Ensembled Spectral Reweight Boost Clustering For Energy Aware Target Object Detection In WSN

T.S.Prabhu, Dr.V.Jaiganesh

Abstract: WSN comprises a collection of sensor nodes (SNs) distributed with small in size. To monitor the presence or absence of a particular target within the communication range, the SNs are deployed in the network. Energy is a foremost resource in target detection since the SN has inadequate battery capacity. Energy limitation of SN leads to lessen the network lifetime (NL). The several methods are developed for target detection but it still not improving the detection accuracy with minimum energy consumption (EC). In order to improve target object detection with improved NL, an Ensembled Spectral Reweight Boost Clustering Based Target Object Detection (ESRBC-TOD) technique is introduced. At first, numbers of SNs are arbitrarily positioned in the network. Then, ensemble clustering is performed by measuring the initial energy and residual energy (RE) of SN. The ensemble clustering technique initially constructs the ‘n’ weak learners. The spectral clustering algorithm is used as weak learner to cluster the SNs based on the RE level. The Reweight boosting technique combines the weak learners and converts a strong one. Then, the SNs are grouped into diverse clusters with higher accuracy and lesser error rate. For energy efficient target detection, the cluster head (CH) is chosen in WSN. The cluster comprises one CH and several member nodes. Cluster member identifies the target node within the cluster and transmits the information to CH. After that, CH gathers information of target object and transmit to sink node via the neighboring CH. Sink node sends the gathered information to base station (BS) for finding the target objects. This leads to increases the target object detection accuracy (TODA). Simulation is performed with different metrics namely EC, TODA, false alarm rate (FAR) and target object detection time (TODT). The observed results show that the ESRBC-TOD technique effectively improves the TODA and minimizes the EC, FAR as well as TODT than the state-of-the-art methods.

Keywords: WSN, Target Object Detection, Residual Energy, Spectral Clustering Algorithm, Reweight Boosting Technique, Cluster Head

1. INTRODUCTION

Wireless sensor network (WSN) includes the SNs to observe and gather the data and organizing the data at BS. SNs are scattered in monitoring field and coordinate with other SNs to produce high-quality information about the target object. Target object detection is an important application in WSN where the SNs monitor and report the location of objects entered into the network. Target object detection is applied in different various applications namely battlefield surveillance, wildlife monitoring, security and so on. However, the energy efficient target detection plays a challenging issue resulting in minimizes the NL. Therefore, energy efficient target detection is performed to increase the NL using ensemble clustering techniques. In [1], a novel mobile target detection algorithm (NMTDA) was presented depending on information theory and adaptive clustering algorithm to enhance the TODA. The designed algorithm minimizes the FAR of target detection but it does not design an algorithm with greater robustness and lower EC. An improved energy-efficient tracking cluster structure was developed in [2] to predict the target object with minimum EC. The multi-target detection and tracking were not performed with minimum time. An adaptive-head clustering algorithm was designed in [3] for obtaining better energy efficiency and target tracking quality using a master node. The designed algorithm failed to improve object detection accuracy. A density-based clustering method was developed in [4] for multi-target detection. Though the method minimizes the misdetection, the energy resource was not considered in the target detection for increasing the NL. A Neyman–Pearson detection method was developed in [5] for cluster-based WSN. The exact target detection was not performed. A fuzzy c-means clustering approach was developed in [6] for improving the target detection performance with less false alarm probability. The designed method failed to choose the CH for minimizing the target detection time. Consensus-based distributed target detection and tracking algorithms were designed in [7]. The designed algorithms failed to detect the multiple existences of the targets within the network. Generalized locally-optimum techniques were introduced in [8] for identifying the non-cooperative target. Though the techniques minimize the false alarm rate, the target detection time was not lessened. Based on energy control mechanism, a k-means++ clustering algorithm was designed in [9] to detect the target. The designed clustering algorithm increases the target detection rate but the performance of target detection time remained unsolved. An index Modulation method was developed in [10] for cluster-based target-detection with minimum decision error rate. The method failed to perform the energy efficient target detection for enhancing the NL. From the existing survey, the conventional techniques have a few limitations such as lack of improving the TODA, more detection time, high false alarm rate, high EC and so on. Such kinds of issues are addressed by introducing a novel clustering technique called ESRBC-TOD to improve TODA.

The major contribution of the proposed ESRBC-TOD technique is summarized as follows,

- To enhance the TODA with lesser EC, ESRBC-TOD technique is proposed. For detecting the target object, the number of SNs is deployed in sensing area. To cluster the SNs, the reweight boosting technique utilizes spectral clustering algorithm as weak learner. The higher energy nodes are selected as CH that gathers information of target object from cluster members and transmit to sink node with lesser EC. Sink node transmits the gathered information to BS. BS discovers the target object within the network based on the received information.

- To lessen the FAR, CH finds the nearest CH via Euclidean distance measure to send the information of target object to sink node. The sink node act as a data collector which gathers the sensed information and sent to BS for target object detection. This process reduces the incorrect data transmission of SNs.
To minimize the target object detection time, the CH collects the sensed information’s from their cluster member. The sink node collects the sensed information from higher energy CH instead of collecting from all the nodes in the network.

This paper is ordered into five different sections. Section 2 discusses the reviews of the related works and their limitations. Section 3 provides a detailed explanation of our proposed technique with neat diagram. Section 4 describes the simulation settings with diverse parameters. Section 5 presents the results and discussion of ESRBC-TOD technique and existing methods with different metrics. Section 6 provides the conclusion.

2. RELATED WORKS
Integration of collaborative fusion and sequential detection was developed in [11] to minimize the target detection latency. But it failed to consider the node energy for target detection in WSN. In [12], a novel multiple decisions fusion rule was designed for target detection. But, it does not calculate the false alarm and detection probabilities. A new strategy was developed in [13] based on a target-motion probability model for identifying the untrackable targets. The perfect target detection was not performed with minimum time. An efficient and adaptive node selection technique was developed in [14] for detecting a target with high accuracy and less energy cost. But the performance of the FAR was not minimized. A Dynamic Clustering Algorithm was developed in [15] for detecting the target with higher precision. However, it does not suitable for multiple targets environment. A hybrid cluster-based target tracking was presented in [16] with lesser EC and local node cooperation. But, the target tracking accuracy was not improved. A generalized Kalman filter was introduced in [17] for energy efficient target tracking with higher accuracy and maximizes the lifespan. The target tracking time was not minimized. To enhance the TODA, a distributed inner-network inference method was designed in [18]. But, TOTD was not reduced. For detecting the Mobile target with minimum delay, a Target Detection with Sensing Frequency scheme was designed in [19]. The designed scheme lessens the EC but the detection accuracy was minimal. In [20], an energy-efficient information fusion approach was designed to identify the mobile target. The approach minimizes the EC and FAR but the accurate target detection was not performed. The issues of existing techniques are conquering by proposing an ESRBC-TOD technique. The process of ESRBC-TOD technique is explained in the below sections.

3. METHODOLOGY
WSN includes the number of SNs which gathering the information and communicating with another node. SNs are small in size with less battery power. Therefore energy conservation plays a major role in many applications particularly in target detection. The main problem of WSN is detecting target objects for several applications. Target detection is a demanding task since every SN in a network usually contains a minimum power supply and it failed to prolong the NL. Fully distributed algorithms improve the target detection quality with minimum EC but it takes more time to perform the specific tasks. Therefore, an efficient technique is needed to enhance the target object detection performance with lesser time. Based on this motivation, an efficient ESRBC-TOD technique is introduced in WSN for energy efficient target object detection.

3.1 System model
The system model of ESRBC-TOD technique is presented in this section. Let us assume the squared sensing area ‘$m \times m$’, where SNs are deployed randomly. WSN represented in graph ‘$G = (V, E)$’ where ‘$V$’ represents a sensor nodes $SN_1, SN_3, ..., SN_n$’ and ‘$E$’ represents set of edges i.e. links between SNs. Here, SNs are grouped into different clusters. To identify the Target Object ($T_0$), each cluster has one cluster head ($C_i$) and transmitted the collected information to BS through the sink node (S). Based on this system model, the brief description of the proposed ESRBC-TOD technique is presented in the following sections. Figure 1 illustrates an architecture diagram of the proposed ESRBC-TOD technique to identify the target object in WSN. The SNs are dispensed in the sensing area. Initially, the dispensed SNs have similar energy level. The initial energy gets degraded based on the sensing capability of the nodes. Therefore, the node energy and RE is calculated for grouping the SNs. Based on the energy level, the ensemble clustering technique cluster the SNs. CH is selected which gathers the data from sensors and relay these data to BS for target detection. The detailed process of ESRBC-TOD technique is explained in the following subsection.

3.1 Ensembled Spectral Reweight Boost Clustering Based Target Object Detection in WSN
Initially, the SNs in WSN have similar energy level before performing the certain task. Energy of SN is calculated based on the product of power and time which is formalized as below,

$$E_{SN} = P \times T$$ (1)
In (1), the energy of sensor nodes is denoted as $E_{SN}$. $P$ denotes a power measured in watts and $T$ represents the time measured in seconds (Sec). Energy of SN is measured in joule (J). Energy level of the SNs gets degraded based on the capability of environmental sensing. Therefore, the energy efficient nodes are identified by calculating the RE. RE of SNs is considered to prolong the NL since SNs are battery powered. To estimate the current RE of a WSN, total energy and consumed energy is considered. The RE is computed as follows,

$$R_E(SN) = E_t - E_c \quad (2)$$

In (2), $R_E(SN)$ denotes the residual energy of sensor node, $E_t$ is total energy (i.e. initial energy) of SN, $E_c$ is the consumed energy of SN for sensing. Residual energy of SNs is calculated using (2).

The SNs are grouped using ensemble clustering technique along with their energy level. The reweight boosting is an ensemble technique for improving the performance of any given learning algorithm by converting the performance of weak learner into strong ones. The weak learner is single clusters which lack of providing the accurate results. In contrast, a boosting is a strong ensemble of clusters that provides accurate results by combining all the weak learners. By using the reweight boosting ensemble algorithm, the ESRBC-TOD technique enhances the performance of weak cluster. Reweight boosting algorithm utilizes spectral clustering algorithm as weak learner to cluster the SNs based on their RE level. The flow process of ensemble clustering technique is depicted in figure 2 to enhance the SNs clustering performance. Ensemble clustering technique takes a set of training samples i.e. a number of SNs. The set of weak learners $w_1(SN_1), w_2(SN_2), w_3(SN_3), ..., w_n(SN_n)$ are constructed to train the SNs and combined into strong one. Reweight boosting uses weak learners as a spectral clustering algorithm. Based on their RE level, spectral clustering algorithm utilizes spectrum (eigenvalues) of similarity matrix of SN for grouping process. Based on their RE, the spectral cluster computes similarity among two SNs. Dice similarity discover the similarity between the SNs. The dice similarity is the ratio of mutual dependence and independence between the two SNs. The dice similarity is measured as follows,

$$\rho (SN_1,SN_2) = 2 \cdot \frac{|SN_1 \cap SN_2|}{|SN_1 \cup SN_2|} \quad (3)$$

In (3), $\rho (SN_1,SN_2)$ denotes a similarity between the two sensor nodes, the intersection symbol ‘$\cap$’ denotes a mutual independence which denotes two sensor nodes are statistically independent. The union symbol ‘$\cup$’ denotes a mutual dependence which denotes two sensor nodes are statistically dependent. Then the weight matrix is constructed with the similarity function $\rho (SN_1,SN_2)$.

$$\alpha_{ij} = \rho (SN_1,SN_2) \quad (4)$$

In (4), $\alpha_{ij}$ denotes a weight matrix, $\rho (SN_1,SN_2)$ represents a similarity between the two SNs. Then the unnormalized Laplacian matrix is constructed with the diagonal matrix and weight matrix using following mathematical formula,

$$L_{ij} = D_{ij} - \alpha_{ij} \quad (5)$$

From (5), $L_{ij}$ denotes a Laplacian matrix, $D_{ij}$ is the diagonal matrix, $\alpha_{ij}$ is the weight matrix. The eigenvalues and eigenvectors of $L_{ij}$ are then used to cluster the SNs. The diagonal matrix with the degrees $b_1, b_2, ..., b_n$ on the diagonal which is expressed as follows,

$$D_{ij} = \begin{pmatrix} b_1 & 0 & \cdots & 0 \\ 0 & b_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & b_n \end{pmatrix} \quad (6)$$

From (6), $D_{ij}$ denote a diagonal matrix. By using the diagonal matrix, normalized Laplacian matrix is created as below,

$$L'_{ij} = D_{ij}^{-1/2} \rho (D_{ij}^{-1/2}) \quad (7)$$

From (7), $L'_{ij}$ represents a normalized Laplacian function, $D_{ij}$ denotes a diagonal matrix, $\rho$ represents a similarity. The normalized Laplacian matrix is constructed based on Eigen vectors ‘$v$’ and Eigen values ‘$e$’. Let ‘$A$’ be the matrix whose columns are the eigenvectors corresponding to the k
The training error rate is computed for each weak learner. After assigning the weight, the training error is defined as a square difference between the actual and predicted output.

\[ \text{Err} = (Y_i - w_i(SN))^2 \]  

(12)

In (12), \( \text{Err} \) denotes a training error, \( Y_i \) denotes an actual output and \( w_i(SN) \) denotes an observed output from the weak learner. Each weak learner is reweighted based on their error rate. The weight is increased if the weak learner incorrectly grouped the SNs. The weight is decreased if the weak learner correctly grouped the SNs. By this way, the weak learners are reweighted. The reweighted results of the weak learner are obtained as follows,

\[ B(SN_i) = \sum_{i=1}^{n} \delta' \times w_i(SN) \]  

(13)

From (13), \( B(SN_i) \) denotes an output of the strong clustering results, \( \delta'' \) denotes an updated weight of the weak learner \( w_i(SN) \). Then the boosting technique exploits the gradient descent function to find the weak learner with minimum training error.

\[ f(x) = \arg \min \text{Err} \ (w_i(SN)) \]  

(14)

In (14), \( f(x) \) represents the gradient descent function, \( \arg \min \) stands for argument of the minimum. \( \text{Err} \) denotes an error of weak learners \( w_i(SN) \). As a result, the SNs are grouped in various clusters based on the RE level. CH is selected after clustering the SNs. Every cluster includes one CH and numerous member nodes. CH gathers the data from cluster members and sends to BS via sink node for target detection. Thus, the higher RE node than the other nodes is chosen as CH within the cluster. The target detection in a monitored area is performed for identifying the locations of moving objects. If the target object entered into the network, then the nearby SNs sense and detect the target object in the cluster. After that, the SN informs to CH where a new target object entered in the network.
\[ S \xrightarrow{T_{o(D)}} BS \quad (17) \]

In (17), \( S \) represents the sink node, \( BS \) indicates a base station. \( BS \) examines the sensed data of target node to detect the target with lesser EC.

**Input:** Number of sensor nodes \( SN_1, SN_2, SN_3, ..., SN_n \)

**Output:** Improve target detection accuracy

**Begin**

1. For each \( SN_i \)
2. Compute energy \( E_{SN} \) and residual energy \( R_{E(SN)} \)
3. Construct ‘n’ number of weak learners
4. Measure the dice similarity between two sensor nodes \( \rho(SN_3, SN_2) \)
5. Construct unnormalized Laplacian matrix \( L_{ij} \) with the diagonal matrix \( D_{ij} \) and weight matrix \( a_{ij} \)
6. Find first k eigenvectors
7. Construct normalized Laplacian matrix \( L_{ij} \)
8. Define ‘k’ number of clusters and their mean value \( \mu_j \)
9. Group data \( SN_i \) into clusters \( j \) using \( \text{arg min} \) function
10. Combine weak learners into strong \( B(SN_j) = \sum_{i=1}^{n} w_i(SN) \)
11. For each \( w_i(SN) \)
12. Initialize the similar weight ‘\( \delta \)’
13. Calculate training error \( \text{Err} \)
14. Adjust the weight \( \delta'' \) based on the error value
15. **End for**
16. Find weak learner with minimum error \( \text{arg min} \text{Err} (w_i(SN)) \)
17. Obtain strong clustering results
18. For each cluster \( C_k \)
19. Select the cluster head (\( C_H \)) with higher residual energy
20. **End for**
21. If the target object node (\( T_0 \)) entered into network then
22. Nearby \( SN \) detects \( T_0 \) within the transmission range (\( T_r \))
23. \( SN \) sends the \( T_0(D) \) to \( C_H \)
24. \( C_H \) sends \( T_0(D) \) to sink node via neighboring \( C_H \)
25. Sink node sends the \( T_0(D) \) to \( BS \)
26. \( BS \) finds the target object within the network
27. **End if**
28. **End for**

**End**

Algorithm 1 Ensembled Spectral Reweight Boost Clustering Based Target Object Detection

Algorithm 1 describes the efficient target object detection with higher accuracy. Based on the RE level, the numbers of SNs are clustered. SNs are grouped by applying the ensemble clustering technique. CH is chosen for each cluster to coordinate the SNs within the cluster. SNs send the information of target node to CH. Via a neighboring CH, CH sends the gathered information to sink node. Finally, the sink node sends the information of target object to BS. This in turn, BS detects the target object in the network. The ensemble clustering process increases the target object detection and target detection time.

**5. RESULTS AND DISCUSSIONS**

The simulation results of ESRBC-TOD technique and existing methods are NMTDA [1] and energy-efficient tracking cluster structure [2] are discussed in this section with different parameters such as EC, TODA, FAR and TOIT with number of SNs. The results are described with the assist of table and graph.

**5.1 Performance analysis of energy consumption**

EC is measured as amount of energy taken by SNs for detect the target object in the network. EC of SNs are calculated as follows,

\[ EC = \text{No. of sensor nodes} \times E \text{ (single sensor node)} \quad (18) \]

From (18), \( EC \) denotes energy consumption, \( E \) represents the energy of single SNs. EC is calculated in joule.
The result of EC is described in table 2 with a number of SNs varied from 50 to 500. Totally ten different results are performed with different SNs. The reported results clearly state that the EC of ESRBC-TOD technique is minimized when compared to existing clustering techniques. The simulation results are plotted in the graph.

Table 2 Energy consumption versus no. of sensor nodes

<table>
<thead>
<tr>
<th>No. of sensor nodes</th>
<th>ESRBC-TOD (joule)</th>
<th>NMTDA (joule)</th>
<th>Energy-efficient tracking cluster structure</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>22</td>
<td>25</td>
<td>30</td>
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<td>100</td>
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<tr>
<td>500</td>
<td>56</td>
<td>61</td>
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</table>

The result of EC is illustrated in figure 4 with number of SNs. The graphical results show that the EC of ESRBC-TOD technique is minimized when compared to existing clustering technique. The simulation results are plotted in the graph.

The result of EC is described in table 2 with a number of SNs varied from 50 to 500. Totally ten different results are performed with different SNs. The reported results clearly state that the EC of ESRBC-TOD technique is minimized when compared to existing clustering techniques. The simulation results are plotted in the graph.

Table 3 Target object detection accuracy versus no. of sensor nodes

<table>
<thead>
<tr>
<th>No. of sensor nodes</th>
<th>Target object detection accuracy (%)</th>
<th>ESRBC-TOD</th>
<th>NMTDA</th>
<th>Energy-efficient tracking cluster structure</th>
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<tbody>
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</table>

The result of EC is described in table 2 with a number of SNs varied from 50 to 500. Totally ten different results are performed with different SNs. The reported results clearly state that the EC of ESRBC-TOD technique is minimized when compared to existing clustering techniques. The simulation results are plotted in the graph.

5.2 Performance analysis of target detection accuracy

TODA is described as how the BS identifies the object in WSN. It is measured as ratio of number of SNs accurately provides information about target object to the total number of sensor nodes used for the simulation.

\[
TODA = \frac{\text{No.of SNs correctly provides the sensed information}}{\text{No.of sensor nodes} \times 100}
\]

From (19), TODA denotes Target object detection accuracy, \(n\) denotes a number of sensor nodes (SN). It is calculated in percentage (%).

Table 3 describes the TODA versus no. of sensor nodes. Let us consider the number of SNs is 50, 46 sensor nodes provide accurate information to find the target object using ESRBC-TOD technique and their TODA is 92%. The target objects detection accuracy of other clustering techniques NMTDA [1] Energy-efficient tracking cluster structure [2] is 90% and 88% respectively. Similarly, the nine different accuracy results are obtained as shown in table 2. The graphical results of TODA are shown in figure 5.

The result of TODA is depicted in figure 5 with number of SNs. The graphical results show that the TODA of ESRBC-TOD technique is enhanced when compared to conventional clustering technique. This is because, ESRBC-TOD technique initially defines the no. of SNs in network. After that, the spectral clustering clusters the SNs based on their RE level. The spectral clustering results are grouped into a single cluster for boosting the weak learner results. Target
node is identified by selecting the CH for each cluster. The cluster members sense the new object entered into the network. Then the information is sent to CH since the CH responsible for SNs in the group. Via the sink node, CH sends accurate information of target object to BS. After that, sink node gathers information from CH and distributes to BS. Based on the information from SNs, the BS finds the target object. This in turn improves the TODA. Therefore, the ESRBC-TOD technique enhances the TODA by 4% and 6% as compared to existing [1] and [2].

5.3 Performance analysis of false alarm rate
FAR is measured as the ratio of no.of sensor nodes incorrectly provides the information about target object to total no.of sensor nodes. FAR is computed as follows,

\[
FAR = \frac{\text{No.of SNs incorrectly provides the sensed information}}{\text{No.of sensor nodes}} \times 100
\]  

(20)

From (20), FAR denotes false alarm rate. It is computed in percentage (%).

Table 4 describes the results of FAR with number of SNs varied from 50 to 500. From the table 4, it is evident that ESRBC-TOD reduces the FAR as compared to existing techniques. The ten different results are shown in the below two-dimensional graph.

Figure 6 Simulation results of false alarm rate versus no. of sensor nodes

The simulation results of FAR is depicted in Figure 6 with no. of sensor nodes. The graph shows that the FAR is considerably minimized using ESRBC-TOD technique. The ESRBC-TOD technique clusters the SNs based on the energy level. The node has minimum RE, not able to hold more information at longer duration. This may lose sensed information about the target node or incorrectly provides information about the target objects. The ESRBC-TOD technique overcomes the above-said problem by using ensemble clustering technique. Based on the RE, the ensemble clustering technique groups the SNs into various clusters. The clustering process computes the training error for avoiding the incorrect cluster members. This helps to minimize the false alarm rate. In addition, the energy efficient CH collects the sensed information about the target node from the cluster members. Next, the CH discovers the nearest CH for sending the information to sink node. The neighboring CH is determined using a Euclidean distance measure. After that, the BS receives the collected information from the sink node. BS examines the information to discover the target object within the cluster. This reduces the incorrect data transmission among the SNs and the BS. Therefore, the FAR of ESRBC-TOD is reduced by 20% and 29% than the existing [1] and [2].

5.4 Performance analysis of target object detection time
TODT is measured as the amount of time taken to detect target object in distributed SNs. The TODT is mathematically calculated as follows,

\[
TODT = t_{end} - t_{start}
\]  

(21)

From (21), TODT denotes a target object detection time and, \(t_{end}\) denotes an ending time, \(t_{start}\) denotes a starting time of target object detection and it measured in terms of milliseconds (ms). Consider the number of SNs is 50, the ESRBC-TOD technique takes 13ms for detecting the target object. The existing clustering techniques take 16ms and 20ms for detecting the target object within the network. Then ten various results of TODT is reported in table 5.

Table 5 Target object detection time versus no. of sensor nodes

Table 5 shows the simulation results of TODT with numbers of SNs. From Table 5, it is evident that the TODT of ESRBC-TOD is minimal than the existing clustering techniques. The simulation result of TODT is shown in figure 8.
The simulation result of TODT is depicted in figure 8 with number of SNs. TODT results is considerably reduced using ESRBC-TOD technique as compared to existing methods. This is because; the CH gathers sensed information’s from their cluster member. The information from higher energy CH is collected by the sink node instead of every node in network. Sink node sends the information to BS with minimum delay. The target object entered in the network is identified by the BS. The simulation result of proposed ESRBC-TOD technique is compared with the results of existing clustering technique. Then, the TODT is reduced by 12% and 22% as compared to existing [1] and [2] respectively. The above results and discussion of the various parameters show that the proposed ESRBC-TOD technique effectively finds the target object entered into the network with minimum time, EC and high accuracy.

6. CONCLUSION
For detecting the target object, an efficient technique called ESRBC-TOD is developed in WSN with greater accuracy and lesser time. Based on their RE level, the ensemble clustering groups the SNs than the conventional clustering technique. The NL is improved by selects the node with maximum RE as CH. CH coordinates every members in the group. The sink node collects the information regarding the target object from the CH instead of collecting entire nodes which results in minimum target object detection time. The BS uses the information which is sent from the sink node and identifying the target objects with high accuracy. The simulation is performed with different metrics such as EC, TODA, FAR and TODT. The simulation results evident that the ESRBC-TOD technique enhances the TODA, with lesser EC, time as well as FAR than the conventional methods.

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