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Optimal Configuration Of Lora Transceiver-Based Iot Network Using Support Vector Machine Model

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Abstract **This work presented optimal configuration of LorRa transceiver-based IoT network using Support Vector Machine (SVM) learning model. Specifically, the SVM algorithm is used to model the relationship between transmission parameters and energy efficiency by learning optimal decision boundaries in non-linear feature space. The dataset used in this work was generated by simulating the LoRa-based IoT network where some of the parameters values were specified as input while the other set of parameters were computed by the simulation program. The dataset had 10 features and 3000 records. The SVM model results showed energy prediction of 0.1003mJ at transmission distance (TD) of 105.82 m which increased significantly to predicted energy of 3.4023 mJ at TD of 886.98 m. The model maintains high PDR at short ranges; for example, 98% at 10.85 m, but suffers a steady decline as transmission distance increases. Most entries are favorable, with efficiency scores above 95% at mid-ranges, such as 317.19 m (95.00%) and 416.39 m (96.20%). However, at 792.6 m, the efficiency drops drastically to 17.37%, which is driven by high energy consumption and very low packet delivery ration (PDR).**

Keywords— **Packet Delivery Efficiency, Support Vector Machine Model, LoRa Transceiver, IoT Network, Energy Efficiency**

1. Introduction

As the years go by, advancements in wireless communications, electronics and technologies associated with programmability of devices and system give rise to smart systems which are changing the way we live and interact with one another [1,2,3]. More so, the technologies have given rise to interconnection of everything; human, machine and virtually anything that can connect and interact via sensors [4,5].

As the IoT driven smart systems era advance, researchers are perpetually seeking for ways to enhance the performance of the devices and system associated with the IoT network [6,7]. One area that has attracted great research is the energy management in the highly resource constrained sensor nodes [8,9,10]. Such nodes are mostly battery powered and installed in remote areas. As such, it requires ways of enhancing the energy utilization of such sensor so as to increase on the nodes lifespan. In the case of LoRa enabled IoT sensor nodes, there are several options that can determine the energy utilization of the sensor node [11,12]. In that case, achieving optimal energy utilization requires careful selection of the sensor node parameters. Accordingly, this work employs Support Vector Machine (SVM) learning model to predict the values of each of the different parameters of the IoT sensor network such that the effective energy consumption is minimal with the maximum packet delivery performance [13,14]. Such high performance IoT network is realized when the SVM model is properly trained and validated using the dataset extracted from the case study IoT network. The details of how such study is conducted on the case study IoT network are presented in the remaining sections of this study.

2. Methodology: The Support Vector Machine (SVM) Model for LoRa Optimal Parameter Configuration

Support Vector Machine (SVM) is generally a supervised learning approach; it works by creating optimal hyperplanes which it employs to carry out classification or regression task [15,16]. For this study, SVM for regression (SVR) is used to predict energy efficiency. SVM is particularly well-suited to this domain due to its robustness in high-dimensional, non-linear, and sparse data environments, such as those found in LoRa networks with heterogeneous configurations (e.g., SF, BW, CR, ToA, DC, TD). Specifically, the SVM is used here to model the relationship between transmission parameters and energy efficiency by learning optimal decision boundaries in non-linear feature space.

Now, let $D = \{(x_i, y_i)\}_{i=1}^{n}$ be the dataset where, $x_i \in R^d$ is the feature vector for LoRa configuration, $y_i \in R$ is the target variable; SVM function approximates:

$$f(x) = \langle w, \phi(x) \rangle + b \quad (1)$$

Where, $\phi: R^d \to H$ is a feature mapping into high dimensional space, w is the weight vector, and b is the bias term. The SVR introduces an ε-insensitive loss function

$$L_\varepsilon(y, f(x)) = \max(0, |y - f(x)| - \varepsilon \quad (2)$$

This means that small errors within $\pm\varepsilon$ are ignored, encouraging a flat function that generalizes well as a key property for modeling energy systems with minor fluctuations. The SVM taining problem becomes:

$$\min_{w,b,\xi_i,\xi_i^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \quad (3)$$

Subject to the following three conditions:

$$y_i - \langle w, \phi(x) \rangle - b \leq \varepsilon + \xi_i \quad (4)$$

$$\langle w, \phi(x) \rangle + b - y_i \leq \varepsilon + \xi_i^* \quad (5)$$

$$\xi_i, \xi_i^* \geq 0 \quad (6)$$

Where C is the penalty term, ξ_i, ξ_i^* are slack variables allowing violation of margins. In order to avoid computing $\phi(x)$ explicitly, the dual problem is solved using kernels:

$$K(x_i, x_j) = \langle \phi(x_i), \phi(x_j) \rangle \quad (7)$$

Linear kernel is selected and it is given as:

$$K(x, z) = x^T z \quad (8)$$

The solution becomes:

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i, x) + b \quad (9)$$

Where the non-zero α_i vectors only actually contribute significantly in the prediction. Once trained, SVR predicts $\hat{f}_{SVR}: (SF, BW, CR, TD, DC, Payload) \to Efficiency$. This surrogate model can be used in optimization frameworks to improve efficiency while optimizing energy consumption.

The dataset used in this work was generated by simulating the LoRa-based IoT network where some of the parameters values were specified as input while the other set of parameters were computed by the simulation program. The dataset had 10 features and 3000 records. The statistical summary of the dataset is presented in Table 1. The correlation matrix for the 10 features is captured in Figure 1. The SVM model after being trained using about 75% of the entire dataset was then used to predict the configurations of the LoRa IoT network parameters for optimal energy efficiency. Notably, the parameter set is predicted for any given transmission distance (TD).

Table 1 Statistical summary of the LoRa-based IoT Network Dataset

Feature	Count	Mean	Std Dev	Min	25%	50% (Median)	75%	Max
NodeID	3000	1500.50	866.17	1.00	750.75	1500.50	2250.25	3000.00
TD (m)	3000	153.00	85.00	10.04	79.03	150.59	227.46	1000
SF	3000	9.43	1.73	7.00	8.00	9.00	11.00	12.00
BW (Hz)	3000	292125.00	155319.51	125000.00	125000.00	250000.00	500000.00	500000.00
CR	3000	2.53	1.09	1.00	2.00	3.00	3.00	4.00
DC	3000	0.0560	0.0261	0.0100	0.0334	0.0571	0.0785	0.1000
Payload Size (bytes)	3000	30.13	11.86	10.00	20.00	30.00	41.00	50.00
PDR	3000	0.8227	0.0865	0.6501	0.7504	0.8247	0.8946	0.9890
P_Tx (mW)	3000	632.31	539.70	18.68	144.97	473.87	1054.07	1820.36
ToA (s)	3000	0.00010	0.000075	0.000008	0.000045	0.000076	0.000133	0.000457
Energy (mJ)	3000	0.0631	0.0831	0.0004	0.0099	0.0319	0.0834	0.6965

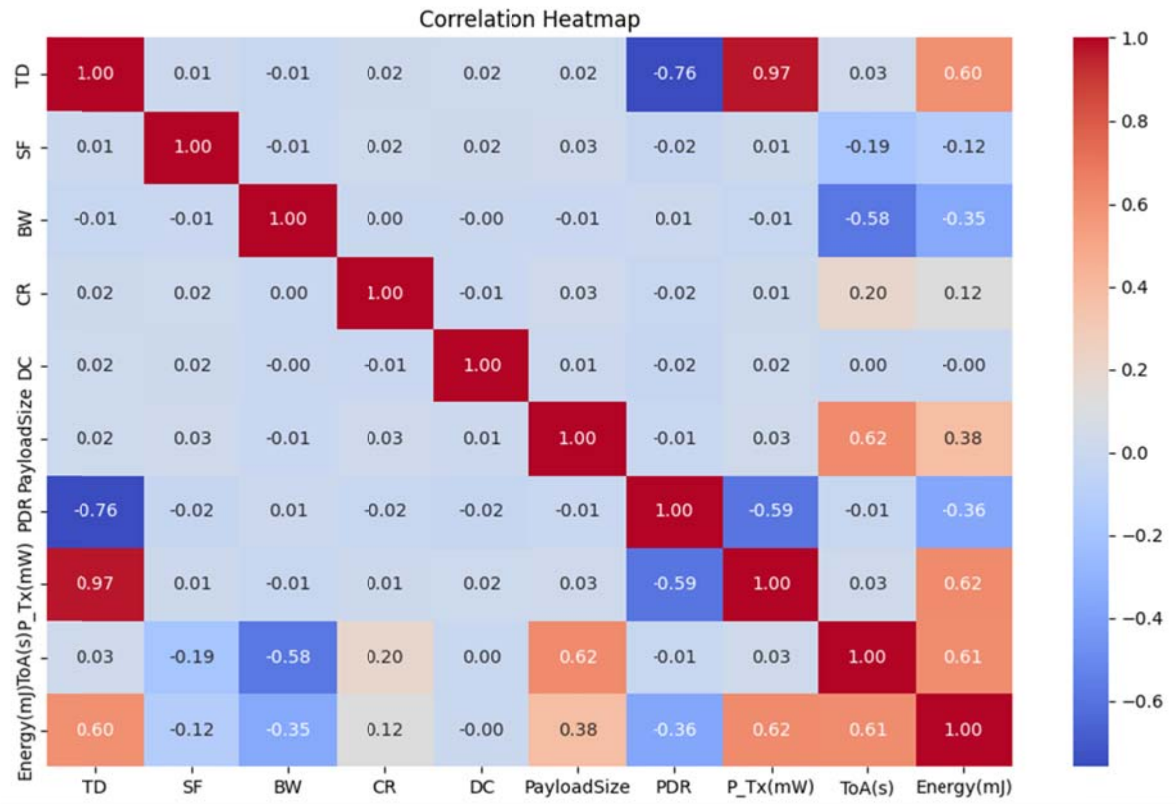

Figure 1: Feature correlation matrix

3. Results and discussion

The results of the energy predictions generated by the baseline SVR model for the transmission distances (TD) in the range of 10 m to 1000m presented in Figure 2. It has energy prediction of 0.1003mJ at TD of 105.82 m which increased significantly to predicted energy of 3.4023 mJ at TD of 886.98 m. However, the high values at relatively moderate payload sizes and duty cycles, as observed in Figure 2 suggest that SVR may overestimate energy under congested transmission conditions, especially with high SF or CR combinations.

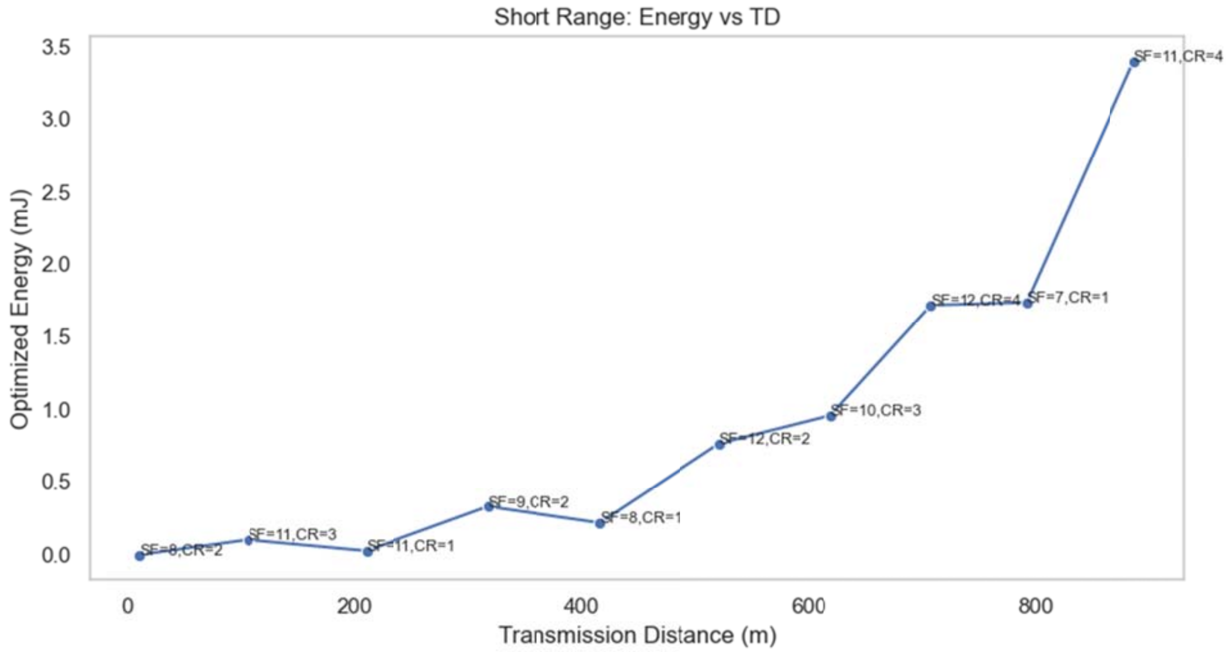

Figure 2: Optimal parameter configuration energy optimization

The packet delivery ratios (PDR) associated with the optimal configurations from the SVR model are reported in Figure 3. The model maintains high PDR at short ranges; for example, 98% at 10.85 m, but suffers a steady decline as transmission distance increases. By TD = 886.98 m, PDR plummets to 7%, indicating poor link reliability and inadequate parameter adaptation for long-range communication. Notably, even though SF values are high at longer distances, the predicted configurations fail to fully compensate for signal degradation, revealing SVR's limited dynamic flexibility in optimizing parameters jointly for reliability and efficiency.

Figure 3: Packet delivery ratio for optimal configuration

The packet delivery efficiency shown in Figure 4, represents how well the SVR model balances energy and reliability. Most entries are favorable, with efficiency scores above 95% at mid-ranges, such as 317.19 m (95.00%) and 416.39 m (96.20%). However, at 792.6 m, the efficiency drops drastically to 17.37%, which is driven by high energy consumption and very low PDR. These extremes highlight the fragility of SVR's optimization behavior, it either significantly overfits or underperforms when parameters are not tuned under optimization constraints. Thus, while SVR can suggest reasonably efficient configurations under moderate conditions, it is unsuitable as a standalone predictive engine for high-reliability scenarios without proper constraint enforcement.

The graph in Figure 5 demonstrate that the SVR model reasonably captures the signal degradation trend across increasing distances. The SNR declines steadily from 102.95 dB at 10.85 m to 51.40 dB at 886.98 m, accurately reflecting the inverse relationship between signal quality and distance in LoRa networks.

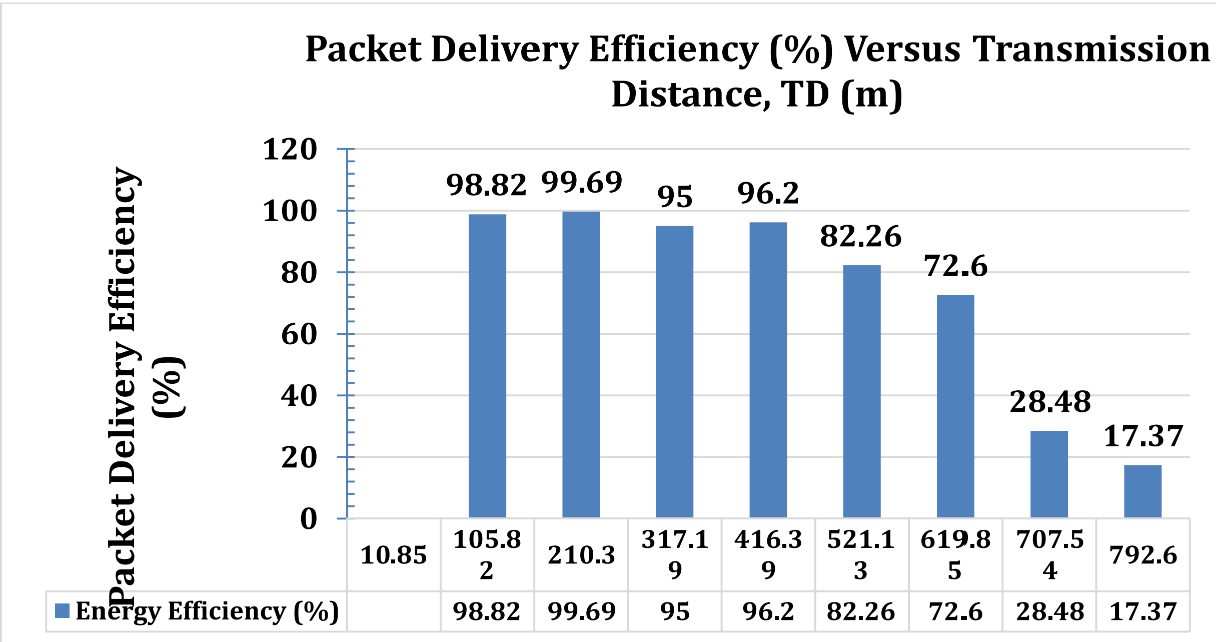

Figure 4 : Packet delivery efficiency for optimal configuration

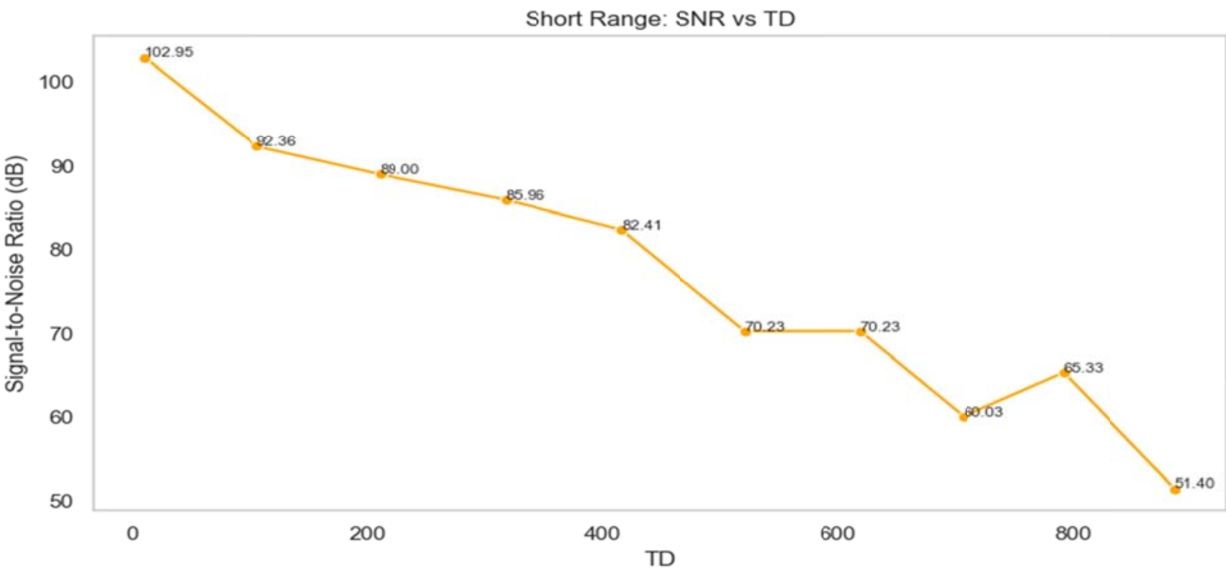

Figure 5: SNR for optimal configuration

In all, the baseline SVR model exhibits moderate competence in modeling core transmission behaviors such as ToA and SNR. However, it fails to consistently produce physically valid outputs for energy and packet delivery efficiency, especially at short and long extremes of the transmission spectrum. The negative or exaggerated values in energy prediction compromise node lifetime estimation and affect PDR indirectly. Thus, SVR is better suited as a feature-support model, and must be augmented with optimization strategies.

4. Conclusion

The IoT network based on LoRa transceiver is studied. The Support Vector Machine (SVM) model is used to determine the parameter values combination for each transmission distance such that energy efficiency if the highest. In this case the energy efficiency is measured as the consumed energy per successfully transmitted packet. The dataset for the study was generated by simulation and the results showed that though the SVM model showed promising capability in the selection of the network configurations for optimal energy efficiency, however, it failed in some cases to make the correct selection. Thus, the SVR is better suited as a feature-support model, and must be further augmented with optimization strategies.

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