Development Of Random Forest Model For Optimal Configuration Of Lora Transceiver Parameters In Iot Network

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***Abstract*— In this work, the development of Random Forest (RF) model for optimal configuration of LoRa transceiver parameters in IoT network is presented. The dataset for the LoRa transceiver and the IoT network along with the energy consumption and the battery life span are generated via simulation over period of operation of the IoT network and based on the dataset, the RF model is trained and then used to predict the values of each of the parameters that will give optimal energy consumption in the IoT network. The energy consumption, the signal to noise ratio (SNR), the number of retransmission and packet delivery ratio (PDR) at optimal configuration are the key performance metrics used. At short transmission distances (TD = 10.85 m), the network achieved extremely low energy consumption (0.0037 mJ), with spreading factor (SF = 11). However, energy demand scales rapidly with both TD and suboptimal configuration choices; at TD = 886.98 m, energy roses significantly to 3.4736 mJ, influenced by high payload size and compounded by an SF of 11 and Coding Rate (CR) of 4. Also, a strong PDR of 95% is observed at TD = 10.85 m, but this sharply declines to just 7% at 886.98 m. In all, the results showed that while the optimal energy increases with transmission distance (TD), the SNR, the packet delivery ration and number of retransmissions decreases with increase in TD.**

Keywords*— *Random Forest Model, IoT Network, Optimal Configuration, LoRa Transceiver, Packet Delivery ratio

1. Introduction

Nowadays, internet of Thing (IoT) technologies have find wide applications in diverse disciplines [1,2,3]. Their applications has become the major driver for smart systems that are already being deployed across the globe such as smart agriculture, smart grid, smart transport , smart city , among many other examples [4,5,6]. The IoT networks rely heavily on resource constrained sensors most of which are powered using battery [7,8]. In view of the limited battery energy lifespan, effort is always made to optimize the energy consumption of the IoT sensor nodes thereby extending the battery lifespan [9,10].

Basically, IoT networks consists of sensor nodes with transceiver along with gateways or base stations and internet connections [11,12]. The transceiver considered in this work is based on LoRa technology. The sensor nodes are distributed across the network coverage area and each of the sensor nodes communicates with other sensor nodes or base station. In practice, the energy consumption of the LoRa based IoT sensor network is dependent on a number of parameters with the transmission distance as a key parameter; the higher the transmission distance, the higher the energy consumption [13,14]. In order to accommodate high transmission distance, LoRa transceiver provides different parameters that can be tuned for long range communications and also for short range communication [15,16]. Each configuration has its energy consumption which can be optimally tuned based on the selected parameters.

Accordingly, in this work, the Random Forest (RF) model used to predict the parameter configuration settings for the LoRa transceiver and the IoT network such that optimal energy utilization is realized [17]. Such data driven approach is particularly useful for automated adaptive configuration for efficient energy utilization in the LoRa-based IoT network.

2. Methodology

The Random Forest (RF) model is used in this work to predict values of each of the various LoRa parameters which will yield optimal energy utilization. The dataset for the LoRa transceiver and the IoT network along with the energy consumption and the battery life span are generated via simulation over period of operation of the IoT network and based on the dataset, the RF model is trained and then used to predict the values of each of the parameters that will give optimal energy consumption in the IoT network.

Notably, the Random Forest (RF) model is a robust, ensemble-based learning algorithm that integrates multiple decision trees to improve predictive accuracy and generalization. In the context of this work, RF serves as non-parametric regression model that learns from key transmission parameters like spreading factor (SF), bandwidth (BW), transmitter power (P_Tx), transmission distance (TD), and time on air (ToA)) to predict energy-related metrics such as Energy Consumption and Efficiency (PDR/Energy) which are vital for optimizing LoRa network performance. In LoRa systems, efficiency in energy utilization is typically influenced by:

i. Spreading Factor (SF): Affects Time on Air (ToA)
ii. Bandwidth (BW): Higher BW results in lower ToA but higher power
iii. Payload Size, Transmission path length or Distance (TD), P_Tx: Core determinants of energy cost
iv. PDR: Affected by signal attenuation and SF

The target variable in this study is energy efficiency expressed as;

$$Efficiency = \frac{PDR}{Energy} \quad (1)$$

Let $D = \{(x_i, y_i)\}_{i=1}^{n}$ be the dataset where, $x_i \in R^d$ denotes the feature vector for LoRa configuration, $y_i \in R$ denotes the variable that is the target which is Efficiency; Random forest builds T decision trees $\{h_t(x)\}_{t=1}^{T}$, using $D_t \in D$ for training the T trees where D_t is used to denote the training set. The averaged prediction becomes the output and is given as:

$$\hat{y}_{RF}(x) = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \quad (2)$$

Each decision tree is created by randomly selecting a feature within the feature space. The nodes are split using feature and threshold that minimizes the mean squared error (MSE):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (3)$$

Where $N$the total number of nodes is, y_i denotes the actual output and $\hat{y}_i$ denotes the predicted output. The RF model learns the mappings expressed as: $:(SF, BW, CR, TD, DC, Payload) \rightarrow Efficiency$, where CR is the coding rate, DC is duty cycle and payload is the payload size. In this case, the mapping is used to predict the efficiency in a situation where the transmission configurations is unseen and as such it serves as the objective function which can then be used in an optimization algorithm. Hence, RF provides a surrogate model $\hat{f}(x)$ which helps the optimization algorithm to select the specific configurations that maximizes the efficiency predicted by the model.

$$\max_{x \in X} \hat{f}_{RF}(x) = Predicted\ Efficiency \quad (4)$$

Where X denotes the feasible space of transmission parameters constrained by the hardware and protocol limits.

The parameters used in the simulation are presented in Table 1. The TD are categorized into short range, medium range and long range as follows: [short range: TD ≤ 200 m; medium range: 200 m < TD ≤ 600 m and long range: TD > 600 m].

Table 1 The parameters used for the simulation

S/N	Parameter description and acronym used	Parameter value or category selected
1	Transceiver technology	LoRa
2	Physical layer Technology	LoRaWAN based on Semtech SX1276 transceiver specifications
3	Frequency (f)	868 MHz
4	Transmission range (TD)	10 m to 1000 m
5	Coding rate (CR)	Range 4/5 to 4/8
6	Spreading Factor (SF) range	7 to 12
7	Duty cycle range (DC)	1 % to 10 %
8	Bandwidth range (BW)	125 KHs, 250 KHz and 500 KHz
9	Transmitter energy range (P_tx)	2 dBm to 14 dBm
10	Payload size (payload)	10 to 150 bytes
11	Battery capacity (B_{cap})	1000 mAh

Other parameters are calculated and they include time on air (ToA), packet delivery ration (PDR) and energy consumed (Energy). The efficiencies obtained of the data entire dataset is normalized and expressed in percentage using the minmax approach with the value multiplied by 100 to appear in %. The RF model is trained with 75% of the dataset and then validated using 25 5 of the dataset.

3. Results and Discussion

The results of the optimal configurations predicted by the RF model are presented, focusing on some key parameters of interest. The results in Figure 1 outline the predicted energy consumption across different transmission distances (TDs) under the baseline Random Forest model. At short distances (e.g., TD = 10.85 m), the model achieves extremely low energy consumption (0.0037 mJ), reflecting ideal conditions where the link budget is minimal, and high spreading factor (SF = 11) allows successful decoding with minimal retries. However, energy demand scales rapidly with both TD and suboptimal configuration choices. For instance, at TD = 886.98 m, energy rises significantly to 3.4736 mJ, influenced by high payload size and compounded by an SF of 11 and Coding Rate (CR) of 4. This trend reinforces the need for adaptive parameter tuning, particularly as network nodes operate over varying distances.

The Packet delivery ratio (PDR) results in Figure 2 indicate that signal integrity degrades with increasing distance and poorer configuration selection. A strong PDR of 95% is observed at TD = 10.85 m, but this sharply declines to just 7% at 886.98 m, suggesting severe link reliability degradation despite using a high SF and bandwidth.

The SNR generally declines as TD increases as shown in Figure 3. The SNR gradually deteriorated from 96.88 dB at path distance of 10.85 m, to 53.68 dB at path distance of 886.98 m; this confirms the expected impact of increase in the path distance on the path loss and attenuation. The trend is consistent with standard radio propagation models, affirming that longer-range links require more energy or adaptive modulation techniques to maintain link quality. The result also suggest that higher SFs at long ranges (e.g., SF = 12) do not always compensate for degradation, especially when bandwidth and CR are not tuned synergistically.

This metric in Figure 4.25 evaluates the node's energy endurance under repeated transmissions. As expected, short-range configurations (TD = 10.85 m) allow for millions of rounds (2.7 million) before depletion. Conversely, long-distance setups with high energy draw drastically reduce lifespan (e.g., 2,878 rounds at TD = 886.98 m). Interestingly, intermediate distances like 210.30 m offer balanced longevity (413,152 rounds) due to optimal ToA and low payload demands. The drastic drop in rounds for certain configurations (e.g., TD = 707.54 m) shows how poor configuration tuning, particularly in terms of SF and CR, accelerates node death, even when energy per packet remains manageable.

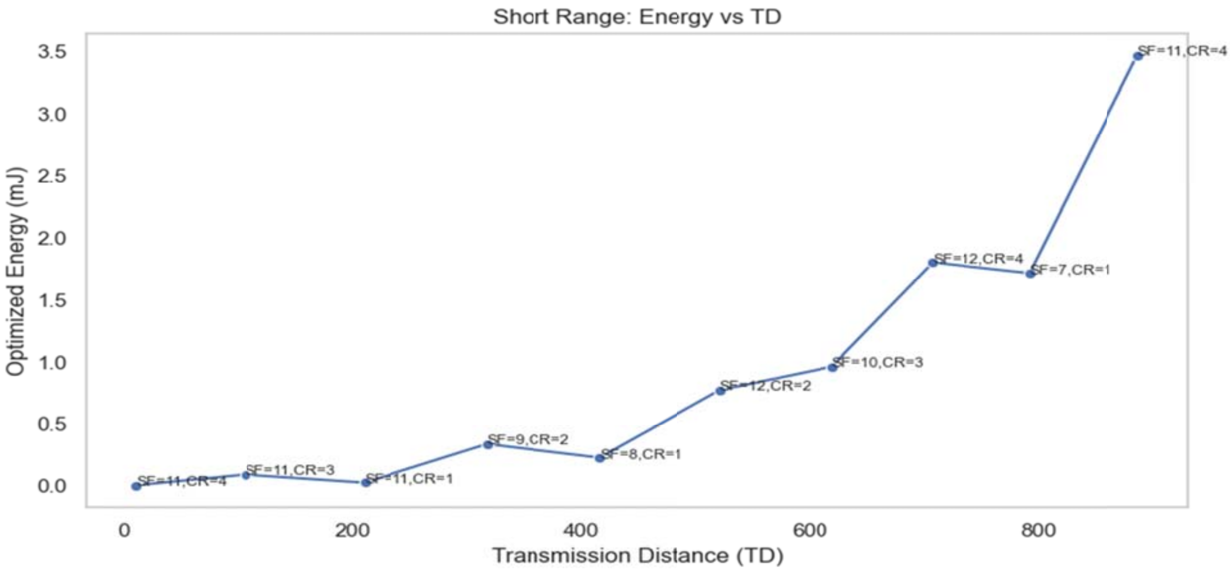

Figure 1: Optimal parameter configuration energy optimization

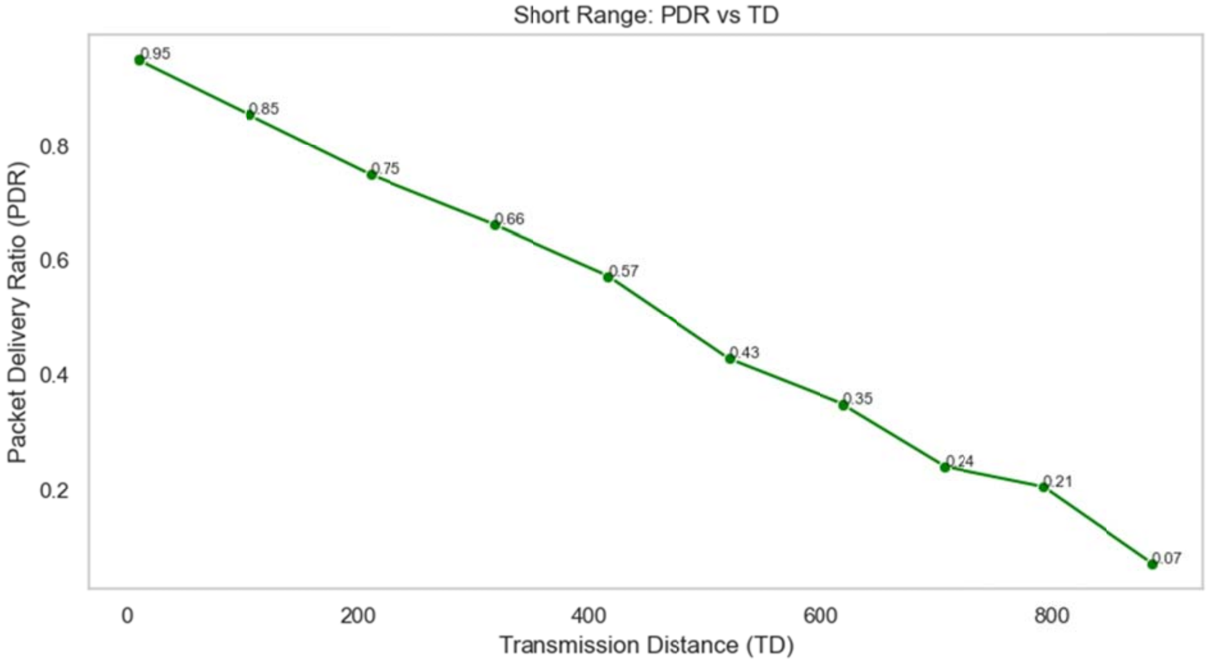

Figure 2: The PDR at the optimal parameter configuration

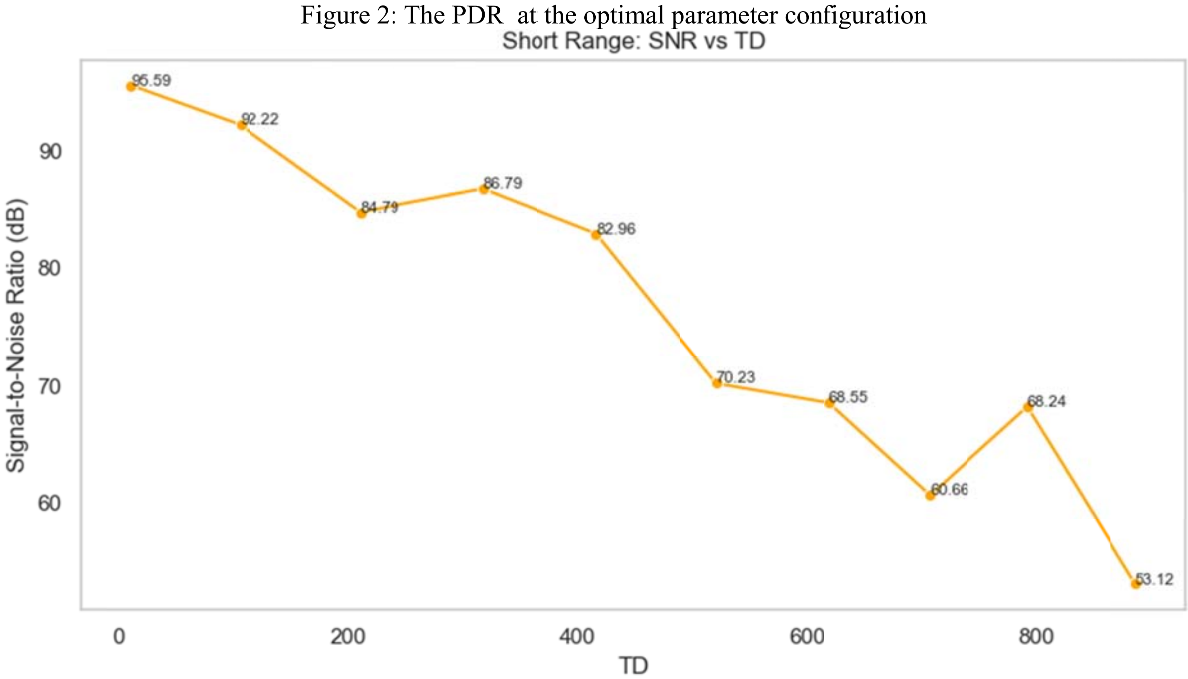

Figure 3: The SNR for the predicted optimal configuration

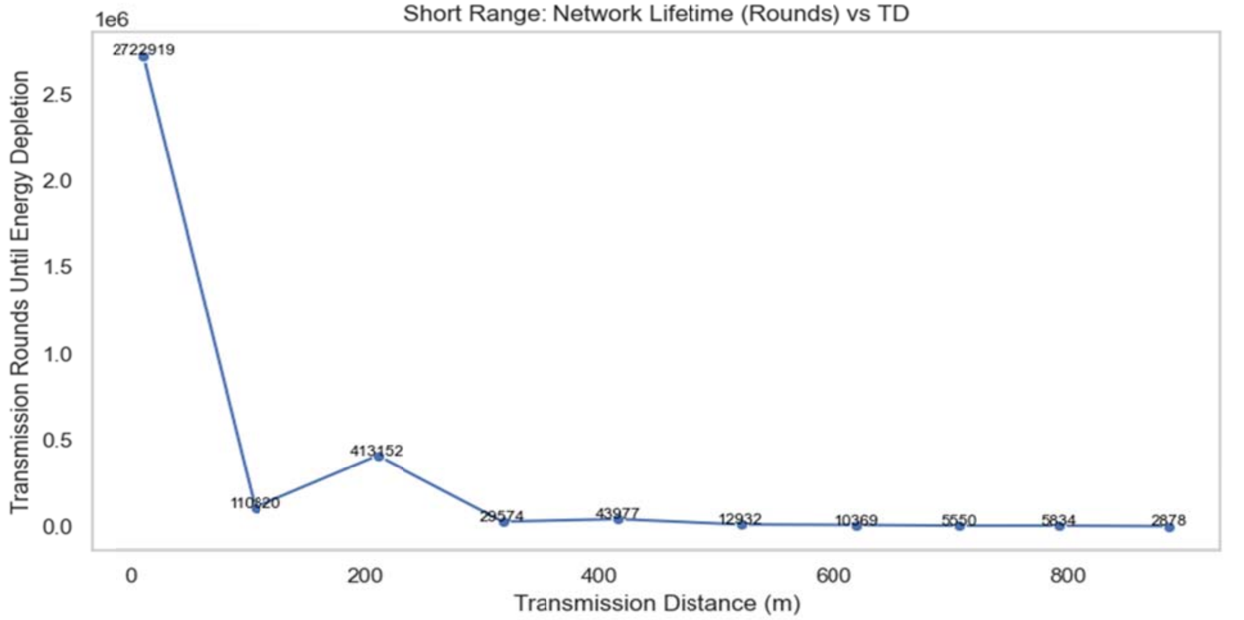

Figure 4: Number of transmission rounds before the node dies for optimal configuration

4. Conclusion

The optimal configuration of LoRa transceiver used in IoT network is presented. The optimal parameters are determined and selected using Random Forest (RF) model. The dataset was simulated for the case study IoT and LoRa transceiver. The simulated dataset is then employed in training the RF model which helped in predicting the combinations of the various parameters that yielded the optimal energy consumption. The energy consumption, the signal to noise ratio (SNR), the number of retransmission and packet delivery ratio at optimal configuration are the key performance metrics used in the evaluation of the model performance. The results showed that while the optimal energy increases with transmission distance (TD), the SNR, the packet delivery ration and number of retransmissions decreases with increase in TD.

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