

An Efficient Allocation System for Centralized Network Slicing in LoRaWan

Fatima Zahra Mardi, Miloud Bagaa, Yassine Hadjadj-Aoul, Nabil Benamar

▶ **To cite this version:**

Fatima Zahra Mardi, Miloud Bagaa, Yassine Hadjadj-Aoul, Nabil Benamar. An Efficient Allocation System for Centralized Network Slicing in LoRaWan. IWCMC 2022 International Wireless Communications and Mobile Computing, May 2022, Dubrovnik, Croatia. pp.806-811, 10.1109/IWCMC55113.2022.9825330 . hal-03911337

HAL Id: hal-03911337

https://inria.hal.science/hal-03911337

Submitted on 22 Dec 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

An efficient allocation system for centralized network slicing in LoRaWAN

Fatima Zahra Mardi, Miloud Bagaa, Yassine Hadjadj-Aoul, Nabil Benamar
Moulay Ismail University, Meknes, Morocco. Aalto University, CSC, Espoo, Finland
University of Rennes, Inria, IRISA, France
fa.mardi@edu.umi.ac.ma, miloud.bagaa@aalto.fi, yassine.hadjadj-aoul@irisa.fr, n.benamar@est.umi.ac.ma

***Abstract*—The new emerging technologies enable the appearance of the 5G system and beyond that offers a plethora of services and target new verticals. One of these verticals is the large-scale Internet of Things (IoT) that is expected to be used everywhere in our daily lives. The traffic would likely be increased due to these emerging verticals. To overcome such challenges, network slicing and softwarization will play a crucial role in addressing these requirements and ensuring service level agreements (SLAs). Thus, there is a need to provide efficient and flexible network slice management mechanisms to handle the hurdles that come with the emerging industrial verticals. This paper focuses on network slicing in LoRa networks. We suggest a centralized coalition game-based network slicing strategy to manage LoRa nodes efficiently. According to the K-means clustering algorithm, the proposed solution is deployed within clustered players to maximize reliability while ensuring the SLA of the LoRa slices. Simulation results clearly show that our proposed approach improves Packets' Success Rate (PSR), Network Energy Consumption (NEC), and guarantees prioritization between slices.**

***Index Terms*—Internet of Things (IoT), LoRa, network slicing**

I. Introduction

The widespread adoption of IoT in our daily lives has permitted billions of physical and virtual objects to connect and communicate through standard communication protocols. With the increase of IoT application areas and deployments, Low Power Wide Area Networks (LPWANs) is a new set of technologies with long-range, low-power, and low-cost communication that promise to bring convenient connectivity to large-scale IoT deployments. The LoRaWAN open standard is one of the main famous and influential LPWAN protocols. Low Power Wide Area Network (LoRaWAN) defines the MAC layer specifications for the LoRa physical layer. LoRa technology enables the physical layer to communicate over long distances by adapting the chirp-spreading spectrum (CSS) modulation [1]. The CSS modulation used in LoRa converts each data symbol into a chirp, which is a signal whose frequency linearly increases or decreases over time [2].

While these networks can theoretically support a large number of wireless sensors, they do not really guarantee any quality of service for the supported networks. In fact, as the number of devices increases, the amount of traffic also increases, making it difficult to effectively control these devices and comply with the service level agreements.

To solve this problem, this paper proposes a novel approach that provides easy and low-cost scalability of the overall network. In our solution, we augment the LoRaWAN transmission protocol with network slicing to improve network reliability and provide a specific service level agreement for each slice.

Adapting slicing for resource sharing between services is a fairly recent topic in IoT networks [3]. In such an approach, the assignment of IoT devices to slices is generally achieved using a static grouping of IoT devices based on their requirements. This static grouping is performed prior to the resource allocation approach, which induces sub-optimality of the proposed solution. Thus, the main research problem targeted in this paper is to determine the optimal way to assign LoRa nodes to slices in order to improve the overall performance of a LoRa network, while guaranteeing the SLA of each slice. The main contributions of this paper are:

- We propose a machine learning technique for LoRa nodes grouping based on their requirements. We assign, then, each LoRa node to the requested slice to form the initial coalitions.
- We propose a coalitional game based on the initial coalitions to improve the network performances and ensure the desired SLA of each network slice by transferring LoRa nodes from one coalition to another until convergence.

We have assessed our proposed approach by taking into consideration the transmission parameters. The obtained results show the efficiency of our proposed solution to reach the desired goals. Our approach provides better network reliability and achieves the targeted SLAs.

The remainder of this paper is organized as follows. While section II introduces the related work, section III describes the network model and problem formulation. Section IV presents the proposed centralized network slicing LoRaWAN framework. The performance evaluations are conducted and provided in Section V. Finally, section VI concludes the paper.

II. Related work

Although the LoRaWAN specification was released in 2015, many research works are still ongoing to evaluate this technology and to enhance its performances via simulations and real test experiments [4], [5]. In particular, the analysis of the impact of co-spreading factor interference caused by unruly same channel transmissions using the same Spreading Factor (SF) [6], and by considering cumulative co-SF interference and inter-SF interference alone, as well as the cumulative impact of both [7]. Moreover, in [8], the authors studied the

optimization configuration of LoRa parameters and their effect on the scalability. Meanwhile, the authors in [9] show that the LoRa network performance regarding the packet delivery ratio (PDR), the average energy usage per transmission, and the average energy utilization due to packet collision per node highly depend on the configuration of the SF, the Coding Rate (CR), and the bandwidth.

Nowadays, the question of how to support effectively constrained services in LoRaWAN remains an open issue, with very few contributions in the literature [10]. In 5G, a recently introduced technique, named "Network Slicing", consists in implementing a virtual network – meeting all the service's requirements – for each service to be supported on top of the substrate network [11]. Supporting such techniques in LoRaWAN is, however, very complicated, since LoRaWAN networks are by design Best Effort networks.

Some recent work has attempted to enable network slicing in LoRaWAN. In [12], the authors investigate an adaptive dynamic network slicing strategy for LoRaWAN, in which they proposed a four-step methodology consisting of : (1) clustering IoT devices into slices, (2) estimating their needs in terms of bandwidth using the maximum likelihood estimation of the required throughput, then (3) allocating resources to the slices and finally (4) optimizing the devices' parameters. The proposed strategy clearly improves the traditional LoRaWAN by avoiding resources' starvation and prioritizing slices based on their Quality of Service (QoS). In order to improve IoT communications with network slicing for large-scale networks, the authors in [13] seeks to find the optimal slicing strategy with the correct SF and transmission power configurations that simultaneously maximize the QoS indicators in the slicing and also minimize the power consumption while increasing reliability. The authors in [14] proposed a machine learning approach using the Mini Batch Gradient Descent and the Gaussian Mixture Model to dynamically allocate the channel resources for the slices' members.

These different techniques come from more or less the same authors, and present a unique methodological approach, as described above. Resource allocation assumes abundant resource availability, as no admission control is proposed and no limitation on the number of channels is assumed. Moreover, the methodological approach involves grouping terminals at first (fixed grouping) and optimizing their parameters at last, which necessarily impacts the amount of requested resources, while no rectification of resources' demands is applied.

In this paper, we propose an efficient centralized technique to allow a dynamic allocation guaranteeing the SLA of the supported slices.

III. Network Model and Problem Formulation

A. Network Model

Fig. 1 illustrates a typical architecture of a LoRaWAN network that consists of a set of LoRa nodes $LNs = \{1, \cdots, n\}$, a set of LoRa Gateways $GWs = \{1, \cdots, g\}$, a set of channels on each gateway $C = \{1, \cdots, c\}$, and a Network Server (NS). The LNs forward the data to the GWs, which further forwards the data to the NS. LNs use the LoRaWAN protocol, while GWs uses non-LoRaWAN protocols to transmit data.

Network slicing is a concept for running multiple virtual networks on top of a shared network in order to support a variety of services. This makes it possible to meet the requirements of each slice. The slicing layer is composed of a set $L = \{1, \cdots, l\}$, of l slices, each with its own constraints.

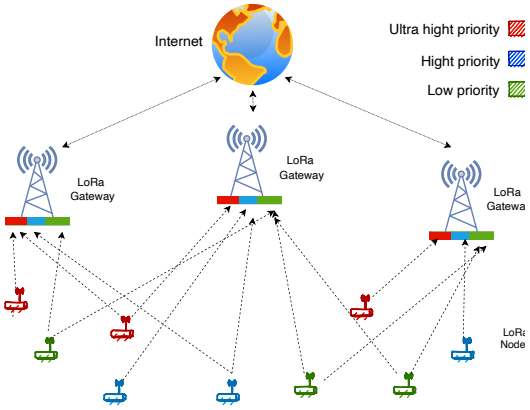


Fig. 1. Network Slicing Architecture

1) Communication Range: In order to communicate with the gateway (GW), each LN uses specific transmission parameters, Transmission Power (TP), Carrier Frequency (CF), Spreading Factor (SF), Bandwidth (BW) and Coding Rate (CR) that have a direct impact on the communication range and the number of collisions. A transmission packet is successfully received at a GW if the received signal power P_{rx} is higher than the sensitivity threshold S_{rx} of the receiver which is affected by the LoRa parameters SF and BW [15] .The received signal power P_{rx} can be expressed as follows:

$$P_{\text{rx}} = P_{\text{tx}} + G - L - L_{\text{pl}} \tag{1}$$

where P_{tx} denotes the transmission power, G the antenna power gains, L the power losses at the transmitter, and L_{pl} the path loss. In the following we use the log-distance path loss model, which is described as:

$$L_{\text{pl}}(d) = L_{\text{pl}}(d_0) + 10\,\Gamma\,\log\left(\frac{d}{d_0}\right) + X_\sigma \tag{2}$$

where $L_{\text{pl}}(d)$ is the path loss, d the length of the path in meters, $L_{\text{pl}}(d_0)$ is the mean path loss at the reference distance d_0, Γ is the path-loss factor and $X_\sigma \sim N\left(0, \sigma^2\right)$ is the normal distribution with zero mean and σ^2 variance to account for shadowing.

Equation (3) is the formula for calculating the LoRa receiver sensitivity (S), where *BW* is the bandwidth, *NF* is the noise figure of receiver and *SNR* is the signal-to-noise ratio [15].

$$S = -174 + 10\,\log(BW) + NF + SNR \tag{3}$$

Using (1), (2) and (3), we can assume that any received packet with $SF = i$ whose power is below the threshold S_i

cannot be detected by the gateway; if, instead, the received power is above S_i, then it can be detected. In this case we can denote that the latter is a factor that leads to a loss of a packet due to the lack of sensitivity. The determination of a packet arrival at the GW above or below sensitivity thresholds can be described formally as follows.

$$R = \begin{cases} 1 & P_{\text{rx}} > S_{\text{rx}} \\ 0 & \text{Otherwise.} \end{cases} \tag{4}$$

2) Collision checking: Packet collisions are the main factor in the loss of transmitted data, which directly impacts the system performance. Packet collisions occur when at least two LoRa nodes in the network attempt to send data packets at the same time. Several conditions determine the collisions that may occur on a GW channel between two packets, such as Carrier Frequency (CF), Spreading Factor (SF), power and timing [15].

We finally model in (5), the Packet Success Rate (PSR), where N_s is the total packets sent by the LoRa node and N_l is the total packets' lost, which includes collided packets and packets that have not been received by the gateway.

$$\textit{PSR}_{n,c} = \left(\frac{N_s - N_l}{N_s}\right) \times 100 \tag{5}$$

where the $\textit{PSR}_{n,c}$ represents the packet success rate of a LoRa node n when using the channel c.

In addition to the *PSR*, the Energy Consumption (EC) formulated in (6), is defined as the energy consumed by each LoRa node when using the channel c for a successful message. Where V is the operating voltage, N_s is the total number of packets sent, n is the LoRa node index, P_{tx}^n is the transmission power consumed by the LoRa node n.

$$\textit{EC}_{\text{n,c}} = (\text{airtime}_n \times (P_{\text{tx}}^n)) \times V \times N_s \tag{6}$$

B. Problem Formulation

In this section, we present a detailed formulation of the problem that constitutes one of the most critical challenges for massive data transmission over LoRaWAN. The main idea is to find an optimal way to assign the LoRa nodes to the slices in order to achieve the slice's SLA. The SLA in each slice is determined by its priority, which is indicated by a desirable level of *PSR* and the *NEC* by each slice. Due to the huge variety of services, we propose a novel architecture composed of three virtual slices.

It is worth noticing that the number of channels at which LoRa nodes transmit is equal to the number of slices we have in our architecture. Each slice is related to a service. The first slice has the highest slicing priority, which may include some prioritized services such as IoT applications for security or e-health. The second slice includes other sensing applications. While the third slice is assigned to the lowest priority class, which includes for example scale-reading applications.

Based on (5), the Packet Success Rate in each slice is denoted by (PSR) and evaluated in (7)

$$\text{PSR} = \sum_{n \in \textit{LNs}} x_{n,c}(\textit{PSR}_{n,c}), \quad \forall c \in C \tag{7}$$

where $x_{n,c}$ is a decision variable that shows if the LoRa node n is using the channel c. Thus, $x_{n,c}$ is equal to 1 if the node n uses channel c, 0 otherwise.

Therefore, we also consider the Network Energy Consumption over each slice, which is denoted by (NEC) and evaluated in (8)

$$\text{NEC} = \sum_{n \in LN} x_{n,c}(1 - \textit{EC}_{n,c}), \quad \forall c \in C \tag{8}$$

The goal is to maximize the reliability metric defined by the total utility function U_t of a transmission over each channel $c \in C$, which can be formulated as :

$$U_t = \text{PSR} + \text{NEC}, \quad \forall c \in C. \tag{9}$$

The problem introduced above would be expressed as follows:

$$\max U_t$$

subject to

$$\sum_{c \in C} x_{n,c} = 1, \quad \forall n \in \textit{LNs} \tag{10a}$$

$$x_{n,c} \in \{0, 1\}, \quad \forall n \in \textit{LNs}, \forall c \in C \tag{10b}$$

In the above-mentioned optimization problem, constraint (10a) ensures that each LoRa node selects one and only one slice to be used for transmitting packets. Constraint (10b) limits the value of the decision variable to $\{0, 1\}$. On the other hand, the objective function aims to increase the packets' success rate and reduce the energy consumption over a channel $c \in C$. Due to the high number of collisions between the LoRa nodes, a coalitional game is introduced, in the next section, to maximize the reliability metric.

IV. Proposed solution

In order to assign LoRa nodes to the slices, while ensuring the targeted SLA in each slice, this paper proposes a solution based on K-means and coalition game. The game is defined among a set of users A, where each LoRa node is considered as a player. The goal is to maximize the coalition's characteristic function based on performance measures.

Note that $A = \{a_1, \cdots, a_n\}$ is the set of players who interact with each other and form a cooperative group, namely the coalition S. Note that the number of coalitions is equal to the number of slices. Let $S = \{1, \cdots, I\}$ be the set of coalitions $S \subseteq A$.

In the proposed coalition formation game, the implementation of the game starts with partition of players into coalitions by applying the K-means Clustering. K-means is classified as a partitioning clustering method that separates players into K groups [16]. In order to partition the network players, the K-means algorithm is applied as described below.

Given a collection of n players $\{a_1, \cdots, a_n\}$ and a number of K cluster, with K equals to the number of slices, so we choose $K = 3$, we aim to partition these n players into K

clusters, to minimize the average squared distance $\|a_n - c_i\|^2$ between each player a_n and its nearest centroid c_i.

$$\min \sum_{i=1}^{K} \sum_{a_n \in C_i} \|a_n - c_i\|^2 \tag{11}$$

The initial centroids are determined by choosing K players from the set, indicating their SF value as the cluster's center, and then allocating each player to its nearest centroid, i.e., each player with an SF value will be allocated to its closest centroids on the basis of SF value. Then, the players in each sub-cluster are assigned to a slice forming a cooperative group, namely the coalition S. Therefore, based on their coalitions, slicing reconfiguration can be useful to ensure priority by moving a player initially in one coalition to another one when this relocation improves coalition performances.

Note that in the considered scenario, we grouped the IoT devices according to their SF, in order to prioritize terminals consuming the least resources (i.e., time on air). However, other groupings could have been considered.

The performance of a coalition S will strongly depend on the number of players in the coalition. Take two coalitions that contain an entirely different set of players; i.e., $\forall S_1, S_2 \in S : S_1 \neq S_2 \implies S_1 \bigcap S_2 = \emptyset$.

The characteristic function that represent the total revenue obtained by a coalition corresponding to each non-empty subset S of A is defined as follows:

$$w(S) = (\text{PSR} + \text{NEC}) \tag{12}$$

The characteristic function is strongly related to the performance measures of the LoRa nodes, that were defined in terms of the network's energy consumption and the packet's success rate, presented in section III.A.

Thus, the number of players in the game can also be changed, allowing different coalitions to be formed among the players. Each player is allowed to move from one coalition to another in order to get a better $w(S)$ after transformation; therefore, the size of the coalition can change dynamically with the addition and removal of new members. For this purpose, we define the transfer operation that allows players to change their coalitions. This operation must guarantee that the partitioning is associated with a better characteristic function after transfer operation.

Definition: *A player n belonging to a coalition S_i $(n \in S_i)$ would be transferred to another coalition S_j $(S_i \neq S_j)$ if:*

$$S_i \rhd_u S_j \Leftrightarrow \begin{cases} w(S_j) > w(S_i) & (13.1) \\ \quad \text{and} \\ w(S_i \backslash \{u\}) + w(S_j \cup \{u\}) > w(S_j) + w(S_i) & (13.2) \end{cases} \tag{13}$$

Equation (13) implies that a player n would be transferred from a coalition S_i to another coalition S_j, if a player is able to improve the resulting coalition gain when the structure changes from S_i to S_j (13.1), whereas the resulting state of the two concerned coalitions, together, have better gain compared to their original states (13.2). Players continue to change coalition until each slice's SLA is met.

Algorithm 1 shows our solution with an initial partition based on K-means. Afterwards, the transfer function of two coalitions $S_i, S_j \in S$ is executed.

Algorithm 1 Coalitional Game Algorithm.

System Initialization using K-means

Require: $S = \{S_1, \ldots, S_I\}$

while true do
  Stable = **true**
  for each two coalitions $S_i, S_j \in S$ **do**
    for each player $n \in S_i$ **do**
      if $S_i \rhd_n S_j$ **then**
        $S_i = S_i \backslash \{n\}$
        $S_j = S_j \cup \{n\}$
        Stable = False
      end if
    end for
  end for
  if Stable **then**
    break
  end if
end while

This process is repeated until it reaches convergence in which the stable variable is used in Algorithm 1 to characterize the stable partition. The stable partition is the optimal version that maximizes the total sum of payoffs where players have no reason to leave their coalition.

Theorem 1. *Given a partition of players on coalitions, it is guaranteed that Algorithm 1 converges to a stable and optimal final partition.*

Proof.

As defined in Algorithm 1, the initial partition will be subject to player transfers, we suppose that time is divided into several slots $t_k (k = 0, 1, ...)$, and after each slot (state) a set of players subject to transfer operation from one coalition to another. Let us express this transfer as follows:

$$\left(S^{t_0}, S^{t_1}, \ldots, S^{t_m}, \ldots, S^{t_k}, \ldots\right) \tag{14}$$

where each S^{t_k} represents the coalitions set after the transfer operation from one state to another, and its sequence number is denoted as t_k, and S^{t_0} is the first partition at state t_0. Since the number of coalitions and players is limited, so are the coalition states. If the partitions after the transfer allow the desired level of priority, the sequence defined in (14) converges to a final partition. The transfer operation defined in (13) controls this sequence, which indicates the result gain of the two coalitions. Furthermore, other coalitions that aren't involved by the transfer operation will be unaffected. In other

words, their gains are unchanged. Consequently, we can write the following.

$$S^{t_k} \rightarrow S^{t_l} \Rightarrow \sum_{S_i^{t_k} \in S^{t_k}} w(S_i^{t_k}) < \sum_{S_j^{t_k} \in S^{t_k}} w(S_j^{t_l}). \quad (15)$$

According to Algorithm 1, which converges to a stable final partition based on the transfer operation, and as shown in (15), the sum of the gains of the resulting coalitions increases after a transfer operation. This shows that the final partition obtained has the largest sum of gains and is thus optimal, which proves Theorem 1. □

V. Simulation Results Discussion

To evaluate our solution, we have adopted the LoRaSim simulator [15]. The latter is a discrete-event simulator built by Bor et al. using Simpy simulator to evaluate the scalability and collision in LoRa networks.

In all the simulation scenarios, we consider only one LoRa gateway. We have conducted a set of experiments by varying the number of LoRa nodes from 100 to 1000 nodes in steps of 100 nodes. At each simulation scenario, the LoRa nodes are uniformly distributed around the LoRa gateway. We used the 868 MHZ band with three frequency channels at 868.10MHz, 868.30MHz and 868.50MHz. We have fixed the transmission parameters TP, CF, SF, BW, and CR of each LoRa nodes as depicted in Table I. Furthermore, the transmission behavior of each LoRa node is also described by the packet transmission rate (λ), which is defined as 1×10^{-6} and the packet payload size has been fixed to 20 bytes.

TABLE I
Simulations Parameters

Parameter	Value
Average time between transmissions	10000 ms
Simulation time	86400000 ms
Nodes	from 100 to 1000
Carrier Frequency (CF)/Channels number	868 MHz/3
Transmission Power (TP)	14 dBm
Spreading Factor (SF)	{7,8,9,10,11,12}
Bandwidth (BW)	125 KHz
Coding Rate (CR)	4/5

We have evaluated the proposed solution in terms of network reliability, which is defined as the Packet Success Rate (PSR) and the Network Energy Consumption (NEC), respectively. We have evaluated the network reliability while varying the number of LoRa nodes.

1) Packet Success Rate (PSR): Fig. 2 shows the impact of the number of LoRa nodes on the PSR at each slice. The first observation that we can make from this figure is the number of LoRa nodes has a negative impact on the PSR at each network slice. In the absence of an admission controller, this result is consistent with the expectations. As described previously, the proposed procedure gives priority to one slice over another. However, it can be noticed that the third slice has obtained the worst PSR compared to the two others. Note that we have configured the third slice with the lowest priority, thus a large number of LoRa nodes have been assigned to this slice comparing to the others. This leads to a significant increases in the number of collisions in this slice.

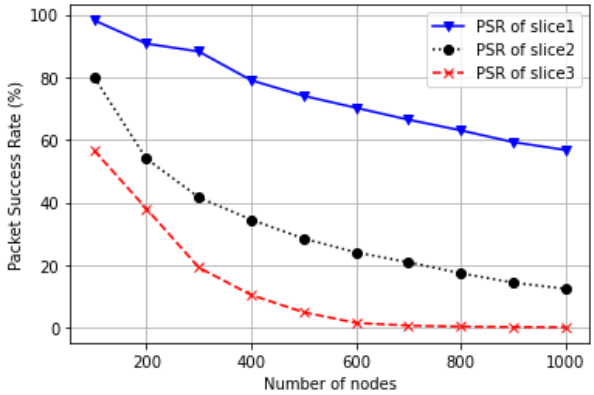


Fig. 2. Packet Success Rate evaluation.

At this point, the PSR is related to the number of packet collisions. Consequently, there is a relationship between both, as the number of nodes increases, the collisions increase, which leads to a decrease in PSR. In fact, the same is true for the other two slices, but taking priority into account, it can be seen that slice 2 is more reliable than slice 3. Therefore, a medium set of nodes assigned to this slice implies that the number of collisions will be minimal, and therefore the PSR is lower. While slice 1 is the one characterized by high reliability with high PSR. Finally, we can conclude that the higher the priority of the slice, the higher the PSR.

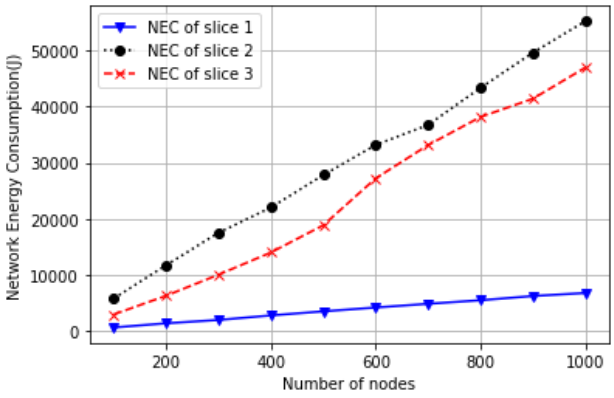


Fig. 3. Network Energy Consumption evaluation.

2) Network Energy Consumption (NEC): As depicted in Fig. 3, the total energy consumption for each slice depends on the number of assigned nodes. It shall be noted that the energy consumption proportionally increases with the number of LoRa nodes in the network regardless the network slices. We also observe that the LoRa nodes consume more energy in the third network slice. This can be explained as follow, the third network slice has the lowest priority, then a large number of LoRa nodes are assigned to this slice. Therefore, the

LoRa nodes need to re-transmit many times before succeeding to transmit their packets. In contrast, the second network slice, which is designed to guarantee the medium reliability, consumes the lower energy consumption comparing to the third network slice. In fact, a lower number of LoRa nodes are affected by this network slice, causing a reduced number of packets' transmission and hence better energy saving. Meanwhile, the first network slice is the most efficient in terms of energy consumption compared to the two previous ones. This refers to the priority process with which this network slice is mapped, consequently a small set of LoRa nodes assigned to it. This means that the number of packets sent is lower, and hence the energy consumed by this slice is lowest.

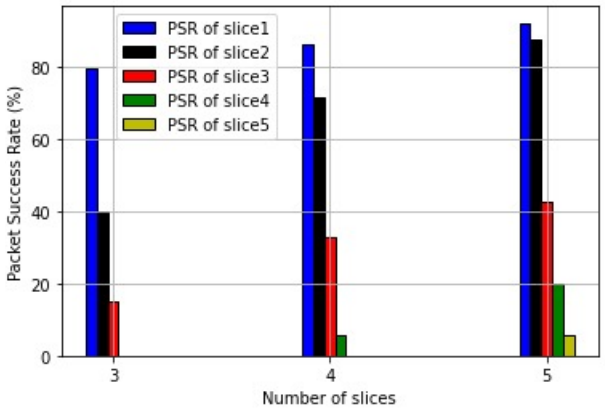


Fig. 4. Variation of slices evaluation.

In Fig. 2 and 3 illustrates our solution on three slices in terms of PSR and NEC, while Fig. 4 represents the PSR results for a variable number of services varying from three to five slices, with a fixed number of 400 LoRa nodes. As we can see in Fig. 4, with an increased number of slices, the PSR increases as well, this indicates that LoRa nodes are able to send their packets to a large number of channels, which leads to a reduced number of collisions. Furthermore, Fig. 4 illustrates the efficiency of the proposed solution of the coalitional game on which a sequence of player transfer operations will be applied. As shown in equation (15), the transfer operation between slices is applied until the SLA (priority between slices) of each slice is satisfied. In this paper, we have demonstrated that the assignment of LoRa nodes to slices directly impacts the performance of the latter, in terms of PSR and NEC while ensuring the SLA in terms of priority. Beyond the solution proposed, we have shown that it is possible to support several services, with different requirements, in a LoRaWAN network, which opens the door to the use of these networks for sensors requiring particular QoS requirements.

ACKNOWLEDGEMENTS

This work was partially supported by the Intelligentsia, ANR project.

VI. CONCLUSION

In this paper, we propose an allocation scheme for slicing the LoRaWAN network. It aims to improve the reliability of the network and to guarantee the SLA of each slice. To this end, a coalition game solution has been proposed, where the players are initially partitioned efficiently by integration k-means clustering. Therefore, we proposed a transfer operation that allows players to change their coalitions. Simulation results showed that the proposed approach improves packet success rate (PSR), network energy consumption (NEC), while guaranteeing prioritization between slices.

In future work, we aim to extend this study by using an admission technique compatible with LoRaWAN networks to ensure a better quality of service.

REFERENCES

[1] F. Van den Abeele, J. Haxhibeqiri, I. Moerman, and J. Hoebeke, "Scalability analysis of large-scale lorawan networks in ns-3," *IEEE Internet of Things J.*, vol. 4, no. 6, pp. 2186–2198, 2017.

[2] T. T. Nguyen, H. H. Nguyen, R. Barton, and P. Grossetete, "Efficient design of chirp spread spectrum modulation for low-power wide-area networks," *IEEE Internet of Things J.*, vol. 6, no. 6, 2019.

[3] S. Dawaliby, A. Bradai, and Y. Pousset, "Joint Slice-based Spreading Factor and Transmission Power Optimization in LoRa Smart City Networks," *Internet of Things*, Sep. 2019. [Online]. Available: https://hal.archives-ouvertes.fr/hal-02301022

[4] K. Mikhaylov, J. Petaejaejaervi, and T. Haenninen, "Analysis of capacity and scalability of the lora low power wide area network technology," in *European Wireless 2016*. VDE, 2016, pp. 1–6.

[5] D. Magrin, M. Centenaro, and L. Vangelista, "Performance evaluation of lora networks in a smart city scenario," in *2017 IEEE Int. Conf. on Communications (ICC)*. ieee, 2017, pp. 1–7.

[6] O. Georgiou and U. Raza, "Low power wide area network analysis: Can lora scale?" *IEEE Wireless Communications Letters*, vol. 6, no. 2, pp. 162–165, 2017.

[7] A. Mahmood, E. Sisinni, L. Guntupalli, R. Rondón, S. A. Hassan, and M. Gidlund, "Scalability analysis of a lora network under imperfect orthogonality," *IEEE Trans. on Industrial Informatics*, vol. 15, no. 3, pp. 1425–1436, 2018.

[8] J. Petäjäjärvi, K. Mikhaylov, M. Pettissalo, J. Janhunen, and J. Iinatti, "Performance of a low-power wide-area network based on lora technology: Doppler robustness, scalability, and coverage," *Int. J. of Distributed Sensor Networks*, vol. 13, no. 3, p. 1550147717699412, 2017.

[9] R. Harwahyu, A. Presekal, and R. F. Sari, "Lorawan performance evaluation with optimized configuration," *Int. J. of Future Generation Communication and Networking*, vol. 11, no. 4, pp. 51–68, 2018.

[10] R. Kufakunesu, G. P. Hancke, and A. M. Abu-Mahfouz, "A survey on adaptive data rate optimization in lorawan: Recent solutions and major challenges," *Sensors*, vol. 20, no. 18, 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/18/5044

[11] S. E. Elayoubi, S. B. Jemaa, Z. Altman, and A. Galindo-Serrano, "5g ran slicing for verticals: Enablers and challenges," *IEEE Communications Magazine*, vol. 57, no. 1, pp. 28–34, 2019.

[12] S. Dawaliby, A. Bradai, and Y. Pousset, "Adaptive dynamic network slicing in lora networks," *Future generation computer systems*, vol. 98, pp. 697–707, 2019.

[13] ——, "Network slicing optimization in large scale lora wide area networks," in *2019 IEEE Conf. on Network Softwarization (NetSoft)*. IEEE, 2019, pp. 72–77.

[14] S. Messaoud, A. Bradai, and E. Moulay, "Online gmm clustering and mini-batch gradient descent based optimization for industrial iot 4.0," *IEEE Trans. on Industrial Informatics*, vol. 16, no. 2, pp. 1427–1435, 2019.

[15] M. C. Bor, U. Roedig, T. Voigt, and J. M. Alonso, "Do lora low-power wide-area networks scale?" in *ACM Int. Conf. on Modeling, Analysis and Simulation of Wireless and Mobile Systems*, 2016, pp. 59–67.

[16] A. Fahim, A. Salem, F. A. Torkey, and M. Ramadan, "An efficient enhanced k-means clustering algorithm," *J. of Zhejiang University-Science A*, vol. 7, no. 10, pp. 1626–1633, 2006.