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Absolute sensing-Area Coverage using Extended Genetic Algorithm

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***Abstract*: Wireless sensor networks have turn out to be more and more admired and have been extensively used in recent times. Wireless sensor networks typically comprises a hefty amount of sensors for diverse applications of sensing that includes medical, armed forces, civil, adversity management, environmental, and commercial applications. Sensors are device that produces a measurable response in changing the environmental conditions like temperature, humidity, pressure etc. As the sensor have the limited energy, to boost the duration of network and maintaining coverage preservation, we necessitate an approach that involves least sensors in communication of sensed data to base station, In this paper, we exploit the extended conception of genetic algorithm to circumvent gratuitous energy burning which is due to superfluous nodes.**

***Index Terms*: Energy-efficiency, full coverage preservation, network life span addition, sensor scheduling, WSNs**

I. INTRODUCTION

Wireless Sensor Network is a specific kind of wireless networks without constant infrastructure consisting of a collection of sensor nodes, and running on limited magnitude of battery strength. In the WSNs, each sensor node can sense, process and transmit data to base station (BS). WSNs have attracted an awful interest for the duration of the latest years and some business implementations such as environmental surveillance functions are being developed because of their many benefits such as restrained size, minimal reminiscence and electricity necessities and true computation ability, as well as their lower priced and dense. But a lot of work is required to lower the sensor node power consumption at minimum level. If all the packets are passed to BS straightforwardly by sensor nodes, the nodes which are for away from BS will depart untimely. Alternatively, amongst sensor nodes transmitting packets via a couple of hops, sensors nodes which are in close proximity to the BS are inclined to depart untimely. Thus some areas of network become totally un-examined and network partitions are created. Lifetime of sensor nodes is required to be extended by minimum consumption of power in transmission[1].

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A. K Coverage Setback

In the k-coverage setback, minimum k sensor nodes covers every point of concern (POC) inside the sensing range. The assessment of k is determined according to diverse requirement of application-specific WSNs. In this research work, we aim to keep the value of k minimum. Thus we focus on one-coverage setback, where every POC is covered by minimum one sensor node. Typically, the superfluous sensor nodes, which are chosen by scheduling policies[2-4], should be kept in sleeping mode for energy preservation. As soon as the lively node loses its entire energy, there is urgent need to wake up one or more sleeping nodes to reinstate that dying node. As a consequence, the coverage control is assured and original coverage is preserved after switching off superfluous nodes.

B. Genetic Algorithm

In genetic algorithms, we have a set or a populace of feasible solutions to the given hitch. These solutions are then subjected to recombination and mutation (as in natural genetics).

Fitness value is determined for each candidate solution and the greater suit persons are given a larger likelihood to breed superior "vigorous" individuals. This is driven by theory of Darwinian that is "Survival of the fittest". In this way, we proceed to "evolve" with higher individuals or solutions over generations, until we attain a criterion of detention. In the genetic algorithm we repeat Selection, Crossover and Mutation procedure unless a pre-defined criterion is fulfilled.

II. LITERATURE REVIEW

Currently, many academicians have investigated the optimization algorithm for the coverage and location of nodes in wireless sensor networks. M Cardei's TianD algorithm [6], Wang's CCP algorithm [7] and Liang's Huang algorithm[5] are some effective approaches in this context.

Chia-Pang Chen et al. [8] proposed a fusion memetic scaffold (Hy-MFCO) for optimizing coverage. From real-world experimentations and computer simulations, they produced the outcomes that specify that Hy-MFCO is proficient in maximizing detection coverage and, at the same moment, attaining energy effectiveness.

Liang Ying et. al. [5] proposed a method that uses the adaptive group head communication method (group head communication) to guarantee that power burning is unprejudiced throughout the network and can perk up the network time phase.

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Mihaela Cardei et. al. [6] designed a scheme to ascertain a "maximum separation set coverage problem". In this scheme the nodes that are incorporated in the utmost separation coverage area are in operation, while residual nodes remains in dormant state. Thus much energy is saved and life cycle of the network is enhanced. Jia Jie, et.al.[9] presented a weighted genetic algorithm and optimization coverage mechanism based on the genetic restriction algorithm. According to the fitness function generated to perform the operation of the genetic algorithm, a complete coverage province is needed for the guessing the finest set of nodes and the absolute assortment of the work node, thus prolonging the endurance of the network. Youn-Hee Han [10] proposed a scheme anchored in a genetic algorithm coverage programming and evolutionary inclusive search techniques to monitor all the targets and that can discover the optimum coverage set, extending the life span of the network.

III. PROPOSED APPROACH

In this research work, we presume that all the sensors are homogenous and stationary and their location is known.

A. Sensing Coverage representation

A set of sensor nodes in target area A is delineated as S = $\{s_1, s_2, s_3, \ldots, s_M\}$, where s_i is located at coordinates $\{a_i, b_i\}$, where i varies from 1 to M and M be the total nodes which are deployed in area A. Each sensor has sensing radius Ra.

Let P be set of POCs distributed over the area A. If N is number of POCs then P = $\{p_1, p_2, \ldots, p_N\}$, where POC p_j is situated at $\{a_j, b_j\}$, where j varies from 1 to N. A binary Coverage variable $C_{i,j}$ which signifies whether sensor s_i covers the POC p_j is defined as follows:

$$C_{i,j} = \begin{cases} 1 & if\,(a_i - a_j)^2 + (b_i - b_j)^2 < Ra^2 \\ 0 & Otherwise \end{cases}$$

B. Energy disbursement Model

We exploit the model illustrated by Heinzelman[11] to compute the power disbursement for both kind of communication (transmission as well as reception). This power disbursement model is portrayed in Figure 1.

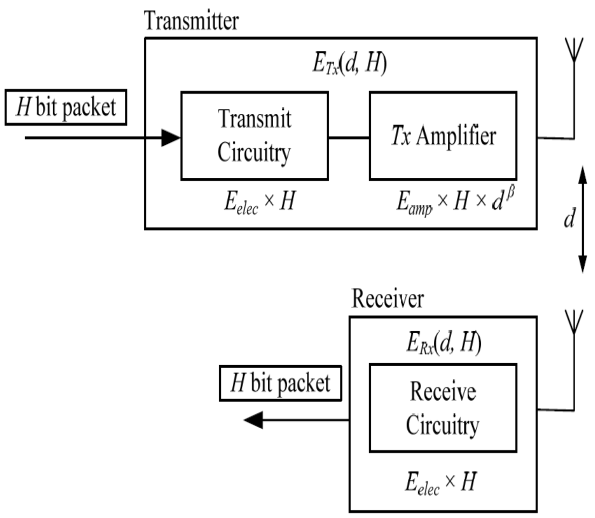

Fig. 1: The energy disbursement model[11]

In Figure 1, transmit circuitry or receive circuitry consumes E_{elec} nano-joule energy in transmission or reception of per bit. Energy expenditure in the power amplification of each bit is depicted by E_{amp}. β denotes the exponent for path loss. As a result, when a transmitter transmits a packet of H-bit to the receiver, the overall energy expenditure can be determined as follows:

$$E_{Tx}(d, H) = E_{elec} \times H + E_{amp} \times H \times d^{\beta}$$

$$E_{Rx}(d, H) = E_{elec} \times H ,$$

C. Problem Formulation

In this study, the focal point of our work is to manage the POC coverage with least energy efficiently. Consequently our endeavor is to locate such specific set of sensor nodes such that each POC is covered by at least one node. This hitch can be devised mathematically as follows:

Optimization Model:

$$\text{Min} \sum \text{Cost}_i \,.\, a_i \qquad i = 1,2,3,4\ldots M$$

Subject to:

$$\sum C_{i,j} \cdot a_i \geq 1 , \qquad j = 1,2,3,4\ldots.N$$

$$x_i = 1 \text{ or } 0 , \quad i \in [1, M] ,$$

where $Cost_i$ is outlay of stimulating i^{th} sensor node; a_i's are the key assessment variables which are determined by proposed approach. The proposed approach decides the value of a zero if it should be inactive otherwise a is set 1. The objective function diminishes the total number of nodes required to be activated such that each POC in sensing vicinity is covered.

D. Proposed Absolute sensing-Area Coverage Using extended Genetic Algorithm

The proposed Absolute sensing-Area Coverage Using extended Genetic Algorithm" (ASCeGA), comprises two optimization strategies: an extended GA approach for schedule determination for sensor nodes and a stir-up proposal. The foremost scheme deactivates superfluous nodes in clustered WSN in accordance with the proposed schedule for nodes. The working of proposed approach is exemplified in figure 2. The subsequent stir-up proposal handles the energy-proficient coverage optimization in every time. The initial populace is usually produced in random manner. Selection, crossover and mutation are genetic operations, which are used in evolutionary process.

In the ASCeGA, we use the fitness function to evaluate the rectitude of every individual solution(gene). After completion of genetic operations, we apply the extended search to further improve the rectitude of the solutions. After extended search, a novel populace of superior genes is produced. Individuals in the novel populace are h in the vicinity of to the overall finest solution. Additionally, when termination criterion is satisfied, it will be assumed that finest solution has been found and thus the evolutionary process will be ended.

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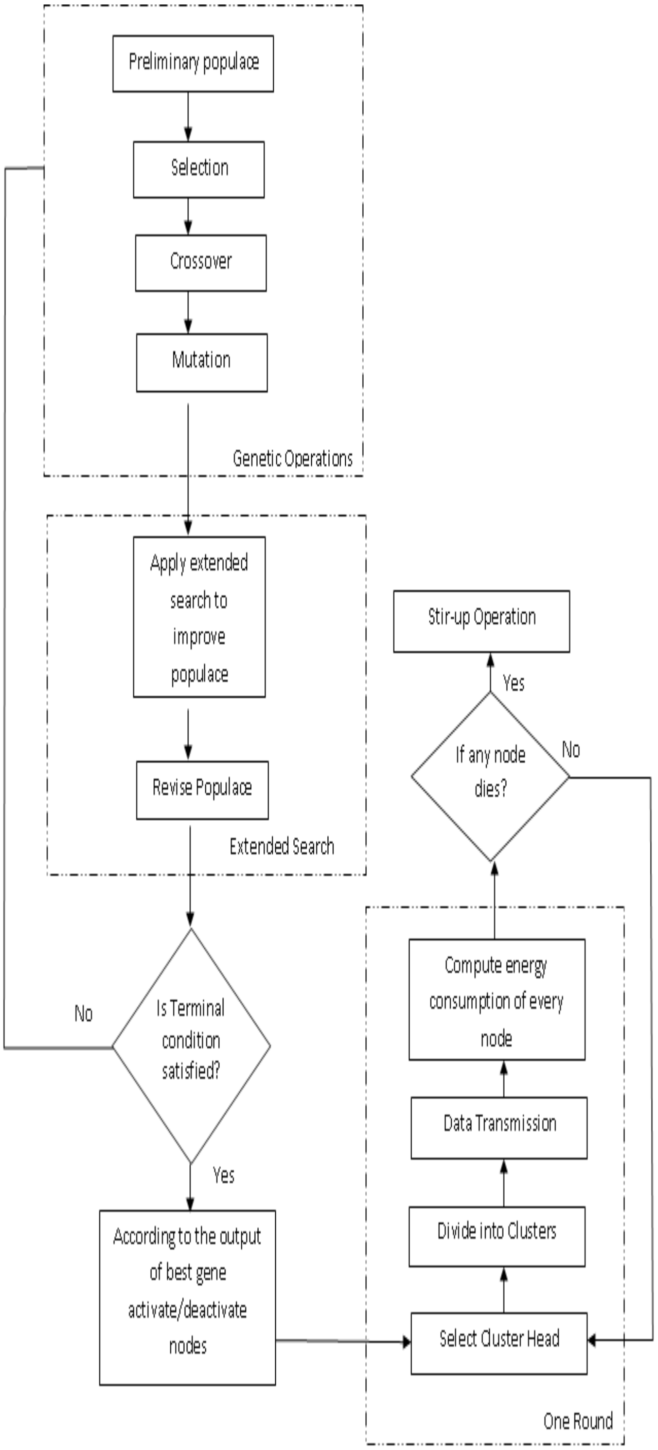

Fig. 2: Flowchart of the ASCeGA

Figure 3 depicts the genetic representation for the power-proficient coverage optimization. There are X number of genes and allele $l_{i,j}$ denotes whether sensor node s_j in gene I is active or not. As there are N nodes so the length of each gene is N. Here we take fixed size of populace size for every populace generated in each generation. With the aim to save power and attain the finest coverage ratio, a best schedule for nodes is included into the ASCeGA to dormant these superfluous nodes.

	$l_{i,1}$	$l_{i,2}$	$l_{i,3}$	$l_{i,j}$	…	$l_{i,M}$
gene 1	1	0	0	1	…	1
gene 2	0	1	0	0	…	0
. . .						
gene *i*	1	1	1	0	…	1
:						
gene X	0	1	1	1	…	0

Fig. 3: Genetic representation used in the ASCeGA

We also propose a coverage vector CV to characterize the coverage of each POCs. By using the sensing coverage model (section 3.1), we delineate the coverage vector of s_i as $CV_i = [C_{i,1}, C_{i,2}, \ldots, C_{i,N}]$, where $s_i \in S$. Likewise, for another sensor node $s_j \in S$, the coverage vector is would be $CV_j = [C_{j,1}, C_{j,2}, \ldots, C_{j,N}]$, where $i \neq j$. By using binary model, following synthetic coverage vector(SCV) can be delineated for s_i and s_j to symbolize whether a specified POC is covered by these sensors.

$SCV(s_i, s_j) = CV_i \vee CV_j = [C_{i,1} \vee C_{j,1}, C_{i,2} \vee C_{j,2}, \ldots\ldots, C_{i,N} \vee C_{j,N}]$

where SCV designates a synthetic coverage vector, which determines whether s_i and s_j cover every POC in combined manner or not. Consequently, the SCV for a gene *k* is delineated as follows:

$$SCV(k) = (l_{k,1}.\ CV_1) \vee (l_{k,2}.\ CV_2) \ldots\ldots \vee (l_{k,M}.\ CV_M)$$

As the coverage assessment procedure is made simpler into binary operations, the working of ASCeGA can be enhanced significantly. Additionally, we can establish the coverage ratio(CoR) for the gene *k* by:

$$CoR_k = \frac{\|SCV(k)\|}{N}$$

where $\|SCV(k)\|$ represents the number of POC covered by gene k . The utility ratio (*UR)* of nodes for gene *k* is computed by:

$$UR_k = \frac{\sum_{p=1}^{N} l_{k,p}}{M}$$

where $\sum_{p=1}^{N} l_{k,p}$ represents total nodes that have been chosen to be stimulated. We delineate fitness function f_k as the goodness of gene *k* and devise it as:

$$f_k = CoR_k - UR_k$$

Substituting CoR_k and UR_k:

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$$f_k = \frac{\|SCV(k)\|}{N} - \frac{\sum_{p=1}^{N} l_{k,p}}{M}$$

The constrained boundaries are $0 \leq CoR_k \leq 1$, $0 \leq UR_k \leq 1$ and $1 \leq f_k \leq 1$. Thus, the solution encoded in gene k is considered better if it has higher value of f_k .

E. Genetic Operations

Selection, crossover and mutation are the operations generally used in genetic algorithms. For selection we have numerous strategies but proportional fitness, roulette wheel and fixture selection are mostly used. The fixture selection strategy has been exploited in proposed ASCeGA. It is just because it seeks the best fitness of each generation more powerfully. In the fixture assortment approach, a competition is organized among arbitrarily selected individuals and then chooses the conqueror for crossover. In proposed ASCeGA, every allele signifies the state of a sensor which is kept 1 for active and 0 for dormant. The gene with higher fitness value implies that the clustered WSN has an improved schedule for sensor nodes while applying ASCeGA.

The result of selection procedure is used for crossover. A single-point crossover is used in crossover task.

After the crossover we apply the mutation operation which changes one or more values in any probable gene allele. It supports the whole GA to thwart the populace from being ensnared in a local best solution. T herefore the newly constructed individual(gene) is added to the original gene pool. The concluding offspring have an elevated fitness because of iterative operations of crossover as well as mutation.

F. Extended Search Scheme

In this research work, an extended exploration plan is derived so that proposed ASCeGA converges rapidly thus further perk up the righteousness of the populace computed by genetic operations. In this approach we alter the value of every allele from one to zero and keep the updated gene if the fitness value of new gene is greater than the fitness value of original gene.

In this way gene can be polished to an improved one if superfluous nodes are found. Contrasting the traditional genetic approaches, the proposed ASCeGA gives superior outcome by performing the extended search process. Using the developed extended exploration scheme, the ASCeGA converges swiftly.

The ASCeGA keeps sprouting until a extinction condition is fulfilled. Here the evolutionary process is finished when its optimal result is unaffected for η subsequent generations.

G. Stir-up

Our stir up mechanism comes into picture when active node loses its entire energy. When such situation occurs some POC becomes uncovered. Thus some dormant nodes are required to be stimulated to recover the coverage of uncovered POCs.

After each transmission, each active sensor of gene is checked whether it is still active or exhausted its whole energy. If one sensor s_i drains its entire energy, the BS will re-examine the coverage of network and find the uncovered POCs $\left(CV_{uncovered}^{S_i}\right)$ by taking exclusive OR between the original SCV of all sensor nodes including sensor *si*, and the SCV without sensor *si*.

Let node $s_i \in S$, where S is the set of all sensor nodes, and i=1,2,3…..M .The u_i signifies the set of all adjacent sensors of s_i, where i =1,2,3…..M . If SCV(synthetic coverage vectors) of some sensors have overlapping with $CV_{uncovered}^{S_i}$,

let OP_i be the set of such sensors. Additionally, let $S_{OP_{i,k}}$ characterizes the *k*-th probable subset of OP_i and w is total number of subsets in OP_i.

Process of the stir-up proposal

best_comb, best_value = 0;
map,res = [0, 0, ... ,0], length = N ;

If sensor s_i has exhausted its energy and cannot work acceptably then
{ Loop k =1 to w

{ Loop every element d of S_{OP_k}

{ map $=CV_d \cup$ map ;

res=map$\cap CV_{uncovered}^{S_i}$

if $\sum_{a \in res} a + \frac{1}{size(S_{OP_k})+1}$ > best_value then

best_value= $\sum_{b \in res} b + \frac{1}{size(S_{OP_k})+1}$

best_comb= S_{OP_k} ;
}
}
output = best_comb;
}

The chief intention of the stir-up proposal is to spawn a best schedule to stimulate some sensors in a dormant mode. As mentioned above, some dormant nodes will be activated by BS according to the finest schedule of nodes generated by the stir-up method at the commencement of the next round. If any sensor loses its complete energy yet again, the stit-up method will re-examine the coverage and resolve to stimulate some other sensor nodes to convalesce the uncovered POCs. In this way, we succeed to preserve the coverage of POCs in effective manner.

IV. EXPERIMENTAL EVALUATION

We simulated our proposed approach in a field with dimensions 100m×100m where 64 POCs and 400 nodes disseminated uniformly in a sensing field. MATLAB is used to implement the simulations. Other simulation parameters are shown as follows:

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a) The sensing range Ra is 12.618 meters considering 5% (20 sensors) supposed to be active.
b) Nodes with space less than 12.618 meters are delineated as neighbors.
c) $\eta = 20$.
d) Crossover rate (R_C) is 0.5 and mutation rate (R_m) is 0.07.
e) Transmit/receive energy (E_{elec}) is 50 nJ/bit, Amplification energy (E_{amp}) is 100 pJ/bit/m^2, Data aggregation energy E_{DA} is 5 nJ/bit/report, $\beta = 2$.
f) Location of base station is (50, 200).
g) Data packet size is 2,000 bits.
h) Initial energy of each node is 0.25 Joules.

Figure 4 depicts the deployment of nodes and coverage for POCs after applying the proposed optimal schedule.

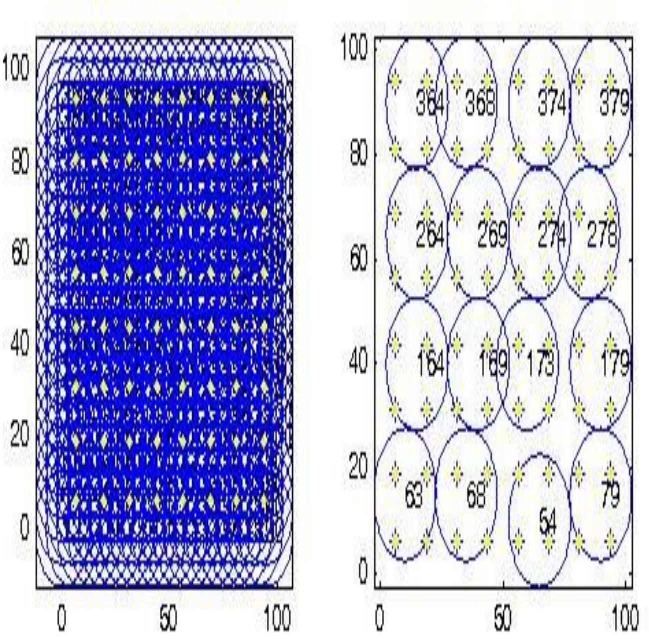

Fig. 4: Unvarying deployments of sensors and POCs

We evaluate our proposed approach with LEACH [12] and PEGASIS [13] and K coverage GA[14]. We conducted simulations using the identical network mentioned previously under unvarying deployments of nodes and POCs.

The sensing coverage ratio is exemplified in figure 5 against number of rounds. This figure noticeably designates that PEGASIS and LEACH provides meager capabilities in maintaining coverage ratio(CoR). While the ASCeGA reaches to 0% sensing coverage ratio at round number approx 4000 which greater than all other compared approaches.

Figure 6 shows the comparison of life span of propose and other approaches. We detect that the sensors loose entire energy rapidly using PEGASIS and LEACH methods because of lack of scheduling strategy. Conversely, the K coverage GA and ASCeGA can inactivate the superfluous sensor nodes via node-scheduling strategy that accumulate a large amount of energy, so the network life span can be enhanced.

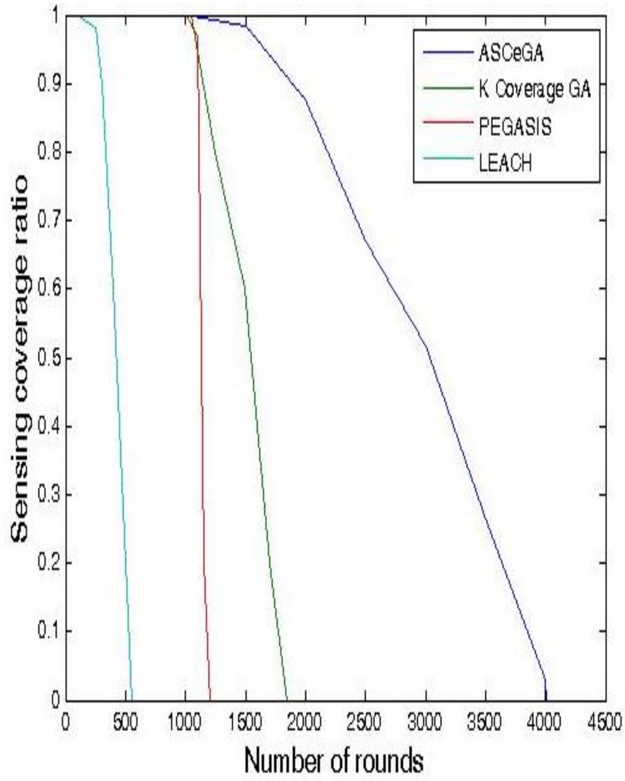

Fig. 5: The number of rounds verses sensing coverage ratio versus

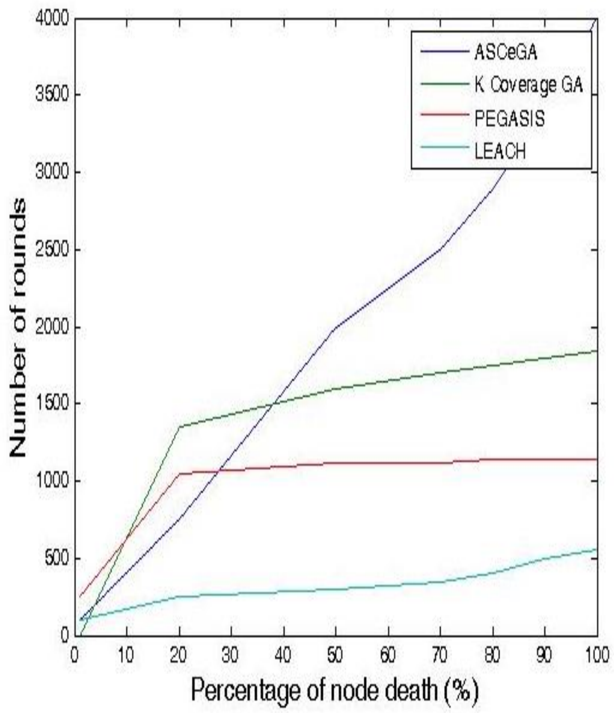

Fig. 6: Percentage of dead nodes versus the number of rounds

V. CONCLUSION

As sensor partake in the network operations only for the time they have energy, then energy competence in the blueprint of every aspect of such nodes is required.

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Energy burning in sensors occurs chiefly due to computational processing. In this paper we designed an energy proficient approach by exploiting the genetic algorithm so that only minimum nodes should be active at any time and participate in communication. If any active node dies, any sleeping node to recover the network coverage is woken. Our experimental evaluation shows that by using the extensive genetic algorithm we attained the better network life span and coverage.

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