# Energy Aware Generalized Gaussian Distributive Sammon Regularization Analysis for Target Object Tracking in WSN

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***Abstract***

A wireless sensor network (WSN) is a network of small devices, called sensors, used for sensing and monitoring the environmental conditions at various locations through wireless links. Target object tracking is the most important application of WSN where energy conservation plays an important role. Several methods have been developed for target object tracking in WSN with minimal energy consumption. But, the accuracy level was not increased by existing tracking techniques. In order to address these problems, a novel targets object tracking method called Energy Aware Generalized Gaussian Distributive Sammon Regularization Policy Learning (GDSR) for efficient target object tracking in WSN.

The GDSR method consists of three major processes namely reference node selection, target detection, and trajectory prediction. First, the energy of the sensor nodes is measured. Then apply Wilcoxon rank-sum test for identifying the reference node based on higher residual energy. When the target node arrived in the network, the reference node transmits the beacon message to all sensor nodes for detecting the target node's location. The sensor node transmits the target information to the base station through the reference nodes. After that, the base station performs target detection by using Akaike Gaussian distributive Generalized Tikhonov Regularization Analysis with the sensed data. Finally, the target object trajectories are identified using Sammon projective on-policy learning algorithm to predict the target trajectories based on the state transition property. In this way, energy-efficient target object tracking is accurately performed in WSN.

Experimental evaluation is carried out on factors such as energy consumption, target object tracking accuracy and target object tracking time, and prediction error with respect to a different number of sensor nodes. The performance results and discussion reveals that the proposed GDSR method efficiently increases the target tracking accuracy and minimizes the time and error rate than the existing techniques.

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## 1. INTRODUCTION

Target tracking in WSN is to detect the occurrence of a target and track it continuously. Moving target tracking is a major application of WSNs. Localization and tracking of moving targets mainly depends on energy efficiency. However, moving object tracking consumes much more energy to perform high-frequency sensing and data transmission. Therefore, a great challenge is energy-efficient target tracking in WSNs. To save energy and extend the lifetime of networks while tracking a moving object effectively, this paper proposes a novel machine learning method that predicts the trajectory of the moving object.

A sequence-to-sequence learning model (Seq2Seq) was developed in [1] to predict the trajectory of a moving object and minimize the computation time. However, the accuracy of target prediction was not improved. A lightweight Auto Regressive Neural Network (ARNN) was developed in [2] for accurate and energy-efficient target tracking. But the time consumption of target tracking was not minimized.

A novel energy-efficient management approach was developed in [3] for target tracking. But it was not efficient to prolong its network lifetime for target tracking. A fault-tolerant sensor scheduling method was introduced in [4] for target tracking and improving the network lifetime with minimum prediction errors. However, it failed to focus on the energy harvest tracking network.

A Target Detection and Target Tracking (TDTT) model was developed in [5] for continuously tracking the target objects and trajectories. But it failed to track the multiple targets in the sensing region. A partition-based target tracking method was developed in [6] to achieve flexible and energy-efficient tracking. However, the time consumption of energy-efficient tracking was not minimized. Multi-target positioning algorithm was designed in [7] based on a multi-dimensional scaling approach. But the energy-efficient target positioning was not performed.

A computationally efficient multi-target localization method was developed in [8]. But, the designed method has higher complexity for target localization. A multi-algorithm genetically adaptive multi-objective strategy was developed in [9] for reliable sensor node selection to perform target tracking. But the error rate of target tracking was not minimized. A deep learning algorithm was introduced in [10] for target motion detection with minimize the error. But it should not minimize the error.

**Contributions of the paper**

The important contributions of the proposed GDSR method are described as given below,

- To improve the traffic-aware target tracking accuracy in WSN, a novel GDSR method is introduced based on three processes namely reference node selection, target defection, and target trajectory prediction.
- To improve the energy-efficient target tracking, Wilcoxon rank-sum test is employed in GDSR for reference node selection. The energy efficiency of the sensor nodes enhances the network lifetime.
- Next, the Akaike Gaussian distributive Generalized Tikhonov Regularization Analysis is performed to track the target objects within the sensing region of sensor nodes. The Akaike information criterion is applied for measuring the target detection probability. Followed by, the Gaussian distributive Generalized Tikhonov Regularization analysis is used to minimize the actual target state and the observed target state. This helps to improve the target tracking accuracy and minimizes the time.
- Finally, Sammon's projective on-policy learning algorithm is employed to identify the target trajectories based on the state transition property. The on-policy learning algorithm is a State–action–reward–state–action for predicting the updated state of the moving target based on the current state along with two consecutive time intervals. Sammon's projective function reduces the target trajectory prediction error.

**Organization of the Paper**

The rest of the paper is organized into five different sections as follows. Section 2 reviews the related works. Section 3 provides a brief description of the proposed GDSR technique with a neat architectural diagram. Section 4 simulation is conducted with different parameter settings. In section 5, the performance results of the proposed technique and existing methods are discussed. At last, Section 6 provides the conclusion of the paper.

## 2. RELATED WORKS

A three-dimensional space target tracking method was developed in [11] for minimizing the error rate of observation. But, the multiple target detection was not performed. A reliable multi-object tracking model was introduced in [12] with the deep learning approach. However, the energy efficiency was not improved in the multi-object target tracking. An enhanced least-square algorithm based on improved Bayesian was developed in [13] for tracking the targets. However, it failed to consider multi-target localization and tracking.

A hybrid filtering algorithm was designed in [14] for multi-target tracking and detection based on WSN. However, the performance of the error rate was not minimized. The multi-target localization and tracking method was introduced in [15] by eliminating abnormal measurements. But the accuracy and stability of target localization and tracking were not improved.

Face-based Target Tracking Technique (FTTT) was developed in [16] to track the object by reducing the energy depletion and extending the lifetime of the sensor node. But, it failed to use the efficient technique for track object tracking to minimize the error. The support vector machine (SVM) and an improved Kalman filter (KF) were developed [17] to estimate the target‟s position based on the RSSI. But the time consumption of the target‟s position estimation was higher. A multi-step tracking model of the Kalman filter (KF) along with particle swarm optimization (PSO) was developed in [18] to measure the trajectory and location of the target. But the machine learning techniques were not applied for improving the accuracy of target detection.

A Heuristics-base-Dispensed-Advert-Oriented algorithm (HBDAO) was introduced in [19] for energy-efficient target tracking with minimum time. However, the error rate of target tracking was not minimized. A two-dimensional target coverage model was developed in [20] for detecting the target position and the visual sensor position. The designed model has less computational complexity but accuracy of target detection was not reduced.

### 3. METHODOLOGY

The main objective of target tracking in WSN is to locate and monitor the movement of the target continuously. The target tracking is carried out by the means of various sensor nodes deployed in the sensing environment. The deployed sensor nodes are typically small in size and are equipped with low-battery power. Therefore energy management is the most significant issue in numerous applications of WSN, especially in target tracking. The higher energy consumption of the dynamic nodes reduces the network lifetime. Therefore, energy-efficient target tracking is a major challenge in WSN to enhance the lifetime of the network. Based on this motivation, a novel machine learning technique called GDSR is introduced to track moving targets and saved energy to expand the lifetime of the WSN in the centralized structure.

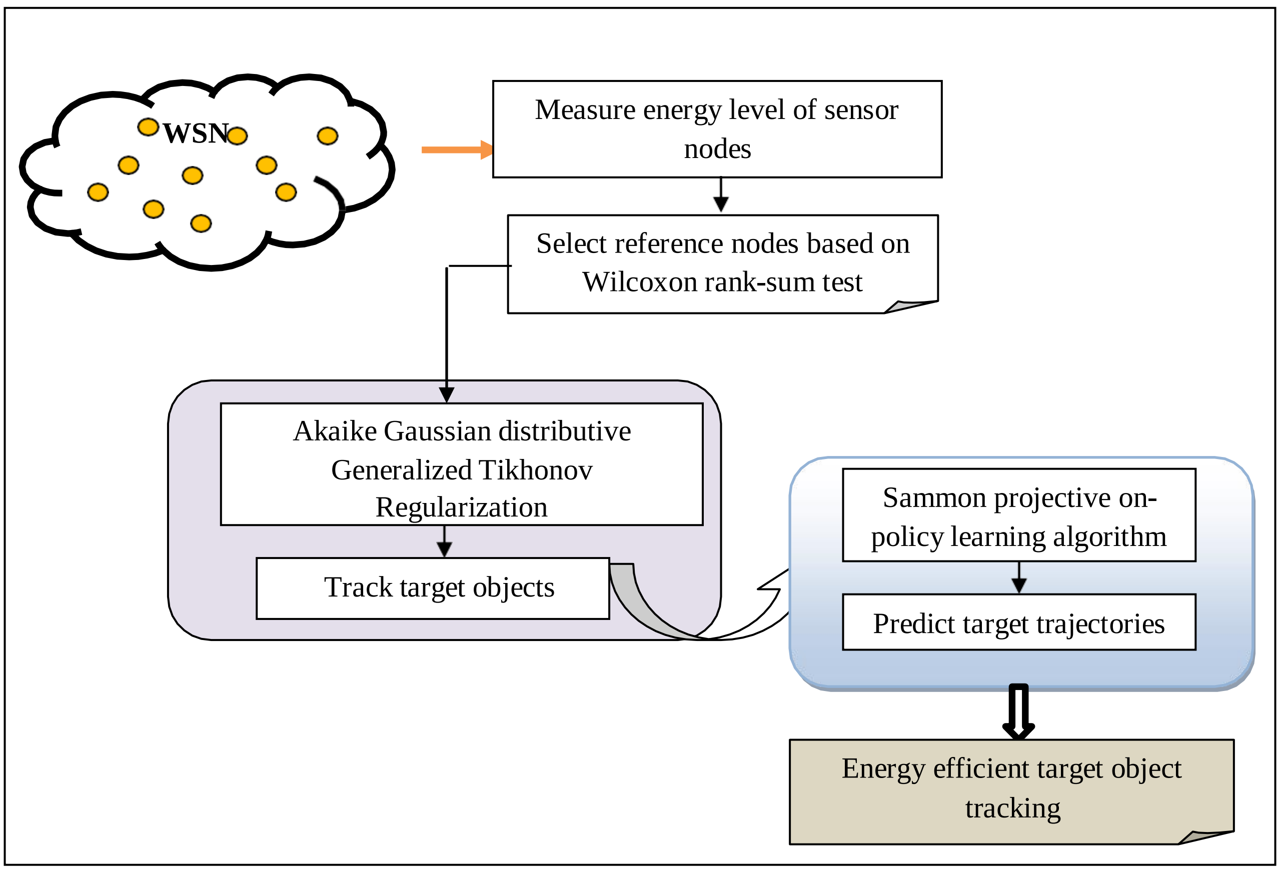


**Figure 1 Architecture Diagram of Proposed GDSR Method**

Figure 1 illustrates the basic architecture diagram of the proposed GDSR method for target object tracking in WSN. First, the number of sensor nodes $Sn_i \in Sn_1, Sn_2 \dots Sn_n$ are distributed in a squared network within the transmission range „$T_r$". In the proposed technique, the energy of all the sensor nodes „$E(SN_i)$" is measured. After that, the Wilcoxon rank-sum statistic analysis is performed to identify the energy-efficient nodes called reference nodes in the network. Wilcoxon rank-sum test is a statistical test used to analyze the relationship between two statistical data (i.e. Energy of the sensor nodes and threshold value). The selected reference node sends the beacon message to the entire sensor node for identifying the target node location in the WSN.

When a target object arrived in a network, the nearby sensor node senses and monitors the target node and transmits the information to the higher energy reference nodes. The reference node receives the sensed information from the sensor node and transmits it to the base station for target tracking. After that, the base station uses the Gaussian distributive Generalized Tikhonov Regularization analysis with the sensed data to find the target object location with minimum energy consumption.

After that, the base station uses the Sammon projective on-policy learning algorithm to identify the target trajectories based on the state transition property. The on-policy learning algorithm predicts the updated state of the target object from the current state at two consecutive time intervals. After predicting the path, the Sammon projection is used for minimizing the target trajectory prediction error.

These three processes of the proposed GDSR method are briefly explained in the following subsections.

**Wilcoxon rank-sum test-based reference node selection**

The WSN consists of many sensor nodes distributed in the sensing region. However, the entire sensor node does not contribute to the overall process of target tracking due to higher energy consumption. Therefore, the proposed GDSR method selects the energy-efficient nodes for target tracking with the help of the Wilcoxon rank-sum test. The Wilcoxon rank-sum test is the statistical process that helps to measure the relationship between the energy of the sensor nodes for selecting the reference node in a distributed network. In the case of WSN, the reference node is one having the maximum energy located in a specified region.

Let us consider the number of sensor nodes $Sn_i \in Sn_1, Sn_2 \ldots Sn_n$ in network. Initially, all the sensor nodes have similar energy levels. Then the initial energy of the sensor node gets degraded due to the sensing ability of that node. The energy level of the sensor node is mathematically computed as given below,

$$E\ (Sn_i) = P_{er} * time \qquad (1)$$

Where $E\ (Sn_i)$ indicates the energy measurement of the sensor nodes is measured based on the product of the power ($P_{er}$) and time. The energy of the node is measured in terms of a joule. The energy level of each sensor node gets degraded after the sensing and monitoring process. Therefore, the residual energy level of all sensor nodes is measured based on the initial and consumed energy. The residual energy is the remaining energy of the sensor node.

$$E\ (Sn_i)_{RES} = E\ (Sn_i)_{Ini} - E\ (Sn_i)_C \qquad (2)$$

From (2), $E\ (Sn_i)_{RES}$ indicates residual energy of sensor nodes, $E\ (Sn_i)_{Ini}$ denotes initial energy and $E\ (Sn_i)_C$ indicates the consumed energy level of the nodes. The relationship between the Energy of the sensor nodes is analyzed by setting the threshold level.

$$W_t = R\ [E\ (Sn_i)_{RES}, \delta_{RES}] \qquad (3)$$

Where, $W_t$ indicates a Wilcoxon rank-sum test, $R$ indicates a relationship between the residual energy of the sensor nodes ($E\ (Sn_i)_{RES}$) and threshold level ($\delta_{RES}$).

$$R\ [E\ (Sn_i)_{RES}, \delta_{RE}\ ] = \begin{cases} 1, & if\ E\ (Sn_i)_{RES} > \delta_{RES} \\ 0, & if\ E\ (Sn_i)_{RES} < \delta_{RES} \end{cases} \qquad (4)$$

From (4), relationship test „$R$" returns „1" indicates the residual energy of the node is greater than the threshold. Otherwise, it returns „0". As a result, the node which has higher energy than the threshold is selected as a reference node for accurate target tracking with minimum time. The Wilcoxon rank-sum test-based reference node selection algorithm is given below,

| **Algorithm 1: Wilcoxon rank-sum test-based reference node selection** |
|---|
| **Input:** Number of sensor nodes $Sn_i \in Sn_1, Sn_2 \dots Sn_n$<br>**Output**: Select reference node |
| **Begin**<br>**1**: **Number** of sensor nodes $Sn_i \in Sn_1, Sn_2 \dots Sn_n$ taken as input<br>**2**: **For each sensor node** '$Sn_i$'<br>**3:** Calculate the energy '$E\ (Sn_i)$ and residual energy „$E\ (Sn_i)_{RES}$"<br>**4:** **End for** |

**5:** Apply Wilcoxon rank-sum test „W$_t$" for measuring the relationship between the residual energy and threshold

**6:** ***If*** „($R\ [E\ (Sn_i\ )_{RES},\ \delta_{RES}] = 1$) **then**

7: Select reference node

**8: else**

**9:** Check another node

10: **End *if***

**11: Return (**reference nodes**)**

**End**

Algorithm 1 describes the step-by-step procedure of reference node selection to enhance the network lifetime. First, the residual energy of the sensor nodes is measured. After that, Wilcoxon rank-sum test „W$_t$" is applied for measuring the relationship between the residual energy and threshold value. If the correlation returns „1", then the node is selected as the reference node. Otherwise, the energy level of the other sensor node is analyzed. In this way, energy-efficient reference nodes are selected for energy-efficient target tracking in WSN.

**Akaike Gaussian distributive Generalized Tikhonov Regularization Analysis based target detection in WSN**

The second process of the proposed GDSR method is to perform the target detection by identifying the position of the target with help of Akaike Gaussian distributive Generalized Tikhonov Regularization Analysis. The Akaike information criterion is applied to identify the probability of target detection by determining the best fit for a given set of data. Then Generalized Tikhonov Regularization Analysis is used to minimize the problem of multicollinearity in linear regression with large numbers of parameters. The multicollinearity refers to a condition in which more than two explanatory variables (i.e. independent variables) are linearly correlated. The independent variables are represented as input data (i.e. target information) that helps to perform target detection.

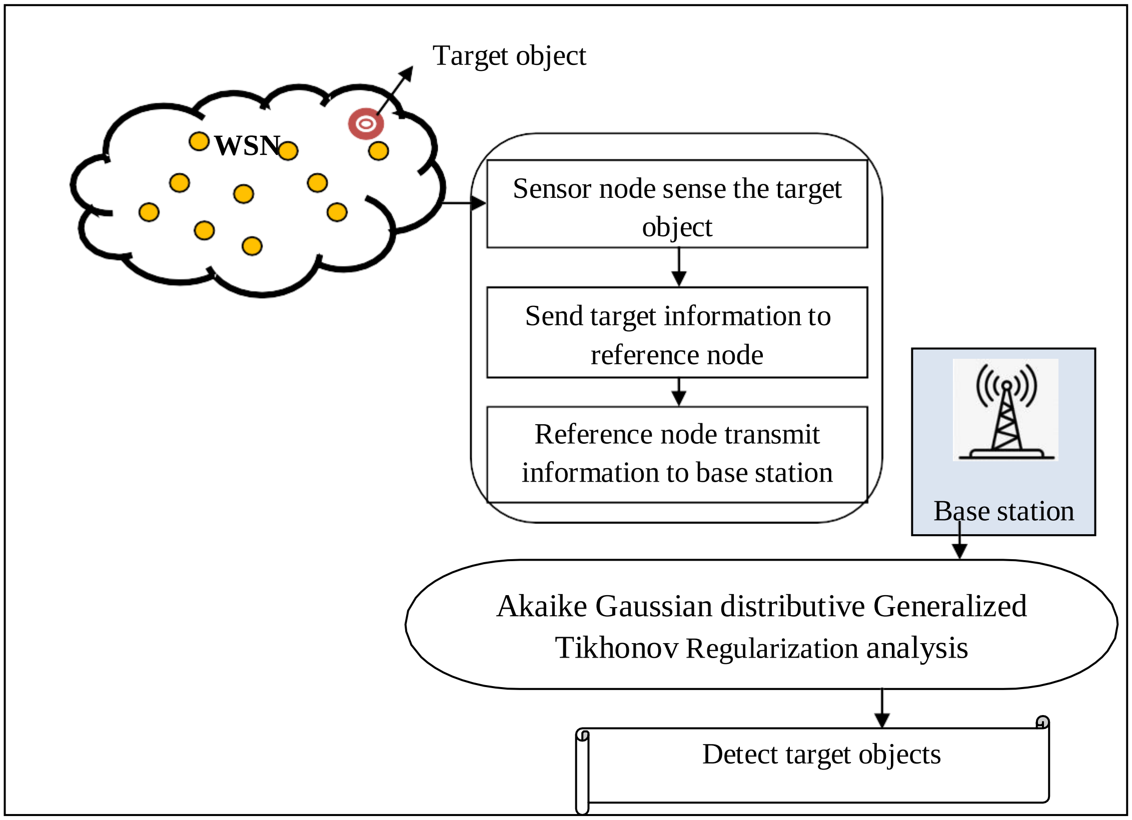


**Figure 2 Akaike Gaussian Distributive Generalized Tikhonov Regularization-based target Tracking**

Figure 2 illustrates the flow process of Akaike Gaussian distributive Generalized Tikhonov Regularization analysis for target tracking in WSN. When the target is entered into the network, the selected reference nodes first transmit the beacon message to the nearest sensor nodes in the network for identifying the target node's location. The nearest sensor node monitors the target movement within the sensing range. The sensing range is defined as the coverage region of a sensor node in meters (m). The sensor node finds the nearest reference node to send the target information using Manhattan distance.

$$d_{ij} = \arg min\,|Sn_i - Rn_j| \quad (5)$$

Where, $d_{ij}$ denotes a Manhattan distance between the sensor node $Sn_i$ and the nearest reference node „$Rn_j$ ‟. arg $min$ indicates an argument of the minimum function. After finding the nearest reference node, the sensor node sends the target information.

The reference node receives the target information from the nearest sensor nodes and it sends to the base station. The base station performs accurate target detection using Akaike Gaussian distributive Generalized Tikhonov Regularization.

In WSN, Let us consider „$n$" sensor nodes „$m$" reference nodes are positioned for target detection operation with „$T$' duration in the preferred sensing region '$r_s$'. A target object is assumed to be in motion in the sensing region. Then the proposed method uses the Akaike information criterion for identifying the probability of the sensor node „$i$" detecting the target. Akaike information criterion is a probability distribution model used to determine the best fit (i.e. target location) for a given set of data.

$$C_{AI} = 2\ (1 - \log\ L\,(\mathrm{B}|r_{s_i}\ )) \qquad (6)$$

$$L(\mathrm{B}|r_s) = \begin{cases} 1; & if\ (x_t, y_t) \in r_{s_i} \\ 0; & otherwise \end{cases} \qquad (7)$$

Where, $C_{AI}$ denotes an Akaike information criterion to find the likelihood probability of target (B) „$L(\mathrm{B}|r_s)$" detection in the sensing range of $i^{th}$sensor node „$r_{s_i}$ „„ $(x_t, y_t)$ denotes a location of the target at a time „$t$'. Let us consider the coordinates of the sensor node $(x_1, y_1)$ and the coordinates of the target node$(x_t, y_t)$. The distance is calculated to identify the location of the target object from the sensor node in the two-dimensional plane as shown in figure 3.

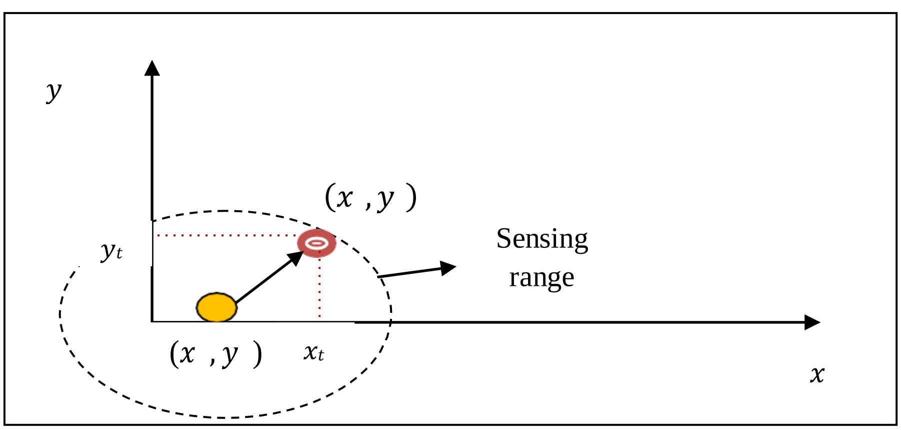


**Figure 3 Distance Between The Sensor Node and Target**

The distance $(D)$ between the locations of the target object from the sensor node is calculated as given below,

$$D = \sqrt{(x_t - x_1)^2 + (y_t - y_1)^2} \qquad (8)$$

Based on the distance measure, the target state is detected by the base station. Finally, the base station uses the Gaussian kernel for a Generalized Tikhonov Regularization Analysis to accurately detect the target by minimizing the actual target state and the observed target state.

$$R = \arg\min\,[\exp(0.5 * "Y_T - Y_e\ "^2)] + \mu\ \ \omega^2 \qquad (9)$$

where, $R$ indicates a Regularization outcome, $Y_T$ denotes an actual target state, $Y_e$ indicates an estimated target state, $\mu$ indicates a regularization parameter (or tuning parameter), $\omega^2$ denotes squares of model coefficients, $"Y_T - Y_e\ "^2$ denotes a loss function, $\mu\ \ \omega^2$ indicates a regularized term. In this way, the proposed technique finds the target object's location inside the network. The Akaike Gaussian distributive Generalized Tikhonov Regularization Analysis-based target detection algorithm is given below.

| **Algorithm 2: Akaike Gaussian distributive Generalized Tikhonov Regularization Analysis based target detection in WSN** |
|---|
| **Input:** Number of sensor nodes, Reference node<br>**Output**: Improve Target detection accuracy |
| **Begin**<br>**1**: **If 'target objects entered into the network then**<br>**2.** Reference node transmits beacon message to all sensor nodes<br>**3.** Nearby sensor nodes detect targets within the sensing range<br>**4.** Sensor nodes transmit the targets information to the reference node<br>**5.** **end if**<br>**6.** **for each** reference node<br>**7.** Transmits the targets information to the base station8:<br>**End for**<br>**9:** **Base station uses** Akaike information criterion for detecting the probability of target<br>10**:** $\boldsymbol{if}$ $((x_t, y_t) \in r_{s_i})$ **then**<br>11: $L(T\|r_s)$ returns „1"<br>12: **else** |

$L(T|r_s)$ returns „0"
**end** $\boldsymbol{if}$
**for each** sensor node location $(x_1, y_1)$
**for each** target node location $(x_t, y_t)$
Calculate the distance „$D$"
**end for**
**end for**
**Apply** Generalized Tikhonov Regularization „$R$"
Accurately detect the target by minimizing the estimated target state and the observed target state.
**End**

Algorithm 2 describes the step-by-step process of target detection using Akaike distributive generalized Tikhonov regularization analysis in WSN. The reference node alerts the sensor nodes by transmitting the beacon messages while the target objects entered the network. The sensor node monitors the target object within the sensing range and transmits the information to the reference node. The reference node sends the target information to the base station. Then the base station starts to measure the target detection probability with help of the Akaike information criterion. The probability is „1" when the target is located inside the sensing region. Otherwise, the probability is „0". Then the base station finds the distance of the target object within the sensing range from the sensor node. Finally, the Gaussian distributive Generalized Tikhonov Regularization is applied to minimize the squared difference between the estimated target state and the actual target state. The process helps to improve the accurate target prediction.

### Sammon projective on-policy learning algorithm based target trajectory identification

During the process of target tracking, the position of the target gets changed randomly due to their dynamic motion in the monitoring field. Therefore, trajectory prediction is necessary to predict the moving path of the target in WSN. The proposed GDSR method uses the Sammon projective on-policy learning algorithm to identify the target trajectories based on the collected information. Sammon projection maps the target path from high-dimensional space to the lower dimensionality for preserving the distance by using an on-policy learning algorithm. The on-policy learning algorithm is a State–action–reward–state–action for predicting the updated state of the target based on the current state along with two successive time sequences. This algorithm enables the prediction of the next immediate location of the target object under tracking. This information is transmitted to neighbouring sensors at a minimum distance.

When the target object moves from one location to another, the sensor node sends the alert message to neighbouring sensors to track the path.

$$Sn_i \xrightarrow{Msg_A} Sn_j \quad (10)$$

Where, $Sn_i$ denotes sensor node sends the alert message „$Msg_A$" to the neighboring sensors $Sn_j$ . The state transition of the target node is estimated between two successive time intervals '$t$" and „ $t+1$"

$$L_{t+1} \leftarrow L_t + r\,[\omega_t + \mathrm{P}\,(L_{t+1}) - L_t] \qquad (11)$$

Where,$L_t$" denotes a current state of the target, „next updated state is $L_{t+1}$, $r$ indicates a learning rate (0< $r$ <1), $\omega_t$ denotes a discount factor slightly lesser than 1, P denotes a positive reward when the algorithm accurately predicts the target moving path. Based on a state transition, the target trajectory is correctly predicted. Sammon's projection aims to minimize the error function i.e. predicted trajectory and actual trajectory in the original space.

$$F = \min\ E \quad (12)$$

$$E = \frac{1}{n}\,(P_{tt} - A_{tt}) \qquad (13)$$

Where $F$ denotes a Sammon's projection, $E$ indicates an error, $P_{tt}$ denotes a predicted target trajectory, $A_{tt}$ indicates an actual target trajectory. $n$ denotes a number of sensor nodes

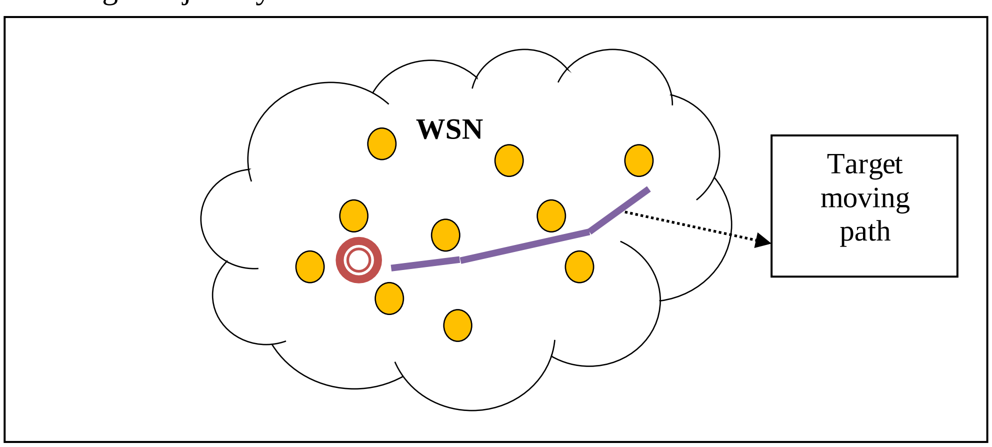


**Figure 4 Target Trajectory Predictions in the Sensing Region**

Figure 4 illustrates the target trajectory predictions in WSN.The Sammon projective on-policy learning algorithm is explained as follows,

**Algorithm 3: Sammon projective on-policy learning algorithm**

**Input: Number** of sensor nodes, reference node, target

**Output**: Predict the target trajectory

**Begin**

Target object moves from one location to another

Sensor node sends an alert message to neighboring sensors ' $Sn_i \xrightarrow{Msg_A} Sn_j$ ‟

**For each step**

Measure the state transition from ' $t$‟ to „ $t+1$‟

Measure the updated state of the target „$L_{t+1}$‟ from „$L_t$‟

Predict the target trajectory '$P_{tt}$'

Sammon projection minimizes the error „$E$‟

**End for**

**End**

Algorithm 3 given above illustrates the step-by-step process of target trajectory prediction. When the target object is randomly moved in a network, the sensor node transmits the alerting message to the nearest sensor node. For each step, state transition from one location to another is measured and gets an updated state of the target. Finally, the target moving path is predicted. The Sammon projection function minimizes the error function between the actual and predicted target moving path.

## 4. SIMULATION SETTINGS

In this section, the simulation of the proposed GDSR and existing methods namely the Seq2Seq model [1] and ARNN [2] are performed by the NS2.34 network simulator. In order to conduct the simulation, 500 sensor nodes were deployed in a squared area of $1100 * 1100$ using the Random Waypoint mobility model. The sensor nodes moved at a speed of 0-20m/sec. The total simulation time is set at 300seconds in WSN. A Dynamic Source Routing (DSR) protocol is employed for target tracking in WSN. Table 1 represents simulation parameters.

**Table 1 Simulation parameters**

| Simulation parameters | Values |
|---|---|
| **Network Simulator** | NS2.34 |
| **Simulation area** | 1100 m * 1100 m |
| **Number of sensor nodes** | 50,100,150,200,250,300,350,400,450,500 |
| **Number of data packets** | 30,60,90,120,150,180,210,240,270,300 |
| **Mobility model** | Random Waypoint model |
| **Nodes speed** | 0 – 20 m/s |
| **Simulation time** | 300sec |
| **Routing Protocol** | DSR |
| **Number of runs** | 10 |

## 5. PERFORMANCE RESULTS AND DISCUSSION

The simulation results of the GDSR technique and Seq2Seq model [1] and ARNN [2] are discussed in this section with different performance metrics such as energy consumption, target tracking accuracy, target tracking time, prediction error with respect to a number of sensor nodes. The performance of proposed and existing methods is discussed with help of a table and graph.

### Impact of energy consumption

Energy is the most significant metric to enhance the lifetime of the network. The minimum energy consumption of the sensor node enhances the network lifetime and performs accurate target tracking. Energy consumption is referred to as the amount of energy consumed by the sensor nodes to perform the target tracking in the network. The formula for calculating the energy consumption is given below,

$$Conp_E = n * E_c\ (SSn)\ (14)$$

Where, $Conp_E$ indicates energy consumption, $n$ denotes the number of sensor nodes, $E_c$ indicates energy consumed by the single sensor nodes $(SSn)$. The performance of energy consumption is measured in terms of a joule (J).

**Table 2 Comparison of Energy Consumption**

| Number of sensor nodes | Energy consumption (joule) | | |
|---|---|---|---|
| | **GDSR** | **Seq2Seq model** | **ARNN** |
| **50** | 21.5 | 24 | 27.5 |
| **100** | 24 | 27 | 30 |
| **150** | 28.5 | 34.5 | 37.5 |
| **200** | 32 | 36 | 40 |
| **250** | 37.5 | 40 | 43.75 |
| **300** | 42 | 45 | 48 |
| **350** | 45.5 | 49 | 52.5 |
| **400** | 48 | 52 | 56 |
| **450** | 51.75 | 56.25 | 58.5 |
| **500** | 55 | 65 | 70.5 |

Table 2 reports the performance assessment results of energy consumption with a number of sensor nodes using three different methods GDSR method and Seq2Seq model [1] and ARNN [2]. For the simulation purposes, the number of sensor nodes is taken in the ranges from 50 to 500. For each method, ten different results are observed with respect to the number of sensor nodes. The observed results indicate that the performance of energy consumption using the GDSR method is considerably minimized when compared to existing methods. Simulation is conducted with 500 sensor nodes and the energy consumption for target tracking is $21.5 Joule$ using the GDSR method. Similarly, the performance of energy consumption by applying existing [1] and [2] are observed as $24 Joule$ and $27.5 Joule$ respectively. Likewise, various performance results are observed for each method with respect to various counts of input. With this, the overall performance of the GDSR method is compared to the results of existing methods. The overall comparison results confirm that the performance of energy consumption using the GDSR method is comparatively reduced by 10% when compared to [1] and 17% when compared to [2] respectively. The simulation results are plotted in the graph.

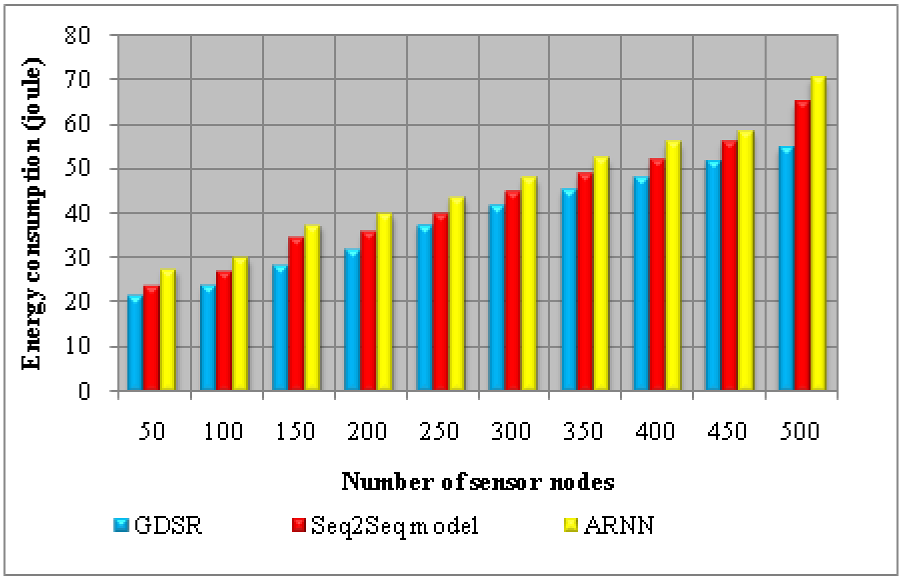


**Figure 5 Graphical Representation of Energy Consumption**

Figure 5 reveals the performance analysis of energy consumption against a number of sensor nodes using three different methods namely the GDSR method and existing [1] and [2]. As shown in figure 5, the energy consumption of all three methods gets increased while increasing the number of sensor nodes. But comparatively, the GDSR method decreases the performance of energy consumption when compared to the two existing methods. This performance improvement is achieved by applying the Wilcoxon rank-sum test-based reference node selection. For each sensor node, residual energy is measured. Then the energy is analyzed with the threshold level. The node with a higher energy level is selected as the reference node. The sensor node transmits the target information to energy efficient reference node. The reference node collects the target information and sent to the base station for further processing. In this way, energy-efficient reference nodes are contributed to the target tracking process resulting in minimizing the energy consumption and enhancing the network lifetime.

**Impact of Target tracking accuracy:**

The accuracy of target tracking is calculated based on the number of (No. of) sensor nodes that correctly transmit the target object information to the base station. Therefore, the accuracy is mathematically calculated as given below,

$$Tar\_Trac_{Acc} = \left(\frac{No.of\ Sns\ correctly\ \ transmits\ the\ information}{n}\right) * 100 \ (15)$$

Where, $Tar\_Trac_{Acc}$ denotes target tracking accuracy, $n$ denotes the number of sensor nodes. It is measured in terms of percentage (%).

**Table 3 Comparison of Target Tracking Accuracy**

| Number of sensor nodes | Target Tracking Accuracy (%) | | |
|---|---|---|---|
| | GDSR | Seq2Seq model | ARNN |
| **50** | 94 | 90 | 88 |
| **100** | 93 | 89 | 87 |
| **150** | 92.66 | 88.66 | 86.66 |
| **200** | 92.5 | 88.5 | 86.5 |
| **250** | 92.4 | 88 | 86 |
| **300** | 92 | 87.66 | 85.66 |
| **350** | 91.71 | 87.42 | 85.42 |
| **400** | 91.5 | 86.75 | 85 |
| **450** | 91.33 | 86.44 | 84.44 |
| **500** | 91.2 | 86 | 84 |

Table 3 reports the simulation results of the target tracking accuracy versus the number of sensor nodes. The number of sensor nodes considered for simulation varied from 50,100 …500. The table value indicates the performance results of target tracking accuracy using three methods GDSR method and Seq2Seq model [1] and ARNN [2]. Among the three methods, the GDSR outperforms well in terms of achieving higher accuracy. With the consideration of 50 sensor nodes in the first iteration, the observed target tracking accuracy is94%. Followed by, nine different results are obtained for each method. The observed performance results of the GDSR are compared to the results of existing methods. The average is taken for ten comparison results. The overall results indicate that the performance of the target tracking accuracy of the GDSR is considerably increased by 5% and 7% than the existing [1] [2] respectively.

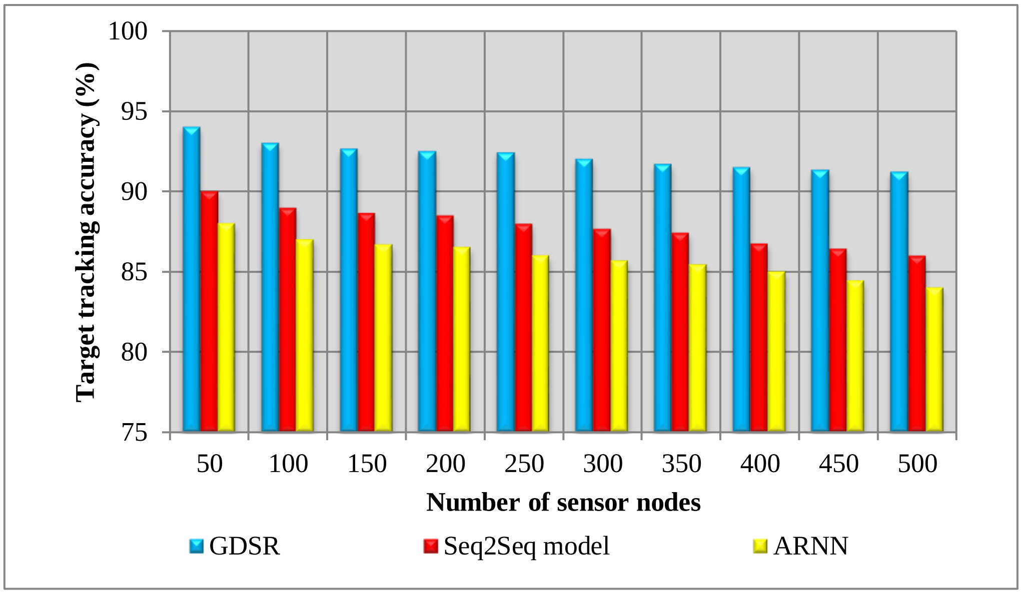


**Figure 6 Graphical representation of Target Tracking Accuracy**

The above figure 6 illustrates the performance of target tracking accuracy with respect to a number of sensor nodes. As shown in the graph, the performance of the tracking accuracy is observed at the $y$ -axis and the number of sensor nodes on the $x$ -axis. The graphical results indicate that the performance of the GDSR provides improved performance than the other two existing methods [1] [2]. This is because the GDSR uses the Akaike distributive generalized Tikhonov regularization analysis in WSN. While the target objects entered the network, the energy-efficient reference node collects the information from the nearby sensor node. The reference node transmits the target information to the base station. Then the base station uses the Akaike information criterion for detecting the target tracking probability inside the sensing region of the sensor node. Then the base station also determines the location of the target object from the sensor node based on distance estimation. The Gaussian distributive Generalized Tikhonov Regularization is applied in GDSR to minimize the deviation between the estimated target state and the actual target state. This process enhances the accurate target tracking in WSN.

**Impact of Target tracking time**

It is defined as the amount of time consumed by an algorithm to track the target objects in WSN. Target tracking time is measured in terms of milliseconds (ms).

$$Tar\_Trac_{time} = n * time\ (TOT) \quad (16)$$

Where, $Tar\_Trac_{time}$ indicates a target tracking time, $n$ denotes the number of sensor nodes, $TOT$ denotes a target object tracking.

**Table 4 Comparison of Target Tracking Time**

| Number of sensor nodes | Target Tracking Time (ms) | | |
|---|---|---|---|
| | GDSR | Seq2Seq model | ARNN |
| **50** | 15 | 18 | 20 |
| **100** | 18 | 20 | 24 |
| **150** | 22.5 | 24 | 27 |
| **200** | 26 | 28 | 30 |
| **250** | 30 | 32.5 | 35 |
| **300** | 33 | 36 | 39 |
| **350** | 35 | 38.5 | 42 |
| **400** | 36.8 | 40 | 44 |
| **450** | 42.75 | 44.1 | 47.25 |
| **500** | 49 | 52.5 | 54 |

The comparative performance analysis of the target tracking time with respect to a number of sensor nodes is shown in Table 4. In order to measure the performance analysis of target tracking time, the numbers of sensor nodes are taken in the ranges from 50 to 500. When conducting the simulation with 50 sensor nodes in the first iteration. By applying GDSR, the observed target tracking time is 15 $ms$. Similarly, the target tracking time of existing [1] [2] is 18% and 20% respectively.

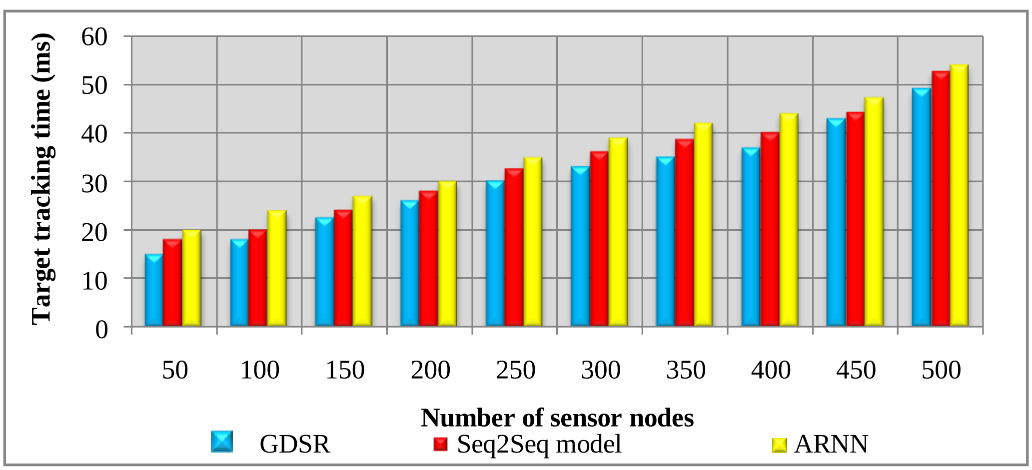

**Figure 7 Graphical representation of target tracking time**

For each method, ten outcomes are observed with respect to different numbers of sensor nodes. The overall observed results of the proposed GDSR, are compared to the existing methods. Finally, the average of ten results indicates that the performance of the target tracking time of the GDSR is considerably reduced by 8% when compared to [1] and 16% when compared to [2].

Figure 7 depicts the simulation results of target tracking time versus a number of sensor nodes. The above figure clearly illustrates that the target tracking time is linearly increased for all three methods while increasing the number of sensor nodes. But, the time consumption of GDAR is minimized when compared to conventional methods. This is due to the GDSR method initially selecting the energy-efficient reference node for target tracking instead of using all the sensor nodes in the network. The energy-efficient node quickly performs the data transmission than the normal node. After that, the base station collects the information and finds the target object's location within the sensing range of sensor nodes. This in turn improves the target detection with minimum time consumption.

## Impact of Prediction error

The prediction error is measured as the ratio of the difference between the actual target trajectory and estimated target trajectory to the total number of sensor nodes. The prediction error is measured using$E = \frac{1}{n}(P_{tt} - A_{tt})$. Lesser the error, the method is said to be more efficient.

**Table 5 Comparison of Prediction Error**

| Number of sensor nodes | Prediction Error(%) | | |
|---|---|---|---|
| | **GDSR** | **Seq2Seq model** | **ARNN** |
| **50** | 0.02 | 0.028 | 0.036 |
| **100** | 0.032 | 0.038 | 0.041 |
| **150** | 0.042 | 0.047 | 0.05 |
| **200** | 0.052 | 0.06 | 0.065 |
| **250** | 0.055 | 0.061 | 0.067 |
| **300** | 0.057 | 0.066 | 0.07 |
| **350** | 0.060 | 0.071 | 0.077 |

| | | | |
|---|---|---|---|
| **400** | 0.063 | 0.072 | 0.08 |
| **450** | 0.064 | 0.075 | 0.082 |
| **500** | 0.068 | 0.078 | 0.084 |

Table 5 and figure 8 given above show the graphical representation of the prediction error with respect to the number of sensor nodes. The above figure indicates that the prediction error using the proposed GDSR method was found to be closer to minimized than using the existing methods, [1] and [2]. The reason was owing to the application of the Sammon projective on-policy learning algorithm to identify the target trajectories based on the state transition property. The target object is arbitrarily moved in a network. For each movement, state transition from one location to another is measured and gets updated. Finally, the target moving path is predicted. The Sammon projection function minimizes the error function between the actual target moving path and the predicted target moving path. As a result, the prediction error rate using the GDSR method was found to be comparatively lesser than [1] and [2] by 15% and 22% respectively.

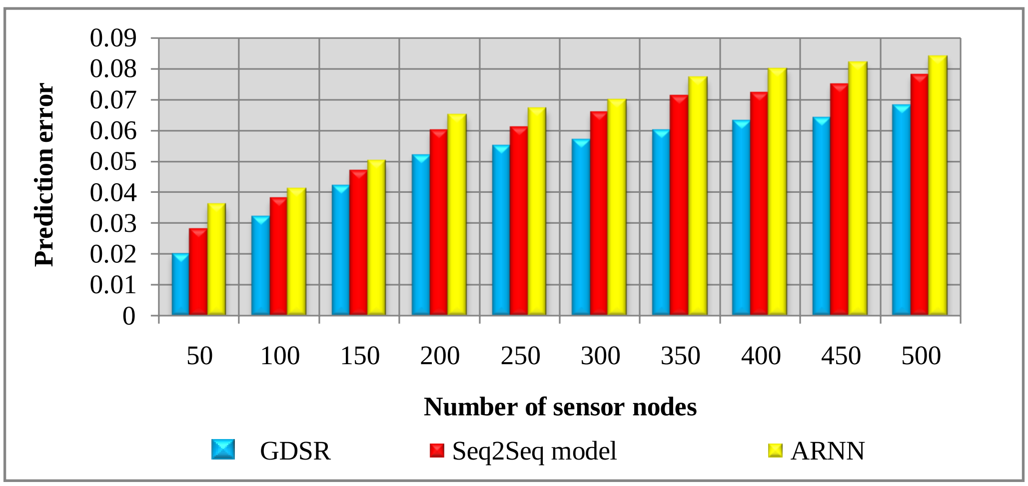


Figure 8 Graphical Representation of Prediction Error

## 6. CONCLUSION

Tracking target objects provide a lot of challenges in WSNs. In this paper, a novel GDSR method is developed for accurately tracking a target with minimum time. First, the energy-efficient sensor nodes are identified for increasing the network lifetime. After selecting the energy-efficient nodes, the target object detection process is carried out at the base station with help of Akaike Gaussian distributive Generalized TikhonovRegularizationAnalysis.

In this way, energy-efficient target tracking is performed in WSN. Experimental evaluation is carried out on factors such as energy consumption, target object tracking accuracy and target object tracking time, and prediction Error with respect to a different number of sensor nodes. The simulation is conducted on various performance metrics such as energy consumption, target tracking accuracy, target tracking time, and prediction error. The discussed results have revealed that the GDSR technique has considerably improved the target tracking accuracy with minimum time as well as error rate than the existing methods.

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