Evaluation of Multi-Gateway LoRaWAN with Different Data Traffic Models

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***Abstract*—In this paper, We analyze the performance of popular low-power wide-area networking technology called long rage (LoRa) using different data traffic generation models, and by varying the number of gateways in a LoRa network cell. Moreover, we also analyze LoRa's performance in the presence of multiple concurrent applications in a LoRa network. Here, we also present an extension for an existing LoRa simulator called LoRaSim to simulate multiple concurrent applications in the presence of multiple gateways in a LoRa network. Our results demonstrate that, a LoRa communication setting that supports diversity in terms of bandwidth, spreading factor, and coding rate demonstrates good performance for different data traffic models mostly without requiring multiple gateways in a LoRa network cell. Through simulation case studies, we also demonstrate effectiveness of our extended LoRaSim simulator.**

I. Introduction

The Internet of Things (IoT) promises to create an ecosystem of billions of connected devices [1]. To support multitude of IoT applications many low-power wide-area radio technologies have emerged, however long range (LoRa) [2] is the most popular technology. The long range characteristic of LoRa mostly results in a star network topology, hence network deployment and maintenance become relatively simple [3]. LoRa is popular low-power wide-area networking (LPWAN) technology due to its openness and open source software support, and it provides a number of communication settings to support broad operating range. Motivated by this, here we analyze the impact of LoRa physical layer communication settings on different IoT applications using different data traffic models, and our traffic models can be associated with popular IoT applications, such as smart metering, smart street lighting, smart street parking, and vehicle fleet tracking. We also investigated the communication settings performance using multiple gateways in a single LoRa cell. Our study does not only consider a single application based LoRa/LoRaWAN network, but it also considers multiple concurrent application in the same network.

Our study uses a popular LoRa/LoRaWAN simulator called LoRaSim [4]. Currently, LoRaSim can only simulate a single application inside a LoRaWAN network. However, invariably real deployments aim at supporting multiple concurrent applications in a single LoRaWAN network. Therefore, we extend LoRaSim so that it can simulate multiple concurrent applications in a LoRa/LoRaWAN network and our extension also supports multiple gateways in the same LoRa cell. The following are our main contributions: (i) analysis of the impact of multiple gateways and LoRa physical layer communication settings on the performance of different data traffic generation models, (ii) analysis of the impact of multiple gateways and different LoRa physical layer communication settings on a multiple concurrent applications, and (iii) extension for an existing state-of-the-art LoRa/LoRaWAN simulator so that it can simulate multiple concurrent IoT applications .

The rest of this paper is organized as follows. Section II presents related work. Our data traffic models for different IoT applications are presented in Section III. LoRa communication settings performance analysis is presented in Section IV, and extension for LoRaSim are presented in Section V. Finally, conclusions are presented in Section V.

II. Related Work

LoRa throughput is analyzed in [5], [4], and [6]. Primarily, the throughput analysis work has been performed for Class A LoRa devices. It has been shown that the throughput of nodes at the edge of the network can be as low as 100 bps [7]. Moreover, it has also been shown that although LoRaWAN uses the Aloha protocol, due to LoRa's robust modulation technique an increase of up to 1000 nodes per gateway results in 32% more packet losses compared to the same scenario in simple Aloha-based networks where the losses amount up to 90% [6]. In [8] and [9] LoRa gateway coverage and scalability are analyzed. It has been shown that in harsh propagation conditions, a LoRa cell can cover approximately a 2 km radius, but nodes at the network edge are only guaranteed the lowest bit rate. Therefore, a nominal coverage of 1.2 km must be assumed. In [10] and [11] an analysis of LoRa is presented from the perspective of neighboring LoRa network interference and co-spreading factor interference. It is shown that to combat interference, using multiple gateways is a better option compared to directional antennae as it yields substantially higher increase in PDR.

Existing research on analyzing LoRa is limited as a number of factors have not yet been fully considered. These factors include traffic generation models for IoT applications and the impact of multi-gateway LoRa cell on a network's performance. Moreover, multiple concurrent IoT applications' impact on a LoRa/LoRaWAN network performance is also ignored. Hence, this study fills the mentioned research gaps.

III. Our Data Traffic Models

Traffic Model A: Our traffic model A is a periodic data reporting model. It targets those IoT applications that transmit a single packet per day. Typically, a smart electricity, gas, or water meter transmits daily meter readings to the utility provider's server. The problem with periodic data reporting is that, if all smart meters transmit their reading at the same time, there is a very high data packet collision probability. Therefore, in our experiments, we assume that an application waits for a random duration of time to transmit a data packet. In our experiments, the data packet transmission is delayed using a uniformly distributed random time interval in the range [0, 500] seconds. Hereafter, we refer model A as smart metering (SM) model.

Traffic Model B: Our traffic model B represents an event-driven data generation model. In some IoT applications, an event may depend on a preceding event. Hence, our model B captures this event dependency feature. A suitable candidate for our model B can be a smart street parking system in a city center of a metropolitan city. We model arrival and departure of cars using Poisson processes. We assume that whenever a parking space becomes available, it is occupied within 5 minutes, hence λ for occupying a parking space is 5 minutes. Moreover, a vehicle can use a parking space for 1 hour, therefore λ for a parking space to become free is 1 hour. Hereafter, we refer model B as smart parking (SP) model.

Traffic Model C: Our traffic model C represents a hybrid model. A smart street lighting system is a representative of hybrid data traffic model. In this model, we assume that during typical sunlight hours the lights remain switched off, and they are turned on just before sunset. After midnight, the lights remain off, and they are only switched on once a movement on a street is detected. Just after sunrise the lights remain off until sunset. In our experiments, we assume that sunset is at 7 pm, and sunrise is at 7 am. We model movement on a street after midnight as the Poisson arrival process with mean $(\lambda) = 30$ minutes. Hereafter, we refer model C as smart street lightning (SSL) model.

Traffic Model D: Our traffic model D also represents an event-driven model, however it targets frequently occurring events. We consider a vehicle fleet tracking application as an example for model D. A number of events can be tracked, such as speeding, long idle time, and position information in response to a random position update query. In our analysis, we model traffic generated by such an application through the Poisson process with mean arrival rate $(\lambda) = 5$ minutes. Hereafter, we refer model D as vehicle fleet tracking (VFT) model.

IV. Performance Analysis

For performance analysis we use the LoRaSim simulator [4]. The simulator only supports uplink traffic, therefore our analysis does not consider data frames that require an ACK from the gateway. Typically, $860\,MHz$ transmit frequency is used, unless otherwise stated. For our experiments, we use a payload size of 20 bytes. This payload size is large enough to facilitate the different IoT applications we consider. The duration of each simulation is 1 month, and in our experiments we vary the number of nodes in a LoRaWAN network cell from 200 to 1000 nodes in steps of 200. Moreover, we vary the number of LoRa gateways in a network from 1 to 4. We use reliability as our performance benchmark and for reliability we measure and report packet delivery ratio (PDR). We analyze the impact of the following LoRa setting on different IoT applications:

SN^1**:** This setting uses the following parameters: SF12, BW = 125 KHz, and CR = $\frac{4}{8}$. We analyze this setting because it is the slowest data rate setting and it provides the highest level of resilience against interference.

SN^2**:** Similar to SN^1, however randomly chooses between three different transmit frequencies (860, 864, and 868) MHz. We are interested in analyzing this setting because it can help us to understand the impact of frequency diversity.

SN^3**:** Randomly selects BW (125, 250, 500) KHz, SF (7, 8, ..., 12), and CR (4/5, 4/6, 4/7, 4/8). We analyze this setting to explore the impact of random communication parameter selection in a multi-gateway LoRa cell.

Single-Application-Based Analysis: Fig. 1(a) - Fig. 1(d) show the impact of different LoRa communication settings on our SM application. In general, as we increase the number of gateways in the network, the PDR demonstrated by the evaluated settings improves. For SN^1 and SN^2 with an increase in the number of nodes in the network the PDR drops. Mostly, SN^3 demonstrates nearly perfect PDR. SN^1 and SN^2 use the lowest possible BW in LoRa and highest possible SF, hence these communication settings' airtime is higher compared to SN^3, hence these settings are more impacted by contention. Because of diversity in transmit frequency SN^2 demonstrates better performance than SN^1. Generally, as we increase the number of gateways in the network, the improvement in PDR slowly diminishes.

Fig. 1(e) - Fig. 1(h) show the impact of different settings on our SP application. Mostly, the trends shown in the figures are similar to the trends demonstrated by the SM application. However, comparison of both applications confirms the following: event-based data generation model positively impacts performance of SN^1 and SN^2, and SN^3 demonstrates similar performance in our periodic and event-based (traffic model B) data generation models. On an average a lower number of nodes transmit simultaneous in our SP application compared to our SM application, this results in the SN^1 and SN^2 settings enhanced performance.

Fig. 1(i) - Fig. 1(l) show the impact of different settings on our SSL application based on our hybrid data traffic model. The evaluated settings demonstrate higher PDR compared to the PDR demonstrated by them in our SM and SP applications. The following are reasons for higher PDR: (i) in our results event-based traffic has shown better performance, and in our SSL application the number of packets generated in repose to an event are higher compared to periodic data packets, hence higher PDR corresponding to the event-based traffic offsets some of the negative impact of periodic traffic on the PDR,

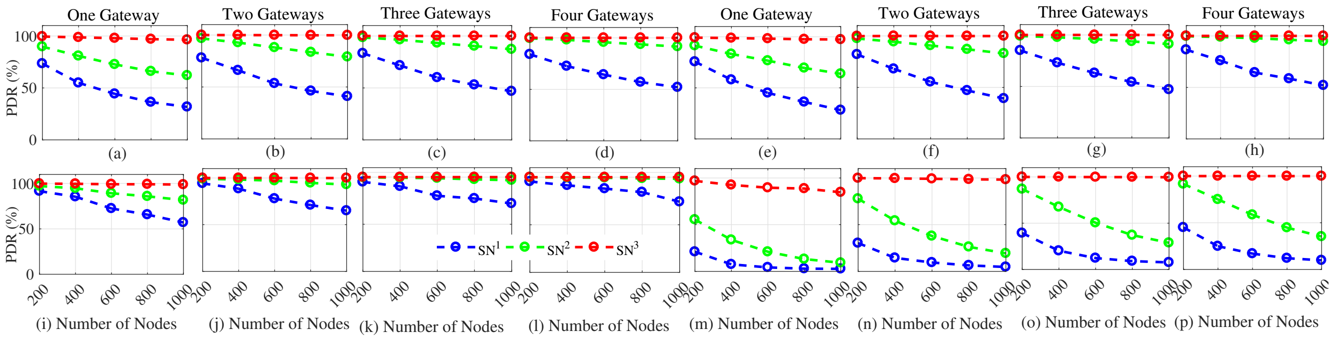

Fig. 1. IoT Applications' Performance Comparison Using Different LoRa Communication Settings

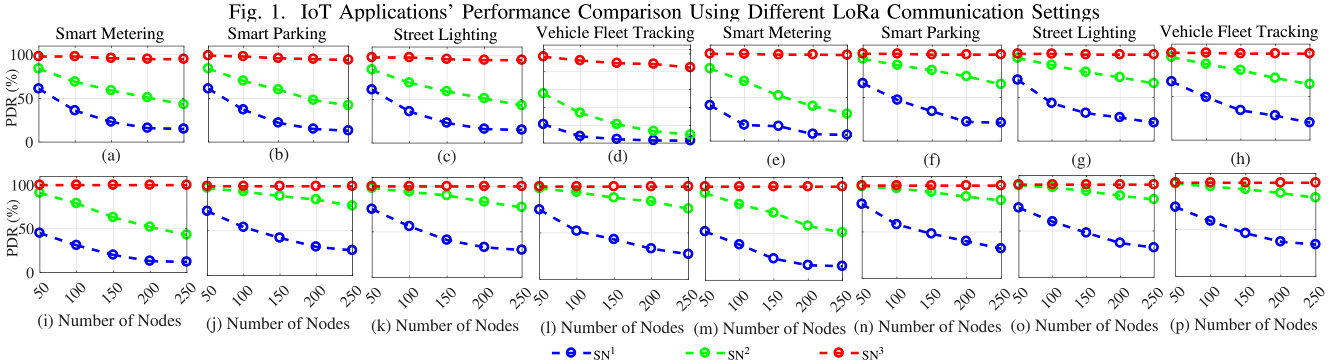

Fig. 2. Concurrent IoT Applications' Performance Comparison Using Different LoRa Communication Settings

and (ii) λ in case of our SSL application is relatively high, hence lower number of collisions and better performance.

Fig. 1(m) - Fig. 1(p) show the impact of different settings on our VFT application. This is an event-based application, and events are occurring at a relatively higher rate. The PDR demonstrated by SN^1 and SN^2 is very low regardless of the number of gateways, hence these settings cannot be used in those event-based IoT applications that generate data packets at a relatively high rate. Moreover, SN^3 can only handle such applications in the presence of multiple gateways in a LoRa cell.

Concurrent Multiple Applications Based Analysis: Here, we analyze the LoRa communication settings performance in the presence of multiple concurrent applications by varying the number of gateways in a LoRa cell. LoRaSim does not simulate multiple concurrent application, therefore we modified LoRaSim to simulate concurrent applications based on our data models. We vary the total number of nodes in a network from 200 to 1000 in steps of 200 nodes. In each setup, equal number of nodes are assigned to different IoT applications corresponding to our data models. All other simulation parameters are the same as discussed before.

Fig. 2(a) - Fig. 2(d) show the PDR demonstrated by different applications using different settings in case of a single gateway. SN^3 demonstrates nearly optimal PDR in all evaluated applications apart from VFT application. However, SN^1 and SN^2 demonstrate poor performance. The VFT application demonstrates poorest PDR because of its highest data generation rate. These results again emphasis that a communication setting's air time and diversity in terms of BW, SF, and CR impact the setting's performance.

Fig. 2(a-h), Fig. 2(i-l), and Fig. 2(m-p) show the PDR demonstrated by the applications in case of two, three, and four gateways in a LoRa cell respectively. In general, SN^3 demonstrates scalability in terms of number of nodes and type of application. However, SN^1 and SN^2 neither exhibit scalability in terms of the number of nodes nor in terms of application type. The reasons for $SN3's$ good performance and other settings poor performance are similar to what we have discussed in our analysis based on a single application.

V. Multi-Application LoRaSim with Multiple Gateways Support

Here, we present an extension for the LoRaSim simulator. Our extension differs for LoRaSim in the following aspects: (i) it can simulate multiple concurrent IoT applications using multiple gateways, (ii) for each application, a user can specify the applications data generation model along with data packet size, supported data generation models include the following: exponentially distributed traffic (Poisson process), randomly distributed traffic, and periodic traffic, (iii) a user can specify the number of nodes corresponding to each application.

Configuration File I	Configuration File II
50 –P 86400000 80 100 -E 3600000 60 50 -R 43200000 40	50 -P 86400000 80 100 -E 3600000 60 50 -R 43200000 40 100 -P 3600000 20 50 -E 1800000 30 100 -R 3600000 10

Fig. 3. Simulation Conf. Files

To use our extended LoRaSim with multiple gateways support, a user is required to create a simulation configuration file. A record in the file comprises of the following information: *no_of_nodes, data_distribution_id, pkt_generation_rate,* and *pkt_size*. The interpretation of *pkt_generation_rate* is dependent on *data_distribution_id*. *data_distribution_id* can take one of the following values: *'-P'* for periodic data generation, *'-E'* for exponentially distributed data generation, and *'-R'* for random data generation. Typically, IoT applications generate data packets periodically or in response to an event, therefore our LoRaSim extension supports the mentioned data packet generation models. *pkt_generation_rate* is specified in milliseconds (ms), for *data_distribution_ id* corresponding to *-P*, *-E*, and *-R* it represents periodic packet generation interval, mean packet generation interval, and upper limit on the time after which a packet should be generated, respectively. A single record in the configuration file corresponds to an application.

To run the simulator the following command line arguments are required: *configuration file, LoRa communication setting number to simulate, required number of gateways, total simulation duration,* and *full stack collision check indicator*. LoRa communication settings numbers can be found in [12].

To elaborate on the functionality of our extended LoRaSim, we present different simulation case studies based on simulation configuration files shown in Fig. 3. Our LoRaSim extension supports all LoRa settings supported by LoRaSim, however here we only present simulation results pertaining to the SN^1, SN^2, and SN^3 settings.

Fig. 4 shows the PDR demonstrated by different applications w.r.t. the different communication settings and by varying the number of gateways in a LoRaWAN cell. Fig. 4 highlights the following: SN^1 demonstrates poorest performance, applications that transmit data packets periodically achieve lowest PDR, and increasing the number of gateways in a LoRaWAN cell improves the applications' PDR. SN^1 demonstrates poor performance because air time corresponding to SN^1 is high and it does not use frequency diversity as used by SN^2. SN^3 also does not use frequency diversity, however it still demonstrates better performance, SN^3 corresponds to the fastest data rate possible in LoRa, hence it exhibits lowest air time. The lower air time reduces the probability of collision using Aloha MAC, hence SN^3 demonstrates better performance. Applications 1 and 4 both transmit data periodically, however application 4 demonstrates higher PDR. The reason being, application 4 transmits short data packets, hence air time for its data packet is shorter. The shorter air time results in the lower number of collisions, hence better performance.

VI. Conclusions

We analyzed different LoRa communication settings' impact on different IoT applications by varying the number of gateways in a LoRa cell. We not only analyzed the communication settings' in the presence of a single application, but also considered multiple concurrent applications. Moreover, we also presented an extension for LoRaSim that enables it to simulate multiple concurrent applications in a LoRa/LoRaWAN cell. Our analysis demonstrated that in a LoRa cell with a reasonably number of nodes, SN^3 scales w.r.t. the number of nodes, the data generation models, and in different scenarios considered in this paper. LoRa's slowest data rate setting

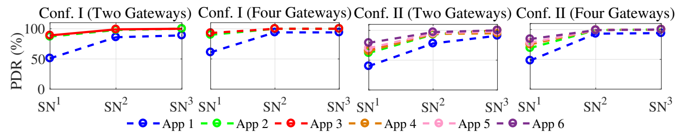

Fig. 4. Simulation Results

(SN^1) is not useful in any of the analyzed scenarios. For our periodic data generation model SN^1 and SN^2 are not appropriate. In harsh communication environments, SN^2 with multiple gateways can be used for the dependent event-based data traffic model. In the presence of multiple concurrent applications, SN^3 is the only suitable setting.

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