Chapter 5

A Bayesian game based approach for associating the nodes to the gateway in LoRa network

5.1 Introduction

Each LN in the network needs to choose the suitable LGs for efficient data forwarding to the NS. Best association among LGs and LNs depends on the reputation of the LGs [68, 69]. A LN creates interference to all other LNs those they are simultaneously transmitting data by using the same LG. Estimation of the optimal data transmission time from a LN to a LG is important for network performance [70,71]. However, because of lack of the availability of complete network information at each LN, low processing power, and selfish behavior of the LNs, deciding optimal transmission time durations for each LNs on every LGs is crucial. The problem of estimation of time durations for association of LNs to LGs is more challenging in IoT because low packet loss and communication delay are prerequisites of such solutions. In this chapter, we address the problem: *How long a LN can associate with the best available LGs to transmit the data of EUs given that the LNs can transmit data at different power levels.* For solving the above problem, we propose a game theoretic approach for determining optimal time duration for data transmission on best available LGs within the communication range of the LNs without sharing the complete information. The motivations and major contributions of this chapter is as follows.

5.1.1 Motivation of this work

Prior studies on LoRa for IoT solutions have following limitations which motivated this work.

• *Challenge during association of LNs to LGs:* Most of the existing work use the random association of LNs to LGs. The authors in [56, 72] demonstrated that randomly association of LNs to the LGs drastically reduces the network performance due to the imbalance of load on the LGs. Each LN randomly forwards its data to the available LGs which leads to collisions and decreases the throughput of the network [71, 73, 74].

• *Allocation of time duration on different LGs:* Authors in [15, 18] proposed fixed and random time channel allocation schemes for forwarding data from LNs to LGs. Each LG in fixed time duration approach reserves the time slots for LNs even when they do not have data for transmission. Such empty time slot cannot be used by other LNs that wish to transmit data and therefore decreases the average utility of the LGs. The average utility of LGs improves with random time allocation but here some LGs are overloaded whereas some do not receive any data from LNs for forwarding to the NS.

• *Transmission power levels of LNs:*The existing literature [14–16, 18, 75] that analyse the performance of LoRa network usually work under the assumption that power level used by LNs to transmit data is fixed. However, such power levels are private information and unknown by other LNs while making a decision on time duration to send data to the LG.

5.1.2 Major contributions

To the best of our knowledge this is the first work to consider different transmission power levels of each LN while determining the time duration of transmitting to the LGs. We make following major contributions:

• We propose reputation model using feedback mechanisms for evaluating as how successfully a LG relays the data from a LN to the NS. The model helps to select the suitable LGs from the available multiple LGs inside the communication range of a given LN. The selection of suitable LGs improves the packet delivery ratio and reduces trasmission delay.

• We use the reputation model and present an approach for estimating the association time duration between each LN and the LGs for transmitting the data of EUs. The approach uses BG strategy which played among the LNs. The BG accommodates unknown private information of players (*i.e.*, transmission power of the LNs which are unknown to other LNs), as in real life network scenarios.

• The BNE is attained when all LNs maximize their utility by choosing optimal transmission time for different power levels. We proof the existence of BNE and derive the sufficient conditions on the uniqueness of BNE.

• We validate the approach by simulating the LoRa network on Network Simulator-3 [16]. We consider random allocation, fixed allocation, and proposed approach to show the effectiveness of the proposed work. We demonstrate the impact of number of EUs, various game parameters, and network topology on the performance of the network.

• We also demonstrate an application of the proposed work in deployment of a **T**raffic Information acquisition system based on **Lo**ng **Ra**nge network called **TILR**. TILR detects reckless driving action and estimates the vehicle speed.

The rest of the chapter is organized as follows: next section presents the preliminaries and system model. Section 5.3 formulates association problem and presents the solution. It is evaluated in Section 5.4 and Section 5.5 presents an application of the work. Finally, Section 5.6 concludes the chapter.

5.2 Preliminaries and system model

This section presents the system model which consist of network model, Bayesian Game model, and reputation model.

5.2.1 Network model

In this chapter, we consider a LoRa network where the road side units (LNs) collect and transfer the information of bike rider (EUs) to the traffic signal (LG). The LG forwards the information to the NS and finally AS. Figure 5.1 illustrates the scenario of the network. The LoRa network consists of sets $\mathcal{N}=\{1, 2, \cdots, N\}$ and $\mathcal{M}=\{1, 2, \cdots, M\}$

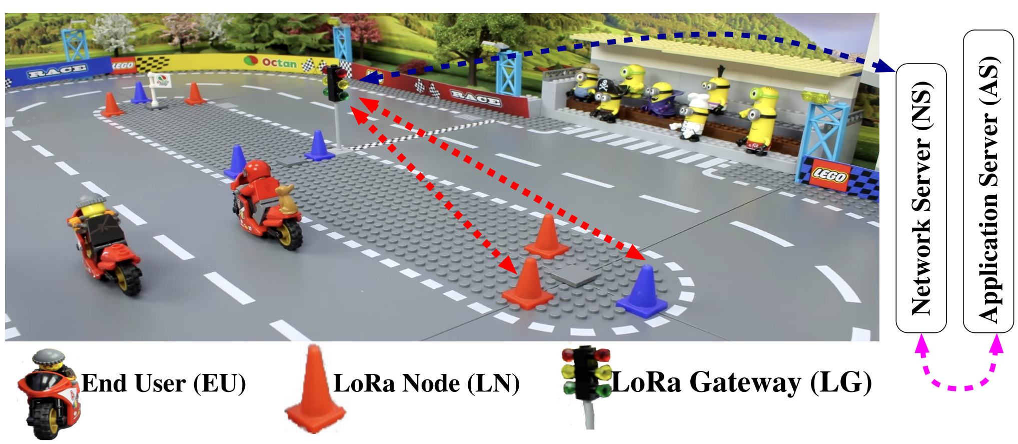


Figure 5.1: Illustration of deployment of LoRa network.

of LNs and LGs, respectively. Let $\mathcal{F}=\{7, 8, \cdots, 12\}$ be the set of possible SF at each LG. Multiple EUs in the network are connected with a LN. Each LN can communicates with multiple LGs using allocated SFs. LGs are forwarded data of EUs from LNs to the NS. Let assume that Non-LoRaWAN network uses a high-speed communication channel to transfer the data from LG to AS via NS. Therefore, it reduces the interference problem at the LG and NS to a smaller value (*i.e.*, negligible). The EUs are randomly moving and LNs and LGs are deterministically placed inside the given region. Define n and m

as LN and LG index, respectively. Let t_n^m be the transmission time duration of $n \in \mathcal{N}$ on $m \in \mathcal{M}$. The time vector for n is given as $\mathbf{t}_n = [t_n^1, \cdots, t_n^m, \cdots, t_n^M]^T$. The random movement of EUs creates the unequal load on the LNs and finally on the LGs.

5.2.2 Bayesian game model

We use BG model among the LNs, where each LN does not have complete information about other LNs. The rational anticipation regarding the game, made by the players, is restricted by the knowledge of the players [76, 77]. LNs transmit their data to the LGs using different power levels. Power level on a LoRa can be adjusted from 2 dBm to 20 dBm. This power level is the private information and not known by the other LNs in the network. This is usually modeled by introducing a *type* for the players and the *beliefs* associated with these types. These beliefs are represented by probabilistic distributions. A *strategy* for a player in BG is an action set that covers every strategy for every type that player might choose.

Definition 5.1 *(Bayesian Nash equilibrium) A BNE is defined as a strategy set that maximizes the expected utility for each player given their beliefs and the strategies played by the other players.*

For a LN (player) $n \in \mathcal{N}$, let Θ_n, $\mathcal{A}_n$, π_n and $U_n(a_1, \ldots, a_N, \theta_1, \ldots, \theta_N)$ denote type set, action set, prior belief, and utility function, respectively. A strategy set S_n is a mapping from players action to the players type, i.e., $S_n : \mathcal{A}_n \longrightarrow \theta_n$. A strategy profile is a BNE if and only if for every LN n, keeping the strategies of every other LN fixed s_{-n}, strategy s_n^* maximizes the expected utility U_n of n according to its beliefs θ_n. Formally, BNE can be expressed as

$$U_n(s_n^* | s_{-n}, \theta_n) \geq U_n(s_n | s_{-n}, \theta_n), \tag{5.1}$$

for all $s_n(\theta_n) \in S_n$ and $\theta_n \in \Theta_n$.

5.2.3 Reputation model

The reputation of LG $m \in \mathcal{M}$ with respect to LN $n \in \mathcal{N}$ evaluates as how successfully m relays the data of n and other connected $\mathcal{N}/n$ to the NS. The weightage of feedback from LN n, at the time of reputation calculation of LG with respect to the LN n, is higher than the other $\mathcal{N}/n$. Therefore, we have divided connected LNs to a LG into the two sets, one is of that LN which is calculating reputation of LG and another set consists all other connected LNs to the LG. Let the successful relaying of the data is a binary event that can be represented using Beta distributions. Beta distribution function often used in the scenarios where one entity has collected binary opinions/observation about the other entity. Let k+1 LNs (n and other k LNs from $\mathcal{N}$) are connected with m and $(n+k)^{+}m$ and $(n+k)^{-}m$ denote the positive and negative reputation feedback of m by LN n and other k number of LNs, respectively. The reputation function $f(\mathbb{P} \mid (n+k)^{\pm}m)$ of m by LN n and other k number of LNs is defined as

$$f(\mathbb{P} \mid (n+k)^{\pm}m) = \frac{\Upsilon((n+k)^{+}m + (n+k)^{-}m + 2)}{\Upsilon((n+k)^{+}m + 1)\Upsilon((n+k)^{-}m + 1)} \times \mathbb{P}^{(n+k)^{+}m}(1-\mathbb{P})^{(n+k)^{-}m}, \tag{5.2}$$

where probability $\mathbb{P} \in \{0, 1\}$ and $0 \leq (n+k)^{\pm}m$, [78]. Let $f(\mathbb{P} \mid n^{\pm}m)$ and $f(\mathbb{P} \mid x_i{}^{\pm}m)$ are the reputation function for LN n and other x_i LNs, respectively, where $1 \leq i \leq k$. Then, the positive and negative reputation feedback of $m \in \mathcal{M}$ by n and other LNs are calculated as Steps 11 and 12 in Procedure 5.1, respectively, where $0 \leq \omega \leq 1$ is bias factor which indicates the importance of n on the reputation of m. The expected value of the reputation function with random variable $\mathbb{P}$ and two parameters $(n+k)^{+}m$ and $(n+k)^{-}m$, given by $E[(n+k)^{\pm}m]$, is equals to $\int_{\mathbb{P}=0}^{\mathbb{P}=1} \mathbb{P} f(\mathbb{P} \mid (n+k)^{\pm}m) d\mathbb{P}$ which is calculated as in Step 13 in Procedure 5.1.

Procedure 5.1: Reputation of LG $m \in \mathcal{M}$ for LN $n \in \mathcal{N}$

Connected LNs from m is set $\mathcal{X} = \{n, x_1, x_2, \cdots, x_k\}$;
for $i \leftarrow 1$ *to* k **do**
    if *(x_i gives positive feedback)* **then**
        $x^+m = x^+m + 1$;
    if *(x_i gives negative feedback)* **then**
        $x^-m = x^-m + 1$;
if *(LN n gives positive feedback)* **then**
    $n^+m = n^+m + 1$;
if *(LN n gives negative feedback)* **then**
    $n^-m = n^-m + 1$;
$(n+k)^+m = \omega n^+m + (1-\omega)x^+m$;
$(n+k)^-m = \omega n^-m + (1-\omega)x^-m$;
$E[(n+k)^{\pm}m] = \frac{(n+k)^+m+1}{(n+k)^+m+(n+k)^-m+2}$;
return $E[(n+k)^{\pm}m]$;

5.3 BG based approach for associating LNs to LGs

This section presents Bayesian Game (BG) parameters when the LNs are not sharing the complete information, formulates the problem, and presents the solution. It also presents the proof of the existence and uniqueness of BNE among the LNs.

5.3.1 Bayesian Game (BG) parameters

The non-cooperative game among the LNs with incomplete information can be formulated as a BG which is defined as,

5.3.1.1 Players of the BG

The set of players $\mathcal{N}$ is the existing LNs in the network, $\mathcal{N} = \{1, \cdots, n, \cdots, N\}$.

5.3.1.2 Action of player

The action of a player n is the *required time duration* to transmit data to the LGs and is denoted as $\mathcal{T}_n$, where $1 \leq n \leq N$.

5.3.1.3 Types of player

Power level used by a LN to transmit the data, works as the *type* of the player, is an important parameter for successfully transmission of data. Such power levels are the unknown information of the LNs and are not known to the others. Power level can be adjusted from 2 dBm to 20 dBm. BG considers the power level used by the LNs for transmitting data, to lie in a set of discrete power levels that are used to classify the LN to different types. Even though the types of each LNs may be different but lies in the range of $[2-20]$dBM, therefore the cardinality of each set is assume to be the same. All types of players have a set of strategies available to maximize their own preferences, in response to the strategies of others. For high power level type LN, the preference is to maintain reliability for fast communication, whereas for low power level type, the preference is to ensure the long range communication. Let $\mathcal{P}_n$ denotes the power level set of n, where $1 \leq n \leq N$. Let each LN can transmit on v different power levels, *i.e.,* the type set $\mathcal{P}_n$ of LN n has $|\mathcal{P}_n| = v$ and actual type at any instance is p_n, where $\mathcal{P}_n = \{p_n^1, p_n^2, \cdots, p_n^v\}$. Since type set for all players are same, which means where $\mathcal{P}_1 = \mathcal{P}_2 = \cdots = \mathcal{P}_N$. Let π_n is the probability distribution of the type of player n.

5.3.1.4 Utility function of the LNs

The utility function of a LN n consists of the following terms:

• **Price gain from the LGs for providing the data:** NS pays price to the LNs through LGs for providing the EUs data. The price depends on the reputation of the LGs. LGs with low reputation pay high price to balance the load on the LGs with high reputation. Reputation is the accumulation of the historical performance of the LG. It can be used to identify the probability of a LG to successfully relay the data. Let α is the initial fixed price which is same for all LGs and $E^\tau[(n+k)^{\pm}m]$ is the reputation of LG $m \in \mathcal{M}$ for LN $n \in \mathcal{N}$ at time instance τ then base price of LG m based on reputation is denoted as b_n^m and defined as

$$b_n^m = \frac{\alpha}{\sum_{\tau'=1}^{\tau} \beta^{(\tau-\tau')} E^{\tau'}[(n+k)^{\pm} m]}, \tag{5.3}$$

where $\beta^{(\tau-\tau')}$ with $0 \leq \beta \leq 1$ indicates that most recent information is more relevant than the past.

Let h_n^m and W are the channel gain and bandwidth of a link between n and m, respectively. The transmission power of n to transmit data on m is denoted by p_n^m and σ^2 is the power of white Gaussian noise. Let d_n^m be the number of LNs in the system which are using the same or lower SF from the SF of n for m. Such d_n^m LNs create the interference problem to n because they also transmit at the equal or higher transmission power during transmission of data to the LG. Using Shannon channel capacity [46], the transmission rate of n to m in the presence of other d_n^m LNs is given by

$$R_n^m = W \log \left(1 + \frac{p_n^m h_n^m}{\sum_{k=1}^{d_n^m} p_k^m h_k^m + \sigma^2} \right). \tag{5.4}$$

The price gained by a LG depends on the reputation and total data transmit to the LG which is the product of the time duration and transmission rate. We model this cost as an oligopoly market [28], where LNs compete with each other to achieve the highest profit by controlling the quantity of the supplied commodity. In this game, commodity is the transmitted data. Therefore, price function can be defined as

$$\rho_n^m(\mathbf{t}) = b_n^m - \delta \sum_{i=1}^{N} t_i^m R_i^m, \tag{5.5}$$

where δ is the constant which makes the commodity to the same order of magnitude as the cost and $\mathbf{t} = [t_1^m, \cdots, t_n^m, \cdots, t_N^m]$. The price gain from LGs is given by

$$L_g(\mathbf{t}_n) = \sum_{m=1}^{M} \rho_n^m(\mathbf{t}) t_n^m R_n^m. \tag{5.6}$$

• **Data acquisition cost:** The LoRa consists EUs which provide data to the LNs. Due to the privacy concern, vehicle owner does not want to share the data collected from the EUs willingly. Therefore, LN gives the incentive to motivate the owner for providing their sensory data collected from EUs. Let c_n be the collection cost per unit data paid by LN n. The data acquisition cost function due to collection for t_n^m time duration from end users to LG using LN n is given as

$$L_c(\mathbf{t}_n) = \sum_{m=1}^{M} c_n t_n^m R_n^m. \tag{5.7}$$

• **Cost occurred due to switching behavior:** LNs provide data to the NS via multiple LGs. There are advantages to use multiple LGs to distribute load instead of using one LG. However some additional cost such as delay and enegry cost due to switching has to be paid in multiple LGs network. This cost occurs due to switching behavior of LNs from one LG to another. Let $L_s(\mathbf{t}_n)$ denotes the cost occurred due to switching behavior of LN n which is defined as

$$L_s(\mathbf{t}_n) = \gamma_n \left(\sum_{m=1}^{M} (t_n^m)^2 + \nu \sum_{\substack{j=1 \\ j \neq m}}^{M} t_n^m t_n^j \right), \tag{5.8}$$

where γ_n is the switching cost and parameter $\nu \in [0.0, 1.0]$ depicts the effect of switching behavior. If $\nu = 1.0$, utility of a LN highly effected by switching to the other LGs. On the other hand, if $\nu = 0.0$, LN is not affected by switching and only acquisition cost on LG is considered.

The $\mathbf{t}_{-n}$ is the strategies vector for all the players except of player n. The utility of a player $n \in \mathcal{N}$ is therefore the difference of the price gained from the LGs and the cost paid to the end users and due to switching behavior, *i.e.*,

$$U_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) = L_g(\mathbf{t}_n) - L_c(\mathbf{t}_n) - L_s(\mathbf{t}_n). \tag{5.9}$$

5.3.2 Problem formulation and solution using BG

5.3.2.1 Problem formulation

The problem expresses that the LN n optimizes the strategy to maximize its utility. The constraint imposes that the duration of forwarding data from EUs to the LG must not be greater than its duty cycle ${t_n}^{max}$ and the LN n no need to use all LGs, where $n \in \mathcal{N}$. Duty cycle is defined as the maximum percentage of time during which a LN can occupy a channel which is 1% in the case of LoRa network. The problem can be formulated as Equation 5.10:

$$\begin{aligned} \max_{\mathbf{t}_n} \quad & U_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) \\ s.t. \quad & \sum_{m=1}^{M} t_n^m \leq {t_n}^{max}, \\ & t_n^m \geq 0, \quad 1 \leq n \leq N, 1 \leq m \leq M, \end{aligned} \tag{5.10}$$

where first and second constraints impose the duty cycle and the non-neccessity of the use of all LGs, respectively.

5.3.2.2 Solution of the problem

Due to the incomplete information, the power level used by LNs for transmitting data may be uncertain. The expected utility of player n is given by

$$\begin{aligned} \mathbb{U}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) &= E[U_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})] \\ &= \sum_{m=1}^{M} \Bigg((b_n^m - \delta t_n^m R_n^m - \delta E\Bigg[\sum_{i=1, i\neq n}^{N} t_i^m R_i^m \Bigg] - c_n) t_n^m R_n^m \\ &- \gamma_n \Bigg((t_n^m)^2 + \nu \sum_{j=1, j\neq m}^{M} t_n^m t_n^j \Bigg) \Bigg). \end{aligned} \tag{5.11}$$

Let $\chi(t_{-n})$ denotes the average time duration to send data from LNs except n. Then $E[\sum_{\substack{i=1\\i\neq n}}^{N} t_i^m R_i^m]$ is given by

$$E\left[\sum_{\substack{i=1\\i\neq n}}^{N} t_i^m R_i^m\right] = \chi(t_{-n})\left[\sum_{\substack{i=1\\i\neq n}}^{N} R_i^m\right]. \tag{5.12}$$

Let $\mathcal{T}_n = (\mathbf{t}_n(1), \mathbf{t}_n(2), ..., \mathbf{t}_n(A))$ be the possible actions of the player n where $\mathbf{t}_n(1) < \mathbf{t}_n(2) <, ..., < \mathbf{t}_n(A)$. We define $\pi(a)$ as the probability distribution of action a such that $\sum_{a=1}^{A} \pi(a) = 1$. Thus the expected time duration of players except n can be obtained as [79]

$$\chi(t_{-n}) = \sum_{a\in A} \pi(a)t(a). \tag{5.13}$$

Using $\chi(t_{-n})$ from Equation 5.13 in Equation 5.11, the utility of n is

$$\begin{aligned}\mathbb{U}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) = \sum_{m=1}^{M}\Bigg(& (b_n^m - \delta t_n^m R_n^m - \delta\chi(t_{-n})\left[\sum_{\substack{i=1\\i\neq n}}^{N} R_i^m\right] - c_n)t_n^m R_n^m \\ & - \gamma_n\Bigg((t_n^m)^2 + \nu\sum_{\substack{j=1\\j\neq m}}^{M} t_n^m t_n^j\Bigg)\Bigg).\end{aligned} \tag{5.14}$$

Theorem 5.1 *Let t_n^m be the strategy of a LN $n \in \mathcal{N}$ for data forwarding time duration on using LG $m \in \mathcal{M}$. The best response $t_n^{m\star}$ of the LN n is given as*

$$t_n^{m\star} = Q_n^m - \frac{1}{C_n^m \sum_{m=1}^{M} \frac{1}{C_n^m}} \sum_{m=1}^{M} Q_n^m - t_n^{max}, \tag{5.15}$$

where

$$\begin{aligned} Q_n^m &= \frac{(b_n^m - c_n - \delta\chi(t_{-n})\sum_{\substack{i=1\\i\neq n}}^{N} R_i^m)R_n^m - \gamma_n\nu\sum_{\substack{j=1\\j\neq m}}^{M} t_n^j}{C_n^m}, \\ C_n^m &= 2\delta t_n^m R_n^m + 2\gamma_n \quad \text{and} \quad \chi(t_{-n}) = \frac{u - u' + w}{1 + v - v'}. \end{aligned} \tag{5.16}$$

Proof: Using Lagrangian multipliers $\lambda_{n,1}$ and $\lambda_{n,2}$ for constraints defined in Equation 5.10,

$$\mathcal{L}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) = \sum_{m=1}^{M} \Bigg((b_n^m - \delta t_n^m R_n^m - \delta \chi(t_{-n}) \Bigg[\sum_{i=1, i\neq n}^{N} R_i^m \Bigg] - c_n) t_n^m R_n^m$$
$$- \gamma_n \Bigg((t_n^m)^2 + \nu \sum_{j=1, j\neq m}^{M} t_n^m t_n^j \Bigg) \Bigg) + \lambda_{n,1} t_n^m - \lambda_{n,2} (\sum_{m=1}^{M} t_n^m - t_n^{max}),$$
$$s.t. \qquad \lambda_{n,1} t_n^m, \lambda_{n,2} (\sum_{m=1}^{M} t_n^m - t_n^{max}) = 0 \text{ and } \lambda_{n,1}, t_n^m \geq 0, \lambda_{n,2} > 0. \tag{5.17}$$

By taking the partial derivative of $\mathcal{L}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})$ with respect to the action of LN n *i.e.*, t_n^m we have,

$$\frac{d\mathcal{L}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})}{dt_n^m} = (b_n^m - 2\delta t_n^m R_n^m - c_n - \delta \chi(t_{-n}) \sum_{\substack{i=1 \\ i\neq n}}^{N} R_i^m) R_n^m - \gamma_n \Bigg(2t_n^m - \nu \sum_{\substack{j=1 \\ j\neq m}}^{M} t_n^j \Bigg)$$
$$+ \lambda_{n,1} - \lambda_{n,2}. \tag{5.18}$$

To obtain the closed-form expression of the unique BNE in the game, put Equation 5.18 equals to 0 and rearrange,

$$t_n^{m\star} = \frac{(b_n^m - c_n - \delta \chi(t_{-n}) \sum_{\substack{i=1 \\ i\neq n}}^{N} R_i^m) R_n^m - \gamma_n \nu \sum_{\substack{j=1 \\ j\neq m}}^{M} t_n^j + \lambda_{n,1} - \lambda_{n,2}}{2\delta t_n^m R_n^m + 2\gamma_n}. \tag{5.19}$$

Let $\lambda_{n,1} > 0$, time duration t_n^m must be zero from the constraint $\lambda_{n,1} t_n^m = 0$. Put the value of t_n^m into the constraint $\lambda_{n,2}(\sum_{m=1}^{M} t_n^m - t_n^{max}) = 0$, we have $\lambda_{n,2} = 0$ which is the conradiction from the constraint of Equation 5.17 *i.e.*, $\lambda_{n,2} > 0$. Therefore the value of $\lambda_{n,1}$ is equals to zero. By putting value of $\lambda_{n,1}$ and t_n^m into the constraint of Equation 5.17, we get

$$\lambda_{n,2} = \frac{1}{\sum_{m=1}^{M}\frac{1}{C_n^m}}\sum_{m=1}^{M} Q_n^m - t_n^{max}, \tag{5.20}$$

where $Q_n^m = \frac{(b_n^m - c_n - \delta\chi(t_{-n})\sum_{i=1, i\neq n}^{N} R_i^m)R_n^m - \gamma_n\nu\sum_{j=1, j\neq m}^{M} t_n^j}{C_n^m}$ and $C_n^m = 2\delta t_n^m R_n^m + 2\gamma_n$. On substituting $\lambda_{n,2}$ from Equation 5.20 into Equation 5.19

$$t_n^{m\star} = Q_n^m - \frac{1}{C_n^m\sum_{m=1}^{M}\frac{1}{C_n^m}}\sum_{m=1}^{M} Q_n^m - t_n^{max}. \tag{5.21}$$

From Equation 5.13, expected time duration of the player except n at action a is

$$\begin{aligned} E[t(a)|a\in A] &= \sum_{a\in A}\pi(a)t(a) = \sum_{a\in A}\pi(a)\left(Q_n^m(a) - \frac{1}{C_n^m(a)\sum_{m=1}^{M}\frac{1}{C_n^m(a)}}\sum_{m=1}^{M} Q_n^m(a) - t_n^{max}\right) \\ &= u - vE[t(a+1)|a\in A] - u' + v'E[t(a+1)|a\in A] + w, \end{aligned} \tag{5.22}$$

where $u = \sum_{a\in A}\pi(a)\times\left(\frac{(b_n^m - c_n)R_n^m - \gamma_n\nu\sum_{j=1,j\neq m}^{M} t_n^j}{C_n^m}\right)$, $v = \sum_{a\in A}\pi(a)\frac{\delta\sum_{i=1,i\neq n}^{N} R_i^m R_i^m}{C_n^m}$, $u' = \frac{1}{C_n^m\sum_{m=1}^{M}\frac{1}{C_n^m}}\sum_{m=1}^{M} u$, $v' = \frac{1}{C_n^m\sum_{m=1}^{M}\frac{1}{C_n^m}}\sum_{m=1}^{M} v$, and $w = \frac{1}{C_n^m\sum_{m=1}^{M}\frac{1}{C_n^m}} t_n^{max}$.

Since we know that $E[t(a)|a\in A] = E[t(a+1)|a\in A]$, hence we have

$$\chi(t_{-n}) = \frac{u - u' + w}{1 + v - v'}. \tag{5.23}$$

From Equations 5.21 and 5.23, we can find out the transmission time duration of each LN $n\in\mathcal{N}$. □

• **Time Complexity of Algorithm 5.1:** Let k be the number of iterations at which BNE in the network is calculated. As LoRa network uses different types of LNs present in the network ($|\mathcal{P}_1| = |\mathcal{P}_2| = \cdots = |\mathcal{P}_N| = v$), Step 6 of Algorithm 5.1 runs for all v of a LN. Therefore, for all N LNs present in the network Algorithm 5.1 requires

Algorithm 5.1: Bayesian Nash Equilibrium among LNs

input : Precision threshold η, $\kappa \leftarrow 0$, $t_n^m[0]$;
output : Optimal strategy $t_n^{m\star}$ of n;

/* Run the following at each LN $n \in \mathcal{N}$ for each type $\mathcal{P}_n$. */
do
  $\kappa \leftarrow \kappa + 1$;
  /* BNE among LNs: Each n maximizes its net utility */
  /* Using Equation 5.15 for estimating $t_n^m[\kappa+1]$. */
  $t_n^m[\kappa+1] = Q_n^m[\kappa] - \frac{1}{C_n^m \sum_{m=1}^{M} \frac{1}{C_n^m}} \sum_{m=1}^{M} Q_n^m[\kappa] - t_n^{max}$;
while $(\|t_n^m[\kappa+1] - t_n^m[\kappa]\| > \eta)$;

$O(kNv)$ time. As the types of LNs (power level) lies in the range of $[2-20]$ dBM due to which v is of constant time. Therefore, it does not contribute in the calculation of time complexity. As a result, the time complexity to find the BNE in the LoRa network is $O(k \times N)$.

5.3.3 Proof of existence and uniqueness BNE among LNs

Lemma 5.1 *The proposed BG has at least one pure BNE, in which the strategy is a nondecreasing function of type if it satisfies the following condition*

$$\frac{\delta R_n^m \sum_{i=1, i \neq n}^{N} R_i^m}{\delta (R_n^m)^2 + \gamma_n} < 2. \tag{5.24}$$

Proof:

$$\frac{d^2 \mathcal{L}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})}{d t_n^{m2}} = -2\delta (R_n^m)^2 - 2\gamma_n. \tag{5.25}$$

$$\frac{d^2 \mathcal{L}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})}{d t_n^m d\chi(t_{-n})} = \delta R_n^m \sum_{\substack{i=1 \\ i \neq n}}^{N} R_i^m. \tag{5.26}$$

The sufficient condition that implies there exists atleast one Bayesian Nash equilibrium is given in [28].

$$\left| \frac{d^2\mathcal{L}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})}{dt_n^m d\chi(t_{-n})} \Bigg/ \frac{d^2\mathcal{L}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})}{dt_n^{m2}} \right| < 1 \tag{5.27}$$

From Equations 5.25 and 5.26, we can ensure that the condition in Equation 5.27 holds provided that $\frac{\delta R_n^m \sum_{\substack{i=1 \\ i\neq n}}^N R_i^m}{\delta (R_n^m)^2 + \gamma_n} < 2$ is satisfied. The proof is then completed. □

Lemma 5.2 *The BG has a unique pure BNE if it satisfies the following three condition [80].*

1)Positivity: $\forall p_n^m \geq {p'}_n^m, t_n^m \geq {t'}_n^m, p_{-n}^m, t_{-n}^m, n \in \mathcal{N}$

$$\Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) - \Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p'}_n, \mathbf{p}_{-n}) \geq 0. \tag{5.28}$$

2)Monotonicity: $\forall p_n^m \geq {p'}_n^m, \mathbf{t}$ *and* $n \in \mathcal{N}$

$$|\Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t}'_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) - \Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t}'_n, \mathbf{t}'_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})| \leq 0. \tag{5.29}$$

3)Scalability: *There is a* $\mu \geq 1$ *such that*

$$\mu\Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}'_n, \mathbf{p}_{-n}) - \Delta\mathbb{U}_n(\mu(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}'_n, \mathbf{p}_{-n})) \geq 0. \tag{5.30}$$

Proof: Here we first prove condition 1 of the **Lemma 5.2**. Define the incremental utility of player n when changing its action from ${t'}_n^m$ to t_n^m as

$$\Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t'}_n\mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) = \mathbb{U}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) - \mathbb{U}_n(\mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}). \tag{5.31}$$

On taking second derivative of $\mathbb{U}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})$ and $\mathbb{U}_n(\mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})$ with respect to t_n^m and ${t'}_n^m$, respectively, we can get

$$\frac{d^2\mathbb{U}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})}{d{t_n^m}^2} = -2\delta(R_n^m)^2 - 2\gamma_n. \tag{5.32}$$

$$\frac{d^2\mathbb{U}_n(\mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})}{d{{t'}_n^m}^2} = -2\delta(R_n^m)^2 - 2\gamma_n. \tag{5.33}$$

Here it is clearly seen that $\frac{d^2\mathbb{U}_n(\mathbf{t}_n,\mathbf{t}_{-n};\mathbf{p}_n,\mathbf{p}_{-n})}{d{t_n^m}^2}$ and $\frac{d^2\mathbb{U}_n(\mathbf{t'}_n,\mathbf{t}_{-n};\mathbf{p}_n,\mathbf{p}_{-n})}{d{{t'}_n^m}^2}$ return negative value hence $\mathbb{U}_n(\mathbf{t}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})$ and $\mathbb{U}_n(\mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})$ is non decreasing function of t_n^m and ${t'}_n^m$, respectively. As per the assumption *i.e.,* $t_n^m \geq {t'}_n^m$ for all $n \in \mathcal{N}$, $\Delta\mathbb{U}(\mathbf{t}_n, \mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})$ returns always non-negative value and increases with the increase in p_n^m. Similarly, $\Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p'}_n, \mathbf{p}_{-n})$ returns always non-negative value and increases with the increase in ${p'}_n^m$. Therefore for all $p_n^m \geq {p'}_n^m$

$$\Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) - \Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p'}_n, \mathbf{p}_{-n}) \geq 0.$$

Hence positivity is proved.

The utility of LN n is represented as follows:

$$\mathbb{U}_n(\mathbf{t}_n\mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) = \sum_{m=1}^{M}\left((b_n^m - \delta t_n^m R_n^m - \delta\chi(t_{-n})\left[\sum_{\substack{i=1\\i\neq n}}^{N} R_i^m\right] - c_n)t_n^m R_n^m - \gamma_n\left((t_n^m)^2 + \nu\sum_{\substack{j=1\\j\neq m}}^{M} t_n^m t_n^j\right)\right). \tag{5.34}$$

From the Equation 5.34 and ${p_{-n}}^m \geq {p'_{-n}}^m$, $\Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n})$ returns always non-negative value and decreases with the increase in p_{-n}^m. Similarly, $\Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p'}_n, \mathbf{p}_{-n})$ returns always non-negative value and decreases with the increase in ${p'_{-n}}^m$. Therefore for all ${p_{-n}}^m \geq {p'_{-n}}^m$

$$\Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t'}_n, \mathbf{t}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) - \Delta\mathbb{U}_n(\mathbf{t}_n, \mathbf{t'}_n, \mathbf{t'}_{-n}; \mathbf{p}_n, \mathbf{p}_{-n}) \leq 0. \tag{5.35}$$

Hence monotonicity is proved.

To prove Scalability, we have

$$\begin{aligned}\mu\Delta\mathbb{U}_n(\mathbf{t}_n,\mathbf{t}_{-n};,\mathbf{p}_n,\mathbf{p'}_n,\mathbf{p}_{-n}) &= \mu(\mathbb{U}_n(\mathbf{t}_n,\mathbf{t}_{-n};\mathbf{p}_n,\mathbf{p}_{-n}) - \mathbb{U}_n(\mathbf{t}_n,\mathbf{t}_{-n};\mathbf{p'}_n,\mathbf{p}_{-n}))\\ &= \mu\,(\sum_{m=1}^{M}(t_n^m(R_n^m - {R'_n}^m)(b_n^m - c_n) - \delta t_n^{m2}(R_n^{m2} - {R'_n}^{m2})\\ &- \delta t_n^m\chi(t_{-n})(R_n^m\sum_{i\neq n}{R'}_i^m - {R'_n}^m\sum_{i\neq n}{R'}_i^m)\,)\,. \qquad (5.36)\end{aligned}$$

$$\begin{aligned}\Delta\mathbb{U}_n(\mu(\mathbf{t}_n,\mathbf{t}_{-n};,\mathbf{p}_n,\mathbf{p'}_n,\mathbf{p}_{-n})) &= \sum_{m=1}^{M}(t_n^m(R_n^m - {R'_n}^m)(b_n^m - c_n) - \mu\delta t_n^{m2}(R_n^{m2} - {R'_n}^{m2})\\ &- \mu\delta t_n^m\chi(t_{-n})(R_n^m\sum_{i\neq n}{R'}_i^m - {R'_n}^m\sum_{i\neq n}{R'}_i^m). \qquad (5.37)\end{aligned}$$

$$\mu\Delta\mathbb{U}_n(\mathbf{t}_n,\mathbf{t}_{-n};\mathbf{p}_n,\mathbf{p'}_n,\mathbf{p}_{-n}) - \Delta\mathbb{U}_n(\mu(\mathbf{t}_n,\mathbf{t}_{-n};,\mathbf{p}_n,\mathbf{p'}_n,\mathbf{p}_{-n})) = (\mu-1)\sum_{m=1}^{M}(t_n^m(R_n^m - {R'_n}^m)(b_n^m - c_n)). \qquad (5.38)$$

Since $\mu > 1$, Equation 5.38 return positive value. Hence condition 3 of Lemma 2 is proved. □

5.4 Evaluation of the proposed work

This section conducts extensive simulation using Network Simulator-3 [16] to validate the effectiveness of the proposed work. We have modified the traffic control model (lorawan-tracing-example.cc) to implement the propsoed technical in Network Simulator-3. Most of the network parameters are obtained from the datasheet of *LoRaWAN Multitech mDot* [49]. All LNs and LGs are configured to use the same 125 kHz BW with 868.100 MHz channel frequency. We consider that all LNs have a duty cycle of 1%. The parameters ν and ω are set within the range of $[0-1]$. The communication delay between LNs and LG are 42.4ms and 3.2ms for uplink and downlink, respectively, M=10, and N=50 . We also assume that each EU generates 5 packets per unit time and each experiment runs 100 time unit. We repeat each experiment 100 times for changing the location of EUs and LNs and take the average of them. We consider $\eta = 0.2$ unless otherwise specify.

• **Schemes for the results:** We consider two schemes, including: Random Allocation (RA) and Fixed Allocation (FA) for the comparison with our proposed GAme based scheme (GA). In RA scheme, association between LNs and LGs is done by uniform random choice whereas in FA scheme, fixed allocation of LGs to the LNs are carried out based on the equal load of LNs on each LG. These two schemes are the baseline and widely used schemes for the allocation of LGs which motivates to consider them for comparison [18, 81, 82]. In RA scheme, the LNs are randomly connected with LGs. Therefore, some LGs are overloaded while some are free. Equal number of LNs are connected with each LG in FA scheme. However, each LN does not have equal number of EUs and similar to RA scheme, some LGs are overloaded while some are free. The proposed scheme allocates the LG to the LNs based on the demand and therefore LGs are neither overload nor free.

• **Evaluation metrics:** This section considers Packet Delivery Ratio (PDR) and Packet Delivery Delay (PDD) as evaluation metrics, where PDR = $\frac{\sum_{i=1}^{M} m_i}{\sum_{j=1}^{N} n_j}$ and PDD = $\frac{\sum_{i=1}^{M}\sum_{j=1}^{m_i} \text{Receiving-sending time of packet j}}{\sum_{i=1}^{M} m_i}$, m_i and n_j are the number of packets received and send by LG M_i and LN N_j, respectively. To remove the dimension in the results, all results are shown *w.r.t.* y number of EUs, *i.e.* matrix a (PDR or PDD) for x users equals to the ratio of a for x to y. For example if a=PDR, $x = 300$, and $y = 50$ then PDR for 300 EUs equals (PDR for 300)/(PDR for 50).

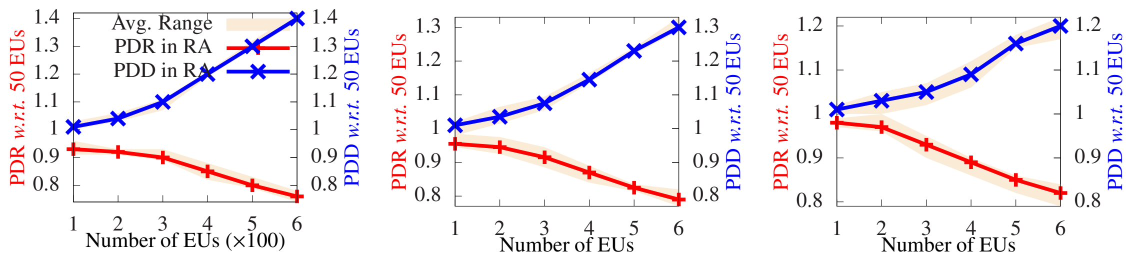
• **Overview of the results:** This section answers the following questions:

- What is the impact of number of end users on PDR and PDD of network using different schemes.

- What is the impact of network topology on PDR and PDD of network using different schemes.
- Is game parameters effect the reputation of LGs, PDR, and PDD using different schemes.

5.4.0.1 Impact of the number of end users

First, we study the impact of the number of EUs on PDR and PDD of the network. For different schemes, we increase the number of EUs from 100 to 500 as shown in Figure 5.2 and ω=0.5. We consider all the results *w.r.t.* 50 EUs in percentage. The number of packets transmit from EUs to the NS is increased with increased the EUs in the network. Figure 5.2 illustrates that PDR and PDD are decreased and increased, respectively, with increase the EUs. When U=100, the GA, FA, and RA provide 98%, 95%, and 92%, respectively, PDR *w.r.t.* U=50. When the EUs are increased from 100 to 500, the PDR decreases 15%, 18%, and 20% in GA, FA, and RA decrease, respectively. We conclude that RA and FA schemes consist poor PDR as compared with GA scheme. Similarly, GA, FA, and RA increase 1%, 2.6%, and 3.5%, respectively, PDD when U changes from 50 to 100. Moreover, when EUs are increased from 100 to 500, the PDD increases 18%, 27%, and 35% in GA, FA, and RA decrease, respectively. This is because, some LGs in RA scheme are connected with large number of LNs while others are free. Therefore, PDR on heavy loaded LGs sharply goes down. The PDD in RA is also high because each LG has fixed SFs to transmit the data and each LN needs to wait for accessing the SF on the heavy loaded LGs. FA schemes does not suffer the unequal connectivity of the LNs. However, it also suffers unbalanced network load because unequal number of EUs are connected with LNs and such LNs create load unbalance on the LGs. The LNs in proposed GA scheme are connected with LGs based on the utility where network load is part of the analysis which makes the load balance on the LGs. Moreover, GA scheme consists reputation of LGs which helps to select suitable LG to the LNs.



(a) RA Scheme (b) FA Scheme (c) GA Scheme

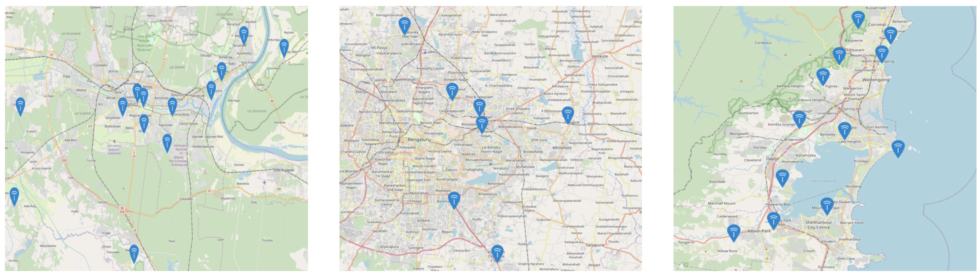
Figure 5.2: Impact of EUs on the PDR and PDD with different schemes.

5.4.0.2 Impact of the network topology

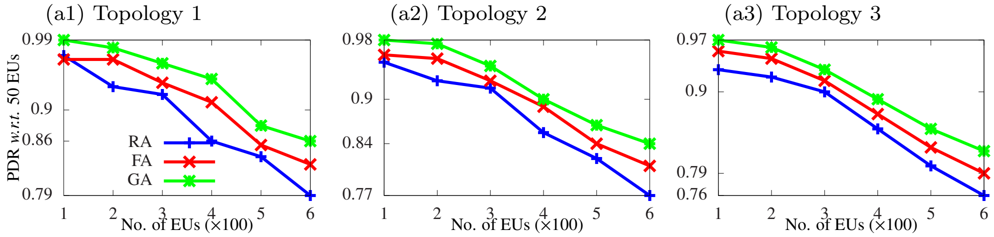
Next, we illustrate the impact of the network topology on PDR and PDD. It has been observed that the packet communication of EUs from LNs to LGs depend on the location of the LNs and LGs. To evaluate the performance of the schemes, we have performed experiments on three real-world network topologies, listed in Table 5.1. The location information (longitude and latitude) of LGs is obtained from [83] and shown in Parts (a1)-(a3) of Figure 5.3. Along with this, we randomly deployed 50 LNs in the given region. Parts (b1)-(b3) and (c1)-(c3) of Figure 5.3 show the impact of increase the number of EUs from 100 to 500 on PDR and PDD, respectively. Figure 5.3 shows that the proposed GA scheme always give high PDR and low PDD then the RA and FA schemes in all three topologies. The reason is as discussed in previous result, the RA and FA schemes suffer unequal network load. Parts (b1)-(b3) illustrate that maximum and minimum PDR are in Tp_1 and Tp_3, respectively. Similarly, parts (c1)-(c3) illustrate that minimum and maximum PDD are in Tp_1 and Tp_3, respectively. This is because, Tp_1 consists less density per LN than Tp_2. Tp_3 gives worst PDR and PDD because all traffic (packets of EUs) comes form one side of the region and therefore the load on the LNs are unequal.

Table 5.1: Real-world network topologies used in experiments [83].

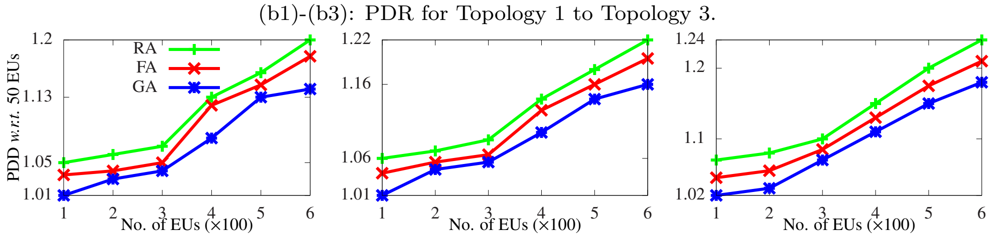
Name	U	M	**Objective**
Topology 1 (Tp_1)	50-500	13	Urban deployment: low density per LN
Topology 2 (Tp_2)	50-500	7	City: Denser and full use of LGs
Topology 3 (Tp_3)	50-500	12	Sea beach: All traffic from city side



(a1) Topology 1 (a2) Topology 2 (a3) Topology 3



(b1)-(b3): PDR for Topology 1 to Topology 3.



(c1)-(c3): PDD for Topology 1 to Topology 3.

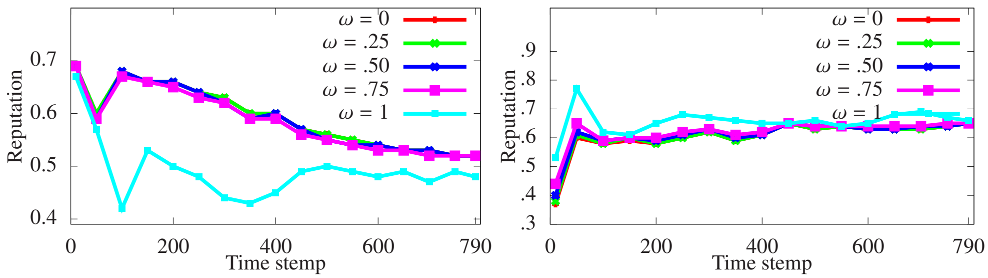
Figure 5.3: Impact of the network topology on PDR and PDD.

5.4.0.3 Impact of the parameters used in analysis

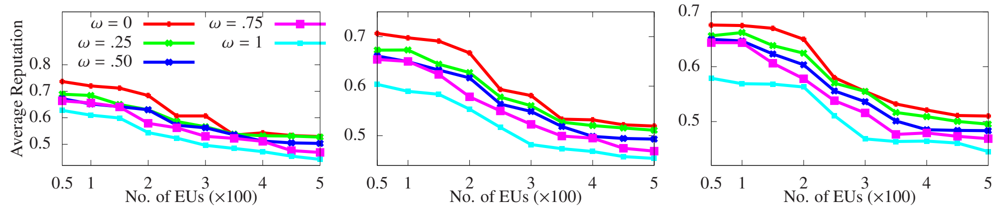
Next, we study the impact of the reputation weight parameter ω (Step 11 and Step 12 of Procedure 5.1) on the Average Reputation of LGs (ARL). The result of the impact of ω on the average reputation of LGs is illustrated in parts (a1)-(a2) of Figure 5.4, where $\omega = 0$ shows the reputation of the LG when consider only one LN. We conclude that if the network consists small number of LNs then the feedback of each LN is importance for ARL. Parts (b1)-(b3) of Figure 5.4 illustrate the ARL for Tp_1, Tp_2, and Tp_3, respectively. For example, ARL at U=50 are 0.73, 0.70, and 0.67 for Tp_1, Tp_2, and Tp_3, respectively. The reason is same as previous, the LGs are equally loaded in Tp_1 and worth used in Tp_3. Parts (c1)-(c3) and (d1)-(d3) illustrate PDD and PDR when using $\omega = 0$. The first observation from this result is that the proposed GA provides best PDR and PDD in all scenarios, *i.e.*, GA provides 6% and 9% more PDR than FA and RA, respectively. This is because, GA balances the load on the LGs and improves the PDR and PDD. The next observation is that Tp_1 and Tp_3 provide bast and worst PDR and PDD in all the results. The reason is the proper utility of LGs in Tp_1 but not in Tp_3. Finally, The PDR goes down sharply when EUs increases 400 to 600 as compare 100 to 400. The reason is that upto a given number of EUs, the network can handles the load but beyond it the PDR is very high and therefore PDD also goes down. Similarly, parts (e1)-(e3) and (f1)-(f3) illustrate PDD and PDR when using $\omega = 1$. Here, the ω at each LG fully depends on the all the associated LNs. In this case, the results are not as good as when we use $\omega = 0.5$ as shown in Parts (b1)-(b3) and (c1)-(c3) in Figure 5.3. Here, the selection of the LG may not be suitable for the associated LN.

5.4.0.4 Comparison with the existing work

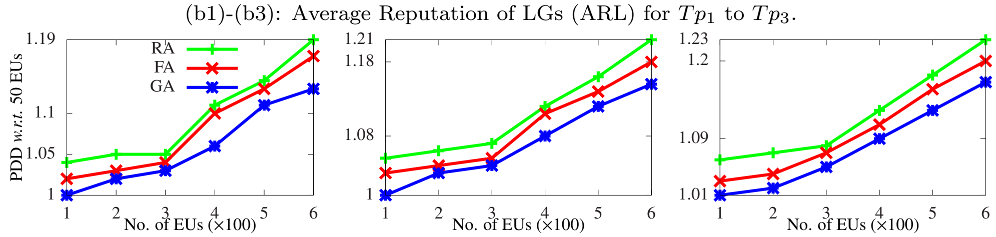
This section compares the proposed approach with existing work on the LG allocation schemes for improving network performance. We compare the proposed Game Approach (GA) with Random Based (RB), Distance Based (DB), Fixed Based (FB) and Equal-Interval (EI) based allocation schemes [14], as shown in Figure 5.5. The proposed scheme for SF allocation scheme outperforms all the other schemes for any number of EUs. This is because the proposed approach considers interactions among LNs and takes the allocation decision that can maximize the utility of all LNs using game theory.



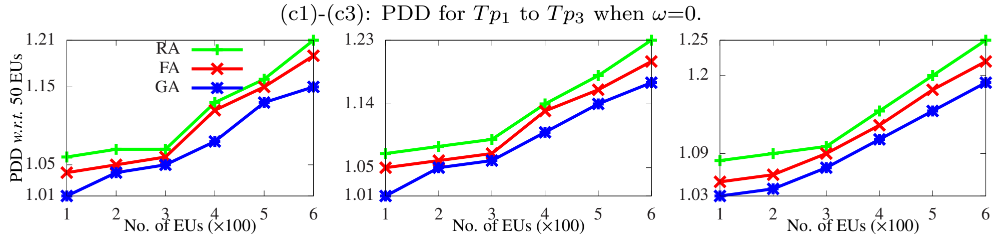
(a1) Number of EUs=250 (a2) Number of EUs=50



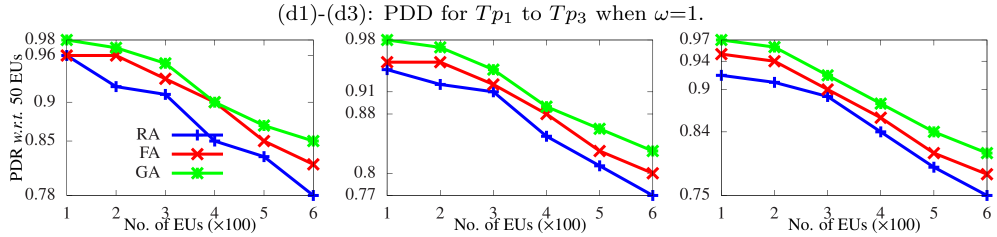
(b1)-(b3): Average Reputation of LGs (ARL) for Tp_1 to Tp_3.



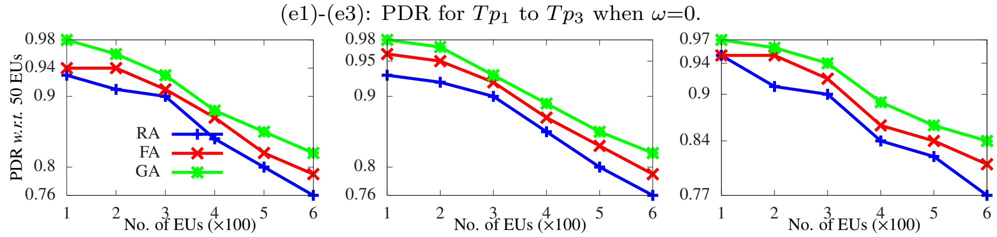
(c1)-(c3): PDD for Tp_1 to Tp_3 when ω=0.



(d1)-(d3): PDD for Tp_1 to Tp_3 when ω=1.

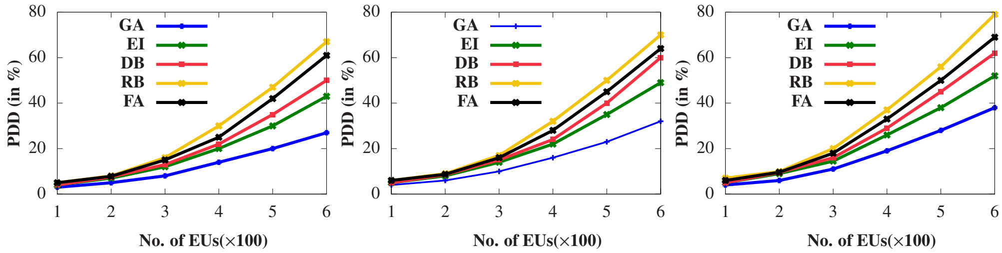


(e1)-(e3): PDR for Tp_1 to Tp_3 when ω=0.

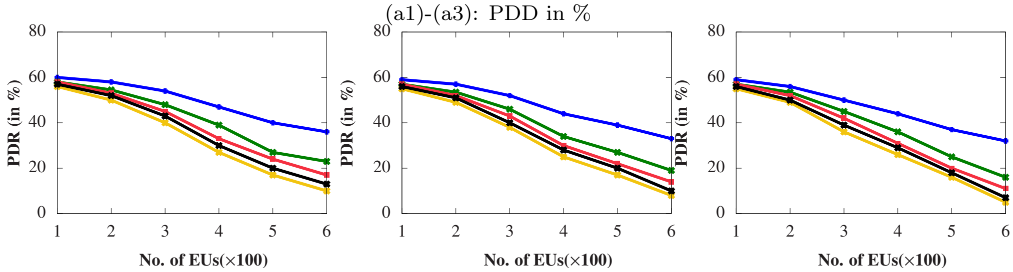


(f1)-(f3): PDR for Tp_1 to Tp_3 when ω=1.

Figure 5.4: Impact of weight parameter on ARL, PDD, and PDR.



(a1)-(a3): PDD in %



(b1)-(b3): PDR in %

Figure 5.5: Comparison of the proposed approach with existing work.

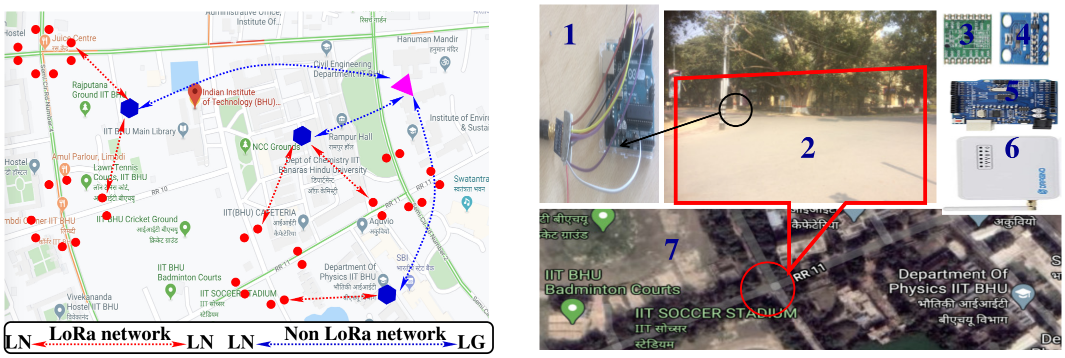
5.5 An application of the proposed approach

This section demonstrates how the association of LNs to LGs for a fixed time duration, can be used to deploy a **T**raffic **I**nformation acquisition system based on **L**o**R**a (TILR). TILR detects reckless driving action and estimates the vehicle speed without the use of multihop or power hungry network.

5.5.1 Overview of TILR

TILR uses two types of nodes: LNs embedded with sensor and LGs. The vehicles on the road are working as EUs. Parts (a) and (b) of Figure 5.6 illustrate the configuration of TILR and prototype devices to form a connected network, respectively. TILR uses BH1750 light intensity sensor where the resistance of light intensity sensor varies inversely with the intensity of the light falling on it. With a sufficiently high intensity of light, the resistance of the light sensor drops to a low value and produces an electrical signal. The output of the sensor is connected to the analog-to-digital converter on the LN. The digital output is henceforth referred *sensory data*, which lies in the range of 0 to 1000 representing complete darkness and very bright light conditions. We used

Dragino LG01-S open source single channel Gateway as LG in TILR. At the NS, the sensory data from LGs are cumulated the data and takes final decision.



(a) TILR on the road. (b) Prototype devices.

Figure 5.6: Illustration of TILR. The LNs, LGs, and NS in part (a) are indicated by circle (●), hexagon (⬢), and triangle (◀), respectively. Numbers in part (b) denote the LN, deployment of LN, SX1278 (Ra-02) LoRa module, BH1750 light intensity sensor, ATmega328P Arduino Uno processing board, gateway, and deployment region.

5.5.2 Campus experiment

We deployed TILR on the road in our campus, a photograph of which is showed in Part (b) of Figure 5.6. The experiments were carried out on a bidirectional two-lane road and intersection junction. Since we choose BH1750 light sensor to detect the vehicles, we conducted the experiments at night. We deployed 32 LNs and three LGs along the roads, to ensure that the EUs must be tracked and the network is connected with a high probability. To validate the vehicle data collected by the network, we used a video camera to record the vehicle movement and accuracy was computed by comparing the data from these two sources.

5.5.3 Experimental results

5.5.3.1 Use cases

It is sometimes observed that drivers take wrong left or right turn, U-turn, or vehicles are driven on the wrong side of the road. These are the examples of reckless driving.

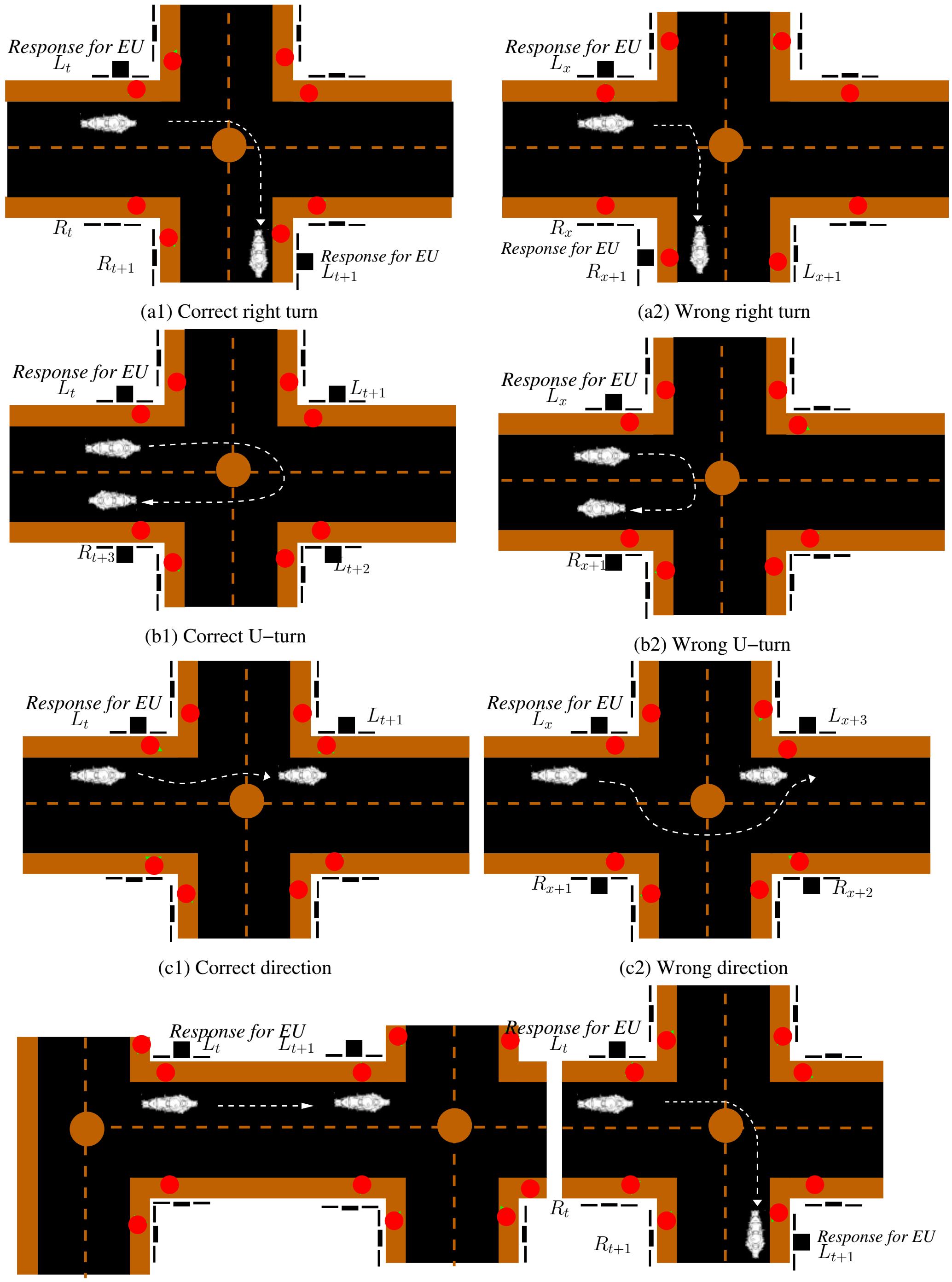
On a highway, reckless driving is a serious issue due to high speed of the vehicles. In this experiment, we use TILR to detect vehicles which takes wrong turns or drive in the wrong direction. Figure 5.7 shows the scenarios where LNs are placed along the boundaries at the turns and a vehicle passes through the road. Such LNs are associated with LGs for transferring the data for a fixed time period as estimated by Algorithm 5.1. The LGs further transferred the data to NS which cumulates the data and takes final decision.

• **Reckless driving detection:** Parts (a1) and (a2) of Figure 5.7 show $L_t = \{0, 1, 0\}$ and $L_x = \{0, 1, 0\}$ at time instance t and x, respectively, indicating that a vehicle passed from the left-side of the road. The sensory data of a left-side and right-side sensors are high at time $t + 1$ and $x + 1$ ($L_{t+1} = R_{x+1} = \{0, 1, 0\}$), respectively, as shown in parts (a1) and (a2) of Figure 5.7, respectively. Based on the above sensory data, we can conclude that a vehicle takes correct and wrong turn at time $t + 1$ and $x + 1$, respectively, since no other vehicle was detected by the sensors. Similarly, parts (b1)-(b2) of Figure 5.7 show $L_t = \{0, 1, 0\}$ and $L_x = \{0, 1, 0\}$ at time instance t and x, respectively, indicating that a vehicle passed from the left-side of the road. Part (b1) of Figure 5.7 shows that $L_{t+1} = R_{t+2} = R_{t+3} = \{0, 1, 0\}$ which indicates that the vehicle takes U-turn with full circle. However, part (b2) of Figure 5.7 shows that $R_{x+1} = \{0, 1, 0\}$ which is only possible when the vehicle takes wrong U-turn. Such signal values are transmitted from LNs to the NS via LG and detects the reckless driving. Part (c2) of Figure 5.7 shows $L_x = R_{x+1} = R_{x+2} = L_{x+3} = \{0, 1, 0\}$ which indicates that the vehicle changes the direction. It also shown in part (c1) of Figure 5.7 that the values of $L_t = L_{t+1} = \{0, 1, 0\}$ if the vehicle goes perfectly.

• **Vehicle speed estimation:** The ability to estimate the speed of the vehicles is desirable in building an intelligent transportation system. As mentioned in the previous section, a vehicle is detected by a LN if light of the vehicle falls on the sensor embedded with LN. It can be seen from parts (d1)-(d2) of Figure 5.7 that sensory data values at time instance t and $t+1$ are $L_t = L_{t+1} = \{0, 1, 0\}$, respectively. Since the LNs are deterministic placed along the road inside the campus, therefore the NS knows the location of the LNs. Let d_t and d_{t+1} denote the locations of LNs which detected the vehicle at time instances t and $t+1$, respectively. The distance between d_t and d_{t+1} is denoted by D and time interval between t and $t+1$ is T. Once the sensory data of LNs reaches to the NS via LG, the NS easily calculates the speed of the vehicles, *i.e.*, D/T.

5.6 Conclusion

In this chapter, we propose an approach for identifying best LGs within the communication range of the LNs and optimal time duration for data transmission on those LGs. We used BG for modeling the LoRa network in which the transmission power of LNs can vary. BNE is obtained, using backward induction, among the connected LNs at which all LNs choose their optimal transmission time when the transmission power of LNs is uncertain. We proved the existence of BNE and derived the sufficient condition on the uniqueness of BNE. We demonstrated an application of the analysis to design a TIS based on LoRa network called TILR. TILR was deployed along the road-side to gather the information of EUs. It does not involve multi-hop communication or power hungry technologies and reduces the effort of replacement of batteries.



(a1) Correct right turn (a2) Wrong right turn

(b1) Correct U−turn (b2) Wrong U−turn

(c1) Correct direction (c2) Wrong direction

(d1) Speed of EU (d2) Speed during turn

Figure 5.7: Experiment scenarios of TILR, where a vehicle (EU) is detected by a sensor (LN) is indicated by (_■_) signal strength. t and x denote the time index. The LNs are indicated by circle (●).