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Heuristic Selection of Right Functioning Node for Iterated Unscented Kalman Filter-based Mobile Target Tracking System in WSN

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Abstract: Node tracking is one of the essential techniques in many military and cellular communication-related applications. Wireless Sensor Network (WSN) has a limited sensing range which influences target tracking and energy consumption. Optimization models in target tracking are well-desired solutions, as they maintain good convergence and reliability. In this work, an efficient approach is developed to perform the target tracking in WSN. At first, the tracking reliability requirement is ensured by selecting the right functioning nodes in the WSN with the help of the Tiger Beetle Algorithm (TBA). The TBA adopts energy as an objective function for attaining better performance in the node selection process. The overall energy consumption of WSN is enhanced with the help of optimum selection of right functioning nodes which is used to prolong the network lifetime. After selecting the right functioning nodes, the target tracking is performed using the Iterated Unscented Kalman Filter (IUKF). Finally, evaluation is conducted to verify the performance of the developed optimized IUKF target tracking model. Root Mean Squared Error (RMSE) validation was performed in the suggested TBA-IUKF-based mobile target tracking model and accomplished 5.63, which is less than classical techniques. The proposed TBA-IUKF has achieved a minimal comparative energy consumption value of 12.5%, 10.3%, 14.8%, and 9.8% compared to existing optimization techniques.

Keywords: Wireless sensor network, Target tracking, Functioning nodes selection, Tiger beetle algorithm, Iterated unscented Kalman filter.

1. Introduction

Wireless Sensor Networks (WSNs) services are well-equipped and suitable for several communication-related applications. WSN has a dynamic setup and is structured through low-cost and battery-operated sensory devices [1]. The sensor data is placed in different environments to capture the surrounding information and send it to the base station. Network lifetime is one of the primary concerns in building the WSN setup, especially for Target tracking-related applications [2]. Target tracking aims to trace the path of a moving target, and identify the position in the communication area. Target tracking requires continuous tracing and monitoring, and thus the energy of nodes must be carefully utilized. For building a successful target-tracking model, the effectiveness related to resource allotment, energy efficiency, device memory, tracking speed, and reliability plays an important role [3]. Target tracking is achieved in WSN through single-node target tracking or collaborative tracking. Single-node tracking requires high energy and fails to provide high-quality results; Collaborative tracking has high processing ability and accurately measures the trajectories and velocity of the moving target [4]. The target tracking model aims to identify the spatial coordinates of the moving target and successfully tracks the spatial path and trajectory. As WSN has a dynamic architecture, when a moving target enters the system, every sensor must act and identify the motion of the target [5].

Filter-based techniques have been proved well-appropriate for achieving an effective target-tracking model [6]. Choosing the right filter-based techniques is necessary for target tracking, as challenges like different filter variants, large filter norms, and so on [7]. Maintaining the accuracy of the moving path is a prime concern in target tracking while retaining the maximum energy in nodes. Filter-based techniques like the Kalman filter and its variants have proven to be effective in target tracking of WSN. Particle filter-based techniques have also been used in this scenario, but their ability to track multiple targets is compromised [8]. Estimating the non-linear and Gaussian system states is a necessary factor of the filtering techniques, and it can be achieved through Kalman filtering techniques [9]. As energy consumption is one of the major concerns in WSN, the operations of filtering-based techniques must be refined to improve energy-related metrics [10]. Selecting the right functioning node before using the filtering technique for target tracking improves the accuracy of the process, and also aids in reducing overall energy consumption. Optimization algorithms come in handy in selecting appropriate sensor nodes for tracking. This allows for overcoming the issues related to node failure, target recovery, improved coverage, and latency in target tracking. In this work, the challenges in target tracking are overcome through an optimization-based filtering approach, and an energy-efficient target tracking model is created.

Towards creating an efficient target tracking system in WSN, the following contributions are presented in this work:

To develop an effective filter-based target tracking technique, to maintain better energy efficiency. The proposed target tracking model ensures to selection of an optimal right functioning node, improves the speed and effectiveness of target tracking, and overcomes the noise, resource, and environment-related challenges.

To develop the target tracking model through the Iterated Unscented Kalman Filter (IUKF) model incorporated with the Tiger Beetle Algorithm (TBA) optimization procedure. The TBA aids the IUKF by selecting the optimal right functioning node and increases the tracking ability of the target trajectory. Optimal selection improves the closeness in tracking the path and improves energy efficiency. The IUKF model addresses the nonlinear variations and reduces the error in target tracking.

The remaining sections of this work have the following sections: Section 2 shows the recently developed target tracking models and the challenges associated with target tracking. Section 3 presents the general system model of target tracking, and briefs the architecture model of the proposed filter-based tracking model. Section 4 describes the selection procedure for the right functioning node and description of the proposed filtering model. The simulation and comparative results are explained in Section 5, a case study is discussed in Section 6 and the conclusion is presented in Section 7.

2. Literature survey

2.1 Related works

In 2023, Madhavi et al. [11] presented a target-tracking model by implementing the Particle Filter (PF) and Support Vector Machine (SVM). The model was created as an energy-efficient model without compromising the accuracy of target tracking. It aimed to resolve the localization problems and achieve suitable target tracking results. Experimentation showed the ability of the model to effectively target tracking and energy consumption.

In 2023, Zhu et al. [12] designed a Recursive Robust Set-Membership Fusion Estimator (RSMFE) for tracking the target in mobile WSN. The model was well understandable for the locations with Unknown But Bounded (UBB) and had improved tracking accuracy. The location uncertainty was well-tracked, and it achieved suitable results with high stability and accuracy. A new formula was developed for RSMFE to reduce the computational complexity through its novel decoupling and equivalent transformation strategies. The new fusion update ensured high tracking accuracy and reduced complexity. The effectiveness of the technique was measured through the different anchor location settings, and the results against the comparative techniques were better in terms of various tracking error measures.

In 2021, Zhou et al. [13] used a new hierarchical tracking model designed through the Edge Intelligence (EI), and the model was well adaptable for Mobile Target Tracking with WSN (MTT-WSN). The proposed model was well aware of the location of the mobile nodes and thus was able to predict the location of the edge servers and moving nodes. The use of EI improved real-time tracking, as it used a resource allocation strategy for consecutive tracking. The optimal resource allocation was built into the model, and it improved the accuracy of the tracking scenario. The results of the model were compared to reinforcement learning techniques, and the results indicated a better performance in real-time target tracking. The results of the scheme were better than the non-cooperative scheme, and it achieved significant tracking performance.

In 2021, Zhu et al. [14] presented a target-tracking strategy by analyzing the received signal strength. An adaptive environment was developed with the event-driven stimulator for presenting the locations of the moving target. The scenario was built for the resource constraint environment, and it achieved improved tracking performance through bounded modeling. The target location was identified through the adaptive event-triggered mechanism, which tracked the location of the moving target near anchors. This model thus provided accurate tracking and ease of communication. The entire process provided guaranteed localization accuracy and reduced overall computational complexity.

In 2024, Khiadani and Hendessi [15] defined the protocol setup for energy-efficient tracking. The model initially adopted a Kalman filter for tracking the target position. The filter through its non-linear properties ensured high computation and also eased the tracking performance. The proposed selected a leader node for following the lead and tracking the position of the target. When the leader exhausted their energy, a new leader was selected, and the tracking task was continued. To achieve less computational complexity, the model performed target tracking in two different phases. The phase change ensured better tracking and energy constraints for WSN.

In 2023, Zhu et al. [16] designed a novel mobile target tracking framework Environmentally Adaptive Event-driven Robust Square Root Cubature Kalman Filter (EAERCKF) technique for tracking the moving targets in the WSN. Initially, the scheduling procedure was executed using adaptive procedures for identifying the anchor distribution density between the moving objects. Later, the motion states of the moving targets were identified by EAERCKF and then different validations were executed in the suggested technique for identifying the target tracking efficiency over other techniques.

In 2023, Khedr et al. [17] suggested a new Energy-Aware Radial Clustering Deep Convolutional Learning (EARC-ODCL) technique along with a Piecewise Regressive Multi-objective Golden Eagle Optimizer (PRMGOA). Here, the developed PRMGOA optimization technique was employed to choose the optimal cluster heads and then sensor node boundaries were identified by a convolutional network. Later, network congestion issues were identified using the piecewise linear regression technique, which helped to reduce the data loss. Later, different analyses were executed in the developed EARC-ODCL over classical mobile target tracking models.

In 2024, Siva and Merline [18] recommended an efficient mobile target tracking framework named Ensemble Random Bayes Support Vector-based Random Electric Eel (ERBS-REE) for improving object detection efficiency. The major goal of the developed technique was to track the objects accurately without any error in WSN. Next, the target tracking procedure was executed by ensemble techniques. Moreover, a novel optimization strategy was employed for tuning the efficiency of the developed network. Then, different performance analyses were executed in the suggested technique to verify its efficiency over classical techniques.

In 2024, Ramadevi *et al.* [19] proposed an energy-saving-based target-tracking framework for mobile WSNs with two different phases. In the initial phase, mobility target tracking procedures were performed by considering the Angle of Arrival (AOA) and Received Signal Strength (RSS) input factors, and in the next phase target movement prediction procedures were executed. Moreover, the Lion Mutated-Crow Search Algorithm (LM-CS) was used to execute the prediction procedures optimally. Then, different performance analyses were executed in the suggested framework over classical techniques.

2.2 Problem statement

Target tracking using WSN can be influenced by challenging environments, and different communication scenarios built through dynamic setup. The target tracking should match different quality of services, and ensure to retain maximum energy without compromising other services. Several advancements and complications presented in the classical mobile target tracking framework in WSN are offered in Table 1.

From analyzing recent works, some research ideas can be gathered, and they are pointed out below:

- WSN follows a dynamic structure, and thus the location of the sensor nodes, and communication link differs from time to time. Thus, it is computationally difficult to reach high localization accuracy. Target tracking through WSN should achieve high accuracy without compensating the energy and other QoS metrics.
- Filter-based techniques have proven to be effective in WSN target tracking. Filtering techniques through their less complex design, and low cost, achieve less complex target

tracking. Also, the filtering techniques can better handle the non-linearity and state changes. As WSN lifetime is limited to battery life, it is necessary to design the target tracking model to be energy efficient.
- Optimization algorithms are better in node selection and this can be applied for active target tracking. Using the optimization algorithms ensures better results of sensing, data processing, and communication. It is necessary to coordinate the target tracking through an optimization algorithm and improve the reliability.

3. Mobile target tracking system in WSN with overall model description

3.1 System model description

Target tracking is a prime need in many applications like wildlife monitoring, rescue operations, military, radar and aviation services, communication services, and so on. WSN is one of the effective target tracking models as it tracks the moving target through its sensor devices. A moving target can enter and exit the sensor environment, and the sensor locates the target by sending information from the target. Target tracking through WSN is commonly adopted in surveillance-based applications. Sensor nodes establish wireless links between the sensors and sink node and notify the base station related to the location of the target. A general description of the target tracking model in WSN is represented in Fig.1.

The sensors in the WSN module are mobile/static, and when a target enters the system, the sensor nodes track its position by calculating its coordinates. Consider the WSN sensing region with R static sensors, each sensor statistically dispersed in different locations, and it is arranged as $S_i : i=1, 2\ldots R$. The location of the sensor in WSN is noted through its coordinates, and for the sensor S_i, the coordinate is given as (u_i , v_i). The coordinates can indicate the size of the sensor.

Consider the moving target M entering the sensing environment and it starts to displace from one position to another. The location of the moving target is denoted by (u_M , v_M). WSN performs the target tracking through any mechanisms and aims to correctly predict the location of the target.

The target tracking mechanism must take account of tracking error, as it defines the accuracy of the tracking process. The actual spot of the moving target is denoted as (u_M, v_M). After tracking the path of the target, the system aims to reduce the tracking error. The tracking error is identified from the deviation in the predicted location and the actual location. The target tracking system continuously tracks the path of the moving target for each time interval. The target tracking performance is denoted as in Eq. (1).

$$\arg \min_{(\hat{u}_M, \hat{v}_M)} fs = \frac{1}{M} \sum_{M}^{j=1} \sqrt{(\hat{u}_M - u_M)^2 - (\hat{v}_M - v_M)^2} \tag{1}$$

For target tracking, the original location (u_M, v_M) is considered to be a known instance.

Table 1. Features and challenges of classical mobile target tracking models in WSN

Author [citation]	Methodology	Features	Challenges
Madhavi *et al.* [11]	PF-SVM	• High target tracking efficiency • Low energy consumption achieved through a reliable communication mechanism	• Dynamic path alters the tracking efficiency.
Zhu *et al.* [12]	RSMFE	• Achieves better stability and tracking accuracy • Less computational complexity	• Does not guarantee anchor localization.
Zhou *et al.* [13]	MTT-WSN	• Achieves real-time tracking. • Adopts rescheduling to reach the optimal target path.	• Even though, consecutive target tracking is achieved; it faces challenges from dynamic constraints.
Zhu *et al.* [14]	Robust set membership fusion	• Adaptive event-trigger reduces the overall computational complexity. • High localization accuracy.	• Does not ease the communication burden within complex scenarios.
Khiadani and Hendessi [15]	Kalman filter	• Achieves high precision target, and improves tracking accuracy.	• Faces challenges in the initial phase of target tracking. • High time complexity.

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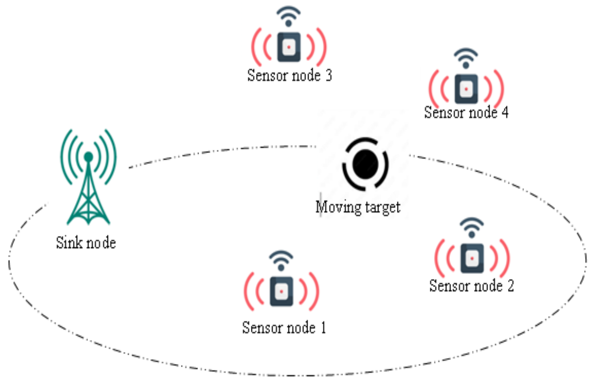


Figure. 1 Basic representation of target tracking model

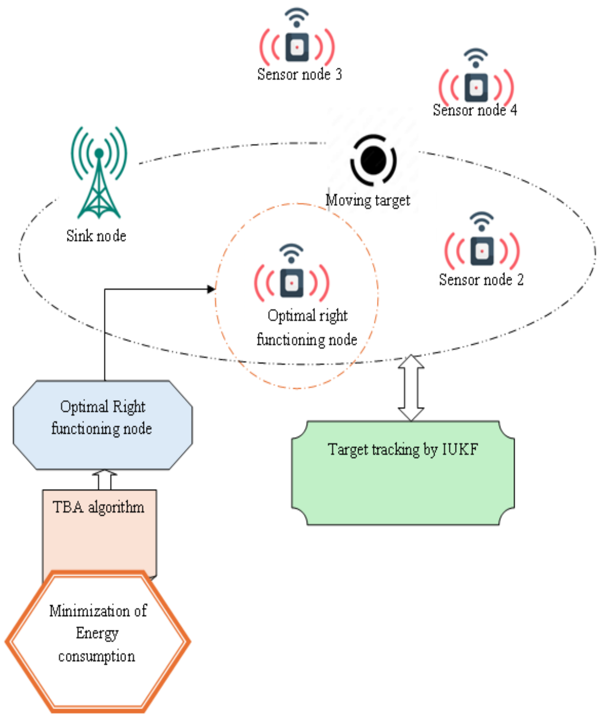


Figure. 2 Architectural illustration of proposed target tracking model for WSN

3.2 Developed mobile target tracking system in WSN

Target tracking in WSN requires high energy optimization, as the nodes in the sensing environment are limited to batteries. Developing an energy constraint target tracking model with high accuracy can aid in many monitoring and surveillance systems. Optimization algorithms have been effectively adopted in the routing mechanism of WSN, and have led to significant improvement in WSN quality metrics. Using the optimization for selecting the right optimal functioning node can reduce the complexity of the tracking, and also create an energy-aware target tracking model.

The developed mobile target tracking in WSN is realized through two major phases 1) Selection of optimal right functioning node, and 2) Target tracking with the optimized WSN. When a moving target enters the system, the sensors begin to track the position of the target. Here, the right optimal functioning node is selected among various sensor nodes through the TBA optimization procedure. This ensures to reduction in the total number of active nodes involved in the target tracking, and thus gradually reduces the energy consumed in target tracking. TBA selects the optimal right functioning node through minimal energy consumption as its objective and thus realizes a high network lifetime for WSN. The optimal right functioning node selected by TBA engages in tracking the location of the target, and the entire tracking process will be handled through the IUKF technique. The IUKF mechanism aims to reduce the tracking error through its reliable tracking steps and create an energy-efficient tracking model. Fig.2 shows the architecture model of the proposed target tracking model for WSN.

4. Optimal functioning node selection for iterated unscented Kalman filter-based mobile target tracking system in WS

4.1 Optimal functioning node selection with TBA

Optimal functioning node selection can improve the tracking ability and also sustain the energy requirement for target tracking. Nodes of WSN are battery operated, and thus using a single node for target tracking can result in loss of data and quality. When a single node performs the target tracking, it's possible for excess energy consumption, as the sensing range of each sensor is limited. This can reduce the overall accuracy of target tracking and also reduce the lifetime of the network. One of the important needs in WSN-based target tracking is presenting an efficient target-tracking model without compromising the energy needs of the tracking system.

Optimization plays a crucial role in selecting the nodes suitable for target tracking. Selecting the right functioning node with minimal energy consumption is a prime need for target tracking. Here, the TBA [20] is involved in selecting the optimal right-functioning node. The TBA algorithm has high convergence properties and also provides the optimal solution faster. As it mimics the hunting and deceptive characteristics, it has strong content for exploration and exploitation updates. Here, for selecting the right functioning node, the TBA engages in finding the optimized WSN with an optimal right functioning node with minimal energy consumption as its objective. In the mobile target tracking framework, the TBA technique is employed to select the optimal nodes. Executing optimal node selection procedures in mobile target selection techniques aid in improving the performance of the network and helps to accomplish quick data transmission with higher reliability. Moreover, the TBA technique helps to minimize energy utilization and also improves the lifespan of the network. The TBA mechanism helps to choose the essential nodes according to their target position. Furthermore, the TBA technique helps to overcome the communication overhead issues by eliminating the redundant data transmission that aids in enhancing the communication among the network. Good node selection helps for tracing the targets in the mobile with node sensing performance enhancement without any error. The pseudo-code of TBA in generating the optimal right functioning node is presented as in Algorithm 1.

Algorithm 1: TBA
Input: Initialized data of WSN with R nodes $S_i : i= 1,2..R$
Output: Optimal right functioning node S_j^{opt}
Parameters: Population size = 10; Chromosome length = 10; Maximum iteration: 100
Calculation of fitness through Eq. (2)
For $t <$ max
Perform the update based on the TBA algorithm.
End for
Return to the Optimal right functioning node. S_j^{opt}

The steps behind selecting the optimal right functioning node are as follows:

1) Initialize the WSN data and the positions of the sensor nodes. Initialize the algorithm parameters and the iteration count.

2) Find the fitness based on minimal energy consumption. The TBA procedure defines its objective function based on the minimization of energy consumption, and it is defined in Eq. (2).

$$Fit = \underset{\left\{S_j^{opt}\right\}}{arg\ max} \left(\frac{1}{E_C}\right) \tag{2}$$

$$Ec = P_{tr} * T_{tr} + P_{Rx} * T_{Rx}$$

The energy consumption is defined based on the transmitted energy P_{tr}, received energy P_{Rx}, and time required for data transmission T_{tr} and data reception T_{Rx}.

3) After computing the fitness, the TBA procedure begins and performs the solution update according to the general update rule.

4) At the end of the procedure, the TBA defines the optimal right-functioning nodes as the return solution.

4.2 Mobile target tracking using IUKF

The IUKF [21] is used for performing mobile target tracking. The IUKF technique is the enhanced version of UKF, where different iterations are employed to execute the prediction process and also updating procedure is performed under the single filtering cycle that aids in accomplishing precise state validation outcomes in the mobile target tracking phase. The IUKF technique accomplishes superior state estimation results by observing the predicted state with extra information along with repeated updating while dealing the non-linear systems. IUKF mechanism is highly efficient in tracking the mobile target and also it easily collects and handles the non-linearity for detecting the state without considering the Jacobians. In the IUKF, outcomes attained from prior iteration are used as input in the upcoming mobile target tracking phase. Using IUKF in the nonlinear system helped to improve the accuracy as well as robustness in the initial estimation stages. Moreover, the IUKF model aid in accomplishing superior convergence, and also it easily handles the non-Gaussian noise distributions while tracing the mobile targets. Observations displayed that the developed IUKF technique easily tracks the moving objects from the noisy environment and uncertain dynamics.

Furthermore, The IUKF obtains more accurate state and covariance estimation than the UKF, especially for strongly complicated nonlinear systems. The theory proves that UKF can capture the true mean and covariance of state distribution with 3rd-order accuracy for any nonlinearity using a set of sigma points. However, there is one drawback of UKF the number of sigma points is often not very large, so the sigma points cannot adequately represent complicated distributions. A natural idea of IUKF is to improve performance by embedding iteration processes into the UKF framework. Finally, the IUKF technique accurately predicted the movements in the mobile target tracking phase.

Therefore, the implementation steps of IUKF can be summarized as follows:

Step 1: The optimal right functioning node S_j^{opt} is provided to the IUKF. State estimates of the target location are initialized as $\widehat{m}_0$, and its corresponding covariance matrix is defined as $\hat{c}_0$, and its expression is defined in Eqs. (3) and (4).

$$\widehat{m}_0 = Y(m_0) \tag{3}$$

$$\hat{c}_0 = Y\left((m_0 - \widehat{m}_0)(m_0 - \widehat{m}_0)^T\right) \tag{4}$$

Step 2: Consider the time step s, and for each time step, the state and covariance matrix are redefined accordingly as a UKF update.

Step 3: Set the values of $\widehat{m}_{s,1} = \widehat{m}_s$, and $c_{s,1} = c_s$.

Step 4: Now, new Sigma points X_n are generated, and it is expressed as in Eq. (5).

$$X_n = \begin{bmatrix} m_{s,n-1}, \widehat{m}_{s,n-1} + \left(\sqrt{(a+\emptyset)c_{s,n-1}}\right)_f, \\ \widehat{m}_{s,n-1} - \left(\sqrt{(a+\emptyset)c_{s,n-1}}\right)_f \end{bmatrix} \tag{5}$$

Step 5: Calculate the values of $\widehat{m}_{s,n-1}$ and $c_{s,n-1}$, for each iteration n.

Step 6: Define the inequality for state and covariance update.

Step 7: Based on inequality redefine the update, or else return the position of a target for each time instance.

Based on the following steps, the IUKF identifies the state value of the moving target and engages in energy-efficient target tracking. The IUKF-based mobile target tracking model is offered in Fig. 3.

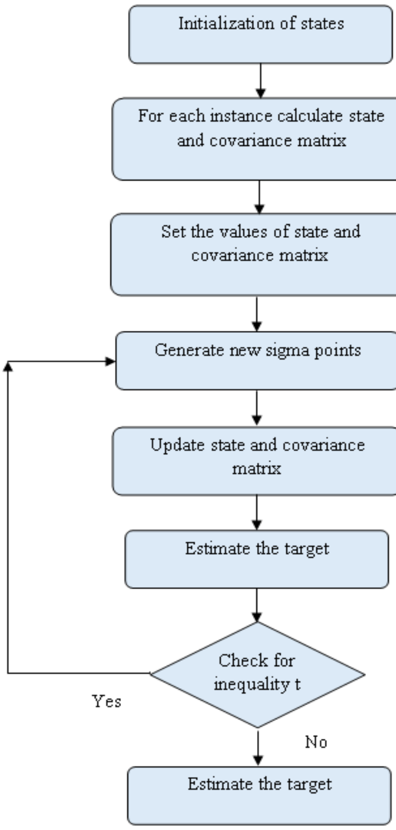


Figure. 3 Operation flow of developed IUKF-based mobile target tracking model

5. Results and discussion

5.1 Network setup

The entire simulation of the proposed IUKF-based target tracking model was implemented in MATLAB tool, and a necessary setup for the WSN model was created for target tracking. Evaluation of the target tracking through IUKF was compared with several recent models, and the robustness of the proposed IUKF with TBA was experimented with. Various optimization techniques employed for the validation of the mobile target tracking model in WSN were given as follows Golf Optimization Algorithm (GOA) [22], Namib Beetle Optimization Algorithm (NBOA) [23], Equilibrium Optimizer (EO) [24], Addax Optimization Algorithm (AOA) [25] and TBA. Classical techniques employed for the analysis of mobile target tracking were PF-SVM [11], RSMFE [12], Kalman filter [15], MTT-WSN [13], and IUKF. Various newly designed mobile target tracking models were EAERCKF [16], EARC-ODCL [17], ERBS-REE [18] and LM-CS [19]. For the mobile node target tracking, a simulation environment was created with varying sink nodes, and different other parameters initialized for evaluation are briefed through Table 2.

5.2 Overview of comparative algorithms

Presently, various heuristic optimization techniques like GOA [22], NBOA [23], EO [24], and AOA [25] are employed for tracking the mobile target in WSN.

- GOA [22] is a widely known metaheuristic technique, which has the efficiency to overcome real-world issues. It needs minimal parameters and also tackles the local minimal issues.
- NBOA [23] has the efficiency to minimize the dimension issues while selecting the features. Moreover, its validation cost is minimal with reduced training procedures.
- EO [24] has a simple implementation procedure and also it offers higher

adaptability and stability in all complicated cases. In the exploitation and exploration phase, it offers superior balancing efficiency.

- AOA [25] provides strong convergence over the global optimum regions and also needs minimal parameter tuning. Moreover, it provides higher robustness with quick convergence to the optimal solutions.

Optimization techniques are employed to tackle the optimization-based issues presented in the network. Yet, these techniques are prone to several complications like minimal convergence, poor balancing issues in exploitation as well as exploration region, sensitivity to parameters initialization phase, higher consumption of time, and so on. The developed framework used the TBA technique for selecting the optimal nodes to verify the movements in the mobile target tracking model. The TBA technique is designed by including the hunting procedures of the tiger beetle to identify the optimal solutions. The TBA technique has the efficiency to handle the balancing among the exploitation and exploration phases. Moreover, the TBA mechanism offers better outcomes to overcome optimization-based issues. Based on these several advantages, the TBA technique is considered in the developed research work.

Table 2. WSN Parameters for developed mobile target tracking model

Parameters	**Value**
Data count	1000
Total number of sink nodes	[3,4,5,8]
Radius	25
Field Dimension of WSN	{100,100}
Probability of node to become CH	0.1
Total data packets	1000
Initial Energy considered	0.3
Energy spent by transmit and receive nodes	0.00000005
Efs	0.00000000001
Emp	0.0000000000000013
Data aggregation energy	0.000000005
Total % of advanced nodes	0.1
Alpha %	1

5.3 Performance measures

Different performance measures used in the developed TBA-IUKF-based mobile target tracking model are offered as follows.

- The largest absolute value of several elements in a set is termed as Infinity Norm Ag and it is provided in Eq. (6).

$$Ag = \max_{1 \le CM \le Yj} |Em_{CM}| \tag{6}$$

- The average variations among the target and actual values are termed as Root Mean Squared Error (RMSE) Qf and it is computed by Eq. (7).

$$Qf = \sqrt{\frac{\sum_{CM=1}^{Yj}(Rd_{CM1} - Ph_{CM2})^2}{Yj}} \tag{7}$$

- The measures used to validate the target tracking accuracy with time series analysis is known as Symmetric Mean Absolute Percentage Error (SMAPE) Kv is given in Eq. (8).

$$Kv = \frac{100\%}{Yj} \sum_{CM=1}^{Yj} \frac{|Ph - Rd|}{\frac{(|Rd| + |Ph|)}{2}} \tag{8}$$

- The mean used to validate the absolute error in the targeted values is known as Mean Absolute Scaled Error (MASE) Ug and it is computed by Eq. (9).

$$Ug = \frac{Ph}{\frac{1}{Yj-1}\sum_{CM=2}^{Yj}|Rd_{CM} - Rd_{CM-1}|} \tag{9}$$

- The metric used to validate the average magnitude of the absolute errors among the target and original values is specified as Mean Absolute Error (MAE) Jr and it is verified by Eq. (10).

$$Jr = \frac{\sum_{CM=1}^{Yj}|Ph - Rd|}{Yj} \tag{10}$$

- The measure used to validate the distance among the vectors by summing the absolute values of every vector component is known as L1-Norm Nt_1 and it is analyzed using Eq. (11)

$$Nt_1 = \sum_{CM=1}^{Yj}|Em_{CM}| \tag{11}$$

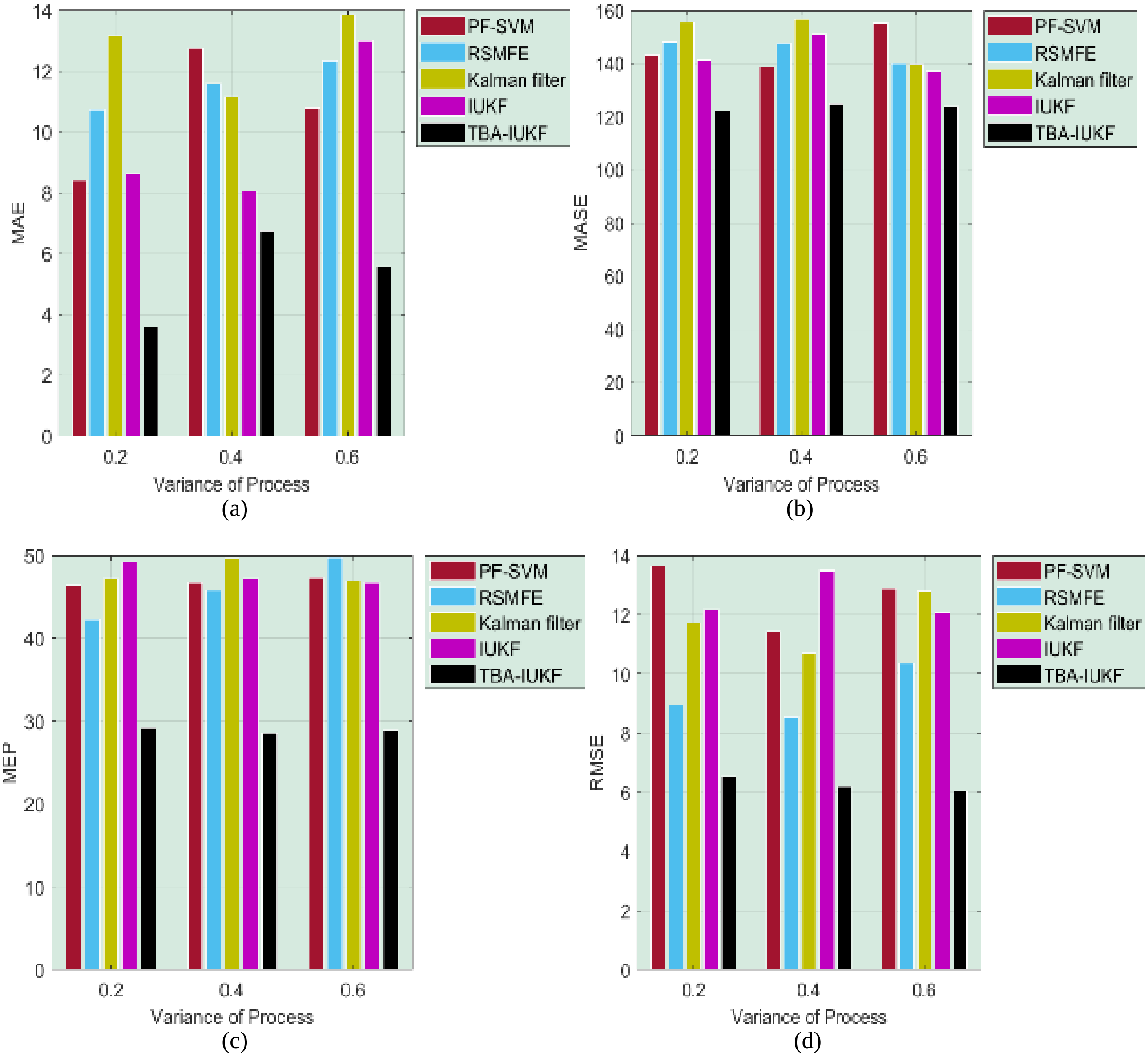


Figure. 4 Performance analysis of developed TBA-IUKF-based target tracking model over classical techniques regarding: (a) MAE, (b) MASE, (c) MEP, and (d) RMSE

- The average percentage of error among the target and original values is termed as Mean Percentage Error (MPE) By and it is offered in Eq. (12).

$$By = \frac{100\%}{Yj}\sum_{CM=1}^{Yj}\frac{Rd-Ph}{Rd} \tag{12}$$

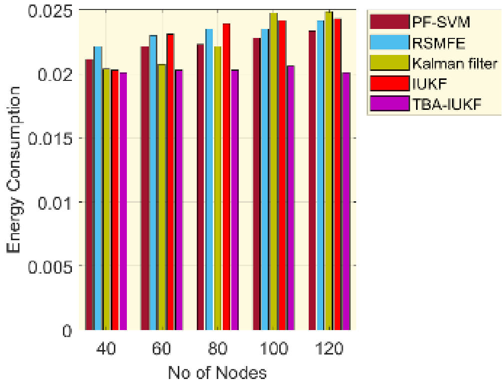
- The metric used to validate the shortest span among the target and vector origin region is known as L2-Norm Nt_2 and it is represented in Eq. (13).

$$Nt_2 = \sqrt{\sum_{CM=1}^{Yj}|Em_{CM}|^2} \tag{13}$$

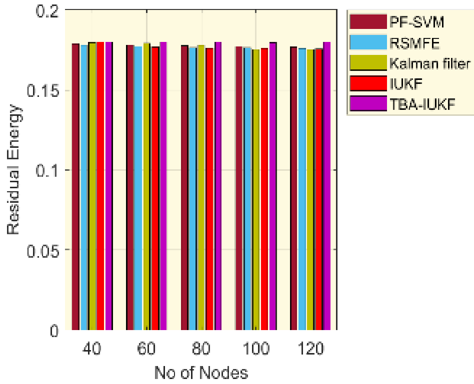
Here, the mean values are specified as Ea, computational values are denoted as CM, a matrix is indicated as Em, real values are given as Rd, fitted points are termed as Yj and predicted values are denoted as Ph.

5.4 Performance analysis of TBA-IUKF target tracking model for the varying variance of the process

The variance of the process is one of the indicators for node target tracking. Different values of variance of the process show the ability to track for different noise factors and different tracking scenarios. Here, the graph in Fig. 4 shows the performance of different tracking models for different variance of process, and the performance of

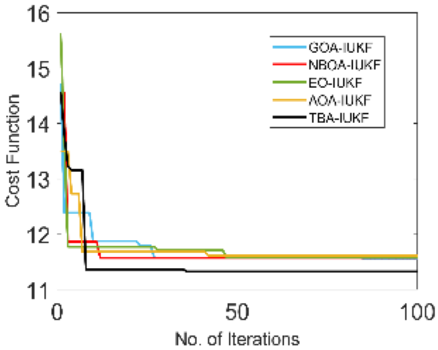


(a)

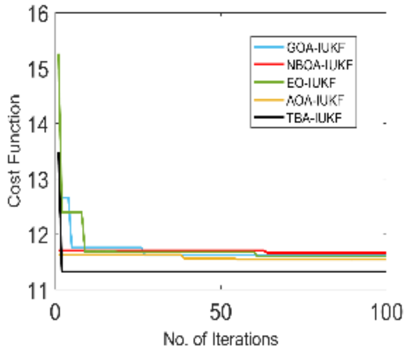


(b)

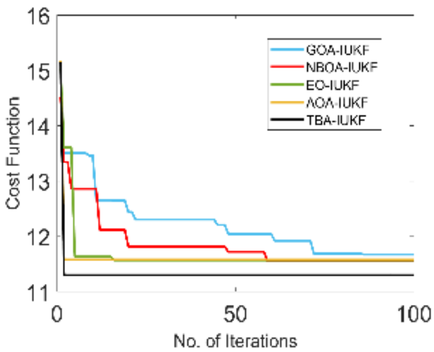
Figure. 5 Comparative analysis of proposed TBA-IUKF-based target tracking model over existing models with (a) Energy consumption, and (b) Residual energy



(a)



(b)



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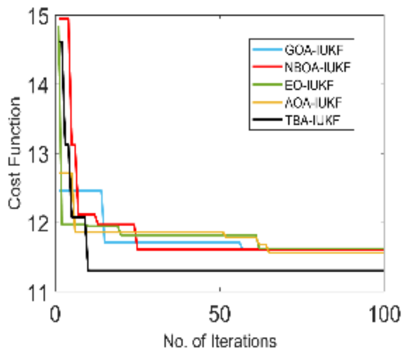

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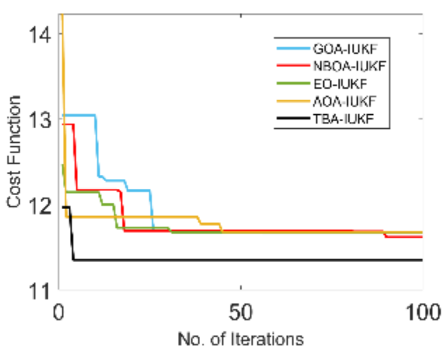
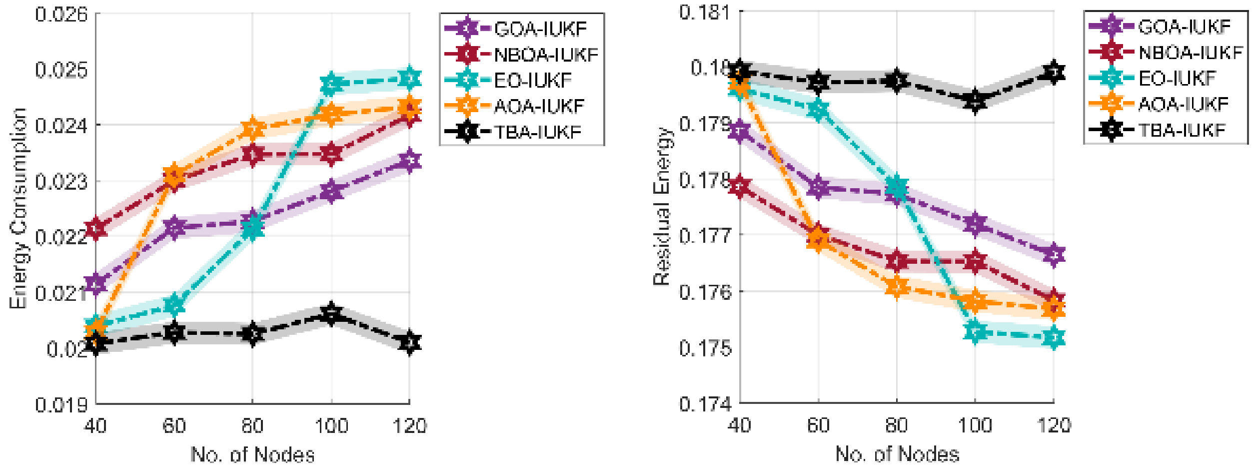


(e)

Figure. 6 Convergence analysis on recommended TBA- IUKF-aided target tracking model with: (a) WSN node count as 40, (b) WSN node count as 60, (c) WSN node count as 80, (d) WSN node count as 100, and (e) WSN node count as 120



(a) (b)

Figure.7 Algorithmic analysis of TBA-IUKF target tracking model for different nodes for: (a) Energy consumption and (b) Residual energy

models is noted against the error metrics like MAE, MASE, MEP, and RMSE respectively. While selecting the variance of the process as 0.6, the proposed TBA-IUKF has shown a great performance with minimal values of MAE at less than 45.2%, 53.2%, 14.8%, and 53.9% than PF-SVM, RSMFE, Kalman Filter, and IUKF respectively. Similarly for other error candidates like MASE, MEP, and RMSE, the proposed TBA-IUKF has achieved comparatively improved performance for different values of variance of process.

5.5 Comparative analysis of TBA-IUKF-based target tracking model

The target tracking models established through WSN should ensure great skills in preserving the energy of the nodes. As the optimal right-functioning node is selected for improving energy conservation, it can improve the overall lifetime of the network. Here, the proposed TBA-IUKF is compared through recent target tracking models based on energy-based metrics for choosing different node setups in WSN, and the results are shown in Fig. 5. The energy consumption and residual energy are important measures for improving the performance of the WSN. Here, the performance of the IUKF filter is measured through different node counts. For a node count of 120, the proposed TBA-IUKF has achieved minimal comparative energy consumption values of 13.04%, 16.66%, 20.1%, and 16.66% than PF-SVM, RSMFE, Kalman Filter, and IUKF respectively. For the same case, the residual energy achieved by the proposed TBA-IUKF is better as 5.88%, 2.85%, 3.44%, and 3.44% than PF-SVM, RSMFE, Kalman Filter, and IUKF, accordingly. This shows the TBA-IUKF has combined achieved an effective target tracking, and improved the network lifetime.

5.6 Convergence analysis of TBA-IUKF-based target tracking model for different node setup

The convergence shows the performance of TBA in selecting optimal functioning nodes for TBA, and graphs under different node counts are provided as in Fig. 6. The proposed TBA-IUKF has jointly achieved a better energy consumption rate, and has achieved good performance through optimal functioning node selection. The node selection has reduced the complexity of the tracking scenario, and non-linear changes in the target path are successfully tracked. For varying node count, the proposed TBA-IUKF has performed better in comparison to the recent optimization models like GOA-IUKF, NBOA-IUKF, EO-IUKF, and AOA-IUKF respectively. For iteration, the performance of TBA is stable and thus improves the target tracking performance.

5.7 Energy-based validation of TBA-IUKF-based mobile target tracking model

The energy metrics are analyzed for the TBA-IUKF against the recent optimization techniques and it is depicted in Fig. 7. For a node count of 120, the proposed TBA-IUKF has achieved minimal comparative energy consumption value of 12.5%, 10.3%, 14.8%, and 9.8% than GOA-IUKF, NBOA-IUKF, EO-IUKF, and AOA-IUKF respectively. Similarly, the residual energy achieved by the proposed TBA-IUKF is better at 7%, 10.3%, 14.8%, and 9.5% than GOA-IUKF, NBOA-IUKF, EO-IUKF, and AOA-IUKF respectively. This indicates the use of an optimization algorithm can have a major impact

Table 3. Statistical evaluation of proposed TBA-IUKF based mobile target tracking framework.

Terms	GOA-IUKF [22]	NBOA-IUKF [23]	EO-IUKF [24]	AOA-IUKF [25]	Proposed TBA-IUKF
Node count = 40					
Best	11.566	11.571	11.582	11.613	11.325
Worst	14.714	14.552	15.624	13.497	14.58
Mean	11.716	11.657	11.715	11.728	11.486
Median	11.572	11.571	11.582	11.613	11.325
Standard Deviation	0.38272	0.42404	0.45151	0.36594	0.56187
Node count = 60					
Best	11.625	11.666	11.601	11.546	11.322
Worst	12.659	11.704	15.262	11.627	13.487
Mean	11.695	11.69	11.734	11.579	11.344
Median	11.625	11.704	11.678	11.562	11.322
Standard Deviation	0.20498	0.01845	0.40703	0.038261	0.21644
Node count = 80					
Best	11.673	11.553	11.568	11.578	11.3
Worst	13.505	14.517	15.028	15.174	15.148
Mean	12.199	11.861	11.671	11.614	11.339
Median	12.047	11.722	11.568	11.578	11.3
Standard Deviation	0.53183	0.49452	0.48634	0.35965	0.38473
Node count = 100					
Best	11.606	11.612	11.621	11.561	11.302
Worst	12.459	14.951	14.85	12.715	14.616
Mean	11.771	11.849	11.797	11.783	11.443
Median	11.715	11.612	11.818	11.863	11.302
Standard Deviation	0.28333	0.68603	0.33345	0.25509	0.54726
Node count = 120					
Best	11.665	11.618	11.675	11.677	11.351
Worst	13.041	12.939	12.474	14.228	11.963
Mean	11.896	11.796	11.751	11.775	11.369
Median	11.693	11.693	11.675	11.677	11.351
Standard Deviation	0.43222	0.28702	0.16546	0.26198	0.10505

on the performance of target tracking, and it can actively reduce the total active nodes involved in target tracking, thereby reducing energy consumption.

5.8 Statistical evaluation of proposed TBA-IUKF based mobile target tracking for different node setup

Table 3 shows the statistical evaluation through best, worst, mean, median, and standard deviation measures for different node counts. In the developed framework, statistical validations are executed to verify the efficiency of the mobile target tracking technique using various optimization approaches. Executing statistical validation in the recommended target tracking technique helps to verify the node selection efficiency of the TBA-IUKF technique. The statistical analyses are executed by considering 50 iterations. Once, the execution is done among the 50 iterations, higher values are termed as the worst value, minimal values are considered as the best value, an average of 50 iterations is termed as mean and the middle value of 50 iterations is known as median. Here, 5 optimization techniques like GOA-IUKF,

Table 4. State-of-the-art evaluation of the proposed TBA-IUKF-based mobile target tracking model

Terms	**PF-SVM [11]**	**RSMFE [12]**	**MTT-WSN [13]**	**Kalman filter [15]**	**Proposed TBA- IUKF**
MEP	49.137	47.626	47.167	46.096	34.718
SMAPE	1.242	1.6149	0.92589	1.2609	0.49495
MASE	147.97	138.55	156.89	139.78	122.96
MAE	9.0421	12.713	13.786	11.195	3.9444
RMSE	13.848	12.318	10.535	12.64	5.6369
L1-Norm	601.07	542.11	609.62	679.19	447.27
L2-Norm	81.645	83.259	85.558	85.767	69.611
L-Infinity Norm	17.509	15.074	17.254	14.073	11.766

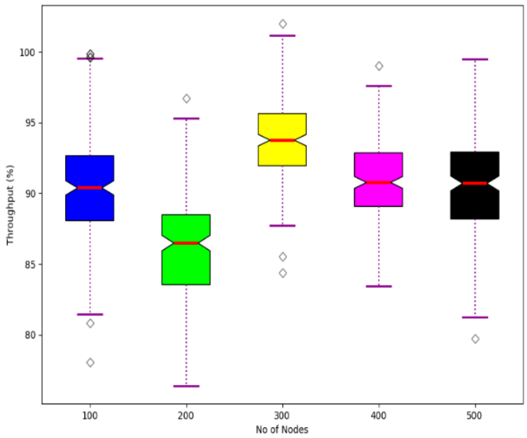


Figure. 8 Scalability validation on developed TBA-IUKF-based mobile target tracking model

Table 5. Computational complexity analysis

Technique	**Computation Complexity**
GOA-IUKF [22]	$O[M_{Itr} + 1 + Nop + 2 + Cl + 1]$
NBOA-IUKF [23]	$O[M_{Itr} + Nop + 2]$
EO-IUKF [24]	$O[M_{Itr} + 1 + Nop + 1 + Cl]$
AOA-IUKF [25]	$O[M_{Itr} + Nop + 3 + Cl]$
TBA-IUKF	$O[M_{Itr} + Nop + 1]$

NBOA-IUKF, EO-IUKF, AOA-IUKF, and TBA-IUKF are considered for the validation with 50 values for each algorithm in the convergence validation. However, it creates difficulties in the analysis procedures. To tackle these issues statistical validation is executed to assure the efficiency of TBA-IUKF by considering different specifications like mean, best, standard deviation, worst, and median. In this phase, optimization techniques are employed to obtain the optimal solutions with good decision-making efficiency. This analysis shows the gradual performance of target-tracking models under different node counts. The statistical measurements are undertaken based on energy consumption measures achieved through TBA and other comparative algorithms. For the best measure, the TBA-IUKF achieved values of 2.12%, 2.17%, 2.26%, and 2.54% higher than GOA-IUKF, NBOA-IUKF, EO-IUKF, and AOA-IUKF respectively. In different statistical validations, the recommended TBA-IUKF-based mobile target tracking technique secured superior efficiency in tuning the nodes that aid in identifying the target movements without any delay. Several advancements in the outcomes displayed that the recommended TBA-IUKF technique accomplishes higher efficiency in choosing the optimal outcomes. Finally, the experimental outcomes indicate that the TBA was better suited to improve the target tracking performance of IUKF than recent optimizers.

5.9 State-of-the-art comparison of developed TBA-IUKF-based mobile target tracking model

Table 4 shows the performance of TBA-IUKF against some of the recently developed target tracking models like PF-SVM, RSMFE, MTT-WSN, and Kalman filter. The performance of the model is compared with the error-based measures related to target tracking. The proposed TBA-IUKF has notably shown better error performance than the recent models and thus shows robustness in target tracking. In the case of MEP measure, the IUKF with TBA has outclassed outcomes with values of 41.5%, 37.17%, 35.85%, and 32% better to PF-SVM, RSMFE, MTT-WSN, and Kalman filter respectively.

5.10 Scalability validation on developed TBA-IUKF-based mobile target tracking model

Scalability computation performed in the developed TBA-IUKF-based mobile target tracking model is offered in Fig. 8. In this phase, scalability computations are executed by considering the node counts over throughput. Executing scalability

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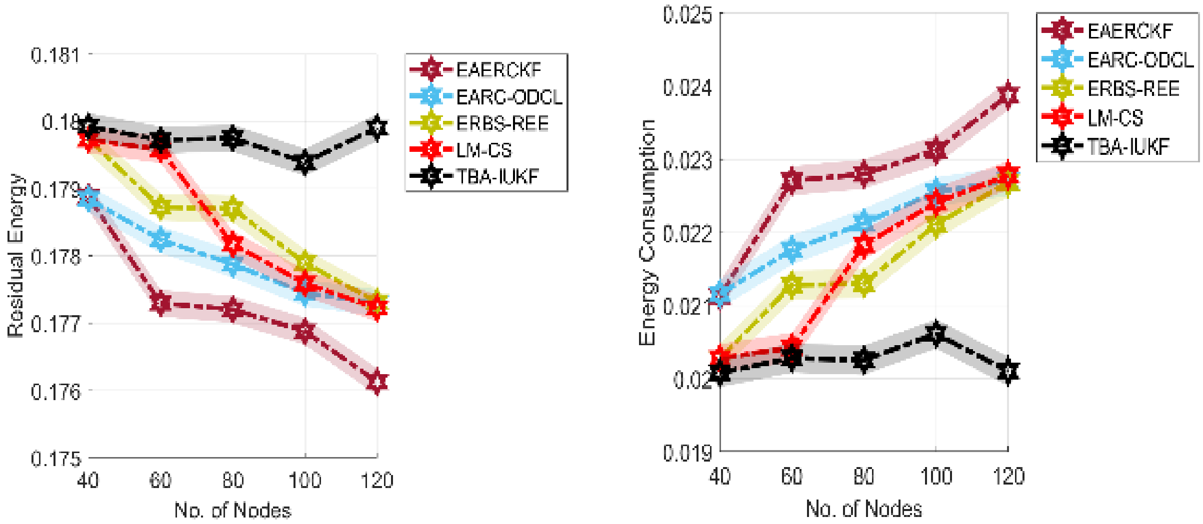
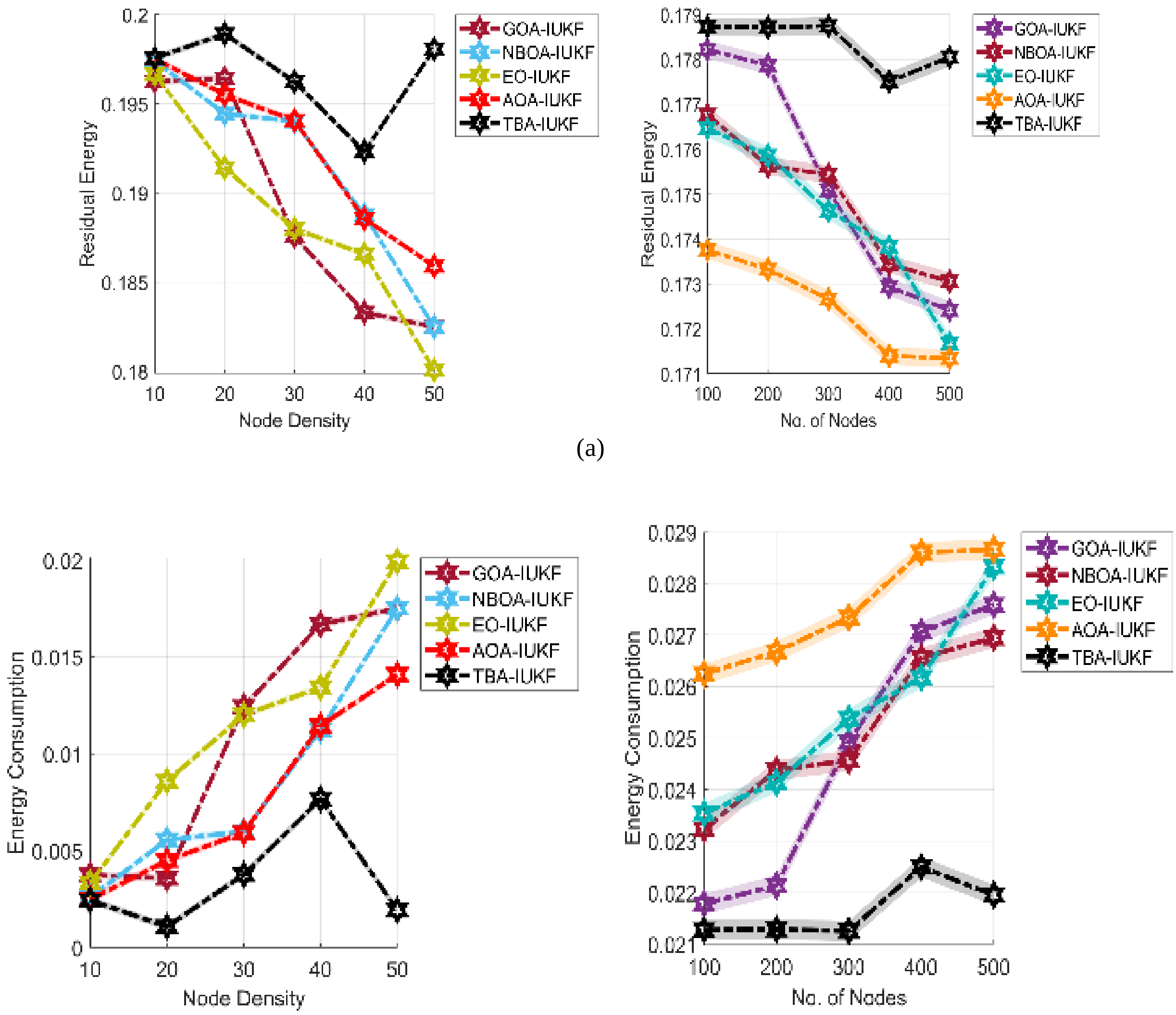


(a) (b)

Figure. 9 Performance analysis on developed TBA-IUKF-based mobile target tracking model over recent techniques for: (a) Residual energy and (b) Energy consumption



(a)

(b)

Figure.10 Validation on developed TBA-IUKF model by varying node density over: (a) Residual energy and (b) Energy consumption

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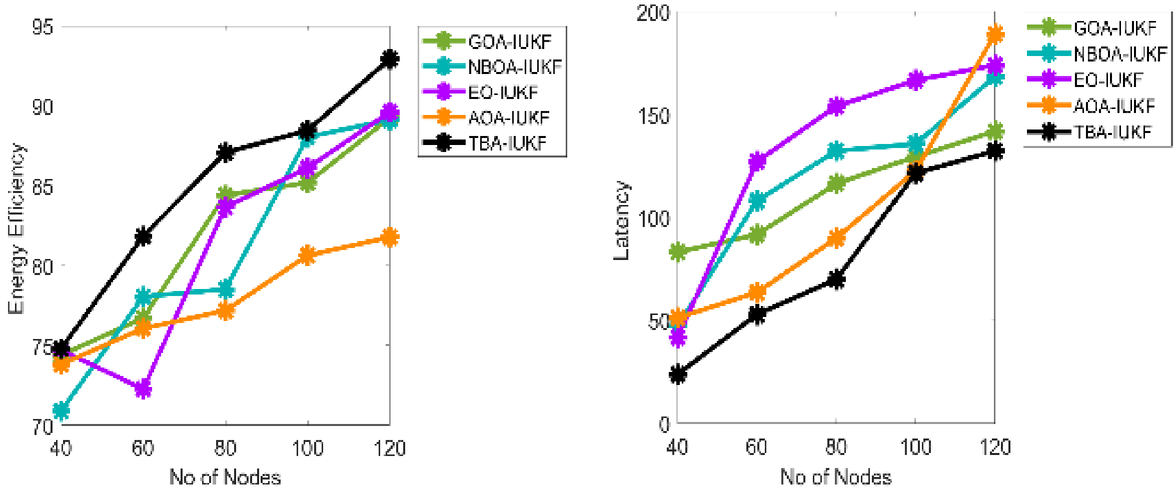

(a) (b)

Figure. 11 Efficiency analysis on suggested TBA-IUKF-based mobile target tracking framework over: (a) Energy efficiency and (b) Latency

validation in the recommended TBA-IUKF helps to enhance the target tracking efficiency in the complicated background. Observing the developed TBA-IUKF over numerous nodes reduces network interruptions and aids in obtaining better mobile target tracking outcomes without any error in a minimal time.

5.11 Computational complexity validation on suggested TBA-IUKF-based mobile target tracking model

In this phase, computational complexity analysis executed in developed TBA-IUKF is tabulated in Table 5. Here, the term M_{Itr} indicates the maximum iteration, Cl specified chromosome length, and Nop specifies the number of population. Computation complexity validation performed in the suggested TBA-IUKF model helps to tackle complicated issues while target tracking is executed in mobile networks. Moreover, this validation helps to verify the performance of the suggested TBA-IUKF model in various scenarios.

5.12 Performance validation on developed TBA-IUKF over recent techniques

In this phase, different performance analyses are executed in the developed TBA-IUKF-based mobile target tracking model over the recent techniques are provided in Fig. 9. In this phase, residual energy and energy consumption validation are executed to verify the target tracking efficiency of the developed TBA-IUKF model. Here, the target tracking performance of the suggested TBA-IUKF technique is identified by varying the node counts. While analyzing the residual energy in the developed TBA-IUKF model, more energy remains than in the classical models once they are used for tracking the targets. Attained higher residual energy by the developed framework displayed the developed TBA-IUKF technique gained superior performance than the classical techniques while tracking the mobile targets. Moreover, the developed TBA-IUKF technique gained minimal energy consumption than the existing approaches.

5.13 Performance analysis of developed TBA-IUKF over node density

Performance analysis on the suggested TBA-IUKF-based mobile target tracking model over node density is offered in Fig. 10. Here, the validation is executed in the developed TBA-IUKF technique by varying the node density as 10, 20, 30, 40, and 50. While observing the residual energy of the developed technique, it accomplishes superior residual energy than the classical techniques like GOA-IUKF, NBOA-IUKF, EO-IUKF, and AOA-IUKF, respectively. The energy consumption validation displayed that the suggested technique gained minimal energy utilization than the existing models while tracking procedures were performed.

5.14 Efficiency validation on recommended TBA-IUKF

In this phase, energy efficiency and latency validation performed in the suggested TBA-IUKF model over different techniques has been offered in

Fig. 11. In this phase, computations are executed by varying the node count to 40, 60, 80, 100, and 120. In the energy efficiency validation, the suggested TBA-IUKF model gained superior energy efficiency than the classical models. Accomplishing better energy efficiency in the suggested technique helps to obtain good communication among other nodes. In the latency validation, the suggested TBA-IUKF technique gained minimal latency, which refers to the suggested model improving the efficiency of the network and also aids in increasing the experience of the users. Moreover, delay issues attained in the network were also resolved effectively.

6. Case study

This section discusses various case studies related to wildlife monitoring using the target tracking procedures.

Case Study 1 [26]: This case study was conducted in Southern Nepal at the Terai Arc Landscape (TAL) near the River Yamuna. The TAL-Nepal regions have five biological corridors, two world heritage sites, and three Ramsar sites. TAL-Nepal is a biodiversity hotspot and it supports endangered species like Gharial and Gangetic Dolphin and also the flagship species like the Asian Elephant, Greater One-Horned Rhinoceros, and Bengal Tigers. In TAL-Nepal, the Greater One-Horned Rhinoceros were monitored by collecting data from the wildlife within the protected regions of the Department of National Parks and Wildlife Conservation (DNPWC) along with the support from international domestic organizations with modern monitoring wildlife techniques. Various equipment used for monitoring the wildlife were radio collars, camera traps, and also wildlife monitoring technologies like Global Positioning System (GPS) collars, conservation drones, and Self-Monitoring, Analysis, and Reporting Technology (SMART).

Case Study 2 [27]: This case study was conducted in Podlaskie Voivodeship village in the regions of Sloja, Bialousy and Szerokie Laki. This research was executed to identify the deer species in the Sloja region. Here, the deer species were captured through photographs. The regions of Podlaskie Voivodeship village were equipped with Canon RGB and thermal imaging cameras. Moreover, different pictures were taken when the flights were utilized to create the orthomaps. In this case study, a multicopter was used with a GoPro camera to view the location of the flights. Furthermore, a flight control station was used with Mission Planner software and a laptop to execute the monitoring procedures.

7. Conclusion and future work

Here, a TBA-IUKF-based target tracking model was developed for the WSN platform to perform effective more accurate tracking of moving objects. The selection of the right functioning node was improved through the TBA algorithm, which selected the appropriate nodes through energy as its objective. The target tracking through IUKF was eased through the TBA selection approach, and it ensured improvement in the network lifetime. The IUKF through its adaptive estimation procedure was able to improve the effectiveness of target tracking and improve the target reaching ability. Experimental results through the evaluations indicate the IUKF with TBA achieved significant improvement in target tracking. The proposed TBA-IUKF has achieved minimal comparative energy consumption value of 12.5%, 10.3%, 14.8%, and 9.8% than GOA-IUKF, NBOA-IUKF, EO-IUKF, and AOA-IUKF respectively. In the case of MEP measure, the IUKF with TBA has outclassed outcomes with values of 41.5%, 37.17%, 35.85%, and 32% better to PF-SVM, RSMFE, MTT-WSN, and Kalman filter respectively. This shows the robustness and reliability of TBA-IUKF-based target tracking in WSN, as it has shown satisfactory performance in reducing the energy consumption for moving target tracking.

Challenges in the developed framework TBA-IUKF: The developed TBA-IUKF framework takes more time to identify sensor failures due to environmental interferences. These types of complications generate errors and also don’t offer accurate data as the outcome. Moreover, the developed framework wasn’t able to adapt the rapid motion changes attained in the network when tracking is executed. In some cases, network fluctuation issues affected the tracking performance. The developed TBA-IUKF technique also needs to overcome the computation overhead issues in the network attained while updating the information in corresponding nodes.

Future work: Even though the target tracking through IUKF was much more effective and reliable; it can increase the complexity of the model, and increase the power consumption of the overall process. This can be improved through deep learning representations, and make it adaptable to resource-constrained applications. Moreover, real-world validations for mobile target tracking will be considered in upcoming works to enhance the accuracy of target tracking in different conditions.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, and software have been done by 1st author. validation, formal analysis, investigation, resources, and data curation have been done by 2nd and 3rd authors. Writing-original draft preparation has been done by 1st author, writing-review and editing, visualization has been done by 1st author. Supervision of the work has been done by 2nd and 3rd authors.

References

[1] S. Xiang, and J. Yang, "A novel adaptive deployment method for the single-target tracking of mobile wireless sensor networks", *Reliability Engineering & System Safety*, Vol. 234, p.109135, 2023.

[2] X. Liu, L. Mihaylova, J. George and T. Pham, "Gaussian Process Upper Confidence Bounds in Distributed Point Target Tracking Over Wireless Sensor Networks", *IEEE Journal of Selected Topics in Signal Processing*, Vol. 17, No. 1, pp. 295-310, Jan. 2023.

[3] Y. Zhang, Z. Zhang, J. Yu, D. Guo, Q. Li, X. Li, "Clustering-Based Distributed Fault-Tolerant Target Tracking for Sensors With Decreased Detection Accuracy", IEEE Sensors Journal, Vol. 24, No. 11, pp. 18428-18443, 2024.

[4] M. Cheng, C. Chen and M. R. K. Aziz, "Cooperative Tracking for WSN With DOA-Based Factor Graph Technique", *IEEE Sensors Journal*, Vol. 24, No. 24, pp. 41675-41684, 2024.

[5] S. Tabatabaei, "A Fault-Tolerant Clustering Approach for Target Tracking in Wireless Sensor Networks", *Wireless Personal Communications*, Vol. 137, pp. 2303-2322, 2024.

[6] K. Zhang, X. Yang, S. Zhong, G. Wang, J. He, C. Xu, B. Peng, and Min Li, "Hierarchical fusion with maximum correntropy decentralized extended information filtering for target tracking in clustered WSNs", *Control Engineering Practice*, Vol. 149, pp. 105973, 2024.

[7] F. Delavernhe, A. Rossi, and M. Sevaux, "An online method for robust target tracking using a wireless sensor network", *Expert Systems with Applications*, Vol. 230, pp. 120549, 2023.

[8] Y. Lu, B. Li, H. R. Karimi, and N. Zhang, "Measurement outlier-resistant target tracking in wireless sensor networks with energy harvesting constraints", *Journal of the Franklin Institute*, Vol. 360, No. 12, pp. 8973-8996, 2023.

[9] D. Peng, K. Xie1, M. Liu, "WSN Mobile Target Tracking Based on Improved Snake-Extended Kalman Filtering Algorithm", *Journal of Beijing Institute of Technology*, Vol. 33, No. 1, pp. 28-40, 2023.

[10] H. T.T. Binh, N. T. Hanh, N. P. Tan, L. V. Quan, D. T. Ngoc, N. H. N. Minh & H. C. Phap, "A heuristic node placement strategy for extending network lifetime and ensuring target coverage in mobile wireless sensor networks", *Evolutionary Intelligence*, Vol. 17, pp. 3151-3168, 2024.

[11] K.R. Madhavi, M.N.M. Nawi, B.B. Reddy, K. Baboji, K.H. Kishore, and S.V. Manikanthan, "Energy efficient target tracking in wireless sensor network using PF-SVM (particle filter-support vector machine)", *Technique. Measurement: Sensors*, Vol. 26, p.100667, 2023.

[12] H. Zhu, J. Luo, M. Luo, and J. Minane, "A Recursive Robust Set-Membership Estimator for WSN-Assisted Moving Targets Tracking With UBB Anchor Location Uncertainty", *IEEE Transactions on Vehicular Technology*, Vol. 72, No. 5, pp. 6547-6557, 2023.

[13] L. Zhou, S. Leng, Q. Liu, H. Chai, and J. Zhou, "Intelligent sensing scheduling for mobile target tracking wireless sensor networks", *IEEE Internet of Things Journal*, Vol. 9, No. 16, pp.15066-15076, 2021.

[14] H. Zhu, H. Chen, and M. Luo, "Adaptive event-driven robust set-membership estimation for received-signal-strength-based moving targets localization", *IEEE Internet of Things Journal*, Vol. 9, No. 14, pp.12825-12835, 2021.

[15] N. Khiadani, and F. Hendessi, "An Energy Efficient Prediction Based Protocol for Target Tracking in Wireless Sensor Networks", *Ad Hoc Networks*, p.103688, 2024.

[16] H. Zhu, H. Wu and M. Luo, "Environmentally Adaptive Event-Driven Robust Cubature Kalman Filter for RSS-Based Targets Tracking in Mobile Wireless Sensor Network", *IEEE Internet of Things Journal*, Vol. 10, No. 6, pp. 5530-5542, 2023.

[17] A. M. Khedr, S. S. Rani and M. Saad, "Optimized Deep Learning for Congestion-Aware Continuous Target Tracking and Boundary Detection in IoT-Assisted WSN", *IEEE Sensors Journal*, Vol. 23, No. 7, pp. 7938-7948, 2023.

[18] T. Siva and A. Merline, "Optimizing network lifetime: ERBS-REE for resilient object detection and tracking in resource-constrained WSN environments", *Signal, Image and Video Processing*, Vol. 18, pp. 5189-5201, 2024.

[19] N. Ramadevi, M. V. Subramanyam & C. Shoba Bindu, "Adaptive Mobility Target Tracking with Metaheuristic Aided Target Movement Prediction Scheme in Wireless Sensor Network", *Wireless Personal Communications*, Vol. 134, pp. 1959-1985, 2024.

[20] A. Saihood, M.A. Al-Shaher, and M.A. Fadhel, "A New Tiger Beetle Algorithm for Cybersecurity, Medical Image Segmentation, and Other Global Problems Optimization", *Mesopotamian Journal of CyberSecurity*, Vol. 4, No. 1, pp.17-46, 2024.

[21] R. Zhan, and J. Wan, "Iterated unscented Kalman filter for passive target tracking", *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 43, No. 3, pp.1155-1163, 2007.

[22] Z. Montazeri, T. Niknam, J. Aghaei, O.P. Malik, M. Dehghani, and G. Dhiman, "Golf optimization algorithm: A new game-based metaheuristic algorithm and its application to energy commitment problem considering resilience", *Biomimetics*, Vol. 8, No. 5, p.386, 2023.

[23] M. Chahardoli, N.O. Eraghi, and S. Nazari, "Namib beetle optimization algorithm: a new meta-heuristic method for feature selection and dimension reduction", *Concurrency and computation: practice and experience*, Vol. 34, No. 1, p.e6524, 2022.

[24] A. Faramarzi, M. Heidarinejad, B. Stephens, and S.Mirjalili, "Equilibrium optimizer: A novel optimization algorithm", *Knowledge-based systems*, Vol. 191, p.105190, 2020.

[25] T. Hamadneh, K. Kaabneh, O. Alssayed, K. Eguchi, S. Gochhait, I. Leonova, and M. Dehghani, "Addax Optimization Algorithm: A Novel Nature-Inspired Optimizer for Solving Engineering Applications", *International Journal of Intelligent Engineering & Systems*, Vol. 17, No. 3, 2024, doi: 10.22266/ijies2024.0630.57.

[26] Y. Shrestha, "Modern Wildlife Monitoring Technologies: Conservationists versus Communities? A Case Study: The Terai-Arc Landscape, Nepal", *Conservation and Society*, Vol. 16, No.1, 2018.

[27] R. Perz, K. Wronowski, R. Domanski, I. Dąbrowski, "Case study of detection and monitoring of wildlife by UAVs equipped with RGB camera and TIR camera", *Aircraft Engineering and Aerospace Technology*, Vol. 95, No. 10, 2023.