Adaptive NDF Classification for SF Allocation in Arbitrary Node Distribution in LoRaWAN

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Abstract In this paper, we introduced the Adaptive NDF (Node Density Factor) classification method to enhance the performance of the original ADR (Adaptive Data Rate) scheme used in the LoRa (Long-Range) network in scenarios with arbitrary distributed nodes. The core concept of Adaptive NDF Classification is the NDF factor calculation, determined by the ratio of nodes in a specific section to the total number of nodes. The coverage area spanning from 2 to 10 kilometers was systematically observed for variations in NDF and DER values. The Adaptive NDF classification method boosted the DER to 78% in the area beyond 4 kilometers, around 18% over the original ADR. In other words, the Adaptive NDF classification method represents a valuable enhancement to the ADR scheme, offering improved performance when nodes are irregularly distributed.

Keyword LoRaWAN, Internet of Things, Adaptive Data Rate, Smart dairy farm, SF Allocation

1. Introduction

The LoRaWAN (Long-Range Wide Area Network) is a pivotal low-power networking technology tailored for the IoT (Internet of Things) landscape. It has garnered significant recognition within the IoT domain due to its versatile applications, encompassing smart devices, healthcare solutions, urban infrastructure (smart cities), and agricultural management (smart farms), among others. One of the fundamental strengths that distinguishes LoRaWAN is its cost-effectiveness, minimal power consumption, and expansive network coverage. This technology is especially adept at facilitating low-data-rate transmissions over extensive geographic areas.

The ADR (Adaptive Data Rate) scheme was developed as a core feature to enhance LoRaWAN performance. However, in certain network scenarios, ADR encounters challenges when attempting to assign the most suitable SF (Spreading Factor) to nodes that define the data rate and node's property. This challenge arises due to the presence of multiple nodes sharing the same SF values, leading to increased chances of data collision. In response to this issue, researchers are diligently exploring solutions to optimize SF assignments.

Previous research has explored numerous avenues for optimizing the ADR scheme. Researchers have considered a range of related parameters to enhance overall performance. For instance, V. Hauser et al. [1] introduced an algorithm that assessed TX (transmission power) and retransmission timing to determine the appropriate SF assignment for nodes. F. Cuomo et al. [2-3] proposed the EXPLoRa-SF algorithm, which leveraged RSSI (Received Signal Strength Indicator) levels, while EXPLoRa-AT utilized ToA (Time-On-Air) for SF optimization. Additionally, EXPLoRa-TS considered time symbols, and EXPLoRa-K Mean employed AI techniques to analyze and enhance ADR performance. D. Suluja [4] presented an SF allocation scheme based on SNR, demonstrating improvements in real-world LoRaWAN network experiments. Despite these advancements, challenges persist in addressing dense or other arbitrarily distributed SF values within the LoRaWAN network.

The statistical analysis is a solution to examine the distribution of RSSI values in the abovementioned network. In previous works, [5] and [6] introduced QCVM (Quantile Classification of Variance from the Mean) and SD (Standard Deviation) classification algorithms, respectively. Both methods delve into the probability, mean, and SD of RSSI to optimize performance. This paper concentrates on statistical analysis and puts forth a classification method based on statistical data.

In contrast, we introduce an innovative approach called Adaptive NDF (Node Density Factor) classification. This method categorizes all nodes into sections and assesses the NDF factor. The NDF factor is a crucial factor in determining the appropriate subdivision of nodes into subgroups (n) and guiding the allocation of SF values, which is believed to enhance the success of data transmission in the network of arbitrarily distributed nodes.

In this study, we employed the LoRaWAN technology to enhance the efficiency of smart estrus detection nodes for dairy farms. Our research focused on surveying dairy farms located in Photharam district, Ratchaburi, Thailand, covering an area spanning approximately 2 kilometers and comprising of approximately 1,200 identified dairy cows or nodes. Subsequently, we expanded our investigation to 10 kilometers, by simulating approximately another 20% or 300 dairy cows or nodes at random locations. We utilized the LoRaSim simulator to simulate pertinent attributes of all nodes. Our evaluation criteria include measuring the DER (Data Extraction Rate) values at each coverage area, as detailed in Section 4.

2. RELATE WORKS

2.1. LORAWAN

LoRaWAN stands as a pivotal technology for facilitating data transmission within the IoT network. It harnesses LoRa as its physical layer, operating within the ISM band ranging from 902 to 928 MHz in Thailand. The LoRaWAN architecture [7] in Figure 1 comprises four essential components: end nodes, gateways, network servers, and application servers.

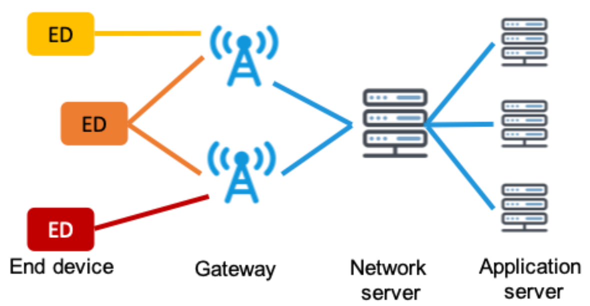

Fig 1. LoRaWAN architecture [7].

End node: The hardware device detects substantial stimuli and transmits the data to a gateway using the LoRa protocol.

Gateway: The gateway receives data from the node, screens it, and subsequently forwards it to the network server using the TCP/IP protocol.

Network server: This component plays a critical role in managing network performance. It oversees tasks such as deduplicating information, establishing routing protocols, selecting data channels, and assigning SF values. Additionally, it can configure the ADR mechanism to enhance overall network performance.

Application server: This component receives raw data from the network server, performs data analysis, and then presents the analyzed information.

The ADR scheme in LoRaWAN dynamically determines the SF value by comparing the RSSI of the node with its sensitivity level. The RSSI represents the signal strength level, and it is contingent upon factors such as the TX (transmitter power) and the path loss values, which can be expressed as follows:

$$RSSI = P_{TX} - P_L(d) \quad (1)$$

where $RSSI$ is a signal strength level (dBm)

P_{TX} is a transmitting power (dBm).

P_L indicates the function of path loss (dB) related to d (distance) from the node to a gateway in meters.

The sensitivity level is a critical parameter that dictates the SF value. Sensitivity is computed in relation to specific bandwidth, noise floor, and SNR values [5]. This calculation can be expressed as follows:

$$S = -174 - 10 \log BW + NF + SNR_{lim}, \quad (2)$$

where S represents sensitivity (dBm).

BW corresponds to the bandwidth, set at 125 kHz.

NF indicates the noise floor, set at 6 dB.

SNR_{lim} signifies the SNR limit or the threshold for the signal-to-noise ratio level.

The values for BW, NF, and SNR_{lim} are contingent upon the specific receiver device, as detailed in Table 1.

TABLE 1. THE SENSITIVITY LEVELS AND SNR LIMIT

SF	SNR limit (dB)	Sensitivity (dBm)
7	-7.5	-124.53
8	-10	-127.09
9	-12.5	-129.53
10	-15	-132.03
11	-17.5	-134.53
12	-20	-137.03

2.2. THE SD CLASSIFICATION METHOD [6]

The SD Classification Method allocates SF values by analyzing the means and SDs of the nodes' RSSI values. The process initiates with the categorization of nodes according to their sensitivity levels. Subsequently, the mean and SD are computed for each group. Following this, each RSSI group is further divided into four subgroups, denoted as 'n = 4'. The breakpoints for these subgroups are determined based on 0.5 SD, 1 SD, and 1.5 SD. Ultimately, this procedure results in the assignment of new SF values to the end nodes.

It is of significance to underline that while this method effectively determines the most suitable SF values for end nodes based on RSSI distribution, the unchanging 'n' value represents a critical aspect for observation. This raises inquiries about the implications when the end nodes do not conform to a normal distribution pattern.

This research aims to address these intricate issues by dynamically adjusting the 'n' value to align with the distribution characteristics observed in the end nodes, introducing the proposed method called 'Adaptive NDF Classification Method.' A comprehensive and detailed presentation of this method is provided in the next section.

3. The Adaptive NDF Classification Method

In order to enhance the performance of ADR scheme, we propose the utilization of the Adaptive NDF Classification method. This approach was developed as an extension of the previously established SD classification method. The core concept behind Adaptive NDF Classification centers around the calculation of the NDF factor, determined by the ratio of nodes in a specific section to the total number of nodes in the dataset. Figure 2 illustrates the process of Adaptive NDF.

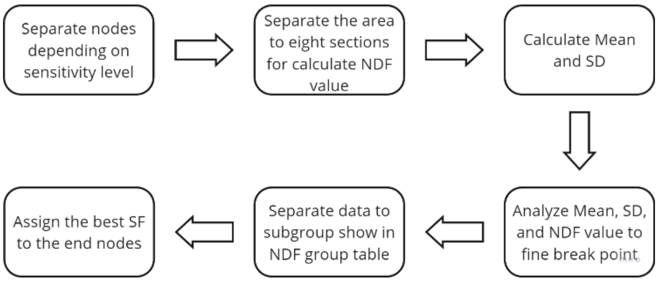

Fig 2. The Adaptive NDF Classification process

In the initial phase of our approach, we began by categorizing nodes based on their sensitivity levels, as detailed in Table 1. The gateway is responsible for transmitting data to the designated endpoint to validate this process.

Following the sensitivity-based node separation, we analyzed the geography of the dairy farm and the NDF values in Figure 3. Subsequently, we first partitioned the network area into eight distinct sections, accommodating approximately 1,500 nodes, all within a 2-kilometer radius. Note that, the 1,200 node locations obtained from the farms were fixed, and the additional 300 node locations were random by simulation. Both segments together demonstrated the arbitrary node distribution.

Next, we calculated the mean and SD for each section, followed by an analysis of these metrics along with the NDF to identify optimal separation points. Subsequently, the data were divided into new subgroups, with the assignment of the most suitable SF values. This adaptive process enhances our ability to detect variations and improve the ADR scheme. The result is represented in Table 2.

In our simulation setup, we extended our observations to a range spanning from 2 to 10 kilometers, keeping the same number of nodes, to investigate the impact of DER and NDF values at larger coverage. Table 3 highlights the significance of various parameters within our study.

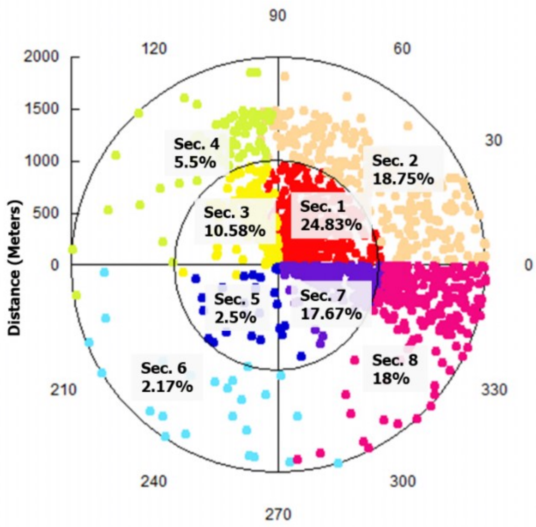

Fig 3. The positions of the 1,500 nodes are separated into eight sections.

Table 2. The NDF Value Classification and Newly Assigned SF

NDF Value	Number of Subgroups	Break Point	New SF
NDF < 0.2	1	None	7
0.2 < NDF < 0.3	2	$\pm 1\sigma$	7, 8
0.3 < NDF < 0.4	3	$\pm\sigma 0.5$, $\pm 1\sigma$	7, 8, 9
NDF > 0.4	4	$\pm\sigma 0.5$, $\pm\sigma 1$, $\pm\sigma 1.5$	7, 8, 9, 10

Table 3. The parameters in the simulation

Parameters	Values
Nodes	1,500
Gateway	1
Transmitted power	14 dBm
Simulation time	43,200 sec (12 Hours)
Message time	1,800 sec (30 minutes)
Bandwidth	125 kHz
Frequency	923 MHz
Pathloss model	Hata Okumura : Rural
Payload size	255 bytes
Coverage area	2 to 10 km.

4. Results and Discussion

This section presents the simulation results and delves into their implications. Table 4 provides the overview of the NDF values obtained during the expansion of the study area.

Upon investigating of the 2-kilometer radius, the placement of fixed nodes is allocated to sections 1, 2, 7, and 8, as illustrated in Figure 3. In Section 1, the NDF value surpasses 0.2, prompting the division of this section into two subgroups. However, as the coverage area expands, the allocation of fixed nodes evolves. In the case of a 4-kilometer radius and beyond, the fixed nodes are redistributed within Section 1 and Section 7. This redistribution has the effect of elevating NDF values to exceed 0.4 and 0.3, respectively. Consequently, Section 1 is further divided into four subgroups, while Section 7 is divided into three subgroups. After the simulation was performed, the comparative analysis of the original ADR, EXPLoRa_SF [2], and the proposed method in terms of the overall DER are shown in Figure 4.

Table 4. The NDF values when expand the coverage area

Area (km)	Sec. 1	Sec. 2	Sec. 3	Sec. 4	Sec. 5	Sec. 6	Sec. 7	Sec. 8
2	0.248	0.188	0.106	0.055	0.025	0.022	0.177	0.180
3	0.383	0.061	0.135	0.018	0.023	0.024	0.249	0.107
4	0.413	0.020	0.148	0.021	0.019	0.020	0.336	0.024
5	0.422	0.017	0.143	0.022	0.013	0.023	0.348	0.014
6	0.420	0.018	0.144	0.026	0.018	0.014	0.339	0.020
7	0.422	0.018	0.130	0.023	0.013	0.024	0.343	0.028
8	0.437	0.017	0.126	0.023	0.021	0.019	0.334	0.023
9	0.418	0.024	0.145	0.016	0.020	0.018	0.346	0.013
10	0.426	0.021	0.143	0.023	0.021	0.017	0.335	0.015

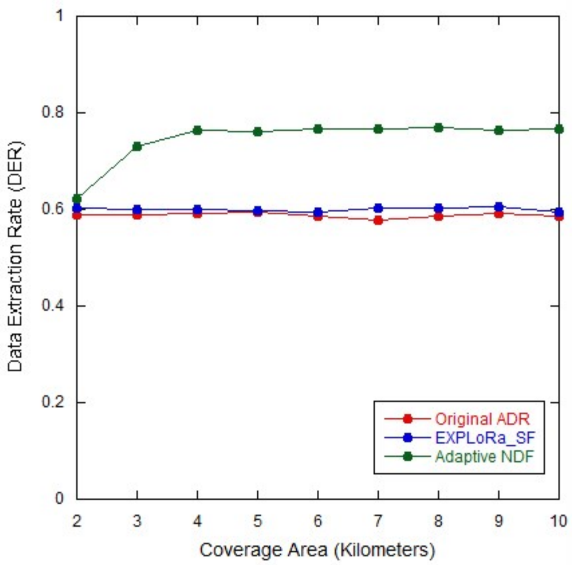

Fig 4. The overall DER vs the coverage area

At the 2-kilometer coverage, a common distribution of nodes is observed across all methods, resulting in DER values hovering around 0.6 or 60%. However, as the node density increases significantly, particularly in Sections 1 and 7 at larger coverage area, our proposed method demonstrates its efficacy. It significantly enhances the DER value to approximately 0.78, or 78%. In summary, our proposed method proves to be highly effective in scenarios with dense node populations, contributing to a substantial improvement in DER values.

5. Conclusions

In this paper, we introduced the Adaptive NDF classification method, aimed at enhancing the performance of the original ADR scheme approach, particularly in scenarios with arbitrary distributed nodes. Our research was conducted within the context of simulated dairy farms situated in Photharam district, Ratchaburi, Thailand, covering an initial area of 2 kilometers and involving a network of 1,200 fixed nodes and 300 random nodes. We expanded this experimental area to encompass 10 kilometers, systematically observing variations in NDF and DER values.

Our findings revealed that within the 2-kilometer radius, nodes were commonly distributed, leading to all methods achieving the DER of approximately 60%. However, as the study area is expanded beyond 4 kilometers, the Adaptive NDF classification method exhibited remarkable effectiveness, boosting the DER to a notable 78%. This observation underscores the significant impact of our proposed method, particularly in environments with intensive node deployments.

In conclusion, the Adaptive NDF classification method represents a valuable enhancement to the ADR scheme, offering improved performance when nodes are irregularly distributed. Our research underscores the adaptability and potential applicability of our approach in scenarios with high node density, such as the agricultural landscape of dairy farms.

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