Energy Efficient Coverage Using Artificial Bee Colony Optimization in Wireless Sensor Networks

J Roselin and P Latha

1Department of Computer Science and Engineering, Regional Office, Anna University Tirunelveli Region, Tamil Nadu, India
2Department of Computer Science and Engineering, Government College of Engineering, Tirunelveli, Tamil Nadu, India

In mission critical applications, all critical points (CPs) are to be monitored effectively. Even a single node failure in the Wireless Sensor Network (WSN) may cause coverage hole, reducing the lifetime of the network. The sensor has non-rechargeable battery which makes energy supervision inevitable. The proposed Energy Efficient Coverage based Artificial Bee Colony Optimization (EEC-ABC) approach exploits intelligent foraging behaviour of honeybee swarm to solve Energy Efficient Coverage (EEC) problem, and thereby maximizes the network’s life time. It adheres to Quality of Service (QoS) metrics such as coverage, residual energy and life time. The simulation results demonstrated effectiveness of the residual energy and coverage in enhancing network lifetime.

Keywords: Artificial Bee Colony, Critical points (CPs), EEC-ABC, Surveillance, WSN.

Introduction

Wireless Sensor Network (WSN) is an emerging technology that has many potential applications in monitoring various physical and environmental conditions including biological detection, forest fire detection, flood and natural calamities. In those mission critical surveillance applications, there are certain regions or points that are prone to mishaps. These points are known as Critical Points (CPs), and they need more attention than the other regions. Hence, it is vital to devise an efficient point coverage mechanism. In point or target covered WSN, every sensor is able to monitor all the CPs within its sensing range. The sensors involved in these applications are expected to work for a longer period without energy exhaustion, but at the same time enhancing the lifetime of the network. But the wireless sensors are battery powered having limited energy. The energy of the sensor decreases as the monitoring continues. This affects the coverage efficiency and lifetime of the network. To avoid this, the battery of the sensors needs to be replaced or recharged, which is impractical and also expensive. Such issues make energy supervision is inevitable. There are many deployment optimization algorithms available in the literature to alleviate battery wastage. As it is difficult to configure each mobile node individually towards a particular location, the above techniques the sensor’s energy decreases due to mobility. In order to save the mobility energy, the sensors are to be moved towards its closest critical point. Moreover, these approaches lack in balanced coverage; some critical point has dense coverage, some sparse, and few with no coverage. As an alternate to deployment optimization, the activities of sensors could also be scheduled to avoid energy wastage and to maintain required coverage. There are two states in scheduling: active state and sleep state. Some of the redundant sensors are maintained in sleep state so that their energy can be utilized for future purpose. In these approaches set of sensors are divided into disjoint sets such that every set completely covers all CPs. These disjoint sets are activated successively, such that only one set is active at any moment of time. The network lifetime is extended proportionally by a factor equal to the number of disjoint sets. While activating these sets, energy levels of those sensors are not verified. So, there is a possibility of a node failure which could induce coverage hole in a network. In the present study, we propose an Energy Efficient Coverage based Artificial Bee Colony Optimization (EEC-ABC) approach to address the shortcomings of the above methods, and thereby maximize the network’s life time.

Experimental details

Table 1 lists the configuration parameters of wireless sensor network.
Our Network Model
We assume a typical redundant wireless sensor network based on probabilistic sensor detection model, where sensors are deployed uniformly at random manner around all the critical points in the target area.

To specify our network model, we assume that the sensors are tiny electronic devices; each sensor has non-renewable battery as energy source, has limited sensing, computational and communication capabilities. To ensure connectivity, transmission range of sensor should be twice of its sensing range. Also, we assume that a sensor becomes inoperable, when its energy source is exhausted; sensors know its position and remaining energy; positions of CPs are known exactly; and that there is no obstacles and noise in the target area.

Probabilistic sensor detection model
Practically, sensors detect the event being monitored by measuring the Received Signal Strength (RSS). The RSS value is exponentially attenuated with the distance between the critical point and the sensor. The probabilistic detection model as proposed by Zou and Chakrabarty\textsuperscript{13} considers this uncertainty unlike the boolean disc model. Hence, we chose the

<table>
<thead>
<tr>
<th>Configuration parameters</th>
<th>Notation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target Area</td>
<td>TA</td>
</tr>
<tr>
<td>Number of Sensors</td>
<td>$N_s$</td>
</tr>
<tr>
<td>Set of sensor nodes</td>
<td>$S = {s_1, s_2, s_3 ... s_{N_s}}$</td>
</tr>
<tr>
<td>Number of Critical Points</td>
<td>$N_{CP}$</td>
</tr>
<tr>
<td>Set of Critical Points</td>
<td>$CP = {CP_1, CP_2, CP_3 ... CP_{N_{CP}}}$</td>
</tr>
<tr>
<td>Sensing range of sensors</td>
<td>$r_s$</td>
</tr>
<tr>
<td>Transmission range of sensors</td>
<td>$r_t$</td>
</tr>
<tr>
<td>Euclidean distance between sensor $s_i$ and $CP_j$</td>
<td>$d_{ij}$</td>
</tr>
<tr>
<td>Probability of detection of events at $CP_j$ by sensor $s_i$</td>
<td>$\lambda_i(j)$</td>
</tr>
<tr>
<td>Decay parameters ($a, m = 0.5$)</td>
<td>$a, m$</td>
</tr>
<tr>
<td>Remaining energy of sensor $s_i$</td>
<td>$RE_i$</td>
</tr>
<tr>
<td>Energy heuristics of sensor $s_i$</td>
<td>$EH_{S_i}$</td>
</tr>
<tr>
<td>Coverage heuristics of sensor $s_i$</td>
<td>$CH_{S_i}$</td>
</tr>
<tr>
<td>Number of employee bees</td>
<td>$N_E$</td>
</tr>
<tr>
<td>Set of employee bees</td>
<td>$E = {E_1, E_2, E_3 ... E_{N_E}}$</td>
</tr>
<tr>
<td>Dancing area of an employee bee $E_i$</td>
<td>$C_{DA}(E_i)$</td>
</tr>
<tr>
<td>Reporting area of an employee bee $E_i$</td>
<td>$C_{RA}(E_i)$</td>
</tr>
<tr>
<td>Consignment capacity of employee bee $E_i$</td>
<td>$C_i$</td>
</tr>
<tr>
<td>Nectar Value of employee bee $E_i$</td>
<td>$N_{E_i}$</td>
</tr>
<tr>
<td>Number of onlooker bees</td>
<td>$O = {O_1, O_2, O_3 ... O_{N_O}}$</td>
</tr>
<tr>
<td>Set of onlooker bees</td>
<td>$\phi_i(j)$</td>
</tr>
<tr>
<td>Reporting probability of employee bee $E_i$ to onlooker bee $O_j$</td>
<td>$O_{A_i}^{E_i}$</td>
</tr>
<tr>
<td>The account of employee bee $E_i$ created by onlooker bee $O_j$</td>
<td>$E_{A_i}$</td>
</tr>
<tr>
<td>Set of employee bees active in time slot $t_s$</td>
<td>$E_{t_s}$</td>
</tr>
<tr>
<td>Number of employee bees active in time slot $t_s$</td>
<td>$NE_{t_s}$</td>
</tr>
<tr>
<td>Ranks the set $S$ based on the parameter $p$</td>
<td>$L_{Rank}(S, p)$</td>
</tr>
</tbody>
</table>
above model as it gives more practical approach to solve the EEC problem. Let \( \lambda_i(j) \) denote the probability of detection of event at critical point \( CP_j \) by sensor \( S_i \). Euclidean distance between sensor \( S_i \) and critical point \( CP_j \) is the sensing range of sensor and \( r_u \) is the transmission range of sensor, \( a \) and \( m \) are decay factors. The event detection probability is 1 if the CP is within sensing range of a sensor. The detection probability of event at CP is exponentially decreased when the distance between sensor and CP is greater than \( r_u \). When the distance is greater than the transmission range, the detection probability of sensor is zero.

\[
\lambda_i(j) = \begin{cases} 
0 & \text{if } d_{ij} > r_u \\
\exp^{-a(d_{ij} - r_u)^m} & \text{if } r_u < d_{ij} \leq r_u \\
1 & \text{if } d_{ij} < r_u
\end{cases}
\]  

Problem description

The practical objective here is switching the states of sensors to maximize the lifetime of the network under the integrated constraint of energy efficient coverage. To achieve this, all the CPs in the target area should be covered with lesser number of sensors. It requires trade-off between total number of CPs and number of CPs covered by each sensor. During selection, sensor which covers more than one CP, is given the highest priority. To increase reliable facet of the network, sensor which may more prone to failure is avoided despite its coverage.

Depiction of solution space

Further, we need to maximize the lifetime of the network with energy efficient coverage. We adopted solution representation as given below:-

The coverage or energy heuristic of any sensor \( S_i \) is calculated as significance of its own coverage or energy contribution in par with the remaining sensors in the target area.

- \( EH_{S_i} \) - Energy heuristic is the remaining energy units of the sensor \( S_i \) over other sensors in the target area.

\[
\frac{RE_{S_i}}{\sum_{i=1}^{N_S} RE_{S_i}}
\]  

- \( CH_{S_i} \) - Coverage heuristics of a sensor \( S_i \) calculated as the summation of its coverage over the total coverage of every critical point it covers.

\[
CH_{S_i} = \sum_{j=1}^{N_CP} \frac{\lambda_i(j)}{\sum_{i=1}^{N_S} \lambda_i(j)}
\]  

The sensor that covers the critical point which is left uncovered in the target area is said to have crucial coverage. The heuristics finds the own contribution of a sensor over others in the network. Hence, the sensors with critical contribution are elevated to ensure its importance.

Remark 1 - Coverage heuristic elevate the crucial coverage sensor and improves its possibility of selection. The Energy heuristic elevate the sensor with critical (less) battery and reduces its possibility of selection.

The sensing coverage and the remaining energy are the two important independent parameters which decide the quality of the sensor. To get the impact of both the parameters, we multiplied it together and obtained a new value, called fitness of a sensor.

- The sensor is made active based on its fitness value. Higher the fitness value greater the probability of its selection, where

\[
Fitness_{S_i} = EH_{S_i} \times CH_{S_i}
\]  

- To ensure reliable coverage, every critical point’s detection probability is maintained as \( \Delta \), where \( \Delta = 0.97 \).

- The detection probability of a critical point \( CP_j \) is calculated as

\[
\delta_{CP_j} = \sum_{i=1}^{N_S} \lambda_i(j)
\]  

Remark 2 - For every time slot, fittest node got selected to be in solution set which ensures reliability of the solution set.

Remark 3 - The optimized solution for given timeslot \( ts \) is the set of selected sensors that covers all the critical points in the target area for that time slot. The remaining sensors are at sleep state which helps to preserve the energy of those sensors for future use. Thus, the life time of the network can be enhanced. The set \( Optimized\_Solution_{ts} \) has the set of selected sensors that covers all the critical points in the target area for the time slot \( ts \). The set of sensors \( S' \), here \( S' = S - Optimized\_Solution_{ts} \) is at sleep
status for the timeslot \( ts \), which helps to preserve the energy slot of those sensors. Thus, the life time of the network can be enhanced.

Remark 4- If any of the CP left uncovered, the network is no longer effective and its lifetime comes to an end.

**Energy Efficient Coverage Based Artificial Bee Colony (EEC-ABC) Optimization**

‘Swarm Intelligence’ based metaheuristic optimization solves problems of incomplete or imperfect information\(^\text{14}\). It makes few assumptions about the problem being solved and finds a better solution with less computational effort than other mathematical optimization and iterative algorithms. In literature, wide range of applications have been solved with evolutionary computation techniques with best proven results\(^\text{15}\)-\(^\text{17}\). Hence, here we adopted swarm intelligence technique for solving energy efficient coverage problem. Inspired by the intelligent behaviour of honeybee swarm\(^\text{18}\), we made extensive study of Artificial Bee Colony (ABC) optimization technique and devised Energy Efficient Coverage based Artificial Bee Colony optimization (EEC-ABC) approach to maximize the life time of the network.

**Bee Colony in Real World Scenario**

Fig. 1 explains bee colony in natural scenario. There are two types of bees named employee bees and onlooker bees. The employee bee ventures out in search of food source i.e., flower (from where honey is extracted). There is no conflict arises among the employee bees in searching the food source. Each employee bee on finding a food source, evaluates the amount honey that can be extracted, memorizes its location, and returns to the hive and performs waggle dance to communicate. Onlooker bee dwells in its region inside the hive. The onlooker bee verifies the waggle dance of those employee bees and chooses the best one. Honey is extracted from those selected flowers. The employee bee in abandoned food source becomes scout bee. Fig. 1 maps the bee colony in real world scenario to the proposed Energy Efficient Coverage based Artificial Bee Colony optimization (EEC-ABC) technique. There are six employee bees named E1-E6, three onlooker bees O1-O3, and the box represents the hive. The onlooker bees are inside the hive dwelling in its region. The swarm intelligence technique that mimics the behaviour of natural honey bees is called Artificial Bee Colony Algorithm (ABC). The EEC-ABC optimization technique has the following assumptions that: target area is assumed as hive; CPs are assumed as onlooker Bees; sensors are assumed as employee bees; sensing area \( C_{rs}(s_i) \) of a sensor \( s_i \) is assumed as dancing area of that employee bee \( E_i \); transmission range of a sensor \( r_u \) is assumed as the maximum reporting distance of an employee bee; probability of detection \( \lambda_i(j) \) of events at \( CP_j \) by sensor \( s_i \) is equivalent to the reporting probability \( \varphi_i(j) \) of employee bee \( E_i \) to onlooker bee \( O_j \); the remaining energy of the sensor \( s_i \) is assumed as the consignment capacity \( C_i \) of the employee bee \( E_i \); the fitness of a sensor \( s_i \) is assumed as the Nectar \( C_{rs}(s_i) \) of employee bee \( E_i \) and the employee bee becomes scout bee if it has no nectar. In Fig. 1, the employee bees and their dancing areas are differentiated by different colours. As sensing area of sensors may overlap, we assumed that the dancing area of employee bee might also overlap. The employee bee reports to the onlooker bees that lie within its reporting distance.

![Fig. 1—Waggle dance of employee bee](image)

**Energy Efficient Coverage based Artificial Bee Colony Optimization (EEC-ABC)**

The EEC-ABC is an optimization technique based on the intelligent foraging behaviour of honey bee swarm. In EEC-ABC also there are two types of bees namely employee bee and onlooker bee. Table 1 shows the list of configuration parameters used in EEC-ABC. The EEC-ABC optimization technique has 4 phases viz.: (i) Account creation - Onlooker bee; (ii) Nectar estimation - Employee Bee; (iii)
Reporting Nectar - Employee Bee; and (iv) Employee Bee evaluation and Selection - Onlooker Bee. In our EEC-ABC optimization approach, sensors are ranked based on their fitness value. The energy and coverage heuristics of a sensor is evaluated as its fitness value. Before activating the fittest sensors for the current time slot, once again it was assured with required energy for monitoring. If sensor’s energy was null or very less for monitoring it was removed from the network. Sensors were selected until desired coverage criterion satisfied, and thereby sorting out the Energy Efficient Coverage problem.

Account creation - Onlooker bee

Each employee bee calculates its reporting probability $\phi$ for all onlooker bees in the hive. The employee bee’s reporting probability is 1 for the onlooker bee which lies inside its dancing area and 0 for the onlooker bee which lies outside its reporting area. The reporting probability decreases exponentially if the onlooker bee lies inside the reporting area but away from the dancing area of the employee bee. The employee bee reports to the onlooker bees within its reporting area.

The onlooker bee $O_j$ creates an account $OA_{E_i}^{O_j}$ for every

**EEC- ABC Optimization**

```plaintext
for i = 1 to N
for j = 1 to N_o
if $\phi_{i}(j) > 0$ // $\phi_{i}(j)$ reporting probability of $OA_{O_j}$
    // Nectar Value of Employee bee $E_i$
    Nectar_{E_i} = $\sum_{j=1}^{N_o} \phi_{i}(j) \times \frac{E_{i}}{\sum_{k=1}^{N_o} E_{k}}$
    if Nectar_{E_i} == 0 // Value of $E_i$ is NULL so $E_i$ becomes scout bee
        \forall O_j \in O, iff OA_{O_j}^{E_i} \in OA_{O_j}, Delete OA_{O_j}^{E_i};
    endif
    \forall O_j \in O, iff OA_{O_j}^{E_i} \in OA_{O_j}, OA_{O_j}^{E_i} = Nectar_{E_i};
    //Reporting Nectar to all $O_j$ which has $E_i$ account.
End for

for j = 1 to N_o
    if OA_{O_j} == ø
        // if all $E_i$ in the account of $O_j$ were became scout bees, termination is reached;
        return ts;
    endif
End for

L_{Rank} (OA_{O_j}, Nectar_i); // Rank $E_i$ in OA_{O_j} based on its nectar value
initialize Current_Highest_Rank = 0;

While $\sum_{i=1}^{N_E} Error_{B_i}$

$NE_{i}^{E} = NE_{i}^{E} + 1;
Current_Highest_Rank = Current_Highest_Rank + 1;
E_{i}^{A}[NE_{i}^{E}] = E_{i}^{A} \cup OA_{O_j} [Current_Highest_Rank];$
End While

End for
\forall E_i \in E_{ts}, Update C_i;
// updates consignment capacity of all the employee bee active for the Timeslot t
Until Termination reached
return ts
```
employee bee $E_i$ reporting to it. From Fig. 1, we observe that the employee bees $E_1$ and $E_6$ report their nectar value to onlooker bee $O_1$. The employee bees $E_2$, $E_3$ and $E_4$ report to onlooker bee $O_2$. The employee bees $E_4$ and $E_5$ report to onlooker bee $O_3$.

**Nectar Evaluation - Employee Bee**

Nectar of each employee bee is evaluated in two phases. In phase I, the meticulousness is calculated as the number of onlooker bees the employee bee is reporting over the number of employee bees reporting to the same onlooker bee.

\[
meticulousness \quad E_i = \sum_{j=1}^{N_O} \frac{\varphi_i(j)}{\sum_{l=1}^{N_E} \varphi_l(j)} \quad \ldots (6)
\]

In the second phase, fitness of the employee bee is evaluated as its consignment capacity, the amount of honey extracted from the flower selected by it over others. The nectar of the employee bee is the product of the meticulousness and the consignment value of it.

\[
consignment \quad capacity \quad E_i = \frac{C_i}{\sum_{l=1}^{N_E} C_l} \quad \ldots (7)
\]

\[
Nectar_{E_i} = \sum_{j=1}^{N_O} \frac{\varphi_i(j)}{\sum_{l=1}^{N_E} \varphi_l(j)} \times \frac{C_i}{\sum_{l=1}^{N_E} C_l} \quad \ldots (8)
\]

**Reporting Nectar - Employee Bee**

For every time slot, each employee bee reports to onlooker bees which have an account of it and updates its nectar in the account. If any employee bee’s nectar value is 0, its consignment capacity is null. The flower from which it extracts honey is drained. Hence, it becomes scout bee. It is removed from all onlooker bees which maintain its account.

**Employee Bee Selection - Onlooker Bee**

The onlooker bee $O_j$ stores the nectar of the employee bee $E_i$ reported to it in its account $OA_{O_j}^{E_i}$. Each Onlooker bee has the responsibility of evaluating all the reporting employee bees to determine the best honey extractor. To evaluate the nectar of the employee bee, each onlooker bee ranks employee bee in their account $OA_{O_j}$ based on its nectar value using $L_{Rank}$ function as below.

\[
L_{Rank} \left( OA_{O_j}, Nectar \right); \quad // \text{Rank } E_i \text{ in } OA_{O_j} \text{ based on its nectar value}
\]

For the time slot $ts$, employee bees are activated from every onlooker bee account $OA_{O_j}$ based on its rank until the reporting probability of active employee bees for the onlooker bee $O_j$ is less than the threshold $\Delta$.

Termination state - If any onlooker bee has null account then all employee bees in its account become scout bees. Such onlooker bees become inactive. However, if the scout bees of the onlooker bee account finds a new flower it can be active.

In wireless sensor network, it equals coverage hole. The lifetime is reported as the total number of time slots $ts$ the algorithm got evaluated.

**Simulation Results and Discussion**

A series of simulations conducted to verify the effectiveness of EEC-ABC method. The proposed method is first of its kind to increase the lifetime of wireless sensor network as the energy and coverage issues of each sensor is properly elevated and addressed separately. The effectiveness of energy, coverage has also been analyzed in detail.

**Scenarios**

For detailed analysis, the sensors with different scales and redundancy were employed for simulations. The sensors were deployed around all CPs randomly in target area. There were 25 scenarios (s1 to s25) categorized into 5 subsets based on the sensing range of sensors and target area. Each scenario had different set of sensors, critical points. Table 2 shows the scenario setup.

---

Table 2 — Simulation settings

<table>
<thead>
<tr>
<th>TA (m x m)</th>
<th>Scen</th>
<th>$N_S$</th>
<th>$N_{CP}$</th>
<th>Scen</th>
<th>$N_S$</th>
<th>$N_{CP}$</th>
<th>Scen</th>
<th>$N_S$</th>
<th>$N_{CP}$</th>
<th>Scen</th>
<th>$N_S$</th>
<th>$N_{CP}$</th>
<th>Scen</th>
<th>$N_S$</th>
<th>$N_{CP}$</th>
<th>Scen</th>
<th>$N_S$</th>
<th>$N_{CP}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>25 x 25</td>
<td>5</td>
<td>S1</td>
<td>10</td>
<td>4</td>
<td>S6</td>
<td>40</td>
<td>15</td>
<td>S11</td>
<td>52</td>
<td>30</td>
<td>S16</td>
<td>64</td>
<td>35</td>
<td>S21</td>
<td>76</td>
<td>43</td>
<td></td>
<td></td>
</tr>
<tr>
<td>40 x 40</td>
<td>7</td>
<td>S2</td>
<td>13</td>
<td>8</td>
<td>S7</td>
<td>42</td>
<td>23</td>
<td>S12</td>
<td>55</td>
<td>20</td>
<td>S17</td>
<td>66</td>
<td>33</td>
<td>S22</td>
<td>82</td>
<td>47</td>
<td></td>
<td></td>
</tr>
<tr>
<td>50 x 50</td>
<td>9</td>
<td>S3</td>
<td>24</td>
<td>11</td>
<td>S8</td>
<td>45</td>
<td>24</td>
<td>S13</td>
<td>57</td>
<td>32</td>
<td>S18</td>
<td>68</td>
<td>39</td>
<td>S23</td>
<td>88</td>
<td>44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>75 x 75</td>
<td>11</td>
<td>S4</td>
<td>30</td>
<td>16</td>
<td>S9</td>
<td>48</td>
<td>26</td>
<td>S14</td>
<td>59</td>
<td>15</td>
<td>S19</td>
<td>71</td>
<td>40</td>
<td>S24</td>
<td>94</td>
<td>55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>100 x 100</td>
<td>13</td>
<td>S5</td>
<td>37</td>
<td>18</td>
<td>S10</td>
<td>50</td>
<td>29</td>
<td>S15</td>
<td>61</td>
<td>34</td>
<td>S20</td>
<td>73</td>
<td>41</td>
<td>S25</td>
<td>100</td>
<td>58</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Simulation Setup
The simulations were carried out in MATLAB simulator. All the simulations were put to 30 independent runs.

Lifetime of wireless sensor network
Total number of timeslots all the CPs in the target area were monitored effectively without any node failure due to energy depletion and coverage hole. A time slot is the actual duration, the set of sensors activated for energy efficient coverage. Normally, it depends upon the battery capacity of a sensor. If $e$ is the energy consumed by a sensor for an active time slot, and its initial energy is $E$, the total number of active time slots the sensor is $T = E/e$. Normally, energy conception model of the sensor depends upon $e_s$ energy consumed for sensing, $e_r$ energy consumed for reception and $e_d(d)$ energy consumed for transmission to the distance $d$. In our present proposal, the remaining energy of each sensor is just a score to be got selected over others. Hence, we replaced energy conventional conception model. In our model, the active sensor consumes constant amount of energy per each time slot, whereas the inactive sensor does not consume any energy. Also, we assume that each sensor is with the same initial energy of one Joule which can last for ten active timeslots. An active sensor consumes 0.1 Joule of energy per timeslot and the sensor which is in sleep state (not active) does not consume any energy. These assumptions are made for fair comparison among the sensors during selection process of the algorithm.

Analysis of Computation Complexity
Our EEC-ABC approach consists of two phases. During phase 1, each employee bee calculates its nectar and report the nectar value to onlooker bees which lies inside its reporting area. In second phase, each onlooker bee evaluates the nectar of employee bees reported to it and selects the best for honey extraction. It is obvious that the first phase takes constant time for operation, thus the time complexity is equal to $O(1)$. The second phase can be further divided into two components: evaluation of the nectar of employee bees and the selection of the best employee bee. The onlooker bee evaluates the nectar of the reported employee bee by ranking it. For selecting the best employee bee for honey extraction, each onlooker bee first verifies the selected bee list and moves the highest ranked employee bee of if requires. The overall time complexity for the second phase is equal to $O(n^2) = O(n^2) + O(n)$. Concluding above discussion, the time complexity of EEC-ABC is equal to $O(n^2)$.

Comparative study between EEC-ABC and ABC
In this section, we compared the performance of EEC-ABC with ABC. Table 3 and Table 4 compare average lifetime and computation time of EEC-ABC vs. ABC, respectively. Both the tables show better results for EEC-ABC as compared to ABC for each scenario. The average lifetime for scenarios S1, S2, S3, S4, S7, S11 and S23 using EEC-ABC was nearly 1.5 times more than that of ABC; and for other scenarios it was nearly 1.2 times more. The computation time of ABC was significantly high compared to EEC-ABC. According to Table 3, EEC-ABC calculates the solution with a minimum of 1.68 ms and maximum of 32.5 ms. The ABC algorithm selects sensor randomly and adds it to the solution set, until the formed subset covers all the critical points. As energy and coverage heuristics is not considered while selecting sensor, the computation time increases and the life time of the network decreases.

Comparing EEC-ABC with its variants C-ABC and E-ABC
E-ABC and C-ABC are the two variants of EEC-ABC. The E-ABC considers energy heuristic and C-ABC considers coverage heuristic for sensor selection. Simulation results showed that EEC-ABC outperforms its variants E-ABC and C-ABC. Table 3 and Table 4 show the lifetime and computation time (average of 30 trail runs) of ABC, C-ABC, E-ABC

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>ABC</th>
<th>C-ABC</th>
<th>E-ABC</th>
<th>EEC-ABC</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>0.0078</td>
<td>0.0046</td>
<td>0.0027</td>
<td>0.0021</td>
</tr>
<tr>
<td>S7</td>
<td>0.4165</td>
<td>0.3146</td>
<td>0.1597</td>
<td>0.0748</td>
</tr>
<tr>
<td>S13</td>
<td>0.6878</td>
<td>0.4458</td>
<td>0.4223</td>
<td>0.4107</td>
</tr>
<tr>
<td>S19</td>
<td>0.8694</td>
<td>0.6814</td>
<td>0.6769</td>
<td>0.6405</td>
</tr>
<tr>
<td>S25</td>
<td>4.0215</td>
<td>2.2626</td>
<td>2.2389</td>
<td>2.1866</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>ABC</th>
<th>C-ABC</th>
<th>E-ABC</th>
<th>EEC-ABC</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>8</td>
<td>10</td>
<td>11</td>
<td>16</td>
</tr>
<tr>
<td>S7</td>
<td>27</td>
<td>29.43</td>
<td>37.03</td>
<td>49.37</td>
</tr>
<tr>
<td>S13</td>
<td>71</td>
<td>73.47</td>
<td>80.17</td>
<td>103.73</td>
</tr>
<tr>
<td>S19</td>
<td>127</td>
<td>140.77</td>
<td>149.63</td>
<td>155.97</td>
</tr>
<tr>
<td>S25</td>
<td>239</td>
<td>250.9</td>
<td>274.57</td>
<td>307.73</td>
</tr>
</tbody>
</table>

Table 3—Average Computation Time

Table 4—Average WSN Lifetime
and EEC-ABC for selected scenarios. From the simulation, we observed that the WSN life time and the computation time varies with the number of sensors and the CPs employed. To simulate practical environments, we opted different sensing range of sensors and number of sensor deployed to cover CPs and number of CPs to be covered under various target area. The Fig. 2 represents box plot for the selected scenarios S1, S7, S13, S19 and S25. In box plot x-axis represents the EEC-ABC and its variants, y-axis represents WSN lifetime in time slots. The box plot is a graphical representation of data that shows a data set’s lowest value, highest value, median value, and the size of the first and third quartile. A box plot is a better alternative or complement to a histogram for showing several simultaneous comparisons, especially to indicate a skewed distribution and also potential unusual observations (outliers) in the data set. The Fig. 2(a) represents the box plot for scenario-1. For ABC, life time ranged from 4 to 12 with an average of 8. There was no outlier recorded for this scenario. In C-ABC, the life time below 8 and above 12 were recorded as outliers. The mean of C-ABC was 10, where time slot 14 and 16 were identified as extreme outliers. For E-ABC, the time slots 6, 12 and 15 were identified as extreme outliers where mean was 11. For EEC-ABC, mean was 16, in the positive skew with the maximum of 26. Fig. 2(b) represents the box plot for scenario-7. There were no outliers for this scenario. From simulation, we noted E-ABC to be in negative skew, whereas EEC-ABC in positive skew. Fig. 2(c) represents the box plot for scenario-13. ABC and E-ABC were with outliers. EEC-ABC was in positive skew and others had negative skew. Like scenario-19, scenario-27 is explained through box plot in Fig. 2(d) and Fig. 2(e). By above observation, one can track the performance of each variant in a simple and effective manner.

![Box plot simulation results of Lifetime for the scenarios](image)
Impact of Energy Heuristic

E-ABC considers only the energy heuristic while sensor selection. The sensors which cover more CPs with less remaining energy are ignored compared to sensors which covers less CPs with more energy. Number of sensors required for overall coverage also increases. Hence, WSN lifetime decreases and computation time increases.

Impact of Coverage Heuristic

C-ABC considers only coverage heuristic for the sensor selection. Thus, the sensors with more coverage are repeatedly selected which leads to energy drain of those sensors compared to other sensors with less coverage. The C-ABC induces the possibility of coverage hole at the earliest and thereby reduces WSN lifetime.

Impact of Energy and Coverage Heuristic

EEC-ABC assures energy and coverage balanced sensor selection. It improves the WSN lifetime reliably and reduces the computation time. This can be observed from the Table 3 and Table 4. Experimental results showed that EEC-ABC outperforms its variants E-ABC, C-ABC and the conventional ABC algorithm. From the simulation results, we proved that energy and coverage are the best selection paradigm to increase the lifetime of wireless sensor networks.

Conclusion

In the present study, we proposed a new approach for maximizing life time of the wireless sensor network by managing energy and coverage issues of every individual sensor appropriately. This approach addressed the coverage hole or node failure due to energy depletion. The proposed EEC-ABC approach has been shown to solve the EEC problem using energy and coverage heuristics for fitness evaluation to accelerate sensor selection. Thus, the proposed approach not only maximizes the lifetime of the network but also minimizes the computation time compared to its variants E-ABC, C-ABC and conventional ABC. The proposed model is the most realistic approach and the solution is arrived under continuous space. We changed position values for sensors and CPs to formulate 25 different scenarios which showed that EEC-ABC is a promising method to solve EEC problem and to increase the lifetime of wireless sensor networks. The proposed EEC-ABC approach can be applied to full target area coverage by adopting a suitable fitness function.

References