Leveraging BLE and LoRa in IoT Network for Wildlife Monitoring System (WMS)

Eyuel D. Ayele[1], Kallol Das[2], Nirvana Meratnia[1], Paul J.M. Havinga[1]
[1]Pervasive Systems Research Group
[2]Centre for Telematics and Information Technology (CTIT)
University of Twente, Enschede, the Netherlands
Email: {e.d.ayele, k.das, n.meratnia, p.j.m.havinga}@utwente.nl

***Abstract*—In this paper we propose a new dual radio IoT network architecture for wildlife monitoring system (WMS). WMS leverages bluetooth low energy (BLE) in low power wide area networks (LPWANs) by dynamically changing the operating radio based on the proximity among herd of wild animals. This approach will facilitate ultra-low power IoT devices to be deployed for sustainable wildlife monitoring application. In addition we present an analytical model to investigate the performance of the proposed IoT network in terms of energy consumption under a wildlife monitoring use-case. The simulation results show that the dual radio network leads to a higher energy efficiency when compared to the network utilizing only LPWAN. Moreover, our network readily doubles the network life time for various data traffic rates.**

***Keywords*—LPWAN, LoRa, internet of things (IoT), Bluetooth low energy (BLE), energy consumption modeling, wild life monitoring.**

I. Introduction

During the last few years, the advances in low power wireless network technologies have attracted many new application domains to utilize the potential of the internet of things (IoT). Wildlife monitoring is one of such trending IoT applications where a number of heterogeneous sensors (e.g. accelerometer and gyroscope, etc) are deployed either as collars or buried in the ground, to monitor the activities of wild animals dwelling in a remote and geographically large habitat [1]. While wild animals usually form a compact herds of con-species with short inter-herd proximity during their regular activities (e.g. grazing), they often show a level of movement which could change the spatial proximity in case of distressing situations (e.g. pursuing a prey or running from danger such as illegal hunters or poachers). Therefore, wildlife monitoring systems (WMS) need to detect the type of herd activities in real time (e.g. grazing, running, etc.) as well as provide network services such as localization, proximity detection, data pre-processing, and cluster nodes management. To these ends, it is required to achieve (i) high energy efficiency, since the sensors used in a WMS will operate with a limited source of energy, (ii) good reliability to avoid false alarms, and (iii) low latency for a responsive WMS design.

Given the characteristics of wild animals and the target application requirements, numerous wireless technologies could be potential candidates for WMS. While major IoT applications, such as smart city [2], industrial monitoring [3], mostly rely either on short range wireless technologies such as Bluetooth [4], WiFi, or on long range wireless technologies such as cellular to communicate among network devices, WMS imposes a mixed set of requirements. In the past, radar, GPS and satellite based systems have been deployed to track and monitor wild lives [5]. However, the inherently high cost and intolerable communication latency made these approaches less attractive. Some efforts have also been made to develop wireless sensor network (WSN) based WMS, where short range wireless technologies (e.g., ZigBee) are utilized by forming multi-hop mesh networks [6, 7]. Most of these systems are developed on top of IEEE802.15.4 standard [8], which often suffers from huge overheads due to the complex implementation and scales poorly [9, 10]. More recently, the energy efficient version of Bluetooth known as *Bluetooth Low Energy (BLE)* or *Bluetooth Smart*, has surfaced as an appealing alternative due to its higher data rate (upto 1Mbps), lower latency (typically 6ms), better energy efficiency and wider coverage over IEEE802.15.4 based solutions [4]. While making some progress in energy efficiency aspect, short range wireless technologies are still not suitable for wide and sparse monitoring applications. Although this aspect can be addressed by using long rage wireless technologies (e.g., cellular), they are often considered power hungry. In addition, remote areas where wild animals dwell are often out of cellular coverage.

Fortunately, emerging low power wide area network (LPWAN) technologies such as LoRa, Sigfox, etc. promise to provide better coverage with a low energy consumption that seem to support many requirements of remote wild life monitoring application [2, 11]. Among LPWAN technologies, LoRa is believed to have high potential for realization of LPWAN IoT goals. LoRa is utilized for low data rate, low power, and long range IoT applications. LPWANs in general are fundamentally designed to ensure very long battery lifetime and provide seamless interoperability among end-devices without the need for complex local installations. However, IoT applications requiring high data rate and low latency are not particularly the strength of LPWANs mainly due to the generic low bit-rate, stricter duty-cycle restrictions and the larger packet header associated with it. Thus to realize the WMS design requirements, a mechanism to control the trade-off between energy versus data rate is necessary, which is not practically achievable by using a single category of wireless technology alone. Although a few works have been conducted to address this issue by proposing an architecture for WMS [12], to the best of the authors' knowledge, none of these works include the LPWAN technologies in their approach.

Therefore, in this paper we propose a new dual radio based IoT network for WMS that exploits the LPWAN and short range wireless technology by switching the operating radio based on proximity measures for optimal performance. The results and analysis presented in this paper are modeled by considering LoRa as an LPWAN technology and BLE as a short range wireless technology. WMS optimizes the system bandwidth and energy requirement through local data pre-processing and concatenation that merges multiple BLE packets under a single larger LoRa header. However, the design approach can also be applied when using other LPWAN and short range wireless technologies. The main contributions of this work are listed below.

- A new dual radio based IoT network architecture for wildlife monitoring is proposed.
- A theoretical analysis is introduced to evaluate the network energy consumption of BLE and LoRa radios.
- Design guidelines for WMS are presented based on LPWAN and short range wireless technology.

The rest of the paper is organized as follows: Section II presents the proposed network architecture and details the constraints for a WMS design. Section III further describes the energy consumption modelling. Section IV discusses the use case scenario and presents the evaluation results. Finally, Section V outlines the concluding remarks and future research challenges.

II. Proposed WMS Model

In this section, we present the dual radio network model for WMS. Next, we present the design constraints as well as the analytical model for critical range.

A. Dual Radio Network Architecture

The proposed dual radio network architecture is shown in Figure 1 in layered hierarchical layout. The bottom layer consists of a network of clustered wireless sensor nodes among collared animals. The collars include inbuilt sensors coupled with BLE and LoRa radio platform. For details on LoRa and BLE technology, the readers are referred to [2, 4, 11]; in this paper we mainly focus on its utilization to WMS. Within a herd or cluster of animals, the end-devices use short range BLE, to communicate with each other and long range LoRa radio to link to the gateway. The inter-cluster cooperation among the sensor networks allows run-time monitoring of events in the area while reducing false alarms. The cluster-head (C) coordinates communication and concatenates the data to be forwarded to the central system via LoRa gateway (LG), which reduces the total overhead associated with each LoRa transmission. Since the range among animals changes depending on the living activity, the WMS adapts to changes

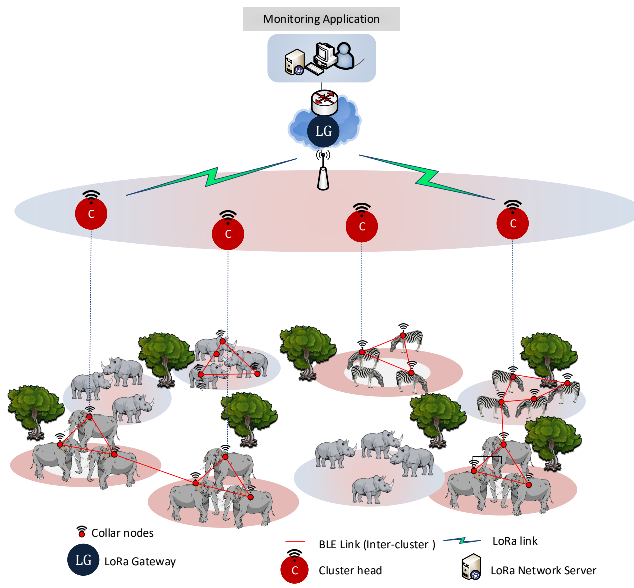

Fig. 1: Proposed dual radio based network architecture for animal monitoring application.

by configuring its network topology based on the proximity information among animals. LoRa gateway (LG) serves as the main component by relaying data to the central server. Gateway backbone network is based on LoRa [11], which is particularly suitable due to its long range communication provision at much lower power compared to the other existing IoT protocols [11]. LoRa network server runs the operation and management application, and run-time event monitoring and mapping will be provided in this layer.

B. Design Constraints

Generally when a signal is transmitted through a wireless channel several factors will influence its propagation range; in this section, we present the calculation of the critical range-d_c beyond which there is no connectivity between two nodes. It is expressed by Equation 1 for both BLE and LoRa radios, by considering parameters such as: (i) transmitter power level (P_t), (ii) minimum receiver sensitivity ($P_{r_{min}}$) and (iii) outage probability under path-loss (K) and shadowing ($\sigma_{\psi_{dB}}$).

$$d_c = \begin{cases} 10^{\frac{P_t - P_{r_{min}} + \sigma_{\psi_{dB}} \times C_{inv} - K}{D}} & \textit{for LoRa} \\ 10^{\frac{P_t - P_{r_{min}} + \sigma_{\psi_{dB}} \times C_{inv} - K}{10 \times \gamma}} & \textit{for BLE} \end{cases} \tag{1}$$

The path-loss (K) is determined by empirical models such as Hata Cost-231 and simplified path-loss model. Hata Cost-231 is used for LoRa radio, since it is suitable for path loss estimation with large and open rural cell (0 to 20 km), and lower frequency (f_{LoRa}=868MHz) [13]. However, since BLE is often utilized for shorter range communication and the frequency is relatively higher (f_{BLE}=2.4GHz), the simplified path-loss model is adopted as suggested in [13]. Thus the path-loss K is expressed in Equation 2, where: $c = 2.8 \times 10^8$m/s, $ahMS = (1.1 \times log10(f_{LoRa}) - 0.7) \times h_r - (1.56 \times log10(f_{LoRa}) - 0.8)$; and $C_m = 0$ for flat rural environment; $D = 44.9 - 6.55 \times log10(h_t)$. All mathematical notations are summarized in Table I.

$$K = \begin{cases} 46.3 + 33.9 \times log10(f_{LoRa}) - 13.82 \times log10(h_t) - ahMS + C_m & \textit{for LoRa} \\ 20 \times (log10((4 \times \pi \times d_0)/(c/f_{BLE}))) \approx 40.04 & \textit{for BLE} \end{cases} \tag{2}$$

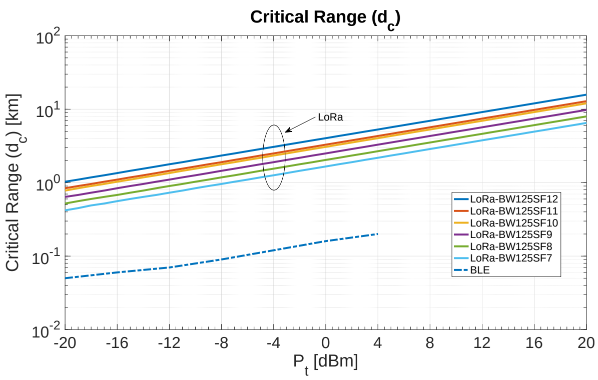

Fig. 2: Critical Range (d_c), plotted by extrapolating the P_t levels from the specified P_t in levels in the data sheets: for LoRa = [-1, -20]dBm; in steps of 1dBm, for BLE = [-20, 4]dBm; in steps of 4dBm. BW = Bandwidth, SF=Spreading Factor. $Cov(C) = 97\%$, σ = 3.65dB

The critical range that could be achieved by BLE and LoRa radios under rural flat environment is shown in Figure 2. A high transmission power results in a higher received signal strength, increasing the range of reception. In an open field, the range of BLE could reach up-to 200m at maximum P_t = 4dBm. The maximum d_c for LoRa for BW125SF12 setting is 15.7km, this range is achieved at the highest SF and P_t configuration. Figure 2 shows that for every increase in SF, the transmission range increases accordingly. Higher SF indicates longer range with better reception, and but longer packet duration.

TABLE I: Symbol Notations

P_t	transmit power
P_r	received power
d_c	range from transmitter at a specific transmit power (P_t)
d_0	near-field range, d_0 is typically assumed to be $1m$ for BLE
$\sigma_{\psi dB}$	log-normal shadowing model $\sigma_{\psi_{dB}} = 3.65dB$
γ	path-loss exponent $\gamma = 3.71$
f_{LoRa}	868MHz
f_{BLE}	2.4GHz
h_t	effective base station antenna height [m]
h_r	mobile node height
$Cov(C)$	coverage area probability
$P_{r_{min}}$	receiver sensitivity

Algorithm 1, summarizes the basic procedures towards enabling dual radio based IoT network architecture. The system computes max possible critical range $d_{c BLE(max)}$ and $d_{c LoRa(max)}$; using the P_t, P_{min}, path-loss (K) and log-normal shadowing ($\sigma_{\psi_{dB}}$), coverage probability ($Cov(C)$) parameters configured as per Eq. 1. Consequently, based on the critical ranges computed from the minimum received power, transmission power and environment information, the system chooses to operate at a specific radio platform. We are aware of the practical complexity associated with the proposed model such as various modeled wireless parameters are not directly available for the physical radio hardware. However, in the future, we plan to investigate a simple distributed online proximity estimation scheme similar to exponential moving average (EWMA) [14].

Algorithm 1 Towards Adaptive Radio Scheme

Input: P_t, P_{min}, path-loss (K) and Log-normal shadowing ($\sigma_{\psi_{dB}}$), area coverage ($Cov(C)$).
Output: Critical range d_c, max critical range $d_{c BLE(max)}$, $d_{c LoRa(max)}$.

procedure ADAPTIVE RADIO
  top:
  $P_r \propto (P_t - K + \sigma_{\psi_{dB}} \times C_{inv})$
  $Log(d_c) \propto (P_t - P_{r_{min}} - K + \sigma_{\psi_{dB}} \times C_{inv})$
Determine the max critical ranges $d_{c BLE(max)}$, $d_{c LoRa(max)}$
  $d_{c BLE(max)} \leftarrow Eq.\ 1$
  $d_{c LoRa(max)} \leftarrow Eq.\ 1$
  if $0 < d_c < d_{c BLE(max)}$ **then**
    $\leftarrow Select\ BLE\ Radio$
  end if
  if $d_c > d_{c BLE(max)}$ **then**
    $\leftarrow Select\ LoRa\ Radio$
  end if
  goto *top*
end procedure

III. Network Energy Consumption Model

In this section, a more practical network wide energy consumption comparison of the proposed network architecture with a typical LoRa star network is introduced. To investigate the energy performance, the network presented in Section II-A is modeled as a network Λ defined as $\Lambda(n, L)$, where n is the total number of nodes in the network and L is the total number of established links in the network (Fig. 3).

Assuming the wireless link is reliable, and the sleep mode power consumption is negligible (which is typically less than 0.1% of transmission or reception mode). Therefore, the energy (E) consumed to transmit a packet of length PL bytes over a link L is:

$$E = ToA \times (P_t + RXP) \tag{3}$$

where: P_t is determined by Eq. 1 with respect to critical range d_c, RXP is power required to run the receiver circuit [15] Therefore, the per-packet energy overhead for a packet depends on the ToA and P_t. The time on air (ToA) has a direct impact on the energy consumption of a typical radio. The time on

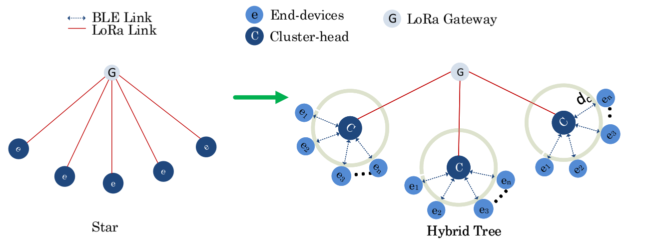

Fig. 3: Proposed generic tree topology, compared with the conventional star network of LoRa.

air of a packet is determined by the user payload size (PL), spreading factor (SF), bandwidth (BW), and coding Rate (CR). ToA for LoRa and BLE is expressed in Equation 4.

In LoRa radio physical layer parameters such as Spreading factor (SF), Bandwidth (BW), and Coding Rate (CR), influence the effective Time-On-Air (ToA), its resistance to interference, and ease of decoding. Theoretically, a high SF results in an easily decodable and lower minimum receiver sensitivity, but it results in a high (ToA). A higher CR transmits more redundant data bits, consequently, increasing its resilience to packet errors.

$$ToA(PL) = \begin{cases} (T_s) \times \left((T_{pre}) + max \left\{ \lceil \Gamma \rceil \times (CR+4), 0 \right\} \right) & \textit{for LoRa} \\ 8 \times \frac{(n_{preamble} + AddressH + PL_{BLE} + CRC)}{DR} & \textit{for BLE} \end{cases} \tag{4}$$

where: $AddressH$ the number of address header bytes for BLE (6 bytes), DE indicates LoRa robustness of the transmission to frequency variation, H = 1 without header mode, H = 0 with header mode, for BLE (CRC = 2bytes), in case of LoRa (CRC = 1 when on, 0 when off) and symbol period $T_s = (2^{SF}/BW)$, the preamble duration $T_{pre} = (n_{preamble} + 12.25)$, $n_{preamble}$ is LoRa (8 symbs.) and BLE (1 byte), $\Gamma = \left\lceil \frac{8PL_{LoRa} - 4SF + 28 + 16CRC - 20H}{4 \times (SF - 2DE)} \right\rceil$.

The total packet header excluding the user payload (PL) is 24bytes for LoRa including at least 13bytes of LoRaWAN header, and 17bytes for BLE. Thus, the exclusive ToA overhead for LoRaWAN (at SF = 7, CR = 1, DR = 5kbps) and BLE (at DR = 250kbps) is 46ms and 0.544ms respectively. Packets to the same destination will be concatenated at the cluster-head (C) before being relayed to Lora gateway, The concatenated LoRa PL would be $PL_{LoRa} = [(PL_{BLE})_1 || (PL_{BLE})_2 ... || (PL_{BLE})_n] + 13$. Here, $||$ denotes the concatenation operator. The maximum size of a concatenated packet may reach to the maximum LoRa packet size (i.e. 256 bytes). For instance, as shown in Figure 4, using Eq. 3 for the same $p_t = 4dBm$, as the number of nodes (n) increases, the per packet energy overhead for LoRa star network ($2354 \times n\mu J$) will be significantly higher than the proposed hybrid mesh ($43 \times n + 2354\mu J$). This is mainly attributed to the larger preamble duration of LoRa compared to the shorter ToA of BLE. Therefore, instead of direct LoRa

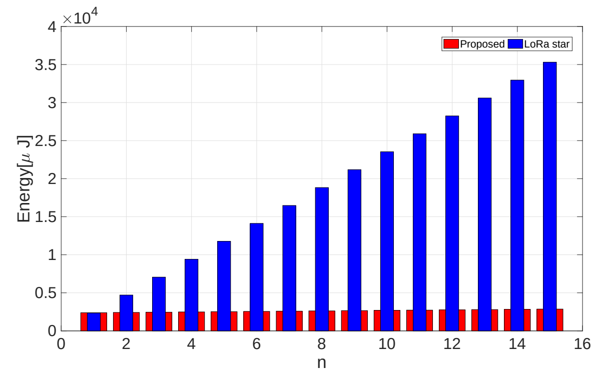

Fig. 4: Per-packet energy overhead comparison of LoRa star and proposed hybrid tree (BLE mesh plus LoRaWAN link) with data concatenation applied at the cluster head.

connectivity as in star topology, utilizing data concatenation at the cluster head will drastically reduce the overall energy overhead. Moreover, due to the 1% transmission duty-cycle restriction in case of LoRaWAN, end-devices are not allowed to access the channel for at least $T_{offsubBand} = 99 \times ToA$ seconds, which will contribute to the high network latency for star based LoRa networks. In our proposed WMS scenario, however, packet concatenation is proposed as an alternative to reduce the packet header energy cost and decrease overall latency.

Next we present the network wide energy consumption. There are three parts to network wide energy overhead: (i) initial (node joining) phase (k), (ii) per packet energy consumption (E) given by Eq. 3, and (iii) periodic synchronization phase (k_{resync}). In our energy modeling we are aware of the implementation complexity associated with mesh networking, however, for the sake of simplicity we made few assumptions. First, cluster-head (C) is performs concatenation, and end-devices are assumed to be tightly synchronized with the cluster-head. And all links have equal packet transmission and reception capacity. Second, for a given configuration, the typical time of channel activity detection (CAD) $ToC = (2^{SF} + 32)/BW$ seconds for LoRa, and $ToC = 1.28ms$ for BLE. And time of reception (ToR), in hybrid tree network is $((ToR) = ToA_{BLE} + ToC)$. The classical approach of sender-receiver synchronization is used for inter-cluster node syncing [16].

Thus the total number of packets exchanged for one synchronization would be ($TX_{pckt} = 2 \times n - 1$) and $RX_{pckt} = 3 \times (n-1)$ is the total received packets to maintain network synchronization and joining. Therefore, the network overhead for the initial phase (k) is:

$$k = (2n-1) \times ToA_{BLE} \times P_{tBLE} + 3 \times (n-1) \times (ToR) \times (RXP_{BLE}) \tag{5}$$

Then the period of resynchronization can be calculated with the knowledge of relative drift and required accuracy bound. Considering the desired worst-case accuracy bound between a pair of neighboring motes in the network is $\delta = 10ms$. Therefore, the resynchronization period is $(x = (\delta - ppm)/4.75 \times 10^{-6})$

[16]; where ppm is the clock accuracy and depends on the radio hardware used. The total number of packets exchanged in resynchronization are ($TX_{pckt} = 2 \times (n-1)$) and ($RX_{pckt} = 2 \times (n-1)$). Therefore, the network overhead with periodic resynchronization (k_{resync}) of the link ($e->C$) is given by:

$$k_{resync}(t) = \begin{cases} 0, & \text{if } 0 \leq t < x \\ \lceil t/x \rceil \times 2 \times (n-1) \Big((ToA_{BLE}) \times (P_{tBLE}) + (ToR) \times (RXP_{BLE}) \Big), & \text{otherwise} \end{cases} \tag{6}$$

where t is total simulation duration, if $0 \leq t < x$ is time before the start of the first resynchronization. Here $k_{resync}(t) = 0$ because the first synchronization overhead already included in k as per Eq. 5. Hence, the energy cost for the hybrid mesh network topology with aggregation at the cluster-head node, including the packet network overhead and ToR are given by Equation 7. For star topology (i.e. LoRa only) is expressed in Equation 8.

$$E_{Tree} = N_p \times E + \lceil t/IPI \rceil \times \Big[(n-1) \times [*] + (ToA_{LoRa}) \times (P_{tLoRa}) \Big] + k + k_{resync}(t) \tag{7}$$

$$E_{Star} = \lceil t/IPI \rceil \times n \times (ToA)(P_t) \tag{8}$$

Therefore, the energy consumption for the proposed proximity adaptive approach is given by Equation 9.

$$E_{Proposed} = \begin{cases} E_{Tree}, & \text{for } 0 < d_c < d_{BLE} \\ E_{Star}, & \text{for } d_c > d_{BLE} \end{cases} \tag{9}$$

Where: ToA_{LoRa} is the concatenated LoRa packet's ToA, $[*] = \big(ToA \times \big(P_t + RXP\big) + ToC \times RXP\big)$ for $(e->C)$ link, t the simulation time, IPI inter-packet interval, N_p is the total number packets sent, and E is the energy per packet given by Eq. 3.

IV. Evaluation

In this section, our proposed approach is compared with the typical LoRa star network for a wildlife monitoring use case scenario.

A. Simulation Set-up

The animal herd (group) size (n) and number of groups are proportional to the number of animals in a herd at grazing time, which are uniformly deployed [7, 17]. Depending on the animal species, empirical and modelled data have shown that the optimal average group size in a herd is in the range of n = [1,400], for instance, impala and zebra has a mean cluster size of $n \leq 70$ [18]. Hence, in this evaluation we assume the group size to be 70 without loss of generality. Within a cluster the distance among animals is d_c. We the proposed network is simulated in Matlab. At anytime, the radio transmission is assumed to cover a disk area of radius d_c. The carrier frequency is set to BLE (2.4GHz) and LoRa (868MHz). For all simulation set-up, we assume that the nodes are homogeneous in their initial amount of energy [7, 11]. To avoid the effect of cluster-head location on the over-all performance, in each case the cluster-head is assumed to be placed at the center of the WSN area coverage equidistant from the end-devices. Tree and star network topology are considered to simulate a more practical data collection scenario (Fig. 3). For tree topology, a number of sender nodes generate packets to the cluster-head (C) as per the clustering algorithm in [19], C relays aggregated packet to the gateway through a LoRa link. The tree topology utilizes BLE radio in a cluster depending on the proximity of nodes. LoRa radio is utilized in star mode to communicate with the gateway. To observe the impact of LoRa spreading factor, LoRa Link to the gateway is set to the highest (BW125SF7) and lowest (BW125SF12) bit-rates. Table II summarizes the simulation parameters set.

TABLE II: Generic Input Simulation Parameters

frequency	868MHz (LoRa)/2.4GHz (BLE)
$\sigma_{\psi_{dB}}$	3.65 dB
γ	3.71
h_t	20m
$Cov(C)$	97%
Spreading Factor (SF)	7/12
LoRa Bandwidth (BW)	125KHz
Data Rate (DR)	BLE(250kbps)
P_t	max (20dBm), min (2dBm)
RXP	LoRa(35.64mW), BLE(41.58mW)
Number of nodes (n)	70
PL_{BLE}	22 bytes
Resync. Period (x)	34 minutes
Number of resync period (m)	1000
Simulation duration (t)	$m \times x$

B. Network Energy Consumption

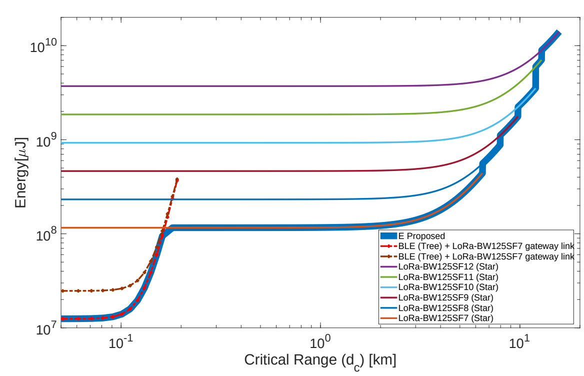

Fig. 5: Network wide energy consumption with respect to transmission range d_c considering path-loss and shadowing for rural (flat) environment.

A more interesting practical scenario for the energy consumption overhead is presented in Figure 5, while considering path-loss and shadowing for rural (flat) environment into account. In general the energy consumption is directly related to the ToA and transmission range (which in-turn is related to transmission power). As the the transmission range increases, there is a trend of increased energy consumption due to the higher transmission power need to reach the respective range. This relationship is specially more prevalent after 100m for BLE and after 6km for LoRa radio (Fig. 5). In a slight contrast to the energy consumption depicted in Fig. 7, LoRa (star) topology only performs better in-terms of energy compared to tree BLE mode after 150m at lower bit-rate. However, for ranges less than 150m, tree BLE mode performs better than LoRa. The proposed approach takes advantage of this at the shorter ranges to make the overall system more efficient in-terms of energy and bit-rate trade-off by utilizing the relatively high bit-rate BLE (250kbps) instead of low bit-rate LoRa (less than 5kbps). As presented in Figure 5, when the range becomes greater than 150m, then the proposed approach switches to the conventional LoRa mode instead of tree LoRa mode.

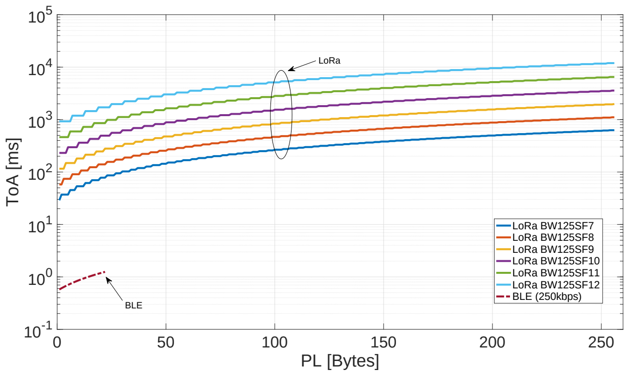

Fig. 6: Time-On-Air (ToA) for LoRa and BLE.

Figure 6, shows the ToA comparison of LoRa and BLE, with respect to payload size for each radio types. As shown in Figure 5 and 6, senders located closer to the receivers can transmit using high bit-rate (i.e. with shorter ToA and less energy), thus for shorter ranges utilizing BLE is more efficient than LoRa. The ToA duration for BLE is relatively shorter than LoRa radio, this is due to the higher modulation bit rate of BLE (250kbps) compared to LoRa (max 5.46kbps). In case of LoRa, for higher SF setting the ToA increases considerably, reducing the bit-rate. In theory, LoRa device can transmit or receive at maximum size of 256bytes in LoRa mode, at any SF settings. Higher SF provides a more robust transmission to environmental interference at a cost of slower bit-rate. However, at high SF (i.e. SF=12), the ToA for a payload of 256bytes will be impractically long (i.e. 7708ms). It is often suggested that, if a long payload is desired to be transmitted with a low data rate, the payload should be fragmented into smaller payloads. The maximum range for BLE radio is 200m, however, LoRa allows adjustment of the SF for transmitting over a greater range at the expense of lower bit-rate.

Hence, our approach proposes to adaptively change the radio mode, where the network switches to use a higher bit-rate for shorter ranger links (i.e. BLE) and lower bit-rates in case of longer ranges. This shortens the ToA, and enables to send burst of packets in a very short time, consequently, reducing energy usage considerably (Fig. 5). Overall, the proposed approach decrease the energy of LoRa based star network by up-to 97%, by adaptively changing the radio mode. Hence, as long as the communication range is within the proximity range among animals while in herds or groups (i.e. $d_c < 200m$) [6, 7], it is optimal to utilize the proposed approach with BLE radio.

C. Impact of Packet Generation Rate (PGR) and Node Density

To make a fair evaluation of the impact of packet generation rate on the network life time, the radio range is fixed by setting the transmission power of BLE and LoRa radio to a fixed value equal to the maximum transmission power of BLE radio, i.e. 4dBm. This is because even at maximum power settings BLE reaches upto 200m, which is in the range of the LoRa radio at BW125SF7 and BW125SF12 settings. In this evaluation set-up, the proposed approach would be in one of the radio configurations (i.e. BLE or LoRa mode). Given a battery capacity $Q_p[mAh]$, and supply voltage (v), the network life-time N_l of node n is defined as:

$$N_l = \frac{n \times Q_p \times V}{E \times PGR} \tag{10}$$

Assuming $V = 1.225v$; $Q_p = 1150mAh$ $(1mAh = 3.6J)$, PGR is the packet generation rate.

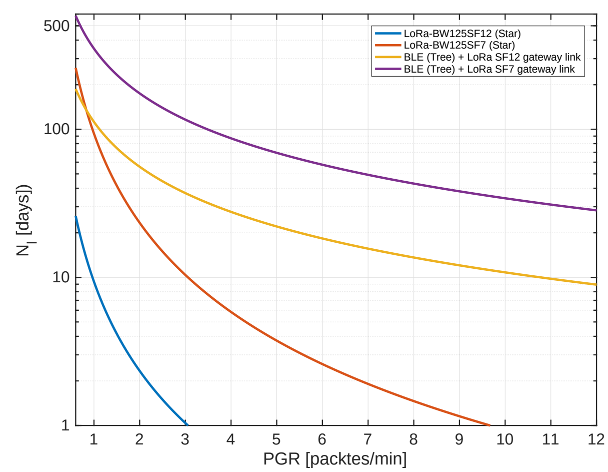

Fig. 7: Impact of PGR on the network life-time for rural (flat) environment, for $V = 1.225v$, $Q_p = 1150mAh$.

As shown in Figure 7, for both BLE tree and LoRa star topology, the network life-time depicts a decreasing trend as network packet generation rate (PGR) increases. However, for higher PGR, LoRa star networks has relatively shorter life-time compared to the BLE tree mode, confirming that LPWAN networks are not suitable during high rate of packet exchange, as it often happens in wildlife monitoring applications. This is mainly attributed to the higher bit rate of BLE radio (250kbps) compared to LoRa (5kbps). Overall, for high PGR the BLE tree mode almost doubles the network life-time compared to LoRa. This shows how the tree based approach is more optimal than LoRa based LPWAN network for animal monitoring applications requiring high data rates. As shown in Figure 8, the energy consumption increases as the node number increases, and as expected the BLE tree network saves more energy than LoRa star. BLE mode of the tree topology shows less energy consumption. It is clear from Figure 8, in general higher node density in the network will contribute to having a higher network energy consumption.

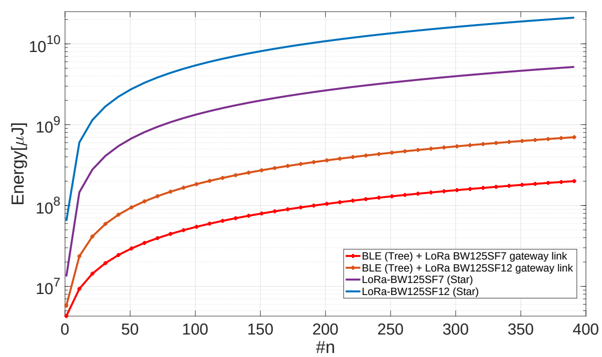

Fig. 8: Impact of node density on energy consumption for rural (flat) environment.

V. Conclusion

In this paper, we proposed a new dual radio IoT network architecture for wildlife monitoring that achieves wider control on the trade-off between energy consumption and range. This is achieved by adaptively changing the operating radio of WMS based on proximity measures and applying data concatenation scheme at the cluster-head. The evaluation results indicate that the proposed network outperforms the traditional systems that use a single type of transceiver radio alone (i.e. LoRa or BLE). On average, our approach reduced the energy consumption of LPWAN (LoRaWAN) by up-to 97%. In addition the architecture improved the network life time by up-to 99% for various packet traffic rates in the network. Therefore, for con-speciously sparse animal population, our approach is more optimal to deploy than utilizing only LoRa network. Moreover, in the future, we plan to validate these simulation results by performing a detailed implementation of the proposed model in higher level simulator and a real world sensor devices by building a collar prototype with dual radio platform. We are aware of the practical limitations associated with the proposed model, such as the path-loss based range calculation and the various modeled wireless parameters are not directly available for the physical radio hardware. However, we plan to test various techniques to address this issues, for instance, to develop a simple on-line received signal based proximity estimation scheme similar to exponential moving average. We also plan to perform a practical performance test for LoRa radio (e.g. coverage, robustness to interference, etc.) in the actual wildlife environment.

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