**e** used as the upper bound of $\boldsymbol{CS_i}$. However finding the maximum number of full cover subsets are formulated as NP-complete problem [33], to focus on this problem we be able to compute the upper bound of $\boldsymbol{CS_i}$. When all the deployed sensors are active state, the target area is rationally classified into a number of *fields*, each of which is a set of points covered all the way through the same set of sensors.

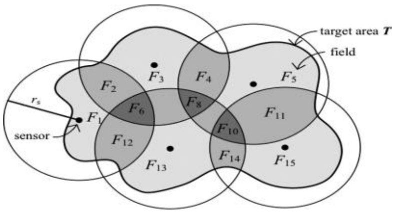


**Figure 1. Fields in the target area**

Figure 1 shows the fields in the target area, where each dot in the figure represents a sensor, and the circle centered on the dot in the figure represents the sensing range of the sensor. Each $F_i$ $(i = 1, \ldots, 15)$ denotes field in the coverage area. A field $F_i$in darker shade is covered by more sensors. Figure 1 illustrates an example of five sensors formed with fifteen fields. Each and every one of them covered with least number of sensors is described as the Critical Fields (CF) (e.g., $F_1$, $F_3$, $F_5$, $F_{13}$, and $F_{15}$). If a group of sensors are proficient to form complete target coverage area, every CF is enclosed with at least one sensor. The no. of sensors covering in a CF is capable to be estimated as the upper bound of the number of full cover subsets [34-35]. Consequently, the least number of sensors in the covering region is denoted by $\widehat{CS}_i$, be capable to be utilized as the upper bound of $CS_i$.

## B. PROPOSED TFMGA -MDCCKC METHODOLOGY FOR NETWORK LIFETIME MAXIMIZATION

In this work introduces a new Trapezoidal Fuzzy Membership Genetic Algorithm (TFMGA) in order to maximize the number of Disjoint Connected Covers (DCC) and K Coverage (KC) (TFMGA-MDCCKC). Consequently, energy efficiency have been becomes a most important issue in HWSNs. To solve this problem, Markov Chain Monte Carlo (MCMC) is introduced in this work. In TFMGA-MDCCKC algorithm initially converts the coverage problem and energy efficiency problem into a Constructed Graph (CG) model. In the CG model, vertex is denoted as the assignment of a device in a subset. Heuristic information from TFMGA is used for calculating its constraint violations such as DCC and KC for coverage problem, routing constraints and energy constraints. A dynamic representation of nodes in the TFMGA is worked based on the TFM .This improves the optimal MDCCKC solutions by updating of Coverage Set (CS) nodes. For performing this task, TFMGA-MDCCKC approach is initially introduced for network lifetime maximization and above mentioned constraints is checked simultaneously under the number of connected covers in a HWSN. Let us consider the coverage constraint solution as $\mathrm{SOL} = \{\mathrm{Sol}_1, \mathrm{Sol}_2, \ldots, \mathrm{Sol}_\mathrm{N}\}$ where $\mathrm{SOL_i} \subseteq \mathrm{SEN} \cup \mathrm{SIN}$ denotes a subset of sensors $\mathrm{U_i}$and $\mathrm{V_i}$ sinks, $\mathrm{i} = 1, 2, \ldots, \mathrm{N}$, and N be the total number of subsets. Each cover subset is Disjoint and K Coverage Constraint (DCKCC) by each other's and the combination of the N subsets equals to the set of $SEN \cup SIN$.

***Coverage Constraint:*** The coverage percentage of each sensor nodes in the cover set $CS_i$ is calculated directly and it is used as the coverage criterion for coverage constraint. At this point if the target is under group of separate points, then coverage percentage is the part of covered points. If the target is obtained via the computation of coverage percentage $\kappa_i$ .The coverage ratio $\kappa_i$ is computed as the number of covered fields to the number of presented fields, i.e.,

$$\kappa_i = \frac{|\bigcup_{SEN_j \in SOL_i} F_j|}{|F|} \tag{10}$$

***K Coverage Constraint***: From the above mentioned constraints and connected descriptions, the target K Coverage (KC) is computed via the sensors in $SEN_i$ during their energy is considered as objective function is calculated as follows,

$$E_i = E^r - \sum_{l=1}^{|d_i|} E\,(d_i^l) \tag{11}$$

Here $r_s$ is the sensing range of the cover set $CS_i$.

***Collection Constraint:*** Term a sensor through at least one sink in its transmission range as a composed sensor. Obviously, a cover subset during a larger proportion of collected sensors is capable that must assure the collection constraint. The percentage $\chi_i$ of collected sensors in $SOL_i$ is capable to be measured as the criterion, i.e.,

$$\chi_i = \frac{H_i}{U_i} \tag{12}$$

where $H_i$ is the total number of collected sensors in $SOL_i$.

***Routing Constraint****:* Let us assume that the Constructed Graph(CG) model as $\mathrm{G_i}$ , with $\mathrm{V_i}$ sinks in $\mathrm{SOL_i}$. Includes of vertex set and edge set as $\{(\mathrm{SIN_j}, \mathrm{SIN_k}): \left\|\mathrm{SIN_j} - \mathrm{SIN_k}\right\| \le \mathrm{R_t}, \mathrm{SIN_j}, \mathrm{SIN_k} \in \mathrm{SOL_i}, \mathrm{j} \ne \mathrm{k}\}$. The sinks in $SOL_i$ denotes a connected network iff $G_i$ is a connected graph. From the above mentioned graph theory, the connectivity of a graph is computed via the relative size $\lambda_i$ with its largest connected subgraph [36]. The routing constraint criterion is calculated as follows,

$$\lambda_i = \frac{B_i}{V_i} \tag{13}$$

where $B_i$is the number of sinks in $G_i$. After computing four criteria's then compute the $N$ subsets, the objective value $\phi(SOL)$ must be computed as follows,

$$\phi(SOL) = we_1 \sum_{i=1}^{N} (\kappa_i + \chi_i + \lambda_i + \mathrm{Pr_i})/4 + we_2 CS \tag{14}$$

where $we_1, we_2 > 0$ are the weights values which are predefined initially, and $CS$ is represented as cover set in $SOL$. The $\phi(SOL)$ is calculated from objective function with two major parts. The first part represents the constraint violations of each one of the subsets. The second part represents the objective value for connected covers$(CS)$. The objective of TFMGA-MDCCKC is to compute an optimal solution that maximizes the number of Disjoint Connected Covers and K coverage constraints; the objective value should rise as $C$ increases. In this work set $we_1 = 1$ and $we_2 \ge \widehat{CS}$.

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$$\frac{we_2}{we_1} \geq \widehat{CS} \tag{15}$$

**Construction Graph(CG) Model:** Figure 2 shows the realtime example of CG model with five Sensors (SEN) and three Sinks(SIN) (|SEN| = 5, |SIN| = 3, , K=4 and $N_t$ = 5) ,where $N_t$ is the number of existing subsets at iteration t. Each vertex $v_{ij}$ $(i = 1,2\ldots., N_t\ j = 1,2,\ldots,|SEN| + |SIN|)$ in the 'G' denotes a device allocation to a subset. If j is smaller than $|SEN|$, $v_{ij}$ denotes the assignment of sensor $SEN_j$ to $L_i$ . Else, $v_{ij}$ is allocated to sink $SIN_j - |SEN|$ to $SOL_i$ . Every pair of vertices $v_{ij}$ is associated via undirected arc graph model, which represents an optimal route of gene. Genes following the arcs during the CG 'G' model selects precisely one vertex from each column, ensuing in a solution through $N_t$ disjoint subsets. The general path $(v_{11}, v_{42}, v_{23}, v_{34}, v_{15}, v_{36}, v_{27}, v_{48})$ differentiate a solution $SOL = \{Sol_1, Sol_2, Sol_3, Sol_4, Sol_5\}$ , where $sol_1 = \{SEN_1, SIN_5\}, Sol_2 = \{SEN_3, SIN_2\}\ Sol_3 = \{SEN_4, SIN_1\}, Sol_4 = \{SEN_2, SIN_3\}$ , and $Sol_5 = \emptyset$ lies inside of $N_t$ .

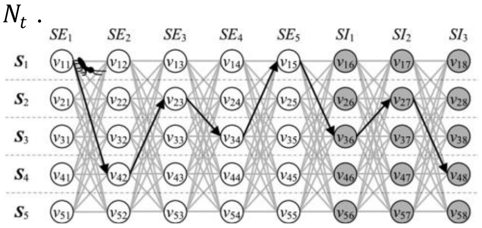


**Figure 2. Example of the construction graph with |*SEN*| = 5, |*SIN*| = 3, K=4**

## C. MARKOV CHAIN MONTE CARLO (MCMC) ALGORITHM FOR ENERGY CONSUMPTION

In MCMC algorithm, search begins with the initial residual energy values of each SEN and SIN node. Following a backbone transition, the condition energy values are calculated from individuals of the initial condition of the transition. A path finishes when its connected energy level becomes zero. For example, if data transmission starts from SIN to SEN nodes with the purpose of reaches destination node, followed by SIN node becomes dependent on SEN and go towards to destination node. The CG model is modeled by a directed edge in the G, i.e., $SIN_i \rightarrow SEN_j$. In this work make use of the Bayesian network theory to store probabilistic dependencies in the CG model, Residual Energy Measurement Table (REMT) is generated and associated with each vertex. This REMT predetermine how the data transmission flows with vertex from its sink nodes of incoming edges to its children nodes. For example, if some of the sink nodes vertices of a vertex turn into tainted directly, the REMT in the vertex saves the probability to the vertex also obtain infected. Bayesian examination provides easy step for energy consumption value estimation of each SEN nodes in the CG model at the time of data transmission. Known set of energy consumption value of each SEN nodes are represented as $S_i$, calculate a probability distribution p(z). The energy consumption value of each sensor node SEN is computed before performing data transmission process. Subsequently compute how the observed data 'x' relates to z by computing a likelihood function $p(SEN(E^r_{|SEN|})|z)$. Finally, apply Bayes' rule

$$p(z|SEN(E^r_{|SEN|})\ ) = \frac{p(z)p(SEN(E^r_{|SEN|})|z)}{\int p(z)p(SEN(E^r_{|SEN|})|z)dz} \tag{16}$$

In the previous step, Bayesian likelihood is considered as optimization problem by introducing a parameterized posterior approximation $q_\theta(z|SEN(E^r_{|SEN|}))$ by choosing parameters $\mathcal{L}$ toward reduce a lower bound L on the marginal likelihood:

$$\log p(SEN(E^r_{|SEN|})) \tag{17}$$
$$\geq \log p(SEN(E^r_{|SEN|})\ )$$
$$- D_{KL}(q_\theta(z|SEN(E^r_{|SEN|})\ )||p(z|SEN(E^r_{|SEN|})\ ))$$
$$= \mathbb{E}_{q_\theta(z|x)}[\log p(SEN(E^r_{|SEN|})\ ) \tag{18}$$
$$- \log(q_\theta(z|SEN(E^r_{|SEN|})\ )]$$

A variational inference, MCMC starts by computing random distribution $z_0$ from initial distribution $q(z_0)$ or $q(z_0|SEN(E^r_{|SEN|})\ )$. Before optimizing this random distribution function, on the other hand, MCMC consequently apply a stochastic transition operator toward the random distribution $z_0$:

$$z_t \sim q(z_t|z_{t-1}, SEN(E^r_{|SEN|})\ ) \tag{19}$$

By thoughtfully selecting the transition operator $q(z_t|z_{t-1}, SEN(E^r_{|SEN|})\ )$ and iteratively applying it several times, the result of this procedure, $z_T$ , determination be a random variable with the purpose of converges in distribution to the accurate posterior $p\left(z\middle|SEN(E^r_{|SEN|})\right)$. The major advantage of this MCMC is that the sensor nodes it provides approximate value from the posterior distribution with stochastic Markov chain for energy computation is computed as follows,

$$q(z|\ SEN(E^r_{|SEN|})) \tag{20}$$
$$= q\left(z_0|SEN(E^r_{|SEN|})\right)\prod_{t=1}^{T} q\left(z_t\middle|z_{t-1}, SEN(E^r_{|SEN|})\right)$$

As a variational approximation is extended by considering $y = z_0, z_1, \ldots, z_{t-1}$ toward be a set of secondary random variables into the variational lower bound (18), is calculated as follows,

$$\mathcal{L}_{aux} \tag{21}$$
$$= \mathbb{E}_{q(y, z_T|, SEN(E^r_{|SEN|})\ )}[\log p(, SEN(E^r_{|SEN|}), z_T) r(y|, SEN(E^r_{|SEN}$$
$$- \log(q(y, z_T|, SEN(E^r_{|SEN|})\ )]$$

where $r(y|, SEN(E^r_{|SEN|})\ , z_T\ )$ is an secondary Bayesian distribution with marginal posterior approximation designed for energy computation between SIN node to SEN node is defined as follows,

$$q\left(z_T\ \middle|, SEN(E^r_{|SEN|})\right) = \int q\left(y, z_T\ \middle|, SEN(E^r_{|SEN|})\right) dy \tag{22}$$

The marginal approximation $q\left(z_T\ \middle|, SEN(E^r_{|SEN|})\right)$ is currently a mixture of distributions of the form $q(z_T\ |SEN(E^r_{|SEN|}), y)$. The selection of $r(y|, SEN(E^r_{|SEN|}), z_T) = q(y|, SEN(E^r_{|SEN|}), z_T\ )$ should be optimal to a reasonable degree. The particular case of auxiliary inference distribution from Markov structure is computed by posterior approximation [37]:

$$r(z_0, \ldots, z_{t-1}|, SEN(E^r_{|SEN|}), z_T) \tag{23}$$
$$= \prod_{t=1}^{T} r_t\ (z_{t-1}|, SEN(E^r_{|SEN|}), z_t)$$

Here the lower bound consumed energy value of each sensor nodes have been rewritten as follows

 

$$\log \mathrm{p}\left(SEN(E^{r}_{|SEN|})\right) \geq \mathbb{E}_{\mathrm{q}}[\log \mathrm{p}(SEN(E^{r}_{|SEN|}), \mathrm{z_T}) - \log\left(\mathrm{q}\left(\mathrm{y}, \mathrm{z_T}\middle|SEN(E^{r}_{|SEN|})\right)\right)] + \log \mathrm{r}(\mathrm{z_0}, .. \mathrm{z_{t-1}}|SEN(E^{r}_{|SEN|}), \mathrm{z_T}) \quad (24)$$

Markov Chain Monte Carlo (MCMC) is introduced in this work to solve the energy efficiency problem and network lifetime maximization in HWSN.

### D. TRAPEZOIDAL FUZZY MEMBERSHIP GENETIC ALGORITHM (TFMGA)

Genetic Algorithms (GA) is a category of evolutionary algorithms with the purpose of use evolution as a basis of stimulation to discover the solution for several optimization problems. The chromosomes are created from Constructed Graph (CG) Model and each dimension of these sensor nodes is able to be considered to be a gene. Each generation has a particular number of chromosomes also named as the population. The most key process of MGA is the use of fitness function; here the fitness function is computed based on the optimal coverage constraint and energy constraint value for chosen sensor nodes. This fitness functions ($\phi(SOL)$) of each sensor nodes are described in equation (14). The fitness value then computes the proximity of the sensor nodes from chromosome to the optimal fitness value. The sensor nodes from chromosomes with optimal coverage constraint value are chosen for reproduction. The form of reproduction are mostly relies on crossover and mutation. Crossover is the interchange of two sensor nodes between the CG model and mutation is the randomly modify in the sensor nodes. Mutation is regularly done on weak sensor nodes from CG model; therefore that it adds diversity to the sensor nodes (population) not including actually impeding the development towards the optimal solution. The chromosomes that have reproduced are replaced by the new sensor nodes, irrespective of the fitness values of the new sensor nodes. This results in the formation of the new sensor nodes generation. These sensor nodes (chromosomes) are now passed through the fitness function again and the strongest sensor nodes are chosen to reproduce .This results in a new sensor nodes iteration, with a new set of chromosomes and ideally closer to the optimal coverage constraint value and energy constraint values. The most considerable GA operators are described as follows:

- Selection operator chooses sensor nodes in the population for reproduction. This operator is generally stochastic and introduced to choose sensor nodes the optimal coverage constraint of the chromosomes from the CG model.
- Crossover operator selects sensor nodes and replaces the sensor nodes in the chromosomes before and after the sensor nodes to create new sensor nodes offspring.
- Mutation operator randomly flips the sensor nodes thus creating a new sensor nodes paths offspring.

**Elitism:** At the same time as replacing chromosomes from CG Model from iteration N to iteration N+1, sensor nodes with a highly good coverage constraint value may be replaced by sensor nodes with a poor coverage constraint value. Consequently, this might result in the selection of optimal coverage constraints value. In elitism, the top sensor nodes of every iteration are classified as elite individuals. These sensor nodes will participate in the new population generation, however will not be changed by any sensor nodes from the next iteration. This step is named as Simple Elitism. In Global Elitism, each sensor nodes from iteration N+1 can replace its parent sensor nodes from iteration N, iff its performance is increases. The drawback of this function is that coverage constraint value is updated to only present sensor nodes in the CG model. To solve this problem dynamic Elitism is used in this proposed work.

**Trapezoidal Fuzzy membership function :**Then Trapezoidal Fuzzy membership function is introduced to automatic representation of coverage constraint value into equal ranges [0-1]. The trapezoidal curve is a function of a coverage constraint value, Y, with four parameters such as a, b, c, and d, as represented as follows by equation (25)

$$f(y,a,b,c,d) = \begin{cases} 0, z \leq a \\ \dfrac{z-a}{b-a}, a \leq x \leq b \\ 1, b \leq x \leq c \\ \dfrac{d-x}{d-c}, c \leq x \leq d \\ 0, d \leq z \end{cases} \quad (25)$$

**Dynamic Population Size:** The general issue of conventional GA is the fixed representation of population size. Thus increases the computational complexity if the number of k chromosomes increases. At the same time GAs prefers a reproduction operation, thus increases the time complexity. So global elitism operation is introduced to GA thus overcomes computational complexity. In the modified GA, a cut-off on the coverage constraint and energy constraint has been considered as objective function and every sensor nodes with the purpose of has a fitness value less than this objective function is discarded. If at any point after the cutoff, the number of sensor nodes is greater than the original population size, the original population size is increased, if less then original population size is decreased. Accordingly, in this manner the number of sensor nodes on any point will never be greater than the size of the original population from graph model, thus ensuring computational effectiveness.

**Dynamic Elitism:** The global elitism is applied to sensor nodes in the direction of sink node basis are considered as elite individuals. MGA is being used with the best number of sensor nodes is self-motivated, i.e. it is varying from generation. The advantage of this TFMGA method is that sensor nodes are straightforwardly proportionality with the fitness function.

**Aging factor:** A new parameter named the age of the sensor nodes has been measured and used for simulation. The fundamental principle following to the use of this parameter is that the sensor nodes which are fit to live on for a several number of iterations have previously reproduced in the earlier iterations. Consequently, allowing these sensor nodes to reproduce again will reduce the diversity of the node population to graph model and hence should cause a premature convergence. Thus, the fitness values of the sensor nodes with the purpose are measured for new population generation are not directly proportional to the age of the sensor nodes.

## IV. SIMULATION RESULTS

In this section simulation work is experimented and measured results between methods are Trapezoidal Fuzzy Membership Genetic Algorithm (TFMGA) - Disjoint Connected Covers (DCC) and K Coverage (KC) namely (TFMGA-DCCKC), BFO-MDCCKC, ACO-MNCC and Energy-efficient Distributed Target Coverage (EDTC) algorithm. The simulation work is simulated using network OMNET++ simulator tool with three different sets of HWSNs environment is used with varied scales and redundancy. In Set A, WSNs are formed by the use of randomly positioning sensors and sinks in a 50 x 50 area. Table 1 describes the details of simulation setup parameters for HWSNs which consists of scale $|\boldsymbol{SEN}|$, $|\boldsymbol{SIN}|$, $r_s$ , $r_t$ of sensors, $R_t$ of sinks, and the upper bound $\hat{C}$ of the number of connected covers. From the simulation results it concludes that TFMGA-DCCKC, BFO-MDCCKC and ACO-MNCC are able to determine a solution via the use of $\hat{C}$ connected covers designed for each case. Accordingly, the value of maximum number of connected covers is $\hat{C}$ in the Set A. In the simulation setup, initially the energy value of sensors nodes is predefined to 50 units. The sensing range of each sensor node is predefined to 50m. The initial phase ends with 8 seconds, and the period of a round is 10 minutes.

**Table 1. Test cases**

| No | \|SEN\| | \|SIN\| | No | \|SEN\| | \|SIN\| | $r_s$ | $r_t$ | $R_t$ | $\hat{C}$ |
|---|---|---|---|---|---|---|---|---|---|
| A1 | 200 | 100 | B1 | 179 | 76 | 10 | 18 | 36 | 6 |
| A2 | 400 | 100 | B2 | 295 | 69 | 10 | 20 | 40 | 8 |
| A3 | 400 | 200 | B3 | 328 | 154 | 15 | 20 | 40 | 21 |
| A4 | 600 | 100 | B4 | 444 | 75 | 8 | 20 | 40 | 8 |
| A5 | 600 | 200 | B5 | 496 | 156 | 11 | 18 | 36 | 19 |
| A6 | 800 | 100 | B6 | 464 | 60 | 8 | 15 | 30 | 5 |
| A7 | 800 | 200 | B7 | 586 | 137 | 10 | 18 | 36 | 16 |
| A8 | 800 | 400 | B8 | 639 | 268 | 12 | 18 | 36 | 29 |
| A9 | 1000 | 100 | B9 | 773 | 71 | 5 | 18 | 36 | 6 |
| A10 | 1000 | 200 | B10 | 848 | 147 | 6 | 15 | 30 | 11 |
| A11 | 1000 | 400 | B11 | 883 | 301 | 9 | 16 | 32 | 25 |

To measure the simulation results the following parameters has been used in this work for measuring the results of several approaches in HWSNs. The parameters description is specified as follows:

I. Average Energy consumption of each and every one node in the known area for transmitting a data packet to the nearest sink.

II. Network lifetime of the node is measured as the network running out of its energy and how in the direction of increasing the lifetime.

III. Success Ratio is computes the success ratio in the direction of sending packets from source to destination node.

IV. Loss Ratio computes the loss ratio in the direction of sending packets from source to destination node.

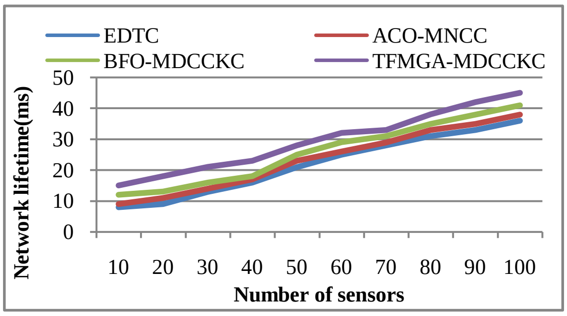


**Figure 3. Network lifetime vs. No. of sensors**

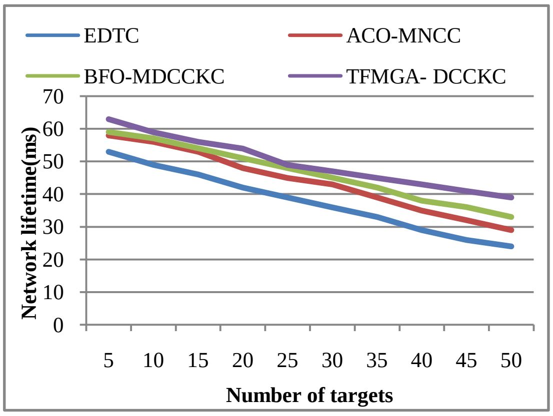


**Figure 4. Network lifetime vs. No. of targets**

Figures 3 shows the results of network lifetime are measured by varying the number of sensors node between 10 and 100. At the same time the number of targets and attributes are assumed to 25 and 4 equally. From the simulation results it concludes that the proposed TFMGA- DCCKC produces maximum network lifetime results of 45 ms for 100 no. of nodes which is 4 ms, 7 ms, and 11 ms higher when compared to BFO, ACO and EDTC methods respectively. The network lifetime is maximized when number of sensors increases since more sensors provide additional opportunities in the direction of covers the targets (shown in Figure 3).

Figure 4 shows the performance comparison results of network lifetime in terms of number of targets. From the results it concludes that the proposed TFMGA-DCCKC produces network lifetime results of 39 ms for 100 numbers of nodes which is 6ms, 10ms, 13ms higher when compared to BFO, ACO and EDTC methods respectively. It concludes that the proposed TFMGA-DCCKC work performs better when compared to other methods (shown in Figure 4).

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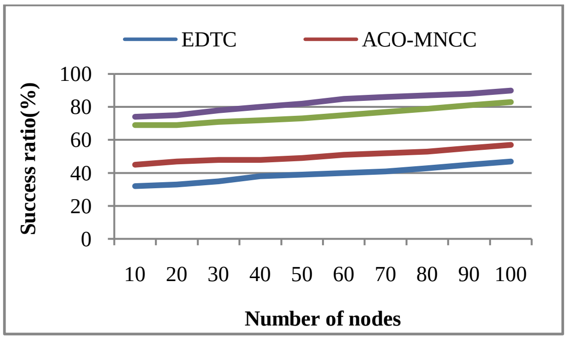


**Figure 5. Success Ratio vs. No. of nodes**

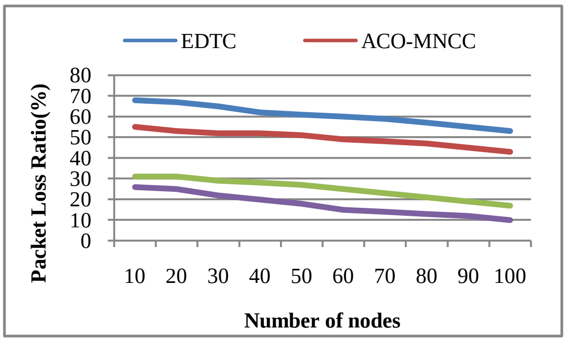


**Figure 6. Packet Loss Ratio (PLR) vs. No. of nodes**

As a result, TFMGA-DCCKC is more suitable and gives best results in terms of network lifetime and data transmission. Figure 5 shows the performance comparison results of success ratio in terms of number of nodes. From the results it concludes that the proposed TFMGA-DCCKC produces higher success ratio results of 90 % for 100 no. of nodes which is 7%, 33%, 43% higher when compared to BFO, ACO and EDTC methods correspondingly. From the simulation results it demonstrated that the proposed TFMGA-DCCKC approach produces better results when compared to existing methods. It demonstrated that if the number of nodes increases the success ratio of the proposed TFMGA-DCCKC system is moreover increases (shown in Figure 5).Figure 6 shows the performance comparison results of Packet Loss Ratio (PLR) in terms of number of nodes. From the results it demonstrated that the proposed TFMGA-DCCKC produces lesser PLR results of 90 % which is 7%, 33%, and 43% lesser when compared to other existing BFO, ACO and EDTC methods correspondingly. It demonstrated that the proposed TFMGA- DCCKC work better when compared to other methods. It demonstrated that if the no of nodes increases the PLR results of the proposed TFMGA- DCCKC system becomes increases however decreases when compared to other existing methods (shown in Figure 6).

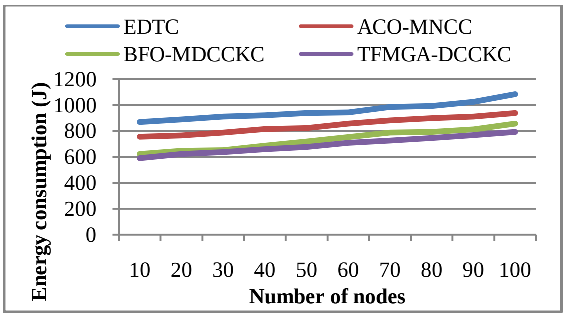


**Figure 7. Energy Consumption vs. No. of nodes**

Figure 7 shows the performance comparison results of energy consumption in terms of no of nodes. From the results it demonstrated that the proposed TFMGA-DCCKC consumes lesser energy results of 792 J which is 64J, 146J, 292J when compared to other existing BFO, ACO and EDTC methods correspondingly. It demonstrated that the proposed TFMGA-DCCKC work better when compared to other methods. It demonstrated that if the no of nodes increases the energy consumption results of the proposed TFMGA- DCCKC system becomes increases, however it decreases when compared to other existing methods. Since the proposed work energy efficiency is solved by using MCMC (shown in Figure 7).

## V. CONCLUSION AND FUTURE WORK

In this research paper we focus on resolving target coverage problem under MDCCKC in HWSNs with the purpose of network lifetime maximization and energy efficiency constraints. This work mainly addresses energy-efficient target coverage problem under maximize the number of Disjoint Connected Covers (DCC) and K Coverage (KC) namely MDCCKC in HWSN. Here Trapezoidal Fuzzy Membership Genetic Algorithm (TFMGA) is introduced to MDCCKC problem known as TFMGA-MDCCKC for solving target coverage problem. A distributed target coverage algorithm is presented in this work to HWSN with many sensing units which saves energy and extend network lifetime. The main principle behind of TFMGA is to introduce the concept of sensor priority, which is obtained by integrating three parameters together, which are the Coverage, Routing constraint, and the remaining energy. The simulation results demonstrate that the proposed TFMGA-MDCCKC approach performs betters in terms of network lifetime maximization, energy efficiency and Packet Delivery Ratio (PDR). In the future work, it is expected with the purpose of the different optimization methods are integrated to TFMGA for further decreasing the computational time in large-scale HWSNs and real time environments.

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