An Improved Energy-Efficient Prediction-based Model for Animal Tracking in Wireless Sensor Networks

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ABSTRACT
Most of the existing algorithms in Wireless Sensor Network (WSN) used to track the movement of animals consumes a lot of energy. These have led to discontinuation of tracking when the energy runs down. In this paper, an energy-efficient animal tracking model is proposed to improve the connection availability and duration of tracking by decreasing the energy consumption for sensing. An existing animal tracking model, which employed an energy-saving algorithm approach was selected. A simulation was carried to observe the energy consumption of the model using connection availability and connection duration as performance metrics. Then, an energy-efficient model was formulated by employing Prediction-based Variable Radius Sensor Activation algorithm (PRVARSA). A 15 minutes simulation was performed in a Wireless Sensor network consisting of 50, 100 and 200 sensor nodes randomly distributed in the network area. The performance of the formulated model was evaluated by benchmarking it with the existing model using the same metrics. The results showed that the average energy consumption of proposed and existing models are 3.93 J and 24.38 J respectively. It was observed that the proposed model consumed less energy for sensing and kept tracking the target after 13 minutes with an average energy consumption value below 20 J. Also, the proposed model provided higher connection availability of 115 compared to 0 for the existing model. The study concluded that the proposed model provides better energy-saving and thus extended the lifetime of the Wireless Sensor Network in a tracking system.

General Terms
Wireless Sensor Network

Keywords
Tracking, Energy efficient, Network lifetime, Prediction-based Algorithms

1. INTRODUCTION
One of the most rewarding applications of WSNs is target tracking which aims at locating one or several mobile objects and depicting their trajectories over time. A tracking sensor network is a sensor network which is used to track one or multiple moving objects within its visibility range. The target could be an animal, a vehicle, a robot or a person, which is moving under the coverage area of the network. The target tracking algorithm might track a malicious moving object while ignoring other objects in the tracking field. Among all applications of target tracking, wildlife monitoring has drawn tremendous attention in recent years to protect animals, which are endangered to extinctions or warn vehicles about an upcoming animal trespassing a roadway.

An animal, for example, Cattle are naturally free-ranging animals and are known to invade farmlands, and other environments, the results of such invasion has led to societal conflicts and damage to properties [1]. For example in Nigeria, the stealing of grazing cattle has increased in recent times. Cattle reared in free-range sometimes feed on farmlands thereby leading to a crisis between farmers and herdsmen. The development has given the herdsmen an excuse to carry dangerous weapons. As a result of this, many soldiers are deployed to watch cattle, herders and farmers instead of engaging them in more defense resourceful ventures [2].

The concept of animal tracking has been around for some time now. Classical cattle identification and tracking methods such as ear tags, branding, tattooing, and electrical methods have long been in use; however, their performance is limited due to their vulnerability to losses, duplications, fraud, and security challenges [3]. A fundamental challenge common to studies of animal movement, behavior, and ecology is the collection of high-quality datasets on spatial positions of animals as they change through space and time. Recent innovations in tracking technology have allowed researchers to collect large and highly accurate datasets on animal spatiotemporal position while vastly decreasing the time and cost of collecting such data [4].

With the emergence of more widespread use of location data within animal studies, reviewing and identifying appropriate methodologies for tracking led to the emergence of Wireless sensor networks (WSNs). WSNs as an emerging technology generated a large amount of scientific interest due to the possibility of obtaining more data of a physical phenomenon in real-time and are also considered as the backbone for the emerging Internet of Things (IoT). Research works on the use of wireless sensor nodes to monitor herd behaviour and social interactions and grazing patterns of cattle has been done by researchers [5-8] etc.

A WSN- based animal tracking system tracks a moving animal that is traversing a WSN with sensing capability of sensors. The locational and positional information of the moving animal is constantly studied in each time instance. Sensor networks are composed of a large number of sensor nodes that are densely deployed either inside the phenomenon or very close to it. These sensor nodes have sensing, processing and communicating capabilities. One of the most important tasks of these sensor nodes is a systematic collection of data and transmits gathered data to a distant Base Station (BS), hence network lifetime becomes an important parameter for an efficient design of data gathering schemes for sensor networks.

In the WSNs, power consumption is a very important issue in many mobile target-tracking applications because sensor nodes are usually operated on limited batteries. Accordingly, well-designed transmission power control algorithms are required to reduce energy consumption and improve the channel capacity. The limitation of energy resources is the most challenging issue in all applications of WSNs. In radio components, selecting the data rate is a compromise of energy efficiency and communication speed. Also, frequent use of radio components may deplete the energy of the sensor nodes. Sensor activation algorithms select which subset of sensor nodes to keep awake and for how long to improve the energy efficiency while the minimum requirement of the application is met. All the components of the sensor nodes even the processor can switch between sleep and active mode to save more energy. Sensor activation has drawn lots of attention in recent studies to maximize the efficient utilization of energy. The main aim of these approaches is to prolong the lifetime of the sensor network while fulfilling the requirements of the application. Thus, it was noted that energy saving is one of the main challenges in the design and implementation of animal tracking sensor networks. Also, limited process power and low memory size are factors which restrict protocol design of the networks.

Target tracking in WSN is more challenging because WSNs have issues such as limited battery power, unpredictable environments, high mobility of nodes as well as targets and failure of sensor nodes at runtime. Several works have been carried out to address these problems. According to [9-10], there exist three main approaches for target tracking in WSNs: tree-based, cluster-based and prediction-based algorithms. The prediction-based algorithm has proven to be better since it is built upon the tree-based and the cluster-based methods, with added prediction models. Prediction methods are used to predict the future position of the mobile object. Only sensor nodes located near this position are turned on to detect the target, while the other nodes remain in sleep mode to conserve energy. It was noted that prediction-based algorithm addressed the issue of energy efficiency object-tracking sensor network systems, however, it was found that energy efficiency and positional accuracy are often two contradictory goals [11]. By changing the sampling rate of location information, a WSN can trade higher energy consumption for better positional accuracy. Thus, there is a need for a prediction-based algorithm that will ensure a high target tracking accuracy while maintaining the energy consumption.

Therefore, in this paper, an attempt was made to enhance and increase the network lifetime and reduce the target-missing rate during the tracking period and to keep more sensors active. This was intending to enhance the energy saving of the tracking network maximally.

2. RELATED WORKS

The problem of sensing energy consumptions of the sensor nodes has been addressed in the literature by covering the AoI using active sensors and sending the other sensor nodes to sleep [12]. According to [12], algorithms for sensor activation are categorized into six groups: Naive Activation (NA), Periodic Activation (PA), Coverage Guarantee Activation (CGA), Randomized Activation (RA), PRediction-based Activation (PRA) and Periodic PRediction-based ctivation (PPRA). It was noted in the literatures [13-14] that Prediction-based algorithms that employed cluster activation mechanisms are the most promising algorithms proposed for sensor activation.

Prediction- based algorithms are mechanisms that predict next location of a target and with attention to estimated location, only select some nodes that are near to this location for tracking and other nodes remain in sleep mode for energy saving. Several kinds of research have been carried out using this approach. Prediction-based Energy Saving (PES) [15] addressed the energy consumption in Object tracking sensor networks, by minimizing both the sampling frequency and the number of nodes involved in object tracking, while balances off the overhead caused by missing the objects. Meanwhile, the moving patterns of the mobile objects were not considered in the study, thus having poor accuracy results.

Dual Prediction-based Reporting DPR [16] reduces the energy consumption of radio components by minimizing the number of long-distance transmissions between sensor nodes and the base station with reasonable overhead. The sensor nodes make intelligent decisions about whether or not to send updates of objects movement states to the base station and thus save energy.

Distributed Predicted Tracking DPT [17] is a protocol that uses a clustering-based approach for scalability and a prediction based tracking mechanism to provide a distributed and energy-efficient solution. The protocol is robust against node or prediction failures which may result in temporary loss of the target and recovers from such scenarios quickly and with very little additional energy use.

A prediction-based energy-efficient target tracking protocol (PET) [18] accurately predict the future location of the target, using the two-dimensional Gaussian distribution. PET scheme suffers from a high missing rate when the node's sensing range is small. A PRediction-based Activation (PRA) algorithm which is a prediction-based clustering algorithm for target tracking was presented by [19]. The PRA activates a cluster of sensor nodes in the predicted Area of Interest (AoI) in each tracking time interval. A sensor node is selected as the current Cluster Head (CH) and decides which sensor node to wake up for the next time slot as the CH. A cluster might include one or more sensor nodes. This approach consumes more energy, since, in each measurement period, sensor nodes transmit a large number of packets towards their cluster head.

In [20], a Clustering and Prediction-Based Protocol (CPBP) for Target Tracking in WSNs was also proposed. Also, the Base Station (BS) was exploited as a cluster formation manager and target movement predictor. The simulation results of the model represented the desirable performance of the presented protocol. An object tracking scheme based on prediction mechanisms was proposed in [21]. In this approach, the frequency at which the prediction mechanism is invoked depends on the object's movement. When the object moves at high speed, the prediction algorithm is called several times to estimate the target's position. The problem with this scheme is that it uses a very complex prediction algorithm that consumes larger energy.

These studies [19-21] proved that the prediction-based mechanisms that employed Cluster activation algorithms for target tracking in WSNs performed well compared to the conventional solutions. However, [22] stated that Cluster activation algorithms are not energy-efficient as they need to activate a number of nodes at each interval. In addition, these algorithms need to exchange information between the cluster head and cluster members, which is an overhead in communication energy consumption, thus still leaving energy consumption a critical constraint in wireless sensor networks (WSNs) for target tracking. It was also discovered in [22] that the consumed energy for sensing in a sensor node depends on the radius of the covered area by the sensor. Active sensing technologies provide the opportunity to adjust the sensing range of each sensor in real-time which can lead to deploy a more energy-efficient algorithm with better tracking quality.

Thus, a model called VAriable Radius Sensor Activation Scheme (VARSA) for target tracking using Wireless Sensor Networks was proposed in [22]. VARSA algorithm decrease the sensing energy consumption of tracking applications using WSNs by using a dynamic sensing radius adjustment. VARSA was compared to PRediction-based Activation (PRA) and Periodic PRediction-based Activation (PPRA) algorithms. It was noted that VARSA outperforms PRA and PPRA by prolonging the lifetime of the network and decreasing the missing rate of the target over time. However, In VARSA, only the source node decides the next node to wake up in which the current node can start an auction and asks all the candidates to communicate with each other and agree on one node to continue the tracking. This increases the communication energy consumption.

Meanwhile, in a target tracking WSN, the entire network nodes supposed to collaborate in sensing and the gathered data will be aggregated in a sink node, which uses the reported data to estimate the trajectory of one or several mobile targets. Also, sensors in most applications are expected to be remotely deployed in large numbers and to operate autonomously in unattended environments.

Thus, an attempt was made in this paper, to incorporate a real-time sensing radius adjustment approach into clustering activation-based mechanism to address these problems.

3. METHODOLOGY

In this study, an improvement was made on an existing energy-saving model called Prediction Based Activation (PRA) [19] in a Wireless Sensors Network. In [19] approach, two parameters were considered: distance from predictable location and energy of nodes, to select tracker sensor nodes. The existing algorithm in Figure 1 is divided into two main phases: clustering and tracking. In the clustering stage, CHs form their clusters by sending hello messages to the other nodes. In the second stage, the CH having detected the target in the network selects three nodes of its members to perform the sensing task. These sensors send their distance from the moving object. Based on these distances, the CH calculates the position of the target. Then, it predicts its next location and reselects and activates three sensor nodes in the next iteration before the target reaches that location. The selection is made based on the distance to the predicted location and the remaining energy of the node in the network.

The present cluster head decides which sensor to wake up for the next time slot as the cluster head. Each cluster consists of a set of one or more nodes. A cluster might include one or more sensor nodes. Size of the cluster is a trade-off of energy efficiency and localization accuracy. The minimum size of the cluster to satisfy a Mean Squared Error (MSE) for the target location can be estimated. MSE is the average of the squared errors on the estimated location of the target and its actual location.

```
Define:
  PL: Predicted Location
  CRL: Current Location
  PRL: Previous Location
  CCL: Calculated Current Location
  Thr: User-defined threshold
  Send (Transmitted Message, Receiver)
  Receive (Received Message, Transmitter)
  Predicted Next Location= Predict (Current Location, Previous
  Location, Δt)

Active-CH:
  PL= Predict (CRL, PRL, T)
  For each sensor node i
    If father[i] = Active-CH
      Selection[i] = RemainingEnergy[i] / DistanceFromPL[i]^2
    End If
  End For
  (s1, s2, s3) = Three sensor nodes with highest selection[i]
  Leader= Sensor node from (s1 & s2 & s3) with lowest distance from
  Active-CH
  (m1, m2)= Two other sensor nodes from (s1, s2, s3) except Leader
  Send (WakeupMsg, Leader & m1 & m2)
  PRL= CRL
  If receives LocationMsg(CCL) from leader
    CRL= CCL
  Else
    CRL= PL
  End If
  Send (LocationMsg(CRL), Sink)

Leader Node:
  Receive (DistanceMsg, m1 & m2)
  CCL= Localization (m1, m2, Leader)
  If (|CCL – PL| > Thr)
    Send (LocationMsg(CCL), Active-CH)
  End If
```

Figure 1: Pseudocode of the existing model

The cluster head or sink node is responsible for data fusion and transmitting the sensed data to the cluster head in the next predicted cluster. The factors to determine which node to activate in each tracking period is a function of the available energy in the sensor node, its initial energy and the number of times that the sensor had been scheduled for sensing and the transmission power is directly related to the distance.

3.1 Model Scenario

In this study, the target animal is cattle. Each animal was equipped with a sensor, which represents an animal. There are four groups of the animals with each group consisting of five animals. It was assumed that a subset of sensors nodes was activated in the Area of Interest (AOI) for enhancing the sensing energy consumption and still maintain the quality of tracking. The assumed N numbers of sensors, S1...SN, that is located on (xi, yi) coordinates in two-dimensional area of tracking. In this scenario, N was assumed to be 50, 100 and 200. The proposed model determines, which of the sensor Si is to be in communicating mode and sensing radius Ri over are given tracking period. It was also assumed that all sensors deployed has the same characteristic, i.e. same processing and battery, while the sink node is located at coordinate (0, 0) with unlimited energy. The sink node is responsible to collect information about the target and shows its route.

The proposed animal tracking system architecture is presented in Figure 2. The basic operation of the animal tracking system is that when a violation of the animal's safety is detected, a specific sensor in the animal module will produce a signal. This signal will be sent from these sensors and GPS to microcontroller then through the transmitter to the system module. The system module will take the decision and start the violation handling procedure. Mainly, the architecture consists of two modules:

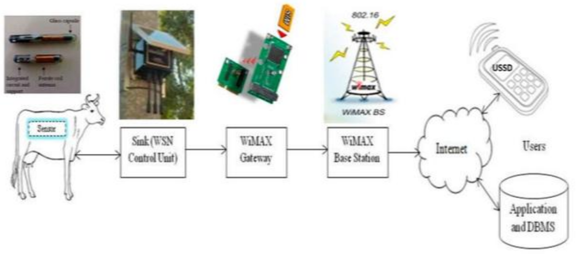

Fig 2: System architecture

(i) Animal Module: The animal module is attached to the animal. Its primary role is to periodically receive messages and in response send messages to the system module and alert the system if the animal is in danger. The animal module also has a buzzer alarm that sounds whenever the state of the animal is alarming. This allows a system to more easily locate the troubled animal.

(ii) The Sink Module: All the communication in WSNs take place between source and destination, the base station or sink is referred to as the destination in a WSN.

3.2 Model Description

In this study, the Random Walk Mobility Model [23] was adopted for the animal mobility model. So, the cattle movement parameters in the model were used in this study. Precisely, the model assumes that the animal performs the two activities i.e. waiting and moving with probability x_1 and $x_2 = 1 - x_1$ at a regular basis, where x_1 and x_2 are the priority of the activity drawn from a random distribution p(x). If the animal moves, it changes its context and therefore its likelihood to move or stay also changes [24].

The existing protocol requires that all the sensor nodes in a cluster transmit their distances from the target to the active CH to select three nodes that have maximum selection parameter values as tracker sensors that form Cluster Members (CMs). However, this is not energy efficient since the higher the number of messages transmitted or received by the nodes, the lower will be the network lifetime or connection duration.

The proposed model leveraged on the approach of PRediction-based Activation (PRA) [19] tracking system and offers an improvement to it by the introduction of:

(i.) Received Signal Strength Indicator (RSSI) module to the circuitry aspect of the existing system. The Received Signal Strength (RSS) is the average received signal power within a specified bandwidth. It is measured in decibel milliwatt (dBm), the range of RSS value is encoded using 3 bits; that is from 000 (minimum power) to 111 (maximum power) and the threshold was set as 010., RSS was calculated as:

$$RSS = \frac{\sum_{i=1}^{B} s_i}{B} \quad (1)$$

where s_i is the received symbol at instant i and B is the specified bandwidth.

(ii.) VAriable Radius Sensor Activation (VARSA) protocol [22] for sensing radius adjustment to the computation aspect of the existing system.

In this study, by employing the RSSI constraint, all the nodes within the Area of Interest (AoI), i.e. where the target is located, do not have to transmit their distances to the CH because only the nodes whose RSS values are equal to or greater than the threshold should transmit their distances. This implies that nodes below the threshold would not waste energy, as they would be set to sleep mode, which invariably makes the entire network more energy efficient.

3.3 Formulation of Energy-Efficient Model

The computational aspect of the proposed system model is referred to as PRediction-based Variable Radius Sensor Activation (PRVARSA). The PRVARSA involves the addition of the variable sensor coverage radius to the existing PRediction-based Activation (PRA) tracking model. The energy consumed for transmitting K-bit of a message by a sensor is given as:

$$E_T(K,r) = (E_{TE} \times K) + (E_{amp} * K * R^2) \quad (2)$$

where K is the number of bits in a message, R is the radius of coverage of the sensor, ETE is the energy needed for modulating one bit of message and $Eamp$ is the energy needed by the amplifier module to transmit one bit to an area of radius R.

From Equation (2), it can be seen that the energy required by a sensor node to transmit message is a function of the square of the radius of the area of coverage. This implies that reducing the radius of coverage of each active node where necessary would invariably reduce the rate of energy consumption in the network.

The existing PRA model assumes the radius R of coverage of the sensor is fixed but the proposed model intentionally varies R for energy-saving purpose and Equation 2 is modified as:

$$E_T(K,r) = (E_{TE} \times K) + (E_{amp} * K * \delta^2) \quad (3)$$

Such that: if the radius of coverage should be decreased

$$\delta = \frac{R_{curr}}{z} \quad (4)$$

and, if the radius of coverage should be increased

$$\delta = R_{curr} + \left(\frac{R_{max} - R_{curr}}{z}\right) \quad (5)$$

where $Rcurr$ is the current radius of coverage of sensor, $Rmax$ is the maximum allowable radius of coverage of sensor, and z is the factor for reducing the radius of coverage.

In a cluster, each active node, i.e. a Cluster Member (CM), which has located the target, would reduce its radius of coverage to the lowest possible value that can keep track of the animal (i.e. target). If the target is immobile for a time interval, the CMs can be sent to sleep after the target has been located. The next location of the target after a given time can be predicted after a given time t using the current and previous locations as:

$$x_{i+1} = x_i + vtcos\theta \quad \text{and}$$

$$y_{i+1} = x_i + vtcos\theta$$

Where

$$v = \frac{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}}{t_i - t_{i-1}}$$

$$\theta = cos^{-1}\left(\frac{x_i - x_{i-1}}{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}}\right) \qquad (6)$$

Where v is the target speed; θ is the direction of motion of the target, $(x_i,)$ is the coordinate of the target. After calculation (x_i+1, y_i+1), if this location is placed in the current cluster, active CH select three sensor nodes for target tracking in the next tracking period, using the selection algorithm, and release a wake up massage, however, if the next location of the target is out of the coverage area or outside the Area of Interest, then the active CH selects another CH that is nearest to that location as the current CH, the pseudocode for prediction of animal location is shown in Figure 3.

Therefore, the proposed algorithm achieves an improved energy saving capability with the use of a threshold value, as against the two parameters, distance and energy, used by the existing prediction-based methods to determine which sensors to send to sleep or wake-up mode and also by reducing or increasing the radius of coverage of a sensor when necessary. These approaches help to prolong the battery life of the sensors and invariably improve the connection availability and duration of tracking.

```
BEGIN

Set initial parameter values

x(1) is x-coordinate
y(1) y-coordinate
v(1) is the target speed
theta(1) is direction of motion of target
t(1) is initial time

i = 2;

WHILE i < Last_count

v = squarroot{(x(i)-x(i-1))^2 + (y(i)-y(i-1))^2}/t(i)-t(i-1)

theta = arccos{(x(i)-x(i-1))/((x(i)-x(i-1))^2 + (y(i)-y(i-1))^2)}

x(i+1) = x(i) + v*t(i)*cos(theta)

x(i+1) = x(i) + v*t(i)*sin(theta)

NEXT i

END
```

Fig 3: Pseudocode for prediction of target location

3.4 Model simulation

The existing PRA [19] and the proposed PRVARSA models were simulated in the MATLAB 2015 environment as shown in Figures 4 and 5 respectively. The models were simulated in a WSN consisting of a set of 50, 100 and 200 sensor nodes i.e. blue dots randomly deployed in an area of 200m×200m. The typical value for assumed sensor type MICA2DOT (MPR 500) [25]. There are 4 groups of animals that could move around within the network area with each group consisting of 5 animals represented by the diamond shape marker. The input simulation tracking parameters with the respective specified value(s) used for the system simulation are presented in Table 1. The WSN deployed in a homogeneous network in which all sensors nodes have the same characteristic in terms of battery power, processing and communication capability at the time of deployment. It was assumed that the sensors know their location using the integrated GPS module, hence can calculate the location of the target within the network area, and consequently transmit

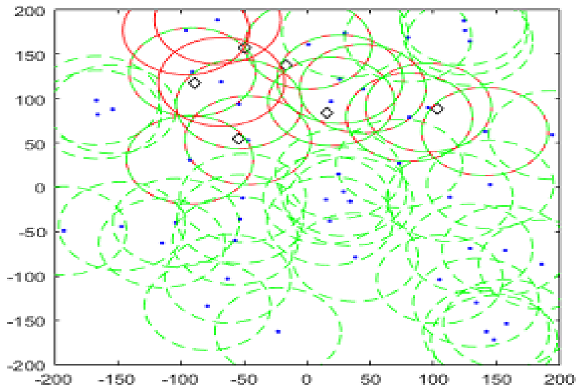

Fig 4: PRediction –based Activation (PRA) tracking system

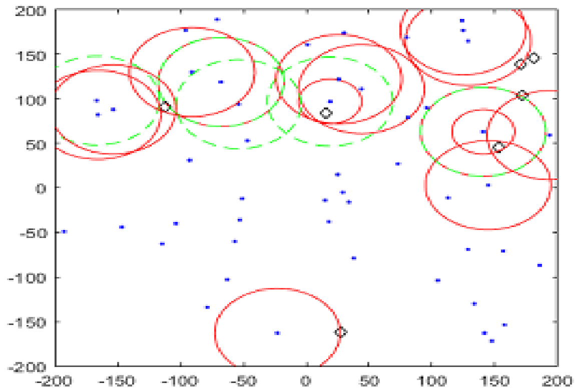

Fig 5: PRediction-based Variable Radius Sensor Activation (PRVARSA) system

Table 1. Simulation input parameters

Input Parameter	Value	Justification for choice of value
Network Area	200m by 200m	Typical value for assumed sensor type MICA2DOT MPR 500) [25]
Initial sensor energy (Joule)	0.1J	Typical value by was used by [19]
Energy to transmit 1 bit	50nJ	Typical value by was used by [19]
Energy to modulate 1 bit	10nJ	Typical value by was used by [19]
Number of bits per data symbol	3bits	Protocol standard for encoding message/control symbol. [25]
Tracking interval (seconds)	20s	Based on parameter tuning experiment by [20]
Report Interval	5s	Based on parameter tuning experiment by [20]
Maximum sensing radius (meters)	50m	A typical value by to overcome pathloss effect. [19-20]
Sensing radius scaling ratio	2m	Based on parameter tuning experiment [19]
Received signal strength indicator, RSSI, threshold (decibels)	60dB	Corresponds to the maximum sensing distance
Target/object speed (meters/second)	1.5m/s	Chosen to be in line with tracking interval [24]
Target/object pause time	10s	Assumed based on animal behaviour i.e. cattle [24]
Number of sensor nodes	50,100, 200	Suitable for sparse environment according to [19]

the target location to a control server or station. Also, each sensor is aware of their neighbor sensor nodes, communicate with each other within 50meters and also produces a signal in respect of the animal in its area of coverage.

The coverage area is a circular area with a radius, Rs covering with the sensor node. An assumption was made that the sensor is an ideal one that produces a positive output when the animal is closer than Rs to the sensor node and negative output when otherwise. The Radius of coverage of each sensor is adjustable in the PRVARSA and fixed in PRA. In this modeling, the sink node has unlimited energy resources and all messages from nodes are sent to the sink and its location is at coordinate (0,0).

Sensors can only be in one of these three states, active, communication active and sleep mode. In an active mode, both the sensing and communication modules of the sensor are active and can track and locate the animal or target in its coverage area and send a message of the target location to the sink node or base station. The communication active nodes send messages to the sink while their sensing module is not active. Lastly, sleep nodes are not active but listen to their low power radio receiver, and it can be awake by a low beacon message by other nodes within the same coverage area. In the Figures 4 and 5, a sensor node that has the dashed green circle around it is switched on or would come on but not sensing/tracking, a sensor node that has the continuous red circle around it is awake and sensing/tracking while a sensor node without any circle around it is in Sleep (or OFF) state.

In the PRA model, the control station activates a cluster of sensor nodes, called Cluster Members (CMs), in the predicted Area of Interest (AoI) in each tracking time interval. A cluster might include one or more sensor nodes as shown in Figure 4. A sensor node is selected as the current Cluster Head (CH) and decides which sensor node to wake up for the next time slot as the CH using the predicted next location of the target. As shown in the Figure 4, all the CMs are to transmit their distances from the target to the CH for selection of some of the CMs as the tracker sensor node(s) based on calculated selection parameter, whereas in Figure 5, the PRVARSA model only allows the CMs with RSSI values equal to or greater than a specified threshold to transmit to the CH for selection. The RSSI is a function of the distance between a sensor node and the target. The shorter the distance between the sensor and the target, the larger will be the RSSI value. It was also observed that in Figure 5 all the nodes that are far away from the target's location are made to remain in sleep mode to prevent energy wastage; while all the nodes in Figure 4 are on and this leads to energy wastage.

Figure 6 presents the simulation of the tracking of the target's location at different times in the simulation of 200-nodes WSN using the proposed PRVARSA system. At the start of the simulation, it was observed that 2 out of the 3 nodes selected to track the target in its initial location reduced their radii of coverage by half and the target still falls within their sensing area. Because the sensor's energy consumption is directly proportional to the square of the radius of coverage, there would be a considerable reduction in the amount of energy the sensors would use for sensing. When the target moves to another location, all the 3 CMs selected reduced their radii of coverage by half and still keep track of the target. At every location of the target, there is a radius of coverage reduction by 1 or more CMs selected to track.

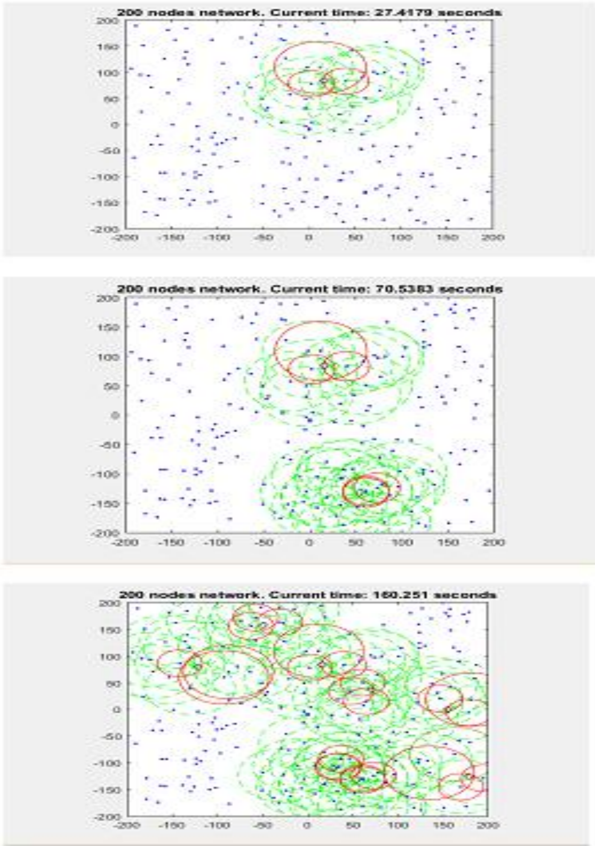

Fig 6: Target tracking by the PRVARSA System

4. RESULTS AND DISCUSSIONS

The detailed results are presented as follows:

4.1 Simulation Results

Both models were run in 20 iterations simulation of 50 and 100 sensor nodes WSN in 1 minute, 9-minutes and 15-minutes of the simulation time using the connection availability, average energy consumed and total energy consumption respectively The details of the results obtained are the average of 20 iterations to provide 95% of a confidence interval. The results of the 50 and 100 sensor nodes In 1 minute are shown in Tables 2 and 3. In general, the results obtained revealed that the proposed PRVARSA tracking system provides energy efficiency for the WSN compared to the conventional PRA.

4.2 Evaluation Results

The performance of the formulated model was evaluated by benchmarking it with the existing model. Each of PRVARSA and PRA models was simulated in a WSN network consisting of 50 sensor nodes randomly distributed in the network area. The algorithms were evaluated by tracking a single target with cattle movement behaviours. The target is made to move from its current location to another after 20 seconds while the nodes around the target are to keep track of it and to report its position to the cluster head. The number of nodes was also increased and the effects were observed. The details are as follows:

Table 2. 1-Minute of simulation of 50 nodes in 20 iterations

Sample No	Connection Availability (s)	Average Energy Consumed (kJ)	Total Energy Consumed (kJ)
1	42	83.6236	4.1812
2	42	92.6799	4.634
3	42	93.4971	4.6749
4	42	93.1856	4.6593
5	42	92.8246	4.6412
6	42	94.8623	4.7431
7	42	94.0763	4.7038
8	42	93.6755	4.6838
9	42	94.7548	4.7377
10	42	94.0189	4.7009
11	42	90.3724	4.5186
12	42	88.6548	4.4327
13	42	89.8357	4.4918
14	42	92.2044	4.6102
15	42	89.7253	4.4863
16	42	90.8598	4.543
17	42	89.4746	4.4737
18	42	92.1412	4.6071
19	42	90.0814	4.5041
20	42	89.3902	4.4695
Confidence Level	**94%**	**95%**	**96%**
Z Value	**1.88**	**1.96**	**2.05**
No of Sample	**20**		
Mean	**42**	**91.4969**	**4.5748**
Standard Deviation	**0**	**0.0406**	**0.1317**
Confidence Level (CL)		**95%**	
Z value for 95% CL		**1.9600**	
Confidence		**9.4229**	**471.1026**
CI Approximation		**9.4200**	**471.1030**
		low limit	**upper limit**

Table 3. 1-Minute of simulation of 100 nodes in 20 iterations

Sample No	Connection Availability (s)	Average Energy Consumed (kJ)	Total Energy Consumed (kJ)
1	85	6.3593	635.93
2	85	6.3472	634.72
3	85	6.3484	634.84
4	85	5.8315	583.15
5	85	6.346	634.6
6	85	6.3723	637.23
7	85	6.3853	638.53
8	85	6.391	639.1
9	85	6.3935	639.35
10	85	6.3824	638.24
11	85	6.3898	638.98
12	85	6.4042	640.42
13	85	6.3918	639.18
14	85	6.4064	640.64
15	85	6.4089	640.89
16	85	6.4088	640.88
17	85	6.395	639.5
18	85	6.4031	640.31
19	85	6.4079	640.79
20	85	6.3932	639.32
Confidence Level	**94%**	**95%**	**96%**
Z Value	**1.88**	**1.96**	**2.05**
No of Sample	**20**		
Mean	**85**	**6.3583**	**635.8300**
Standard Deviation	**0**	**0.1226**	**12.2553**
Confidence Level (CL)		**95%**	
Z value for 95% CL		**1.96**	
Confidence		**6.3046**	**630.2123**
CI Approximation		**6.3000**	**630.2000**
		low limit	**upper limit**

4.2.1 Network Connectivity

Performance of PRVARSA and PRA models in terms of network connectivity was evaluated using Connection Availability and Connection Duration as metrics. Connection Availability (measured in "number of nodes") refers to the number of sensor nodes that are still alive, having battery power, after a period of tracking. The nodes that have exhausted their battery power are termed dead nodes. Connection Duration, which is also referred to as Network Lifetime (measured in seconds), is taking in this study as the time in which 50% of the sensor nodes died.

The Connection Availability performances of PRVARSA and PRA for a period 1 to 15 minutes are presented in Figure 7. Taking 5 minutes as a reference, the number of nodes that are still alive or available for tracking in PRVARSA and PRA are 49 nodes and 19 nodes respectively. This reveals that for the same tracking period, the PRVARSA tracking system provides better connection availability because more nodes remained available for tracking when compared to that of PRA. Also, it could be observed that with the PRA system, all the 50 sensor nodes were dead after 9 minutes of tracking period while the PRVARSA lost only 2 nodes. This is because the PRVARSA conserves energy by making a node to sense or transmit only when necessary while PRA allows all the nodes to participate in transmitting or sensing.

Also, the Connection Duration performances of PRVARSA and PRA for a period 1 to 15 minutes are presented in Figure 8. In 5 minutes of tracking, the PRVARSA system gives 282 seconds while the PRA gives 143 seconds. This implies that PRVARSA can operate longer than PRA because the battery power utilization of the sensor nodes in the PRVARSA tracking system is minimized.

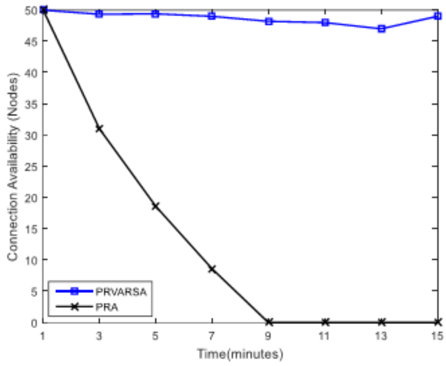

Fig 7: Connection availability of the network

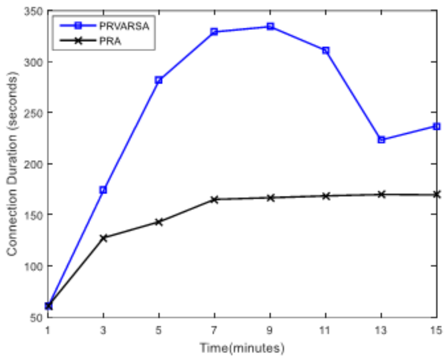

Fig 8: Connection duration of the network

4.2.2 Energy Efficiency

In terms of energy efficiency, performances of PRVARSA and PRA models were evaluated using Average Energy Consumption and Total Energy as metrics. Average Energy Consumption (measured in Joules) is the amount of energy utilized on the average by each node throughout the tracking period. The evaluation result is shown in Figure 9. Taking 5 minutes as a reference, the Average Energy Consumption for PRVARSA and PRA are 3.93 J and 24.38 J, respectively. It is observed that PRVARSA consumes less energy for sensing compared to the PRA and it keeps tracking the target after 13 minutes with average energy consumption value still below 20 J. This implies that the PRVARSA tracking system is more energy-efficient than the PRA.

Total Energy Consumption (measured in Joules) is the overall energy consumption of the network as shown in Figure 10.

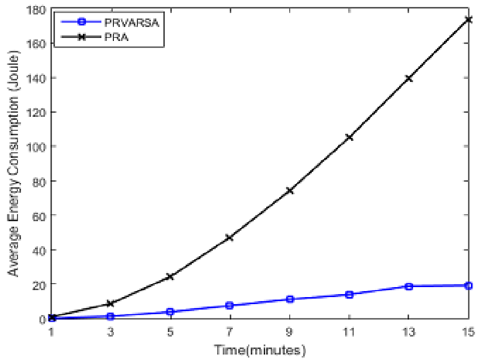

Fig 9: Average energy consumption of the sensor nodes

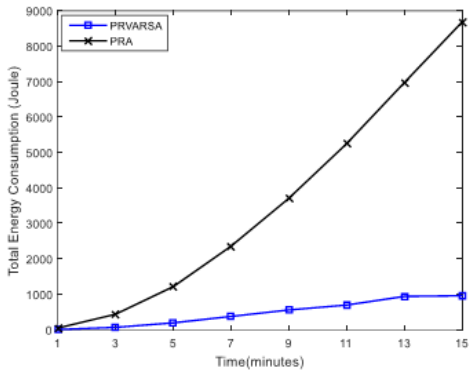

Fig 10: Total energy consumption of the network

Taking 5 minutes as reference, PRVARSA's total energy consumption is 196.72 J while PRA's total energy consumption is 1218.90 J.

If the total energy consumable in the network is 5000 J, then all the sensor nodes are dead after 9 minutes of network operation and there is no more residual energy to be used for tracking in the PRA. However, PRVARSA keeps tracking with total network energy consumption below 1000 J to 15 minutes of the tracking period. It is observed that PRA's energy consumption increases exponentially with time thereby making all sensor nodes to die quickly than necessary while the PRVARSA keeps operating over a longer period. This implies that the PRVARSA tracking system is more energy-efficient than the PRA. Details of results obtained from the simulation of 50-nodes WSN using the PRVARSA and PRA tracking systems are available in Tables 4 and 5 respectively.

4.2.3 Effects of Number of Sensor Nodes on the performance of PRVARSA and PRA

The effects of the number of sensor nodes deployed in the WSN area were also investigated for PRVARSA and PRA tracking systems in terms of Connection Availability (Nodes), Connection Duration (seconds), Average Energy Consumption (J), Total Energy Consumption (J). The results for 50, 100 and 200 sensor nodes in turn for 15 minutes of tracking period were obtained and comparisons are made between PRVARSA and PRA. Figure 11 shows the effect of the number of sensor nodes on connection availability. It is observed that PRVARSA provides much higher connection availability compared to PRA, and the average connection availability for PRVARSA and PRA are 115 and 0 respectively. This implies that in PRA, all the nodes were already dead during 15 minutes of target tracking.

Table 4: Results of PRVARSA in the simulation of 50-nodes WSN

Time (minutes)	Connection Availability (Nodes)	Connection Duration (seconds)	Average Energy Consumption (J)	Total Energy Consumption (J)
1	50	61	0.15	7.65
3	49	174	1.37	68.49
5	49	282	3.93	196.72
7	49	329	7.56	377.91
9	48	334	11.20	560.14
11	48	311	13.96	697.78
13	47	223	18.84	941.91
15	49	237	19.21	960.57

Table 5: Results of PRA in the simulation of 50-nodes WSN

Time (minutes)	Connection Availability (Nodes)	Connection Duration (seconds)	Average Energy Consumption (J)	Total Energy Consumption (J)
1	50	61	1.00	50.20
3	31	128	8.78	439.20
5	19	143	24.38	1218.90
7	9	165	47.21	2360.30
9	0	167	74.20	3710.20
11	0	169	104.99	5249.70
13	0	170	139.45	6972.50
15	0	170	173.63	8681.50

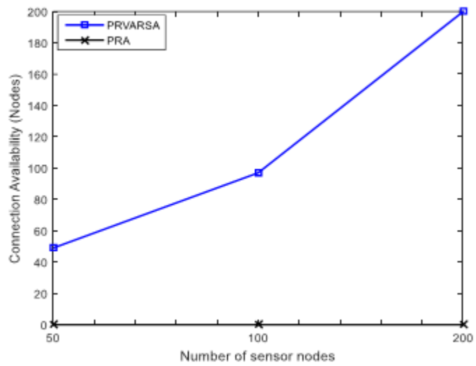

Fig 11: Effect of number of sensor nodes on connection availability

Also, connection availability increases with an increase in the number of deployed sensor nodes. The effect of the number of sensor nodes on connection duration is presented in Figure 12. It is observed that PRVARSA provides relatively higher connection duration, with an average of 603.33 seconds, compared to PRA with an average of 268.33 seconds. This also reveals that PRVARSA operates longer than PRA due to its better energy utilization capability. Figure 13 shows the effect of the number of sensor nodes on average energy consumption. It is observed that sensor nodes in PRVARSA system consume much lower energy on the average as against the PRA, and the average value obtained from 50, 100 and 200 nodes for PRVARSA and PRA are 14.07 J and 128.51 J, respectively. It is also observed from the results that average energy consumption by each sensor node decreases with the increasing number of sensor nodes deployed in the same WSN area size. The effect of the number of sensor nodes on total energy consumption is presented in Figure 14. It is observed that PRA gives tremendously higher total energy consumption, with an average of 12856.00J, compared to PRVARSA with an average of 1426.30J. It was observed that the total energy consumption increases with an increasing number of sensor nodes. This was due to the additional sensors and this implies

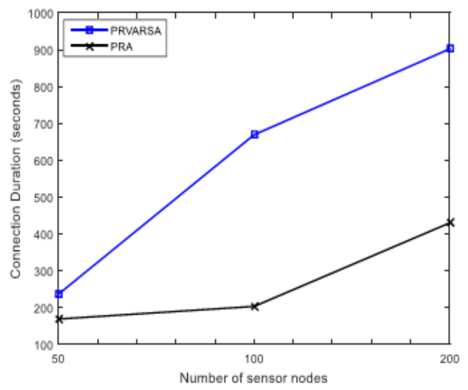

Fig 12: Effect of number of sensor nodes on connection duration

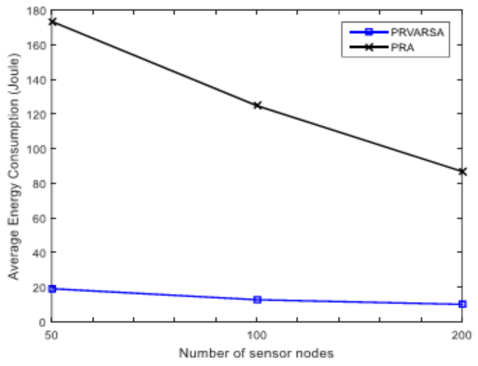

Fig 13: Effect of number of sensor nodes on average energy consumption

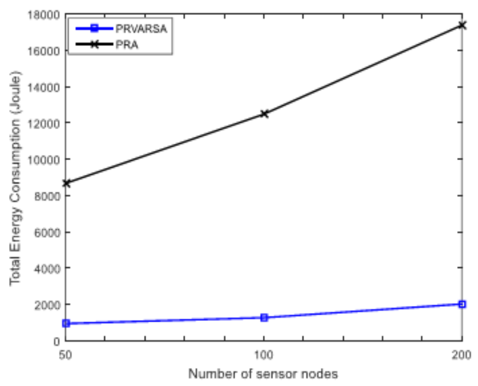

Fig 14: Effect of number of sensor nodes on total energy consumption

more network overhead but with the advantage of reduced probability of missing the target location at every tracking interval.

Details of results obtained from the simulation of 50, 100 and 200 sensor nodes WSN in 15 minutes using the PRVARSA and PRA tracking systems are available in Tables 6 and 7, respectively. Generally, the results obtained reveal that the proposed PRVARSA tracking system provides energy efficiency for the WSN compared to the conventional PRA.

5. CONCLUSION

One of the main limitations of the existing WSNs in animal tracking is limited power. Therefore, saving energy and

Table 6: Results of PRVARSA for 15 minutes of network simulation

Number of Sensor Nodes	Connection Availability (Nodes)	Connection Duration (seconds)	Average Energy Consumption (J)	Total Energy Consumption (J)
50	49	237	19.21	960.57
100	97	670	12.83	1283.40
200	200	903	10.18	2035.00

Table 7: Results of PRA for 15 minutes of network simulation

Number of Sensor Nodes	Connection Availability (Nodes)	Connection Duration (seconds)	Average Energy Consumption (J)	Total Energy Consumption (J)
50	0	170	173.63	8681.50
100	0	204	124.94	12494.00
200	0	431	86.96	17392.00

increasing network lifetime has always been a crucial issue under research. In this paper, the proposed model for energy-saving energy for animal tracking system using WSNs was analyzed and compared with the existing PRA system. The system employed the use of Prediction-based Variable Radius Sensor Activation object tracking algorithm (PRVARSA). Both PRVARSA and PRA models were simulated in a WSN network consisting of 50, 100 and 200 sensor nodes randomly distributed in the network area. The target is made to move from its current location to another after 20 seconds while the nodes around the target are to keep track of it and to report its position to the cluster head. Performance comparison between the PRVARSA and PRA models in terms of network connectivity are made using two major metrics namely; Connection Availability (measured in "number of nodes") and Connection Duration (measured in "seconds"). Connection Availability refers to the number of sensor nodes that are still alive, having battery power, after a period of tracking. The nodes that have exhausted their battery power are termed dead nodes. Connection Duration, which is also referred to as Network Lifetime, is taking in this study as the time in which 50% of the sensor nodes died. In general, the results obtained reveal that the proposed tracking system provides energy efficiency for the WSN compared to the conventional PRA. Thus, adoption of this technology by commercial and Government institution is expected to improve security, reduce societal conflicts and reduce stealing of grazing animal.

6. FUTURE WORKS

In near future, it is envisaged considering the coordination of multiple mobile sinks for data collection in WSN. This strategy will certainly decrease both the energy consumption at sensors and the data latency by reducing the average distance between nodes and the closest base station. Also, another interesting area is multi-hop wireless charging scheme, future directions should include the case when a transmitter can transfer energy to multiple receivers at a time.

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