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ENERGY EFFICIENT ALGORITHM FOR TRANSMISSION PARAMETER SELECTION IN LORA WIRELESS NETWORKS

LORA СЫМСЫЗ ЖЕЛІЛЕРІНДЕ ЖІБЕРУ ПАРАМЕТРІН ТАҢДАУДЫҢ ЭНЕРГИЯНЫ ҮНЕМДЕЙТІН АЛГОРИТМІ

ЭНЕРГОЭФФЕКТИВНЫЙ АЛГОРИТМ ВЫБОРА ПАРАМЕТРОВ ПЕРЕДАЧИ В БЕСПРОВОДНЫХ СЕТЯХ LORA

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Keywords:
LoRa, energy efficiency, wireless sensor networks, XGBoost, packet delivery rati (PDR).

ABSTRACT
Wireless communication technologies play a key role in providing efficient and reliable Internet of Things (IoT) networks. Among them, Long Range (LoRa) technology and the LoRaWAN protocol are widely known for their ability to provide long-range communications with low power consumption and cost-effectiveness. One of the main challenging issues in deploying autonomous wireless networks is the ongoing need to optimize transmission parameters to minimize node energy consumption (EC) and maximize packet delivery ratio (PDR). This study introduces a novel transmission parameter selection algorithm such as Spreading Factor (SF) and Transmission Power (TP), leveraging machine learning (ML) methods such as XGBoost, GRU, and RBFN. The algorithm predicts the distance to a node based on the received RSSI, and subsequently forecasts EC and PDR, substantially enhancing network performance. The proposed approach demonstrates high prediction accuracy, achieving 99%, while reducing EC by 20.43% and increasing the PDR by 23.72% compared to the traditional adaptive data rate (ADR) algorithm.

Түйінді сөздер:
LoRa, энергия тиімділігі, сымсыз сенсорлық желілер, XGBoost, пакеттерді жеткізу коэффициенті (PDR).

ТҮЙІНДЕМЕ
Сымсыз байланыс технологиялары Заттар Интернеті (IoT) желілерінің тиімді және сенімді жұмысын қамтамасыз етуде маңызды рөл атқарады. Олардың ішінде, ұзақ қашықтықтағы байланыс мүмкіндігін, төмен қуат тұтыну мен экономикалық тиімділікті қамтамасыз ететін Long Range (LoRa) технологиясы мен LoRaWAN хаттамасы кеңінен танымал. Автономды сымсыз желілерді іске асырудағы негізгі мәселелердің бірі – түйіндердің энергия тұтынуын (EC) азайту және пакеттерді жеткізу коэффициентін (PDR) барынша арттыру үшін жіберу параметрлерін оңтайландыру қажеттілігі болып табылады. Бұл зерттеу барысында машиналық оқыту (ML) әдістерін, соның ішінде XGBoost, GRU және RBFN қолдана отырып, Spreading Factor (SF) және Transmission Power (TP) сияқты жіберу параметрлерін таңдау үшін жаңа алгоритм ұсынылды. Алгоритм қабылданған RSSI негізінде түйінге

дейінгі қашықтықты болжайды және содан кейін EC және PDR болжамдарын жүргізеді, сол арқылы желінің жұмысын айтарлықтай жақсартады. Ұсынылған әдіс жоғары болжам дәлдігін көрсетіп, 99 %-ға жетті, ал дәстүрлі адаптивті деректер жылдамдығы (ADR) алгоритмімен салыстырғанда EC-ті 20,43 %-ға төмендетіп, PDR-ді 23,72 %-ға арттырды.

Ключевые слова:
LoRa, энергоэффективность, беспроводные сенсорные сети, XGBoost, коэффициент доставки пакетов (PDR)

АННОТАЦИЯ

Технологии беспроводной связи играют ключевую роль в обеспечении эффективных и надежных сетей Интернета вещей (IoT). Среди них технология Long Range (LoRa) и протокол LoRaWAN широко известны своей способностью обеспечивать связь на больших расстояниях с низким энергопотреблением и экономической эффективностью. Одной из основных сложных проблем при развертывании автономных беспроводных сетей является постоянная необходимость оптимизации параметров передачи для минимизации энергопотребления узла (EC) и максимизации коэффициента доставки пакетов (PDR). В этом исследовании представлен новый алгоритм выбора параметров передачи, такой как коэффициент распространения (SF) и мощность передачи (TP), использующий методы машинного обучения (ML), такие как XGBoost, GRU и RBFN. Алгоритм предсказывает расстояние до узла на основе полученного RSSI, а затем прогнозирует EC и PDR, существенно повышая производительность сети. Предлагаемый подход демонстрирует высокую точность прогнозирования, достигая 99%, при этом EC снижается на 20,43% и PDR увеличивается на 23,72% по сравнению с традиционным алгоритмом адаптивной скорости передачи данных (ADR).

INTRODUCTION

Nowadays, with the rapid growth of IoT applications, there is an increasing demand for high connectivity over long distances while minimizing energy consumption (EC). Consequently, LoRa technology and LoRaWAN protocol have become preferred solutions for establishing networks that enable long-distance communications with low power usage. However, despite these advantages, optimizing transmission parameters continues to be a major challenge for further reducing node EC and enhancing overall network efficiency.

Considerable attention is devoted to studying transmission parameters and their impact on network efficiency. In articles (Porobić et al., 2021; Bor & Roedig, 2017), authors highlight the significance of selecting correct value of bandwidth (BW), SF and TP parameters to achieve optimal network performance. These parameters are critical for ensuring the sustained reliability of LoRaWAN networks, particularly in urban and rural areas (Griva et al., 2023). In (Ghaderi & Amiri, 2024), the authors focus on modeling and analyzing how various transmission parameters influence the reliability and efficiency of networks.

In addition, the ADR data transmission algorithm, is employed in order to improve the energy efficiency of LoRa wireless networks in (Peruzzo & Vangelista, 2018). The standard ADR mechanism can be enabled to adjust the SF assignment and transmit power, based on the SNR readings obtained from the received signal. This algorithm plays an essential role in managing data transfer rate and transmitter power within LoRaWAN networks. The study in (Slabicki, Premsankar & Di Francesco, 2018) discusses how adaptive parameter configuration can improve network performance in dense IoT deployments. In contrast, authors in [Ksiazek & Grochla, 2021] investigates flexibility of the ADR algorithm and its impact on network performance under various operating conditions. However, the ADR algorithm exhibits several limitations, which led to further research in this area. Recent studies have introduced improved versions of the ADR algorithm, including ND-ADR, ADR-MIN, and EARN (Park et al., 2020). These advanced approaches utilize the average Signal-to-Noise Ratio (SNR) to adjust data transmission parameters, leading to enhanced PDR and reduced EC (Babaki, Rasti & Taskou, 2020; Jiang et al., 2021).

Optimizing parameters for LoRa wireless network nodes involves utilizing one of three ML methods: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, one of the network parameters, such as SF or TP, is most often selected and these parameters are predicted based on known data using regression or classification (Cuomo, Garlisi, Martino & Martino, 2020). In addition, regression and classification are used to predict collisions. Reinforcement learning provides a natural framework for optimizing parameters by allowing a wireless network node (agent) to interact with its environment. Through feedback mechanisms, such as rewards or penalties, the agent learns to identify the optimal parameters for efficient message transmission (Minhaj et al., 2023; Chen et al., 2022). Additionally, unsupervised learning is utilized to determine the most efficient operating modes of network nodes (Alenezi, Chai, Jimaa & Chen, 2019).

Therefore, much of the effort in optimizing parameters for LoRaWAN wireless networks involves reaching a compromise between two contradictory parameters: EC and PDR. Reducing EC typically involves reducing TP, which in turn decreases the success rate of message delivery.

MATERIALS AND METHODS

The study is structured into two main stages: online and offline. The online stage involves three simulations of wireless networks, as illustrated in Figure 1. Optimizing network parameters is crucial to reduce EC and increase PDR. This optimization involves studying the interdependence of various parameters. As shown in Figure 1, the study utilizes four different simulations (Sim1, Sim2, Sim3, and Sim4) within the OMNeT++ environment using the FLoRa library, which incorporates essential parameters based on results of physical experiments.

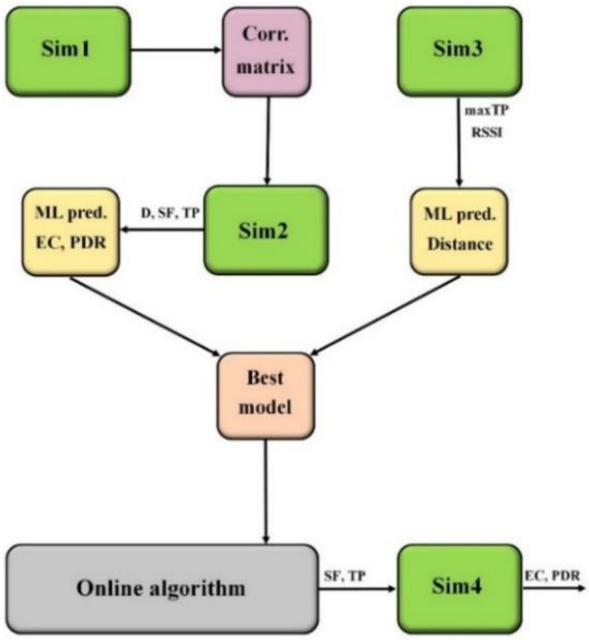


Figure 1. General structure of the study

Note: compiled by the authors

Sim1 is intended for constructing a correlation matrix (Corr. matrix), showing the degree of interrelation of network parameters. Then, data collection for ML is essential to achieve accurate predictions of network parameters under varying conditions, conducted specifically during the Sim2 phase. The model that exhibits the highest predictive performance (Best model) is subsequently employed in collaboration with an online algorithm to identify the most optimal network parameters. Sim3 is designed to collect data to create a model that predicts the transmitter-receiver distance based on Received Signal Strength Indication (RSSI) at maximum TP. The distance prediction results are the input data for the best model, the output of which is the predicted PDR and EC for a given distance and various TP and SF options. The algorithm determines the most optimal values of the SF and TP parameters. Finally, it is essential to evaluate the effectiveness of the predicted parameters for a specific network configuration. This is achieved by simulating Sim4 with the algorithm-selected network parameters and assessing the efficiency of the proposed system using the ADR algorithm.

The simulation Sim1 was performed using various numbers of nodes and gateways, where each node transmits messages to the gateways using different parameter combinations. This approach enabled the collection of a comprehensive dataset, enhancing our understanding of the correlation between PDR and EC in LoRa networks. The simulation results are presented as a correlation matrix in Figure 2.

The correlation matrix illustrates how the average EC and variance (σ) of all nodes depend on several parameters during message transmission: bandwidth (BW), coding rate (CR), SF, TP, number of nodes (N), and number of gateways (GW). Analysis of the matrix reveals that SF and TP exert the most significant influence on node EC.

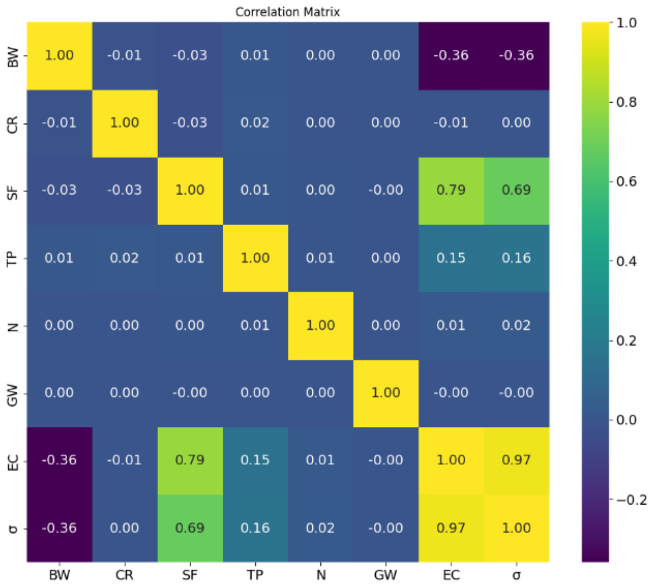


Figure 2. Correlation matrix

Note: compiled by the authors

The SF parameters ranged from 7 to 12, covering all available options. The transmit power varied between 2 dBm and 14 dBm. The maximum power is sufficient for successful message transmissions even from the most remote node. The simulation area spans 350 by 350 meters, with the receiving gateway positioned at coordinates 100 by 100 meters. The lognormal distribution model was used as a signal propagation model. The number of LoRa nodes for data collection in the selected area is 1046.

To collect the database, the parameters SF, TP and Distance will be employed as input value for the Sim2 simulation. During the three-day simulation period, each node will send 216 messages. This is essential for a more precise evaluation of EC and PDR. The time between message arrivals follows an exponential distribution with a mean value of 1000 seconds. When calculating a node's total EC, factors such as each message's sending power, airtime, and additional parameters are taken into account. EC and PDR were obtained as output data, as shown in the block diagram in Figure 3.

Table 1. Simulation parameters in OMNeT++

Parameter	Value
Simulation time	3 d
Simulation area	350 x 350 m
Number of nodes	1046
Spreading Factor SF	[7-12]
Transmit Power TP	[2-14] dBm
Path loss	PL(d0) = 127.41, d0 = 40, n = 2.08, σ = 3.57
Receiver sensitivity	-137 dBm
Carrier frequency	868 MHz
Bandwidth BW	125 kHz
Coding Rate CR	4/8
Note: compiled by the authors	

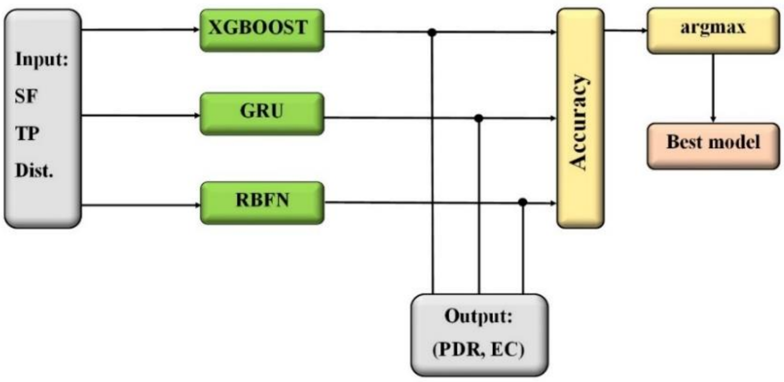


Figure 3. Block-diagram of data collection for ML
Note: compiled by the authors

XGBoost, RBFN, and GRU were used to predict PDR and EC. 85% of the data was used for model training, while the remaining 15% was reserved for the testing phase. Prediction accuracy will be evaluated using R2, MAE, MSE, and RMSE parameters.

The OMNeT++ network simulator provides the ability to calculate the RSSI for each Lora node. It uses several path loss models along the path to estimate the decrease in power of a radio signal as it propagates from the transmitter to the receiver. One example of such a model is the LogNormal Shadowing Model, which considers both deterministic path loss and random signal fluctuations caused by obstacles and reflections.

The lognormal distribution model is an extension of the free space model. It adds a random component to the logarithmic distance function to account for shading. The model equation is presented below:

$$PL(d) = PL(d_0) + 10nlog_{10}(\frac{d}{d_0}) + X_\sigma \tag{1}$$

where: $PL(d)$ – path losses over distances d;

$PL(d_0)$ – losses at reference distance d_0;

n – attenuation coefficient;

X_σ – random value, normally distributed with zero mean and standard deviation σ.

The lognormal distribution parameters were set as follows: PL(d_0)=127.41, d_0=40, n=2.08, and σ=3.57. In article (Slabicki, Premsankar & Di Francesco, 2018), a comparative evaluation of the lognormal distribution model implemented in OMNeT++ using real-world data is presented. The study demonstrate that the model achieves high accuracy in simulating signal attenuation in both urban and suburban environments. These parameters were calibrated based on measurements from various settings and showed favorable performance when compared to actual data.

For the Sim3 simulation, 100 nodes were installed in the selected area. In the OMNeT++ environment, the powers of the received signals were obtained for each node. Leveraging the chosen signal propagation model, it becomes feasible to calculate the distance to a node transmitting at a known power level of 14 dBm.

The proposed algorithm for optimizing the SF and TP parameters is the generation and enumeration of all possible options and the selection of the best depending on the necessary requirements as depicted in Figure 4. The operation requires only the power of the initially received RSSI signal, which is used to determine the distance, as outlined in section 2.5. Based on the obtained distance value, various parameters such as SF and TP are selected. The resulting data list is sent to the best model as input, yielding outputs for EC and PDR.

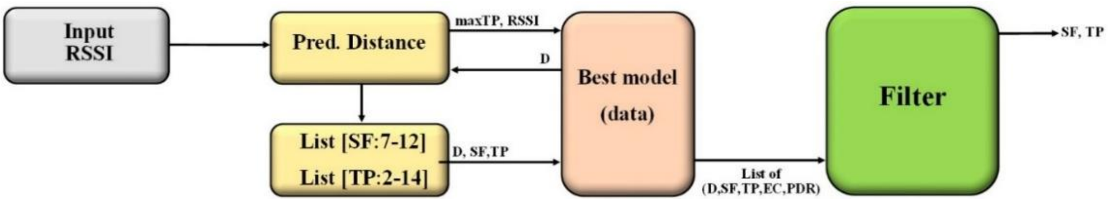


Figure 4. Algorithm for optimizing SF and TP parameters

Note: compiled by the authors

As can be seen from Figure 4, the best model predicts output values for EC and PDR. Subsequently, the results from the best model are sent to the filter, the algorithm of which is shown in Figure 5.

Figure 5 illustrates the operational concept of the proposed filter. Initially, the filter takes as input a dataset comprising 78 lines (D, SF, TP, EC, PDR). Subsequently, the PDR values of each row go through the conditions >5, >25, >30, >40, >50, >75, >80, as well as the maxPDR function, which from the entire list returns the row with the maximum PDR value and the corresponding TP and SF values. Rows meeting these conditions proceed to the next stage, while those not meeting the conditions remain in the input list. This filtering approach effectively establishes a lower threshold for PDR values. After each condition for the lower PDR threshold, the resulting dataset is further filtered based on minimum EC using the minEC function. As a result, for each range of PDR values, the minimum EC value and the corresponding SF and TP values are determined.

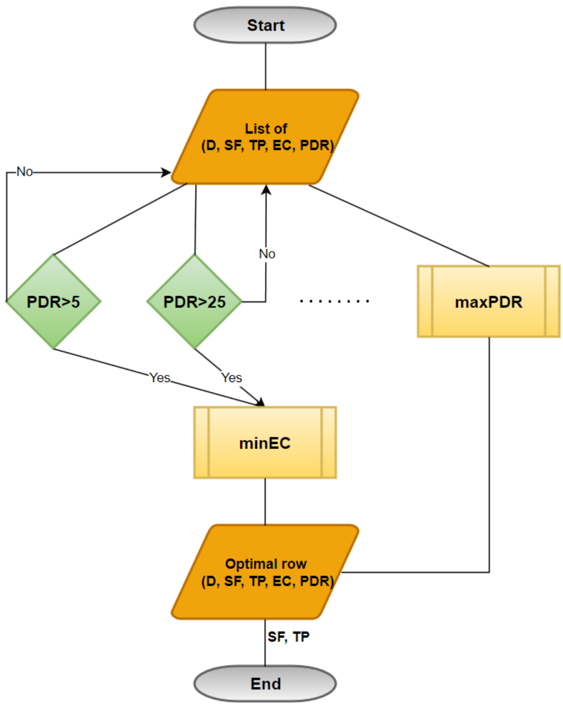


Figure 5. Filter block diagram

Note: compiled by the authors

RESULTS AND DISCUSSION

XGBoost demonstrated the best performance in predicting EC, PDR, and distance. The results were as follows: prediction_EC (R2 Score - 0.99999, MAE - 3.97440, MSE - 6.16825, RMSE - 7.85382) and prediction_PDR (R2 Score - 0.99557, MAE - 1.71041, MSE - 6.11819, RMSE - 2.47349).

Table 2 presents the performance metrics of three models (XGBoost, GRU, and RBFN) in predicting values for the variables EC and PDR.

Table 2. Prediction accuracy of EC, PDR and Distance in ML models XGBoost, GRU and RBFN

	Performance metrics	EC	PDR	Distance
XGBoost	R^2	0.99999	0.99557	0.99571
	MAE	3.97440	1.71041	4.75846
	MSE	6.16825	6.11819	65.40882
	RMSE	7.85382	2.47349	7.45037
GRU	R^2	0.98685	0.97253	0.97520
	MAE	0.95878	4.62209	6.75299
	MSE	1.90047	38.26388	116.23087
	RMSE	1.37857	6.18578	10.78104
RBFN	R^2	0.99837	0.99428	0.98162
	MAE	0.31358	1.99114	6.18024
	MSE	0.24126	7.91164	87.68931
	RMSE	0.49118	2.81276	9.18952

Note: compiled by the authors

The XGBoost model exhibited outstanding results with R2 Score close to 1 for all variables and the lowest MAE, MSE, and RMSE values, indicating its exceptional accuracy. The GRU model showed slightly lower accuracy with R2 Score ranging from 0.97253 to 0. 98685, along with higher MAE, MSE, and RMSE errors. The RBFN model also demonstrated high accuracy with R2 Score between 0.98162 and 0.99837, and moderate MAE, MSE, and RMSE values, which were lower than GRU but not as superior as XGBoost in some instances.

RSSI values are essential for predicting the distance between the transmitter and the gateway. We have gathered RSSI values from 100 test nodes with a maximum transmit power of 14 dBm. The predicted distances from the XGBoost, GRU, and RBFN models were compared with distances acquired from OMNeT++.

All models demonstrated very high prediction accuracy, as shown in Table 2, with XGBoost achieving the best performance (R2 Score: 0.99571, MAE: 4.75846, MSE: 65.40882, RMSE: 7.45037). Using these predictions, the distance to the node after the initial message transmission can be calculated. In subsequent steps, this distance will be utilized in the proposed algorithm. Figure 6 illustrates the relationship between distance and received signal power for various ML methods.

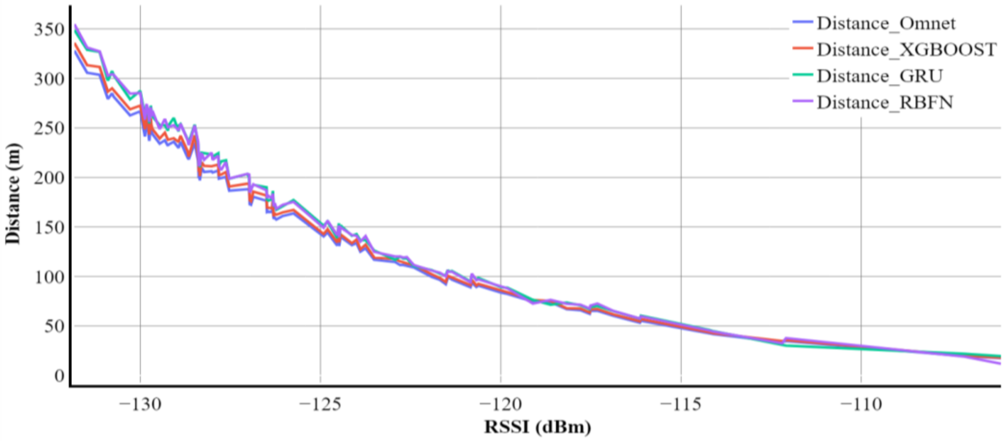
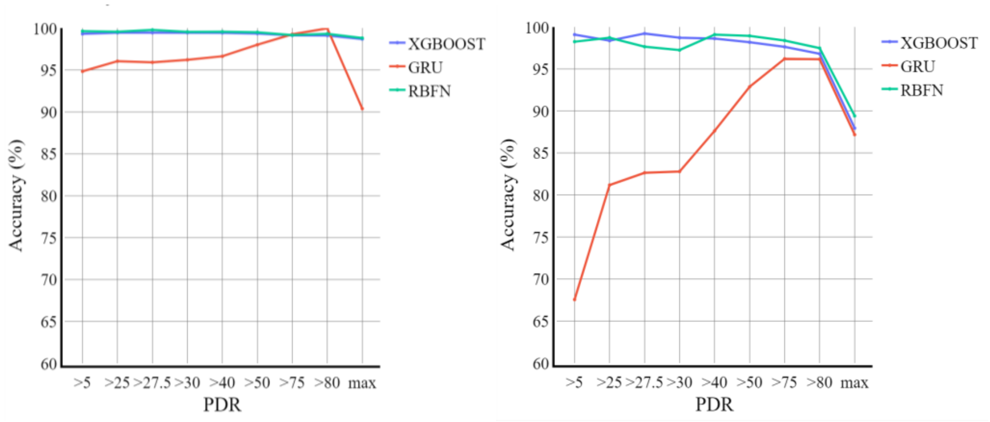


Figure 6. Dependence of distance on received signal power
Note: compiled by the authors

In order to evaluate the performance of the proposed algorithm, a Sim4 benchmark simulation were conducted using 100 test nodes with varying filter parameters. The ADR algorithm was used for comparison. The obtained results were presented in Table 3 for diverse filter settings.

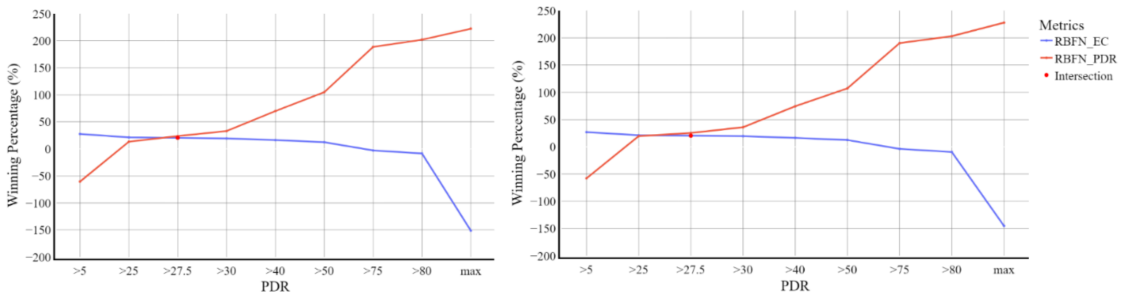
Figure 6 illustrates the accuracy of EC and PDR results from GRU, XGBoost, and RBFN predictions compared to OMNeT++ simulations across various minimum PDR threshold values. The graphs highlight that XGBoost and RBFN models exhibit high accuracy. However, as the minimum PDR threshold increases, the alignment between model predictions and OMNeT++ simulations decrease, particularly evident in the PDR plot (Figure 7b). The highest accuracy is observed at a minimum PDR threshold of >80. Thus, we can conclude that the trained XGBoost and RBFN models demonstrate robust predictive capabilities."

Using the obtained models and the proposed algorithm, we made a comparison with traditional ADR, for which we carried out a simulation of Sim4 with 100 nodes that sent 216 packets over 3 days. Packets were sent with an exponential distribution and an average time between sendings of 1000 seconds. Figure 7 shows the gain of the XGBoost and RBFN models compared to the ADR algorithm depending on the value of the minimum PDR threshold.



a) b)

Figure 7. Determination of accuracy between filter result and OMNeT++ a) EC b) PDR
Note: compiled by the authors



a) b)

Figure 8. Determination of optimal filter parameters: a) XGBoost, b) RBFN
Note – compiled by the authors

From the graphs, it is obvious that increasing the minimum PDR threshold enhances the success rate while reducing EC. The equilibrium point occurs where the PDR and EC graphs intersect at the lower filter threshold of minPDR > 27.5. At this point, we achieve improvements in both EC and PDR. In the optimal prediction model, XGBoost, the success rate in EC was 20.43% higher and in PDR was 23.72% higher compared to ADR. Moving towards an increase in the lower PDR threshold will lead to an increase in the network PDR, but the EC also increases, which is undesirable for network efficiency. Conversely, when moving towards a lower PDR threshold, most messages will not be delivered, even though it improves energy efficiency.

The main difference of our approach is its ability to find the optimal balance between EC and performance, which significantly improves the overall efficiency of the LoRaWAN network. Our proposed method not only improves EC and PDR, but also has high accuracy in predicting optimal parameters. We selected ML methods due to their ability to efficiently process large amounts of data and accurately predict parameters, making them ideal for optimization problems in dynamic and resource-intensive networks.

CONCLUSION

This paper introduces an optimization algorithm for SF and TP parameters in LoRaWAN wireless networks using different ML methods. XGBoost, GRU, and RBFN techniques were utilized to predict optimal parameters, where XGBoost demonstrated the highest accuracy, accounting for 99.5%. The results indicate that our optimized algorithm enhanced energy efficiency by 20.43% and improved PDR value by 23.72% compared to traditional ADR methods.

The key finding of this research is to reach balance between EC and PDR, which can considerably enhance the overall performance of the LoRaWAN network. We proposed an optimal lower limit of PDR that achieves a trade-off between EC and PDR compared to traditional ADR. The relevance of the study lies in its contribution to optimizing LoRaWAN network parameters, which is essential for the long-term and reliable operation of IoT devices.

The obtained data was processed and validated in the OMNeT++ simulator using the FLoRa library. The simulation results are consistent with the model prediction results.

CONFLICT OF INTEREST: The authors declare no conflict of interest.

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