Dependable Object Stalking Model Employing Modified Kalman Filter (MKF) in WSNs

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ABSTRACT:

The Wireless Sensor Networks (WSNs) advances a variety of ground-breaking applications, including localization, target tracking, etc. The bulk of these applications make use of a large number of sensor devices that are linked to the base station, which functions as a gateway to link cloud computing environments and other settings. The primary functions of WSNs are data gathering, data sensing, and data transmission; however, sensor devices collect data and communicate it episodically across the intermediate node in order to make wise decisions from time to time. The main goal of target tracking applications using WSNs is to increase tracking prediction accuracy, network reliability, and lifetime performance for data collected. This study proposes a model for dependable target tracking (RTT) that makes use of WSNs. First, a modified Kalman Filter (MKF) is implemented to increase forecast accuracy. Next, multi-objective-based route optimization and better CH selection are demonstrated. The findings of the experiment demonstrate that the RTT model outperforms the current target tracking approach using WSNs in terms of energy efficiency, tracking accuracy, latency reduction, and communication overhead.

Keywords:

Object Stalking Model, Routing, Clustering, Data aggregation. Energy efficiency, Dependable, Target tracking, Kalman Filter, WSNs.

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1. INTRODUCTION

Target tracking applications greatly benefit from wireless sensor networks' compact size, low cost, self-configurability, and self-organization [1] features. has a significant impact on target tracking applications in both military and civilian settings. The location of the malicious object can be easily and quickly determined using WSNs, but there are certain drawbacks, including energy limitations and poor tracking precision [2]. Researchers have recently concentrated on finding trade-offs between tracking accuracy and energy efficiency [3].Among them, cluster-based target tracking methods are very efficient in addressing limitations such as quality-of-service, latency reduction, and energy efficiency [4]. In dynamic cluster-based routing, the CH collects tracking prediction from a member, performs a fusion of state estimation, and transmits it to the base station for finalizing target state estimation; thereby balancing the energy load of whole networks through dynamic CH selection [5]. In [5] showed the benefit of using Fuzzy optimization in enhancing lifetime performance for homogenous networks only; thus, target tracking application requires heterogeneity performance optimization. In [6] designed a data collection scheme using cluster-based [7] and prediction-based [8]. In [9] the latency is reduced for data collection by employing an evolutionary computing model. However, failed to address the loss of connectivity issue impacting the overall lifetime performance of WSNs [10]. In [11] designed a routing model emphasizing heterogeneous networks; the model showed the necessity of reducing latency and meeting energy constraints. In addressing such issues various heterogeneous optimization such as industrial-WSN [12], dynamic medium access control [13], software defined network, [14], and dynamic traffic optimization [15]. In [16] a multi-path routing method and Fuzzy-rule-based multi-objective optimization for CH selection [17] are designed for reducing latency with minimal energy dissipation [18]; Hence, did not consider the dynamic nature of the environmental of the target tracking application [19], [20]. Thus, inappropriate scheduling leads to loss of packet and energy loss and affects overall target tracking performance [21]-[23]. The existing tracking method is presented for the linear model using the Kalman filter; however, in [24] showed an improved KF for a non-linear environment; However, the model is not tested for WSNs and induces significant computational overhead.

This research work presents a novel design for building energy-efficient routing for the target tracking (RTT) model for WSN. First, the RTT model deploys sensor devices across WSNs.

Secondly, the RTT model presents selection of cluster head efficiently that balances network coverage and improves energy efficiency; thereby reducing latency and communication overhead. The model also presents a modified KF algorithm for predicting the location of maneuvering objects considering non-linear system dynamics using WSNs.

2. ENERGY-EFFICIENT ROUTING DESIGN FOR TARGET TRACKING IN WIRELESS SENSOR NETWORKS

The energy-efficient routing for target tracking (RTT) design for Wireless sensor networks is discussed here. The target tracking applications is done using Modified Kalman Filter (MKF) model presented in this section. The sensor node $\mathcal{K}$ are surrounded with an object tracking sensor nodes with battery for performing data sensing. Hence, the WSN nodes are randomly deployed across the sensing region and gathered data is transmitted to the base stations for further processing. The energy efficiency of WSNs is enhanced by using cluster communication which is of two phases. Firstly, intra-cluster communication phase where sensor devices will transmit data with its cluster head. Secondly, inter cluster communication phase, the cluster head will convey data to its neighboring cluster head device to base stations.

2.1 Modified Kalman Filter for target tracking:

Similar to [24] in this work we consider a non-linear maneuvering object environment [34], where defining measurement model is difficult (i.e., establishing computation of matrices and vectors are difficult). The modified Kalman Filter (MKF) offers a novel way of dealing nonlinear maneuvering object system dynamics. The MKF is designed consider energy-constraint nature of WSN with less computational overhead for performing tracking operations. The proposed MKF algorithm optimize the current estimate of linear KF into non-linear tracking environment; therefore, the state transition and measurement are estimated through following equations

$$y_l = f(y_{l-1}.v_{l-1}) + x_{l-1} \tag{1}$$

$$a_l = i(y_l) + w_l \tag{2}$$

where f defines previous state, y_{l-1}, function, and the control input, y_{l-1}, that gives the current state y_l. i defines the measurement function that relates the current state, y_l, to the measurement a_l. $x_{l-1}$and w_l defines noise through Gaussian process and measurement model with covariance Q and R, respectively.

2.1.1 Cluster head Selection:

Using standard LEACH-based CH selection using threshold function significantly induces overhead to node that is close to base station. In addressing number of multi-objective parameter-based CH selection model are emphasized using different optimization algorithm with good effect. However, failed to address energy-hole and improving network coverage problem. In addressing research issues this work presents an CH selection scheme making use of multi-objective parameters like node position and residual energy. The optimal CH $\mathcal{D}$ selection metrics is obtained through below equation

$$O_{\mathcal{D}} = \gamma * T_h^{\mathcal{D}} + (1-\gamma) * T_m^{\mathcal{D}} \tag{3}$$

where γ defines constant parameter used for optimization process, $T_h^{\mathcal{D}}$ represent the parameter defining average remaining energy ratio between CH and the member nodes, and $T_m^{\mathcal{D}}$ represent the parameter defining average distance ratio between non-CHs-sinks and between CH-base stations. In Eq. (3) the parameter defining remaining energy $T_h^{\mathcal{D}}$ is estimated through following equation

$$T_h^{\mathcal{D}} = \vec{L}_{\mathcal{D}} \Big/ \vec{L}_{\widetilde{\mathcal{D}}} \tag{4}$$

where $\vec{L}_{\widetilde{\mathcal{D}}}$ and $\vec{L}_{\mathcal{D}}$ defines the average residual energy of member nodes and CHs, respectively. The sensor node having higher $T_h^{\mathcal{D}}$ are chosen as CHs. In similar manner to Eq. (4), the parameter $T_m^{\mathcal{D}}$ is estimated through following equation,

$$T_m^{\mathcal{D}} = \vec{E}_{\widetilde{\mathcal{D}}} \Big/ \vec{E}_{\mathcal{D}} \tag{5}$$

where$\vec{E}_{\widetilde{\mathcal{D}}}$ defines average distance among CHs to sink and $\vec{E}_{\mathcal{D}}$ defines average distance among members and CHs. The parameter $T_m^{\mathcal{D}}$ is maximized for achieving enhanced cluster formation and CHs selection.

2.1.2 Fusion and Inter-cluster communication:

Once CH is selected, every member joins the respective CH. Then, the member node sense for the target within its range and communicate the sensed information to nearby CHs using TDMA-based schedules. The CHs fuses the tracking information collected from its member and for carrying out tracking operations. The fused data $\mathcal{B}_{\hbar}$ is mathematical defined through following equation

$$\mathcal{B}_{\hbar} = \sum_{o=1}^{\hbar} b_o \tag{6}$$

where o^{th}sensor node communicated sensed tracking information of b_o bits to its cluster head and $\hbar$ defines cluster member size. Therefore, the packet failure probability $L_{\prime}^{p}$ considering cluster density $\hbar$ is estimated as follows

$$L_{\prime}^{p} = 1 - (1 - L_{\prime}^{b})^{\mathcal{B}_{\hbar}}. \tag{7}$$

where $L_{\prime}^{b}$ defines mean bit error rate of intra and inter cluster communication.

In reducing overhead of CHs, certain intermediate nodes (i.e., CHs) are chosen for transmitting packet to the base station. The intermediate node is defined as $\mathbb{D} = \{\mathbb{D}_1, \mathbb{D}_2, \mathbb{D}_3, \dots, \mathbb{D}_u, \dots, \mathbb{D}_v\}$ and set of normal sensor devices as $\mathbb{S}$. In selection ideal intermediate nodes for inter-cluster communication; first, the intermediate CHs node should have higher energy than normal node; second, the node should be much closer to CH and base stations. The intermediate CHs selection for inter-cluster communication is obtained through following equation

$$O_{\mathbb{D}} = \varphi \times T_h^{\mathbb{D}} + (1-\varphi) \times T_m^{\mathbb{D}} \tag{8}$$

where $T_h^{\mathbb{D}}$ defines the ratio of inter-cluster intermediate nodes residual energy with respect to member nodes are obtained through following equation

$$T_h^{\mathbb{D}} = \frac{\vec{L}_{\mathbb{D}}}{\vec{L}_{\mathbb{S}}} \tag{9}$$

where $|\mathbb{S}|$ defines the number of member nodes, $|\mathbb{D}|$ defines inter-cluster intermediate nodes, $\vec{L}_{\mathbb{D}}$ represent the average residual energy of inter-cluster intermediate nodes. The node having greater energy level are chosen as inter-cluster intermediate node by maximizing $T_h^{\mathbb{D}}$. On same term with Eq, (9) the $T_m^{\mathbb{D}}$ is obtained through following equation

$$T_m^{\mathbb{D}} = \frac{\vec{Z}_{\mathbb{S}}}{\vec{Z}_{\mathbb{D}}} \tag{10}$$

For cluster head selection $\mathcal{D}_y$and its corresponding inter-cluster intermediate CHs mode $\mathbb{D}_u$, the base station position $\mathcal{S}$ and cluster head $\mathcal{D}_y$ is considered. The communication efficiency among CH and inter cluster hop device are improved through maximizing $T_m^{\mathbb{D}}$.

2.1.3 Multi-objective route optimization:

After CH selection and finding packet failure probability, then efficient path $L_{\mathcal{M}}$ is established that minimize energy dissipation with less latency using following equation

$$L_{\mathcal{M}} = \min\left(O_{\mathbb{D}} + \mathcal{G}_l + \vec{L}_{\prime}^{p}\right) \tag{11}$$

where $\mathcal{G}_l$ describe the predictable hop size. The proposed energy efficient routing for target tracking model reduces the latency and energy dissipation for communicating data in WSN network.

3. SIMULATION ANALYSIS AND RESULT

The experimental study using SENSORIA simulation environment [27] is discussed here. Experimental results are showed on Intel quad core processor with 8 GB RAM on Windows 10 operating system. The proposed RTT algorithm and LEACH-based routing design [16], [17] is implemented using C++ and C# programing language. The RTT and LEACH evaluation study is carried through simulation with the parameters shown in Table 1.

Table 1: The performance analysis of LEACH and RTT

Parameter	**Value**
Simulation area	$50 meters \times 50 meters$
Base stations	1
Sensor devices	$300\ to\ 2400$
Transmission range	$5\ meters$
Sensing range	$3\ meters$
Initial energy	$0.05 - 0.2\ Joules\ (j)$
Radio energy	$50\ nj/bit$
Control packets length	$248\ bits$
Data packets length	$2000\ bits$
Data transmission speed	$100\ bit/seconds$
Bandwidth	$10000\ bit/seconds$
Sensing event time	$0.1 seconds$
Idle phase energy consumption ($Eelec$)	$50\ nj/bit$
Signal amplification energy (Emp)	$100 \quad pJ/bit/m2$

3.1 Tracking Accuracy study:

This section studies the tracking prediction performance achieved using proposed modified KF tracking method over existing KF-based tracking [24] method. The Fig. 1, shows the complex two-dimensional maps of non-linear maneuvering of objects considered for target tracking in WSNs. The Fig. 2 defines the target prediction outcome of KF-based (shown in blue) and MKF-based (shown in red) tracking methods. The Fig. 3 shows object location prediction using KF-based (shown in blue) and MKF-based (shown in red) tracking methods. Similarly, the Fig 4 shows the object maneuvering prediction using KF-based (shown in blue) and MKF-based (shown in red) tracking methods. The Fig. 5 shows the tracking error obtained for predicting location using KF-based and MKF-based tracking methods. The Fig. 6 shows the tracking error obtained for predicting maneuvering using KF-based and MKF-based tracking methods. The research work discussed here is proved and authenticated through different experimental processes.

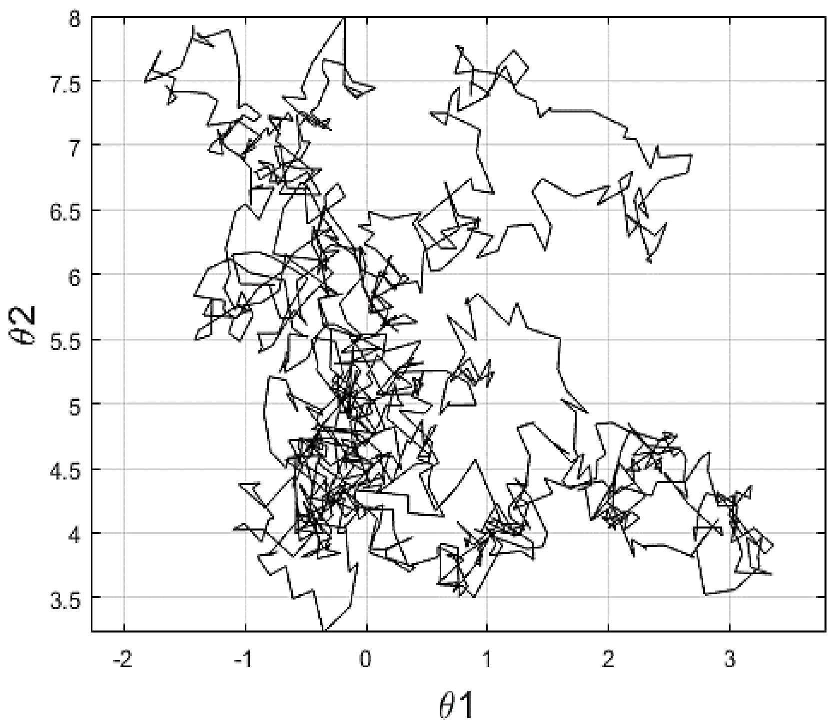

Fig. 1. Target moving trajectory in two-dimensional space.

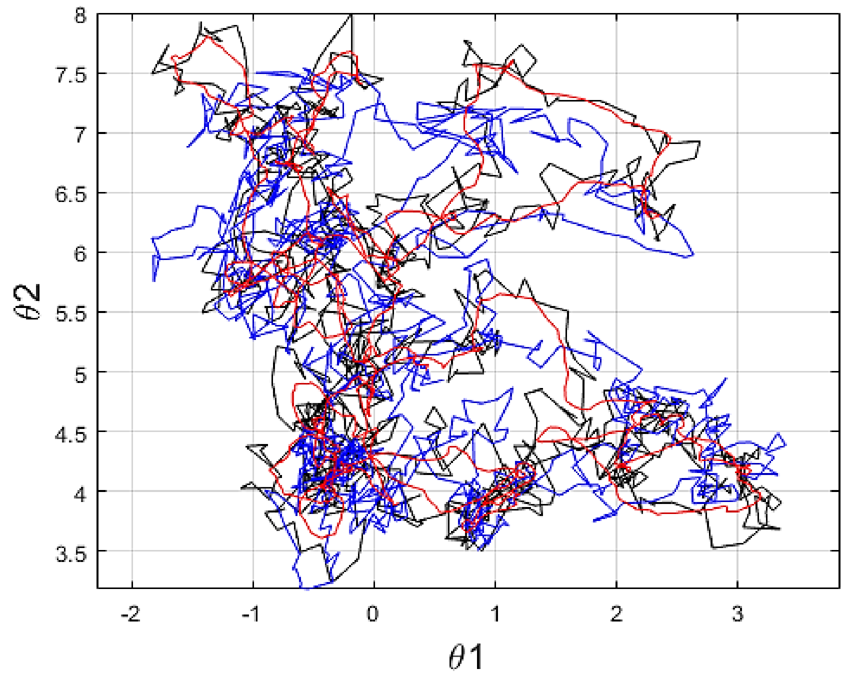

Fig. 2. Target moving prediction using KF-based (blue) and proposed MKF-based (Red).

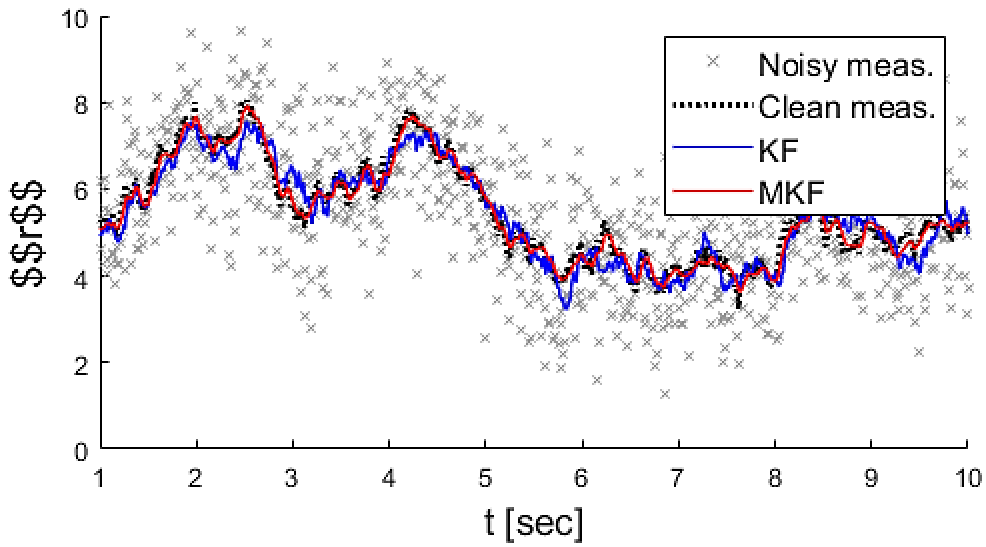

Fig. 3. Target position prediction with varying time instance.

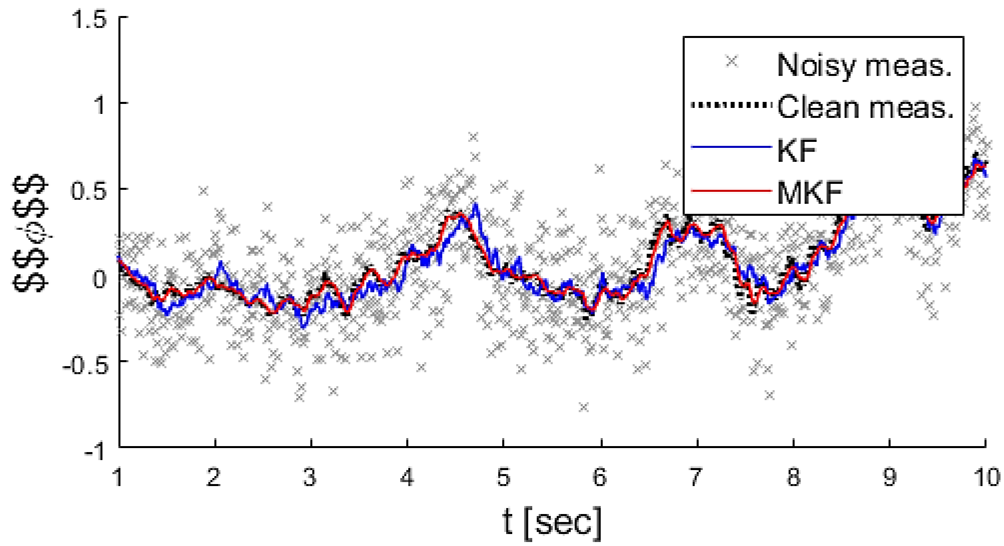

Fig. 4. Target velocity prediction.

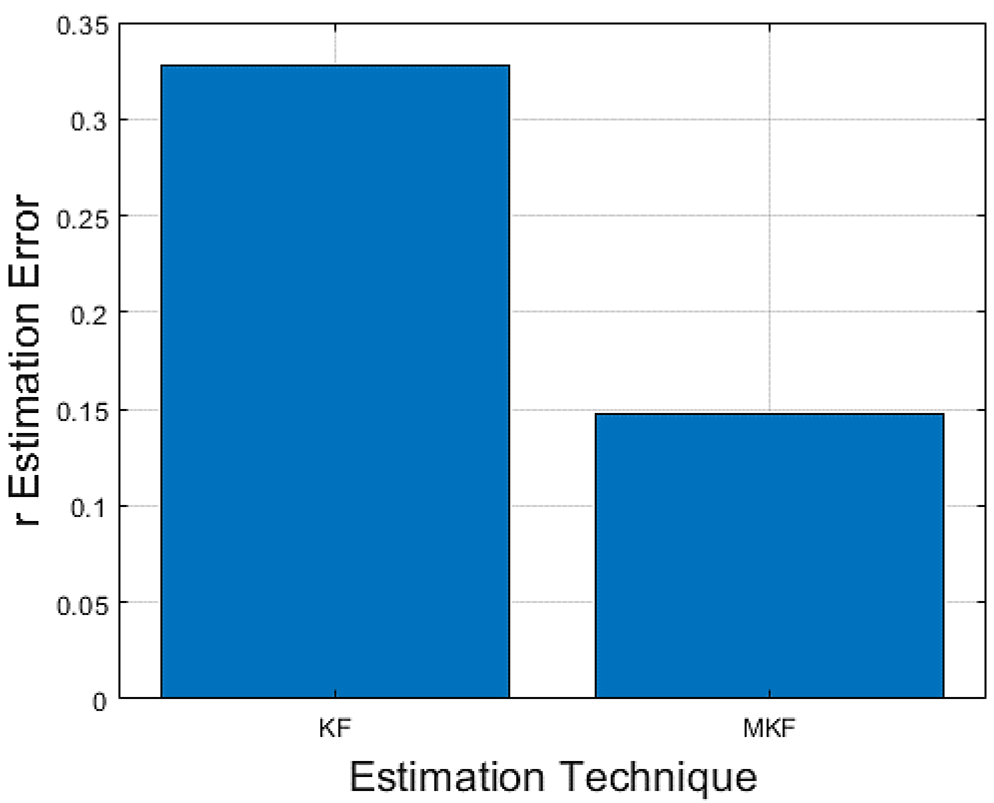

Fig. 5. Target position prediction error.

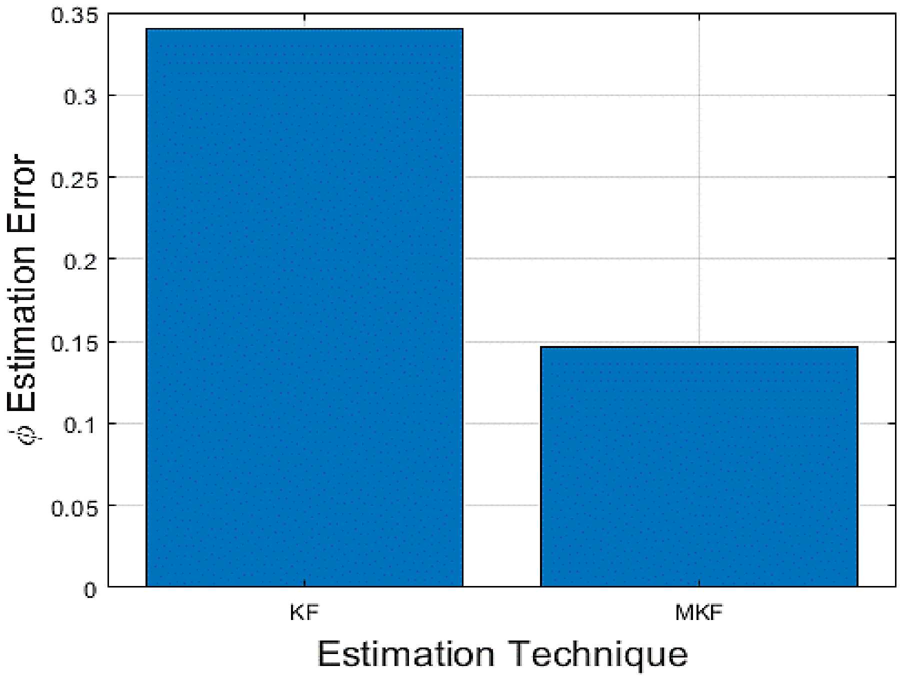

Fig. 6. Target velocity prediction error.

3.2 Network performance Analysis:

This section studies the outcome achieved using RTT over LEACH-based routing method using network performance such as lifetime, communication overhead, and latency. The Fig. 7 shows lifetime performance when the node in entire network dies. The node size is varied between 300 and 2400. RTT improves lifetime by 80.43% on an average in comparison with LEACH-based routing method. Similarly, The Fig. 8 shows lifetime performance when loss of connectivity occurs in network. The node size is varied between 300 and 2400. RTT improves lifetime by 85.1% on an average in comparison with LEACH-based routing method.

The Fig. 9 shows communication overhead i.e., defining control channel overhead under varied node size varying between 300 and 2400. RTT reduces overhead by 34.32%% on an average in comparison with LEACH-based routing method. The Fig. 10 shows latency under varied node size varying between 300 and 2400. RTT reduces latency by 52.7% on an average in comparison with LEACH-based routing method.

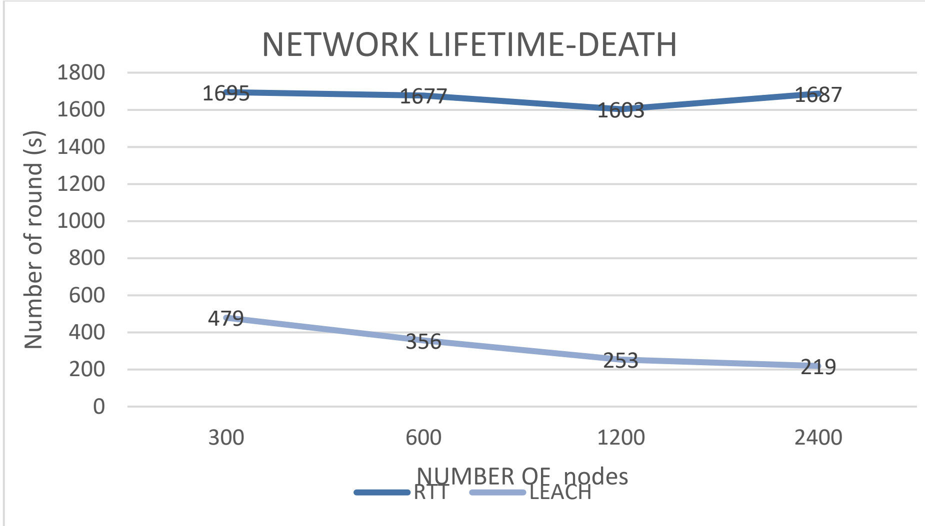

Fig. 7. Network lifetime-Death vs varied node size.

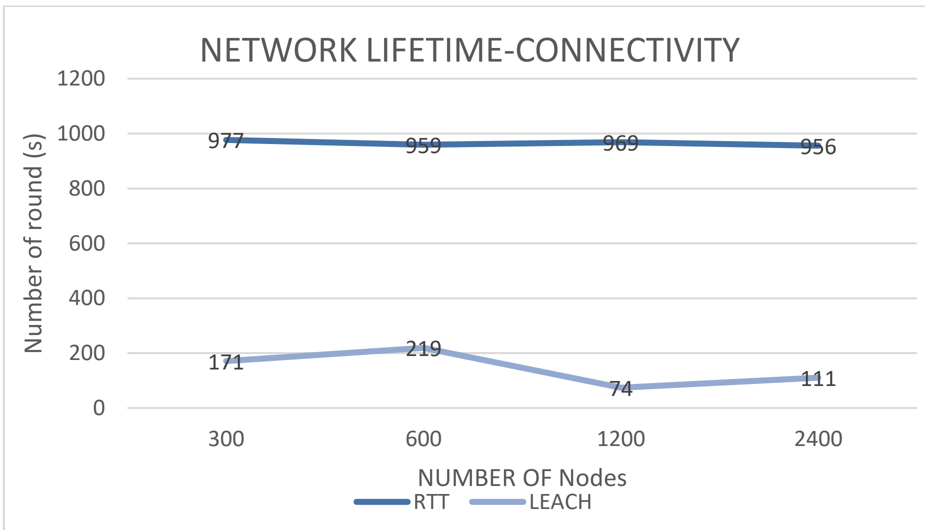

Fig. 8. Network lifetime-connectivity vs varied node size.

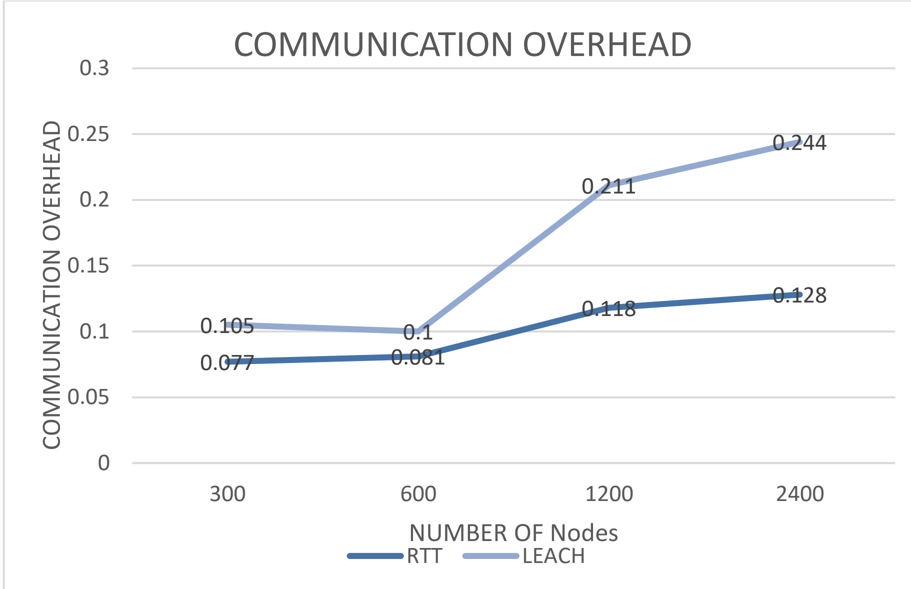

Fig. 9. Communication overhead varied node size.

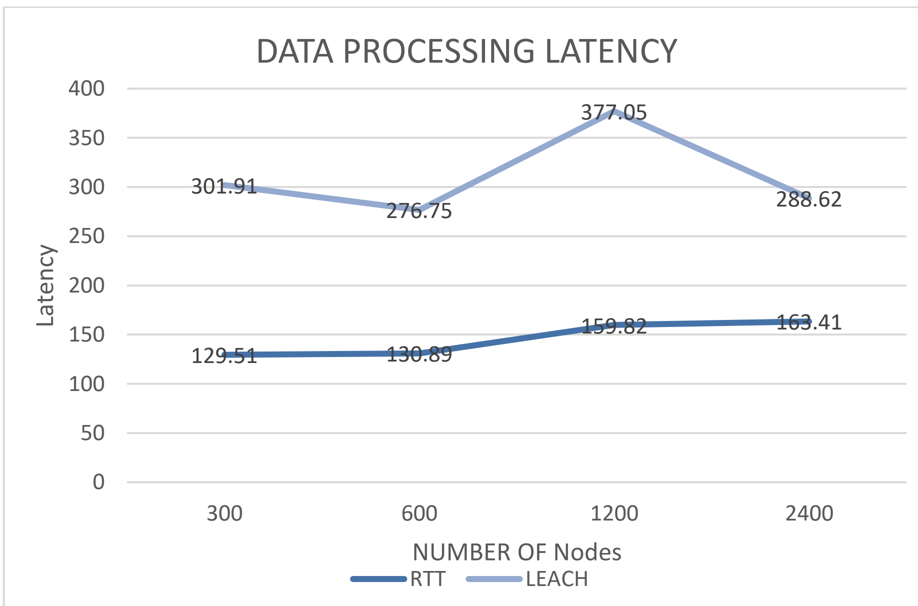

Fig. 10. Latency vs varied node size.

3.3 Comparative analysis:

The experiment is shown for RTT evaluation over state-of-art routing WSN practices. The table 2 shows the RTT evaluation results and different recent routing methodologies over LEACH by considering Total node death, respectively. The RTT model proves to have better lifetime performance with existing routing methodologies [20], [26], and [27] comparatively as shown in Table 2.

Table 2: Network lifetime comparative study

Algorithm	**Lifetime improved over $LEACH$**
Energy efficient dependable routing [10]	15.0%
Multipath data transmission [16]	66.35%
PFuzzyACO [17]	36.48%
Multi Sink Routing, 2020 [18]	60.25
RTT	**80.43%**

4. CONCLUSION AND FUTURE WORK

Minimization of sensor device energy is achieved for target tracking application using WSNs. The big data is the future application and WSN requires real-time data access with low latency. Current approaches will not be applicable for provisioning heterogeneous application that require less latency. Number of optimization technique adopting fuzzy and swarm optimization for transmitting data through multipath has been presented. However, these models don't consider dynamic varying nature of WSN environmental condition. Hence, resulting in higher number packet being lost. This work presented RTT model that enhances energy efficiency of WSN with computation overhead and less latency in comparison with state-of-art routing strategies. Future work would consider validating the routing performance of tracking applications considering different filters.

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