



Article On the Use of LoRaWAN for Mobile Internet of Things: The Impact of Mobility

Mohammad Al mojamed 回

Computer Science Department, Computing College-Al-Qunfudah, UMM Al-QURA University, Al-Qunfudah 28814, Saudi Arabia; mmmojamed@uqu.edu.sa

Abstract: A long-range wide-area network (LoRaWAN) targets both mobile and static Internet of Things (IoT) applications; it is suited to IoT applications, which require a large coverage area while consuming less power at a low data rate; it provides a solution for transferring data between IoT devices with a minimum cost in terms of power, at the expense of higher latency. LoRaWAN was designed for static low-power long-range networks. However, several IoT solution applications involve the use of mobility. Therefore, this study investigates the usage of LoRaWAN in the field of mobile Internet of Things applications such as bike rentals, fleet monitoring, and wildlife and animal tracking applications. Using the OMNeT++ simulator, two different well-known mobility models are used to investigate the influence of mobility on the performance of mobile LoRaWAN. The results show that intense LoRaWAN networks can operate under a high velocity and varying traffic load. It can be observed that the random waypoint model combination yields a better performance, but at the cost of higher collisions and energy consumption. As a consequence, the results suggest the reconsideration of mobile IoT solutions over LoRaWAN.

Keywords: LoRa; LoRaWAN; mobility; IoTs



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1. Introduction

The recent advances in sensing, communication, and microelectronic and embedded systems have opened the door to a wider variety of Internet of Things (IoT) applications. Therefore, the IoT has attracted much attention from the research community and from industry [1,2]; this attention is due to its prospects for improving different aspects of our lives, such as medical and health care, smart cities, agriculture, smart homes, smart manufacturing, the Internet of Robotic Things, oil, and gas, etc., [3,4].

A long-range wide-area network (LoRaWAN) [5], as a type of low power wide area network (LPWAN), targets both mobile and static IoT applications. It is the most adopted technology for IoT applications, which require long range coverage while consuming low amounts of energy at a low data rate [1,6]. It provides a solution for transferring data between end devices with a minimum cost in terms of power, at the expense of higher latency (in seconds) and a limited data rate (a few kbps) [7].

Regarding its architecture, LoRaWAN has a star-of-stars topology; it follows the singlehop connectivity paradigm, where long-range (LoRa) devices send their traffic toward one or several gateway devices. Gateways have the responsibility of forwarding traffic between a network server and LoRa devices, and vice versa. The authentication, identification, and filtering of duplicated packets are managed by the network server [8], which also controls the network configuration through the adaptive data rate (ADR) mechanism to achieve optimal operation. Moreover, another part of the network called the application server has the responsibility of managing user data.

LoRaWAN is an MAC layer grounded on proprietary LoRa modulation; it is issued by a nonprofit organization known as the LoRa Alliance [9]. The physical layer—LoRa technology—was developed by Semtech [10], and operates in the unlicensed sub-1 GHz ISM band. There exist various configuration and transmission parameters that characterize LoRa modulation. Tuning these parameters results in a trade-off between power consumption and communication coverage, as well as the amount of transferred data. The parameters are the bandwidth, spreading factor (SF), coding rate (CR), and transmission power. The bandwidth can be set to 500, 250, or 125 kHz. The spreading factor is the ratio between the symbol rate and the chip rate; it signifies the number of encoded bits per symbol, and ranges from 7 to 12. With larger SF, the time on air for a packet is increased, resulting in an increase in power consumption and a decrease in data rate. The CR can be used by the receiving LoRa device to perform forward error correction to overcome the effect of noise on the received packets; it takes one of the following values: 4/5, 4/6, 4/7, or 4/8.

The overall growth in recent years in the number of connected smart devices has led to a rise in the number of studies related to the IoT, with topics such as big data, number of devices per cell, energy consumption, security [11], and mobility of connected devices. Today, there are a wide range of deployed IoT applications that involve or require mobility. Examples of these applications can be seen in smart cities, smart vehicles, bike rental applications, smart health care, solutions for coping with an aging society, fleet monitoring, and wildlife and animal tracking applications. Therefore, LoRaWAN performance should be investigated while taking into consideration different types of mobility models.

The main goal of this article is to investigate the effects of mobility on the performance of mobile IoT devices. The consideration of mobility in the field of LoRaWAN is not quite new. However, a search of the literature revealed that only a few mobility models with a limited speed or number of end devices have been considered. Moreover, some of the existing works focused on mobility in terms of roaming between different networks, or partial mobility—where only a few devices are mobile. Consequently, there is still a lack of investigations on the effect of mobility on the performance of LoRaWAN. Therefore, the contributions of this paper are as follows:

- Integrating the Framework for LoRa (FloRa) with different mobility models in the OMNeT++ simulator;
- Evaluating the performance of LoRaWAN over different mobility models—namely, random waypoint (RWP), Gauss–Markov (GM), and stationary models;
- Performing a comprehensive evaluation over three mobility models while considering a network consisting of up to 5000 end devices moving at different speeds of up to 25 m/s while using varying numbers of gateways;
- Evaluating the effects of the amount of payload on the performance of mobile LoRaWAN.

The rest of this article is structured as follows: Section 2 reviews the existing works in the literature that consider mobility in the field of LoRaWAN. In Section 3, the mobility models used are briefly presented. In addition, Section 3 outlines the methodology adopted in this study to carry out the investigation; it highlights the simulated scenarios and details the utilized configuration parameters and network settings. The results are introduced and discussed in Section 4. Finally, Section 5 concludes the article.

2. Related Work

The work in [4] evaluated the performance of an unmanned aerial vehicle (UAV) integrated with LoRa technology. The case study focused on finding the impact of the number of UAVs and their flying speed on the overall performance of the UAV–LoRa integrated system using simulation tools. The study included eight different UAV mobility models (random direction, random walk, Gauss–Markov, random waypoint, semi-random circular movement, reference point group mobility, smooth turn, and pathway mobility). It concluded that the best results can be achieved with the random direction mobility model, where lower delays and jitter were achieved with a better delivery rate. However, the focus of this study was on the UAV networks.

The performance of real-world mobile LoRaWAN applications was evaluated in [12]. The authors targeted the evaluation of the latency that traffic may experience while moving from mobile end devices to LoRaWAN network servers. Their experiments consisted of a few mobile devices with a preconfigured itinerary, which was chosen to keep the mobile

devices under the coverage of gateways. Mobile end devices were moving in a car with an average speed of 17 km/h. The results of the experimental evaluation indicate that mobile end devices' traffic experiences the same delay as that of static devices. This is expected, as mobile devices' paths are preconfigured to stay within the coverage area of LoRaWAN gateways, and no interruption of communication was anticipated.

The work in [13] proposed a wildlife monitoring system that incorporated LoRaWAN and an opportunistic mobile network (OMN). End nodes were assumed to be fitted with LoRa and Bluetooth Low Energy (BLE) technologies, where LoRa can be used for long-range communication and BLE can be used for P2P communication among the end nodes. The proposed system was evaluated using a network simulator. Regarding end device mobility, the proposed work used the random waypoint mobility model to express device mobility, as well as another mobility model that was derived from ZebraNet GPS data. The latter was imported to model real animal mobility behaviors and movement. Nodes were simulated with a mobility speed ranging between 10 and 30 km/h for the random waypoint mobility model.

The authors of [14] also considered mobility in their proposed work. However, their paper mainly focused on enhancing the adaptive data rate (ADR) mechanism for LoRaWAN based on estimating the next positions of mobile end devices. This information, then, can be optimized by a LoRaWAN network server to determine the best configuration parameters for an end device. The authors proposed a formula to calculate the estimated positions based on different criteria. Testbeds were used to evaluate the proposal with three gateways and five end devices. The results show an improvement in the overall performance of the system when using the enhanced ADR. Thus, the work overall reflects the importance of the impact of mobility on the performance of LoRaWAN.

The authors of [15] also considered the impact of mobility on the ADR mechanism. They claimed that the mobile devices' locations may change by the time that a new ADR configuration parameter arrives at the end devices from the network server. Consequently, the new parameters would no longer be suitable, due to the movement of the devices to new locations. Their proposal was evaluated using the NS-3 simulator for different scenarios consisting of one gateway. The work assumed that only 50% of simulated end devices were mobile and the rest are static. The random walk model was used to model end devices' mobility, with a minimum speed of 0.5 m/s and a maximum speed of 1.5 m/s.

The benefits of ADR were also investigated for mobile LoRaWAN scenarios in [16]. Their experiments involved mounting LoRa end devices on postal tracks that drive on fixed routes around the city of Antwerp, Belgium. The experiments consisted of 15 end devices and a few gateways. Different ranges of mobility speed were used—4.3 km/h, 4.3–11.4 km/h, and 11.4–32 km/h—to find out the influence of mobility, and how ADR mechanisms would help to overcome the possible effects of movement. The study concluded that with low-mobility scenarios, the ADR strategy of increasing the SF to increase the coverage area is still effective and yields good results; however, its benefits decrease as the mobility speed increases.

The authors of [17] proposed a Gaussian-filter-based ADR and an exponential-movingaverage-based ADR to improve the performance of a LoRaWAN network. Similar to [15], the authors used simulation tools to prove that the movement of end devices results in invalid configuration commands for setting the spreading factor and the transmission power for an end device, which are the parameters for the ADR mechanism; therefore, sent traffic may get lost. The NS-3 simulator was used to discover the impact of mobility on the end device convergence period. To model end-device mobility, the authors used a random walk mobility model with a speed varying between 0.5 and 1.5 m/s in a network consisting of one gateway.

The usability of LoRaWAN in the field of vehicular networks was investigated by [18]. Their experimental study involved fixing a transmitter on a motorcycle moving at various speeds, from 20 to 90 km/h. The experiments were carried out on an elliptical track with dimensions of $135 \text{ m} \times 70 \text{ m}$. The gateway was located in the center of the ellipse. The study

reported robustness of LoRaWAN when data were transmitted in motion, and observed limited signal degradation at high speeds.

3. Mobility Models and Methodology

This section introduces the utilized mobility models, which are typically used to simulate the deployment of mobile devices and their features. The methodology used in this study is then described.

3.1. Mobility Models

Even though LoRaWAN is typically used for static communication scenarios, there exists some usage of LoRaWAN for mobile scenarios. LoRaWAN can be used for mobile scenarios such as fleet monitoring, bike rentals, and wildlife and animal tracking. Therefore, mobility models should be considered in the field of LoRaWAN. However, testing LoRaWAN for mobile scenarios with real devices is costly and difficult due to area-specific restrictions in some scenarios, such as wildlife and animal tracking applications. Consequently, there is a need to evaluate the performance of LoRaWAN for these scenarios in simulated environments while using different mobility models. This study considers the use of two different mobility models—namely, the random waypoint mobility model, and the Gauss–Markov mobility model.

3.1.1. Random Waypoint Mobility Model

The random waypoint mobility model (RWP) [19] is one of the three mobility models that are classified under the random mobility category. The other two models are the random walk and the random direction models. RWP has been widely used in simulating ad hoc networks; it requires three parameters: the simulation area, speed, and pause time. According to RWP, a node selects a random location within the simulated area along with a random moving speed. The node then starts moving toward the selected location at the selected speed. Once the node reaches its selected location, it waits for a time known as the pause time; it then selects another random location to move to and selects a new speed randomly. The process is repeated by each individual node until the end of the simulation period.

3.1.2. Gauss-Markov Mobility Model

This mobility model [20] belongs to the category of temporally dependent mobility models; it applies the historical values of direction and node speed to calculate the next values for both direction and speed. The historical values are used to avoid unexpected changes in the velocity and heading direction. Nodes are randomly placed within the simulation area and given an initial speed and direction. The initial values are used to determine the future values. The model calculates the new speed and direction at each predefined time interval, using different seeds to guarantee randomness.

3.2. Methodology and Simulation Setup

This research was carried out using the Framework for LoRa (FLoRa) [21] in combination with the INET framework [22], based on the OMNeT++ simulator [23]. FLoRa is an open-source simulation library that provides implementations for the LoRaWAN MAC and physical layers; it supports bidirectional communication between the components of the LoRaWAN architecture: end devices, gateway devices, and network servers. FLoRa provides models and implementations for all LoRa layer features, such as the spreading factor (SF), code rate, frequency, transmission power, and bandwidth.

The impact of mobility on the performance of LoRaWAN for the mobile IoT was investigated comprehensively using simulation experiments. Random waypoint and Gauss–Markov mobility models were used to discover the possible effect of mobility on the overall performance of the LoRaWAN network. Furthermore, the stationary model was also used as the baseline, where LoRaWAN devices were kept static throughout the duration of the experiments. The stationary model is the conventional model most commonly used for simulating LoRaWAN networks; it was used here as a reference model for comparison purposes.

In this study, two different main scenarios were considered—namely, a large-area scenario, and a small-area scenario—along with a varying mobility speed, different mobility models, and different message payloads. To simulate a large area, a grid square of 2000 m \times 2000 m was used; it contained four static gateways located at each corner of the square. The gateways were connected to the LoRa network servers. Figure 1 shows the placement of the gateways within the simulation area, as well as the overall structure of the simulated network. This scenario was used to investigate the effect of mobility for environments consisting of up to 5000 mobile end devices.



Figure 1. Large network layout and gateway distributions.

Regarding the small simulation area, the study used a grid square of $1000 \text{ m} \times 1000 \text{ m}$ with two gateways placed at two opposite corners, facing one another, to cover most of the simulation area, as shown in Figure 2. However, the number of participating mobile devices for such scenarios was limited to 2500 end devices.



Figure 2. Small network layout and gateway distributions.

The collision and communication ranges for each end device are considerably reliant on many physical layer parameters, such as the transmission power, code rate, frequency, and bandwidth. Specifically, the transmission is regarded as successful when the received power is larger than the sensitivity of the receiving device. The received power is mainly affected by the amount of transmission power and the loss of signal, which can be caused by shadowing and attenuation.

The log-distance model for path loss with shadowing [24] was used to model the calculation of path loss. This model relies on the distance between the sender and the receiver. The utilized path loss configuration parameters were derived from a real experiment that was performed in [25]. These parameters suit an environment similar to a suburban environment with few buildings.

Regarding the transmission interference and collision, the collision model that was proposed in [26] was used in this study. According to this model, two transmissions can collide with one another if they are in a non-orthogonal channel and overlap in time. However, if the transmissions are in an orthogonal channel, they do not interfere with one another; hence, collision is avoided.

Table 1 lists the used configuration parameters for the simulation experiments. Each individual scenario was repeated five times, and the reported results are the average of these repetitions. The reported results were extracted from 2850 runs in total for all of the different simulated scenarios. Each individual experiment was set to run for six days, with the first day used as a warming-up period. Moreover, the SF for each end device was randomly chosen at the beginning of the simulation from the available SFs (7–12). However, it was then left to the network server to adjust the value of the SF as appropriate using an ADR mechanism, which was used with all of the examined mobility models. According to the ADR mechanism, the network server collects statistics for each individual end device—such as the NSR and RSSI—for the history of the last 20 uplinks; it then changes the SF and transmission power based on the historical statistics for each node. The network-based ADR strategy is suitable for static and high-capacity LoRaWAN applications.

Parameter	Value
Simulator platform	OMNeT++
Simulation model	INET and FLORA
Repetition	5
Simulation duration	6 days including 1 day for network warm-up
Simulation area	1000 m \times 1000 m (small area) 2000 m \times 2000 m (large area)
Number of nodes	Small area: 500, 1000, 1500, 2000, 2500 Large area: 1000, 2000, 3000, 4000, 5000
Mobility models	Random waypoint, Gauss-Markov, stationary
Random waypoint wait time	Random between 10 and 30 s
Mobile end devices	100%
Path loss model	Log-distance
Initial spreading factor	Random between 7 and 12
Transmission power	14 dBm
Mobility speed	5, 10, 15, 20, 25 m/s
Payload packet length	20, 40, 60, 80, 100 B
Time to first/next packet	1800 s
Bandwidth	125 kHz
Coding rate	4/8

Table 1. Simulation parameters.

4. Results and Discussion

The packet delivery ratio (PDR) was selected as the first metric of interest; it was calculated as the ratio of the total number of messages successfully received by the network server to the total number of messages generated by all LoRaWAN devices during the whole period of the simulation. Figures 3 and 4 show the PDR for different network scenarios (small and large network areas) with different numbers of end devices and mobility speeds using the random waypoint, stationary, and Gauss–Markov mobility models.







Figure 4. Packet delivery ratio: (a) packet delivery ratio for a network with 1000×1000 area, 100 B payload, and 25 m/s speed; (b) packet delivery ratio for a network with 1000×1000 area using the random waypoint mobility model.

The best performance was achieved for all scenarios when the number of LoRaWAN devices was at the minimum. This can be justified by the fact that if fewer devices are operating, fewer collisions will occur and, hence, better performance will be achieved compared to networks with a higher number of participating devices. In contrast, the performances of LoRaWAN networks based on different mobility models decrease as the number of devices increases; this is because of the likelihood of traffic interference and collisions. However, LoRaWAN networks based on the random waypoint mobility model maintain better performance compared to networks based on the Gauss-Markov and stationary models for networks consisting of 3000-5000 devices with a speed of 5 m/s, as can be seen in Figure 3a. The figure also shows that networks based on the random waypoint and Gauss-Markov mobility models maintain better delivery ratios with larger network sizes (4000 and 5000 end devices) compared to the stationary-mobility-based networks. The mobility is seen to be the main reason for this achievement. Devices far away from the gateways may move closer and use a lower spreading factor compared to the static distant devices, which may keep using a larger spreading factor that contributes toward higher possibility of collisions. Regarding the influence of the mobility speed, no effects were experienced for Gauss-Markov-based networks or random-waypoint-based networks, as shown in Figures 3b and 4b, respectively.

The total number of collisions is the second metric of interest and is shown for different networks in Figures 5 and 6. Figure 5a shows the collisions for a large network for the three mobility models. In general, the collisions show an increasing trend as the number of end devices increases for all the three models. However, in the stationary-based network, the number of collisions is lower than those for the random waypoint- and Gauss Markov-based networks. This is due to the movements of end devices in the other two models, which results in retransmission and a higher probability of collisions. Moreover, mobility causes the NS to modify the SF for those end devices which move farther from gateways to increase their ability to deliver their traffic. However, higher SF results in higher airtime for transmitted packets and hence, increasing the chance of collisions.



Figure 5. Traffic collisions: (a) collisions for a network with 2000×2000 area, 20 B payload, and 5 m/s speed; (b) collisions for a network with 2000×2000 area, 2000 devices, and 60 B payload across different speeds in m/s.



Figure 6. Traffic collisions: (a) collisions for a network with 1000×1000 area, 2000 devices, and 60 B payload across different speeds in m/s; (b) collisions for a network with 1000×1000 area using the Gauss–Markov mobility model across different speeds in m/s.

The effect of increasing the device velocity on the number of collisions for a network consisting of 2000 end devices with a packet length of 60 is depicted in Figure 5b. For the Gauss-Markov-based network, the number of collisions remains about the same with a speed of up to 20 m/s. However, for the random waypoint model, the increase in the device velocity has a positive impact on the overall number of collisions, while achieving good results in terms of the PDR, as can be seen in Figure 3a. Moreover, Figure 5a shows that a better performance is achieved with the random waypoint model for the same number of devices within a smaller area.

The energy consumption was the third measured metric, and is shown in Figures 7 and 8. The reported value of power consumption is the average consumed energy by each individual end device over the duration of the simulation period; it is calculated as the ratio of the total consumed energy by the whole network to the number of participating end devices in the network. Generally, the average energy consumption by each individual LoRaWAN device increases as the number of participating devices increases for all three mobility models. This is due to interference and possible collisions, which cause the retransmission of lost packets. Thus, higher power is used as the network size grows. Furthermore, the



average energy consumption is negatively affected by the movement speed. This is due to the changes in devices' locations, resulting in a higher SF in some cases. Consequently, higher packet airtime is required, which consumes more power.

Figure 7. Energy consumption: (**a**) average energy consumption per end device for a network with 2000×2000 area, 4000 devices, and 60 B payload across different speeds in m/s; (**b**) average energy consumption per end device for a network with 2000×2000 area using the random waypoint mobility model, with 20 B payload across different speeds in m/s.



Figure 8. Energy consumption: (a) average energy consumption per end device for a network with 1000×1000 area, 20 B payload, and 5 m/s speed across different network sizes; (b) average energy consumption per end device for a network with 1000×1000 area using the Gauss–Markov mobility model, with 20 B payload for different speeds in m/s.

As Figures 7a and 8a show, the random-waypoint-based network consumed more energy compared to the Gauss–Markov-based network. This higher consumption is due to the retransmissions that occur in the random-waypoint-based network. The better results reported for the Gauss–Markov-based network owe to the fact that the Gauss–Markov mobility model optimizes historical values of movement when calculating the new values. This technique is used to avoid unexpected changes in the velocity and the direction of an end device. Consequently, the avoidance of unexpected changes in the movement is reflected in the need for fewer retransmissions, which require energy. Regarding the influence of velocity, it should be noted that changes in the movement speed have no considerable impact on the total average energy per device, as depicted in Figures 7a,b and 8b.

5. Conclusions

LoRaWAN, as a member of the LPWAN family, is the most adopted technology for IoT applications; it provides long-range connectivity with a minimal cost in terms of energy consumption. Recent advances in smart connected devices have paved the way for the study of many topics related to LoRaWAN, one of which is mobility and its influence on the performance of LoRaWAN. The work in this paper investigates the effect of mobility on the performance of mobile IoT devices. In addition to the stationary model, the research considers other two popular mobility models—namely, the random waypoint and Gauss– Markov models.

Through the OMNeT++ network simulator, we extensively evaluated the performance of a mobile LoRaWAN. The experiments were carried out over different network sizes, different numbers of end devices, different mobility speeds, and varying payloads. Our findings indicate that LoRaWAN performs well using both mobility models for intense networks. Moreover, it is also capable of providing good results even with high velocities and larger payloads. The network based on the random waypoint mobility model tends to give better results in terms of the packet delivery ratio, but at the cost of higher collisions and higher energy consumption.

All of the experiments carried out within this study used the standard network-based ADR mechanism. However, the standard ADR strategy is meant to be more suitable for static networks, due to the unpredictable channel attenuations caused by device movements. Therefore, for future works, different ADR strategies such as blind ADR should be used to investigate the performance of LoRaWAN for mobile applications.

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