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UNIVERSITÉ PARIS-EST

**École doctorale n° 533 : Mathématiques et sciences de
l'information et de la communication (MSTIC)**

Thèse de doctorat

Informatique

Vers un réseau LoRaWAN auto reconfigurable pour les applications de la ville intelligente

Toward a self reconfigurable LoRaWAN network for smart city applications

présentée et soutenue publiquement par

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Abstract

Quotation

Start by doing what is necessary, then do what is possible and you will achieve the impossible without realizing it. – Saint François d’Assise

Commence par faire le nécessaire, puis fais ce qu’il est possible de faire, tu réaliseras l’impossible sans t’en apercevoir. – Saint François d’Assise

Nowadays, Internet of things (IoT) applications are witnessing a tremendous evolution due to the increasing growth of IoT devices. In fact, they are used in all areas of life, from weather and environment monitoring to health care assistance passing by logistics and tracking applications. To be able to transmit the measured data to the cloud, IoT devices need to send them through a reliable wireless technology. However, the heterogeneity of wireless technologies and the diversification of IoT applications make IoT more complex to study and comprehend. Indeed, applications like smart building and smart environment are one of hundreds use cases that need to be deployed with these technologies. For this reason, the optimization of transmission parameters for wireless telecommunications typically depends on the type of the application and the size of the transmitted data. Each IoT application has different Quality of Service (QoS) requirements and each wireless technology offers different QoS metrics.

Among different wireless technologies, Low Power and Wide Area Networks (LPWAN) emerged as a promising wireless solution for IoT because they offer a low-power consumption while transmitting the data in a wide area (15 Km). Long Range (LoRa), Sigfox and Narrow Band-Internet of Things (NB-IoT) are the most known technologies with such advantages. Unlike Sigfox and NB-IoT, LoRa is more open for academic research since the specification that governs it is publicly available. In addition, Long Range Wireless Access Network (LoRaWAN) can be deployed as a private network and integrated easily and cheaply with many network platforms (e.g., The Things Network (TTN)). For all these advantages, we focus in this thesis on the optimization of LoRaWAN transmission settings by adapting them to applications’ requirements.

Since LoRa transceivers use a Chirp Spread Spectrum (CSS) modulation scheme, they should be configured according to a set of transmission parameters: Spreading Factor (SF), Transmission Power (P^{tx}), Coding Rate (CR) and Bandwidth (BW). These parameters must be tuned, controlled and adapted to application’s requirements to optimize the network performance especially in a dense network. The default control mechanism of LoRaWAN server called Adaptive Data Rate (ADR), has been proposed in the literature to adapt transmission parameters dynamically based on the recent received packets. However, ADR control system does not adjust parameters considering the evolution of applications’ requirements. Knowing the heterogeneity of services and applications that need to be loaded in IoT devices, the task to adapt at each time the wireless network to the applications running on each end-device becomes a challenging dilemma.

To address this problem, our first contribution is to take advantage of the pattern recognition algorithms by using a clustering process to map LoRa transmission settings to different clusters with different QoS levels. We propose to cluster a set of LoRa transmission settings based on the measured QoS metrics such as the Bit Error Rate (BER), the

Time on Air (**ToA**) and the Received Signal Strength Indicator (**RSSI**). For this purpose, we have developed a **LoRa** transmission adaptation mechanism. We use a fuzzy clustering process rather than a hard clustering to get the membership of each transmission setting to different clusters. The advantage of using this algorithm is the ability to know at which level each transmissions setting is suitable to different **IoT** applications.

Recent works in literature tried to use machine learning algorithms but they start their learning process without any knowledge about wireless transmission qualities. So, they have to learn from scratch at each time the environment change. To be ahead of the game, we tried to find a way to characterize all transmission settings qualities and build a knowledge that we feed to machine learning algorithms to be one step ahead of other machine learning based solutions. To this end, we formulate the problem of transmission settings selections as a Markov Decision Process (**MDP**) problem where actions are transmission settings and states are the recognized quality levels by Fuzzy C-Means (**FCM**). Once we formulate the problem this way, we need to know with which probability the link state could jump from one state to another after the selection of each transmission setting. Thanks to pattern recognition tools, we estimate the link quality level at which each transmission setting leads, by clustering the quality of all possible transmission settings to three main clusters with different levels of qualities.

Once we generate this knowledge in offline mode using **FCM**, we used Q-learning algorithm to converge to the optimal transmission settings in online mode. This means that devices start by sending packets randomly using different transmission settings to explore the quality of transmission settings. The gateways, in their turn, catch the transmitted packets and forward them to the network server. Then, based on the offline learning process, the network server should be able to exploit the transmission settings with the highest quality to increase the data rate iteratively until the policy converges to a steady state. Through intensive simulations and using different numbers of devices and gateways and different packet sizes and rates, we validated the effectiveness of our solution in more than 256 scenarios (4 packet sizes * 4 packet rates * 4 numbers of devices * 4 numbers of base stations). After which, we validate the effectiveness of our solution by studying in depth two scenarios with 100 and 1000 devices. We measure in each scenario other metrics like the **ToA** and the Transmission Energy (E^{tx}) in addition to the Packet Delivery Ratio (**PDR**) and the Data Rate (**DR**).

To offer a customized **QoS** to **IoT** devices, we propose, in our third contribution, to improve the customization of **LoRaWAN** transmission settings by fully integrating the clustering output in the learning process. In fact, even if it offers a better performance than the state of the art, Q-learning algorithm does not take advantage of the whole knowledge provided by the clustering output since it updates its actions based only on the observed next state without taking into account all possible next states. For this reason, we propose to completely initialize the state transition matrix of **MDP** with the knowledge provided by **FCM**. The advantage compared to the Q-learning based solution is the ability to provide to the learning agent an overall view of all possible state transitions after each iteration. Unlike Q-learning and value iteration algorithm, policy iteration algorithm is known for its highest convergence speed as it requires less iterations to converge. To highlight the performance of our approach, we compared the data rate of the traffics generated by three main applications separately rather than the whole traffic like we did previously. Simulation results show that combining exploration with **FCM** and exploitation with **MDP** speeds up the learning process while allowing the adaptation of the **DR**, the **ToA** and the E^{tx} of these applications. Furthermore, results show that the quality of the generated traffic is improved compared to the existing strategies.

Résumé

Quotation

Religion is considered by ordinary people as true, by wise people as false and by leaders as useful - Sénèque

La religion est considérée par les gens ordinaires comme vraie, par les sages comme fausse et par les dirigeants comme utile - Sénèque

De nos jours, les applications d'Internet des objets connaissent une évolution considérable grâce à la croissance d'utilisation des objets connectés. Ces objets sont utilisés dans tous les domaines de la vie, qu'il s'agisse de la météo, la surveillance du changement climatique, l'aide aux soins de santé ou bien la logistique et le suivi des commandes des marchandises, etc. Ces objets ont besoin d'un réseau sans fil pour envoyer et recevoir les données qu'ils collectent.

L'hétérogénéité des technologies sans fils et la diversification des applications ont rendu l'Internet des objets plus complexe à étudier et à comprendre. Des applications telles que la construction intelligente ou la signalisation sont des exemples parmi des centaines d'autres qui doivent être déployés avec ces technologies. La sélection des paramètres de transmissions appropriés pour les réseaux sans fils dépend fortement de la nature des données échangées. En fait, chaque application a des exigences différentes en matière de qualité de service (QoS) et chaque technologie offre différentes métriques de qualité de service.

Les réseaux étendus à faible puissance (LPWAN) sont apparus comme des technologies sans fils prometteuses pour l'Internet des objets, ils offrent une faible consommation d'énergie lors de la transmission des données à longue distance. LoRa, Sigfox et NB-IoT sont les technologies les plus connues qui répondent à ces exigences. SigFox prévoit une couverture mondiale dans 45 pays et régions à travers un seul opérateur. NB-IoT est développé par des opérateurs de télécommunications comme une alternative aux technologies LPWAN. Puisque la technologie NB-IoT utilise un spectre sous licence, elle permet une meilleure fiabilité du trafic par rapport aux autres technologies. Contrairement à Sigfox et NB-IoT, LoRa est plus accessible au monde académique car la spécification de LoRa est publique. En outre, le réseau d'accès sans fil longue portée (LoRaWAN) pourrait être déployé en tant que réseau privé et s'intègre facilement à de nombreuses plateformes de réseau (par exemple, The Things Network (TTN)). Pour toutes ces raisons, nous concentrons notre travail sur cette technologie.

Les émetteurs-récepteurs LoRa envoient des données selon la configuration d'un ensemble de valeurs de paramètres: le facteur d'étalement du spectre (SF), la puissance de transmission (P^{Tx}), le taux de codage (CR) et la largeur de bande (BW). Ces paramètres doivent être ajustés, contrôlés et adaptés aux exigences des applications. Le mécanisme de contrôle par défaut du serveur LoRaWAN appelé Adaptive Data Rate (ADR), a été proposé pour adapter les paramètres de transmission de manière dynamique en fonction de la qualité de réception des paquets récentes. Cependant, ce mécanisme n'ajuste pas les paramètres en fonction de l'évolution des exigences de qualité de service des applications.

Vu l'hétérogénéité des services et la diversification des applications qui doivent être supportées par l'Internet des objets, la tâche d'adaptation à chaque instant de ces paramètres aux applications qui s'exécutent dans chaque objet est devenue un défi d'ampleur pour les opérateurs et les fournisseurs de services. Pour résoudre ce problème, notre première approche consiste à utiliser un mécanisme de segmentation pour regrouper les transmissions LoRa par niveau de qualité de service offerte. Nous proposons de segmenter un ensemble de paramètres de transmission LoRa en 3 ensembles de niveaux de qualité de service différents. Les paramètres basés sur les mesures de la qualité de service telles que le taux d'erreur des bits (BER), le temps de diffusion (ToA) et l'indicateur de la force du signal reçu (RSSI) sont utilisés pour cela. Nous utilisons un processus de segmentation flou pour obtenir le degré d'appartenance de chaque configuration de transmission aux types d'applications.

Ensuite, en se basant sur le processus d'apprentissage hors ligne, le serveur de réseau devrait être en mesure d'exploiter les paramètres de transmission avec la meilleure qualité pour augmenter le débit de manière itérative jusqu'à ce que la politique converge vers un état stable. Grâce à des simulations intensives et en utilisant différents nombres de capteurs et de passerelles avec différentes tailles et fréquence d'envoi des paquets, nous avons validé l'efficacité de notre solution dans plus de 256 scénarios (4 tailles de paquets * 4 taux de paquets * 4 nombres de capteurs * 4 nombres de stations de base). Après quoi, nous validons l'efficacité de notre solution en étudiant en profondeur deux scénarios avec 100 et 1000 capteurs. Nous mesurons dans chaque scénario d'autres métriques comme le temps de propagation et la consommation d'énergie en plus du PDR et le débit.

Pour offrir une qualité de service personnalisée aux capteurs IoT, nous proposons, dans notre troisième contribution, d'améliorer la personnalisation des paramètres de transmission LoRaWAN en intégrant pleinement le résultat du clustering dans le processus d'apprentissage. En effet, même s'il offre une meilleure performance que les travaux de l'état de l'art, l'algorithme Q-learning ne tire pas profit de l'ensemble des connaissances fournies par le clustering puisqu'il met à jour sa politique en se basant uniquement sur l'état suivant observé sans prendre en compte tous les états suivants possibles. Pour cette raison, nous proposons d'initialiser complètement la matrice de transition d'état de MDP avec la connaissance fournie par FCM. L'avantage par rapport à la solution basée sur le Q-learning est la possibilité de fournir à l'agent d'apprentissage une vue globale de toutes les transitions d'état possibles après chaque itération. Comme nous explorons la qualité des paramètres de transmission à l'avance avant même de commencer le processus d'apprentissage en mode hors ligne, l'algorithme d'itération de politique exploitera directement les paramètres de transmission de haute qualité. Contrairement à Q-learning et à l'algorithme d'itération de valeur, l'algorithme d'itération de politique est connu pour sa plus grande vitesse de convergence car il nécessite moins d'itérations pour converger. Pour mettre en évidence la performance de notre approche, nous avons comparé le débit des trafics générés par trois applications principales séparément plutôt que l'ensemble du trafic comme nous l'avons fait précédemment. Les résultats de la simulation montrent que la combinaison de l'exploration avec FCM et de l'exploitation avec MDP accélère le processus d'apprentissage tout en permettant l'adaptation du débit, du temps de propagation et de la consommation d'énergie de ces applications. De plus, Les résultats montrent que la qualité du trafic généré est améliorée par rapport aux stratégies existantes.

Résumé étendu

Quotation

My religion is when I do good, I feel good and when I do bad, I feel bad - Abraham Lincoln

Ma religion c'est quand je fais du bien, je me sens bien et quand je fais du mal, je me sens mal - Abraham Lincoln

L'adoption croissante des technologies sans fil a intensifié le besoin de mieux comprendre le fonctionnement de l'Internet des objets (IoT). Lorsqu'une technologie IoT est utilisée pour surveiller les risques liés aux infrastructures critiques, la fiabilité et l'efficacité deviennent des priorités pour tout opérateur de réseau. La technologie à longue portée (LoRa), est souvent la solution industrielle la plus courante pour connecter des capteurs sans fil dans une zone étendue. Pour pouvoir connecter des appareils alimentés par batterie à l'internet, les clients sont généralement confrontés à trois choix principaux : réseaux à courte portée, réseaux cellulaires et réseaux à longue portée. Les technologies à courte portée comprennent des technologies telles que Bluetooth, NFC/RFID ou Zigbee. Par contre, elles ne sont absolument pas adaptées aux scénarios qui nécessitent des communications à longue distance de plus de 100 mètres. Cependant, les technologies cellulaires [3G, 4G, 5G, etc.] souffrent d'une consommation d'énergie et ne sont pas le meilleur choix pour les appareils à faible puissance. Les besoins de nombreuses applications industrielles IoT ont accentués le développement d'une nouvelle vague de technologies de communication sans fil connues sous le nom de communications sans fil à longue portée (LPWAN). Parmi ces technologies, on peut citer: Narrow Band-Internet of Things (NB-IoT), Sigfox et LoRa. Ils sont idéaux pour les environnements industriels et gagnent en popularité en raison de leurs caractéristiques de communication à longue portée, à faible puissance et à faible coût.

Pour utiliser les nouvelles applications IoT, les clients doivent superviser des opérations qui requièrent une large couverture de communication et une excellente connexion. Pour ce faire, quatre facteurs importants doivent être pris en compte, à savoir: le débit de données, la portée, la consommation d'énergie et la disponibilité de la connexion. La technologie LoRa offre le bon équilibre entre tous ces éléments. Elle garantit une longue distance de transmission avec une portée allant jusqu'à 15 km ou 9 miles avec une autonomie jusqu'à 10 ans. Elle peut être plus rentable que les solutions traditionnelles en réduisant la consommation d'énergie. Elle s'adapte bien à l'ajout de nuds au réseau au fur et à mesure de l'évolution du projet. En outre, elle s'est avérée robuste avec forte résilience contre l'interférence. La sécurité et la confidentialité sont également assurées par un cryptage AES 128 à plusieurs niveaux pour toutes les données envoyées entre les capteurs et le réseau.

Comme nous avons motivé le choix de la technologie LoRa, nous entrons maintenant dans les détails techniques sur le fonctionnement cette technologie. LoRa est proposé comme une nouvelle technologie de couche physique qui module le signal dans les bandes industriels, scientifiques et médicaux (ISM) inférieures à 1 GHz. Elle permet aux utilisateurs individuels de créer et de déployer des réseaux privés sans restrictions, à l'exception de la puissance de transmission maximale autorisée qui devrait être inférieure à 14

dbm. Il s'agit d'un avantage majeur par rapport à Sigfox et NB-IoT, qui sont contrôlés par les opérateurs de réseaux publics.

Pour offrir la meilleure qualité de service (QoS) aux applications IoT, les réseaux sans fil doivent personnaliser leurs paramètres de transmission en tenant en compte la durée de vie de la batterie. Parmi plusieurs technologies sans fil, la technologie LoRa est une solution LPWAN prometteuse dont la consommation d'énergie dépend de l'optimisation d'un ensemble de paramètres de transmission. Dans cette thèse, nous introduisons une nouvelle optimisation du débit de données en utilisant des algorithmes d'apprentissage par renforcement (RL) pour optimiser le débit de données et améliorer la durée de vie du réseau sans intervention humaine. Notre contribution exploite la caractérisation des paramètres de transmission LoRa à l'aide des méthodes de reconnaissance automatisées ou *clusternig*. Ensuite, sur la base des résultats du clustering, nous modélisons le problème de la sélection des configurations des capteurs LoRa en problème d'exploration et d'exploitation. Pour le résoudre, nous utilisons un processus de décision de Markov (MDP) pour converger vers les configurations optimales à l'aide des algorithmes Q-learning et itération de politiques. Pour mettre en évidence la performance de notre solution en termes d'économie d'énergie, nous avons comparé l'énergie de transmission et le débit des données de notre solution avec d'autres solutions, notamment : les pondérations exponentielles pour d'exploration et d'exploitation (EXP3), EXPLoRaTS et Adaptive Data Rate (ADR).

Les systèmes LPWAN étant conçus pour consommer moins d'énergie, le débit et l'énergie doivent être optimisés en tenant en compte la qualité des données transmises. Pour minimiser l'énergie et maximiser le débit de données, les paramètres de transmission, tels que le facteur d'étalement (SF), la puissance de transmission et la bande passante (BW), doivent être optimisés pour converger vers la combinaison de paramètres qui répondent aux besoins des applications. Dans ce contexte, cette thèse vise à améliorer l'optimisation de la consommation d'énergie et du débit de données tout en gardant le débit aussi élevé que possible. Pour atteindre cet objectif, nous proposons d'abord d'acquérir des connaissances sur la qualité de chaque paramètre de transmission par le biais d'une phase de prétraitement. Ensuite, nous utilisons des algorithmes d'apprentissage par renforcement (RL) pour améliorer la durée de vie globale du réseau. Pour ne pas limiter notre travail à la maximisation du débit global du réseau, nous proposons une différenciation du trafic en divisant les paramètres du réseau en trois sous-ensembles avec des niveaux de QoS différents en utilisant un modèle d'apprentissage. Ensuite, en se basant sur les modèles reconnus, les algorithmes devront être capable de distinguer entre les qualités offertes par les paramètres de transmission. Bien que cette solution reste une approche "best effort", elle réussit à adapter la qualité du trafic aux exigences de chaque application.

A partir du contexte présenté ci-dessus, nous cherchons à bénéficier de l'avantage des algorithmes d'apprentissage automatique et en particulier de l'apprentissage non supervisé, du processus de décision de Markov et des algorithmes MAB pour rendre le réseau suffisamment intelligent pour adapter ses paramètres en fonction des exigences des applications IoT. Par conséquent, nous visons à relever les défis émergents pour apporter des réponses efficaces à ces questions : comment améliorer la performance du réseau en tenant en compte plusieurs métriques QoS ? et comment adapter ces métriques à l'hétérogénéité et à la diversification des applications IoT ? Pour cette raison, nous commençons notre étude en examinant de plus près l'état de l'art sur l'optimisation des paramètres de transmission qui déterminent les performances de communication. Notre travail est le seul qui considère tous les paramètres de transmission en commençant par le plus connu qui est le SF, à la puissance de transmission en passant par la bande passante

(BW) et la fréquence de codage (CR). En effet, les solutions proposées dans la littérature souffrent de problèmes liés au temps de convergence et à la reconfiguration en temps réel. Plusieurs techniques ont été proposées dans la littérature pour surmonter ces problèmes. Néanmoins, les contributions actuelles nécessitent encore des investigations plus avancées notamment dans le domaine de l'optimisation multicritères et la personnalisation des paramètres du réseau. En outre, certaines d'entre eux négligent plusieurs scénarios pratiques et limitent leurs expériences à quelques cas sans varier le nombre de cellules, le nombre de terminaux, la taille des paquets transmis et leur fréquence de transmission qui ont un impact important sur le résultat du processus d'apprentissage. Pour cette raison, nous proposons au cours de cette thèse d'utiliser des algorithmes d'apprentissage légers avec un prétraitement à partir du processus de clustering. Plus précisément, nous proposons dans cette thèse d'améliorer le débit de données de la liaison montante en regroupant les paramètres de transmission afin de savoir à quel niveau de qualité se trouve la transmission. Ensuite, nous introduisons cette connaissance, sous la forme de degrés d'appartenance, dans les algorithmes d'apprentissage comme une matrice de transition d'état. Ainsi, les paramètres de transmission conduiront à différents états en fonction de leur degré d'appartenance à différents clusters. Cela signifie que lorsque nous prenons un paramètre d'un cluster particulier, le clustering est capable de reconnaître à quel niveau de qualité de lien nous pouvons nous attendre si nous choisissons une telle action.

En résumé, la solution que nous proposons suit les étapes suivantes :

- 1) Acquérir suffisamment de données pour évaluer la qualité de chaque paramètre de transmission.
- 2) Appliquer le processus de clustering sur les mesures de QoS pour extraire des modèles liés à la qualité de chaque paramètre de transmission en mode hors ligne.
- 3) Utiliser ces modèles dans Q-learning et MDP pour savoir à quel état chaque paramètre de transmission pourrait mener et comment mettre à jour ses fonctions pour converger analytiquement vers les paramètres optimaux.

Le processus commence par la transmission de paquets aléatoires pour permettre au serveur du réseau de rassembler suffisamment de connaissances sur la qualité des transmissions (BW, CR, SF, P) pour chaque dispositif. Ensuite, nous regroupons ces données pour savoir à quel niveau de qualité chaque paramètre de transmission appartient le plus. Une fois cette connaissance acquise, nous appliquons l'itération de politique du processus de décision de Markov en utilisant les degrés d'appartenance des paramètres. Le serveur de réseau arrête ensuite le processus d'apprentissage et attend le changement de topologie pour prendre en compte le nouvel emplacement des dispositifs qui ont été déplacés.

De nombreux travaux dans la littérature ont tenté de résoudre le problème de l'optimisation du débit de données, mais la plupart d'entre eux utilisent des méthodes heuristiques et valident leur solution à l'aide d'un ou deux scénarios avec un nombre limité de capteurs, de stations de base, de terminaux et avec de débits et tailles de paquets fixes. En outre, ils ne prennent en compte que quelques paramètres de transmission, principalement le facteur d'étalement (SF).

Nous validons notre méthode dans tous les scénarios quel que soit le nombre d'appareils, de stations de base et quel que soit la taille et le débit des paquets. Des travaux récents dans la littérature ont essayé d'utiliser des algorithmes d'apprentissage automatique, mais ils commencent leur processus d'apprentissage sans aucune connaissance des qualités de transmission sans fil. Ils doivent donc apprendre à partir de zéro à chaque

fois que l'environnement change. Pour avoir une longueur d'avance, nous avons essayé de trouver un moyen de caractériser toutes les qualités des paramètres de transmission et de construire une connaissance pour nous permette d'avoir une vue d'ensemble sur la qualité des transmissions. À cette fin, nous formulons le problème de la sélection des paramètres de transmission comme un problème de processus de décision de Markov où les actions sont des paramètres de transmission et les états sont les niveaux de qualité reconnus par le clustering. Une fois que nous avons formulé le problème de cette façon, nous devons savoir avec quelle probabilité l'état du lien peut passer d'un état à un autre après la sélection d'un paramètre de transmission. Cette connaissance est obligatoire pour résoudre notre problème. Grâce aux outils de reconnaissance de patterns, nous proposons d'utiliser l'algorithme de clustering Fuzzy C-Means (FCM) en regroupant la qualité de tous les paramètres de transmission possibles en trois catégories principales avec différents niveaux de qualité. Cela signifie que lorsque nous prenons une configuration d'un cluster donné, FCM est capable de reconnaître à quel niveau de qualité nous pouvons nous attendre si nous choisissons une telle configuration. Cette reconnaissance est tout ce que nous recherchions pour résoudre notre problème de décision de Markov. Elle nous permet de savoir à quel état chaque action pourrait mener en sachant à quel cluster appartient chaque configuration.

Une fois que nous avons généré cette connaissance en mode hors ligne à l'aide du FCM, nous appliquons l'algorithme Q-learning et l'itération de la politique pour converger vers les paramètres de transmission optimaux en mode en ligne. Cela signifie que les dispositifs commencent par envoyer des paquets de façon aléatoire en utilisant différentes configurations de transmission. Les passerelles, à leur tour, captent les paquets transmis et les transmettent au serveur du réseau. Ensuite, le serveur de réseau reçoit ces paquets et les classe en fonction des paramètres de qualité mesurés par les passerelles. Une fois cette étape effectuée en mode hors ligne, les capteurs IoT peuvent maintenant commencer le processus d'apprentissage et le serveur réseau devrait être en mesure de suggérer des paramètres de transmission pour augmenter le débit de données. Nous avons comparé plus de 6 algorithmes pour mettre en évidence leurs mesures de performance. Il existe d'autres algorithmes que nous n'avons pas eu le temps de mettre en œuvre, mais il n'existe aucun algorithme dans la littérature qui a atteint un taux de données supérieur à celui que nous avons obtenu. Nous sommes les seuls à avoir considéré :

- 1) Un tel nombre de scénarios avec différents nombres de capteurs, de stations de bases et différents taux d'envoi de paquets.
- 2) Un tel nombre d'algorithmes : MDP, Q-learning, EXP3, EXPLoRaTS et ADR.
- 3) Un tel nombre de paramètres de transmission : SF, CR, BW et puissance de transmission .
- 4) Un tel nombre de métriques : PDR, DR, ToA et énergie.

En général, l'utilisation de LoRa est plus appropriée pour les systèmes de surveillance tels que les exploitations minières qui couvrent généralement de grandes surfaces ou les systèmes de surveillance de l'environnement. Dans les projets de construction et de creusement de tunnels, où les points de surveillance sont souvent répartis sur plusieurs kilomètres, les exploitants ont besoin de données pour répondre aux besoins de leurs clients. LoRa sera un atout partout où un programme de surveillance fiable en temps réel est nécessaire pour garantir l'intégrité des infrastructures et des biens comme les ponts, les barrages, les bâtiments ou d'autres infrastructures. En outre, LoRa offre la possibilité de déployer des réseaux privés, permettant à l'utilisateur d'avoir le contrôle et d'être indépendant des grands opérateurs de réseau. Nous nous concentrons, dans la première

partie de cette thèse, sur le processus de collecte des données en évaluant la qualité de chaque paramètre de transmission utilisant la modulation LoRa.

Nous proposons donc comme première contribution de regrouper toutes les combinaisons de paramètres de transmission en 3 groupes basés sur plusieurs métriques de QoS. Cette étape est fondamentale pour les contributions suivantes puisqu'elle permet d'acquérir des connaissances sur le niveau de qualité de chaque configuration de transmission. Cette phase offre la possibilité au serveur réseau d'obtenir une vue d'ensemble des paramètres de transmission disponibles et de les adapter aux applications. En plus, il pourrait être exécuté séparément en mode hors ligne sans qu'il ne soit nécessaire d'interagir avec les appareils finaux ou de collaborer avec d'autres serveurs réseaux. Cependant, les données collectées par d'autres serveurs doivent gérer la même topologie de réseau pour être traitées efficacement en tenant en compte des mêmes distances entre les capteurs et les stations de base. Sinon, il doit être exécuté en mode en ligne si les capteurs sont mobiles.

Pour cette raison, nous proposons dans notre deuxième contribution de mettre à jour les paramètres du réseau avec Q-learning en utilisant la connaissance acquise lors du clustering. Ce processus s'appuie sur le degré d'appartenance de chaque paramètre aux 3 clusters pour choisir la meilleure configuration qui maximise le débit du réseau. Ainsi, pour reconnaître à quel état chaque action conduit, nous nous servons des degrés d'appartenance des configurations aux clusters. Les configurations sont mises à jours jusqu'à la convergence vers l'ensemble des paramètres de transmission qui surpassent l'état de l'art en ce qui concerne la qualité du trafic de la liaison montante.

Dans la troisième partie de cette thèse, nous étendons notre étude afin d'approfondir l'utilisation de la phase de clustering en analysant la qualité des trafics générés par 3 applications IoT plutôt que de se concentrer sur la qualité globale de l'ensemble du trafic comme dans la deuxième partie. Nous supposons dans cette partie que les capteurs IoT exécutent 3 applications distinctes avec 3 niveaux d'exigences de QoS différents. Nous proposons donc de répondre aux exigences de chaque application en utilisant le model MDP. En plus de mesurer la qualité du trafic global, nous mesurons la qualité de chaque trafic généré par les trois applications. Cela nous permet de voir si les dispositifs qui exécutent une application nécessitant une haute qualité de trafic sont affectés au cluster avec une haute qualité de service. A l'exception de l'introduction et de la conclusion, cette thèse est divisée en quatre chapitres que nous décrivons comme suit.

Chapitre 2 : Etat de l'art, élucide le contexte de notre thèse et les solutions existantes. Il est composé de 2 parties. Dans la première partie, nous étudions les principales contributions de la littérature concernant l'évaluation de la qualité et des performances de LoRa et LoRaWAN. Nous avons divisé cette étude en quatre sous-sections principales afin de distinguer entre les contributions de la couche application, réseau, contrôle d'accès, physique et aussi de l'évaluation des performances. Dans la deuxième partie, nous examinons uniquement les contributions qui appliquent des techniques d'apprentissage automatique dans différents domaines afin de comprendre comment elles sont utilisées et pour quelles raisons. Enfin, nous concluons ce chapitre avec une discussion sur les différents travaux et nous motivons nos contributions.

Chapitre 3 : Le clustering des paramètres réseaux représente notre première contribution dans cette thèse. Dans ce chapitre, nous proposons de regrouper un ensemble de paramètres de transmission LoRa en fonction de la mesure de la qualité de service telles que le taux d'erreur des bits (BER), le temps de propagation du signal (ToA) et l'indicateur de force du signal reçu (RSSI). Nous considérons les vecteurs de l'ensemble des paramètres comme un nuage de points dans un espace vectoriel tandis que les mesures

sont des coordonnées de points. Nous supposons qu'un nuage de points caractérise une configuration appropriée d'une classe d'application particulière. Les "clusterheads" sont les coordonnées représentatives d'un cluster donné. Notre méthode vise à mettre en correspondance un ensemble de paramètres de transmission LoRa qui offrent la même QoS au même cluster. Nous générons un ensemble de paramètres de transmission de manière aléatoire en appliquons l'algorithme de clustering FCM sur les mesures de QoS qui en résultent. Les résultats montrent que l'algorithme de clustering FCM attribue les valeurs d'appartenance qui correspondent le mieux aux exigences de l'application. Ce résultat pourrait être utilisé par les serveurs réseaux LoRaWAN pour cartographier chaque transmission LoRa en fonction de la qualité qu'elle offre. Cela permettra de correspondre chaque paramètre de transmission LoRa à l'application exécutée sur les terminaux finaux. Ce travail a été publié dans la conférence ISNCC.

Chapitre 4 : Nous proposons dans ce chapitre un algorithme d'apprentissage par renforcement avec Q-learning. Nous incluons des paramètres supplémentaires tels que le BW, le CR en tenant en compte plusieurs mesures de QoS comme PDR, ToA, le débit et l'énergie. Pour identifier l'état de chaque transmission, nous nous servons de l'algorithme FCM pour connaître le niveau de qualité des transmissions LoRa. Ensuite, nous utilisons ces connaissances pour identifier le prochain état après chaque mise à jour de la politique d'optimisation. Cela permettra de sélectionner les paramètres de transmission qui pourrait conduire à bien converger vers l'ensemble de paramètres de transmission qui maximise mieux le débit de données de la liaison montante. Pour mettre en évidence la performance de ce processus, nous le comparons avec, EXP3, ADR et EXPLoRaTS. Comme la solution doit s'adapter à de nombreux cas d'utilisation, de nombreux scénarios ont été étudiés en augmentant le nombre de capteurs, de passerelles et en faisant varier la taille des paquets et leur fréquence d'envoi. Les résultats des simulations montrent que l'algorithme Q-learning avec le pré-traitement de clustering (FCM) améliore mieux plusieurs mesures de QoS, notamment la débit, la PDR, la ToA ainsi que l'énergie dans tous les scénarios. Ainsi, le PDR et le débit ont été améliorés de 25% et le ToA et l'énergie ont été réduits de 40%. Une partie de ce travail a été publiée dans computer communication journal.

Chapitre 5 : La reconfiguration contextuelle des paramètres du réseau pour répondre aux exigences des applications, représente notre dernière contribution dans cette thèse. Nous introduisons une nouvelle solution de service différencié utilisant le processus MDP pour améliorer l'adaptabilité des paramètres de transmission LoRa à ces applications. Notre contribution exploite la caractérisation des paramètres en utilisant l'algorithme FCM pour identifier la qualité de chacun d'entre eux. Ensuite, en se basant sur ces résultats de clustering, nous initialisons la matrice de transition d'état de MDP pour révéler la probabilité qu'un paramètre de transmission rend l'état du lien plus fiable pour chaque application. Pour mettre en évidence la performance de notre approche, nous avons comparé la qualité des trafics générés par trois applications principales. Les résultats des simulations montrent que l'algorithme d'itération de politique est capable d'adapter le processus d'apprentissage et d'ajuster la qualité de chaque trafic aux exigences de chaque application. De plus, les résultats montrent que la qualité de tous les trafics générés est meilleure que celle de l'état de l'art. Une partie de ce travail a été publiée dans le journal Computer Communication et l'autre partie a été soumise à la conférence IWCMC.

Acknowledgements

Quotation

Numbers are to analysts what street lamps are to drunks: they provide much more support than light – Jean Dion

Les chiffres sont aux analystes ce que les lampadaires sont aux ivrognes : ils fournissent bien plus un appui qu'un éclairage
– Jean Dion

First and foremost, I am grateful to God, the Gracious and the Merciful, for all that I am and all that I have. Beyond humans challenges, I thank God for the healthy mind and the healthy body that he has given me.

My first thank goes directly to my parents whose education lightened my path to overcome daily obstacles. I am grateful that their efforts and sacrifices have not been wasted.

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The university was the opportunity for me to meet a lot of teachers in many areas. I would like to acknowledge the key knowledge that I learned from them. To cite few of them: Arezki Bouzeghoub, Fayçal Bouyakoub and Alexis Bès. After my Master graduation, I had the opportunity to meet Pr. Guy Pujolle with whom I signed my first job contract, published my first article and attend my first international conference. I would like to thank him for his recommendation to do this thesis.

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Finally, I would like to thank the university and school personals whose advice allowed me to do this thesis in good conditions.

Dedication

Quotation

*Figuring out that life is absurd should not be an end, but only a beginning of something -
Albert Camus*

La prise de conscience que la vie est absurde ne peut pas être une fin, mais seulement un début - Albert Camus

To my dear parents, whose words of encouragement ring in my ears

...

To Pr. Laurent George for giving me the opportunity to do this thesis

...

To all those who fight day and night to bring lighting knowledges to our society

Publications

Quotation

The author in his work must be like God in the universe, present everywhere and visible nowhere – Gustave Flaubert

L'auteur dans son œuvre doit être comme Dieu dans l'univers, présent partout et visible nulle part – Gustave Flaubert

International conferences

- ▣ Aghiles Djoudi, Rafik Zitouni, Nawel Zangar, and Laurent George. [Reconfiguration of LoRa Networks Parameters Using Fuzzy C-Means Clustering](#). In: *2020 International Symposium on Networks, Computers and Communications (ISNCC)*. 2020 International Symposium on Networks, Computers and Communications (ISNCC). Oct. 2020, pp. 1–6
- ▣ Aghiles Djoudi, Rafik Zitouni, Nawel Zangar, and Laurent George. [Do IoT LoRa Networks Support Emergency Evacuation Systems ?](#) In: *2019 International Conference on Information and Communication Technologies for Disaster Management (ICT-DM)*. 2019 International Conference on Information and Communication Technologies for Disaster Management (ICT-DM). Dec. 2019, pp. 1–2
- ▣ Aghiles Djoudi, Rafik Zitouni, Nawel Zangar, and Laurent George. [Genetic Algorithm For LoRa Transmission Parameter Selection](#). In: *The Fourteenth International Conference on Systems and Networks Communications (2019)*, p. 2
- ▣ Rafik Zitouni, Jérémy Petit, Aghiles Djoudi, and Laurent George. [IoT-Based Urban Traffic-Light Control: Modelling, Prototyping and Evaluation of MQTT Protocol](#). In: *2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. 1. July 2019, pp. 182–189
- ▣ Aghiles Djoudi and Guy Pujolle. [Social Privacy Score Through Vulnerability Contagion Process](#). In: *2019 Fifth Conference on Mobile and Secure Services (MobiSecServ)*. 2019 Fifth Conference on Mobile and Secure Services (MobiSecServ). 1. Mar. 2019, pp. 1–6

Journals

- ▣ Aghiles Djoudi, Rafik Zitouni, Nawel Zangar, and Laurent George. [LoRa network reconfiguration with Markov Decision Process and Fuzzy C-Means clustering](#). In: *Computer Communications* 196 (2022), pp. 129–140

Submitted

- ▣ Aghiles Djoudi, Rafik Zitouni, Nawel Zangar, Yassine Hadjadj-Aoul, Laurent George, and Rami Langar. Differentiated services for LoRaWAN with Markov Decision Process and Fuzzy C-Means Clustering. In: *2023 IEEE Wireless Communications and Mobile Computing (IWCMC)*

Contents

Quotation

*It's not the customer's job to know what he
want - Steve Jobs*

*Ce n'est pas le travail du consommateur de
savoir se qu'il veut - Steve Jobs*

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Quotation

Give me six hours to chop down a tree and I will spend the first four hours sharpening my axe - Abraham Lincoln

Donnez moi six heures pour abattre un arbre, je passerai les quatre premières à affûter ma hache - Abraham Lincoln

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List of Algorithms

Quotation

*It is not us who say the words, it is the words
that say us - Witold Gombrowicz*

*Ce n'est pas nous qui disent nos mots, c'est nos
mots qui nous disent - Witold Gombrowicz*

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Quotation

It's quite an art to sell by having nothing to
sell – Stanislaw Jerzy Lec

C'est tout un art de vendre tout en n'ayant rien
à vendre – Stanislaw Jerzy Lec

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A problem without a solution is a poorly stated problem – Albert Einstein

Un problème sans solution est un problème mal posé – Albert Einstein

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List of Nomenclatures

Quotation

Revolutions are prepared by the wise men,
executed by fools and benefit to the cowards -
Matoub Lounes

Les révolutions sont préparées par des sages,
exécutées par des fous et elles profitent aux
lâches - Matoub Lounes

E^{tx} Transmission Energy

P^{tx} Transmission Power

3C Communication-Computing-Caching

ACK Acknowledgement

ADR Adaptive Data Rate

ALOHA Random Access

AMAB Adversarial Multi-Armed Bandit

ANN Artificial neural network

AWGN Additive White Gaussian Noise

BER Bit Error Rate

BR Bit Rate

BS Base Station

BW Bandwidth

CAD Carrier Activity Detection

CBD Central Business District

CCA Clear Channel Assessment

CCG Clear Channel Gap

CDF Cumulative Distribution Function

CE Capture Effect

CF Carrier Frequency

CIR Co-channel Interference Rejection

CR Coding Rate

CRC Cyclic Redundancy Check

CSI Channel State Information

CSMA Carrier Sense Multiple Access with Collision Avoidance

CSS Chirp Spread Spectrum

CT Concurrent Transmission

DC Duty cycle

DR Data Rate

DSSS Direct Sequence Spread Spectrum

ED End Device

ELQET Enhanced Link Quality Estimation Technique

eMBB enhanced Mobile Broadband

ETSI European Telecommunications Standards Institute

EWMA Exponential Weighted Moving Average

EXP3 Exponential weights for Exploration and Exploitation

FADR Fair Adaptive Data Rate Algorithm

FCM Fuzzy C-Means

FDMA Frequency Division Multiple Access

FEC Forward Error Correction

FFT Fast Fourier Transform

FSK Frequency-shift keying

GFSK Gaussian Frequency-Shift Keying

GW Gateway

HR Chip Rate

IH Indicator of Header

IoT Internet of things

ISM Industrial, Scientific and Medical

KPN Dutch landline and mobile telecommunications company

LoRa Long Range

LoRaWAN Long Range Wireless Access Network

LOS Line Of Sight

LPWAN Low Power and Wide Area Networks

LQI Link Quality Indicator

MAB Multi-Armed Bandit

MAC Medium Access Control

MDP Markov Decision Process

MEC Mobile Edge Computing

MFC Microbial Fuel Cell

ML Machine learning

MLE mMaximum Likelihood Estimation

mMTC massive Machine Type Communications

NB-IoT Narrow Band-Internet of Things

NP Number of Preamble Symbols

NS Network Server

OTAA On-The-Air Activation

PDR Packet Delivery Ratio

PER Packet Error Rate

PPP Poisson Point Process

PR Packet Rate

PRR Packet Reception Rate

PS Packet Size

QoS Quality of Service

RAN Radio Access Network

RF Radio Frequency

RL Reinforcement Learning

RPMA Random Phase Multiple Access

RSSI Received Signal Strength Indicator

S-IoT Siradel-Internet of Things

SDN Software Defined Network

SDR Software Defined Radio

SF Spreading Factor
SIC Successive Interference Cancellation
SINR Signal to Interference & Noise Ratio
SIR Signal-to-Interference Ratio
SNR Signal to Noise Ratio
SR Symbol Rate
SW Synchronization Word
TDMA Time Division Multiple Access
ToA Time on Air
TS Thompson Sampling
TTN The Things Network
UCB Upper Confidence Bound
UE European Union
UNB Ultra narrow band
URLLC Ultra Reliable Low Latency Communications
V2X Vehicle to infrastructure
WLAN Wireless Local Area Network
WSN Wireless Sensor Networks

1 | Introduction

Quotation

A single certainty is enough for the one who seeks - Albert Camus

Une seule certitude suffit à celui qui cherche - Albert Camus

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1 Context and motivation

The growing adoption of wireless technologies has intensified the need to better understand how Internet of things (IoT) systems work, what options are available in the market and what differentiates them in terms of performance. When an IoT technology is used to monitor risks in critical infrastructure, ensuring the reliability and the efficiency becomes a priority for every network operator. Long Range (LoRa) technology, in particular, is often the most common industrial solution for connecting wireless sensors and transmitting data in a wide area. To wirelessly connect battery-powered devices to the Internet, customers should mostly deal with three main choices: Short-range, Cellular and Long range. Short-range technologies include technologies such as Bluetooth, NFC/RFID or Zigbee. But they are definitely not adapted to scenarios that require long-distance communications above 100 m. Cellular technologies [3G, 4G, 5G, etc.] can provide higher coverage, but they also suffer from energy consumption and they are not the best choice for low-power devices. The needs of many industrial IoT applications have spurred the development of a new wave of wireless communication technologies known as Long range wireless communications called Low Power and Wide Area Networks (LPWAN). Examples of LPWAN implementations are Narrow Band-Internet of Things (NB-IoT), Sigfox and LoRa, to name only few of them. They are ideal for industrial environments and are gaining popularity due to their long-range, low-power and low-cost communication characteristics.

To use the new emerging IoT applications, wireless customers need to oversee operations that require wide communications coverage and excellent connection availability at the same time. To ensure this, four important factors must be taken into account; namely the data rate, the range, the energy consumption and finally deployment facilities. LoRa technology offers the right balance between all these elements. It guarantees a long transmission distance with a proven range of up to 15 km or 9 miles. The battery of LoRa devices can be extended up to 10 years. It can be more cost efficient than traditional

solutions by reducing power consumption. It scales well when adding new devices to the network as the project evolves. In addition, it has proven to be robust and has strong resilience against interference. Security and privacy are also achieved through AES 128 encryption at multiple levels for all data sent between the sensors and the application server.

As we motivate the choice of **LoRa** technology, we enter now into technical details on how **LoRa** works. **LoRa** is proposed as a new physical layer technology that modulates the signal in the Industrial, Scientific and Medical (**ISM**) bands below 1 GHz. It allows individual users to create and deploy private networks without restrictions except the allowed maximum transmission power that should be under 14dbm. This is a major advantage compared to Sigfox and **NB-IoT**, which are controlled by public network operators. To ensure the interoperability of all Long Range Wireless Access Network (**LoRaWAN**) products and technologies, **LoRaWAN** alliance community works on delivering certifications to manufacturers all around the world. It is becoming the largest and fastest growing alliance in the technology sector. It is constantly working on improving data accuracy and rate. When talking about how different components and devices communicate wirelessly within an **IoT** network, defining and selecting the right topology strategy help to mitigate the waste of network resources. Topologies differ greatly in terms of power consumption, cost and complexity. So, choosing the right one is mandatory to avoid problems in the future.

To offer the best Quality of Service (**QoS**) to **IoT** applications, wireless networks need to customize their transmission settings by taking into account the battery life of end devices. Among several wireless technologies, **LoRa** technology is a promising **LPWAN** solution whose energy consumption depends on the optimization of a set of transmission parameters. In this thesis, we introduce a new data rate optimization using Reinforcement Learning (**RL**) algorithms to improve the network life duration without human intervention. Our contribution exploits the characterization of **LoRa** transmission settings using Fuzzy C-Means (**FCM**) algorithm. Then, based on the clustering output, in chapter 3, to know at which state each action could lead, we use, in chapter 4, the Q-learning algorithm to maximize the overall data rate of the network based on the observed new state after each transmission. However, in chapter 5, we use the policy iteration algorithm that requires to know all possible state transitions without observing the new state after each transmission. To highlight the performance of our approach in terms of data rate and energy saving, we compared both Transmission Energy (E^{tx}) and Data Rate (**DR**) of our solution with other state-of-the-art baselines, including: Exponential weights for Exploration and Exploitation (**EXP3**), **EXPLoRaTS** and Adaptive Data Rate (**ADR**).

Since **LPWAN** networks are designed to consume less energy, both **DR** and E^{tx} should be optimized taking into account the quality of the uplink traffic. To minimize the energy consumption and to maximize the data rate, transmission parameters, such as Spreading Factor (**SF**), Bandwidth (**BW**), Coding Rate (**CR**) and Transmission Power (P^{tx}), should be tuned to converge to the combination of parameters that consumes less power. In this context, this thesis aims at pushing the data rate optimization one step further while keeping the energy consumption as low as possible. To achieve this goal, we propose to acquire knowledge about the quality of each transmission setting through a clustering preprocessing phase. Then, we use Reinforcement Learning (**RL**) algorithms to improve the overall network life duration.

To not limit our work on maximizing the overall data rate of the network, we propose,

in this thesis, a traffic differentiation by splitting network settings to three subsets of settings with different QoS levels using a pattern recognition algorithm: FCM. Then, based on the recognized patterns, the policy iteration algorithm should be able to distinguish between the quality of each transmission setting before even starting the learning process. Although this solution remains a “best effort” approach, it succeeds in adapting the traffic quality to the requirements of each application.

2 Problem statement

From the context presented in the previous section, we aim to benefit from the advantage of machine learning algorithms and particularly unsupervised learning, Markov Decision Process and Multi-Armed Bandit algorithms to make the network enough smart to adapt their settings according to the requirements of Internet of things (IoT) applications. Therefore, we aim to address emerging challenges related to traffic separation and slicing with regard to the overall performance of the network to bring effective answers to these questions: how to enhance the network performance regarding multi criteria metrics like Data Rate (DR), Packet Delivery Ratio (PDR), Time on Air (ToA) and Transmission Energy (E^{tx}) ? and how to adapt these metrics to the heterogeneity and diversification of IoT applications ?. For this reason, in this thesis, we start our study by taking a closer look at the state of the art works on optimizing transmission parameters. Our work is the only one that considers all transmission parameters starting from the known Spreading Factor (SF) to Transmission Power (P^{tx}) passing by Bandwidth (BW), Coding Rate (CR) and frequency channel. Indeed, the proposed solutions in the literature suffer from problems related to time of convergence and real time reconfiguration. Several techniques were proposed in the literature to overcome these problems. Nevertheless, current contributions still require further investigations especially in the multi criteria optimization and customization of network settings. In addition, some of them neglect several practical scenarios and limit their experiments to few cases without varying the number of cells, the number of devices, the size of the transmitted packets and their transmission frequency, which highly impact the outcome of the learning process and slow it. For this reason, we propose in this thesis to use lightweight learning algorithms with a preprocessing phase to acquire knowledge from the clustering process to speedup the learning process and customize transmission settings to the need of each device.

Specifically, we propose in this thesis to enhance the uplink data rate by clustering transmission settings to know at which quality each setting could lead. Then, we feed this knowledge, in the form of membership degrees, to MDP as a state transmission matrix. Thus, transmission settings will lead to different states based on their membership degrees to different clusters. This means that when we pick up one setting from a cluster, Fuzzy C-Means (FCM) is able to recognize at which link quality we can expect to jump if we select such an action. In summary, our proposed solution follows the following steps:

- 1) Acquire enough data to assess the quality of each transmission setting.
- 2) Apply the clustering process on the measured Quality of Service (QoS) metrics to recognize patterns that disclose the quality of each transmission setting in offline mode.
- 3) Use these patterns in Q-learning and policy iteration algorithms to know at which state each transmission setting could lead by updating their policy to converge iteratively to the optimal settings in online mode.

The process starts by transmitting random packets to allow the network server to gather enough knowledge about the quality of different transmission settings (BW, CR, SF, P^{tx}) for each device. Then, it clusters these data to know at which quality level each transmission setting belongs more. Once this knowledge is acquired, it applies the policy iteration using the membership degrees of settings to clusters as probabilities to jump to the next states using the same setting. After convergence, the network server stops the learning process and waits for a topology change to consider the new location of devices that have moved.

Many works in literature tried to solve the problem of data rate optimization but most of them use heuristic methods and validate their solution using one or two scenarios with a limited number of devices, base stations and fixed packet rates and sizes. In addition, they consider only few transmission parameters and mainly the spreading factor. In our work we consider all transmission parameters: SF, CR, BW and transmission power. We validate our method in all scenarios whatever the number of devices, base stations and whatever the size and rate of packets. Recent works in literature tried to use machine learning algorithms but they start their learning process without any knowledge about wireless transmissions quality so they have to learn from scratch at each time the environment changes. To be ahead of the game, we tried to find a way to characterize all transmission settings qualities and build a knowledge that we feed to machine learning algorithms to be one step ahead of other machine learning based solutions. To this end, we formulate the problem of transmission settings selections as a Markov Decision Process problem where actions are transmission settings and states are the recognized quality levels by FCM.

Once we formulate the problem this way, we need to know with which probability the link state could jump from one state to another after the selection of a transmission setting. This knowledge is mandatory to solve our problem. Thanks to pattern recognition tools, we propose to use Fuzzy C-Means (FCM) clustering algorithm to acquire this knowledge by clustering the quality of all possible transmission settings to three main clusters with different quality levels. This means that when we pick up one setting from a cluster, FCM is able to recognize at which link quality level we can expect to jump if we select such an action. This recognition is all what we were looking for to solve our Markov decision problem. It allows us to know at which state each action could lead by knowing at which cluster each setting belongs.

Once we generate this knowledge in offline mode using FCM, we applied Q-learning and the policy iteration algorithms to converge to the optimal transmission settings in online mode. This means that devices start by sending packets randomly using different transmission settings. The gateways, in their turn, catch the transmitted packets and forward them to the network server. Then, the network server receives these packets and clusters them based on the quality metrics measured by gateways. Once this step is done in offline mode, devices can now start the learning process by randomly selecting one transmission setting and the network server should be able to suggest other transmission settings to increase the data rate iteratively until their policy converges to a steady state.

We implemented most known algorithms, EXP3, EXPLoRaTS and ADR, that tried to increase Long Range Wireless Access Network (LoRaWAN) data rate. We compared more than 5 algorithms + random algorithm to highlight their performance metrics. There are other algorithms that we did not have time to implement, but there is no algorithm in literature that achieved a data rate higher than the data rate that we obtained with the

same packet delivery ratio. Compared to the state of the art, we are the only ones that considered:

- 1) such number of scenarios with different numbers of End Devices (EDs), Base Stations (BSs) and different Packet Sizes (PSs) and Packet Rates (PRs).
- 2) such number of algorithms: MDP, Q-learning, EXP3, EXPLoRaTS and ADR.
- 3) such number of transmission parameters: SF, CR, BW and Transmission Power (P^{tx}).
- 4) such number of metrics: PDR, DR, ToA and E^{tx}

In general, the use of Long Range (LoRa) is more appropriate for monitoring systems such as open-pit mining operations that typically cover large areas or large construction projects. For example, in construction and tunneling projects, where monitoring points are often spread over several kilometers, operators need data to be transmitted over long distances using devices that require very little power and are not dependent on signal coverage. For this reason, LoRa will be an asset wherever a reliable real-time monitoring program is needed to ensure the integrity of any structure, such as bridges, dams, buildings or other infrastructure.

3 Methodology and contributions

We focus, in the first part of this thesis, on the data collection process by evaluating the quality of each transmission setting using Long Range (LoRa) modulation. We hence propose as a first contribution to cluster all the combination of transmission settings to 3 clusters based on several Quality of Service (QoS) metrics. This step is fundamental for the following contributions since it allows us to acquire knowledge about the quality level of each transmission setting. This phase offers an advantage for the network server to get a global overview of the available transmission settings and to map them to different quality levels. In addition, it could be run separately in offline mode without the need of interaction with end devices or with collaboration with other network servers. However, the data collected by other servers should manage the same network topology to be efficiently treated regarding the same distances between devices and base stations. Otherwise, it should be run in online mode if devices are mobile.

For this reason, we propose in our second contribution to update the network settings continuously using Q-learning. This process relies on the observation of the new state at which each action leads by looking at which cluster it belongs. For example, if the performed action " a " belongs to the cluster with a high QoS " s ", then the uplink state should be high also. Thus, Q-learning will increase the $Q(s,a)$ value if the packet is well received and action " a " will be promoted for next transmissions. This process is computed continuously until the convergence to the set of transmission settings that outperform the state of the art regarding the quality of the uplink traffic.

In the third part of this thesis, we extend our study to investigate in depth the use of the clustering output by analyzing the quality of the traffics generated by 3 Internet of things (IoT) applications rather than focusing on the overall quality of the whole traffic like in the second contribution. Indeed, we assume in this contribution that IoT devices run 3 distinguished IoT applications with 3 different QoS requirements levels. Thus, we propose to cope with the requirement of each application requirements using the policy iteration

algorithm. The advantage of this algorithm compared to Q-learning is its ability to update its policy by knowing in advance all possible state transitions before even starting the learning process. This allows devices that run an application that requires a high quality to target the transmission settings that belong to the cluster with a high QoS level.

4 Organization of the thesis

Except, the introduction and conclusion, this thesis is released with four major parts which are presented in four chapters:

Chapter 2: State of the art, elucidates the context of our thesis and the related existing solutions. It is composed of 2 parts. In the first part, we elucidate the major contributions in literature regarding Long Range (LoRa) and Long Range Wireless Access Network (LoRaWAN) quality and performance evaluation. We split this survey to four main subsections to distinguish between contributions in application, network, Medium Access Control (MAC) or physical layer. In the second part, we review only contributions that apply machine learning techniques in different domains to understand how they are used and for which purpose. Finally, we conclude this chapter with a discussion about the different works and motivate our contributions.

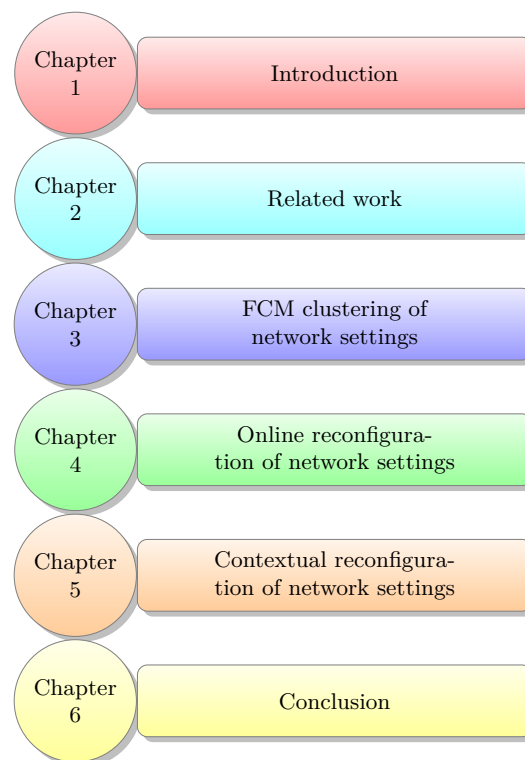


Figure 1.1. Organization of the thesis.

Chapter 3: The Fuzzy C-Means (FCM) clustering of network settings represents our first contribution in this thesis. In this chapter, we propose to cluster a set of LoRa transmission settings based on the measured Quality of Service (QoS) metrics such as Bit Error Rate (BER), Time on Air (ToA) and Received Signal Strength Indicator (RSSI). We consider the set of settings' vectors as a cloud of points in a vector space while measured metrics are points' coordinates. We assume that items in the same cluster characterize the

suitable configurations for a particular Internet of things (IoT) application. Clusterheads are the representative settings of a given cluster. Our method aims to map a set of LoRa transmission settings that offers the same QoS to the same cluster. We generate a set of transmission settings randomly and apply the FCM clustering algorithm on the resulting QoS metrics. Results show that the FCM clustering algorithm assign the membership values that best fit application requirements. This result could be used by LoRaWAN network servers to map each LoRa transmission setting to the application running on end devices. This work has been published in ISNCC conference.

Chapter 4: We apply, in this chapter, the Q-learning algorithm to update the policy that drives to the selection of the optimal settings considering several QoS metrics like Packet Delivery Ratio (PDR), ToA, Data Rate (DR) and Transmission Energy (E^{tx}). However, to be able to run this algorithm, we need to observe the new uplink state where each setting leads. To alleviate this problem, we take advantage of our clustering process in the previous chapter to know at which state each action could lead by knowing at which cluster each setting belongs. As the solution should cope with different scenarios, we vary the number of End Device (ED), Base Station (BS), Packet Size (PS), Packet Rate (PR) and we compare our solution with EXP3, ADR and EXPLoRaTS algorithms. Simulation results show that Q-learning improves better several QoS metrics including the DR, PDR, ToA and E^{tx} . Furthermore, results show that the quality of the generated traffic is improved compared to the existing strategies and both ToA and E^{tx} were reduced by 20%. Part of this work has been published in computer communication journal.

Chapter 5: We propose, in this chapter, to adapt LoRa transmission settings to the requirements of IoT applications. To select the transmission settings that match the required quality, IoT devices need to target the set of transmission settings that offer the same quality as required by applications. Thanks to the clustering outputs in chapter 3, the network server can recognize the transmission settings that match the quality required by an application through the membership degrees of these settings to clusters. We introduce a new differentiated service solution using Markov Decision Process (MDP) to improve the adaptability of LoRa transmission settings to these applications. Unlike Q-learning, the policy iteration algorithm that we propose in this chapter is able to target the recognized quality levels through the state transition matrix. This allows devices to select the transmission settings that fit the quality level of the application that they run by selecting the transmission settings that belong to the same cluster. Thus, we initialize the state transition matrix of the policy iteration algorithm to infer the probability that one transmission setting will make the uplink state match the required state by IoT applications. To highlight the performance of our approach, we compared the quality of the traffics generated by three main applications. Simulation results show that the policy iteration algorithm is able to target the required uplink quality by selecting the transmission settings that belong to the same cluster. In addition, it speeds up the learning process and adapts the DR, the ToA and the E^{tx} to these applications. Thus, the PDR and the DR were improved by 25%, the ToA was reduced by 40% and E^{tx} was reduced by 20%. Part of this work has been published in computer communication journal and the other part has been submitted in IWCMC conference.

2 | Literature review

Quotation

*Who sets his race on a star, never gets lost -
Leonard de Vinci*

*Celui qui règle sa course sur une étoile, ne se
perd jamais - Léonard de Vinci*

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Abstract

Since the appearance of Long Range (LoRa) in 2015, many works have been published in the literature to study the performance of LoRa transmissions and to enhance the uplink quality. However, all contributions in the literature assume that Low Power and Wide Area Networks (LPWAN) devices have the same requirements and try to maximize the data rate using different approaches. This chapter elucidates the main findings in this area. A summary of our literature review is presented in tables at the end on each section to offer an overview of all the papers reviewed in this thesis. Thanks to the reviewed works in this thesis, this chapter highlights the advantage and the drawbacks of each work to understand better the problems that LPWAN networks are facing. As LPWAN devices are very sensitive to energy consumption, many works keep the default ALOHA protocol and propose new adaptive data rate schemes. In fact, ALOHA protocol is the only protocol that consumes less energy since the access to the channel is made randomly without any additional computational process. The randomness of the wireless environment drives us to look for a powerful computational process that alleviates this problem by leveraging the power of machine learning algorithms to maximize network throughput. For this reason, we relate also in this chapter the main findings in machine learning area to understand how they optimize their problems using machine learning algorithms.

1 Introduction

Nowdays, nor WiFi, Bluetooth and ZigBee can cope with the billions of devices that are expected to integrate the Internet of things (IoT) in the forthcoming years. To deal with such a problem, Low Power and Wide Area Networks (LPWAN) emerged in this context as a life buoy to handle the requirements of new IoT applications. Recent related works have sought to assess the performance of Long Range Wireless Access Network (LoRaWAN) in different environments: university campus [45], indoor applications [27], industry [200], dense cities downtown [220], and rural areas [29]. Other studies focused on finding new mechanisms to enhance the performance of Long Range (LoRa). In this context, we classify the literature as follows: (i) works analyzing the current capabilities and limitations of LoRaWAN [53, 34, 215, 204], (ii) works studying its performance with manual/static settings [20, 33, 44]. (iii) works proposing novel approaches and heuristics to optimize the network performance [140, 118, 197, 59]. In this chapter, we elucidate different contributions in both wireless networks and machine learning fields to extract relevant information that drive our research and our contributions.

2 Low Power Wide Area Network (LPWAN)

Knowing the diversification of Internet of things (IoT) applications (see Fig. 2.8a), many works in literature work on analyzing, evaluating and enhancing the performance of Low Power and Wide Area Networks (LPWAN) communications in a wide area. In addition, we relate in this section different solutions that alleviate the limitation of using LPWAN for IoT applications. We divide this section to five main subsections to highlight contributions made in application, Medium Access Control (MAC), network and physical layer.

2.1 Application layer

In the nineteenth century, there was one kind of applications that uses the wireless network, namely military applications to communicate soldiers and troops during the first and the second world wars. After the end of the second war, there was an exponential increase of wireless applications and technologies to dial with our daily life challenges, starting from telephony services to surgery over the network. Since 2015, Long Range (LoRa) technology emerged as one of the technologies that covers the need of agricultural and farming industries and other industries that request wide area coverage like buildings and health emergencies. In this context, many works in the literature tried to use Long Range Wireless Access Network (LoRaWAN) network in various domains. We elucidate here some of these studies to disclose the high potential of LoRa to communicate devices in a wide area with a lower energy consumption.

Many works in literature aim to assess the feasibility of their deployment with different use cases (see Fig. 2.1b) and in different environments. We can cite, smart metering [83], indoor applications [27], university campus [45], dense cities downtown [220], [232], industry [200], and rural areas [29]. All these studies have been carried out using real deployments. It is worth to note that none of them used a high number of network devices. So, it is difficult to validate their models in dense networks.

The scientific contributions on LPWAN and particularly LoRaWAN are slowly expanding but most of them are still related to the link-level evaluation. Many experiments on

LoRaWAN have been made to study its performance [201, 230, 46, 37, 19]. Among these works, we cite different use cases such as: city centers deployments, tactical troop tracking and sailing monitoring systems. Nevertheless, experimental results in real life networks are not reproducible and the MAC layer optimization is difficult due to Industrial, Scientific and Medical (ISM) band limitations. In addition, many of them are deployed in rural and suburban areas [201]. However, it could also be deployed in urban areas as well [230]. For example, Sanchez-Iborra et al. [38] found that coverage evaluations in urban, suburban and rural environments could be extended until 6 km in urban and suburban areas and over 18 km in rural areas [201]. They determine LoRa ranging performance in free space conditions. The payload length experiments conducted in this work show different inconsistencies of Packet Delivery Ratio (PDR) for 80 and 100 bytes but less for 50 bytes.

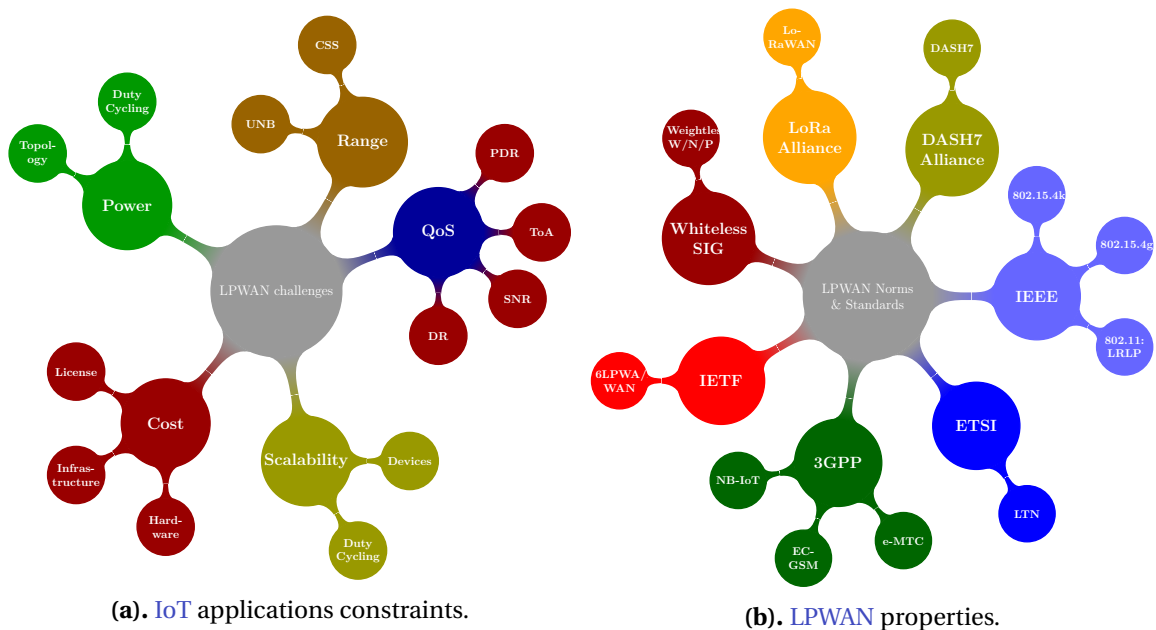


Figure 2.1. LPWAN challenges.

2.1.1 Monitoring applications

To avoid complex and costly relay nodes in short-range technologies, visual surveillance applications with low-cost image sensors are more and more investigated in literature using long-range technologies. For example, Pham [36] propose an activity time sharing mechanism where a pool of image sensors are deployed by a single organization. This means that the activity time of all deployed devices are managed with a shared manner, allowing a device to transmit beyond the 1% duty-cycle limit which is the time interval during which devices could use the channel. The challenge of such an approach is to respect the radio regulations defined for sub-GHz transmissions while managing a larger amount of data produced by image sensors. This solution is implemented on a low-cost image sensor platform and preliminary tests show that it is fully functional. However, authors should push their experiments one step further to evaluate the behavior of their tool in more complex scenarios.

Most recent researches on LoRa and LoRaWAN have focused on analyzing features such as the throughput, network capacity, delay and range [120] [1][219][28]. For example, Augustin et al. [1] analyzed LoRa and LoRaWAN under various sets of configurations

and different conditions by field tests and simulations. Their study led to a number of open research challenges (see Fig. 2.1a), particularly in channel management, such as Time Division Multiple Access (TDMA) over LoRaWAN and Random Access (ALOHA) in unlicensed bands. To setup their experiment made in Paris, a Cisco 910 as a gateway was installed outside at a height of 5 meters. LoRa end-devices were placed in 5 different distances from the gateway: 600 m, 1400 m, 2300 m, 2800 m and 3400 m. The Spreading Factor (SF) values were varied between 7 and 12. Field tests results show that LoRa can offer a coverage up to 3 km in a suburban area even in a dense urban dwelling area. Experimental results show that the PDR is about 90% when SF 9 to 12 are used at 2 km from the gateway. At 3.4 km and with SF 12, the PDR seems to be less than 40%. Simulations were also made in order to evaluate LoRa throughput behavior with a larger number of devices. Simulation results showed that LoRaWAN behaves closely to ALOHA in a dense network: with the maximum channel capacity of 18%, the collision ratio increase to 60% for a link load of 0.48. This work gave new interesting quantified results. However, the Adaptive Data Rate (ADR) and retransmission were not investigated in this work.

Since energy consumption is the major constraint that pushed the wireless community to work on LPWAN, Orfei et al. [30] developed an energy harvester with vibrations caused by vehicles in a bridge. They estimated the time required by the energy harvester to load the supercapacitor to 3.3 V within only 3.5 hours. The microcontroller board requires about 100 μA at 3.3 V when the microcontroller is in deep-sleep mode and about 10 mA at 3.3 V when operating. If the radio frequency transceiver sends 8 bytes of data with 14 dBm at 868.1 MHz in LoRa mode and with SF 12, the measured required energy was around 43 mA at 3.3 V for about 870 ms: $(43 * 3.3 * 0.87)$ 123 mJ. Indeed, the energy consumption could be lower with lower SF, lower Transmission Power (P^{tx}) or with Frequency-shift keying (FSK) modulation.

LPWAN are known for their high coverage and low energy consumption, but they suffer a lot from a low Data Rate (DR). To overcome this limitation, Eriksson et al. [10] investigated the throughput for LoRaWAN by analyzing Co-SF and Inter-SF interferences. The throughput has been shown to vary depending on the amount of the data sent. The packet loss rate was at its lowest level when the channel utilization was around 54%. Inter-SF interference was considered non-significant since the broadcasts on the same channel with different SF could both coexist without a significant packets loss rate.

2.1.2 Wide area applications

Since the appearance of LoRa in the market, research community made a lot of efforts to evaluate the performance of this technology in many domains, including underground, freshwater and agricultural activities. In fact, monitoring the level of phreatic aquifers is very important to protect and to preserve agricultural foods. In this context, Sartori et al. [40] present a smart, ultra-low power, cheap and energy neutral system which is able to monitor periodically and remotely the level of phreatic aquifers. A single terrestrial Microbial Fuel Cell (MFC) is used as a power supply to the whole network. To mitigate the waste of energy, the authors proposed a transient computing paradigm which consists of ultra low power hardware that exploits smart strategies to store and save energy. Thanks to the LoRa radio chip, sensors are able to transmit their data kilometers away keeping the complexity of the network topology very low compared to mesh networks with complicated network protocols to route the packets. However, the authors didn't make experiments to validate their design of an adaptive policy for the radio transmission.

Regarding the type and position of antennas, network performances can severely be damaged especially in dense networks. To study the impact of antennas positions and types on the LoRaWAN performance, Iova et al. [16] showed that having several radiation planes like buildings and vegetation, interference with other technologies and high temperature, significantly deteriorate the communication. However, environmental factors (e.g., temperature and wind) were not measured and quantified to prove their impact on LoRa communication.

To address the problem of limited coverage and high power consumption of the first generation of LoRa technology in rural areas, Two use cases were considered by Li et al. [19] during their experiments. The first case where sink nodes and gateway were all on the water. The second case when a gateway was fixed on the land and sink nodes were on the water. Their results show that the smaller SF or greater Bandwidth (BW) increases the range at the expense of an increase of Time on Air (ToA) and a decrease of DR. In both cases, a good performance in mobility with 20 km/h average speed was observed with a low packet loss rate under 5% and a long range over 2 km in flat zones. Meanwhile, a high packet loss rate over 20% in zones with obstacles such as high buildings and trees were observed. Authors should focus on designing a new adaptive network to get the optimal performance to deal with such conditions.

To enable collaborative and communal wide area networking for telemetry, Dongare et al. [8] proposed OpenChirp; an LPWAN architecture built on top of LoRa and LoRaWAN. This platform will allow researchers around the world to unlock a plethora of creative ideas that are currently either cost or power limited by existing wireless technology. This platform holds a proof-of-concept system deployed at Carnegie Mellon University to assess the feasibility and the scalability of LoRaWAN. Their experimental results show that a few well positioned gateways are able to cover an entire college campus and that low-cost nodes can be deployed to run on batteries for many years. However, many challenges related to LPWAN such as the uplink throughput and network performance measurement were not considered in this work.

Thanks to the work made by Petäjäjärvi et al. [34]. Their results show that when end-devices are required to send only one packet per day, one-cell LoRaWAN can serve up to millions of devices. However, when end-devices are required to send at least one packet per day, only few hundreds of devices may be hosted in one-cell. Beside scalability analysis, Petäjäjärvi et al. [34] also evaluated the performance of the LoRa communication under mobility and environment constraints. Their results show that with SF 12, 14 dBm of transmission power and relative speed above 40 km/h, the quality of the link drops down significantly. Whereas, with a lower mobility, they observe a reliable communication within a distance of 2 to 10 km on the ground and 15 to 30 km on the water. Authors also showed the maximum throughput for different duty cycles per node and per channel.

In the same context, Wang et al. [45] proposed a LoRa transmission performance evaluation for environmental monitoring using a real-life long-term PM2.5 air quality sensors. They measured the quality of the signal by varying transmission power, payload length, antenna angles, distances, indoor/outdoor environments, time of day, weather conditions, etc. Their results show that LoRa transmissions are severely interfered by nearby 4G base stations and suffer from a regular high packet loss rate pattern that is similar to human daily activities. In addition, they found that all LoRa packet losses occurred with less than three consecutive packet losses. This means that carrying the latest three sensed values in a LoRa packet is an effective way for more reliable data transfer.

Rather than increasing the number of gateways to enhance spatial diversity, Hoeller et al. [15] propose to use multiple receive antennas to enhance the signal quality. Their work examines whether multiple receive antennas in a single gateway create a signal diversity to enhance signal quality. Such a work could be easily extended to the case of multiple gateways with multiple antennas. However, further experiments should be made to really believe on the efficiency of their work in dense networks.

To reach the application server, end-devices need to send the data collected from their sensors to the network server through a gateway. However, when the gateway is not connected to internet, the data transmitted can't reach the IoT application server. To overcome this issue, a first study by Barro et al. [3] was conducted on stand-alone LoRaWAN base stations to operate even when Internet is not available. The solution proposed is based on the fact that gateways have the ability to communicate with each other [4]. So, at least one gateway should be connected to the internet to send the re-transmitted data to the cloud server.

To solve the same problem, several studies [3][4][5] aim to study the feasibility of the smart city in developing countries, especially in Africa. Assuming that Internet is not accessible or is intermittent in rural areas, Barro et al. [4] try to forward the collected data to the network server with a round-trip time less than 100 ms passing by multiple wireless communications. This is why it should be wise and judicious to propose an architectural model offering several options of communications which will remain flexible to future evolutions.

2.1.3 Urban applications

Industrial solutions for LPWAN were also proposed in the literature to overcome the limitation of LoRaWAN network in urban areas. For example, Nolan et al. [28] forecasted the LoRaWAN network to capture up to 55% in share of market (SOM) with ten years battery powered devices. The authors compared the Ultra narrow band (UNB) solutions proposed by SigFox and the Chirp Spread Spectrum (CSS) technology proposed by Semtech. Both modulation schemes operate in the ISM bands (EU 868 MHz / US 915 MHz). The authors then proceeded to explore a coverage estimation where they found that three gateways installed 470 m above sea level on three rock mountains can serve a core coverage area of 1380 km². They also conducted a successful real-world range evaluation with SigFox's technology to achieve 25 km of range with 14 dBm since the Signal to Noise Ratio (SNR) consistently exceeds 20 dB over this test link distance.

Like Petajajarvi et al. [230], Wixted et al. [46] test the coverage range and the Packet Error Rate (PER) by means of empirical measurements with multiple gateways in the Central Business District in Glasgow, Scotland. As LoRaWAN gateways can be reached by all nearby end devices, end devices are able to transmit collected data to all these gateways without any handover. When the network server receives multiple message requests from the same device, it drops any copies of this message and replies to the gateway that received the request with the highest Received Signal Strength Indicator (RSSI). To setup their experiment, a LoRa gateway was installed on the roof of the university building with 7 floors. End devices were configured with SF 12 and moved around the city. At each transmission, the RSSI was measured on the gateway. The experiments in this work was not fully built, but results show that it is possible to successfully receive packets at 2.2 km from a node. However, this work didn't study the impact of different LoRa parameters on network performance.

Another work in outdoor environment was made by Erbatl et al. [9] in Duisburg, Germany. A LoRaWAN gateway was installed above a building with eight-stories located in the city of Duisburg. End devices were located in a non-Line Of Sight (LOS) from the gateway where there exist various obstacles such as trees, buildings and cars. The distance varied from 300, 600, 1400 and 1850 m, and 500 frames were sent from each distance. Experiments were made with 21 bytes of payload, SF 10, BW 125 kHz and Coding Rate (CR) of 4/5. Results show that the RSSI log scaling value decreases with increasing the distance. When the distance becomes greater than 1850 m, there was 69% of PDR. To manage the co-existence of LoRaWAN and 4G/5G cellular mobile networks, Navarro-Ortiz et al. [26] proposed a major modification in LoRa gateway to support both infrastructures.

To study the impact of enabling acknowledgements (ACKs), works on urban areas like Sanchez-Iborra et al. [38] showed a PDR of 100% with DR0 to DR5 for distances below 3 km. The 100% PDR was also achieved even below 5km and 6km when DR0 was used. Other DR resulted in a lower PDR between 30% and 50%. This work showed good results. However, the amount of packets used to calculate the PDR was not specified in the paper. In addition, as the PDR is calculated based on acknowledgements, Wixted et al. [46] found that in 2.5% of cases, the data was sent but the device did not receive an Acknowledgement (ACK) which could lead to unfair results.

2.1.4 Tracking applications

Thanks to the high coverage offered by LoRaWAN, many papers explored the usability of LoRa technology for tracking systems. For example, San-Um et al. [37] deployed their network called Universal and Ubiquitous (U-LoRa) in tactical troop tracking systems. The proposed long-range communication system has been implemented based on a commercially available GPS, Raspberry-Pi, and other sensors for physical tracking. Thus, they use end-devices that can be integrated with more than ten types of sensors such as GPS, temperature, humidity, and water sensors. All the received data has been visualized in real-time via monitor station.

2.1.5 Health care applications

Even if LoRa technology was not designed for safety applications, a LoRa based smart wireless paging sensor network for elder care was proposed by Yang et al. [47]. They presented a packet transmission model for a smart wireless paging sensor network (WPSN) based on LoRaWAN. The model is used to study the performance of star topology communication on elderly care via Markov discrete-time M/M/1 queuing system. Moreover, an optimal cluster allocation policy is proposed to improve the Quality of Service (QoS) parameters such as the PDR, the ToA and the Transmission Energy (E^{Tx}). However, authors should consider real life constraints regarding the capture effect and noise that are missing in this work.

Since the appearance of LoRa in 2015, many works related to various fields tried to adapt LoRaWAN to their own use cases. For example, health monitoring motes [33], video surveillance systems [36], monitoring civil infrastructures such as bridges [30] and smart metering application by allocating wireless resources to address the scalability issues [44], etc. In this context, Petäjajarvi et al. [33] analyzed the deployment of LoRa in indoor environments for health care monitoring. Their results show that the PDR was very high even with one base-station to cover an average university campus.

2.1.6 Indoor applications

Deploying **LoRaWAN** in indoor environment was made by Neumann et al. [27] to evaluate the feasibility of such a scenario. The distances between end-devices and the gateway were less than 60 m. Their results show that the **RSSI** log scale decreases quickly while increasing the distance, such behavior is the same even in outdoor environment. However, when the distance becomes very small, packet errors occur frequently due to a bad Cyclic Redundancy Check (**CRC**).

Haxhibeqiri et al. [13] focused on studying the coverage of **LoRa** in an indoor environment with a single gateway and a single network server. The communication path between end devices and the gateway was blocked by the metallic flower trolleys. Their findings highlight the robustness of **LoRa** in bad industrial environments. In indoor environment, the **SNR** values were higher than 0 dB with some negative values at some measuring locations and the average **RSSI** values were above -100 dBm at all measuring locations. In outdoor measuring locations, communication using **SF 7** was not possible and only **SF 12** was relevant. The average **SNR** values were negative with a peak of -16.4 dB and 6% of packets received with wrong **CRC**. To assess the network scalability, simulations were made using 75% of the nodes sending a 20 byte packet every hour and 25% of them sending a 20 byte packet every 5 minutes. Their results show that only 10% packet loss was observed when 6000 end nodes were used. However, authors should take into account the reception of packets by two or more gateways simultaneously to enhance the total network performance.

2.1.7 Outdoor applications

Vangelista et al. [43] present **LoRa** as one of the most promising technologies among **LPWAN**. They mention that **LoRa** presents numerous advantages over Sigfox, Weightless and On-Ramp Wireless. The robust **CSS** modulation against noise and interference, the low energy consumption and the low cost of end-devices make **LoRaWAN** the best choice for **IoT** deployment. However, since **LoRa** is quite a recent technology compared to other wide area networks, it is not mature enough to be used in applications with high **QoS** constraints.

To make **LoRa** configuration dynamic, Petric et al. [35] proposed to optimize **LoRa** parameters regarding the relative elevation and distance between end-devices and the gateways. They deployed a **LoRaWAN** using an Arduino module with **LoRa** transceiver in the city of Rennes. They focused on analyzing the **QoS** of the network under different conditions. However, it is difficult to measure the scaling properties of **LoRaWAN** through their study due to the limited number of end devices considered. In addition, their optimization method does not minimize collisions.

LoRa end-devices can send up to 255 bytes per frame with a limited duty cycle. As the impact of the **LoRaWAN** frame size on **ToA** and transmission power is very significant, Jang et al. [17] were interested in compressing data to reduce the size of the frame sent. This leads to a lower transmission time and a lower energy consumption. To do that, a swapped Huffman tree coding has been used to transmit meaningful data with a compression ratio of 52.3%. Beside the compression performance, authors conduct their experiment without worrying about **LoRaWAN** constraints relating to the channel occupancy time (duty cycle).

To measure the impact of environment factors on channel performance, Marco Cat-

tani et al. [23] studied the relationship between temperature, PDR and RSSI. They evaluated the impact of the LoRa physical layer settings on the DR and energy efficiency for three types of channels (indoor, outdoor and underground). Their results show that high temperatures at the node decrease significantly the PDR and the RSSI. The default ADR of LoRaWAN alliance starts with a default parameter setting. After the reception of some messages, the receiver can notify the transmitter node to step up or down its SF or P^{tx} . ADR uses 8 DR settings and 6 P^{tx} settings selected to balance between PDR and energy consumption. To increase the PDR, authors prefer to decrease the P^{tx} rather than tuning LoRa parameters to reduce the DR.

To compare different testbeds proposed in the literature, Marais et al. [21] made a review of existing implementations of LoRa devices in indoor, outdoor use cases in different cities in the world. Testbeds were compared based on the number of gateways and nodes that they use. The transmission parameters and the reliability of their results were also involved in the comparison. However, many other testbeds were proposed in literature and are not covered in this work.

As shown by Mikhaylov et al. [25] and Croce et al. [209], the perfect orthogonality of LoRa modulation is not a valid assumption. For example, Mikhaylov et al. [25] made an empirical study of interference between two LoRaWAN networks. Particularly, the authors analyze the interference between conventional LoRa modulation and 2-GFSK modulation (used also in IEEE 802.15.4g). The experiments made by Mikhaylov et al. [25] use randomized packet lengths. To simulate transmissions, inter-arrival times for both the sender and the receiver were proposed in this work. Thus, the proportion of time during which the channel is interfered varies depending on the choice of LoRa transmission parameters. Results show that when LoRa modulation is used and the interfering signal is encoded at different SF with less than 6 dB stronger than the target signal, there are good chances (>80%) to decode the original signal.

Magrin et al. [20] implemented a model using the ns-3 simulator to study the performance of LoRa in a typical urban environment. They support a high number of nodes and maintain reasonable network quality if several gateways are carefully placed. A path loss model was developed where devices inside the buildings may be affected by building penetration losses. Simulations with thousands of devices following a Pareto distribution have been proposed to validate their model. The model features MAC commands, different overlapping networks and multi-gateways support. Their results show that LoRaWAN with the ADR scheme may scale well only if there are numerous gateways suitably deployed across the system. This means that a packet success rate of 95% for 15000 devices can be achieved only if there are 75 gateways. The authors show an assignment of SF to each End Device (ED) based on the Gateway (GW) sensitivity by analyzing the radio frequency power signal at the GW. As a result, it lowers the probability of collisions and minimizes the ToA. Then, the GW is chosen based on the received power and SFs are allocated for the transmission. The GW is configured with 8 received paths with 3 channels in total. These receiving paths are assigned to each channel for uplink transmissions. However, in this work, confirmed mode with downlink transmissions has not been considered. In addition, besides the interesting features supported by the simulator, this module has some drawbacks. First, it can only send LoRa messages, so it is impossible to simulate the impact of interference with other transmissions. Next, similar chirp rates do not have an impact on each other. Due to the CSS modulation technique, a transmission with SF 9 with BW 125 kHz has a similar chirp rate compared to a transmission with SF 11 and BW 250 kHz. Another drawback is that all the gateways in this model are virtually directly

connected to the network server, so the packets cannot be routed over IP.

Year/Ref	Parameters	Metrics	Methods	Comments
2015 Pham [36]	Packet Size (PS)	ToA	New protocol, new packet format	No comparison with SOTA
2016 Sartori et al. [40]	Immersion depth, BW	Voltage, Energy	Microbial Fuel Cell (MFC)	No comparison with SOTA
2016 Augustin et al. [11]	SF, PS	RSSI, Throughput	LoRa testbed	Experimental analysis of the LoRa modulation
2016 Nolan et al. [28]	Distance	SNR	Experimental study	No comparison with SOTA
2016 Wixted et al. [46]	nada	nada	Experimental study	No comparison with SOTA
2016 Neumann et al. [27]	PS, Distance, Floors	Time to wait, RSSI, SNR, PDR, E_{PDR}	Experimental study	Performance evaluation of LoRaWAN in an indoor environment
2016 Petric et al. [35]	Location	RSSI, SNR, PDR	Experimental study	Their goal is to define criteria to switch from one spreading factor to another
2016 Jang et al. [17]	Code size, Frequency	Compression ratio	Huffman tree	A new solution to compress and encrypt the data transmitted
2016 Ho et al. [14]	Nada	Temperature, air quality, Traffic	Experimental testbed	Arduino sensors connected to a mobile phone via BLE
2016 Orfei et al. [30]	Vehicle speed	Energy	Testbed	Electronical energy harvester of vibration in a bridge
2017 San-Um et al. [37]	Distance	RSSI, SNR	Testbed	Experimental study with Arduino and Raspberry Pi
2017 Marco Cattani et al. [23]	Temperature	SNR, RSSI, PDR, Energy	Experimental study	Temperature has an impact on PDR
2017 Varsier et al. [44]	SF	PDR	Experimental study	Deep indoor use case in an area of 17km ² and 19 gateways
2017 Petäjäjärvi et al. [33]	SF	PER, RSSI	Experimental study	LoRa deployment in university of Oulu
2017 Eriksson et al. [10]	SF, PS	Throughput, RSSI, SNR	Simulation evaluation	Master thesis on LoRaWAN
2017 Oliveira et al. [29]	Distance,	SNR, RSSI	Experimental study	Received, corrupted, valid packets
2017 Marais et al. [21]	nada	nada	Reviews of testbeds	More comprehensive evaluations using larger testbeds are required
2017 Iova et al. [16]	Distance, angles	PDR, RSSI, SNR	Experimental study	Comparison between smart city and mountainous environments
2017 Haxhibeqiri et al. [13]	# devices	PDR, SNR, RSSI	Experimental study	LoRa is resilient against noise
2017 Mikhaylov et al. [25]	PS, signal interference	PDR	Gnuradio testbed	Orthogonality between SF is verified with CE 6dbm
2017 Li et al. [19]	SF, BW, Location	ToA, PDR	Experimental study	20% of loss due to high buildings and trees.
2017 Dongare et al. [8]	Location, PR, SF	RSSI	Experimental study	No comparison with SOTA
2017 Magrin et al. [20]	DC, # Devices, # Gateways	Throughput	Experimental study	The highlighted energy is spread on the duration of the packet
2017 Petäjäjärvi et al. [34]	Linear, angular Velocity,	PDR	Experimental study	A LoRa end device was mounted on a car's rooftop when measuring PDR
2017 Wang et al. [45]	PS, weather condition	PDR	Air monitoring use case	LoRa packet losses occurred with three or less consecutive packet losses
2018 Yang et al. [47]	PR,	Energy, Delay, PDR	Clustering, Queuing system	Experimental results are made without comparison with SOTA
2018 Hoeller et al. [15]	Distance, replications	PDR	Simulation evaluation	Multiple receive antennas in one gateway are able to enhance signal quality
2018 Erbatii et al. [9]	Distance, Floors,	RSSI, SNR	indoor, outdoor study	A coverage of 1850m is reached with PDR more than 69%
2018 Truong et al. [42]	Time	Water level	Flood detection testbed	A new framework based on Cuda for data processing
2018 Boano et al. [6]	CR, BW, Temperature	PDR, RSSI	Rela world study	An increase in temperature make LoRa link useless
2018 Navarro-Ortiz et al. [26]	nada	nada	Gnuradio radio LoRaWAN-EPC	Integration of LoRaWAN and 4G/5G for the IoT
2018 Feltrin et al. [12]	PR, Distance, # gateways	PDR, Throughput, RSSI	Simulation tests	LoRaWAN based on the applications requirements
2018 Sanchez-Iborra et al. [38]	Location, Distance, SF	PDR, RSSI	Experimental study	LoRaWAN limitations due to the Doppler effect with high transmission DR
2018 Barro et al. [5]	nada	nada	Reviews of LoRaWAN articles	List of applications that require LPWAN
2019 Mekki et al. [24]	nada	nada	Comparison between LPWAN	5G would lead to a global LPWAN solution for IoT applications
2019 Barro [2]	Distance	RSSI	Proof of concept	Environment monitoring by measuring Humidity and temperature
2019 Barro et al. [4]	CPU model	CPU usage	Proof of concept in Africa	No significant results to mention
2019 Paredes-Parra et al. [31]	PS, SF,	Time to wait, RSSI, SNR	Experimental study	An Alternative IoT Solution Based on LoRa for PV Power Plants
2019 Pereira et al. [32]	nada	nada	Embedded design	Up to 4.2 km (urban) and 1.2 km (building site) of range
2019 Chen et al. [7]	SF, BW	ToA, PDR	MPLR protocol	Channel reservation + compressed images (480x320 pixels)
2019 Marais et al. [22]	# retransmissions, Distance	PDR, SNR, RSSI	Experimental study	Enabling retransmissions show an improvement in the PDR
2019 Kim et al. [18]	# channel, PR, # ED, PS	RSSI, PDR	Experimental study (Korea)	No comparison with SOTA
2019 Farhad et al. [11]	SF, # devices	PDR	SF assignment based on RSSI	DC limits the scalability in terms of retransmissions and acknowledgements.
2019 Barro et al. [3]	Nada	CPU usage	Intranet with LoRa	At least one gateway should be connected to the internet
2020 Scitullo et al. [41]	# ED, Distance	PDR, ToA	Lora over smartphones	Enable smartphones to be connected to the internet through LoRa
2020 Santos Filho et al. [39]	# devices	PDR, delay	Simulation evaluation	Handling Telemetry and Alarm Messages in Industrial Applications

Table 2.1. Reviewed papers on the application layer.

2.2 Channel access layer

We detail in this section the LoRaWAN MAC layer that manages the access to the channel and the network signaling overhead. LoRaWAN was designed to transmit over very long distances within a star topology. IoT devices transmit their data directly to gateways that are powered and connected to a backbone infrastructure. Gateways have a powerful radio ability to receive and decode multiple concurrent transmissions at the same time. For this reason, three classes of devices have been defined:

- Class A: Devices transmit to the gateway when needed. After the transmission, end-devices open a receiver window to obtain queued messages from the gateway.
- Class B: Devices behave like Class A with additional receive windows at scheduled receive slots. Gateway beacons are used for time synchronization of end-devices.
- Class C: Devices have maximal receive slots. They open a continuous listening window which makes them unsuitable for battery powered ones.

We detail in the next subsection how each class works, what differentiate them and what are the advantages and drawbacks to use each of them.

2.2.1 LoRaWAN classes

A) Devices of class A In Class-A, a device is always in sleep mode, unless it has something to transmit. Only after an uplink transmission, LoRa server is able to schedule a downlink transmission. Received packets by multiple gateways can be received by the

same network server, but the server will keep only the packet with the highest **RSSI**. After which, the encrypted application payload is forwarded to the application server. In the downlink side, if required, **LoRa** server will transmit the first downlink payload to devices through the gateway that received the uplink packet with the highest **RSSI**. We use in our work devices of class-A since they consume less energy compared to other classes. In addition, they are the only ones that are available in the market today.

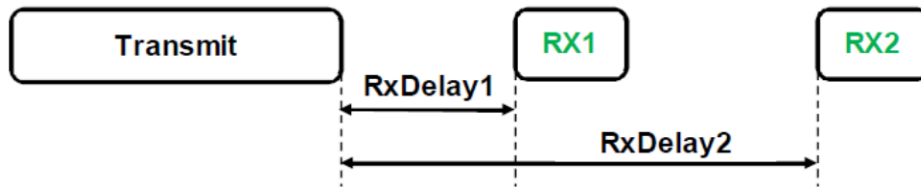


Figure 2.2. Devices of class A.

B) Devices of class B Devices of class B synchronize their internal clock using beacons transmitted by gateways. When the gateway sends a beacon lock request, the device negotiates a listening window duration. The network server is then able to schedule downlink transmissions on each listening window. When the device has acquired a beacon lock, it will schedule the payload for the next free ping-slot in the queue.

When a downlink transmission is requested by the network server while the beacon lock has not yet been acquired, the server should first notify the device to schedule the downlink transmission on the next free listening window once the device has acquired the beacon lock. The timeout of a confirmed class B downlink can be configured according to the device profile. This should be set to a value less than the interval between two opening windows.

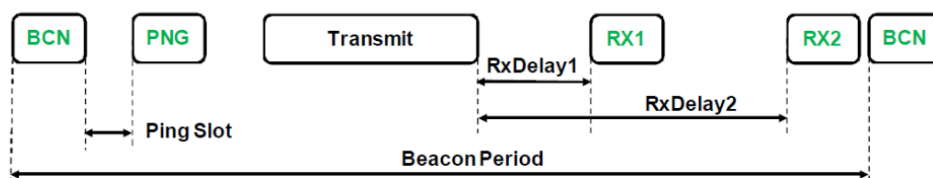


Figure 2.3. Devices of class B.

C) Devices of class C Devices of class C use the same concept as class A. However, the duration of windows is much longer than class A. As soon as the timeout of the confirmed uplink packet is not reached, **LoRa** devices will stay listening the channel waiting for an acknowledgement. The timeout of a confirmed Class-C downlink can be configured regarding the device profile. In the context of **LPWAN**, energy consumption should be minimized. That's why few devices of class C have been purchased in the market.

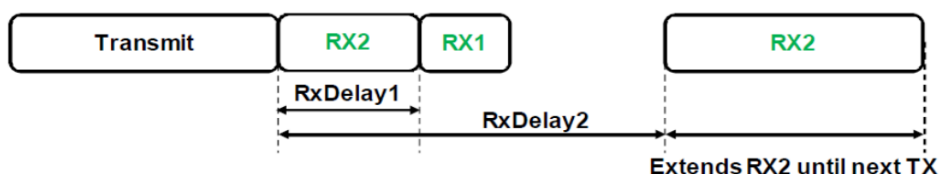


Figure 2.4. Devices of class C.

Like any device that use a wireless network to send its data, **LoRaWAN** devices need a channel access protocol to send and receive data. Many **MAC** protocols have been proposed in the literature for WiFi and cellular network and **LoRaWAN** network can be adapted to use the same protocols. However, due to the listening time required by each protocol to operate, many of them can't be used in the context of **LPWAN** where devices are not allowed to waste their energy for such tasks to increase the life time duration of the network. For this reason, **LoRaWAN** alliance proposed to use a simple ALOHA protocol to mitigate signaling overheads caused by **MAC** protocols to synchronize transmitters and receivers. To investigate this problem, many works proposed several channel access schemes to bring **LoRa** quality of service to upper level and fit higher **IoT** applications constraints.

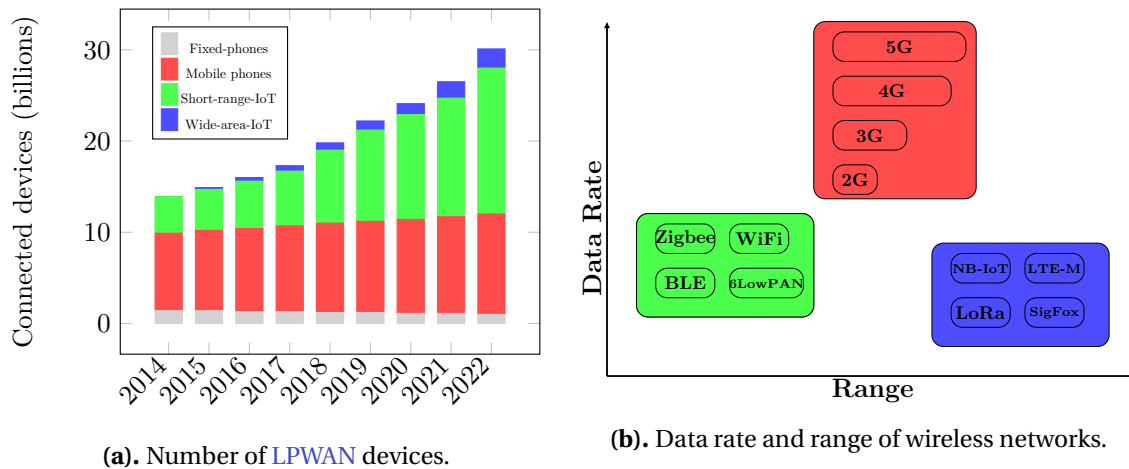


Figure 2.5. Comparison between **LPWAN** devices and other wireless network devices.

2.2.2 Signaling based approaches

In order to face the problem of activity time limitation in video surveillance applications, an activity time-sharing mechanism was proposed by Pham [76] to share the channel occupancy time by end devices. End devices should send their local remaining activity time each cycle (every hour) to the gateway to manage their channel occupancy. Thus, the gateway computes the global activity time of each end device to build a global view of the total remaining activity time. This view is sent back to end devices at the appropriate moments. So, a node that exhausts its **DC** and needs additional time, can borrow the remaining time from the global time. However, only the first applicants can benefit from the shared extra time. Moreover, such an approach requires additional down link packets which increase collisions probability and require additional energy consumption to receive the updated information of the global activity time. Thus, this mechanism would correspond only to class B or C end devices.

In order to measure the spatial and temporal properties of **LoRaWAN** channels, Marcellis et al. [73] used both static and mobile transmitters with different transmission frequency. They found that very low packet reception rates were observed at the limits of transmission range of 7.5 km. To overcome this issue, a coding scheme based on convolutional and fountain codes was proposed for data recovery. Based on their experiments, for 10 byte packets, 21% of the data can be recovered with 42% lower energy consumption than a naive repetition coding protocol.

2.2.3 Reliability optimization

To improve the reliability, capture effect and scalability of LoRaWAN, Reynders et al. [82] proposed RS-LoRa MAC protocol, a protocol that aims to divide end-devices to group the nodes with different P^{tx} level and SFs to balance Co-SF collisions. Based on the RSSI measured by the gateway, each-device selects the SF, the P^{tx} and the channel that makes the RSSI higher than a threshold.

Interference in LoRa could be mitigated by tuning three parameters: the frequency channel, the SF and the P^{tx} . Co-SF interference assumes a perfect orthogonality between LoRa chips. So, interferences are caused only by using the same SF. In the other side, inter-SF interference assumes the non-orthogonality of LoRa chirps. So, interference could happen also by using two different SF. In addition, LoRa transceivers are designed to be able to receive and decode two frames with the same SF but with two different P^{tx} . Few works in the literature considered the capture effect of LoRa transmissions. For example, Abeele et al. [52] designed an error model to tackle both interference and capture effect using LoRa ns-3 module. To analyze the scalability of thousands of nodes per gateway, the authors analyzed the interference between various concurrent communications. Their model considers three different methods to select an efficient SF: random, fixed and dynamic assignment based on PER which finds the lowest SF that causes a PER under a threshold. Authors found that the third method performs better than the two other ones. When 5000 nodes were used, only 9% of PER was observed with the PER based method while 20% was observed with the random one.

To assess the impact of confirmed and unconfirmed messages, authors show that down-link traffics significantly reduce the PDR of the up-link traffic [79]. As LoRa gateways should also respect the duty cycle to save energy and limit downlink traffic, the solution adopted was to increase the gateway density in an area: 70%, 89% and 96% PDR were achieved when 1, 2, and 4 gateways are deployed in an area with 10K nodes that send data every 10 mn. However, this solution only improves the PDR for a low number of devices. Another study of the same authors was to compare the traffic generated by LoRaWAN and pure Aloha in a single-cell network. In this experiment, they increased the data period from 10 minutes to 15 hours, they also varied the number of gateways from 1 to 4. Their findings show that with 125-kHz channel bandwidth, payload of 8 bytes and with a single channel [219], LoRaWAN can send six times more traffic than pure Aloha when the same number of ED per gateway was used.

2.2.4 Scalability optimization

To improve LoRa scalability, To et al. [87] tested Carrier Sense Multiple Access with Collision Avoidance (CSMA) technique with LoRa modulation. To avoid collisions, when a node has a packet to send, it performs a Clear Channel Assessment (CCA) to ask other nodes to clear the channel. If the channel is still occupied, it backs off for a random interval of time. Another variant of CSMA which is CSMA-10 was also proposed to wait a lapse of time 10ms before backing off, the waiting time is called Clear Channel Gap (CCG). Their results show that the proposed method can mitigate collisions probability. Proceeding this way, this solution allows the deployment of 5500 nodes with a 90% PDR when ALOHA allows less than 500 nodes to achieve the same PDR. In order to optimize the number of gateways in an area, Chen et al. [57] proposed an appropriate strategy on signal intensity and sensitivity regarding gateways position.

Scalability issues of LoRaWAN are mainly due to ALOHA MAC protocol. The optimal throughput that could be achieved using pure ALOHA requires the half occupancy of the channel, this drastically decreases the scalability of all wireless networks that use this protocol. In addition, as LoRa end devices require a low energy consumption, down-link traffic is limited by the listening window. For example, Adelantado et al. [53] referred to the duty-cycle constraint of European Telecommunications Standards Institute (ETSI) as a major drawback of using LoRa end-devices. In European Union (UE) (868 MHz), only transmission time of 36 secs in an hour is allowed.

To study the scalability of LoRa, Jetmir Haxhibeqiri et al. [219] made a simulation based on “poisson” process with 3 channels and a 1% duty cycle and measured the PDR for a given packet length and number of nodes. Results show that even with small packets size of 10 bytes, the PDR decreases exponentially due to the increasing number of collisions caused by increasing the number of nodes. 0% of PDR is observed when more than 1500 nodes are deployed, especially when using end-devices with constant transmission parameters. However, due to LoRa’s robust modulation technique, connecting 1000 nodes per gateway results in only 32% more packet losses compared to 90% with other Pure ALOHA based networks [219].

In the same conyext, a new machine learning based scheme has been proposed by Azizi et al. [54] to incese the PDR. The authors proposed a Reinforcement Learning (RL) based resource allocation algorithm enabling LoRa devices to configure their transmission settings in a distributed manner. They proposed a MIX-MAB algorithm which combines two Multi-Armed Bandit (MAB) schemes: Successive Elimination (SE) and EXP3. To highlight the advantage of such combination by comparing it with EXP3 algorithm in five different scenarios. Their simulation results show that they reduce the convergence time to the half of what EXP4 do while achieving a higher PDR. However, such a comparison has been made using 5 scenarios with the same number of devices, gateways and the same packet size. In addition, authors compared only the PDR missing the most important metric which is the data rate. Furthermore, computational overhead caused by their distributed training will not only reduce life time duration of the network but also increase the channel occupancy of the ISM band which is not suitable especially in Europe.

2.2.5 Settings optimization

The default ADR scheme of LoRaWAN suffers from a weak data rate. To help LoRaWAN achieve a high overall data rate, two different heuristic SF allocations algorithms (EXPLoRa-SF and EXPLoRa-AT) are presented in [59] as an alternative to the ADR scheme. The proposed algorithms adapt the configuration of the SF to the number of connected devices, the distance and the received sensitivity, allowing a better equalization of the ToA among the SF channels. Specifically, authors attempt to use a high data rate to offload the traffic of less congested larger SF. EXPLoRa-SF aims to efficiently distribute the SF among end-devices. It selects the SF based on the total number of connected nodes. Particularly, it equally allocates SFs to n nodes based only on the RSSI, where the first $n/6$ nodes with the highest RSSI get SF 7 and then the next $n/6$ nodes get SF 8, etc.

EXPLoRa-AT is more dynamic than EXPLoRa-SF, it equalizes the ToA of packets transmitted with different spreading factors. To extend the coverage of LoRaWAN, two possible solutions could be made: either by increasing the number of gateways in a single-hop network or by using a multi-hop network. Multi-hop network, however, is not taken under account by LoRa Alliance. This didn’t prevent academic researchers to propose novel

methods to make end-devices able to route frames that are not addressed to them. As an example, [137] proposed a practical strategy that transforms a topology from a star to a mesh when the coverage range exceeds 3.2 km.

Assessing the performance of LoRaWAN and finding the best trade-offs by means of analytical tools is not an easy task. For this reason, many academic works tried to build tools to make this task less complex for researchers. For example, Marini et al. [74] present a new MATLAB-based simulator tool covering the physical and the upper layers of the LoRa/LoRaWAN protocol stack. The proposed simulator support multiple gateways with receiving window prioritization. They investigated the impact of different coding rates on interference probability. However, the benefits of increasing the coding rates comes at the price of an increased energy consumption. They showed that as the number of end devices increases, the network operates in heavy interference conditions and increasing the CR in such conditions is counterproductive. They assessed also the impact of downlink transmissions on the average energy consumption of devices. They showed that increasing the number of gateways affects not only the packet delivery rates but also the average energy consumption. However, authors didn't talk about LoRa limitation and they limited their work on building a simulation tool without any enhancement of the technology. Furthermore, authors should consider state of the art contributions and compare their work with existing tools.

A Hybrid Adaptive Data Rate (HADR) control has been proposed recently by Farhad et al. [64] to increase the uplink traffic in cases where there are both fixed and moving devices. Their approach helps to increase the packet success rate compared to Adaptive Data Rate (ADR) and Blind Adaptive Data Rate (BADR). They propose to select the best MAC protocol. For example, with environment monitoring applications, devices need to synchronize their transmission by using TDMA based access control scheme to avoid collisions. However, with event monitoring application, devices will want to notify immediately with a random-access method. Thus, TDMA is not well suited. In addition, such an approach has never been applied for LoRaWAN network but it is not new for wireless community. The same solution has already been investigated in many other wireless networks like WiFi and cellular network. In addition, signaling overhead caused by such an approach to synchronize the selection of the suited protocol could drastically collapse the network especially in a dense network.

In the same context, a game theory solution was proposed by Qin et al. [80] to decide which channel and SF to use. The authors propose to find the optimal transmit power that maximizes the DR for each channel/SF group. As LoRaWAN end-devices support 3 different classes, Cheong et al. [58] evaluate the power consumption of LoRaWAN classes. Results obtained allow to quantify the lifetime of each end-device's class. Such work could be improved by evaluating the impact of different LoRaWAN parameters such as CR, and P^{Tx} on end-devices lifetime.

Similar to [58], Kim et al. [68] evaluate and reduce energy consumption of end-devices. However, only downlink communications with fixed LoRaWAN settings (DR and acknowledged transmission) are considered. Their results show that when end-devices are powered by only two AA batteries, 1 to 13 years battery lifetime could be achieved with 0.44 and 0.05 mJ energy consumption, respectively. However, such findings are obtained using a sleep current of 2 μA , which is significantly lower than the corresponding value in Semtech specification (i.e., 30.9 μA). Song et al. [84] consider the macro reception diversity of long-range ALOHA networks where several base stations receive the same packet

sent by a node.

2.2.6 Simulation & modelisation

LoRaWAN in Europe support bidirectional traffic on the same channel. However, as many works show the limitation of the scalability of this technology, downlink traffics should be minimized to avoid offloading the channel. As the opposite, [79] show how downlink traffic could be tolerated even in a dense network. In order to evaluate how LoRaWAN downlink impacts uplink goodput and coverage probability, they developed LoRaWANSim by extending the LoRaSim simulator and adding support for downlink transmissions. LoRaWANSim include many MAC layer features. Among these features, we cite the possibility to send downlink traffic, acknowledgements, retransmissions, confirmed messages, and special control messages. Authors find that the number of downlink messages (Ack or data) is limited by the duty cycle at the gateway. This problem becomes more severe when the number of end device increases, but can be partially mitigated by using multi-cell networks.

As the ADR scheme decreases the DR when end-devices didn't receive an ACK of each packet transmitted, Pop et al. [79] prove that it is not an efficient way to adapt DR. In fact, if an ACK was not received does not necessarily mean that the link quality has decreased. The collision model proposed in this work is quite different to the one proposed in ns-3 module. In particular, when LoRaWANSim reuses the empirical model from LoRaSim, the collision model of ns-3 module is derived from the complex baseband Bit Error Rate (BER) simulations [87]. Moreover, the SpectrumPhy model in ns-3 enables modeling inter-technology interference, which facilitate studies on the interference between LoRaWAN and other technologies. Beside these differences, both collision models support modeling interference and the capture effect. Finally, the LoRaWANSim simulator does not appear to be open source actually since it is still under revision. With capture effect, LoRa gateways are able to receive an interfered transmission even when there is one or more interferers, as long as the SNR is sufficiently high for the signal to be received error-free. To conclude, this work gives a new insight on LoRaWAN performance evaluation but does not propose any way to improve this performance.

Another module for the ns-3 simulator has been proposed by Reynders et al. [81] to study performance of LoRa transmissions. A single and multi gateway scenarios with unconfirmed and confirmed messages were conducted in this work. The module is highly configurable. New protocols can easily be plugged within its flexible backbone architecture. Distributed gateways are supported and connected over an IP network to the network server that controls the whole network. Base classes are implemented of new applications on the network server and with new MAC commands. Many contributions in the literature was investigated to design this module, such as the effect of interference [233], the effect of different spreading factors [140], the reliability and scalability [82], the effect of downlink messages [79], multiple gateways [52] [239] and, performance evaluation [25] [66][53] [233], etc. For example, Goursaud et al. [66] aim to evaluate the performances of a random Frequency Division Multiple Access (FDMA) in the pure Aloha case. However, the capture effect with little overlap between packets is not considered.

Data delivery policy between end-devices and the gateway in the star topology network is very important to avoid packets collision. Thus, Sørensen et al. [85] have investigated the performance of LoRaWAN uplink transmissions including the throughput, delay and collision rate. A queuing theory was proposed to manage the use of the different

sub-bands. Results highlight the importance of a clever splitting of the channel to different sub-bands to improve the network performance.

While cellular and Wi-Fi based approaches require fast feedback and high data rates to increase the data rate and manage the power control [253], these solutions are not suitable for constrained systems like LoRaWAN. Thus, to make LoRaWAN end-devices interoperable with other IoT devices, new approaches with LoRaWAN constraints consecration should be invented. In fact, rather than adopting existing solutions like 6LoWPAN over LoRaWAN [198], Abdelfadeel et al. [51] developed a new header compression technique to be more suitable for the constraints of LoRaWAN like SF allocation. The main goal of the authors was to ensure an interoperability between LoRaWAN and the native IoT stack with IPv6, UDP/CoAP at the device level.

Year/Ref	Parameters	Metrics	Methods	Comments
2016LoRa-Alliance [71]	All physical parameters	All physical metrics	LoRa specification	LoRa modulation scheme
2016Pham [76]	PS	ToA	Experimental study	Implementation of slotted Aloha
2016Goursaud et al. [66]	PR, # ED, BW	BER	UNB assessment	Slotted aloha vs Unslotted aloha
2017Sørensen et al. [85]	PR	ToA, service ratio	Queueing theory	Comparison between sub-bands with class-c
2017Delobel et al. [60]	SF, # ED	ToA	Simulation of class B	Delay of confirmed downlink frames in Class B of LoRaWAN
2017Cheong et al. [58]	PR,	E^{tx}	Experimental study	Comparison of E^{tx} between LoRa classes
2017Kim et al. [68]	PS	E^{tx}	Dynamic downlink (cooperative)	Low energy consumption compared to LoRa standard protocol
2017Marcellis et al. [73]	Mobility, degree, window size	PDR	DaRe: Data Recovery framework	21% of data can be recovered with 42% lower energy consumption
2017Pop et al. [79]	# devices, # ACKs	PDR, Throughput, Energy	Confirmed vs non-confirmed data	The network do not scale well if many end devices request ACKs
2017Song et al. [84]	Traffic load	PDR	Pure vs slotted ALOHA	The take into account Rayleigh fading, shadowing and capture effect
2017Rizzi et al. [83]	SF	Time interval	Distributed measurement framework	Forwarding packets for distributed management
2017Cuomo et al. [59]	Traffic load, PR, Distance	Throughput, PDR	EXPLoRa-SF, EXPLoRa-AT	Comparison with ADR
2017Abdelfadeel et al. [51]	SF	ToA, compression ratio	Layered Static Context Header Compression	LSCHC outperforms IPHC/NHC
2017Qin et al. [80]	# devices, Distance	PDR	Power allocation Algorithm	comparison with ALOHA
2017Abeele et al. [52]	# devices	PDR	Simulation with NS3	Comparison between confirmed and non-confirmed data
2017Adelantado et al. [53]	PR, # devices, PS	Throughput, PDR, ToA	Simulation evaluation	With 500 devices the throughput is at its highest level
2018Reynders et al. [81]	# devices, # gateways	PDR	NS3 module	Performance evaluation of the module in terms of speed
2018Farooq et al. [65]	# devices	Energy, PDR	CSMA for LoRa	CSMA outperforms ALOHA, DBT, RFH
2018Chen et al. [57]	CR, PS, Distance	Energy, Path loss, PDR	Experimental study	Expected results with no comparison with SOTA
2018Capuzzo et al. [56]	PR, # devices	PDR, % of ACKs	Simulation evaluation	Impact of confirmed data on the network performance
2018Kouvelas et al. [69]	# devices	PDR	P-CSMA with NS3	Comparison made between P values
2018Benkahlal et al. [55]	PS	ToA,	Dynamic duty cycle	4 scenarios based on 4 QoS requirements
2018Reynders et al. [82]	Traffic load, Distance	Throughput, PDR	RS-LoRa: Heuristic algorithm	RS-LoRa outperforms ADR only
2018Piyare et al. [77]	PR, # devices,	ToA, PDR	On-Demand TDMA	No comparison made with SOTA
2018Lavric et al. [70]	PS, SF, # devices, classes, DC	PDR, ToA,	Simulation evaluation	LoRa scalability depends on the DC
2018To et al. [87]	# devices,	PDR, Energy	CSMA-10 with 10 ms before a transmission	CSMA-10 outperforms ALOHA and CSMA
2018Hu et al. [67]	Traffic load	Throughput	Collision Avoidance CA-ALOHA	High performance compared to ALOHA & CSMA
2019Zhou et al. [88]	# devices, Distance, SF	PDR,	Data Rate and Channel Control	High performance compared to ADR only
2019Magrin et al. [72]	PR, # devices	PDR, Throughput	ACK variation strategy	Confirmed data degrades the performance of the network due to ACKs
2019Djouidi et al. [61]	nada	nada	Discussion	Emergency Evacuation Systems with LoRa
2019Sui et al. [86]	# resources blocks,	Energy efficiency	Sliding window-based algorithm	Similar energy efficiency as the exhaustive method with a lower complexity
2019Djouidi et al. [62]	SF, BW, CR	nada	Genetic algorithm	Network selection settings with genetic algorithm
2019Zitouni et al. [89]	With and without MQTT	Delay	Model of Traffic Lights with UPPAAL	Differentiated QoS levels
2019Martínez et al. [75]	# jammers	Throughput, PDR	NS3 simulation	Impact of jamming attack on LoRa modulation
2019Polonelli et al. [78]	Traffic load, SF	Throughput	Simulation evaluation	Comparison between slotted and pure ALOHA
2020Djouidi et al. [63]	SF, BW, CR	ToA, SNR, BER	Fuzzy c-means	3 clusters transmission settings based on their quality
2021Marini et al. [74]	CE, distance, # ED	PDR, DR, E^{tx}	LoRaWANSim tool	No comparison with NS3 and onnet
2022Farhad et al. [64]	Mobility, # devices,	E^{tx} , PDR	Simulation study	Comparison between ADR, BADR and HADR
2022Azizi et al. [54]	SF	PDR, E^{tx}	MAB, EXP3	Comparison with ADR, LoRa-MAB

Table 2.2. Reviewed papers on the channel access layer.

2.3 Network layer

When designing a wireless network solution for the IoT, two main topologies can be used: star and mesh. A star topology organizes devices around the central controller, also known as a gateway. On the other hand, a mesh topology connects each device to another with a point-to-point link.

We can find a lot of advantages and disadvantages of each topology when applied to IoT wireless network scenarios. Depending on the IoT use case applied, the drawbacks can seem less harmful in some cases. Mesh topology is able to handle large amounts of traffic and multiple devices can transmit data simultaneously. In addition, failure of one device does not cause an interruption of the network or data transmission. However, mesh topology is very expensive to install especially for long distance scenarios; the number of hops required increases rapidly. In addition, network configuration and management are complicated due to the high number of connections. Moreover, mesh network requires a high power consumption since nodes must be awake and listening for all messages that need to be relayed. Vulnerability and security issues are also frequently

occurred in this topology since a breach in one of the nodes puts the entire network at risk.

Star topology, in the other side, has a lower costs and installation effort due to less complexity in configuring the network. In fact, the base station is installed at a central point in general and nodes are added as needed during the life of the network. Therefore, new nodes are able to be connected directly to the gateway without affecting the rest of the network. Power consumption is highly reduced in this topology and malfunction of a single node does not affect the rest of the network. However, a failure in a single base station causes the entire network shut down.

Even if [LoRaWAN](#) devices are connected with a star topology in most of the cases, many works in literature propose to use other topologies to allow devices to communicate between each other without the need of gateways. In fact, [LoRaWAN](#) alliance proposes to use a star topology to decrease forwarding load and listening tasks that consume a lot of energy. However, devices of other classes can be used to experiment new light routing protocols to cover wider areas. We elucidate here some of these works that propose to adapt transmission settings to mesh topology and find the short path to the destination.

To enable end devices to rejoin the network easily even when the sink device disappears from the original tree structure, Liew et al. [132] proposed a multi-channel multi-path data collection protocol based on Basketball Net Topology (BNT) by using peer links to communicate with other nodes. This maintains not only a tree-based topology but also the connection between peer nodes located at the same height in the tree. However, connections of peers extend the hop counts to the sink node, which inversely increases the airtime of the entire network. The use of [LoRa](#) enables the coverage range to be extended when a lower data rate with a larger [SF](#) is chosen. As compared to multi-channel assignment algorithms, authors need to consider an approach that would decrease the hop count of each sub-tree using a different [SF](#) while ensuring that the airtime between different sub-trees remains balanced.

In order to build interoperability between [LoRa](#) end-devices and other [IoT](#) devices, the work in [198] proposed an integration of IPv6 into [LoRaWAN](#). This work is inspired by the 6LoWPAN and tried to build a framework to make [LoRaWAN](#) end devices recognize Ipv6 addresses. Nevertheless, this work didn't present a detailed performance evaluation to demonstrate its effectiveness in real world.

The only way to make [LoRaWAN](#) scalable is to use dynamic selection of transmission parameters with multiple sinks. This is what Bor et al. [204] tried to do in their work, they studied [LoRa](#) transceiver capabilities and the limit supported by [LoRa](#) system by building [LoRaBlink](#) protocol for link-level parameter adaptation. To do that, they focused on minimizing transmission power and airtime. To estimate the influence of concurrent transmissions and link behavior, experiments were made in which end-devices sent packets with the same [SF](#) but not the same transmission power. Particularly, evaluate communication range in dependence of [SF](#) and [BW](#). [LoRaBlink](#) was developed to enable direct connection of nodes without using [LoRaWAN](#), and designed to support reliable and energy efficient low-latency bi-directional multi-hop communication.

[LoRaBlink](#) is both a new [MAC](#) protocol and routing cross-layer scheme built to extend the radio coverage of the gateway. It is self-organized network based on beacons and time-slotted channel access method, each beacon contains distance in hops from the sink. Experimental evaluation show that [LoRaBlink](#) may cover a network of 1.5 ha, with 80%

of reliability and 2 years battery lifetime. They evaluate also the capture effect of LoRa transmissions by varying transmission time and power. Results show the effectiveness of separation of channels by using different SF.

In fact when two devices use the same SF to communicate, a third node that use different SF didn't interfere with them. In addition, authors find that simultaneous transmissions can be received with high probability if there is a separation of at least 3 symbol periods between them. To make their experiment, they implement a LoRa simulator called LoRaSim. More over, the paper analyzes the possibility of building a carrier activity detection mechanism. Similarly, they study the collision avoidance scenarios as well as the maximum number of transmitters in a LoRa network.

In the same context. To keep the capture effect above 0.9, Bor et al. [204] found that only 120 users are supported per 3.8 ha using standard LoRa settings and one-cell network. This appears very few compared to the number of nodes that need to be deployed in big cities. This number could be slightly decreased because the simulator used in this work supports only uplink transmissions, downlink traffic can load the channel and consequently decreases the number of nodes that could use the same channel. ADR scheme is a CAPEX-efficient way to optimize the capacity of LoRaWAN, thus, vendors on the market like Dutch landline and mobile telecommunications company (KPN) keep their algorithms as a part of their intellectual property. Beside this trend, academic researchers focus on analyzing the performance of new proposals like Bor et al. [204]. Authors demonstrate that six LoRa nodes can form a network covering 1,5 hectares. They conclude that the lifetime of the network can be extended to 2 years with 2 AA batteries when delivering data each 5 s with reliability of 80%. The experiment was conducted using Carrier Activity Detection (CAD) which is faster than RSSI to detect channel activity and can differentiate between noise and the original signal.

Similar to [204], Bankov et al. [189] study LoRaWAN performance in a scenario with a high number of devices. LoRaWAN in Europe support up to 10 channels with duty cycle restrictions and the same channels are used for uplink and downlink. LoRaWAN in North America have 64 channels with duty cycle restrictions also but with no channel dwell time limitations [100]. To join the network server, LoRa end-devices commonly use 3 common 125 kHz channels for the 868 MHz band (868.10, 868.30 and 868.50 MHz) [27]. Additional channels could be provided by the network server once a node has joined the network,

In urban area, the range of LoRaWAN could not be sufficient to cover all connected end-devices. Thus, Ke et al. [192] proposed a mesh LoRa network as a good solution to solve the coverage problem in urban areas with extensively shadowing buildings. However, they didn't discuss the SF allocation in a multi-hop LoRaWAN. Similarly, the adoption of parallel transmission by using multi-hop network was not investigated deeply. In order to find the short time path in multi-hop network, [197] development of multi-hop communication protocol for choosing the path with the shortest cumulative ToA.

Liao et al. [194] analyze the impact of the simultaneous LoRa transmissions on the communication performance. Particularly, they propose the integration of a Concurrent Transmission (CT) into the technology. CT is basically used to design of the multi-hop networks based on the IEEE-802.15.4 standard, it is an extremely efficient flooding type of protocol. Instead of attempting to avoid packet collisions, CT enables more nodes to send packets with the same content and at the same time. With such synchronized packets collisions, CT enables rapid back-to-back relaying of packets which considerably improve the network performance. Based on this strategy, authors propose to integrate it in

a multi-hop **LoRaWAN**. However, this work didn't precise the maximum number of nodes that can communicate on a channel.

Year	Ref	Parameters	Metrics	Methods	Comments
2016	Qiu et al. [196]	PR, Time	PDR, ToA, Energy	ERGID strategy	ERGID vs SPEED VS EA-SPEED
2016	Weber et al. [198]	nada	nada	IPv6 over LoRaWAN	6LoRaWAN implementation stack overview
2016	Bor et al. [190]	SF, BW	PDR	NetBlocks XRange SX1272 LoRa RF module	LoRaBlink: Protocol with beacons
2016	Bankov et al. [189]	nada	nada	Experiments	Muti channel support in EU and US
2017	Ke et al. [192]	nada	nada	Experimental study	Mesh network in urban area
2017	Sartori et al. [197]	SF	link cost	RPL for LoRa	No comparison made
2017	Liao et al. [194]	# devices/group	RSSI, ToA, # hope, PDR	Multi-Hop LoRa Networks	Competing transmissions without comparison with SOTA
2018	Huang et al. [191]	Distance	PDR, RSSI	Ad hoc On-Demand Distance Vector	The PDR is up to 99%, after a 13.6 km long-distance
2018	Lundell et al. [195]	# hops	ToA	Routing Protocol for LoRa Mesh network	Routing protocol based on AODV and HWMP
2018	Lee et al. [193]	Floor, SF, BW	SNR, SNR, PDR	LoRa Wireless Mesh Network	Hops optimization without comparison with SOTA
2019	Zhu et al. [199]	SF, # devices	# hops, ToA	TSCA: Tree-Based SF Clustering Algorithm	Comparison between BFS, DFS, DBFS

Table 2.3. Reviewed papers on the network layer.

2.4 Physical layer

LoRa is a modulation scheme that uses **CSS** to spread the signal with a higher period to make it more robust against noise and achieve a higher range. According to the distance between **LoRa** devices and the gateways, the spreading factor of the signal should be adjusted to receive the transmitted packet. Many works in literature analyzed **LoRa** modulation and proposed to model the modulation scheme, reduce energy consumption and manage scalability issues. We relate in this section their findings and we highlight the advantages and drawbacks of each contribution.

2.4.1 Scalability issue

Scalability and Interference issues of **LoRaWAN** network are analyzed in several papers [204][215][25]. For example, Voigt et al. [239] show that multiple base stations (multi-cell) improve the network performance under interference. Particularly, they consider the inter-network interference when several independent **LoRa** networks get deployed in the same area. They propose to use directional antenna and to use multiple base stations as a solution to deal with noise and interference. Results of their simulation show that the use of multiple gateways outperforms the use of directional antennas. However, the performances drastically decrease when the link load increases.

LoRaSim is a **LoRa** simulator built with python [204] [239]. It is open source and gives great insights on the **LoRa** performance. However, this simulator does not consider acknowledgements. Thus, it cannot be used to study the network performance based on the presence or absence of feedbacks from the gateway. In another side, Omnet++ implements a **LoRa** module [142]. It implements the default **ADR** scheme where nodes can update their spreading factor and power at runtime.

The Semtech **LoRa** modem calculator [235] helps to analyze the behavior of **LoRa** transmission features (**ToA**, **RSSI**) but it is not useful for network planning. As a commercial tool, we found “Siradel”, it provides a simulation engine called Siradel-Internet of Things (**S-IoT**) that relies on Volcano, a 3D-ray tracing propagation model and a collection of 2D and 3D geo-data. This tool supports sink deployment decisions based on propagation models. It considers an environment with much details than **LoRaSim**. However, it does not provide actual traffic, collisions and details such as capture effect. To overcome this limitation, Bor et al. [204] provided models that could be used to improve **S-IoT**. They address the interference problem and study packet collisions when applying a time offset between each transmission.

LoRaWAN, which is a single-hop network, implements an ALOHA or a slotted ALOHA mechanism on the MAC layer. It uses the ADR mechanism to allow end-devices to increase or decrease their data rate. However, the default ADR, which is based on the number of received acknowledgement (ACK) messages from gateways, does not perform well when the number of end devices increase. To overcome this problem many works [53, 140, 82, 142] propose different approaches to better adapt the data rate to different needs. For example, Mahmood et al. [227] analyze the impact of interference on a LoRa network. They show that interference could be caused either by simultaneous transmissions using the same co-SF (perfect orthogonality) or different inter-SFs (imperfect orthogonality). As SF interferences require a Signal-to-Interference Ratio (SIR) protection to take advantage of capture effect, they derived the SIR distributions to capture the coverage performance and the uplink outage regarding the distance from the gateway. They propose a stochastic geometry to model the interference field. The SIR distributions are derived based on the aggregate co-SF and inter-SF interference power. Their results showed that in a LoRa frequency channel, only few devices can successfully transmit, especially with higher SFs. Consequently, devices waste energy in the retransmissions of collided packets.

The SF represents the ratio between the chirp rate and the data symbol rate and affects directly the data rate and the signal propagation and consequently the range. In order to simplify their experiment, many works [204] [204] assume that SFs are orthogonal while considering only inter-SF interference that comes only from collisions using different SFs on the same channel. Whereas, other works [25] [215] focused on evaluating LoRa scalability while considering co-SF interference that comes from collisions using the same SF on the same channel. Moreover, co-SF directly impact communication reliability, reduces the PDR [209] and limits the scalability of LoRaWAN. Therefore, we hope that co-SF configuration should be considered in upcoming studies related to ADR strategies. As an example, Bor et al. [120] focused on finding the optimal transmitter parameter settings using their own link probing regime to satisfy performance requirements.

Similarly, Jetmir Haxhibeqiri et al. [219] studied the scalability for LoRaWAN deployments, they analyze the number of nodes connected to the same gateway. They developed a LoRa simulator to compare the performance in different deployment scenarios like traffic intensity and the number of nodes. Simulations are performed for a duty cycle of 1%. So, they are limited to 1000 nodes as there is 10 channels. Results show that in such scenario, packet losses increase to 32% taking into account the capture effect which should be considered as low compared to 90% in pure ALOHA for the same load. This shows that the capture effect plays an important role in the LoRa transmission behavior.

In the same context, Blenn et al. [203] analyzed experimental results based on the battery life time and scalability measurements from The Things Network (TTN). They analyze also the influence of the payload on the quality of the received signal. The experiments have been made over 8 months. The results show that the LoRa channel occupancy rate is not evenly distributed, this leads to a decrease in performance. This is mainly due to the fact that the majority of LoRa end-devices use the default settings given by the manufacturer. Consequently, certain channels are overloaded. To solve this problem, they use certain user-defined communication channels according to the Radio Frequency (RF) environment congestion. However, their solutions are limited to the deployment scenario.

From a theoretical perspective, works in [215] [25] [189] analyzed the capacity of LoRaWAN in terms of scalability and node-throughput. Among these works, a stochastic geometry framework for modeling the performance of a single channel for LoRa transmission have

been proposed by Georgiou et al. [215]. The authors investigate LoRa scalability and the effects of interference in a single LoRa cell. To evaluate LoRa transmission propagation assuming a single bandwidth frequency for all the nodes, they used a stochastic geometry by formulating two link-outage conditions; one based on SNR and the other one based on co-SF interference. As LoRa modulation uses CSS modulation scheme, communication range could be extended to reach 15km in a rural area. Another advantage of using CSS modulation scheme is the resiliency against noise and interference. Thus, the authors assume that collisions occur only when signals simultaneously collide in frequency, transmission power, time, and spreading factor (perfect orthogonality). Nevertheless, this could be highly criticized as perfect orthogonality is not really respected in a real world. In order to host a great number of end-devices, experiments made in this work show that LoRa networks are sensitive to network density. The coverage probability drops drastically when the number of end-devices increase even with lower duty cycles. This phenomena is due to the interfering signals using the same spreading factor and weak channel access mechanisms like ALOHA. As a result, authors highlighted the interest of studying spatially heterogeneous deployments. Finally, authors of this work determine the conditions for a better capture effect in the presence of two signals with different SF.

2.4.2 Interference and coexistence

In order to analyze the impact of burst events when generating a significant amount of messages in a short period on LoRa gateways, Gupta et al. [216] found that LoRaWAN does not handle well in such scenario. Especially when there is a spatial or temporal correlation in the transmission behavior. Their simulation was performed with a single gateway located in a densely populated area. End-devices are distributed uniformly on each floor in a building within a coverage range of 2.5 km. Two types of collisions have been highlighted. The first is made by sending two packets with the same SF (co-SF interference). The second is made by sending two packets with different SFs (inter-SF interference) [81]. However, authors fail to provide a solution to the second type. As the main goal of this research was to reduce the PER while increasing the throughput, the proposed algorithm sorts the end-devices based on distance and PS to form distinct groups with separate channels. End-devices in each group communicate on the same channel and with the same SF. Once end-devices regrouped by channel, the sum of the received power and Co-channel Interference Rejection (CIR) are computed. If the CIR is lower than the highest received power, then, the lowest SF is assigned to each group, else, it passes the feasibility check. Results show that the PER decreases up to 42% using this algorithm.

To analyze the effect of the perfect-orthogonality of SFs, Croce et al. [208] found that uplink packet transmissions with different SFs may also suffer from packet losses. They validated their findings by experiments and proposed SIR thresholds for all possible SFs. They conclude that LoRa networks cannot be deployed as a superposition of independent networks because of imperfect SF orthogonality.

Nowadays, there is relatively small amount of devices deployed with LPWAN technologies. This should change drastically in a close future because LoRa and Sigfox promise a big development and more than thousands of connected devices [224]. Consequently, the problem of LPWAN technology coexistence becomes more and more important. For example, Krupka et al. [224] illustrate the LPWAN technology coexistence in IoT environment. They discuss the activity duration of LPWAN technologies on a channel during the day in order to measure the maximum capacity of the channel. They found that occur-

rence on the channel during a day using Sigfox technology is more than twice higher than LoRa. This is mainly caused by different policy choices such as longer range and longer battery life at the expense of resiliency against transmission errors and transmission delay. In order to find the optimal duty cycle, a distribution function of the probability of collision between 2 or more devices shows that it is close to 1 for more than 1000 simultaneously active devices.

To compare the performance of the CSS modulation used by LoRa and UNB modulation used by Sigfox, Reynders et al. [233] proposed a heuristic equation that gives the BER for a CSS modulation as a function of SF and SNR. The performances in terms of PDR and throughput of LoRaWAN and Sigfox are simulated. However, numerous network parameters are not explained enough to be able to reproduce the experiment. They showed that UNB is slightly better than LoRa in terms of capture effect: UNB network enables a strong reception of packets thanks to the capture effect. However, CSS has a higher resiliency against noise and interference. When trying to maximize the throughput, only 5 to 10 devices achieved the highest throughput but results in a packet loss of 63%. To simplify the analysis and consequently the network complexity, authors assume that the SFs adopted by LoRa are perfectly orthogonal. However, this is not the case in the real world. In order to implement LoRa modulation in Software Defined Radio (SDR), Knight et al. [222] presented details on the patented LoRa PHY and introduced gr-lora, an open source SDR-based implementation of LoRa PHY.

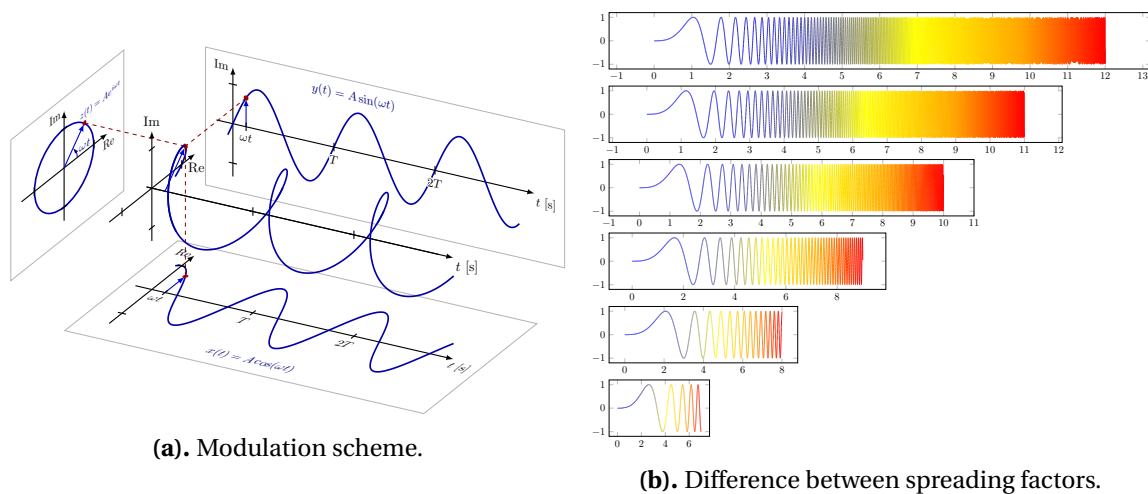


Figure 2.6. The shape of LoRa signal with different spreading factors.

2.4.3 Energy consumption

As the main challenge of LPWAN networks is to transmit the signal in a wide area with a low power consumption. Magno et al. [226] developed a new energy-efficient modulation technique named WULoRa for LoRa devices. They compared their proposal with LoRa and Gaussian Frequency-Shift Keying (GFSK) modulation techniques. They found that communication efficiency could be increased by managing wake up radio. However, details about their implementation is missing in their paper.

As the energy consumption constraint is the main issue that face end-devices to cipher at each transmission the data collected by sensors, Kim et al. [221] propose a secure device-to-device link establishment scheme to evaluate the security performance by comparing the energy consumption of each end device. In fact, to enhance the security

of wireless transmissions, end-devices should consume more energy to cipher the data. This work gives new insights to overcome this problem by compressing the data. In the same context, Costa et al. [207] propose a fuzzy-based approach to dynamically configure the way visual sensors will operate concerning sensing, coding and transmission patterns by exploiting different types of reference parameters. This approach is considered as a use case for multi-systems smart city applications based on visual monitoring.

The ability of LoRaWAN to track a person at street level is far less than might be expected. To achieve better performance, Radcliffe et al. [232] made a testbed for Central Business District (CBD) to overcome this issue. They produced an envelope of ± 10.2 dBm around the model which contained 95% of all data points. The loss-free communication was limited to approximately 200 meters from the base station and there was a total loss of transmission after approximately 600 meters. Similarly, Stan et al. [237] studied the output signal generated by commercial transceivers to understand how information is encoded and embedded in the chirp wave forms.

2.4.4 Simulation & modelisation

Since the appearance of LoRa in 2015, many works in literature tried to model LoRa transmissions to build simulations tools close to the reality. For example, Capuzzo et al. [206] take various configurations parameters to analyze the impact of each parameter on the quality of the signal. These parameters include the number of ACKs sent by the gateway and the SF used for the downlink transmissions. However, multiple retransmissions have not been considered in this work.

For the same purpose, Irio et al. [218] investigates the interference caused by multiple coexisting LoRa devices to a single gateway. They suppose that LoRa devices are distributed according to a homogeneous Poisson Point Process (PPP) considering path loss, fast fading, and shadowing effects. They characterize the distribution of the behavior of interference power, and compute numerical approximations using the Fast Fourier Transform (FFT) algorithm. They consider different channel access probabilities and density of LoRa devices. Results show that the numerical Cumulative Distribution Function (CDF) of the interference fit the CDF obtained with the empirical data.

Ochoa et al. [229] develop LoRa simulation on WSN simulator with C/C++. Authors build both the physical and MAC layers including spectrum used, capture effect and interference. They investigate LoRa network behavior in homogeneous and heterogeneous scenarios with hundreds of nodes. They consider throughput, PDR, energy efficiency and SF allocation in various scenarios. They confirmed the fact that when decreasing GW coverage, nodes with lower SF's shows better performance. They also compare heterogeneous and homogenous configuration of the network, their findings show that heterogeneous networks perform better in terms of PDR, energy consumption and throughput.

To model packet collisions in LoRaWAN, many contributions were made under the assumption that collisions follow a Poisson distributed process. Ferre [214] showed that such assumption is no longer accurate when SFs are perfectly orthogonal. To overcome this issue, they propose closed-form expressions for collision and packet loss probabilities.

In [238] a mathematic model of both LoRa modulation & demodulation processes based on signal processing theory are presented. The paper illustrates the main difference between the performance levels of the LoRa and the FSK modulation regarding the

value of the BER. Their results show that when an Additive White Gaussian Noise (AWGN) channel is used, the LoRa modulation ensures a higher performance level.

Bankov et al. [202] consider LoRaWAN networks with class A end-devices operating with acknowledgements. Authors use Okumura-Hata model without fading for propagation losses to develop a generic mathematical model to evaluate network capacity and transmission reliability. To measure the effectiveness of capture effect, they evaluate the difference between power of the signal from different devices with different SF distributions. Network load threshold was analyzed in this work by estimating the corresponding end-devices throughput. Once this threshold value is reached, the PER increases quickly towards 1.

LoRa offers a massive coverage for end devices. However, this advantage is severely reduced by duty cycles. The increased number of connected end devices significantly elevates packet loss due to collisions. To alleviate this problem, Hoeller et al. [217] exploit time diversity to increase the probability of successful packet delivery in LoRa up-link. They built a model of coverage probabilities of LoRa channels and analyze the use of message replication to create signal diversity. They conclude that there is an optimum number of message replication that avoids high collision probability. They validate the proposed model using numerical simulations.

To be able to send the transmitted signal in wide area, two different modulation schemes are used by LPWAN networks. First, there is UNB used by mostly all LPWAN networks including LTE-M, NB-IoT, etc (see Fig. 2.7b) which relies on using a very small bandwidth to limit the impact of noise on the signal. Second, there is CSS modulation scheme used by LoRaWAN (see Fig. 2.7a) which spread the signal to make it more robust against noise. In this context, Mo et al. [228] investigated the optimal number of message replications in UNB/Sigfox networks. To maximize LoRa network performance, they model and validate the behavior of the network using message replication to discover time diversity using a single gateway and spatial diversity using multiple receive antennas. The work in [15] on message replication differs from [228] However, this work considers UNB networks where each transmission uses a random central frequency, this assumption changes the collision model.

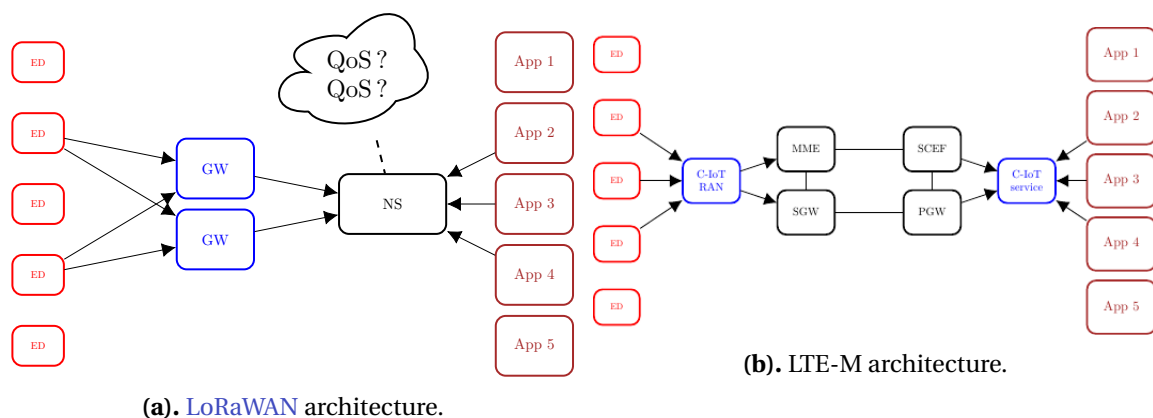


Figure 2.7. Difference between LoRaWAN and LTE-M architectures.

Year/Ref	Parameters	Metrics	Methods	Comments
2014[Aref et al. [201]	Distance,	RSSI	Experimental study	No comparison with SOTA
2015[Petajajarvi et al. [230]	Distance	RSSI	Experiments	Path loss estimation
2015[Kriara et al. [223]	Mobility, Link type, MCS	Goodput, SR	SampleLite, SampleLite+	SampleLite vs RAMAS vs MistrelHT
2015[Semtech [236]	nada	nada	Semtech	Semtech release
2016[Reynders et al. [234]	With and without AWGN, CSS vs BPSK	SNR, BER	Chirp Spread Spectrum (CSS) analysis	Perfect vs not perfect orthogonality
2016[Knight et al. [222]	nada	nada	Gnuradio simulation	Chirp representation with GnuRadio
2016[Bor et al. [204]	# devices,	PDR, Energy,	Mathematical model	Comparison by varying transmission settings
2016[Voigt et al. [239]	Distance, # devices	PDR	Simulation study	Directional antennas vs basic ones
2016[Mo et al. [228]	# replications, # devices	Outage probability	Mathematical model	Validation with varying parameters of the model
2016[Stan et al. [237]	nada	nada	Review	ISM band US vs EU
2016[Reynders et al. [233]	E_b/N_0 , # devices, Distance	BER, PDR, Throughput	Simulation evaluation	Interference between UNB & CSS
2017[Ferre [214]	# devices, PS, PR	PDR	Mathematical model	Validation by varying parameters of the model
2017[Vangelista [238]	SNR	BER	Chirp Spread Spectrum (CSS)	No comparison with SOTA
2017[Croce et al. [209]	SF, chips, SINR, # devices, PR, SF, # GW	BER, PDR	Gnuradio tests	No comparison with SOTA
2017[Angrisani et al. [200]	SF, CR, CR,	SNR, PDR	Experimental study	3D plots of the QoS metrics
2017[Jetmir Haxhibegiri et al. [219]	PR, PS,	PDR, Throughput	Algo: check pkt received with wrong CRC	Comparison between their algorithm and basic one
2017[Blenn et al. [203]	PR, PS, SF, CF	RSSI, PDR, ToA, SNR	Simulation evaluation	No comparison with SOTA
2017[Georgiou et al. [215]	Distance, # devices	PDR	Mathematical model	Comparison with different parameters of the model
2017[Bankov et al. [202]	PR, CR	PER	Mathematical model	No comparison with SOTA
2017[Gupta et al. [216]	# devices,	PDR	Mathematical model	No comparison with SOTA
2017[Krupka et al. [224]	CF	Collisions	Spectrum study (overlap)	Sigfox, LoRa, IQRf
2017[Jorke et al. [220]	Distance	Path loss,	Simulation evaluation	3GPP, ITU, Winner+, Okuuru hata, Oulou
2017[Radcliffe et al. [232]	Distance	RSSI	Literature review	Testbeds comparison
2017[Waspote [240]	nada	nada	Waspote	Waspote release
2017[Magno et al. [226]	Distance, DC	Energy, ToA	WUloRa	WUloRa vs GFSK vs LoRa
2018[Kim et al. [221]	Distance, SF	DR, Energy	Secure D2D messages payload	comparison not secured traffic
2018[Callebaut et al. [205]	PS, P^{tx} ,	Energy,	ADR CNF	ADR CNF, ADR NO CNF, NO ADR NO CNF
2018[Hoeller et al. [217]	Distance, Msg replications	PDR	Mathematical model	Impact of replications on PDR
2018[Daldoul et al. [210]	Distance, CF	Throughput	Rate Ordering Scheme	Minstrel-HT vs Minstrel-HTwRO
2018[Croce et al. [208]	SIR	BER	Simulation evaluation	Imperfect Orthogonality study
2018[Zorbas et al. [241]	BW	PDR	Mathematical model	No comparison with SOTA
2018[Ochoa et al. [229]	# devices, PR,	Throughput, PDR, Energy,	Heterogeneous SF allocation	Homogenous, Heterogeneous, Multi-Homogenous
2018[Dix-Matthews et al. [211]	Path loss, SF, BW, P^{tx}	PDR, Energy, RSSI, Path loss	Simulation evaluation	No comparison with SOTA
2018[Capuzzo et al. [206]	PR, ACKS, DC	PDR,	Mathematical model	Simulator vs their model
2018[Djidi et al. [212]	# devices,	Energy, ToA	LoRa-WuR cluster	LoRa-WuR vs class A
2018[Lim et al. [225]	# devices	PDR	Packet collision model	model, EIB, EAB, Random
2019[Irio et al. [218]	PR	Aggregated interference	Mathematical transmission model	Comparison with different PR
2019[Mahmood et al. [227]	# devices, Distance	PDR	Equal interval Based (EIB)	EIB, EAB, PLB
2020[Pham et al. [231]	CE, SF, # devices	SNR, BER, Throughput, PDR	Mac protocol based on CAD	SIC vs CE vs ALOHA
2021[Elmaghbbub et al. [213]	Indoor vs outdoor	Power spectrum	Experimental study	LoRa enhancement with deep learning neural network

Table 2.4. Reviewed papers on the physical layer.

2.5 Discussion

In summary, contributions made for LoRa technology and LPWAN in general are very attractive and worth to be applied in real world. As shown in Fig. 2.8a, many applications emerged recently to cover the needs of customers to build, travel, monitor and track. For this reason many LPWAN technologies (see Fig. 2.8b) emerged to cover the need of these customers in terms of communication such as LoRaWAN, Sigfox, LTE-M, etc. A lot of findings have been related and commented in the previous sections regarding the robustness and the added value of each contribution. Many papers in literature tried to resume part of these contributions by comparing the advantage and drawbacks of each contribution. We elucidate, at the end of this section, the literature reviews contributions made for LPWAN networks.

Many studies in the literature analyzed the performance of LPWAN [102] considering technologies like (SigFox, Weightless, and Random Phase Multiple Access (RPMA)) in addition to LoRa to highlight their performances. For example, Goursaud et al. [102] studied the performance of the CSS modulation. They calculated the CIR of all SF pairs using simulations and real LoRa link measurements [209]. As LoRa modulation can enable concurrent transmissions, they analyzed pseudo-orthogonality and measured interference probabilities between different SFs and evaluated co-channel rejection between all of SFs. They found also that the strongest transmission suppresses weaker transmissions if the power difference is higher than the CIR of weaker SFs. When SFs are the same, all simultaneous transmissions are lost, except the case when one of the transmissions is received with a higher power than the CIR of the SF. Separating the weakest signal and the strongest signal is called capture effect [204].

Based on the previous literature review of LoRa and LoRaWAN contributions, we conclude that heuristic solutions proposed in literature are limited to increase the data rate and to enhance the quality of the link between end-devices and the gateway. For this

reason, we aim in the next section to explore machine learning contributions to leverage them in LoRa and LoRaWAN adaptive data rate scheme.

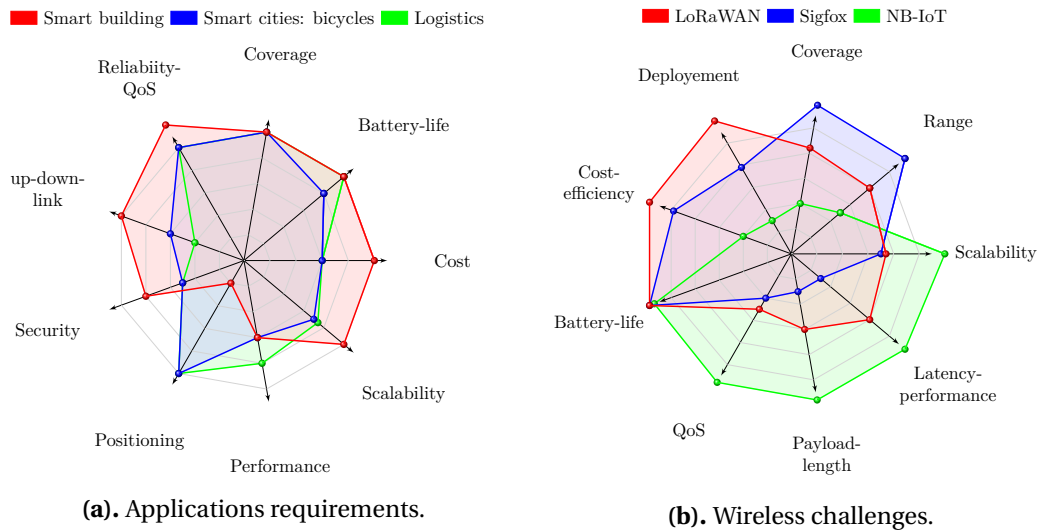


Figure 2.8. Supply and demand in wireless network.

Year	Ref	Parameters	Metrics	Methods	Comments
2015	Goursaud et al. [102]	Frequency dmain	Rejection coeficient	UNB vs CSS	LoRa vs Sigfox vs Weightless vs Ingenu
2015	Al-Fuqaha et al. [91]	nada	nada	Literature review	MQTT vs XMPP vs DDS vs COAP
2016	Al-Kashoash et al. [104]	nada	nada	Literature review	6LoWPAN vs LoRaWAN and Sigfox
2016	Boulogeorgos et al. [95]	nada	nada	Literature review	LoRa, UNB, NB-IoT, LTE-M, EC-GSM
2017	Sinha et al. [110]	nada	nada	Literature review	LoRaWAN vs NB-IoT
2017	Song et al. [112]	nada	nada	Literature review	LoRa vs NB-IoT vs GPRS
2017	Pablo [109]	Frequency, Distance	RSSI, SNR	Experimental study	Master thesis
2017	Charlmers [97]	Distance	RSSI,	Simulation evaluation	Master thesis
2017	Khutsoane et al. [105]	nada	nada	LoRa simulator comparison	Testbeds comparison
2017	Farrell [100]	nada	nada	Literature review	IEEE, ETSI, 3GPP, IETF, Weightless, LoRa, DASH7
2017	Magrin [108]	Traffic load, # devices	Throughput, PDR	NS3 module	Master thesis
2018	Finnegan et al. [101]	nada	nada	Literature review	LPWAN comparison
2018	Haxhibeqiri et al. [103]	nada	nada	Comprehensive review	LoRaWAN tesbeds comparison
2018	Eva Jurado [99]	nada	nada	Experimental/ Theoretical study	Master thesis
2018	Alonso [92]	CR, SF, BW	RSSI, PDR, E^{tx}	LoRa testbed	Heuristic algorithm to enhance LoRa QoS
2019	Ert�urk et al. [98]	# devices, PS	ToA, PDR	Literature review	Sigfox vs NB-IoT vs LoRa vs WiFi vs ZigBee vs Bluetooth
2019	Bembe et al. [94]	nada	nada	Literature review	LPWAN comparison
2019	Aden Hassan et al. [90]	Distance	RSSI	Experimental study	Master thesis
2019	Ayoub et al. [93]	nada	nada	LPWAN comparison	DASH7 vs NB-IoT vs LPWANs
2020	Kufakunesu et al. [106]	nada	nada	Literature review	Comparison based on mathematical model

Table 2.5. Surveys on LPWAN.

3 Machine learning based contributions

The virtualization of the network has opened the field for machine learning algorithms to be applied easily in virtual platforms. Many works in literature proposed various solutions to enhance the performance of the network dynamically. For this reason, we focus in this section on elucidating the main contributions in machine learning field to understand how they applied their Machine learning (ML) algorithms and why they are powerful to solve many optimization problems. We subdivide this section to 4 main subsections to distinguish between works that apply Artificial neural network (ANN), Multi-Armed Bandit (MAB), Markov Decision Process (MDP), and heuristic algorithms.

3.1 Artificial Neural Network (ANN)

Neural networks have been applied in various domains to analytically converge to optimal outputs that best fit activation functions. They are often represented as a circuit

of biological neurons, or, in a modern sense, with artificial neurons or nodes.

The connections between biological neurons are modeled in artificial neural networks as weights between nodes. A positive weight means an excitatory connection while negative values reflect inhibitory connections. In linear combination, inputs are balanced by a weight and summed. Meanwhile, activation functions normalize outputs to reflect the real excitement needed in each layer (see Fig. 2.9). For example, an acceptable range of output is usually between 0 and 1, or it could be between -1 and 1.

Doing this way, many works in literature applied this process and adapted it to their problem.

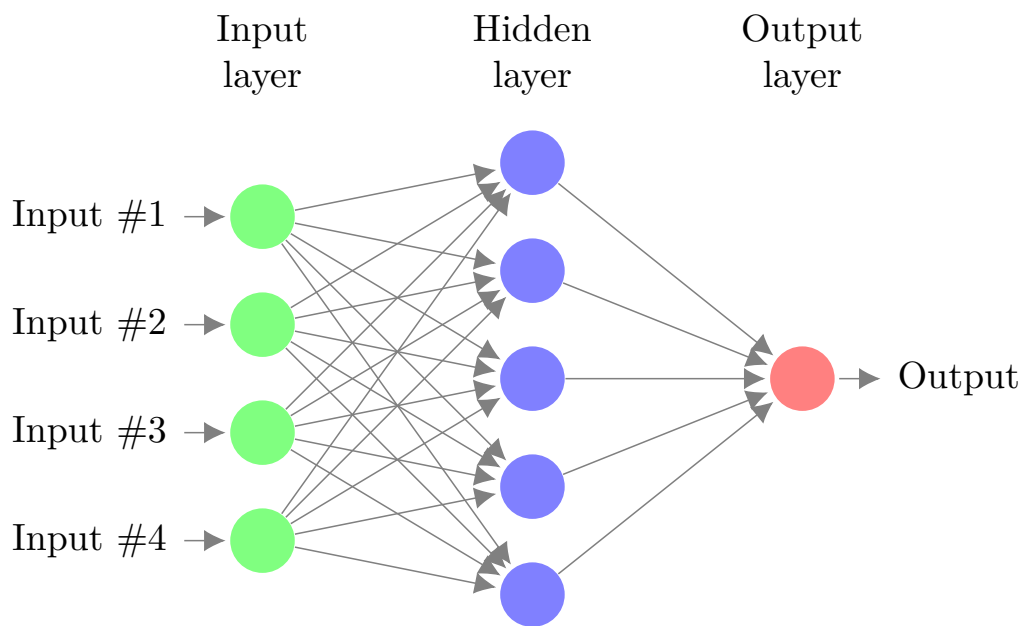


Figure 2.9. Artificial neural network (ANN) layers.

Assigning suitable channels in wireless networks to Internet of things (IoT) devices is mandatory to guarantee a high speed transmission with high reliability. However, the conventional fixed channel assignment algorithms show their weakness to cope with the growing number of devices due to the highly dynamic traffic loads generated. To deal with this problem, Software Defined Networking based IoT (SDN-IoT) is proposed in literature to improve the transmission quality programmatically and mitigate hardware exchange. This virtualization transaction opened the field for deep learning techniques to be applied in wireless network taking advantage of high computational Software Defined Network (SDN) platforms. In this context, Tang et al. [49] proposed a deep neural network based traffic load prediction method to predict network congestion and the future traffic load. A deep learning based channel assignment algorithm (DPPOCA) was proposed to dynamically assign channels to each link in SDN-IoT. This algorithm was extended by combining the deep learning based channel assignment and traffic prediction to propose a novel intelligent channel assignment algorithm called TP-DLPOCA. This combination allows to avoid traffic congestion and quickly assign suitable channels rather than making only predictions. The results show that the obtained throughput and packet losses outperform the conventional channel assignment algorithms proposed in literature. However, their experimental settings were not provided which make it difficult to reproduce the work and compare it with other solutions.

A cooperative federated learning system was proposed by [48] to analyze the transmission and data pricing strategies of a self-organized mobile device. The system is presented as a Stackelberg game model that relies on transferring the model updates between the model owner (central cloud or edge server) and mobile devices. Such interactions may be energy inefficient or even unavailable in mobile environments. To alleviate this problem, Feng et al. [48] built a relay network to construct a cooperative communication platform to support model update transfer. Hence, the mobile devices generate model updates based on their training data and forward them to the model owner through the cooperative relay network. In return, the model owner trains the model and sends it back to mobile devices through the same network (federated learning system). To validate their proposal, they provide a series of analytical and numerical results on the equilibrium of the Stackelberg game.

The new design of 5G networks from 3GPP requires the optimization of the Communication-Computing-Caching (3C) multidimensional resource allocations according to different applications requirements in terms of latency, throughput, and connectivity. In this context, a network slicing architecture based Mobile Edge Computing (MEC) and SDN platforms are proposed by Wang et al. [50] to support flexible 3C resource allocation to support 5G use cases; namely enhanced Mobile Broadband (eMBB), Ultra Reliable Low Latency Communications (URLLC) and massive Machine Type Communications (mMTC). To provide resource allocation decision for the network slicing architecture, authors proposed to use ANN with the aid of data pre-processing techniques to speedup resource allocation decisions. Experimental results from a testbed show that an accurate classification performance can be achieved using their process. However, authors should focus on investigating various pre-process methods for sampling data to improve their training time and accuracy.

Year	Ref	Parameters	Metrics	Methods	Comments
2018	Tang et al. [49]	# switches, # devices	Throughput, Accuracy, Packet Delivery Ratio (PDR)	TP-DLPOCA based on ANN	CoCAG-SBR vs CoCAG-BR vs DLPOCA vs TP-DLPOCA
2019	Feng et al. [48]	# devices	Profit	Federated learning	No comparison with SOTA
2019	Wang et al. [50]	SR, service type, Packet Size (PS)	Training time, CPU usage, PDR	3D resource allocation ANN	eMBB vs URLLC vs mMTC

Table 2.6. Reviewed papers on artificial neural network.

3.2 Multi Armed Bandit (MAB)

The MAB framework can be applied to any problem where there is an abundance of choices where the reward of trying a one choice is known. The exploitation and exploration dilemma relies on a trade-off between making new or old choices to increase the cumulative reward. Humans, in their daily life, are continuously confronted to such a problem and usually raise tremendous questions like, where and what to eat: should I try a new restaurant or go to that Chinese place on the corner? In this section, several use cases of MAB algorithms are presented to motivate the use of such techniques to make decisions in wireless network.

A variant of the Adversarial Multi-Armed Bandit (AMAB) problem was considered by Allesiardo et al. [167] to achieve a regret of $O(NT \log(T))$ with N period, where the time horizon is divided into unknown time intervals where rewards are calculated from stochastic distributions. During each time interval, the optimal arm is updated (see Fig. 2.10). Authors proposed an algorithm taking advantage of the constant exploration of EXP3 to detect when the optimal arm changes. Their analysis shows that when a run is divided into N periods, the proposed algorithms achieve a regret in $O(NT \log(T))$.

Historically, **MAB** algorithms were introduced as simple models for clinical trials, where arms correspond to some treatments with unknown efficiency [245]. Recently, **MAB** models have been proved useful for different use cases, like adaptive data rate, where arms can model the vacancy of radio channels, or parameters of a dynamically configurable data transmission. For example, Kerkouche et al. [179] suggest to optimize the performance of uplink Long Range Wireless Access Network (**LoRaWAN**) communications by using **MAB** algorithms to select both the spreading factor and the transmission power. Simulation results show that transmission parameters can be tuned to find a compromise between energy consumption and packet loss.

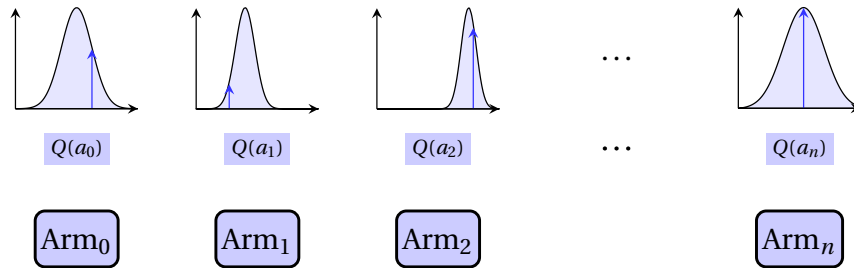


Figure 2.10. Multi bandit arms.

Year/Ref	Parameters	Metrics	Methods	Comments
2008[Braouezec [173]	Items	Features	Non-stochastic bandits	Proof of all bandits theorems
2010[Li et al. [180]	Users profile	News article	Contextual bandits with LinUCB	Personalized news article recommendation
2012[Bubeck [174]	nada	nada	MAB algorithms review	Stochastic, Adversarial and Contextual Bandits
2014[Bouneffouf et al. [172]	Items	Regret/Reward	Contextual Thompson Sampling	Comparison with UCB, EXP4, US, QBC and Random
2015[Allesiardo et al. [167]	Time	Reward, Regret	Adversarial EXP3 with Drift Detection	The adversarial nature of EXP3 makes it robust to non-stationarity
2016[Zhou [188]	Items	Features	A Survey on Contextual MAB	Stochastic & Adversarial Contextual Bandits
2016[Toldov et al. [186]	Channel congestion	PDR	Thompson Sampling	Maximize the probability to receive pkt for each channel
2016[Darak et al. [176]	Channel index	PDR	Bayes-UCB	Maximize the probability to receive pkt in each channel
2017[Toldov [185]	Channel index	PDR	UCB & TS	Proof of Thompson sampling
2017[Gajane [178]	Items	Features	Applications of the MAB problem	Clinical trials, Internet advertising, Online recommendation
2017[Devanand et al. [177]	Posterior Parameters	Features	Thompson Sampling	Comparison with UCB
2017[Tekin et al. [183]	Items	Features	Multi objective contextual bandits	Comparison with UCB
2017[Meyer [181]	Items	Features	Non contextual recommendation systems	Comparison between E-greedy, UCB, Thompson and EXP3
2018[Bonnefoi et al. [169]	SF, channel index	PDR	UCB & TS	Comparison between UCB & TS with different parameters
2018[Bonnefoi et al. [170]	Channel index	PDR	Thompson sampling non-stationary settings	Comparison between Random, E-greedy, USB and Thompson sampling
2018[Tekin et al. [184]	Items	Features	Multi-objective Contextual Bandit	No comparison made
2018[Kerkouche et al. [179]	SF, p^{tx}	E^{tx} , PDR, RSSI	Thompson sampling	Comparison between ADR, UCB, SWUCB, Thompson, EXP3 and EXP3P
2018[Azari et al. [168]	SF, p^{tx}	PDR, E^{tx}	Updated EXP3 and UCB	Comparison with EqLoad and RandSel
2019[Bouneffouf et al. [171]	Items	Features	Use cases of contextual bandits	Healthcare, Finance, Dynamic Pricing, Influence Maximization and Telecommunication
2019[Wanigasekara et al. [187]	Advertisement	Trip preferences	Multi-Objective contextual Bandits	Online Parameter Updates and ranking with LinUCB, PUCB1 and E-greedy
2019[Ta et al. [182]	SF, p^{tx}	PDR, E^{tx}	EXP3	No comparison with SOTA
2020[Zamble et al. [117]	Network resources	Network performances	Contextual MAB	Algorithms to build predictifs models vs policy selection
2020[Chia [175]	Items	Features	Non-linear Contextual Bandits	The Cannon Problem example

Table 2.7. Reviewed papers on multi armed bandit algorithms.

3.3 Markovian Decision Process (MDP)

Markov Decision Process (**MDP**) is a stochastic control process that provides a mathematical framework for modeling decision making process. **MDP** are useful to study optimization problems in dynamic programming. They are used in many disciplines, including economics, robotics and manufacturing. The name of **MDP** comes from the Russian mathematician Andrey Markov. At each time step, the process is in some state s , and the controller select an action a that is available in state s to move the process to a new state s' that could better or worse according to the observed reward $R(s, a)$.

The probability that the process moves to the new state s' is given by the state transition function $P(s, a, s')$. That's why the current state s and action a , are conditionally dependent of all previous states and actions. In other words, the state transitions of an **MDP** satisfy the Markov property. The difference between Markov Decision Process (**MDP**) and Markov chains is that **MDP** supports multiple actions and rewards. If there is only one action for each state and all rewards are the same, then **MDP** can be reduced to a Markov

chain. Since the appearance of MDP in 1950, many works in literature applied it to solve their optimization problem, here we relate some of them. In the same context, Ling Li et al. [156] proposed a three-layer QoS scheduling model for service-oriented IoT. At application layer, authors explore optimal QoS-aware services requirements. The model proposed aims at dealing with scheduling of heterogeneous networks environment at the network layer. At sensing layer, it optimizes resource allocation scheduling for different services.

To reduce handoff cost while maintaining user Quality of Service (QoS) requirements in Radio Access Network (RAN) slicing. Sun et al. [160] propose a multi-agent Reinforcement Learning (RL) based smart handoff policy with data sharing, named LESS, LESS is designed to have two components. First, the LESS-DL which relies on a distributed Q-learning algorithm with small action space to make handoff decisions. It is used to choose both the target Gateway (GW) and Network Server (NS) when a handoff occurs and then updates the Q-values of each user according to LESS-DS. Second, the LESS-DS which is a data sharing mechanism using limited data to improve the accuracy of handoff decisions made by LESS-DL. Simulation results show that LESS can significantly decrease the handoff cost by about 50% compared with traditional handoff policies without learning. In [161], the energy related to the activation of a LoRaWAN node by using the On-The-Air Activation (OTAA) mode is modeled.

The average per-node throughput of LoRa-based networks has been mathematically formulated by Sandoval et al. [158]. To enable end nodes to update their transmission parameters, a centrally-computed global configuration is proposed using tools from the machine learning field. Precisely, the updating process has been formulated as an RL problem whose solution prescribes optimal disseminating policies. The training times of the algorithm have been reduced by using a teacher-student approach that explores new configuration first. The use of these policies together with the optimal network configuration has been analyzed and compared to the state of the art. Results show an increase of up to 147% in the accumulated per-node throughput using RL-based approach. However, other performance metrics were not considered in this work like delay and energy consumption. Moreover, only one scenario was analyzed using only one gateway and 200 nodes which raises question whether this solution could work with higher number of nodes and cells. Authors should also compare their solution to other RL mechanisms to highlight the main finding of this work regarding other RL solutions.

The wide area coverage of Long Range (LoRa) technology makes the probability of collisions higher since the area of potential interferences is extended to $30km^2$. This means that, interference between all nodes in this area can occur if they use the same transmission parameters at the same time. The packet collision among LoRaWAN nodes significantly deteriorates network performance functions. Furthermore, retransmitting packets will severely drain their limited battery power. For this reason, mutual interference management among LoRaWAN nodes is important especially for CSMA/CA access control. For example, Aihara et al. [145] proposed to use Q-learning to learn the wireless environment around LoRaWAN nodes. The knowledge owned during the learning process is utilized for resource allocation in order to improve the PDR performance. To do so, the weighted sum of the number of successfully received packets is treated as a Q-reward and the gateway allocates resources to maximize these rewards. The numerical results show that the proposed scheme can improve the average PDR by about 20% compared to the random resource allocation scheme. However, authors should extend their experiments to compare their solution with other machine learning algorithms to highlight the out-

comes of their proposal.

Due to the benefits of energy harvesting technologies, wireless devices are able to support wireless multimedia services by harvesting energy from the environment. However, due to the unknown dynamics of the Channel State Information (CSI) and the harvested energy, the task to design an efficient routing protocol with an optimal routing and power allocation policies becomes very challenging. In this context, another Q-learning based algorithm was proposed by Zhang et al. [166] for optimizing power and routing policies while satisfying delay constraints over multihop relay networks. The authors established and analyzed the wireless communication model as well as the energy harvesting model. They have formulated an end-to-end effective energy capacity optimization to compare DTMDP and Q-learning based multihop routing algorithms. Their simulation results show that their proposed Q-learning based energy harvesting scheme outperforms other existing schemes in multihop relay networks.

Knowing the diversification of IoT users and applications, the major challenge in designing the 5G network was to support different types of users and applications with different QoS requirements under a single physical network infrastructure. Research community converged to the idea that network slicing is the only way to alleviate this problem. Therefore, RAN slicing has been presented as a promising solution to address these challenges. In this context, Albonda et al. [147] focused on providing two generic services of 5G; namely eMBB and Vehicle to infrastructure (V2X). They proposed a RAN slicing scheme in offline reinforcement learning based on Q-learning algorithm that allocates radio resources to different slices. They consider the utility requirements of each slice in order to maximize the efficiency of the resource utilization. To validate their work, they compared their algorithm with a reference scheme that makes an allocation of resources in proportion to the traffic rate, latency and congestion probability of each slice.

In the same context, Ilahi et al. [150] proposed and evaluated a deep reinforcement learning (DRL)-based PHY layer transmission parameter assignment algorithm for LoRaWAN. Their algorithm mitigates collisions and outperforms the state of the art learning-based technique achieving up to 500% improvement of PDR in some cases. However, this work should be extended to prove the efficiency of DRL-based assignment in different scenarios. In addition, as the authors manage to assign transmission parameters, they should consider other transmission parameters as the Bandwidth (BW), Coding Rate (CR), P^{tx} and frequency channel.

To jointly allocate SF and P^{tx} in the uplink LoRa network, Yu et al. [165] proposed a multi-agent Q-learning algorithm. Based on the interactions between the agent and the wireless environment, the agent updates dynamically its policy to enhance reliability and energy efficiency. They compared their algorithm with a static allocation mechanism. The simulation results show the advantages of using Q-learning algorithm with respect to Signal to Interference & Noise Ratio (SINR), Data Rate (DR) and E^{tx} . However, this work missed a plenty of transmission parameters like CR, BW and channel frequency that should be taken under account to take advantage of machine learning algorithms. In addition, only one scenario was studied with a fixed number of devices, gateways and fixed size of packets and rates of transmissions.

Year Ref	Parameters	Metrics	Methods	Comments
1992 [163]	nada	Reward	Q-learning	Proof of convergence of the algorithm
1994 Berenji [149]	nada	Reward convergence	Fuzzy Q-learning	Proof of the algorithm
1994 Witlox [164]	nada	Reward	Hidden MDP	Known vs unknown model, States completely or partially known
2008 Lin [155]	nada	Reward	Fuzzy Q-learning	Proof of the algorithm
2013 Rojers et al. [157]	Weights	Rewards	Multi objective-MDP	Multiple policies
2014 Jing Li et al. [156]	# devices	PDR, BER	MDP	With and without QoS scheduler
2015 Jamshidi et al. [151]	Not mentioned	PDR	Fuzzy Q-learning	Model-based vs. model free RL
2016 Toussaint et al. [161]	# channels, # ED, % active ED	ToA, E^{tx}	Markov chain	No comparison with SOTA
2017 Karmakar et al. [153]	# GW,	Throughput, SNR,	SmartLA: Markov algorithm	Comparison of SmartLA with SimpleLite and Mistrel
2018 Ajaz [146]	p^{rx} ,	SNR,	Q-learning for slicing	Comparison with heuristic, Round-robin and BCQI algorithms
2018 Sandoval et al. [159]	Not mentioned	PDR, BER, SNR	MDP based algorithm	Comparison with THIEO and AT algorithms
2019 AlQahtani et al. [148]	Transmission time	PDR, response/waiting times, cost	Queueing theory	Impact of vBHU cores on average number of requests
2019 Wang et al. [162]	Resource availability	SLA validation, Reward	Deep Reinforcement Learning	Comparison with Greedy, Best effort and random
2019 Sun et al. [160]	Resource availability	# handoff, outage probability	Multi-agent RL	Comparison of LESS with NS-Prior and Max SINR
2019 Kochovski et al. [154]	Not mentioned	Not mentioned	Probabilistic model	Three QoS level
2019 Sandoval et al. [158]	Packet priority, PS, SF, PR	PDR, DR	RL with evolution strategy algorithm	No comparison with SOTA
2019 Aihara et al. [145]	SF, p^{rx}	PDR, Path loss	Q-value calculation with ANN	No comparison with SOTA
2019 Zhang et al. [166]	Neighborhood Distance	SINR, CSI	Q-Learning Based Routing Algorithm	No comparison with SOTA
2019 Albonda et al. [147]	p^{rx}	DR, Utilization	Q-learning algorithm	Comparison of Q-learning with proportional scheme
2020 Ilahi et al. [150]	SF, p^{rx}	PDR, ToA, E^{tx}	LoRaDRL: Deep RL based ADR	Comparison with MAB
2020 Yu et al. [165]	SF, p^{rx}	SINR, DR	Multi-agent Q-learning algorithm	No comparison with SOTA

Table 2.8. Reviewed papers on markov decision process.

3.4 Heuristic optimizations

Heuristic algorithms are mainly designed to solve a problem in a faster and more efficient way than traditional methods at the expense of accuracy, optimality, precision, or completeness for speed. Heuristic algorithms can be used to solve NP-complete problems. In such a case, there is no known efficient way to find a solution quickly and accurately even if solutions can be verified once obtained. Heuristic algorithms are most often applied when approximate solutions are sufficient and exact solutions are not necessary. However, the computational load requested by such algorithms makes their efficiencies limited to few problems.

Many works in the literature addressed their optimization problem using heuristic algorithms. For example, Feng et al. [125] developed a link adaptation scheme that applies frame aggregation to enhance the uplink data rate of IEEE communications. However, such mechanism do not consider all PHY/Medium Access Control (MAC) enhancements of new Wireless Local Area Networks (WLANs) in their trad-offs. Thus, it is not feasible for IEEE 802.11n/ac in practical scenarios. Another example is SampleLite which was proposed by [223], SampleLite is a pure RSSI threshold-based algorithm. So, it cannot cope up with applications with delay constraints. In another hand, the default rate adaptation methodology that is applied in IEEE 802.11n wireless driver ath9k [254] is Minstrel HT [210]. However, it suffers from exhaustive sampling and is only applicable in IEEE 802.11.

As Multi-antenna systems can provide greater throughput and range coverage than traditional single antenna systems, Nguyen et al. [136] present an evaluation and implementation of a new rate adaptation scheme for multi-antenna systems (RAMAS). Their approach is applicable to off-the-shelf wireless cards. They found that RAMAS is especially efficient in multi-user and interference laden environments. This approach eliminates the complexity of the rate adaptation approaches proposed for IEEE 802.11n in the recent past. Similarly, Deek et al. [124] proposed a rate adaptation scheme based on channel bonding. However, similar to previous frameworks, the mechanism cannot support the new features of PHY/MAC IEEE 802.11n. Dynamic link adaptation of IEEE 802.11 can be classified into link adaptation in static and mobile environment. In static environment, MiRA [138] selects spatial streams and rates based on the receiver's feedback (MIMO). However, in poor channel condition, MiRA performs excessive rate selection and incurs overhead of assigning credit to select data rate.

In [144], authors propose a new method to adapt transmission range to the degree

of importance of sensing data transmitted. Such approach could be extended to adapt the **DR** to the importance level of the data transmitted. Kim et al. [130] proposed a new **ADR** algorithm for **LoRaWAN** end-devices to adapt their transmission parameters. This algorithm requires an active feedback channel, which means that an acknowledgement is required for every transmitted packet. This mechanism would decrease the downlink **PDR** as the same channel is used for both uplink and downlink traffic. In addition, the throughput of uplink traffic will be decreased [79].

To investigate the energy consumption of sending a packet of 50 bytes with different **LoRa** configurations in both star and mesh topologies, Ochoa et al. [137] showed that in a star topology, we can achieve the optimal scaling-up/down strategy of **LoRa** radio parameters to maximize the data rate and range while minimizing energy consumption. The best strategy is to adapt the P^{tx} and then to increment **SF** to obtain the optimal energy consumption. Up to a range of 3 km, the optimal energy consumption is for **BW** 500 kHz. Beyond 3 km, the **BW** must be tuned according to the **DR** and range constraints. In mesh topology, network characteristics (e.g., the network density, the number of hops, the cell coverage) were exploited to optimize the energy consumption. In multi-hop dense networks, the proposed strategy consists of setting the **SF** to 6 and then, progressively increasing the P^{tx} . However, as many works on **LoRa**, exploiting the orthogonality of various **SF** and the spatial reuse of channels was not made in this work.

To determine the quality of uplink traffics using **RSSI** and Link Quality Indicator (**LQI**), an Enhanced Link Quality Estimation Technique (**ELQET**) has been designed by Jayasri et al. [128] with an intuitive combination of the Kalman filter and fuzzy logic. They propose a link quality based adaptive data streaming as a solution for effective deployment of low power Zigbee. The quality score returned by fuzzy logic (based on three efficient link metrics Packet Reception Rate (**PRR**), **SNR**, **LQI**), is smoothened further with Exponential Weighted Moving Average (**EWMA**) for better stability. This approach enhances the quality of transmission while reducing energy consumption and data loss.

Recent research on **LoRa/LoRaWAN** has mainly focused on **LoRa** performance evaluation in terms of coverage, capacity, scalability and lifetime. For example, Bor et al. [120] proposed an optimization problem that minimizes energy spent on data transmission while meeting required communication performance and link quality. They identified 6720 various parameter combinations for **SF**, bandwidth, coding rate and transmission power. The algorithm proposed for adaptive **LoRa** transmission parameters is based on trial and error method for selecting the optimal settings. It performs a binary search of the parameter space while maintaining at least the same link reliability for each step, the mechanism tests each setting for its packet reception rate until a good setting is found from an energy consumption perspective. It aims to find a trade-off between the cost of finding good parameters and the packet delivery rate achieved. The algorithm converge to an optimal setting step by step after multiple transmissions for the fixed distance between the node and the gateways. However, such methods become unsuitable when mobility should be taken in consideration. Moreover, from the gateway perspective, **ACK** packets are not distinguishable from any other **DL** packet, so, they are subject to the same rules and constraints. Thus, it is not convenient when traffic dynamically changes. In addition, only energy perspective is used to select the optimal setting.

Instead of considering the maximum **SNR** value from recent uplink packets like **ADR** do, Slabicki et al. [142] propose to take the average **SNR** of these packets. They proposed an improvement of **ADR** mechanism built at the network server to increase the **PDR**. This

proposal is advantageous only to alleviate the impact of variable channel conditions. The proposed improvement of **ADR** mechanism achieves at least 30% better packet deliver ratio compared to the default **ADR**. Similarly, Abdelfadeel et al. [118] presented Fair Adaptive Data Rate Algorithm (**FADR**) which computes a data-rate and transmission power in order to reduce collision among end-devices and achieve better data-rate.

In order to maximize the network's throughput, a contention aware **ADR** approach was proposed by Kim et al. [131] to track the number of nodes per **SF**. As the **DR** is inversely proportional to **SF**, their approach aims to increase the number of devices using low **SFs**. Other results show that at speeds higher than 40 km/h, the communication performance decreases due to the Doppler effect [34], [38]. Enhanced research regarding the **ADR** scheme was extended since 2017 to manage: scalability [130], throughput [59], **PDR** [140], and contention [131]. As an example, congestion of a channel is estimated through evaluation of network throughput and **RSSI** [130]. Similarly, Abdelfadeel et al. [118] propose **FADR** that uses **RSSI** values when determining **SF** and P^{tx} .

Year	Ref	Parameters	Metrics	Methods	Comments
1984	Bezdek et al. [119]	Any items or features	Membership degrees	FCM	Clustering items based on their coordinates
2002	Ng et al. [135]	Items	Features	Tabu search based techniques	Categorical data clustering
2006	Lin et al. [133]	P^{tx}	RSSI , PDR , LQI	Adaptive Transmission Power Control	Adaptation of P^{tx} to weather conditions
2009	Gan et al. [126]	Political advice	Political advice	FCM	Predict first and second choices of citizens
2011	Nguyen et al. [136]	CR , Modulation , BW	Throughput	Heuristic algorithm	High throughput compared to ARF, MRA, RAMAS
2012	Chen et al. [121]	Velocity	Throughput	Rate Adaptation in Mobile Environments	High DR compared to ARF, RRAA
2013	Khan [129]	BW , P^{tx}	PDR , RSSI , DR	ADR survey	Comparison between ARF, MRR, AMRR, CLRA, ONOE
2013	Deek et al. [124]	Location,	Throughput, PDR	Heuristic algorithm	Comparison of ARAMIS with RAMAS, Mistrel, Ath9k
2013	Pefkianakis et al. [138]	Location,	Throughput	Window-based Rate Adaptation	Comparison of WRA with SampleRate, RRAA, MiRA
2015	Masonta et al. [134]	BW , P^{tx} , channel	Channel saturation	Heuristic algorithm	Adaptive Spectrum Decision Framework
2015	Wannachai et al. [144]	Type of data	Minimize ToA & E^{tx}	A-TRED mechanism	Critical data get lower ToA
2017	Kim et al. [130]	Not mentioned	DR , ToA ,	Heuristic algorithm	No performance assessment
2017	Ochoa et al. [137]	SF , P^{tx} , BW	minimize E^{tx}	Heuristic	Mesh topology is better in dense network
2017	Jayasri et al. [128]		RSSI , PRR , LQI , BER	Kalman filter + Fuzzy system	Evaluate link: Good or poor quality
2017	Bor et al. [120]	SF , BW , CR , P^{tx}	PRR	Probing Algorithm	285 probes allow to find a good setting
2017	Reynders et al. [140]	P^{tx} , SF , # devices, Distance	PDR	Heuristic algorithm	Comparison with distance based scheme
2017	Hauser et al. [127]	SF , P^{tx}	PRR , SNR	ADR algorithm	Trade-off between DR and E^{tx}
2018	Liew et al. [132]	PR	ToA , PDR	Scheduling algorithm	Comparison FAEM with SMM, LSM, CSMA / CA
2018	Slabicki et al. [142]	# devices	PRR , E^{tx}	ADR+ algorithm	ADR+ is more scalable than ADR
2018	Preeth et al. [139]	Routing table	Inter and intra cluster cost	Clustering devices	Low E^{tx} , high PDR , low BER
2018	Kim et al. [131]	SF	Throughput	Gradient Projection	The throughput is higher compared to ADR
2018	Abdelfadeel et al. [118]	SF , # ED , Distance	ToA , E^{tx} , PDR , RSSI	FADR : Heuristic algorithm	No comparison with SOTA
2018	Song et al. [143]	Routing table	LQI	Clustering devices	Low E^{tx} to achieve the sink
2018	Cuomo et al. [122]	SF , Distance, PS	DR , PDR , ToA	EXPLoRa-(AT.TS.KM)	Comparison with ADR only
2019	Dawaliby et al. [123]	BW	SNR , PDR	Dynamic MLE algorithm	Allocations fit slice requirements
2006	Ruspini et al. [141]	Items	Features	Clustering algorithms	Hard, Fuzzy and Probabilistic c-means clustering

Table 2.9. Reviewed papers on heuristic algorithms.

3.5 Discussion

The main advantage of **ML** algorithms is their high adaptability to different scenarios without the need to study each scenario apart from others. We elucidated in this section most known algorithms to explain how **ANN**, **MAB**, **MDP** and heuristic algorithms works and what makes them useful to solve different kind of problems.

	The states are not known	The states are known
The model is known	Heuristics/ game theory	Markov Decision Process
The model is not known	Multi-armed bandits	Reinforcement Learning

Table 2.10. Reasoning under uncertainty [188].

As shown in Table 2.10, depending on our prior knowledge about the environment and the impact of actions on it, we can select the appropriate algorithm that fit well the problem under study. For example, when we don't have any knowledge about the environment and how it behaves when we apply each action, then **RL** algorithms including **ANN** and Q-learning are more suitable to solve the problem. However, when we have a prior

knowledge about the environment and we can predict with which probability each action is able to change the state of the environment, then MDP is the best algorithm to consider in this case. Alternative algorithms that can be used in this case are contextual MAB algorithms since the prior knowledge required in this case is considered by these algorithms as a context. When the environment does not change its state during the learning process, then simple MAB algorithms should be considered.

In this thesis, we try to solve the problem of transmission parameters optimization by building a prior knowledge to disclose at which extent each transmission setting could lead to different uplink states. This knowledge is obtained using a pattern recognition algorithm to split the set of transmission settings to n clusters with n uplink qualities. Then, we feed this knowledge to both Q-learning and MDP algorithm to learn which transmission setting is the best for each uplink state.

Year	Ref	Parameters	Metrics	Methods	Comments
2009	Talbi [115]	nada	nada	Meta-heuristic survey	Population, multi-objective and hybrid heuristics
2010	Szepesvári [114]	nada	nada	MDP survey	How to use decision problems with MDP
2018	Sutton et al. [113]	nada	nada	Introduction for MDP	MAB, MDP, dynamic programming and Monte Carlo Methods
2018	Boutaba et al. [96]	Traffic control parameters	Traffic control metrics	Machine learning survey	Clustering, Classification, Regression and Rule extraction methods
2018	Xie et al. [116]	Traffic control parameters	Traffic control metrics	ML-based SDN	Supervised, unsupervised and reinforcement algorithms
2018	Sutton et al. [113]	nada	nada	Introduction to reinforcement learning	Tabular vs approximate solution methods
2019	Slivkins [111]	nada	nada	Introduction for MAB	Stochastic, Adversarial and Contextual MAB
2020	Lattimore et al. [107]	nada	nada	All MAB algorithms	Stochastic, Adversarial and Contextual MAB
2020	Zamblé et al. [117]	Data flow	Rewards	Contextual MAB	Neural bandit algorithm

Table 2.11. Surveys on machine learning algorithms.

4 Conclusion

Through the intensive literature review of many papers proposed recently to enhance the quality of Low Power and Wide Area Networks (LPWAN) networks, we aim in this thesis to propose new solutions using lightweight machine learning algorithms to optimize network settings. In fact, when it comes to wireless communications, it's very hard to model transmissions behavior due to the high number of factors and use cases that should be considered. Especially when it comes to deal with random wireless transmissions using pure Aloha channel access protocol. In this thesis, we propose novel ideas that have never been proposed in LPWAN networks and even in other wireless networks in general. Particularly, we characterize all possible transmission settings and build a prior knowledge that will feed machine learning algorithms with enough knowledge to converge quickly to the optimal set of transmission settings.

Our work differs from the previous works in many points. First, the pattern recognition mechanisms have never been used to recognize the good, the bad and the medium transmission settings. Second, our comparison includes many works to highlight the effectiveness of our work over many other works proposed in the literature. Third, all transmission settings have been included in the optimization process to find the optimal ones. Fourth, Unlike related works, many scenarios have been included in our experiments to evaluate our solution in many use cases. Fifth, we do not limit our work to analyze the data rate but we include other metrics like Time on Air (ToA) and Transmission Energy (E^{Tx}). Last and not least, our work is a lightweight machine learning solution which means that it does not require much resources to be run.

To outperform state of the art solutions to maximize the data rate of Long Range (LoRa) network, we propose in chapter 3 to recognize the impact of each transmission setting on the uplink quality using pattern recognition tools. This means that we try to

know from all transmission settings what are those who make the uplink state good, bad or medium. Since both Q-learning and the policy iteration algorithms assume that the transmission settings change the uplink state (see Table 2.12), they need to know from all transmission settings (actions) what are those who change the uplink state from one state to another. Thanks to our contribution in chapter 3, the knowledge required by Q-learning and the policy iteration algorithm to jump from one state to another through an action is provided by Fuzzy C-Means (FCM) algorithm. In fact, knowing the membership degrees of action "a" to clusters " c_1, \dots, c_n " will help Q-learning and the policy iteration algorithms to know at which state " s_1, \dots, s_n " action "a" will lead. The difference between Q-learning and the policy iteration algorithms used in chapter 4 and 5, relies on the required knowledge about the environment. Unlike Q-learning that has to observe the new state after each transmission, the policy iteration algorithm requires the impact of each action on the uplink quality before even starting the learning process. For this reason, we propose in chapter 4 to use the Q-learning algorithm and in chapter 5 the policy iteration algorithm and we compare both algorithms with the algorithms proposed in literature. Due to the diversification of Internet of things (IoT) applications, IoT devices need to target the uplink states that best fit the Quality of Service (QoS) requirements of the applications that they run and not to just maximizing their data rate. Since the policy iteration algorithm has all the required knowledge to identify the transmission settings that make the uplink quality match the required quality by IoT applications, we make each IoT device in chapter 5 target the uplink state that best fit the requirement of the application that it runs. This allows these devices to target different uplink states and generate three uplink traffics with different qualities within the same physical network.

	The states are not known	The states are known
The model is known	genetic, EXPLoRaTS Related work	Policy iteration Chapter 5
The model is not known	EXP3 Related work	Q-learning Chapter 4

Table 2.12. The difference between our work and state of the art works.

3 | Pattern Recognition of LoRa Network Settings using Fuzzy C-Means Clustering

Quotation

Think small to accomplish big things -
Michael Phelps

Pensez aux petits détails pour accomplir des
grandes choses - Michael Phelps

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Abstract

Long Range Wireless Access Network (LoRaWAN) emerged as one of the promising Low Power and Wide Area Networks (LPWAN) for IoT applications. It allows end-devices to reach the gateway and then the core network within a star topology in a wide area. Long Range (LoRa) transceivers send data packets according to a set of parameters: Spreading Factor (SF), Packet Size (PS), Bandwidth (BW) and Coding Rate (CR). These parameters must be tuned and adapted to applications requirements. The default Adaptive Data Rate (ADR) control scheme of LoRaWAN has been proposed to adapt modulation parameters dynamically based on the recent received packets. However, it does not adjust parameters according to the requirements of Internet of things (IoT) applications. In this chapter, we propose to cluster all LoRa transmission settings to "n" subsets (clusters) of settings that share the same uplink quality. To recognize the quality of these settings, we measure their Bit Error Rate (BER), Time on Air (ToA) and Received Signal Strength Indicator (RSSI). Based on these metrics, the clustering process will search for the transmission settings that share the same level of quality to put them in the same cluster. We consider

the set of settings' vectors as a cloud of points in a vector space and the measured metrics as points' coordinates. We assume in this work that cluster items characterize LoRa transmission configurations. To map the set of LoRa transmission settings that offers the same Quality of Service (QoS) to the same cluster, we generate a set of transmission settings randomly and apply the Fuzzy C-Means (FCM) clustering algorithm on their resulting QoS metrics. Results show that the FCM clustering algorithm assigns each setting to the cluster that describes better its quality. This result could be used by LoRaWAN network servers to map each LoRa transmission setting to the application running on end devices.

1 Introduction

Knowing the diversification of services and applications that need to be loaded in the Internet of things (IoT), and knowing the heterogeneity of wireless network configurations, the task to adapt the wireless network to the applications running on each end-device became challenging. IoT applications need more and more wireless technologies that can offer low-cost and low-complexity to end devices to be able to communicate in wide areas. IoT end devices are generally powered by battery to allow mobility. For this reason, the power consumption should be carefully studied in order to extend the battery lifetime. The communication range needs to achieve several kilometers, as end-devices are scattered in a large area like in building and agricultural fields. Many Low Power and Wide Area Networks (LPWAN) technologies are already available like SigFox, Narrow Band-Internet of Things (NB-IoT) or Long Range Wireless Access Network (LoRaWAN). SigFox plans to offer a global coverage in 45 countries and regions by a single operator network [24]. NB-IoT is built by telecommunication companies as an alternative to sub-GHz LPWAN technologies. As NB-IoT uses licensed spectrum, it offers better traffic reliability compared to other sub-GHz technologies.

Unlike NB-IoT, LoRaWAN can be deployed as a private network and integrated easily with many network platforms (e.g., The Things Network (TTN)). In addition, LoRaWAN specification is open to academic as well as industrial communities to enhance the quality of the network. Thanks to all of these advantages, many recent research works tried to improve Long Range (LoRa) network performances [103] [98]. Since the first appearance of LoRaWAN in the market in 2015, many research papers [98] have been submitted in different journals and presented in conferences all over the world. For this reason, we use in our work LoRaWAN network and propose a new framework to make the Adaptive Data Rate (ADR) control system [127] more flexible while considering applications' requirements.

To identify the quality of each transmission setting, we start by generating the Quality of Service (QoS) metrics of each LoRa transmission setting by randomly transmitting packets with different settings. From all the measured metrics, we recognize the transmission setting that offer the same quality by applying the Fuzzy C-Means (FCM) clustering algorithm [119] on these metrics. To know the extent at which each transmission setting will lead to the recognized quality levels, FCM generate the membership degrees of each setting to the recognized clusters. In the end, we compute the performance index of the clustering process to get the accuracy of membership values.

To find the set of LoRa transmission settings that best fit each application requirement, we propose to use a fuzzy clustering process rather than a hard clustering to get the membership of each transmission setting to applications. The advantage of using this

algorithm is the ability to know at which level a LoRaWAN transmissions setting is suitable for different type of IoT applications. Hard clustering algorithms like K-means can only generate labels to know at which cluster an object belongs. The advantage of using the fuzzy clustering algorithm is to build a model that discloses whether a transmission setting is good, bad or medium through their membership degrees to the clusters of good, bad and medium settings. Knowing these values is mandatory for the network server to rank LoRa transmission settings and to assign the best setting with a higher membership value to end-devices.

The selection of transmission parameters to enhance the quality of uplink traffics is one the most challenging research areas. For this reason, several research works in Wireless Sensor Networks (WSN) have investigated different transmission power control schemes to increase the datarate and reduce the energy consumption [255]. Thus, WSN should be able to provide transmission power control to adapt the energy consumption and the datarate to applications requirements. Existing solutions to adjust the transmission power depend on the wireless environment. The link quality is either determined by computing the Bit Error Rate (BER) over time and/or by estimation it using Received Signal Strength Indicator (RSSI), Signal to Noise Ratio (SNR) or Link Quality Indicator (LQI). Depending on the link quality at time t , transmission power and rate is adjusted for $t+1$. We follow in our work the same idea regarding this approach. However, LoRa transceivers provide additional parameters like the Spreading Factor (SF) to adapt the wireless transmissions to energy cost. Previous works on WiFi and cellular networks have investigated either i) the transmit power control (e.g. [247]), ii) the transmit rate control (e.g. [252]), or iii) the combination of the two as a transmit power and rate control [248].

Most of the transmission power control schemes try to increase the capacity, and not only decreasing the energy consumption. However, the transmission rate control is often concerned by maximizing the throughput. Compared to LoRa, WiFi packet rates are significantly higher, and the ADR control algorithms run at a much higher rate than in LoRa. For example, the most commonly used transmit rate control algorithm Minstrel [246] evaluates its links every 100 ms. To be able to recognize the transmission settings that fit application requirements, we propose in this chapter to use a the fuzzy clustering process to identify the transmission settings that lead to good, bad or medium uplink qualities. The closest study to our approach is presented in [126]. However, the fuzzy clustering process was applied to get the expected membership values of citizens to political parties. By analogy, in our work, political parties are LoRa network applications, and transmission settings are the citizens.

This chapter is organized as follows. Section 2 introduce all transmission settings and the QoS metrics. Section 3 enunciate the problem statement. In Section 4, we describe how FCM algorithm assigns the membership values to LoRa transmission settings. Our simulation settings and our findings are presented in Section 5. Section 6 concludes this chapter.

2 Transmission settings vs radio performance

Long Range (LoRa) is a proprietary modulation scheme derived from Chirp Spread Spectrum (CSS) modulation whose main objective is to improve the Received Signal Strength Indicator (RSSI) at the expense of the Data Rate (DR). It uses orthogonal Spreading Factors (SFs) and allows to find a trade-off between DR and coverage. LoRa is a physical layer implementation and does not depend on higher layer implementations. This allows LoRa

technology to coexist with different network architectures.

Transmission settings	SF, CR, BW, P^{tx} ,
QoS metrics	SNR, RSSI, BER, ToA
Factors	Spectral Noise
Application settings	Packet Size (PS)

Table 3.1. Settings vs metrics vs factors.

In information theory, the Shannon-Hartley theorem defines the maximum DR at which information can be transmitted in a wireless channel with a specific BW in the presence of noise. From this well-known theorem, it can be concluded that if the BW is decreased, the capacity of the channel decreases as well. To deal with such a problem, LoRa modulation re-shapes (spread) the signal to hold in lower BW (so lower datarate) but in a longer period (so higher ToA).

Applications	PR [pkt/day]	min PDR [%]	PS [Byte]
Wearables	10	90	10-20
Smoke Detectors	2	90	10-20
Smart Grid	10	80	10-20
Waste Management	24	60	10-20
Animal Tracking	100	70	50-100
Environmental	5	90	50-100
Asset Tracking	100	90	50-100
Water/Gas Metering	8	85	100-200
Medical Assisted	8	90	100-200

Table 3.2. Applications requirements [63, 83, 12].

To adapt LoRa modulation settings dynamically, Long Range Wireless Access Network (LoRaWAN) server like The Things Network (TTN) adjusts the modulation parameters of end-devices based on the 20 recent received packets [250]. Finding a set of settings that best fit applications requirements is very challenging due to the number of parameters that should be taken into account to offer a good Quality of Service (QoS). For example, a higher BW gives a higher data rate and a lower ToA, but a lower RSSI due to the additional noise. For example, SF7 increases the DR and decreases the ToA but suffers from a short range compared to other SFs. Actual LoRaWAN network servers available in the market try to adapt the required settings based on different QoS metrics: RSSI, BER and ToA. We describe in detail these metrics in the following subsections. Table 3.1 shows the difference between transmission settings, QoS metrics and factors.

Since the need of high QoS strongly depends on the requirements of applications running on end devices, LoRaWAN network servers need to rank LoRa modulation settings based on their measured quality metrics. For example, if the application running on end-devices should send a packet that requests a high QoS, the network server should select the required settings from a pool or a cluster of settings with a high RSSI, a low ToA and a low BER. In our work, we assume that we need to run three types of applications with different QoS requirements.

To illustrate the requirements of different Internet of things (IoT) applications, Table

3.2 built from [12], [251] and [83] shows different quantitative values according to the need of each application. For example, the PR, the minimum PDR and the Packet Size (PS).

2.1 LoRa transmission settings

To be able to send their frame in a wide area, LoRa devices should be configured by using different transmission settings: P^{tx} , Carrier Frequency (CF), SF, BW and CR. The selection of the optimal set of parameters to achieve the best connection performance with the highest data rate remains a big problem for network engineers especially when it comes to thousands of devices. The combination of these parameters results in around 6720 possible settings [120], allowing the user to fully adjust LoRa to IoT application requirements. According to the transceiver used by devices, the quality of the signal can slightly be different due to the properties of each transceiver. A brief description of these properties are given in Table 3.3.

Module	SX1261/62/68	SX1272/73	SX1276/77/78/79
Modem	LoRa & FSK	LoRa	LoRa
Link budget	170dB	157dB	168dB
Power amplifier	/61: +15dBm 62/68:+22dBm	+14 dBm	+14dBm
Rx current	4.6 mA	10 mA	10 mA
Bit rate	62.5kbps-LoRa 300kbps-FSK	300 kbps	300 kbps
Sensitivity	-148 dBm	-137 dBm	-148 dBm
Blocking immunity	88 dB	89 dB	Excellent
Frequency	150-960 MHz	860-1000 MHz	137-1020 MHz
RSSI		127 dB	127 dB

Table 3.3. LoRa transceivers properties [236].

2.1.1 Bandwidth (BW)

It is the range of frequencies in the transmission band. Higher BW offers a better DR and ToA, but a lower RSSI due to the integration of additional noise. In contrast, lower BW offers a higher sensitivity, but a lower data rate. The data is sent with a chip rate equal to the bandwidth. This means that a bandwidth of 125 kHz corresponds to a chip rate of 125 kcps. LoRa transceivers have three practical bandwidth settings: 500 kHz, 250 kHz and 125 kHz.

2.1.2 Carrier Frequency (CF)

The Carrier Frequency (CF) is the center frequency used for the transmission band. For the SX1272, it is in the range of 860 MHz to 1020 MHz. The alternative radio chip Semtech SX1276 allows adjustment from 137 MHz to 1020 MHz (see Table 3.3).

2.1.3 Coding Rate (CR)

It is the Forward Error Correction (FEC) used by LoRa against interference and can be configured with: 4/5, 4/6, 4/7 or 4/8. A higher CR offers more protection against noise,

but increases the **ToA**. Transmitters with different **CR** can communicate since the **CR** of packets header is always 4/8 encoded.

2.1.4 Spreading Factor (SF)

It is the ratio between Symbol Rate (**SR**) and Chip Rate (**HR**): $SF = \log_2(HR/SR)$ that can range from 7 to 12. A major **SF** not only enhances the **SNR**, the range and receiver sensitivity, but also the **ToA**. Each increase in the **SF** divides the transmission rate by two and doubles the transmission time and energy consumption. The number of chips per symbol is calculated as 2^{SF} . For example, with SF12, 4096 chips/symbol are used. **SFs** can be selected from 6 to 12. Radio communications with different **SF** are orthogonal to each other so network separation using different **SF** is possible.

2.1.5 Transmission Power (P^{tx})

It can range from -2 dBm to 20 dBm, but due to implementation limits, it can be adjusted only from 2 dBm to 14 dBm in industrial products. To reduce radio pollution, a duty cycle less than 1% is required by **LoRaWAN** alliance.

Table 3.4 resumes the relationship between transmission settings and **QoS** metrics. For example, when we increase the spreading factor, we get a higher resiliency to noise, so a higher **SNR** and **RSSI**. However, we consume more energy since the packet size will increase. When we increase the **CR**, we get a lower **BER** with CR 4/8 since we just double the size of packets to be able to recover bit errors. When we increase the **BW**, we get a higher data rate but a lower resiliency to noise, so a lower **RSSI** as the spectral noise will also be increased.

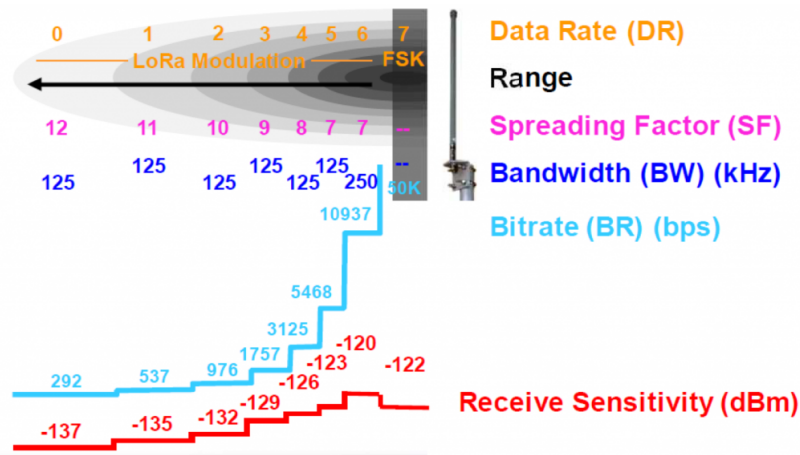
Setting	Values	Rewards	Costs
BW	7.8 \rightarrow 500 _{kHz}	DR	RSSI, Range
SF	6 \rightarrow 12	SNR, RSSI, Range	DR, PS_{max}, E^{tx}
CR	4/5 \rightarrow 4/8	BER	PS_{max}, E^{tx}, ToA
P^{tx}	-1 \rightarrow 14 _{dBm}	SNR, RSSI, BER	E^{tx}
PS	10 \rightarrow 230 _B	PS	E^{tx} , ToA

Table 3.4. LoRa parameters selection.

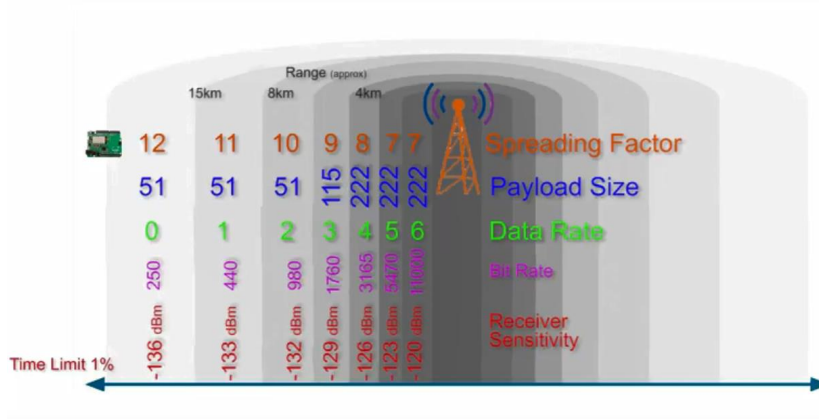
Fig. 3.1a and Fig. 3.1b show the impact of distance on **LoRaWAN** transmission metrics. For example, with SF7, we get the lowest datarate of 262 bps and the lowest **SNR** -137 dbm. In addition, Fig. 3.1b shows that the maximum packet size that can be transmitted using SF12 is 51 bytes.

2.2 Radio performance

To enable **IoT** devices to transmit their data to the cloud in good conditions through wireless networks, applications requirements such as **DR**, **PDR** and **ToA** should be improved to allow network controllers to deal with the diversification of **IoT** applications. We report here the main radio performance metrics considered in our work.



(a). LoRaWAN transmission quality.



(b). LoRaWAN transmission quality with payload size.

Figure 3.1. LoRaWAN transmission metrics.

2.2.1 Received Signal Strength Indicator (RSSI)

The power level measures the power of a signal as a function of its ratio to another standardized value. The abbreviation dB is often combined with other abbreviations to represent the values that are compared. Here are two examples:

- dBm The dB value is compared to 1 mW.
- dBw The dB value is compared to 1 W.

$$P_{[db]} = 10 * \log(\text{signal}) \tag{3.1}$$

Where log: is the logarithm function base 10 and the signal is the power of the measured signal.

For example, if you want to calculate the power in dB of 50 mW:

$$P_{[db]} = 10 * \log(50) = 10 * 1.7 = 17 \text{ dBm} \tag{3.2}$$

The receiver sensitivity (in dBm or mW) is defined as the minimum signal power level with an acceptable BER that is necessary for the receiver to accurately decode a given signal. This is usually expressed with negative values depending on the data rate. For

example, a base station may require an **RSSI** of at least -91 dBm at 1 MB and even higher power -79 dBm to decode 54 MB. This metric measures the received signal sensitivity of **LoRa** gateways [18], it is the relative received output power (dB).

$$\mathbf{RSSI}_{[\text{dBm}]} = -174 + 10 \log_{10} BW + NF + SNR \quad (3.3)$$

Where BW, NF and SNR are Bandwidth, Noise Factor and Signal to Noise Ratio, respectively

2.2.2 Signal to Noise Ratio (SNR)

The noise is any signal that interferes with the transmitted signal. Noise can be the result to other signal processing functions as cordless phones, microwave devices, etc. The noise level is the amount of interference in the wireless environment. Typical environment noise range between -90dBm and -98dBm with little ambient noise. This value may be even higher if there is a lot of RF transmissions on the same spectrum. The **SNR** is defined as the ratio of the transmitted power over the ambient energy present (noise floor). To calculate the **SNR** value, we compute the difference between signal power and the noise power. A positive value of the **SNR** ratio is always better. For example, let's say that the signal power is -55dBm and the noise power is -95dBm. The difference of signal (-55dBm) + noise (-95dBm) = 40db. This means that the **SNR** is equal to 40 db. Note that in the above equation we are not merely adding two numbers, but we compute the difference between the signal and noise power. The lower the number, the lower the difference between transmitted and noise power, which in turn means lower quality of signal. The higher the difference between signal and noise means that the transmitted signal power is much higher than the ambient noise floor, thereby making it easier for the receiver to decode the signal. Table 3.5 represents the **SNR** margin required to mitigate interference between SFs with a capture effect equal to 6dbm. According to the log-distance path loss model, the **SNR** can be calculated according to Equation 3.4:

$$\mathbf{SNR}_{[\text{dBm}]} = P^{tx} - L_{pld0} - 10 \alpha \cdot \log(d/d_0) + 174 - 10 \log_{10} BW - NF \quad (3.4)$$

Where, L_{pld0} : ensemble average value, α : path loss exponent and d_0 : reference distance

The signal attenuation (or signal loss) occurs when the signal passes through air from the transmitter to the receiver. The loss of signal strength is more significant when the signal passes through physical obstacles. A transmission power of 20 mW is equivalent to 13 dBm. Therefore, if the transmitted power at the entry point of a plasterboard wall is equal to 13 dBm, the signal strength will be decreased to 10 dBm when exiting that wall.

2.2.3 Data Rate (DR)

The relationship between the desired Data Rate (**DR**), the Symbol Rate (**SR**), the Coding Rate (**CR**), and the Chip Rate (**HR**) (or bandwidth) for **LoRa**, is presented in Equation 3.5 :

$$\begin{aligned} \mathbf{SR} &= \frac{\mathbf{BW}}{2 \mathbf{SF}} \\ \mathbf{BR} &= \mathbf{SR} \cdot \mathbf{SF} \\ \mathbf{DR} &= \mathbf{BR} \cdot \mathbf{CR} \end{aligned} \quad (3.5)$$

	SF_7	SF_B	SF_9	SF_{10}	SF_{11}	SF_{12}
SF_7	- 6	16	18	19	19	20
SF_8	24	- 6	20	22	22	22
SF_9	27	27	- 6	23	25	25
SF_{10}	30	30	30	- 6	26	28
SF_{11}	33	33	33	33	- 6	29
SF_{12}	36	36	36	36	36	- 6

Table 3.5. Energy matrix [108].

2.2.4 Bit Error Rate (BER)

This metric considers the reliability of communication. It describes the extent at which the transmitted data is fair at the receiver side.

2.2.5 Time on Air (ToA)

It measures the transmission delay taken by one packet to reach the Gateway [10]. The ToA is computed using the Equation 3.6 given by [236]:

$$ToA_{[s]} = \frac{2^{SF}}{BW} ((NP + 4.25) + (SW + \max(J, 0))) \quad (3.6)$$

with:

$$J = \left\lceil \frac{8PS - 4SF + 28 + 16CRC - 20IH}{4(SF - 2DE)} \right\rceil (CR + 4)$$

where:

- Number of Preamble Symbols (NP) = 8 if LoRa
- Synchronization Word (SW) = 8 if LoRa, 3 if GFSK
- Cyclic Redundancy Check (CRC) = 1 if uplink
- Indicator of Header (IH) = 0 if header, 1 else
- DE = 1 if ADR active, 0 else

In our simulation, we set NP and SW equal to 8. As the ADR control system takes the recent received packets (uplink packets), we put CRC to 1 and IH to 0.

2.2.6 Transmission Energy (E^{tx})

It measures the amount of energy consumed to transmit one packet using the following equation:

$$E_{[j]}^{tx} = ToA_{[s]} * P_{[w]}^{tx} * 3.0_{[v]} \quad (3.7)$$

For example when a device sends a packet with 14dbm and with a ToA equal to 0.076s, the energy consumed to send such a packet will be 0.076s x 25 mW x 3v = 5.7 mj.

3 Problem statement

We aim in this section to discuss the problem of transmission selection in depth to allow devices to send their data with the highest quality of service. As the number of In-

Internet of things (IoT) devices continues to grow permanently, wireless resources still the same. For this reason, novel ideas need to be explored to allow the same network to transport heterogeneous data transmitted by devices. To deal with this problem, we thought to experimentally divide network resources (wireless transmission settings) based on the Quality of Service (QoS) that they offer. Network engineers are continuously confronted to the large number of possible transmission settings that should be tuned and adapted to the data that is going to be sent and also to environment conditions. The Problems related to wireless transmission settings selection are not only due to their size but also to their diversity and complexity. This complexity is formally represented by potentially many factors that few of them are known but most of them still unknown. Dealing with the large number and variety of transmission settings requires the ability to organize them into useful classes or clusters. Recent studies in networking strongly suggest that future network function should deal with the complexity of this problem by isolating network resources based on the requirement of IoT devices. Rather than isolating network resources like in the cellular network, we aim in this chapter to distinguish between the quality of each transmission setting using pattern recognition algorithms. Grouping all possible settings into categories that share some key features (qualities) is mandatory in our thesis to overcome state of the art solutions in the next chapters. In fact, all state of the art contributions are based on the same vision, which is "sharing network resources equally between devices". The problem with such a vision is that IoT devices have to target the same uplink state (which is supposed to be the best one) which drives to an average data rate that will not satisfy all devices. To alleviate this problem, we aim in this chapter to recognize the good, the bad and the medium transmission settings to be able to make IoT devices target only the cluster of transmission settings that fit the requirements of their applications and not all the settings like in state of the art. Given the wide diversity and complexity of transmission settings to be clustered, we try in this chapter to recognize their qualities as a collection of clusters sharing common traits. The main idea behind this process is the notion of distinguishability. This means, for a particular decision making purpose, transmission settings in one cluster need to be differentiated from other settings in other clusters based on the Received Signal Strength Indicator (RSSI), the Signal to Noise Ratio (SNR), the Time on Air (ToA), and the Bit Error Rate (BER) that they offer.

We aim here to discuss the problem of clustering transmission settings to create knowledge about the quality level of each transmission setting. It is important to note that we will not create of classifiers by means of supervised methods. In fact, we assume that the quality of transmission settings are not known in advance and are not described neither by a set of axioms nor by labels. We discuss, instead, methods of unsupervised classification based on concepts and ideas from fuzzy-set theory and pattern recognition skills. This assumption is somewhat misleading and motivated solely by the lack of mechanisms that are able to create these axioms and labels accurately. The clustering process is managed by the notions of similarity or, trait sharing, to discover the clusters that may shed light on hidden patterns in the dataset. In our context, the patterns disclose the quality level of transmission settings. Quite often, we aim to discover clusters having the QoS metrics that are similar to others within the cluster but dissimilar to those outside it. This objective, seeks to map transmission settings with the same quality to the same cluster. Which means that, settings in the same cluster will not change considerably the uplink state as they have the same RSSI, SNR, ToA, and BER. This view, seeking to separate traffics generated by transmission settings in each cluster, will be necessary in the following chapters to converge to the optimal set of transmission settings.

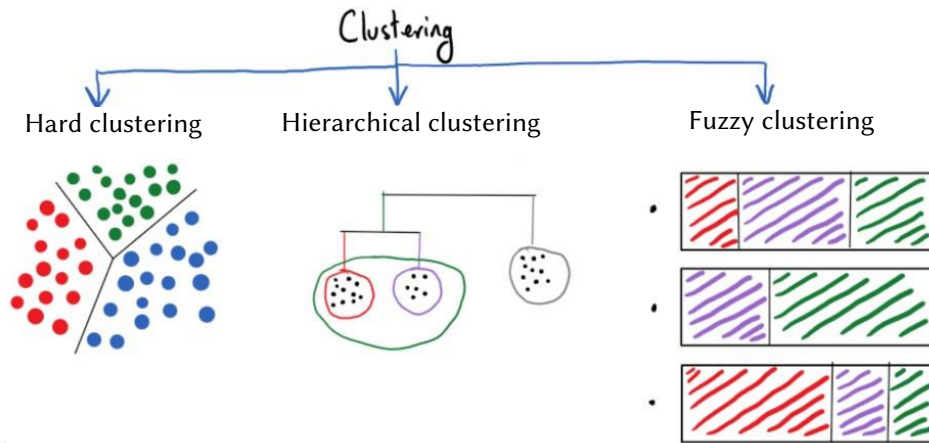


Figure 3.2. Difference between Fuzzy and hard clustering.

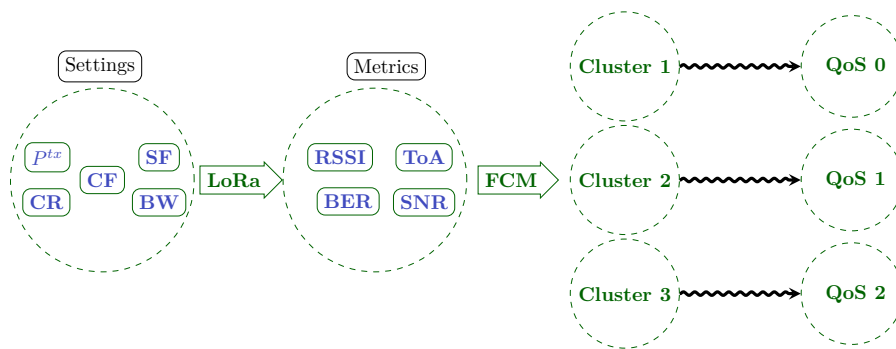


Figure 3.3. Fuzzy C-Means (FCM) clustering of LoRa transmission settings.

Beyond partitioning large datasets into subsets with common traits, what matters in our thesis is the relationship between one item in a cluster and other clusters. From this viewpoint, the clustering process that we need is not merely a collection of clusters of samples but, a structure that, as a whole, yields important insights about the membership degrees of transmission settings to all clusters to disclose at which extent they belong to each cluster. These structures, include important relations between items and clusters. They often allow items to belong to multiple clusters while not requiring every item to belong to one and only one cluster as shown in Fig. 3.2.

We highlight in Fig. 3.3 the main steps of the clustering process to generate the clusters of transmission settings with the same quality. We consider in this chapter only the quality of the signal without taking into account packets collisions that could occur between simultaneous transmissions. This part will be studied in the next chapters using the outcomes of the clustering process.

4 Fuzzy C-Means (FCM) clustering of LoRa transmission settings

We use the FCM clustering algorithm [119] in our work to measure the level at which a given setting matches applications requirements. FCM is an unsupervised clustering algorithm commonly used for features analysis. From these feature spaces, the algorithm classifies the data points into clusters. In our case, the points are networks' settings, the features are Quality of Service (QoS) metrics and the clusters are the recognized quality

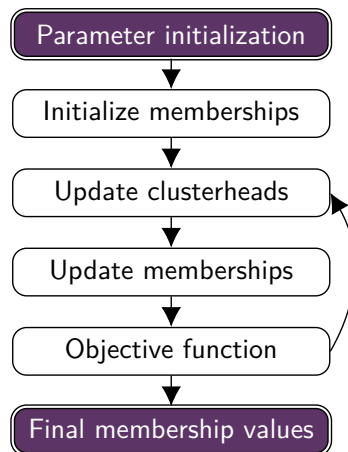


Figure 3.4. The main clustering functions.

levels. Unlike hard clustering algorithm like k-means, Fuzzy C-Means algorithm is able to label the features to more than two clusters and generate values that disclose the extent at which each feature belongs to each cluster. Particularly, in non-fuzzy clustering (or hard clustering) process, the items are divided into different clusters where each item can only belong to exactly one cluster. In fuzzy clustering, these items can potentially belong to multiple clusters at the same time. For example, a transmission setting "x" with a high Signal to Noise Ratio (SNR) and a high Time on Air (ToA) can belong to the cluster with a high quality constraints since it offers a high SNR. However, it can also belong to another cluster with lower quality constraints since it offers a high ToA so a low data rate. In our context, transmission settings are considered good or bad to a certain degree regarding their membership degrees to different clusters. Hence, instead of making the transmission setting "x" belong to the first cluster [cluster1 = 1] and not the second one [cluster2 = 0], it can belong to both of them [cluster1 = 0.6] and [cluster2 = 0.4] at the same time with a degree of membership. These values are normalized between 0 and 1. Such knowledge is mandatory in our study to build a prior knowledge about the consequence of selecting any transmission setting on the quality of the network.

In our context, we build the prior knowledge about the quality of transmission settings by dividing the set of transmission settings to a set of clusters. We map each setting to the cluster that offers the same uplink quality based on the measured QoS metrics. Each transmission setting is projected to a point in a three-dimensional space based on their QoS coordinates. The clustering process is achieved by minimizing the cost function that depends on the distance between settings coordinates and the cluster-heads. At the end of the clustering process, each transmission setting is assigned to the clusters based on their membership-degrees to each cluster. Proceeding this way, when a transmission setting is used by an End Device (ED), the probability that the quality of the transmission link will fit the required quality is known in advance through the membership-degrees matrix. We relate in this section the main functions used to generate the membership-degrees matrix and the cluster-heads matrix using FCM.

Fig. 3.4 and Algorithm 3.1 summarize the application of FCM clustering.

The FCM clustering aims to update the values of the membership matrix M and cluster heads positions H . The algorithm converges after a number of iterations when the threshold error ϵ is reached. The membership values m_{ij} of each setting to each cluster is fuzzy between [0-1].

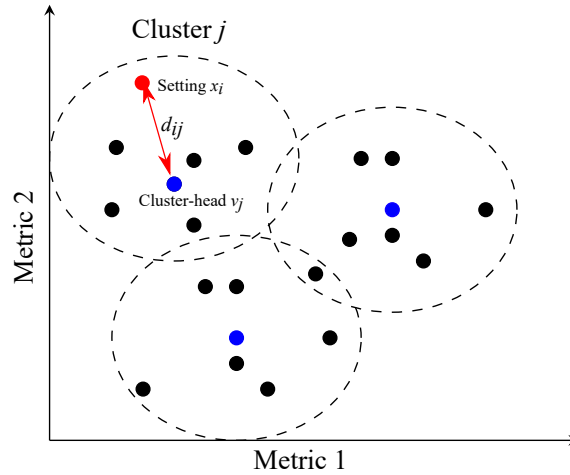


Figure 3.5. Distance between cluster heads and transmission settings.

Algorithm 3.1 Fuzzy C-Means (FCM) clustering algorithm

- 1: **Input:** $X = [x_{11}, \dots, x_{np}]$
 - 2: **Output:** (\mathbf{M}, \mathbf{H})
 - 3: $t = 0$
 - 4: **while** $F_m(\mathbf{M}_t, \mathbf{H}_t) > \varepsilon$ **do**
 - 5: $t = t + 1$
 - 6: Update \mathbf{H}_t from Equation 3.10
 - 7: Update \mathbf{M}_t from Equation 3.9
 - 8: $(\mathbf{M}, \mathbf{H}) = (\mathbf{M}_t, \mathbf{H}_t)$
-

Let n be the number of all LoRa transmission settings (items). Let p be the number of QoS metrics (features) (Bit Error Rate (BER), ToA and Received Signal Strength Indicator (RSSI)). $X = [x_1, \dots, x_i, \dots, x_n]$, with $x_i = [x_{i1}, \dots, x_{ik}, \dots, x_{ip}]$ is a set of p measured QoS metrics of n settings with $x_{ik} \in \mathbb{R}$, $1 \leq k \leq p$, $1 \leq i \leq n$. The FCM algorithm takes as input X and generates two sets: \mathbf{M} and \mathbf{H} . $\mathbf{M} = [m_1, \dots, m_i, \dots, m_n]$, with $m_i = [m_{i1}, \dots, m_{ij}, \dots, m_{ic}]$ is a set of membership values of n settings to c clusters with $m_{ij} \in \mathbb{R}$, $1 \leq j \leq c$. $\mathbf{H} = [h_1, \dots, h_j, \dots, h_c]$, with $h_j = [h_{j1}, \dots, h_{jk}, \dots, h_{jp}]$ is a set of cluster heads of p metrics and c clusters with $h_{jk} \in \mathbb{R}$.

4.1 Objective function

The objective of the FCM algorithm is to find a set of membership values \mathbf{M} and a set of cluster heads \mathbf{H} that minimize the objective function F [119].

$$\min_{(\mathbf{M}, \mathbf{H})} \left\{ F_f(\mathbf{M}, \mathbf{H}) = \sum_{j=1}^c \sum_{i=1}^n \mathbf{m}_{ij}^f \cdot \|\mathbf{x}_i - \mathbf{h}_j\|^2 \right\} \quad (3.8)$$

- Constraint: $\sum_{j=1}^c \mathbf{m}_{ij} = 1, \forall i$
- Degree of fuzzification: $f > 1$

At the beginning of the process, the clusterheads (blue point in Fig. 3.5) are generated randomly. At each iteration, the distance between these points and items (transmission settings) coordinates is updated to decrease the distance between them. After a number

iterations, the clusterheads will be located at the gravity center of each cluster to reduce the mean distance between them and settings coordinates. Once the distance remains stable which mean that the clusterheads are stable, the algorithm converge and the clustering process is stopped. The final distance between clusterheads and settings coordinates (RSSI, ToA, SNR, .etc) highlights the membership of each setting to the clusters.

4.2 Membership matrix

$$[\mathbf{M}] = \begin{array}{c} \text{setting 1} \\ \vdots \\ \text{setting n} \end{array} \begin{bmatrix} \text{cluster 1} & \dots & \text{cluster c} \\ m_{11} & \dots & m_{1c} \\ \vdots & \ddots & \vdots \\ m_{n1} & \dots & m_{nc} \end{bmatrix}$$

To get the membership values of each setting to different clusters, we use the Equation 3.9 to update at each iteration the membership values [119].

$$\mathbf{m}_{ij} = \left[\sum_{j'=1}^c \left(\frac{\|\mathbf{x}_i - \mathbf{h}_{j'}\|}{\|\mathbf{x}_i - \mathbf{h}_j\|} \right)^{\frac{2}{f-1}} \right]^{-1}, \forall j, i \quad (3.9)$$

4.3 Cluster heads

A cluster-head is a vector of the measured metrics that are close to all the measured metrics of the same cluster and are calculated using Equation 3.10. At the beginning of the clustering process, cluster-heads coordinates are initialized randomly and are updated at each step to be closer to the items that belong to the same cluster. When the algorithm converges, the cluster-heads coordinates remain stable, stopping this way the learning process. Once the FCM clustering algorithm converges, the transmission settings can be ranked based on their membership-degrees to the clusters. Thus, the network controller is able to assign the best transmission setting among all the settings available in each cluster [119].

$$\mathbf{h}_{jk} = \left[\frac{\sum_{i=1}^n \mathbf{m}_{ij}^f \cdot \mathbf{x}_{ik}}{\sum_{i=1}^n \mathbf{m}_{ij}^f} \right], \forall j \quad (3.10)$$

4.4 Performance index

In order to measure the performance of the clustering process, we use the Equation 3.11 to compare the euclidean distance between the theoretical gravity center of each cluster and the clusterheads.. If the euclidean distance between cluster heads h_j and the measured metrics x_i is the same as the euclidean distance between cluster heads h_j and the average measured distance $\bar{\mathbf{x}}$, this means that the clusterhads are in the gravity centers of clusters. [119]

$$\min_{(c)} \left\{ P(c) = \sum_{j=1}^c \sum_{i=1}^n m_{ij}^f \left(\|\mathbf{h}_j - \mathbf{x}_i\|^2 - \|\mathbf{h}_j - \bar{\mathbf{x}}\|^2 \right) \right\} \quad (3.11)$$

where:

$$\bar{\mathbf{x}} = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i \quad (3.12)$$

5 Simulation settings and results

Setting	Values
CR _[#]	{1,2,3,4}
BW _[kHz]	{125,250,500}
SF _[#]	{7,8,9,10,11,12}
PS _[B]	[30, 200]
SNR _[dbm]	{-40,-30,-20,-10,0}

Table 3.6. Long Range transmission parameters

Our simulation setup has been carried out in two separated steps. In the first step, we assess the quality of all the combination of transmission settings with regard to different parameters values: **BW**, **CR**, **PS** and **SNR** (see Table 3.6). Since it's difficult to compute the **SNR** that depends on the Transmission Power (P^{Tx}) and the distance, we use it as input to compute the Received Signal Strength Indicator (**RSSI**) and also as output of the first step since it is also a metric that assesses the quality of the signal. In fact, in real environment, the gateways are able to compute the **SNR**, the **RSSI**, the Bit Error Rate (**BER**) and the Time on Air (**ToA**) that we feed to the Fuzzy C-Means (**FCM**) algorithm to recognize the transmission settings with good, bad and medium qualities. In our simulation, we use the same Quality of Service (**QoS**) metrics as output of the first step to match real environment cases.

In the second step, we use the measured **QoS** metrics in the first step to recognize the transmission settings with good, bad and medium **QoS** metrics. The clustering process is based on the difference (distance) between the **SNR**, the **RSSI**, the **BER** and the **ToA** of each setting. Based on this difference, **FCM** should be able to cluster the transmission settings with the same metrics to the same cluster. The clustering process has been implemented as presented in the previous section with a fuzzification degree equal to 1.2 and a threshold error $\epsilon = 0.02$.

Our simulation results illustrate the relationship between **LoRa** transceiver's parameters and the **QoS** metrics as well as applications requirements. The **FCM** clustering characterizes the impact of the parameters' selection on different **QoS** metrics. The results obtained after the **FCM** clustering are the membership values m_{ij} of points i (settings) to cluster j . Three clusterheads are generated to represent a set of settings in the same cluster. Table 3.7 shows a sample of points featured by **BER**, **RSSI** and **ToA** metrics. The fuzzy membership values are obtained based on three clusters C0, C1 and C2.

The **FCM** algorithm updates the membership values until the objective function returns a negligible error value *i.e.*. After which, the clusterheads positions remain in the same position after two successive iterations. We set the error threshold ϵ empirically to 0.02. As shown in Table 3.7, we found that settings with a high **RSSI**, low **BER** or low **ToA** are mapped the same cluster: C2.

We found also that settings with a high **SF** and a low **SNR** have a high membership values to C2, this proves that **LoRa** transceiver is more resilient against noise when **SF** is high

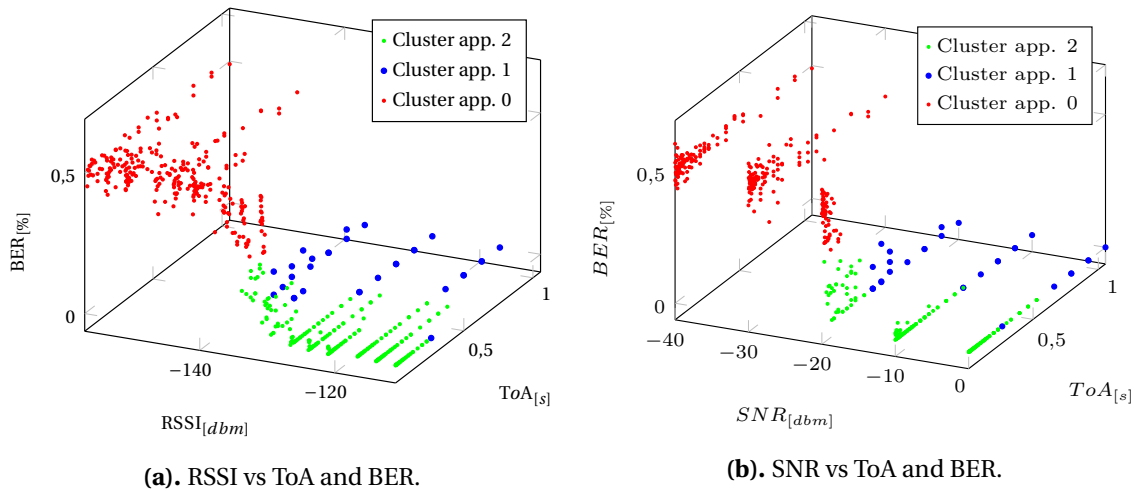


Figure 3.6. RSSI and SNR vs ToA and BER.

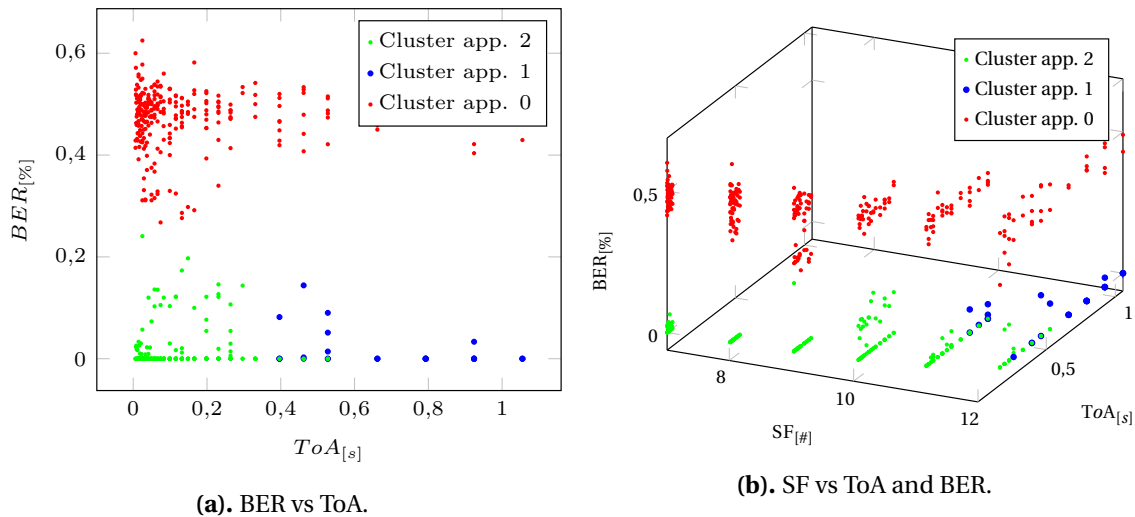


Figure 3.7. Relationship between SF, ToA and BER.

(~12). In another side, when the **RSSI** is low or the **BER** and **ToA** are high, the settings are mapped to cluster C0 that requires a low **QoS**. Based on these findings, Long Range Wireless Access Network (**LoRaWAN**) network servers can easily rank settings that belong to the same cluster and then assign the best one to end-devices. Note that borderline points with equal membership values for two clusters fits at the same time the requirements of two clusters.,

Table 3.7 shows also that most of the settings have a high membership degrees for one cluster and low membership degrees to other clusters. For example, the setting BW125, SF11, PS30, SNR-20, has a membership value of 0.91 for cluster 2 and 0.045 for the others. This means that it is the best choice of applications of cluster 2 when end-devices are far from the gateway.

Table 3.8 represents the final clusterheads features, *i.e.* **QoS** metrics, obtained after the convergence of the **FCM** algorithm. The clusterhead of (C2) has the lowest **BER** and **ToA** and the highest **RSSI** which match well applications with high **QoS** requirements. Whereas, the clusterhead of (C0) has the lowest **RSSI** and the highest **BER** and **ToA** which characterize a set of applications with low **QoS** requirements.

P^{tx}	CR	BW	SF	PS	SNR	BER	RSSI	ToA	C_0	C_1	C_2
~11	2	125	11	30	-20	0.08	-137	0.39	0.045	0.045	0.91
~14	3	125	11	70	-10	0.01	-117	0.46	0.015	0.492	0.492
~14	2	250	10	40	-10	0.2	-127	0.33	0.104	0.791	0.104
~11	2	250	12	90	-20	0.05	-134	0.46	0.030	0.004	0.965
~8	1	500	7	50	-20	0.5	-131	0.09	0.965	0.030	0.003
~11	3	500	12	110	-20	0.1	-131	0.26	0.153	0.734	0.113

Table 3.7. Membership degrees of LoRa transmission settings.

Cluster	BER	RSSI	ToA
2	0.05	-123	0.25
1	0.10	-122	0.50
0	0.43	-150	0.17

Table 3.8. Cluster heads features

Table 3.9 shows the clustering performance of the FCM algorithm. We measured the execution time, the homogeneity and the mutual info score of the fuzzy clustering process and affinity propagation clustering algorithm. The high value of homogeneity indicates that the clustering results match with the expected number of clusters. The same for mutual info score which indicates that the labeling process converge to the same final labels as the affinity propagation clustering algorithm.

Fig. 3.6a illustrates a cloud of featured points grouped in three colored clusters. Each point is a vector of three QoS metrics RSSI, ToA, BER which are calculated based on a set of settings: SF, BW, PS, SNR.

As the main goal of our study was to map all the combination of parameters to the three types of applications based on their QoS requirements, Fig. 3.6a shows clearly the correlation between the memberships values assigned to transmission setting and the required BER, ToA and RSSI of applications. Results show also that settings with a high membership degree to cluster 2 have an RSSI between -135 dBm and -110 dBm, and a BER lower than 0.2% (see Fig. 3.7a). Cluster 1 could be used for applications with a high sensitivity to BER and lower sensitivity to RSSI. In another hand, cluster 0 has the worst RSSI compared to the two other clusters and also the worst BER.

The same Figure plots the relationship between the BER and the ToA of different settings. The same settings of cluster 2 which are presented in Fig. 3.6a have the lowest ToA. This makes them suitable for applications with low latency requirements. Settings of cluster 0 seem to have the same QoS as settings of cluster 1 but Fig. 3.6a shows that they have a higher ToA, such settings should not be used by delay sensitive applications.

Fig. 3.7b shows the impact of the SF on our clustering process. The best candidate settings that match applications with a high QoS requirements are the green points and they are scattered for all SF levels [7-12]. However, when we increase the SF, settings are more mapped to cluster 1 and 2, this is mainly due to the short transmission delay (ToA). Settings with a high BER are mapped to cluster 0 when the SF is close to 7, the reason is that SF 7 is more vulnerable to noise (SNR).

Performance metrics	Value
Time (s)	0.0102
Homogeneity score	0.984
Mutual info score	0.9729

Table 3.9. Clustering performance.

6 Conclusion

The main challenge addressed in this work was to see whether pattern recognition tools like FCM are able to recognize from all possible wireless transmissions that there are " n " different Quality of Service (QoS) levels. We resolved one of the main research issue to recognize the network settings that have the same QoS as required by Internet of things (IoT) applications. Our contribution highlights the effectiveness of applying the Fuzzy C-Means (FCM) clustering algorithm to select the transmission setting that best fit a given application requirement. Simulation results have shown that the FCM clustering algorithm is efficient and is able to cluster all possible settings to the expected three clusters. Furthermore, settings have been ranked based on their membership values to clusters. The proposed process has been developed to present and design a solution that consider Long Range (LoRa) parameters (Spreading Factor (SF), Bandwidth (BW) and Packet Size (PS)), environment conditions (Signal to Noise Ratio (SNR)) and QoS metrics (Time on Air (ToA), Bit Error Rate (BER) and Received Signal Strength Indicator (RSSI)) that are required by applications. We plan in the next chapter to use the knowledge acquired by FCM as an exploration step to be able to exploit directly the best transmission settings since we know now at which link quality each setting will lead.

4 | Online Self Reconfiguration of LoRa Network with Q-learning and Fuzzy C-Means Clustering

Quotation

To have knowledge, add things every day. To have wisdom, remove things every day. - Tao te King

Pour avoir de la connaissance, ajouter des choses chaque jour. Pour avoir de la sagesse, enlever des choses chaque jour - Tao te King

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Abstract

Long Range (LoRa) is a proprietary modulation technique that uses Chirp Spread Spectrum (CSS) modulation for low power and wide area communications. Despite the advantages of LoRa technology, the solutions proposed in the literature to select transmission parameters that maximize the uplink data rate, remain limited to maximize the uplink traffic. In this chapter, we look upon additional parameters such as the Bandwidth (BW) and the Coding Rate (CR) and we apply the Q-learning algorithm to update the policy that drives to the selection of the optimal settings. However, to be able to run this algorithm, we need to know at which uplink state each setting could lead. To alleviate this problem, we take advantage of our clustering process in the previous chapter to know at which state each action could lead by knowing at which cluster each setting belongs. As the solution

should cope with different scenarios, we vary the number of End Device (ED), Base Station (BS), Packet Size (PS), Packet Rate (PR) and we compare our solution with EXP3, ADR and EXPLoRaTS algorithms. Simulation results show that Q-learning with Fuzzy C-Means (FCM) clustering preprocessing improves better several Quality of Service (QoS) metrics including the Data Rate (DR), Packet Delivery Ratio (PDR), Time on Air (ToA) and Transmission Energy (E^{tx}). Thus, the PDR and the DR were improved by 25%, the ToA was reduced by 40% and E^{tx} was reduced by 20%.

1 Introduction

Unlicensed bands are more and more used by all kinds of wireless technologies (Wi-Fi, LTE-U, ZigBee, Z-Wave, Bluetooth, LoRaWAN, Sigfox, Ingenu, Weightless, etc.). This heavy use of unlicensed bands will certainly cause performance decay due to contention problems. Efficient Medium Access Control (MAC) protocols allow devices to avoid such behavior by exchanging extra control messages (signaling overhead). However, due to the high energy consumption required to run such protocols in Internet of things (IoT) devices, new approaches should be investigated using simple ALOHA-based mechanisms [78] with a lower signaling overhead. In this article, we analyze the performances of adapting Long Range (LoRa) transmission settings to enhance the quality of the uplink traffic using the Q-learning algorithm.

We aim in this work to maximize the uplink datarate of LoRa devices and compare it with the solutions proposed in the literature such as Long Range Wireless Access Network (LoRaWAN) alliance that proposed Adaptive Data Rate (ADR) algorithm [71]. Their mechanism adjusts periodically the Transmission Power (P^{tx}) and the Spreading Factor (SF) according to the Received Signal Strength Indicator (RSSI). However, this algorithm [71] suffers from scalability issues and fails to maximize uplink data transmissions in a dense network. In fact, to be able to maximize well the Data Rate, the uplink state between each end-device and the Gateway should be measured and characterized in advance to speed up the convergence and achieve better DR. For this reason, we use characterization process that was proposed by Ruspini et al. [141] to know at which state each action will lead by knowing at which cluster each action belongs.

To deal with the randomness of the wireless environment, the research community has a consensus that future networks must be flexibly designed to deal with this challenge. Therefore, we use in this work an online reconfiguration of transmission settings to make the network smart enough to converge by itself to a set of parameters that best fit environment conditions. For this reason, Reinforcement Learning (RL) algorithms are good candidates to reinforce the selection of the suitable transmission settings after each transmission.

In this chapter, we investigate the problem of LoRa transceivers' reconfiguration to enhance the quality of the uplink traffic. We use the Q-learning algorithm to update the policy that drives to select the transmission settings that maximize better the datarate. To know at which state each setting leads, we use the membership of this setting to the cluster with the highest membership degrees. This means that, if a setting belongs to the cluster of good settings, then, the state of the uplink will be good.

Our main contributions are as follows:

- We propose to use the Q-learning algorithm to maximize the DR of LoRa devices.

- We use the Fuzzy C-Means (FCM) membership degrees to know at which state each transmission setting will lead.
- Through intensive simulations, we assess and compare the DR, Packet Delivery Ratio (PDR), Time on Air (ToA) and Transmission Energy (E^{Tx}) of Q-learning with Exponential weights for Exploration and Exploitation (EXP3), ADR, EXPLoRaTS algorithms.

To overcome the limitation of the default ADR scheme (see Algorithm 4.1) of LoRaWAN alliance [71] that suffers from a weak DR, many works in literature proposed to use either heuristic or machine learning algorithms. For example, two different SF allocations algorithms (EXPLoRaSF and EXPLoRaTS) have been presented in [59] as an alternative to ADR. The proposed algorithms select an SF based on the number of connected devices, the distance and the RSSI, allowing a better equalization of the ToA among the SF channels. Specifically, authors attempt to use a high DR to offload the traffic of the less congested highest SF. EXPLoRaSF aims to efficiently distribute the SF among end-devices. It selects the SF with regard to the total number of connected nodes. Particularly, it equally allocates the SFs to n nodes based only on the RSSI, where the first $n/6$ nodes with the highest RSSI get SF 7 and then the next $n/6$ nodes get SF 8, etc. EXPLoRaTS is more dynamic than EXPLoRaSF since it equalizes the ToA of the packets that were transmitted with different SF.

In the same context, a decentralized management of LoRaWAN has been proposed by Ta et al. [182]. The authors propose to use EXP3 algorithm to maximize the network throughput. They increase the PDR while decreasing energy consumption of each node. However, such an approach requires additional energy consumption for computation and training in end-devices since they are very limited to run such tasks.

All previous works proposed in the literature to maximize the DR proved their weakness since they didn't measure the impact of each transmission setting on the uplink state. They focus only on limited number of parameters and discuss the simulation results without explicit assessment of the quality of the transmission parameters. In this work, we propose to maximize the utility of the network and to enhance the quality of the uplink traffic. The outputs of FCM clustering are given as input to Q-learning to know at which state each action could lead. In our work, states are the network up-link states and actions are the transmission settings. To validate our work, we evaluate the performances of our solution and we compare it to EXPLoRaTS, EXP3, ADR and the random selection of settings.

The key contributions of this chapter are further reported as follows. First, Section 2 enunciate the problem statement. We introduce EXP3 algorithm in Section 3. In Section 4 and Section 5, we explain how Q-learning with FCM are applied to select the suitable set of transmission settings. Simulation settings and our findings are presented in Section 6. Finally, Section 7 concludes this chapter.

2 Problem statement

We formulate the online selection of the suitable set of configurations as an exploration/exploitation dilemma. We propose to maximize the utility of the network to enhance the quality of the uplink traffic. As the main goal of Long Range (LoRa) end-devices is to send their collected data to the cloud with the highest data rate, network utilization (or utility) function is expressed as the Data Rate of the up-link traffic after each transmis-

Algorithm 4.1 Adaptive Data Rate

```

1: H[j]      ← 0 ∀ j ∈ [0, 19]
2: SNRmargin ← 10 dB
3: SNRthreshold ∈ [-7.5, -10, -12.5, -15, -17.5, -20] dBm
4: SF        ∈ [ 7, 8, 9, 10, 11, 12]
5: Ptx      ∈ [ 2, 5, 8, 11, 14, 17] dBm
6: procedure RECEIVE-PACKET(mSNR)
7:   H[i] = mSNR
8:   i++
9:   if i=20 then
10:    ADJUST-ADR()
11:    i ← 0
12: procedure ADJUST-ADR
13:   margin ← max(H) - SNRthreshold[SF-7] - SNRmargin
14:   Nstep ← round(margin/3)
15:   while Nstep != 0 do
16:     if Nstep > 0 (SNR is good, DR is low) then
17:       decrease SF by steps until SF=7
18:       decrease Ptx by steps until Ptx=2 dBm
19:       Nstep --
20:     else
21:       increase Ptx by steps until Ptx=17 dBm
22:       increase SF by steps until SF=12
23:       Nstep ++

```

sion at time t given by Equation 4.1.

$$U(a) = \begin{cases} \text{DR}(a) & \text{if packet received} \\ 0 & \text{else.} \end{cases} \quad (4.1)$$

While fulfilling the utility requirements, this strategy will maximize the utilization of the scarce radio resources. However, finding the transmission settings that maximize the utility function is an NP-hard problem [152] for a practical size of network. Thus, to have a lower complexity, we use Reinforcement Learning (RL) algorithms to converge analytically to the optimal transmission settings that maximize the network data rate. Proceeding this way, the Network Server (NS) will be able to learn which transmission setting fits well environment conditions and devices location and updates its configuration accordingly.

With RL algorithms, an agent tries to obtain as much reward as possible by carrying out the most rewarding action among N actions. For example, in Multi-Armed Bandit (MAB) algorithms [249], the rewards of actions are randomly generated according to an unknown distribution. Therefore, they try to minimize the regret values (due to exploration of new actions) to find the most rewarding arms.

We focus in this work on applying the Q-learning algorithm to measure the quality of actions via Q-values. With Q-learning, an agent updates the quality of actions (Q-values) and learns the best policy by exploiting the previous actions and exploring new ones. However, it does not require an initial knowledge about the environment before

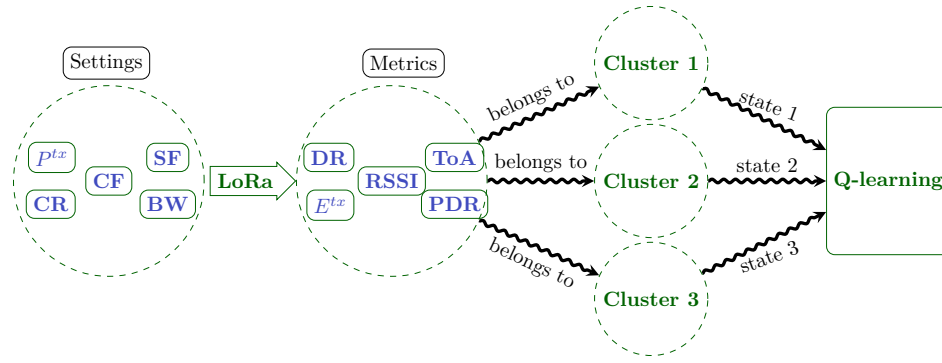


Figure 4.1. LoRaWAN reconfiguration scheme.

starting the learning process. It just requires at which state each action will lead after observing the new state s_{t+1} . Thanks to the clustering outputs in chapter 3, the new state at which action a will lead is known through the quality of the cluster at which action a belongs.

3 Multi-Armed Bandit (MAB)

Notations for Multi-Armed Bandit algorithms
$Q_t(a)$ expected mean of rewards following policy π
$N_t(a)$ number of times action a has been selected before time t
$\pi_t(a)$ selection probability of action a at time t

Table 4.1. Multi-Armed Bandit algorithm notations

MAB algorithms try to maximize the reward of each action based on the previous observations of their rewards. Each action (arm) has an expected or mean reward. Let us call this estimation the action-value of this action. We denote the selected action on time step t as a_t , and the corresponding reward as r_t . The cumulative observed rewards is denoted $G_t(a)$ and computed using the equation bellow:

$$G_t(a) \doteq \sum_{i=1}^t R_i(a) \quad (4.2)$$

The action-value of an arbitrary action a is the expected reward from action a if it will be selected, we denoted it as $Q_t(a)$.

$$\begin{aligned} \mathbf{Q}_t(\mathbf{a}) &\doteq \mathbb{E} \left[G_t(a) \right] \\ \mathbf{Q}_t^* &= \max_a \mathbf{Q}_t(\mathbf{a}) \end{aligned} \quad (4.3)$$

Where, $\mathbb{E}[\cdot]$ is the conditional expectation on the probability $P_t(a)$ of choosing arm a at time t , $P_t(a) = P(a|a_1, \dots, a_{t-1})$. If the value of each action is known, then it would be trivial to solve the k-armed bandit problem: we would always select the action with the highest value. However, as we know only the observed action values G_t and not estimated action values Q_t of each action, the goal of the MAB algorithms is to estimate these values using different approaches: Exponential weights for Exploration and Exploitation (EXP3),

UCB and Thompson, etc. We denote the estimated value of action a at time step t as $Q_t(a)$. We would like $Q_t(a)$ to be as close as possible to the observed average reward of each arm a .

We define in this section the **MAB** problem as follows. There is a fixed number of actions (or arms) n that should be performed. A player has to choose one arm at each discrete time $t \geq 1, t \in N$, denoted as $a \in A$. Selecting arm a at time t yields a reward, $R_t(a) \in R$, and the goal of the player is to maximize the sum of these rewards $G_t(a)$. The sequence of rewards drawn is assumed to be independent and identically distributed with a mean μ_a .

Several types of reward distributions could be considered, such as Gaussian, Exponential, Poisson or Bernoulli distributions. For example, with Bernoulli distribution, $R_t(a) \sim B(\mu_a)$ where $R_t(a)$ is a random variable that represents the reward of action a and $\mu_a = P(R_t(a) = 1)$, the problem parameters $\mu_1, \dots, \mu_k, \dots, \mu_n$ are unknown to the player. Hence, to maximize the cumulated rewards, the player has to learn the distribution that generates these rewards (random variables) to progressively focus on the arm with the highest average reward. Note that, in our context, arms represent different transmission settings and players are the end-devices.

3.1 Epsilon Greedy Approach

A naive approach to estimate well the reward of each arm would be to use an empirical mean estimator of the rewards for each arm and select the arm with the highest estimated mean at each time. This greedy approach (see Equation 4.4) is known to fail since the algorithm will be frozen on the early action with the highest reward. Consequently, the learning process depends only on the first selections. If the first transmission setting fails, the device will never use it again, and if it succeeds, the device will always use it even if other actions could be better.

$$Q_{t+1}(a) = (1 - \alpha) \cdot Q_t(a) + \alpha \cdot \left[Q_t(a) + \frac{R_{t+1}(a) - Q_t(a)}{N_t(a)} \right] \quad (4.4)$$

$$a_t = \operatorname{argmax}_a Q_t(a) \quad (4.5)$$

To overcome this drawback, several algorithms have been proposed in the literature to estimate the mean reward of each arm based on the previously observed reward. We present in the next section one of them called **EXP3** which was recently used to enhance Long Range Wireless Access Network (**LoRaWAN**) Packet Delivery Ratio (**PDR**) in [182].

3.2 Exponential weights for Exploration and Exploitation (EXP3)

EXP3 is one of the known algorithms to solve exploration/exploitation problems. It maximizes the rewards using an unbiased estimation of the cumulative reward at time t to update the selection probability of each action [167] [173]. The algorithm has to control the exploration and exploitation by the parameter $\gamma \in [0, 1]$. A large value means a uniform choice, while a small value means maximizing the instantaneous (estimated) reward.

$$\begin{aligned}
Q_{t+1}(a) &= (1 - \gamma) \cdot \frac{w_{t+1}(a)}{\sum_{a' \in A} w_{t+1}(a')} + \gamma \cdot \frac{1}{|A|} \\
w_{t+1}(a) &= w_t(a) \cdot \exp\left(\frac{\gamma \cdot R_{t+1}(a)}{|A| \cdot Q_t(a)}\right)
\end{aligned} \tag{4.6}$$

Where:

- ▣ $\gamma \in [0, 1]$ controls the exploration and the probability to choose an action “ a ” at round “ t ”.

The algorithm’s regret is updated continuously during the learning process. The parameter γ is called the learning rate. When the learning rate is large, the algorithm exploits more the arm with the highest estimated reward. For small learning rates, the algorithm is more uniform and the algorithm explores more frequently without caring a lot about actual rewards. There are many ways to tune the learning rate, some algorithms make it evolve with regard to the number of times action a has been selected. This allows to explore actions that have never been selected and exploit more the actions that have already been selected.

The learning process is performed using mathematical distributions taking as parameters the estimated reward of each arm. One of the great strengths of MAB algorithms, is the randomness introduced by mixing the exploration and exploitation distributions. Indeed, if an algorithm is deterministic and known to the adversary, it will be simple to rebuild a reward sequence requiring maximum regret. The randomization of MAB choices allows it to protect itself against this type of scenario. However, this will make the algorithm very weak if the arms have similar cumulative rewards but are distributed in different time periods. To deal with this problem, a new method has been proposed based on an implicit exploration [107] using only the Gibbs distribution. This implicit exploration is obtained by replacing the estimation of the cumulative reward by the estimation of the cumulative loss. As the constant exploration has disappeared, the term γ is now used to bias the algorithm and prevent the rewards from being divided by too small probabilities. The more an arm is played, the more its cumulative loss increases, causing an increase in the probability of exploring the other arms.

4 Q-learning algorithm based on FCM clustering

To illustrate the learning process, Fig. 4.2 shows Long Range Wireless Access Network (LoRaWAN) architecture and the interactions between End Devices (EDs), the Network Server (NS) through one or many Gateway (GW). The link from ED to the GWs are the uplink packets with a given transmission setting a . In the downlink side, the NS sends a new suggestion of settings a' to enhance the uplink Data Rate (DR). Thus, we consider the membership degrees of an action to different clusters as the probabilities to jump to the next steps. Whereas, as Q-learning requires from the environment the new state to jump during the learning process and doesn’t require the entire transition probabilities from the beginning, only the new state with the highest membership degree is given as input to jump to the next step.

The interactions between the NS and the wireless environment can be formally defined as a finite Markov Decision Process (MDP). We note: S: a set of states that match the recognized patterns (Quality levels) by the clustering process. A: a set of actions that match

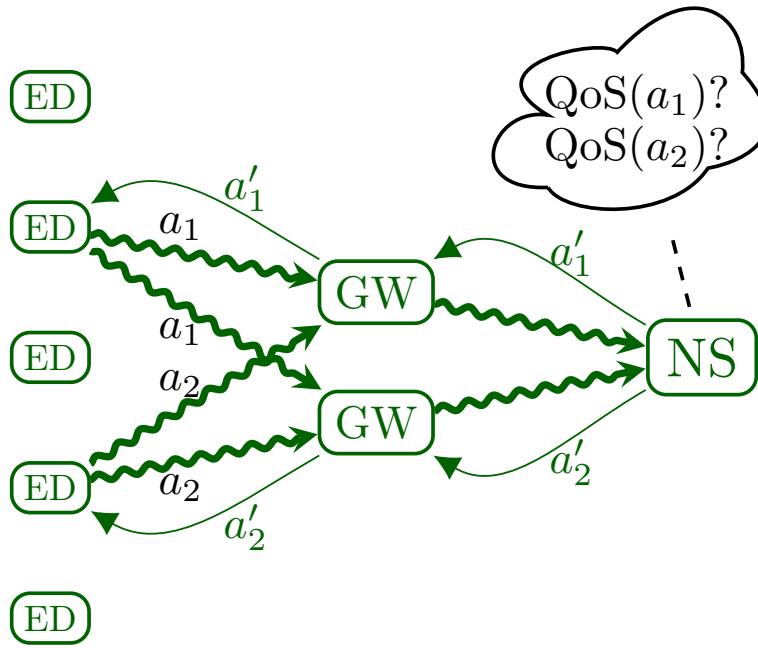


Figure 4.2. LoRaWAN architecture.

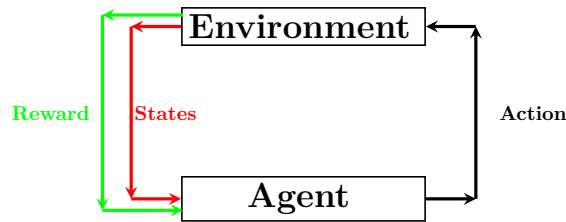


Figure 4.3. Reinforcement learning process.

the transmission settings that we want to optimize, and finally, R : a set of rewards, where $R_t(s, a)$ gives the NS a reinforcement feedback for the state-action pair (s, a) .

Table 4.2 summarizes the general notations used in Q-learning algorithms. The following subsections report how we calculate the cumulative reward and how we get action values (Q-values) and the state at which each action will lead.

- $S = \{s_0, \dots, s_c\}$ is a finite set of states which in our study is a set of uplink state levels.
- $A = \{a_0, \dots, a_n\}$ is a finite set of actions which in our study is a set of possible transmission settings.
- $R_t(s, a)$ is the reward observed when we apply action a on state s . In our case the reward of each action is the gain of DR after each transmission that we compute using the utility function.
- $\gamma \in [0, 1]$ is called a discount factor, it represents the extent at which old rewards should be considered.

Notations for Q-learning and Markov Decision Process	
A	set of actions
a	an action
R	set of all possible rewards, a finite subset of \mathbb{R}
R_t	the reward at time t
t	discrete time step or play number
S	set of all states
$A(s)$	set of all actions available in state s
s, s'	states
π	policy (decision-making rule)
$\pi(s)$	action taken in state s with policy π
$\pi(a s)$	probability of taking action a in state s with policy π

Table 4.2. Notations for Q-learning

4.1 Action-value function of Q-learning

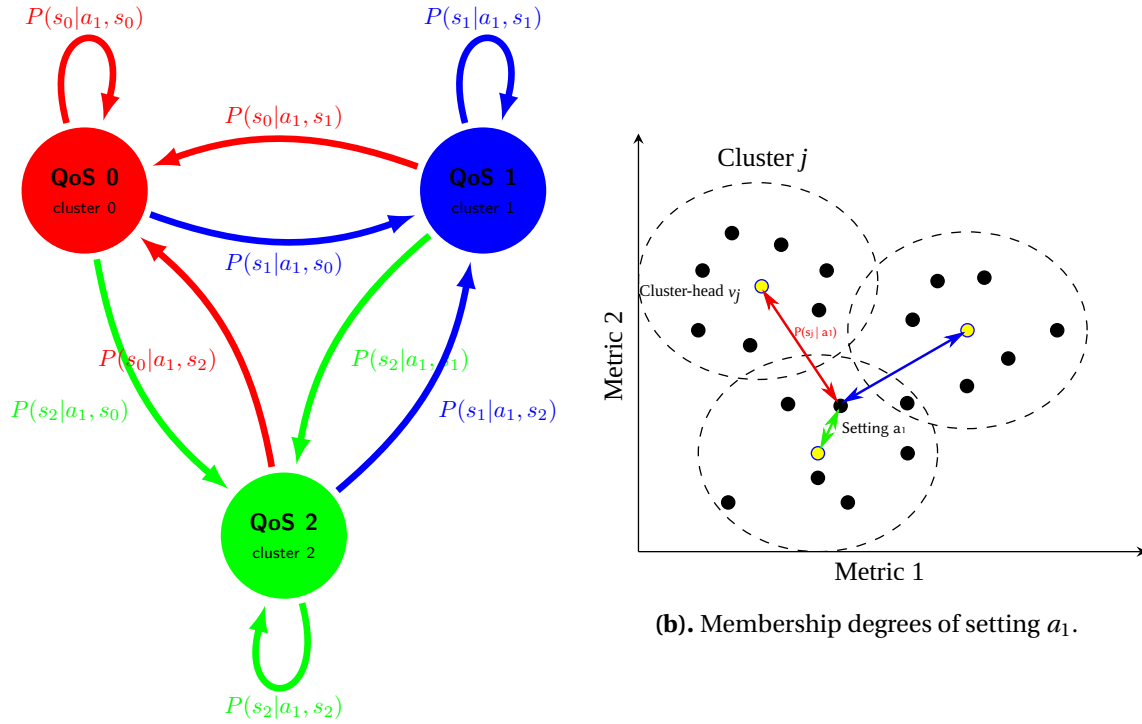
Q-learning is an iterative online learning algorithm that uses the Bellman equation (Equation 4.7) to update its policy. It uses the bellman equation to update its action value function *Q-value* denoted $Q(s, \pi(s))$. It is particularly attractive when state transition probabilities are not known at t_0 when the learning process starts. Nevertheless, according to the Bellman's optimality criterion (Equation 4.8) [163], there is at least one optimal strategy. Hence, after several iterations, the action value function $Q(s, a)$ is guaranteed to converge to $Q^*(s, a)$ [163]. To deal with the complexity of exploring the quality of new actions and exploiting the best explored ones, it combines these two tasks with probability α for the first task (exploration) and $\alpha 1$ for the second task (exploitation).

The Q-learning algorithm requires the new state of environment after performing each action in addition to the reward. The action-value function (*Q-value*) denoted by $Q(s, \pi(s))$ of Q-learning algorithm is the expected long-term discounted reward of state s when strategy π is applied. Proceeding this way, over sufficiently large duration, $Q(s, a)$ is guaranteed to converge to $Q^*(s, a)$ [163]. The ultimate objective of the network server would be to find the optimal strategy (policy) π that maximizes the expected reward considering uplink states. In other words, the objective of the learning process is to find the optimal strategy π that maximizes the action-value function in each state s : After several experimental studies, the controller exploits previously saved Q-values with probability α which we set to 0.9 and explores new actions with probability $1-\alpha$.

$$Q_{t+1}(s, a) \leftarrow (1 - \alpha) \cdot Q_t(s, a) + \alpha \left(R_{t+1}(s, a) + \gamma \cdot \max_{a'} Q_t(s_{t+1}, a') \right) \quad (4.7)$$

$$\pi^*(s) = \arg \max_{a \in A(s)} Q(s, a) \quad \forall s, \pi \quad (4.8)$$

At each transmission, a device with an uplink state s , will try to increase its data rate by selecting action a . To update its policy, it observes the reward R and jumps to the observed new state s_{t+1} . It proceeds step by step and tries to build the best trajectory knowing only the next state at which the current action will lead. The controller learns the



(a). State transitions caused by action a_1 .

Figure 4.4. The probability that a_1 will make the uplink quality jump to QoS_x is measured through the membership of a_1 to clusters x .

optimal Q-value based on the DR of the link at each discrete time-step. At each step, the controller in state s selects action a , earns a reward R and jumps to state s_{t+1} . As actions are selected each time-step, the Q-values are updated using Bellman equation (Equation 4.7).

Algorithm 4.2 Q-learning algorithm based on FCM

- 1: **Input:** $Q(s, a) \leftarrow 0, a_{init}, s_{init}$
 - 2: **Output:** $Q(s, a)$
 - 3: $a \leftarrow a_{init}, s \leftarrow s_{init}$
 - 4: **while** True **do**
 - 5: $a_{t+1} \leftarrow \operatorname{argmax}_{a'} Q(a')$ (Equation 4.8)
 - 6: $s_{t+1} \leftarrow \operatorname{argmax} M[a_{t+1}]$ (From FCM)
 - 7: $R_{t+1}[s, a] \leftarrow U_{t+1}(a)$ (Equation 4.1)
 - 8: $Q_{t+1}[s, a] \leftarrow$ (Equation 4.7)
-

Without knowing at which state each action will lead, Q-learning will not be able to learn which setting can maximize the uplink data rate. For this reason, it requires an additional knowledge about the environment for state transitions. Thus, the probability to switch from one state to another through an action should be observed after performing each action. To take advantage of the power of pattern recognition tools, the new state at which an action leads is recognized through the cluster at with it belongs. Proceeding this way, we consider each resulting cluster as the aggregation of transmission settings that lead to the same uplink state.

For example, Fig. 4.4a shows the state transition probabilities between 3 uplink states. We propose to cluster the transmission settings based on the quality of the link that they offer. Thus, when a transmission setting is performed, the probability that this setting will lead to the three states $QoS_{1,2,3}$ is known through their membership degrees to the clusters $QoS_{1,2,3}$. To find the path (set of actions) that leads to the highest Quality of Service (QoS), we propose in this work to take advantage of our knowledge of the cluster at which each setting belongs to identify the state at which each action leads.

The transmission settings in the same cluster refer to the aggregation of settings with the same uplink state. This means that all transmission settings in cluster QoS 2, for example, will lead to an uplink state equal to QoS 2. This helps the Q-learning algorithm to know at which state action a_1 will probably lead. When a combination of transmission parameters is selected, the link state between EDs and the GW refers to the cluster where each transmission setting was mapped. The advantage of fuzzy clustering compared to hard clustering is the ability to generate membership degrees of each setting to each cluster. Hence, states transitions could be built using these membership degrees which disclose the probability with which an action could lead to each state. Section below describes in details how we compute these transition probabilities.

$$[\mathbf{M}] = \begin{array}{c} \text{state 1} \quad \dots \quad \text{state c} \\ \text{action 1} \\ \text{action 2} \\ \vdots \\ \text{action n} \end{array} \begin{bmatrix} m_{11} & \dots & m_{1c} \\ m_{21} & \dots & m_{2c} \\ \vdots & \ddots & \vdots \\ m_{n1} & \dots & m_{nc} \end{bmatrix}$$

5 Clustering of network settings

To build a prior knowledge about the quality of each Long Range (LoRa) transmission setting, Djoudi et al. [63] proposed a characterization mechanism by clustering a set of LoRa transmission settings based on the measured Quality of Service (QoS) metrics. Based on their findings, we consider the set of settings' vectors as a cloud of points in a vector space while measured metrics are points' features. Our goal is to map a set of LoRa transmission settings that offer the same QoS to the same cluster. Thus, we propose to use Fuzzy C-Means (FCM) which is an unsupervised clustering algorithm [119] for feature analysis. The clustering is achieved by minimizing a cost function that depends on the distance between the points and the cluster-heads. In our case, the points are networks' settings, the features are the QoS metrics and clusters are the uplink quality levels.

5.1 Objective function

The objective of the FCM algorithm is to find a set of membership values M and a set of cluster-heads H that minimize the objective function F [119] :

$$\min_{(\mathbf{M}, \mathbf{H})} \left\{ F_f(\mathbf{M}, \mathbf{H}) = \sum_{j=1}^c \sum_{i=1}^n \mathbf{m}_{ij}^f \cdot d_{ij}^2 \right\} \quad (4.9)$$

Such that:

$$\text{Constraint: } \sum_{j=1}^c \mathbf{m}_{ij} = 1, \forall i \quad (4.10)$$

$$\text{Distance: } d_{ij}^2 = \|\mathbf{x}_i - \mathbf{h}_j\|^2 \quad (4.11)$$

$$\text{Fuzzification degree: } f > 1 \quad (4.12)$$

Let p be the number of QoS metrics (features). Let n be the number of all LoRa transmission settings (points). $X = [x_1, \dots, x_i, \dots, x_n]$, with $x_i = [x_{i1}, \dots, x_{ik}, \dots, x_{ip}]$ is a set of p measured QoS metrics of n settings with $x_{ik} \in \mathbb{R}, 1 \leq k \leq p, 1 \leq i \leq n$.

The FCM algorithm takes as input a set of metrics X and generates two sets: H and M . $H = [h_1, \dots, h_j, \dots, h_c]$, with $h_j = [h_{j1}, \dots, h_{jk}, \dots, h_{jp}]$ is a set of cluster heads of p metrics and c clusters with $h_{jk} \in \mathbb{R}$. $M = [m_1, \dots, m_i, \dots, m_n]$, with $m_i = [m_{i1}, \dots, m_{ij}, \dots, m_{ic}]$ is a set of membership values of n settings to c clusters with $m_{ij} \in \mathbb{R}, 1 \leq j \leq c$.

5.2 Membership degrees M

We use this membership matrix in Q-learning as state transition probabilities P . We consider the membership level of each transmission setting to each cluster as the probability to change the uplink state.

$$[\mathbf{M}] = \begin{matrix} & \text{cluster 1} & \dots & \text{cluster c} \\ \text{setting 1} & \left[\begin{array}{ccc} m_{11} & \dots & m_{1c} \\ \vdots & \ddots & \vdots \\ m_{n1} & \dots & m_{nc} \end{array} \right] \\ \vdots & & & \\ \text{setting n} & & & \end{matrix}$$

The relationship between the membership-degrees of each setting is inversely proportional to the distance between this setting and the cluster-heads. We use the Equation 4.13 to get the membership values of each setting to different clusters [119].

$$\mathbf{m}_{ij} = \left[\sum_{j'=1}^c \left(\frac{d_{ij}}{d_{ij'}} \right)^{\frac{2}{f-1}} \right]^{-1}, \forall j, i \quad (4.13)$$

5.3 Cluster-heads H

A cluster-head is a vector of the measured metrics that are close to all the measured metrics of the same cluster and are calculated using Equation 4.14 [119].

$$\mathbf{h}_j = \left[\frac{\sum_{i=1}^n \mathbf{m}_{ij}^f \cdot \mathbf{x}_i}{\sum_{i=1}^n \mathbf{m}_{ij}^f} \right], \forall j \quad (4.14)$$

As reported in [63], the FCM clustering algorithm is able to cluster all possible settings for the three expected clusters. Furthermore, after the convergence of the FCM algorithm, the settings have been ranked based on their membership degrees. This allows the network server to assign the best settings to end-devices that require an uplink with high quality.

6 Simulation settings and results

To evaluate the performance of Q-learning to learn from scratch the impact of transmission settings on the uplink quality to maximize the data rate, we use a modified ver-

sion of LoRaSim simulator [204]. For each transmission, Q-learning updates its policy regarding the observed reward and state. We recognize the state at which an action leads by knowing at which cluster it belongs. After many packets exchange, Q-learning should be able to select the transmission settings with a high reward and a high state quality. To update its policy, Q-learning updates the transmission settings that include the Bandwidth (BW), the Coding Rate (CR), the Transmission Power (P^{Tx}) and the Spreading Factor (SF). These parameters are tuned automatically to fit the scenario under study. All these parameters and others are described in Table 4.3. The path loss exponent is kept at 2.7 to reflect the spectral noise in sub-urban environment. As we propose an iterative approach to update the transmission settings, we use two channels to exchange the data in the uplink channel and acknowledgements in the downlink channel. In addition, more than 28 scenarios have been tested to study the behavior of the network by measuring different Quality of Service (QoS) metrics such as the Data Rate (DR), the Packet Delivery Ratio (PDR), the Time on Air (ToA) and the Transmission Energy (E^{Tx}). For this reason, we vary the number of End Devices (EDs) from 100 to 10000, Packet Sizes (PSs) from 10 B to 100 B, Packet Rates (PRs) from one packet per min to one packet per 10 min and the number of Base Stations (BSs) from 1 to 10.

Two scenarios have been deployed to evaluate our work, The first scenario has been deployed with one Gateway (GW) and 100 EDs and the second one with four GWs and 1000 EDs. In first scenario, EDs send packets of 70 B every 4 min to one BS. However, in the second scenario, we deal with the scalability of Long Range Wireless Access Network (LoRaWAN) by increasing the number of EDs to 1000 that send packets of 70 B every 4 min to 4 BSs. Both scenarios respect the duty cycle of 1% recommended by LoRaWAN alliance [71]. Other scenarios were also studied and showed the same performances.

Parameters	Values
Environment settings	
Path loss exponent (α)	2.7 (sub-urban)
Number of uplink channels	1
Number of downlink channels	1
Number of pkt sent by ED	100
Capture Effect	6.0 dB
Scenarios settings	
Number of gateways	[1, ... , 10]
Number of end-devices	[100, ... ,10K]
Packet Size	[10,40,70,100] B
Packet Rate	1 pkt per [1,2,...,10] mn
Transmission settings	
Bandwidth	[125, 250, 500] kHz
Transmission Power	[2,5,8,11,14] dBm
Coding Rate	[1,2,3,4]
Spreading Factor	[7,8,9,10,11,12]
Carrier Frequency	868.1 MHz

Table 4.3. Simulation settings.

We measure in this section the efficiency of using Fuzzy C-Means (FCM) to disclose at which uplink state transmission settings could lead by comparing the performance of Q-learning with other algorithms like: Exponential weights for Exploration and Exploitation

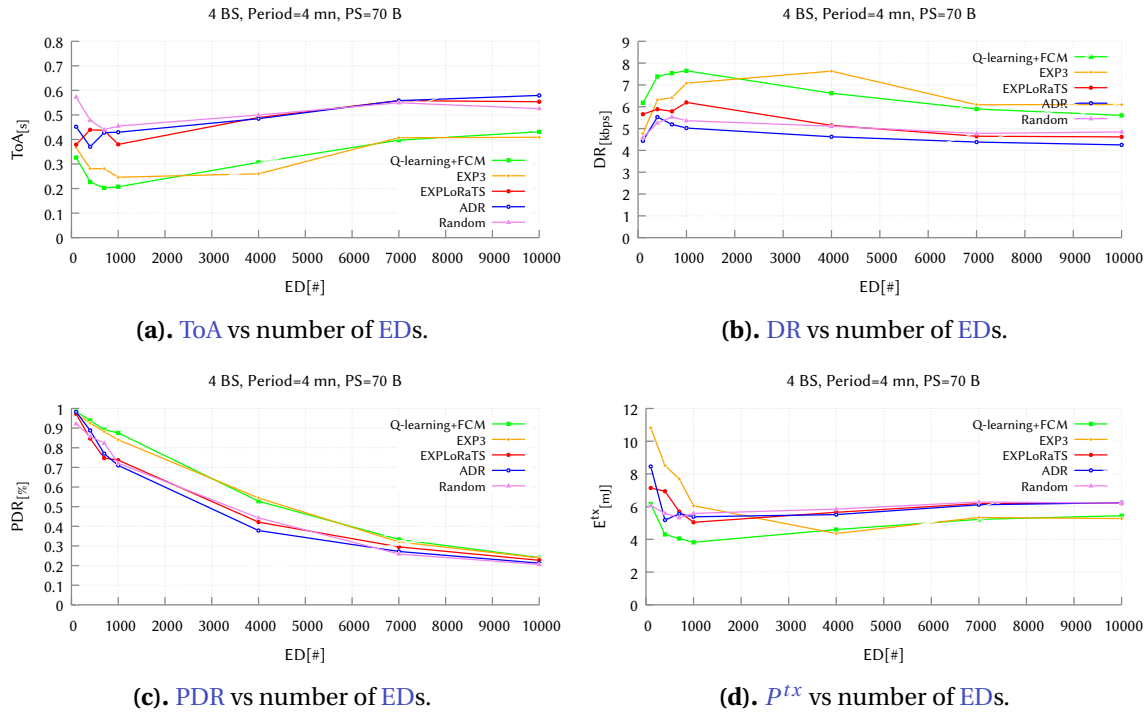


Figure 4.5. PDR, E^{tx} and DR vs number of EDs.

(EXP3), EXPLoRaTS and Adaptive Data Rate (ADR) that don't use the pattern recognition outputs of FCM. Random algorithm has been included based on the uniform random selection of transmission parameters. This section is divided to three subsections. In the first subsection, we measure the DR and PDR in many scenarios with different numbers of EDs and BSs and different PSs and PRs. We measure the data rate offered by each algorithm in each scenario to know in which scenarios algorithms give a better data rate. In the second subsection, we select one scenario with one BS and 100 EDs that send one packet of 70 B each 4min. We extend our measured metrics by adding the measured ToA and E^{tx} in addition to PDR and DR to study the time convergence of algorithms. In the third subsection, we select another scenario with 4 BSs and 1000 EDs that send one packet of 70 B each 4min and we study the same metrics as scenario one.

6.1 Measurements of PDR and DR in different scenarios

The main advantage of machine learning algorithms is their ability to learn how the environment behaves in each scenario. They are able to fit the scenario under study and converge analytically to the optimal set of actions with few assumptions about the environment. To exploit this advantage, we give in this section an overview of the DR and the PDR of all algorithms in all possible scenarios. Particularly, we highlight through Figures 4.5, 4.8, 4.6 and 4.7 the fact that pattern recognition process helped significantly Q-learning to outperform other solutions.

The impact of the number of devices on the performance of the network is presented in Fig. 4.5 to highlight the scalability of Markov process. Fig. 4.5b and Fig. 4.5c show the behavior of DR and PDR when we increase the number of EDs, respectively.

The average data rate of all transmitted packets including the dropped ones is presented in Fig. 4.5b. As the number of EDs increases, the DR reaches its highest value

when the number of end-devices is less than 1000 for all algorithms except EXP3 since it is the only Reinforcement Learning (RL) algorithm that does not take advantage of FCM clustering outputs. Thus, it requires more traffic to update its policy. The DR of Q-learning is the highest one between 8 kbps and 6 kbps when the number of EDs is lower than 3000. It decreases gradually when we increase the number of EDs due to physical limitations to access the channel. EXP3, in its turn, fails to maximize the DR when the PDR still higher than 50% (see Fig. 4.5c). Thus, it can not be used in real deployment since most Internet of things (IoT) applications require at least a PDR higher than 70%. In Fig. 4.5c, we observe a decline of the PDR by increasing the number of EDs. However, RL algorithms: Q-learning and EXP3, always offer a better PDR than other algorithms whatever the number of EDs. As the access to the channel is uniform for all EDs, the advantage of using RL algorithms to increase the uplink traffic is their ability to select transmission settings with low probability of collisions. Among RL algorithms, Q-learning algorithm shows the same PDR but offers a better DR in Fig. 4.5b. This result is mainly due to the prior knowledge acquired using FCM during the learning process. This provides Q-learning an overall view of all possible state transactions that could happen during the training process.

Fig. 4.5d shows the impact of the number of devices on Transmission Energy (E^{tx}) for each algorithm. We observe a decline of the average energy consumption per packet per device by increasing the number of EDs up to 1K devices (4K for EXP3). Whereas, a slight decrease of E^{tx} is observed by increasing the number of devices up to 10K. Indeed, in a dense network (*i.e.*, topologies with more than 1000 EDs), the average distance between EDs and the gateways will be lower than in a sparse network since there will be more devices close to the four gateways. Consequently, the average energy consumed per packet to reach the gateway is higher in sparse topology than in a dense network since EDs will be more scattered and away from the gateways. Whatever the number of end devices, we see that Q-learning algorithm offers a lower energy consumption than other algorithms. It requires more traffic by increasing the number of devices to update its Q-values, but shows a high performance in terms of energy consumption with more than 1K since it uses the prior knowledge of FCM. Other algorithms have a higher energy consumption like EXP3 that has the highest energy consumption up to 3K devices when the data rate is higher than 7kbps.

As packet sizes depend on the application running on end-devices, it can be high in the case of multimedia data transmission or small to transmit warning alerts. In this context, we study in Fig. 4.6b and Fig. 4.6c the impact of PS on DR and PDR, respectively.

In a scenario with 4 base stations and 1000 EDs, the DR in Fig. 4.6b remains stable whatever the PS between 10 B and 100 B. However, if we look at the difference of DR between algorithms, we see that Q-learning offers a higher DR compared to other RL algorithms while keeping the PDR relatively the same. Since there is 4 cells, end-devices are able to use a lower SF to send their packets to the closest BS without interfering with other transmissions in other cells. This decreases considerably the probability of collision. Thus, the PDR in Fig. 4.6c is always higher than 80% whatever the packet size between 10 B and 100 B for RL algorithms. Depending on IoT applications, IoT devices need to send their packets with different sizes that can be high in the case of multimedia data transmission or small to transmit warning alerts. In this context, we study in Fig. 4.6c the impact of PS on PDR. The PDR of EXPLoRaTS and ADR is lower even with small packets since using small PS allows to mitigate collisions by reducing the channel occupancy duration (ToA). As EXPLoRaTS is the only non-iterative algorithm, which means that transmission settings are not updated over time, the PDR decreases drastically when the PS becomes

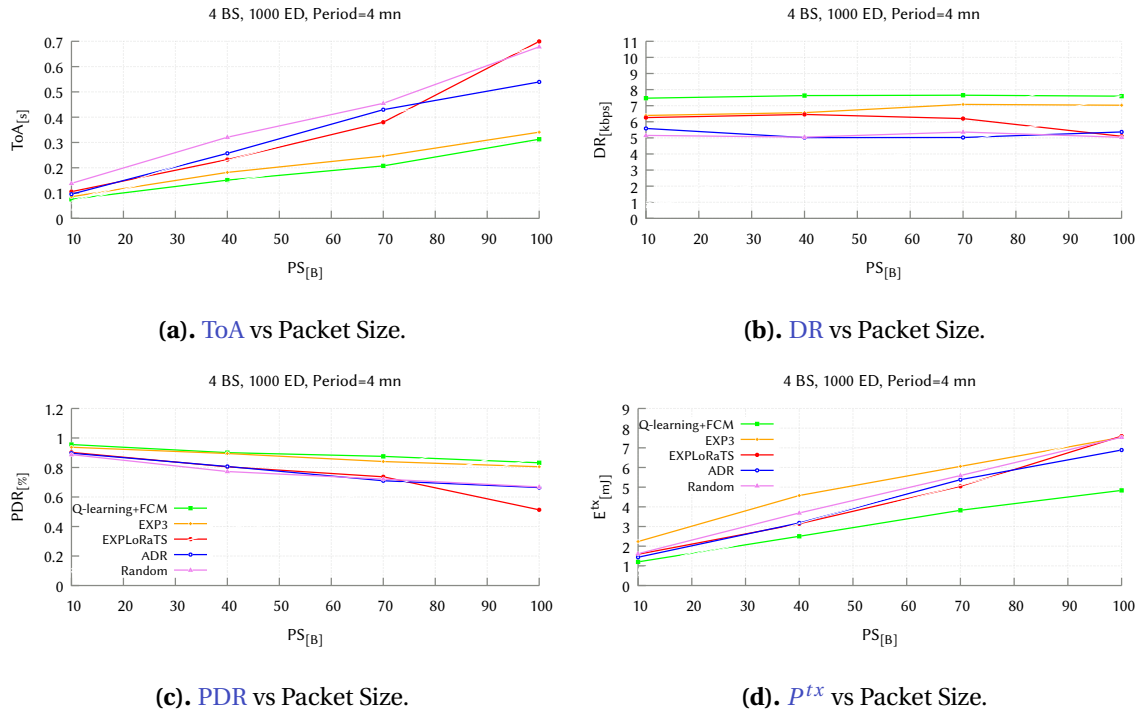


Figure 4.6. Impact of Packet Size on PDR, P^{tx} and DR.

higher than 70B. In addition, even if LoRaWAN alliance specifications recommend to use short packets, the PDR and the DR of ADR algorithm still lower compared to RL algorithms. Such a result is explained by the fact that ADR tries to maximize the DR of each device caring only about the Received Signal Strength Indicator (RSSI) of recent received packets. Hence, if two devices should use the same SF to increase their DR, none of them could reach the gateway since a collision would happen each time they send a packet at the same time.

As the energy consumption depends mostly on the size of the transmitted packets, we evaluate in Fig. 4.6d the impact of increasing the packet size from 10 B to 100 B on energy consumption with each algorithm. By increasing the packet size, the energy consumed increases for all algorithms. However, Q-learning allows to send the same size of packets with a lower energy by avoiding transmissions settings that waste energy without enhancing the uplink traffic. Since there is 4 BSs, end-devices are able to use lower SFs to send their packets to the closest BS without interfering with other transmissions in other cells. This decreases considerably the probability of collision and the energy consumption since lower SFs consume less energy. Thus, the E^{tx} of Q-learning algorithm is always lower than the E^{tx} of other algorithms whatever the packet size between 10B and 100B.

Depending on the frequency of packets transmission or Packet Rate (PR), many transmission settings with a duty cycle higher than 1% are not allowed. For example, if PS is equal to 70 B and SF is equal to 12, the ToA of the transmitted packet is around 2.3s. After which, a node needs to remain silent for around 228s ($2.3 * 99$ a little less than 4min), due to the duty-cycle of 1%. Thus, all scenarios with period less than 4min are not allowed by LoRaWAN Alliance. In this context, Fig. 4.7b and Fig. 4.7c highlight the impact of the Packet Rate on DR and PDR using one channel for uplink and one channel for downlink. After the analysis of Fig. 4.5c and Fig. 4.6c, we fixed the PS and the number of EDs to 70 Bytes and 1000, respectively. Then, we decrease the transmission frequency from one

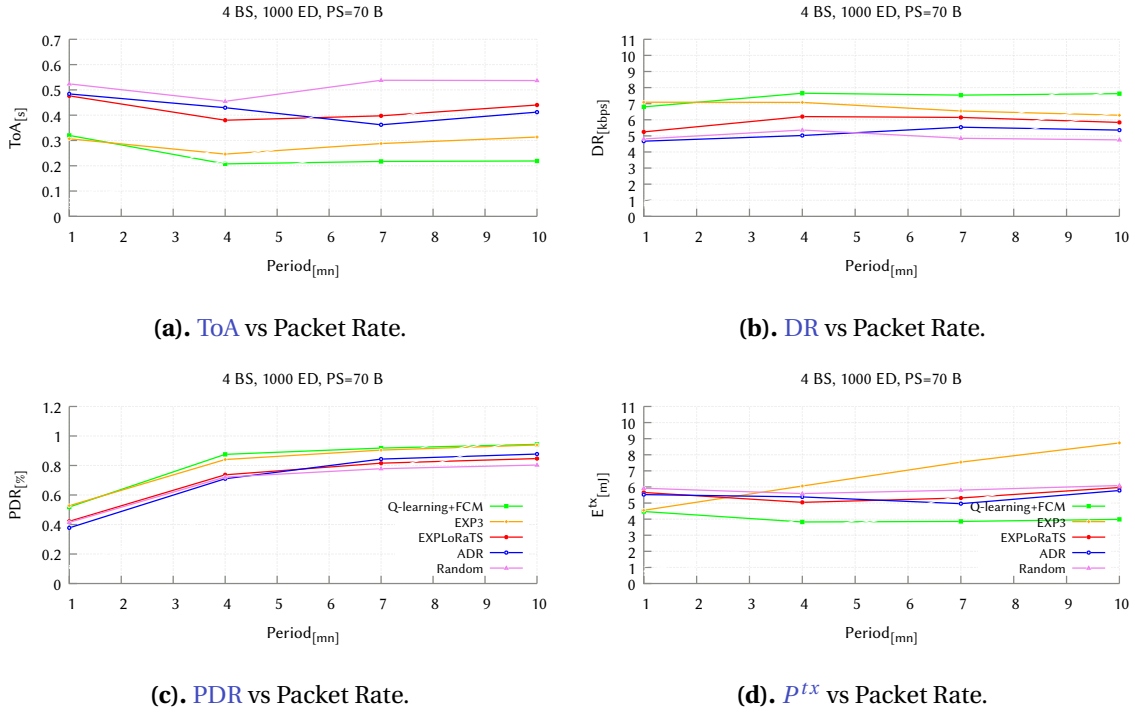


Figure 4.7. Impact of Packet Rate on PDR, P^{Lx} and DR.

packet per min to one packet per 10 min.

As we decrease the PR, we observe an enhancement of the PDR whatever the algorithm in Fig. 4.7c. However, the PDR of RL algorithms is higher than the PDR of all other algorithms. The DR in Fig. 4.7b remains relatively stable for all algorithms except for Q-learning that enhances the DR up to 7kbps. It offers a higher DR whatever the PR between 1 min and 10 min while keeping the same PDR as other RL algorithms. Q-learning is able to take advantage of the output of the clustering process and use it to update its Q-values initialized to zero. EXP3 appears to be sensitive to the frequency of transmission since there is a slight decrease of its DR (6kbps) by decreasing the PR up to one packet per 10 min.

The impact of the number of cells on DR and PDR is highlighted in Fig. 4.8b and Fig. 4.8c, respectively. As Industrial, Scientific and Medical (ISM) band is very tight especially in Europe, it is mandatory to analyze the impact of the number of BSs on the performance of our algorithms since we use one channel for uplink whether the network is private or public. For this reason, Fig. 4.8c shows an increase of the PDR when we increase the number of BSs. In fact, by deploying new BSs, we will reduce the distance between end-devices and BSs. In this case, devices are able to use transmission settings with a lower SF and a higher BW to send their data to the closest BS, reducing this way the interference between cells and enhancing the overall data rate. However, we can conclude from Fig. 4.8 that it is not useful to increase the number of BSs above 6 since the PDR and the DR remains the same above this number. With this result, we can reduce the cost of the network setup by purchasing only the necessary number of BSs. RL algorithms have the ability to select and update the transmission settings according to each scenario, they offer a higher PDR whatever the number of BSs. Indeed, Q-learning is the best algorithm to consider with all topologies especially when there is less than 4 cells (see Fig. 4.8c) since it has a prior knowledge about the quality of each transmission setting through the clustering process.

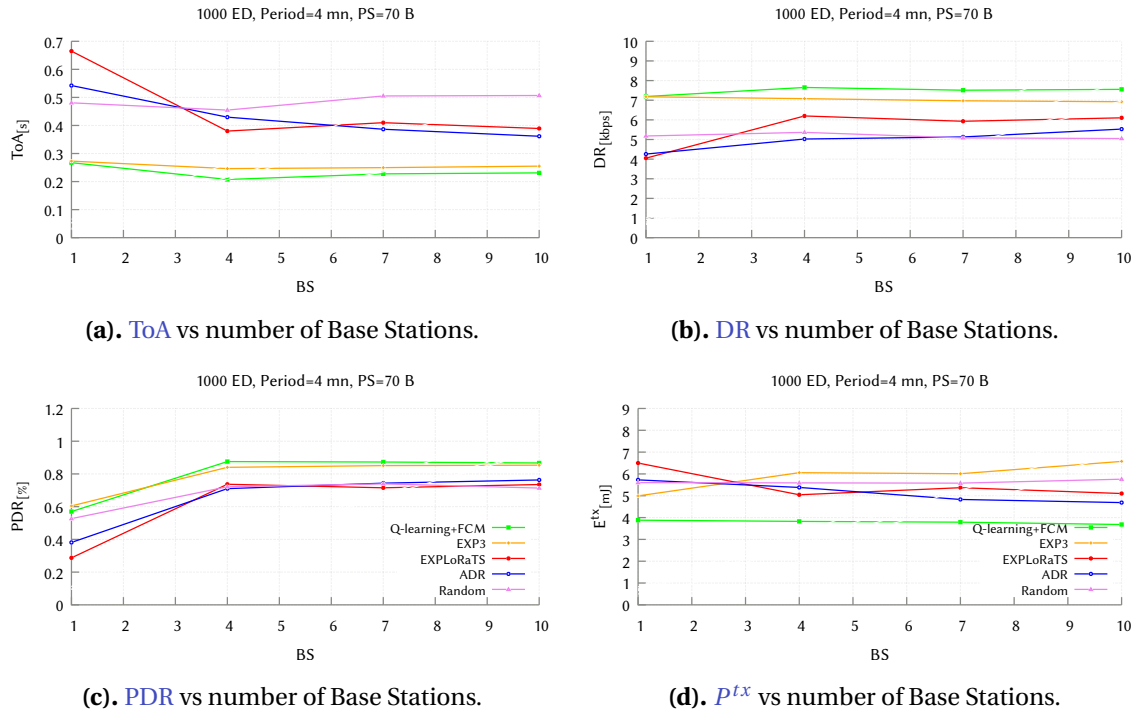


Figure 4.8. Impact of number of Base Stations on PDR, P^{tx} and DR.

ADR and EXPLoRaTS have a lower PDR than random algorithm with less than 4 BSs since these algorithms are known for their weak scaling capability (1000 EDs) especially with few BSs.

6.2 QoS metrics assessment in the first scenario

The process of finding the optimal reconfiguration policy requires a number of iterations *i.e.* packets exchange. As presented previously, Q-learning algorithm, update their Q-values $Q(s, a)$ and converge to the optimal one $Q^*(s, a)$ after a number of state transitions. Whereas, Multi-Armed Bandit (MAB) algorithms update their action values $Q(a)$ based on the number of selected arms. In this section we assess the performance of our solution during the learning process to see how the data rate converge. In the first scenario, we study the performance of all algorithms with 100 devices that send packets of 70 B each 4 min to one base station. In addition, we measure other metrics to observe the impact of maximizing the data rate on ToA, E^{tx} and PDR.

Fig. 4.9 shows the comparison of the average DR of the global traffic using Q-learning, EXP3 ADR, EXPLoRaTS and Random algorithms. The DR of Q-learning outperforms significantly the measured DR obtained with all other algorithms. When the transmitted packets get a DR of 7 kbps using Q-learning, heuristic algorithms like ADR and EXPLoRaTS offer a DR lower than 5.5 kbps. Q-learning algorithm offers a powerful DR since it uses the knowledge of the clustering process to jump from one state to another based of the membership degrees of each transmission setting to clusters. Random algorithm oscillates without any purpose of convergence since it does not apply any strategy that drives to an optimal data rate. Through this figure, we validate the major advantage of applying Q-learning with FCM to outperform state of the art proposals.

In Fig. 4.10, we highlight the advantage of using FCM clustering in Q-learning to max-

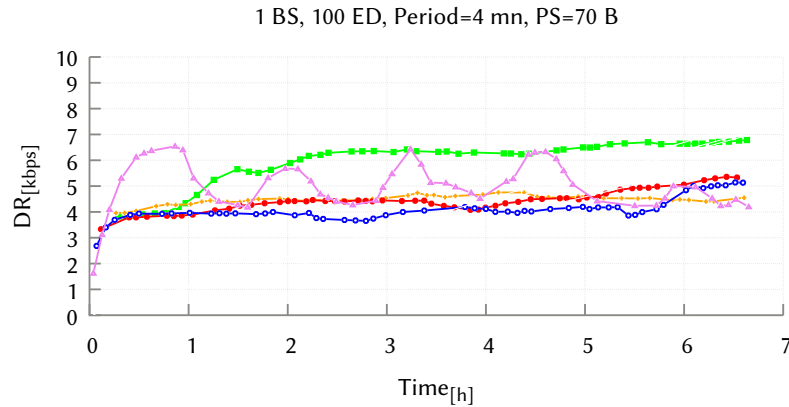


Figure 4.9. Variation of Data Rate.

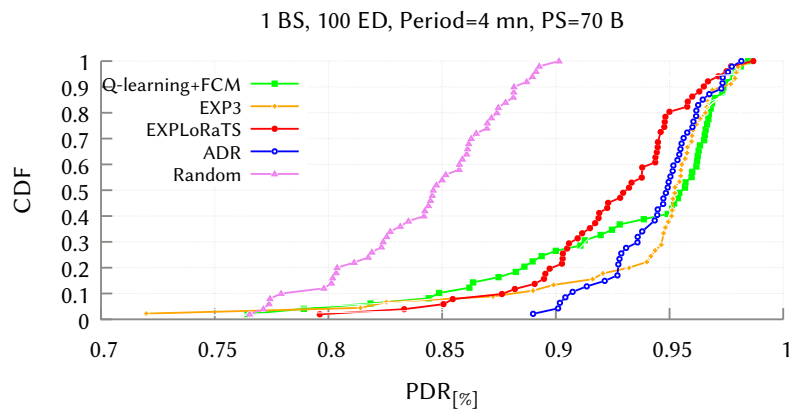


Figure 4.10. CDF of PDR.

imize uplink traffic through the assesment of PDR. As we use in this scenario only 100 devices, heuristic algorithms are able to deal with the low complexity of this scenario and offer a PDR higher than 90%. In fact, as only 100 devices try to access to the channel using ALOHA protocol, the probability of collisions is not significant. Meanwhile, Q-learning has a slight advantage since it has to build its knowledge and update its Q-values that are initialized to zeros at the beginning of the process. ADR offers a high PDR but less than Q-learning and EXP3 since it adjusts the transmission settings regarding the measured RSSI. With one base station and only 100 devices, ADR is able to avoid collisions by selection the transmission setting with the highest RSSI among the 10 previous packets. This simple approach appears to be sufficient in this scenario to get a high PDR. However, the data rate in Fig. 4.9 is not high since ADR does not take into account other transmission parameters such as the BW that has a big impact on the data rate.

As there is a negative correlation between the data rate and the time on air, maximizing the data rate will lead to minimize the time of propagation since transmission settings with a low SF offer a high data rate and a short time on air. In fact, our solution will try to find a set of transmission settings with the lowest SF as long as the packets are well received by gateways. Consequently, selecting the lowest SFs will not only increase the data rate but also mitigate collisions by decreasing the occupancy time of the channel during the transmission. For this reason, Q-learning in Fig. 4.11 is able to decrease the time of

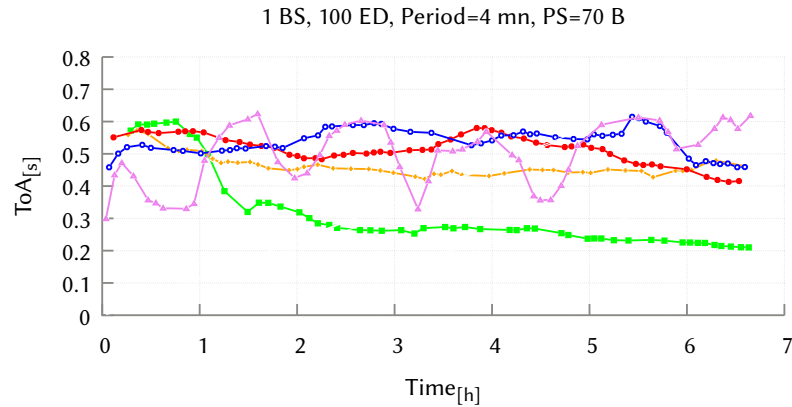


Figure 4.11. Variation of Time on Air.

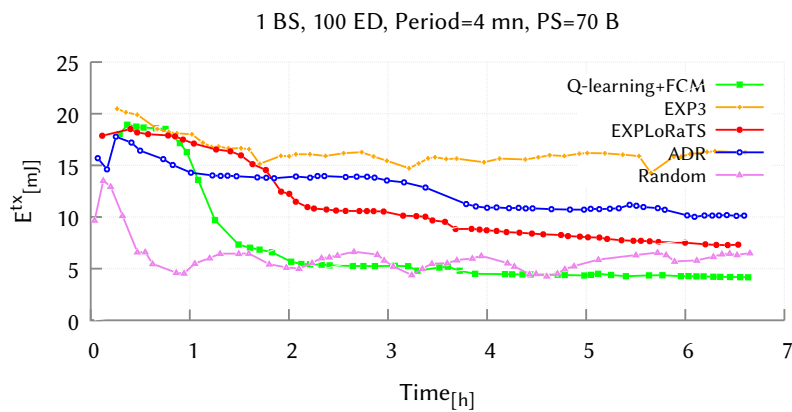


Figure 4.12. Variation of Transmission Energy.

propagation of the signal to 0.2s when all other algorithms offer a ToA higher than 0.4s.

The big advantage of Low Power and Wide Area Networks (LPWAN) networks compared to other wireless technologies is their ability to transmit the signal in a wide area with a low energy consumption. These two properties make LPWAN networks widely used in agricultural industry and fire fighting services to protect wide forests. Long Range (LoRa) devices should optimize their transmission settings to take advantage of these properties to not only increase the uplink traffic but also increasing the life time duration of the network. In this context, our solution mitigates wast of energy by selecting the transmission settings with the lowest SF that can transmit the packets without collision with other transmissions. Hence, Q-learning will avoid transmissions that waste energy by either increasing the P^{tx} directly or by increasing the SF unhelpfully. For this reason, the energy consumed by Q-learning in Fig. 4.12 during the learning process is lower than the energy consumed by other algorithms. This behavior is mainly due to the knowledge acquired during the clustering process to expect in advance at which state each transmission setting could lead.

Through the measurement of different metrics in the first scenario, we validate our assumption to use FCM membership degrees to disclose at which state each transmission setting can lead.

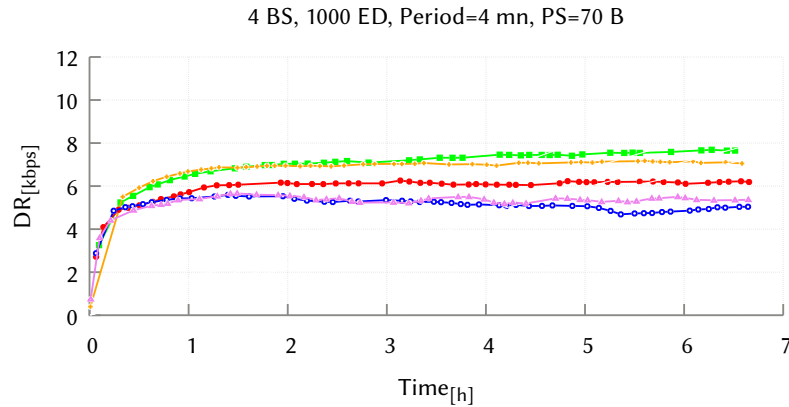


Figure 4.13. Variation of Data Rate.

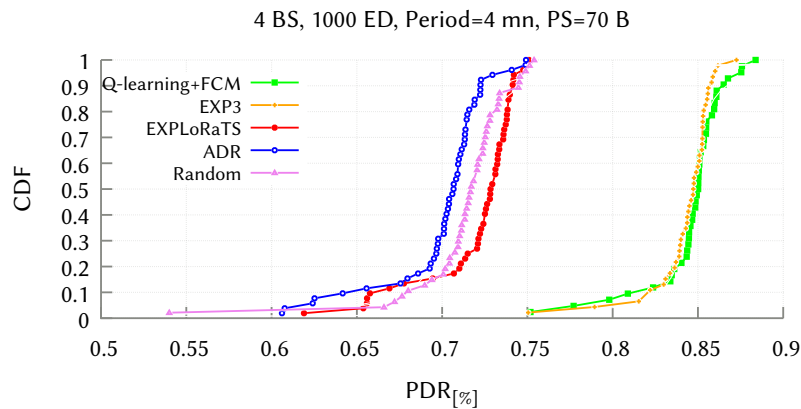


Figure 4.14. CDF of PDR.

6.3 QoS metrics assessment in the second scenario

In the second scenario, we increase the number of devices from 100 to 1K devices. As the PDR is at its highest value when the number of BSs is around 4 (see Fig. 4.8c), we select in this scenario 4 BSs that receive packets of 70 bytes each 4 min from each device. Then, we plot the same metrics as scenario one and we compare the same algorithms presented before.

Fig. 4.13 shows the measured average PDR of all algorithms over time. Since ADR algorithm does not have any knowledge and visibility about the amount of data transmitted and observes only the recent measured RSSI, it gives a lower average DR up to 5 kbps (slightly better than Random) compared to RL algorithms and EXPLoRaTS. On the other hand, when using Q-learning algorithm, the DR is improved significantly to achieve 8 kbps. This result is made by the frequent updates of transmission settings taking into account the state of the link to balance the load of the uplink traffic. MAB algorithms have also the ability to explore enough actions to be able to exploit the better ones and perform better DR. EXPLoRaTS has a better DR compared to ADR but shows its weakness compared to RL algorithms.

When we look at the PDR variation in Fig. 4.14, we see clearly that RL algorithms offer a better successful received packet rate compared to EXPLoRaTS, ADR and random

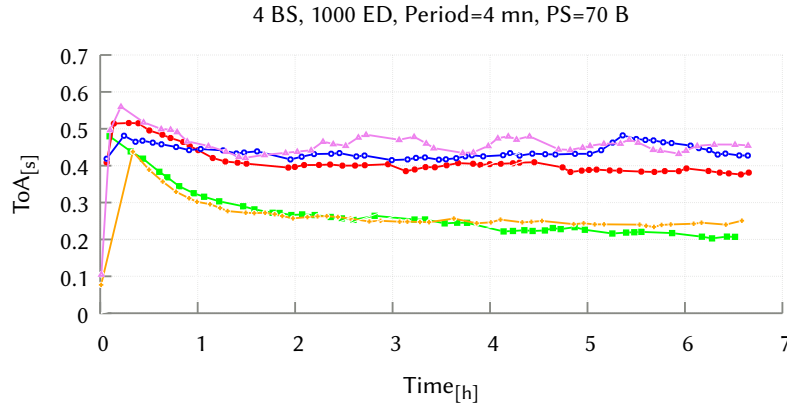


Figure 4.15. Variation of Time on Air.

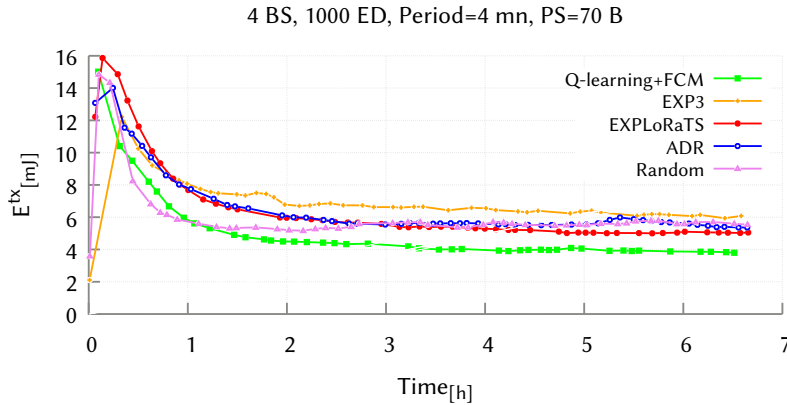


Figure 4.16. Variation of Transmission Energy.

algorithms. This highlights the enhancement of **PDR** by 20%; from 70% to 85%, using **RL** algorithms. **Q-learning** offers a better **PDR** compared to **EXP3** if we look at their Cumulative Distribution Function (**CDF**) in Fig. 4.14. Simulations have been carried out for a period of 7 hours but Fig. 4.13 shows that almost all algorithms reach their highest **DR** after only four hours. The main reason for this is the high density of the traffic that makes the controller receive enough requests from 1000 devices through 4 **BSs** to update its policy.

Many **IoT** applications nowadays become more and more sensitive to the delay of transmissions when it comes to alert or synchronized systems. Thus, we focus in this part on the measurement of the **ToA** during the training process. Fig. 4.15 shows a decrease of the **ToA** from 0.5s to 0.25s when **RL** algorithms are applied. This means that **RL** algorithms are able to reduce the transmission delay by 50% compared to random, **ADR** and **EXPLoRaTS** algorithms. However, **Q-learning** remains the only **RL** algorithm with the best trade-off between all **QoS** metrics including **DR**, **PDR**, **ToA** and E^{tx} in Fig. 4.16. More than 70% of the transmitted packets reach the gateway in only 0.3s using **Q-learning** and **FCM**. In addition, Fig. 4.15 shows that after only two hours, almost all transmitted packets have a **ToA** less than 0.25s in average.

In the context of **LPWAN**, saving devices energy consumption is mandatory to extend the network life time. For this reason, Fig. 4.16 shows the average energy consumption

per packet with each algorithm. As the relationship between SF and E^{tx} is inversely proportional, maximizing the DR leads to the selection of lower SFs that consume less energy. Thus, Q-learning that we use with FCM is able to reduce the waste of energy better than EXP3 and all other algorithms. They have a better energy efficiency with around 4.5mJ per packet when other algorithms consume more than 6mJ in average.

Through the measurement of different metrics in the second scenario, we validate our assumption to use FCM membership degrees to disclose at which state each transmission setting can lead even in a dense network.

7 Conclusion

Long Range Wireless Access Network (LoRaWAN) is among the leading wireless Internet of things (IoT) networks due to its large coverage and low energy consumption. We addressed in this chapter the problem of maximizing the data rate of the network. We addressed the reconfiguration problem of Long Range (LoRa) transceivers' parameters. We proposed a new approach for dynamic reconfiguration using Fuzzy C-Means (FCM) clustering and Q-learning algorithms. Our main achieved goals are: (i) the characterization of transmission parameters based on different Quality of Service (QoS) metrics, (ii) the maximization of the network Data Rate by tuning the parameters via trial/reward process, (iii) and the performance evaluation and comparison with solutions proposed in the literature. Our simulation results show that Q-learning with FCM clustering allow to improve the DR, Packet Delivery Ratio (PDR), Time on Air (ToA) and Transmission Energy (E^{tx}) of the network in many scenarios with different numbers of End Devices (EDs) and Base Stations (BSs). The PDR and the DR were improved by 25%, the ToA was reduced by 40% and E^{tx} was reduced by 20%. However, since Q-learning algorithm does not take advantage of the whole knowledge provided by the clustering process, it is not able to separate the traffic based on the clustering exploration phase. This drawback is caused by the fact that Q-learning requests only the next state at which each setting will lead without caring about all possible next states. For this reason, we plan in the next chapter to use the policy iteration algorithm of Markov Decision Process (MDP) that requests all possible state transitions before even starting the learning process. This advantage will allow LoRa devices to target the transmission settings that belong to the cluster that matches the requirements of the application that they run.

5 | Differentiated services for LoRaWAN with Markov Decision Process and Fuzzy C-Means Clustering

Quotation

Human identity is no longer defined by who we are but rather by what we own – Jimmy Carter

L'identité humaine n'est plus définie par ce qu'on est mais plutôt par ce qu'on possède – Jimmy Carter

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Abstract

To offer the best Quality of Service (QoS) to Internet of things (IoT) services, wireless networks need to customize their transmission settings to applications' requirements. Among several wireless technologies, Long Range (LoRa) technology is a promising Low Power and Wide Area Networks (LPWAN) solution whose QoS depends on the optimization of a set of transmission parameters. In this chapter, we propose to adapt these transmission settings to the requirements of IoT applications. To select the transmission settings that match the required quality, IoT devices need to target the set of transmission settings that offer the same quality as required by applications. Thanks to the clustering outputs in chapter 3, the network server can recognize the transmission settings that match the quality required by application through the membership degrees of these settings to clusters. Unlike Q-learning, the policy iteration algorithm that we propose in this

chapter is able to target the recognized quality levels through the state transition matrix. This allows devices to select the transmission settings that fit the quality level of the application that they run by selecting the transmission settings that belong to the same cluster. Thus, we initialize the state transition matrix of the policy iteration algorithm to infer the probability that one transmission setting will make the uplink state match the required state by IoT applications. To highlight the performance of our approach, we compared the quality of the traffics generated by three main applications. Simulation results show that the policy iteration algorithm is able to target the required uplink quality by selecting the transmission settings that belong to the same cluster. In addition, it speeds up the learning process and adapts the Data Rate (DR), the Time on Air (ToA) and the Transmission Energy (E^{tx}) to these applications. Furthermore, results show that the quality of the generated traffic is improved compared to the existing strategies.

1 Introduction

Nowadays, neither WiFi, Bluetooth, nor ZigBee can cope with the billions of IoT devices expected to be used in the forthcoming years. LPWAN has emerged as a lifebuoy to meet the new challenges of Internet of things (IoT) applications that require a low power consumption with high coverage.

On another hand, the emerging 5G mobile communications will support a range of use cases spanning different vertical industries including IoT applications. Emerging wireless networks like Long Range Wireless Access Network (LoRaWAN) will be inline with this and will need to be designed with flexibility to meet the requirements of different verticals. However, radio resource allocation mechanisms proposed in the literature for 5G networks can hardly be applied for LoRaWAN since Long Range (LoRa) modulation use unlicensed Industrial, Scientific and Medical (ISM) band to send and receive frames. Indeed, any IoT and radio device in the range of 14 km is able to use this band and disturb the estimation of the available resources. Moreover, LoRaWAN end devices use ALOHA Pure protocol to access the channel since there is no channel access control to synchronize transmissions. For these reasons, all heuristic algorithms proposed in the literature fail to enhance network performance since their assumptions do not fit the randomness of the wireless environment.

To overcome this problem, we propose, in this chapter, traffic differentiation using machine learning algorithms with a clustering preprocessing phase to acquire knowledge about the quality of each transmission setting before starting the learning process. Although this solution remains a “best effort” approach, it succeeds in adapting traffic quality to the requirements of all applications.

We assume that both scenarios include devices running three type of applications: i) application with the highest Quality of Service (QoS) requirements (App 2) ii) application with the lowest QoS requirements (App 0), and iii) application with QoS requirements level between the two previous ones (App 1, see Table 5.1).

Our main contributions are as follows:

- We propose to use the policy-iteration algorithm to maximize the Data Rate (DR) of each sub-traffic generated by each application.
- We use the Fuzzy C-Means (FCM) membership degrees in the policy iteration to characterize the probability of transitions between different link states.

Applications	PR _[pkt/day]	PDR[%]	PS _[byte]
Applications 0			
Smoke Detectors	2	90	10-20
Environmental	5	90	50-100
Medical Assisted	8	90	100-200
Applications 1			
Wearables	10	90	10-20
Water/Gas Metering	8	85	100-200
Smart Grid	10	80	10-20
Applications 2			
Smart Bicycle	192	80	50-100
Animal Tracking	100	70	50-100
Asset Tracking	100	90	50-100

Table 5.1. Applications requirements [63].

- ▣ We compare the quality of all generated traffics with the state of the art, and we assess the quality of each traffic based their required QoS metrics.

The notion of differentiated services (DIFFSERV) was proposed in literature for the coexistence of different services and applications within the same network by providing a customized network setting to each service. Knowing the diversification of IoT applications nowadays, differentiated services presented in Fig. 5.1 are highly recommended to cope with the heterogeneity of data transmitted by IoT devices within the same network. For this reason, we highlight different IoT applications based on their QoS requirement such as PR, DR and PDR. We highlight, in the following, LoRa transmission's parameters that will be tuned to fit these requirements.

Recent related works have investigated the performance of LoRaWAN in different environments: university campus [45], indoor applications [27], industry [200], dense downtown [220], and rural areas [142]. Other studies focused on finding new mechanisms to enhance the performance of LoRa devices' settings [59] [130] [144].

The closest paper to our work was proposed by Dawaliby et al. [123]. The authors discuss the application of LoRaWAN slicing. They evaluated the performance of LoRaWAN with the goal of maximizing utilities of each slice using maximum likelihood estimation method. A resource allocation strategy is proposed to meet the QoS requirements of each slice. The effectiveness of this approach is measured by the percentage of satisfied devices with regard to their delay requirements. However, such an approach can hardly be implemented in the real world since resource allocations can easily be unsettled in ISM band by other long range transmissions. In addition, energy constraints of each node have not been considered.

All previous contributions are useful to enhance LoRaWAN performance under various constraints. However, no effort has been made to adapt the parameters' settings to deal with the diversification of IoT applications and the randomness of wireless transmissions. In this work, we address this problem using machine learning algorithm to avoid adding extra signalling overhead and resource allocations with respect to LoRaWAN alliance constraints [71].

This chapter is organized as follows. Section 2 enunciate the problem statement. In

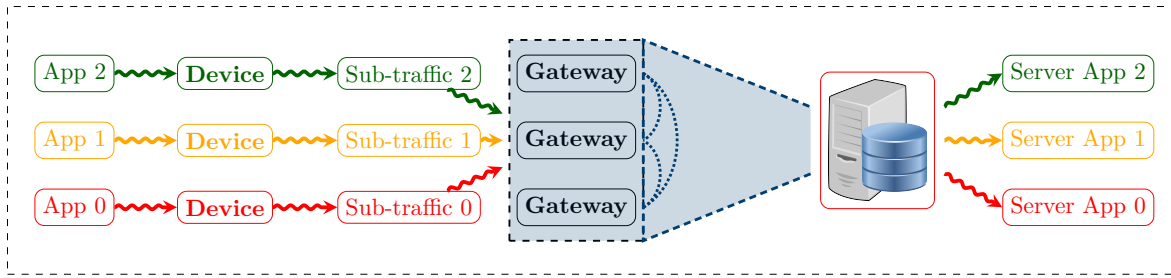


Figure 5.1. Differentiated services for uplink LoRaWAN traffic.

Section 3 and Section 4, we propose our learning process by using the membership matrix of Fuzzy C-Means (FCM) as a state transition matrix in the policy-iteration algorithm. Our simulation settings and our main findings are highlighted in Section 5. Finally, Section 6 concludes this chapter.

2 Problem statement

To make the same physical Long Range (LoRa) network hold different services within the same network, LoRa network servers should cope with the heterogeneity of the transmitted data by offering a customized link quality to each device. Unlike state of the art solutions, we should allow devices to target the uplink quality that they need rather than sharing uplink resources equally between all devices. In fact, the diversification of Internet of things (IoT) applications now day, makes the problem of network reconfiguration harder since we should customize the reconfiguration process based on the need of each application. For example in Fig. 5.1, LoRa devices can run three different applications and select the transmission settings based on their needs. This will lead to the creation of three sub-traffics with different qualities in the same network. As new network operators are required to hold differentiated services without the need of additional network servers, the research space of the transmission parameters that best fit applications requirements should be characterized.

For example, LoRa deployment for tracking services requires more data rate than temperature monitoring since temperature values change less frequently than tracked objects. In this context, we strongly believe that the characterization of the research space should allow devices to distinguish between good, bad and medium settings. This will allow end devices to target the transmission settings with the same quality as required by applications.

We formulate the online selection of the suitable set of configurations as an exploration/exploitation problem. We propose to maximize the utility of the network to enhance the quality of uplink traffic. As the main goal of LoRa end-devices is to send their collected data to the cloud, network utilization (or utility) function is expressed as the Data Rate of the up-link traffic after each transmission at time t given by Equation 5.1.

$$U(a) = \begin{cases} DR(a) & \text{if packet received} \\ 0 & \text{else.} \end{cases} \quad (5.1)$$

We consider in this work the utility of the network to maximize the uplink traffic. We express the network utilization (or utility) function as the DR of the well received packets (see Equation 5.1). In fact, as our main concern is to maximize the DR and to keep it as

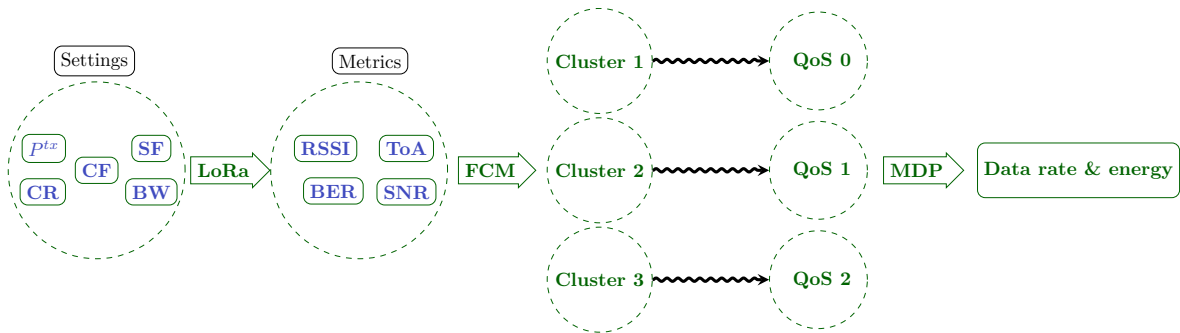


Figure 5.2. LoRaWAN reconfiguration scheme.

high as possible, maximizing the DR will bring end devices to decrease their Spreading Factor (SF) as long as their transmitted packets are well received by gateways. Otherwise, transmission settings with higher SF will be promoted. Finding the set of transmission settings that maximizes the utility function is an NP-hard problem [152] for practical networks' size.

Thus, to have a self-organizing and an adaptable solution, we propose to use the policy iteration algorithm rather Q-learning like in the previous chapter. Unlike Q-learning that tries to learn the impact of each transmission setting on the uplink quality based on the observed state s_{t+1} after each transmission, the policy iteration algorithm requires this knowledge (as a model) before even starting the learning process. Since we have characterized the impact of the transmission settings on the uplink quality previously in offline mode, we try in this chapter to use this knowledge as a model that discloses the probability to make the uplink quality good, bad or medium. Proceeding this way, the policy iteration algorithm will be able exploit faster the required transmission settings since we have already explored the quality of each setting using Fuzzy C-Means (FCM). In this work, we formulate our exploration/exploitation problem as a Markov Decision Process (MDP) to analytically converge to the set of transmission settings that optimize the uplink traffic. Indeed, in machine learning algorithms and particularly Reinforcement Learning (RL) algorithms, an agent tries to obtain as much reward as possible by carrying out the most rewarding action among all possible actions. The most rewarding action will then get a high probability to be selected next time. Based on the same concept, the policy-iteration algorithm measures and updates the quality of actions and build the best policy based on the observed rewards during the learning process. Meanwhile, unlike other algorithms, it requires all possible states transitions to know with which probability each action could lead to each state. This knowledge is known as a state transition matrix.

Fig. 5.2 shows how we use FCM membership degrees outputs in the policy-iteration algorithm to simulate state transition probabilities. As the policy-iteration algorithm requires the entire matrix before even starting the learning process, it has one step further compared to Q-learning that starts without any knowledge about the environment. We explain in the next section how we deal with this problem and how we generate state transition probabilities using FCM clustering.

An overall view of our three-step learning process is described in Fig. 5.3. First, we start by acquiring enough data to assess the quality of each transmission setting by sending randomly several packets with different transmission settings. Next, we apply the clustering process on the measured Quality of Service (QoS) metrics to extract patterns that disclose the quality of each transmission setting in offline mode. And then, we use this

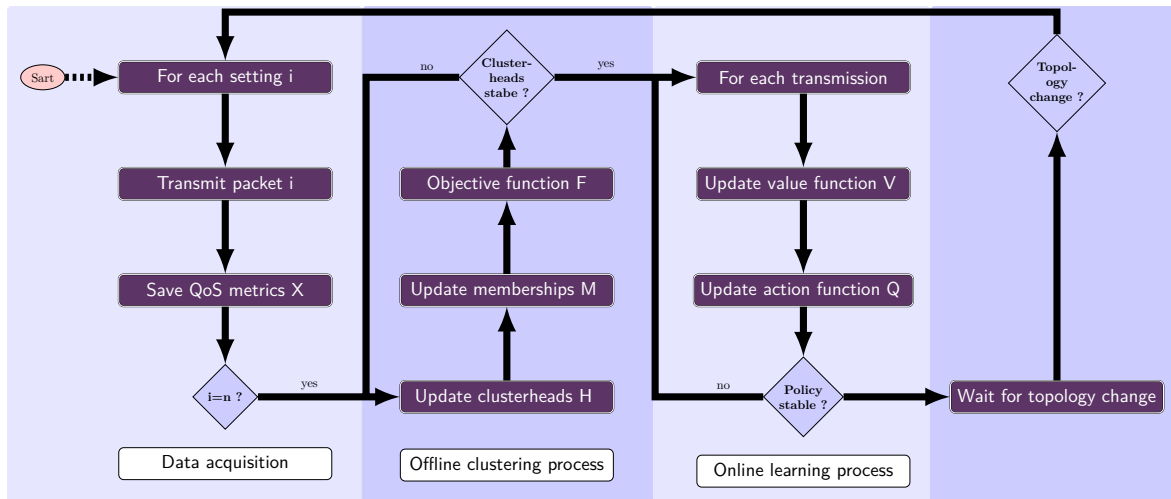


Figure 5.3. Overview of functions.

patterns as a state transition matrix in the policy iteration algorithm to find the right path (set of actions) that lead to the selection of transmission settings that lead to the required link quality. Section 4 gives more details about the state transition matrix and how the policy iteration algorithm updates its functions to converge analytically to the optimal settings in online mode.

3 Network settings customization with the policy-iteration algorithm

We formulate the problem of network optimization as a Markov Decision Process (MDP) to converge to the set of transmission settings that optimize the uplink traffic for each application. In an Reinforcement Learning (RL) problem, an agent tries to obtain as much reward as possible by carrying out the most rewarding action among N possible actions. Therefore, the main goal of RL algorithms is to maximize the reward function after performing each action. The most rewarding action will then get a higher probability to be selected in next steps.

Notations for Markov process	
A	set of actions
a	an action
R	set of all possible rewards, a finite subset of \mathbb{R}
R_t	the reward at time t
t	discrete time step or play number
S	set of all states
$A(s)$	set of all actions available in state s
s, s'	states
π	policy (decision-making rule)
$\pi(s)$	action taken in state s under <i>deterministic</i> policy π
$\pi(a s)$	probability of taking action a in state s with policy π

Table 5.2. Markov Decision Process notations

Based on the same concept, the policy-iteration algorithm measures and updates the

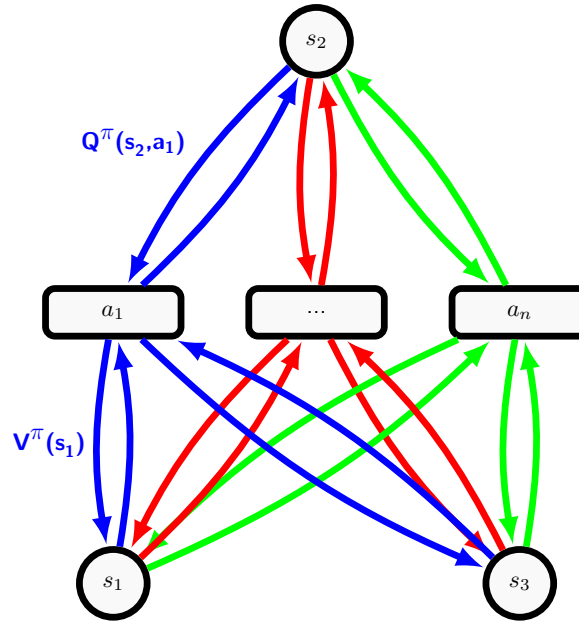


Figure 5.4. The policy-iteration process.

quality of actions and build the best policy based on the reward of each action. However, as the opposite of other RL algorithms, the policy-iteration algorithm needs a prior knowledge about the environment that is trying to learn. This knowledge allows the algorithm to know whether an action will change the state of the system or not. Thus, a state transition matrix should be known to be able to use the policy-iteration algorithm. In our study, we propose to initialize the transition matrix with the membership matrix of the Fuzzy C-Means (FCM) algorithm to get a prior knowledge about the quality of each transmission setting. For example, when a device runs App 2, the policy-iteration algorithm finds out the path (or sequence of actions) that leads to a steady state with Quality of Service (QoS) level 2. Proceeding this way, each device will find the path that makes its uplink quality fit the required quality of the application that it runs.

To model the learning process, we assume that interactions between the network controller and the wireless network are formally defined as a finite the policy-iteration algorithm. We denote: S : a state space. A : an action space. P : a state transition function: $S \times A \times S \rightarrow [0-1]$, where $P(s, a, s')$ gives the probability to jump from state s to s' by taking action a . R : reward function: $S \times A \times S$, where $R(s, a)$ gives a reinforcement feedback for the state-action pair (s, a) .

- ▣ $S = \{s_0, \dots, s_c\}$ is a finite set of states which in our study is a set of uplink states where each transmission setting could lead (QoS level of the transmission).
- ▣ $A = \{a_0, \dots, a_n\}$ is a finite set of actions which in our study is a set of possible transmission settings.
- ▣ $P = (s_{t+1} = s' | s_t = s, a_t = a)$ is the transition probability from state s at step t to state s' at the next step due to an action a ;
- ▣ $R(s, a)$ is the reward observed when we apply action a on state s . In our case the reward of each action is the gain of Data Rate (DR) after each transmission that we compute using the utility function.
- ▣ $\gamma \in [0, 1]$ is called a discount factor, it represents the extent at which old rewards

should be considered.

We relate in the following subsections the main functions used by Markov chain: cumulative discount reward function, the state and action value functions and the state transition function. Table 5.2 summarizes notations used in the policy iteration algorithm.

3.1 Cumulative discounted reward

The cumulative long-term discounted reward of state s at time t is the discounted sum of rewards that could be earned in this state and is given by $G_t(s)$. Each action yields a reward for the current state and represents the earned rewards on the trajectory, denoted $R_t(s, a)$. The cumulative rewards earned when taking action a at state s is given by $G_{t+1}(s, a)$.

$$\begin{aligned} G_t(s) &\doteq \sum_{a' \in A(s)} G_t(s, a') \\ G_{t+1}(s, a) &\doteq \sum_{s' \in S_{t+1}} R_{t+1}(s, a) + \gamma \cdot G_t(s') \end{aligned} \quad (5.2)$$

We define the reward function as the difference between utility functions.

$$R_{t+1}(s, a) = U_{t+1}(a) \quad (5.3)$$

Where γ is the discount factor ($0 < \gamma < 1$), which determines the impact of old rewards on the learning process. If $\gamma = 0$, the agent will be “myopic” and will be focused on maximizing immediate rewards only, while forgetting all previous observations of rewards. In our case and after several experimental studies, we set γ to 0.9 as its the value that offers the highest learning rate considering 90% of the previous rewards observations.

The reward function R_{t+1} measures the data rate gained at each iteration. After performing an action a' , the reward function measures how much data rate each device won compared to the previous action a . the policy-iteration algorithm aims to learn the policy (*i.e.* the sequence of actions) that earns more rewards, *i.e.* more DR, until there will be no possible data rate to win.

3.2 State-value function

The state-value function of an arbitrary policy π is expressed in the following equation.

$$\begin{aligned} V_t(s) &\doteq \mathbb{E}[G_t(s) \mid s_t = s] \\ &= \mathbb{E} \left[\sum_{a' \in A(s)} G_t(s, a') \mid s_t = s \right] \\ &= \mathbb{E} \left[\sum_{a' \in A(s)} Q_t(s, a') \mid s_t = s \right] \\ &= \sum_{a' \in A(s)} \pi(a' \mid s) \cdot Q_t(s, a') \end{aligned} \quad (5.4)$$

Where $\pi(a|s)$ is the probability to select action a at state s . $Q(s, a)$ denotes the estimated cumulative reward earned when action a is selected at state s . The state value function of state s is the estimated reward that could be earned by taking an action in this state. As $E(x) = P(x) \cdot x$, the state value function denotes also the sum of rewards that could be earned by taking action $a \in A(s)$ weighted by its probability to occur.

The main objective of the learning process is to find the optimal policy π^* in Equation 5.5, which is a mapping from S to A that maximizes the expected long-term discounted reward for each state.

$$\pi^*(s) = \operatorname{argmax}_{\pi} V(s) \quad (5.5)$$

3.3 Action-value function

the policy-iteration algorithm has the ability to provide the network with necessary cognitive capabilities to build a transmission setting strategy according to environment conditions. The action value function [113] of action a represents the estimation of cumulative rewards that will be observed by taking this action. These rewards are expressed as the estimation of the sum of the rewards of the current action a and the estimated rewards in the next state s_{t+1} (value function of state s_{t+1}). To get this estimation, this sum is weighted by the probability to jump from state s to $s' \in S_{t+1}$ using action a .

$$\begin{aligned} Q_{t+1}(s, a) &\doteq \mathbb{E}[G_{t+1}(s, a) | s_t = s, a_{t+1} = a] \\ &= \mathbb{E}\left[\sum_{s' \in S_{t+1}} r + \gamma \cdot G_t(s') | s_t = s, a_{t+1} = a\right] \\ &= \mathbb{E}\left[\sum_{s' \in S_{t+1}} r + \gamma \cdot V_t(s') | s_t = s, a_{t+1} = a\right] \\ &= \sum_{s' \in S_{t+1}} P(s' | s, a) \cdot [r + \gamma \cdot V_t(s')] \end{aligned} \quad (5.6)$$

$$\text{with } r = R_{t+1}(s, a)$$

According to the Bellman's optimality criterion [163], there is at least one optimal strategy. Hence, the action-value function for the optimal strategy is given by Equation 5.7:

$$\begin{aligned} Q_{t+1}^*(s, a) &= \sum_{s' \in S_{t+1}} P(s' | s, a) \cdot [R_{t+1}(s, a) + \gamma \cdot V_t^*(s')] \\ V_t^*(s) &= \max_{a'} Q_t^*(s, a') \end{aligned} \quad (5.7)$$

The best action at state s is then expressed as the best action that is generated by the optimal strategy and is given by Equation 5.8:

$$\pi^*(s) = \operatorname{argmax}_{a \in A(s)} Q(s, a) \quad \forall s, \pi \quad (5.8)$$

In this work, we use the policy iteration algorithm to solve analytically our exploration/exploitation problem. This algorithm is better than the value iteration algorithm because it converges faster and better towards the stable policy π^* with less iterations [113]. The key advantage of the policy iteration algorithm is its exploitation of all transition probabilities after performing each action that improves the current policy $\pi_t(s)$, This means that all transition probabilities are considered at each iteration to predict better the next steps and build a more rewarding trajectory [].

3.4 State transition function

In our context, the major advantage of using Markov decision process is the initial knowledge of the environment that is required for state transitions. These transitions contain the probability to switch from one state to another through an action. To get these transition probabilities between states, the transition matrix P in the policy-iteration algorithm is replaced with the matrix M of the FCM clustering process that will be described deeply in the next section.

$$[\mathbf{P}] = \begin{matrix} & \text{state 1} & \dots & \text{state c} \\ \begin{matrix} a_1 \\ \vdots \\ a_n \end{matrix} & \begin{bmatrix} m_{11} & \dots & m_{1c} \\ \vdots & \ddots & \vdots \\ m_{n1} & \dots & m_{nc} \end{bmatrix} \end{matrix}$$

When a combination of transmission parameters is selected, the link state between End Device (ED)s and the Base Station (BS) corresponds to the cluster where each transmission setting was mapped. The advantage of fuzzy clustering compared to hard clustering is the ability to generate membership degrees of each setting to each cluster. Hence, the transition matrix could be built using these membership degrees which correspond to the probability that an action could lead to each state. Section bellow describe in details how we compute the transition matrix P .

Algorithm 5.1 The policy-iteration algorithm

- 1: Sates $S = \{1, \dots, s_c\}$
 - 2: Actions $A = \{1, \dots, a_n\}$, $A: S \Rightarrow A$ ▷ Set of transmission settings
 - 3: Reward function $R: S \times A \rightarrow \mathbb{R}$ ▷ The gain of data rate observed
 - 4: Transition function $P: S \times A \rightarrow S$ ▷ Membership degrees of FCM
 - 5: **procedure** POLICYIMPROVEMENT(S, A, R, P) ▷ Policy Improvement
 - 6: **for** each $s \in S$ **do** ▷ For each state
 - 7: $Q_{t+1}(s, a) \leftarrow \sum_{s' \in S_{t+1}} P(s' | s, a) \cdot [R_{t+1}(s, a) + \gamma \cdot V_t(s')]$
 - 8: $\pi_{t+1}(s) \leftarrow \arg \max_a Q_{t+1}(s, a)$ ▷ Equation 5.8
 - 9: **if** $\pi_t(s) \neq \pi_{t+1}(s)$ **then**
 - 10: **return** $V^* \approx V$ and $\pi^* \approx \pi$
 - 11: **else**
 - 12: $\Delta \leftarrow \infty$ ▷ Policy Evaluation
 - 13: **while** $\Delta > \epsilon$ **do** ▷ While V is not stable
 - 14: **for** each $s \in S$ **do** ▷ For each state/cluster
 - 15: $V_{t+1}(s) \leftarrow \sum_{a' \in A(s)} \pi(a' | s) \cdot Q_{t+1}(s, a')$ ▷ Equation 5.4
 - 16: $\Delta \leftarrow \max(\Delta, |V_t(s) - V_{t+1}(s)|)$
-

4 Initialization of state transitions with FCM

As we aim to map a set of Long Range (LoRa) transmission settings that offer the same Quality of Service (QoS) to the same application, we need to build a prior knowledge about the quality of each LoRa transmission setting. Djoudi et al. [63] proposed a solution to cluster a set of LoRa transmission settings based on their measured QoS metrics such as Bit Error Rate (BER), Time on Air (ToA) and Received Signal Strength Indicator (RSSI). We use FCM which is an unsupervised clustering algorithm [119] commonly used for feature analysis. Each transmission setting is projected to a point in a three-dimensional space based on their QoS coordinates. The clustering is achieved by minimizing a cost function that depends on the distance between each point and the cluster-heads. After the clustering process, each transmission setting is assigned to the three clusters based on their membership-degrees to each cluster. Doing this way, when a transmission setting is used by an End Device (ED), the probability that the quality of the transmission link will fit the required quality of an application (cluster) is known through the membership-degrees matrix. We relate in this section the main functions used to generate the membership-degrees matrix and the cluster-heads matrix using FCM.

4.1 Objective function

Unlike hard clustering algorithm like k-means, Fuzzy C-Means algorithm is able to label features to more than two clusters and generate values that reveal the extent to which each feature belongs to each cluster. Such knowledge is mandatory in our study to build a prior knowledge about the consequence of selecting any transmission setting on the quality of the network.

Let p be the number of QoS metrics (features). Let n denotes the number of all LoRa transmission settings (points). $X = [x_1, \dots, x_i, \dots, x_n]$, with $x_i = [x_{i1}, \dots, x_{ik}, \dots, x_{ip}]$ is a set of p measured QoS metrics of n settings with $x_{ik} \in \mathbb{R}, 1 \leq k \leq p, 1 \leq i \leq n$.

The FCM algorithm takes as input a set of metrics X and generates two sets: H and M . $H = [h_1, \dots, h_j, \dots, h_c]$, with $h_j = [h_{j1}, \dots, h_{jk}, \dots, h_{jp}]$ is a set of cluster-heads with p metrics and c applications where $h_{jk} \in \mathbb{R}$. $M = [m_1, \dots, m_i, \dots, m_n]$, with $m_i = [m_{i1}, \dots, m_{ij}, \dots, m_{ic}]$ is a set of membership values of n settings to c clusters with $m_{ij} \in \mathbb{R}, 1 \leq j \leq c$.

The objective of the FCM algorithm is to find a set of membership values M and a set of cluster-heads H that minimize the objective function F in Equation 5.9 [119].

$$\min_{(\mathbf{M}, \mathbf{H})} \left\{ F_f(\mathbf{M}, \mathbf{H}) = \sum_{j=1}^c \sum_{i=1}^n \mathbf{m}_{ij}^f \cdot d_{ij}^2 \right\} \quad (5.9)$$

Such that:

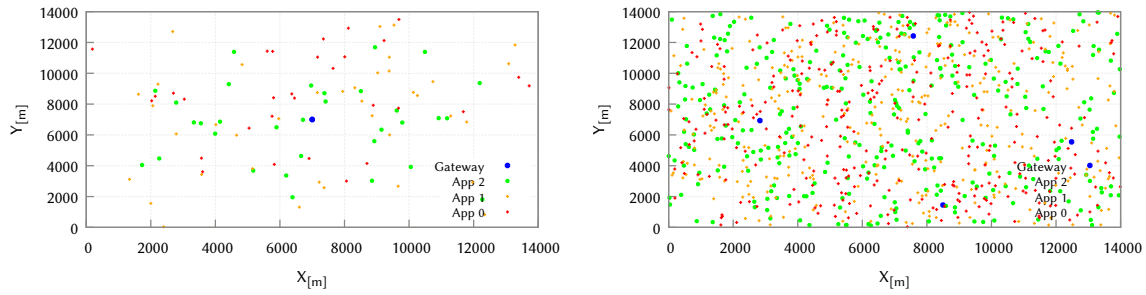
$$\text{Constraint:} \quad \sum_{j=1}^c \mathbf{m}_{ij} = 1, \forall i \quad (5.10)$$

$$\text{Distance:} \quad d_{ij}^2 = \|\mathbf{x}_i - \mathbf{h}_j\|^2 \quad (5.11)$$

$$\text{Fuzzification degree:} \quad f > 1 \quad (5.12)$$

4.2 Membership-degrees

We use the Equation 5.13 to update at each iteration the membership values, to get the membership values of each setting for different kind of applications [119].



(a). Scenario 1: Topology with 100 ED & 1 BS.

(b). Scenario 2: Topology with 1000 ED & 4 BS.

Figure 5.5. LoRaWAN topologies.

$$\mathbf{m}_{ij} = \left[\sum_{j'=1}^c \left(\frac{d_{ij}}{d_{ij'}} \right)^{\frac{2}{f-1}} \right]^{-1}, \forall j, i \quad (5.13)$$

The relationship between the membership-degrees of each setting is inversely proportional to the distance between this setting and the cluster-heads.

$$[\mathbf{M}] = \begin{matrix} & \text{app 1} & \dots & \text{app c} \\ \text{setting 1} & \left[\begin{matrix} m_{11} & \dots & m_{1c} \\ \vdots & \ddots & \vdots \\ \text{setting n} & \left[\begin{matrix} m_{n1} & \dots & m_{nc} \end{matrix} \right] \end{matrix} \right. \end{matrix}$$

4.3 Cluster-heads

A cluster-head is a vector of the measured metrics that are close to all the measured metrics of the same cluster and are calculated using Equation 5.14.

$$\mathbf{h}_j = \left[\frac{\sum_{i=1}^n \mathbf{m}_{ij}^f \cdot \mathbf{x}_i}{\sum_{i=1}^n \mathbf{m}_{ij}^f} \right], \forall j \quad (5.14)$$

The cluster-heads positions are initialized randomly at the beginning of the clustering process and are updated at each step (epoch) to be closer to the large amount of points. When the algorithm converge, the cluster-heads positions remain stable, stopping this way the learning process. Once the FCM clustering algorithm converge, the transmission settings can be ranked based on their membership-degrees to the clusters. Thus, the network controller is able to assign the best transmission setting among the settings available in each cluster.

5 Simulation settings and results

To evaluate the ability of the policy iteration algorithm to target the transmission settings that belong to the cluster of settings that match the requirements of Internet of things (IoT) applications, we use a modified version of LoRaSim simulator [204]. To update its policy, the policy iteration algorithm has to assess the quality of wireless transmissions by trying many transmission settings that include: the Bandwidth (BW), the Coding

Rate (CR), the Transmission Power (P^{tx}) and the Spreading Factor (SF). These parameters are tuned automatically to fit the scenario under study and also the application running on devices. All these parameters and others are described in Table 5.3. The path loss exponent is kept at 2.7 to reflect the spectral noise in sub-urban environment. As we propose an iterative approach to update transmission settings, we use two channels to exchange data in the uplink channel and acknowledgements in the downlink channel.

Parameters	Values
Environment settings	
Path loss exponent (α)	2.7 (sub-urban)
Number of uplink channels	1
Number of downlink channels	1
Number of pkt sent by device	100
Capture Effect	6.0 dB
Scenarios settings	
Number of applications	3
Number of gateways	[1, ... , 10]
Number of end-devices	[100, ..., 10K]
Packet Size	[10, 40, 70, 100] B
Packet Rate	1 pkt per [1, 2, ..., 10] mn
Transmission settings	
Bandwidth	[125, 250, 500] kHz
Transmission Power	[2, 5, 8, 11, 14] dBm
Coding Rate	[1, 2, 3, 4]
Spreading Factor	[7, 8, 9, 10, 11, 12]
Carrier Frequency	868.1 MHz

Table 5.3. Simulation settings.

Unlike the previous chapter, we aim in this chapter to not only maximize the data rate of the network but also to assess our assumption to make each device target the transmission setting that best fit its requirements. We assume that devices are running three type of applications: i) application with the highest Quality of Service (QoS) requirements (App 2), ii) application with the lowest QoS requirements (App 0), iii) application with QoS requirements level between the two previous ones (App 1). Fig. 5.5 shows the deployment of two scenarios with different number of EDs and Gateways (GWs). The first scenario has been deployed with one GW and 100 EDs and the second one with four GWs and 1000 EDs. In first scenario, EDs send packets of 70 B every 4 min to one BS (Fig. 5.5a). However, in the second scenario, we deal with the scalability of LoRaWAN by increasing the number of EDs to 1000 that send packets of 70 B every 4 min to 4 BSs (Fig. 5.5b). Both scenarios respect the duty cycle of 1% recommended by LoRaWAN alliance [71]. Other scenarios were also studied and showed the same performances.

To highlight the performance of the policy-iteration algorithm, we report in this section the Data Rate (DR) measured in our experiments. Two results are studied through our simulations. First, the overall DR improvement over the state of the art, and second, the DR differentiation efficiency. During the learning process, the policy-iteration algorithm is able to target the three link states required by devices and offers 3 different levels of data rate consequently. Before studying the behavior of the data rate and the Packet Delivery Ratio (PDR) during the learning process, we compare the average data rate mea-

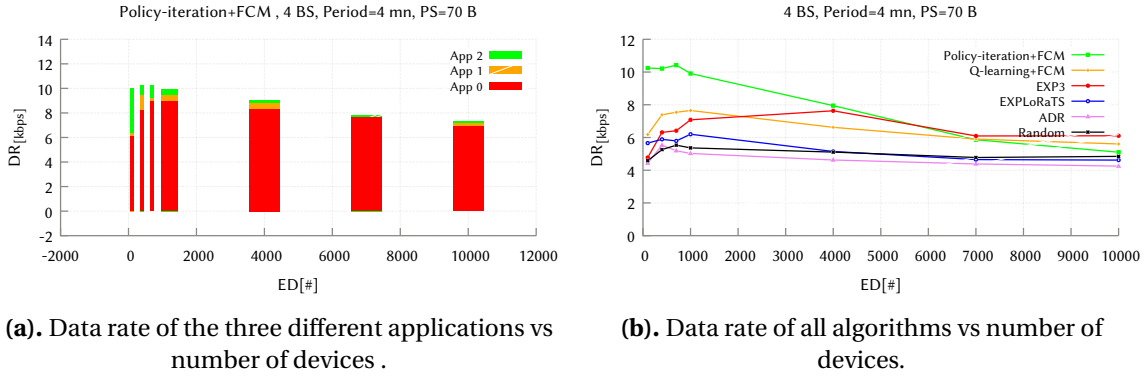
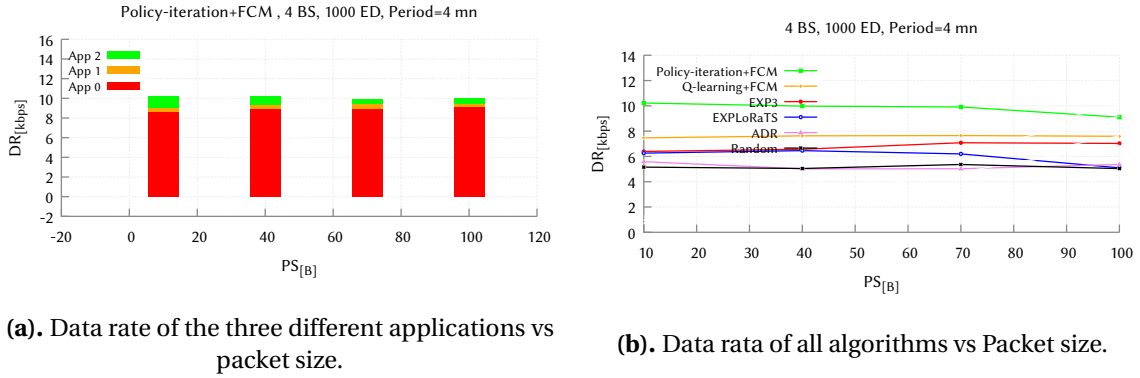


Figure 5.6. Data rate vs number of devices.

sured with the policy-iteration algorithm and the algorithms proposed in the literature (EXP3, Adaptive Data Rate (ADR) [71] and EXPLoRaTS [59]). However, these algorithms have been proposed to enhance only the network DR without dealing with applications requirements. We assess the performance of the policy-iteration algorithm and Fuzzy C-Means (FCM) in many scenarios with different numbers of devices, base stations and different packet sizes and rates as well. Then, we select two scenarios with 100 and 1000 devices and we compare the DR and the energy consumption during the learning process. In all scenarios, the policy-iteration algorithm is able to enhance the DR better than the state of the art. In addition, the policy-iteration algorithm is able to adapt the link quality required by each application and offer three different levels of data rates.

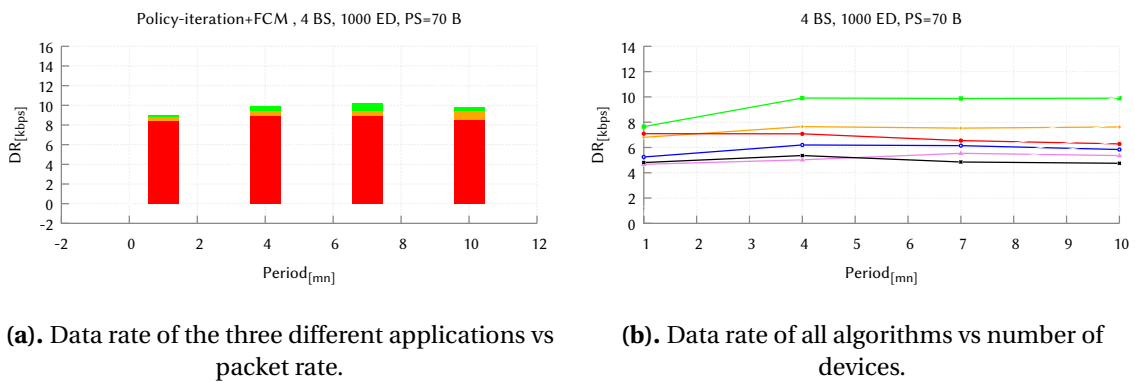
When we look at the data rate of each sub-traffic in Fig. 5.6a, we realize that the traffics generated by applications have different levels of data rate. The sub-traffic generated by application #2 has the highest data rate whatever the number of devices from 100 to 10k devices. Since devices that run application #2 target the cluster with the highest quality metrics, they will automatically select transmission settings that have the highest membership degrees to this cluster to jump and remain in the highest link state quality. In the other side devices with the lowest data rate constraints that run application #0, will target the cluster with the lowest quality metrics. As a consequence, they will select the transmission settings that have the highest membership degrees to that cluster.

The average data rate of all transmitted packets including the dropped ones is presented in Fig. 5.6b. We observe that the DR decreases when increasing the number of devices for all algorithms due to the collisions that occur more frequently by adding devices. However, Reinforcement Learning (RL) algorithms (the policy iteration, Q-learning and EXP3) always offer a better DR than the other algorithms thanks to their ability to learn from the previous transmissions by acquiring knowledge to select transmission settings with less probability of collisions. As the number of EDs increases, the data rate decreases gradually due to the physical limitations to access the channel. The DR reaches its highest value when the number of end-devices is less than 1000 for all algorithms except EXP3 since it is the only RL algorithm that does not take advantage of FCM clustering outputs. Our algorithm shows a higher DR than other algorithms since it takes advantage of the initial knowledge from FCM before starting the learning process. When the DR of the policy-iteration is between 8 and 10 kbps, the data rate of other algorithms does not exceed 7.9 kbps in scenarios with less than 4K devices. As Q-learning requires only to know at which state each action leads, without requiring the entire transition matrix, it requires more traffic to update its policy. It has to build this knowledge during the learn-



(a). Data rate of the three different applications vs packet size.

(b). Data rata of all algorithms vs Packet size.

Figure 5.7. Data rate vs packet size.

(a). Data rate of the three different applications vs packet rate.

(b). Data rate of all algorithms vs number of devices.

Figure 5.8. Data rate vs packet rate.

ing process from scratch and this slightly decreases its performance to enhance the data rate.

The same behavior has been observed when we set packet sizes from 10 to 100 in Fig. 5.7a. Subtraffics generated by our three applications have three different data rate in average whatever the size of the transmitted packets. The main advantage of machine learning algorithms in general is their adaptability to different scenarios. However, by modeling state transitions with FCM, the policy iteration algorithm acquires an initial knowledge of the environment that makes it more adaptable and more knowledgeable before even starting the learning process. Preferences made during the learning process to target the desired state make the data rate of the subtraffic generated by application #2 higher than other subtraffics.

Fig. 5.7b shows the impact of PS on DR with all algorithms. Increasing the packet size from 10 to 100 B has a slight impact on the average uplink data rate since collisions occur more frequently with long packets especially when we exceed the 70 B. However, we observe that our algorithm has a higher data rate (10 kbps) compared to other algorithms when increasing the packet size from 10 B to 100 B. Q-learning stills in the second position with 7.5 to 8 kbps and EXP3 in the third position with 6 kbps. The data rate of EXPLoRaTS and ADR algorithms is lower even with small packets. Random transmissions has the lowest data rate since there is no strategy that leads to data rate enhancement. Since there is 4 cells, end-devices are able to use lower SF to send their packets to the closest BS without interfering with other transmissions in other cells. This decreases considerably the probability of collision if we compare it with one cell topology (see Fig. 5.9b).

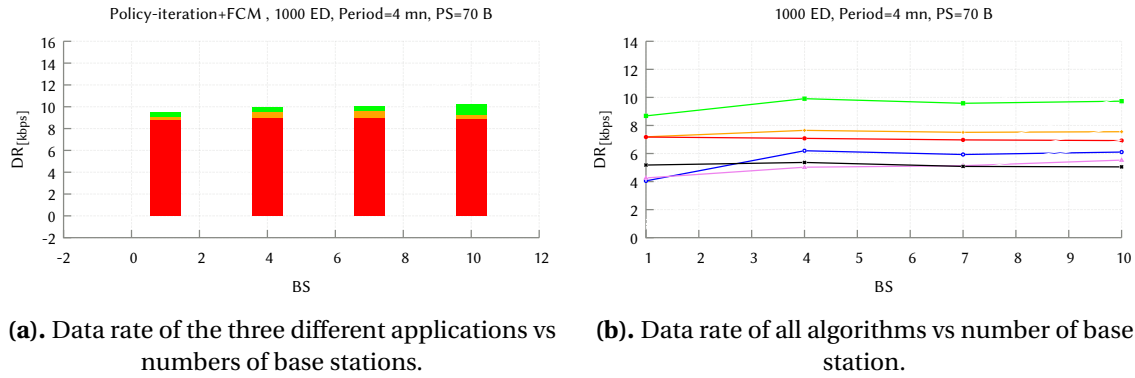


Figure 5.9. Data rate vs number of base stations.

The impact of the packet rate on the data rate of the applications emphasize the power of using machine learning algorithms to fit different scenarios. To this purpose, we plot in Fig. 5.8a the average levels of data rate of the three traffics. When decreasing the packet rate from 1 packet per minute to 1 packet per 10 min, we observe the same rank of data rates levels whatever the packet rate. It worth to be mentioned that scenarios with a higher packet rate than 4mn are strongly prohibited by LoRaWAN alliance since such scenarios do not respect a duty cycle of 1%, especially when it comes to send packets with the highest spreading factors that occupy the channel for a long time denying others to send at the same time to mitigate collisions. Fig. 5.8b shows the impact of Packet Rate (PR) on DR with all algorithms. Due to Duty cycle (DC) restrictions, devices are not allowed to use the channel more than 1% of the time. This means that if the PS is equal to 70 B and the SF equal to 12, the Time on Air (ToA) of the transmitted packet is around 2.3s. If we apply a DC of 1%, a node needs to remain silent for around 228s (2.3 * 99 a little less than 4min), For this reason, Long Range (LoRa) devices are not authorized to send their collected data within less than 4 min especially if they are far from the gateway and should use SF 12 to reach it. In our experiments, the data rate shows a slight increase of data rate by decreasing the packet rate since decreasing the packet transmission frequency decreases the probability of collision. The policy iteration algorithm shows the highest data rate compared to Q-learning and other algorithms. As we aim to maximize the uplink traffic by maximizing the uplink data rate Policy iteration and Q-learning are able to fit each scenario under study and offer the highest uplink traffic than EXP3 and other algorithms. ADR has the lowest data rate such as the random algorithm since it tries to maximize the DR caring only about the Received Signal Strength Indicator (RSSI) of the recent received packets. Hence, if two devices try to use the same SF and the same P^{tx} to increase their DR, none of them could reach the gateway since a collision would occur each time they send a packet at the same time.

By increasing the number of base stations in Fig. 5.9a, we see that the average DR of each traffic generated by each application remains in the same order. This allows a better resources sharing according to IoT devices needs, whether they are high, medium or low. This also highlight the differentiated services offered to LoRaWAN devices by making the same network hold different traffics with different levels of data rate. Whatever the number of cells, devices running application #2, remain at the first position with the highest data rate. Application #1 follows in the second position and application #0 at the third position. Such findings are highly required in IoT markets to separate traffics and offer to applications a customized data rate based on the type of data that they collect.

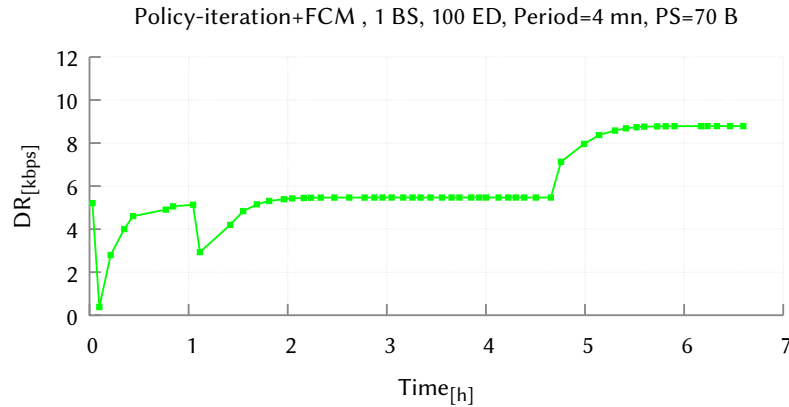
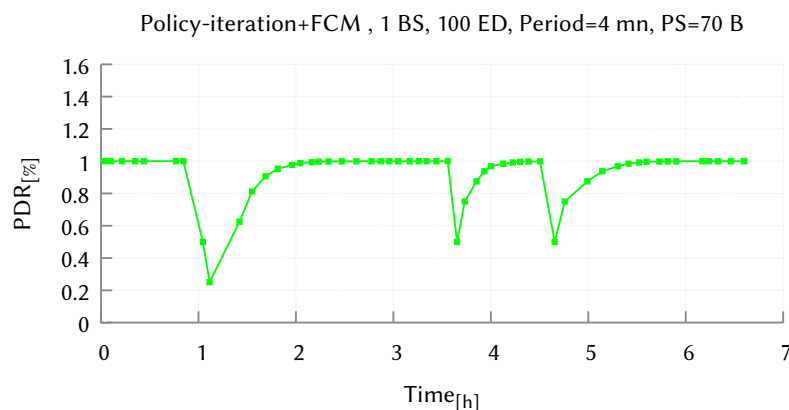
(a). Data rate convergence over time of device n^o 35.(b). PDR convergence over time of device n^o 35.**Figure 5.10.** Convergence of the learning process of device n^o 35.

Fig. 5.9b shows the impact of the number of BSs on the DR for each algorithm. We observe that the data rate is always higher with the policy iteration thanks to the prior knowledge acquired from FCM to generate membership degrees values. EXP3 offers a better data rate than EXPLoRaTS, ADR and random algorithms but lower than Q-learning and the policy iteration algorithms. ADR and random algorithms have the lowest data rate whatever the number of cells since ADR is known for its scalability issue when the number of devices is higher than 500 devices.

We showed in the previous figures the overall data rate measured during our intensive simulation to assess the performance of our work in many scenarios. We focus in the following sections on the time of convergence and we describe in depth the behavior of both data rate and energy consumption during the learning process.

5.1 First scenario

To highlight the advantage of the clustering preprocessing step in the learning process, we measure in this section the data rate and the energy consumption with 100 devices. We compare the overall data rate offered by the policy-iteration algorithm and other algorithms and also the data rate of the subtraffics generated by applications.

Fig. 5.11 shows the comparison between the average DRs of the global traffic using

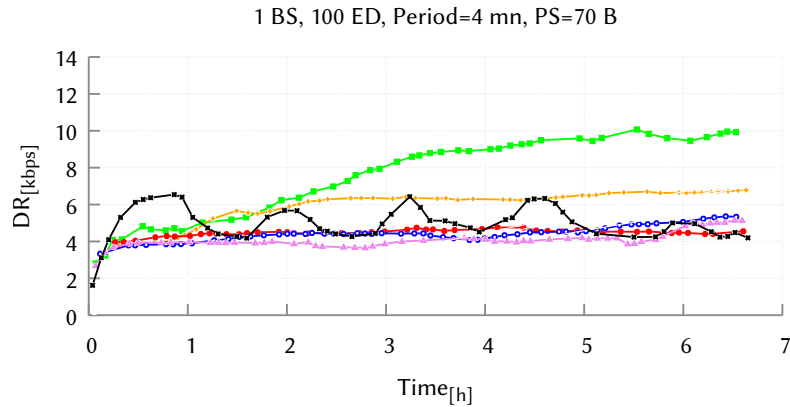


Figure 5.11. DR of all algorithms in the first scenario.

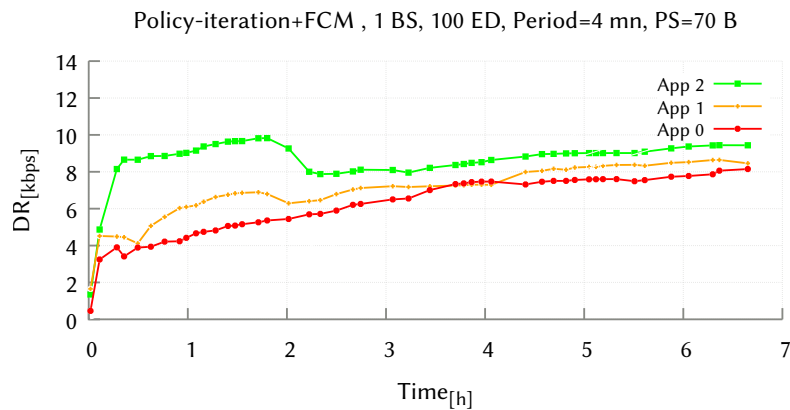


Figure 5.12. Data rate convergence over time in the first scenario.

the policy iteration, EXP3 [ADR](#), EXPLoRaTS and Random algorithms. The [DR](#) of the policy iteration algorithm outperforms significantly the measured [DR](#) obtained with all other algorithms. When the last transmitted packets get a [DR](#) higher than 10 kbps using the policy iteration algorithm, heuristic algorithms like [ADR](#) and EXPLoRaTS offer a [DR](#) lower than 5.5 kbps. Q-learning algorithm offers the second powerful [DR](#) since it uses the knowledge of the clustering process to jump from one state to another based of the membership degrees of each transmission setting to clusters. Random algorithm oscillates without any purpose of convergence since it does not apply any strategy that drives to an optimal data rate. Through this figure, we validate the major advantage of applying the policy iteration algorithm with [FCM](#) to outperform state of the art proposals.

Due to the diversification of [IoT](#) applications, we attempt to find a solution to offer to these applications different levels of data rate rather than a common one. This allows devices with high data rate constraints to use better resources than devices with a low data rate request, avoiding this way waste of resources and energy. In this context, [Fig. 5.12](#) shows the average data rate of the three traffics generated by three applications. End-devices that run App 2 which requires the highest data rate, get their packets transmitted with the highest data rate during all the learning process. Since devices that run App 2 target the best link state with the gateway. The transition state matrix provided by [FCM](#) helps the algorithm to select the transmission settings that lead to this state quickly. Ap-

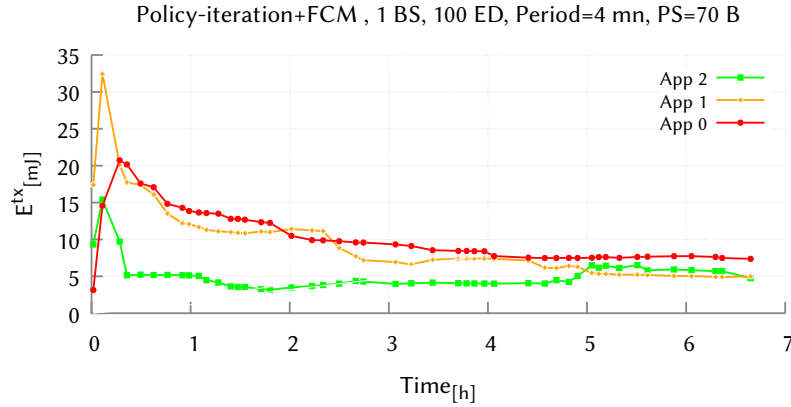


Figure 5.13. Energy convergence over time in the first scenario.

plications with low data rate constraints get a lower data rate but still higher than 8 kbps. Through this figure, we validate the advantage of having three target states and knowing in advance with which probability each transmission setting leads to each state.

Energy consumption is another constraint for many applications and worth to be studied since we work in the context of Low Power and Wide Area Networks (LPWAN). Fig. 5.13 shows the average energy consumption per packet of the three applications. EDs with high energy consumption constraints that run App 2, get the lowest energy consumption compared to other traffic with a consumption of 2 mJ per packet. Fig. 5.13 shows also a decrease in energy consumption over time for all devices. As we maximize the DR, highest SFs that cause a low DR and a high energy consumption are avoided during the learning process as long as they do not enhance the reward.

Through the all previous measured metrics in the first scenario, the data rate of each sub-traffic fits well the required level of data rate by applications. Hence, on-demand customization of the data rate is made possible and can be managed with our solution.

5.2 Second scenario

To highlight the advantage of both FCM and the policy-iteration algorithm in a dense network, we measure in this section the same metrics as scenario one but with 1000 devices. This scenario aims to assess the high adaptability of the learning process and the convergence time in different scenarios. In fact, when there is a high demand of transmission settings by a lot of devices, all transmission settings that belong to the same cluster and offer the same QoS will be selected. Thanks to the clustering reprocessing step, devices running the same application will target transmission settings with high membership degrees to the same cluster.

Like Fig. 5.11 in the first scenario, the DR in the second scenario is shown in Fig. 5.14. The obtained DR was compared with the DR of other algorithms including ADR, EXPLoRaTS and random. Similar to the first scenario, the DR of the policy iteration algorithm outperforms the DR of all other algorithms thanks to the prior knowledge provided by FCM to model the quality level of each transmission setting. In fact, as the number of EDs is higher than in the first scenario, the probability of collisions increase but the policy iteration algorithm is able to reduce it since each device target one of the three states provided by the clustering process. As we assume that there is three target states, we pro-

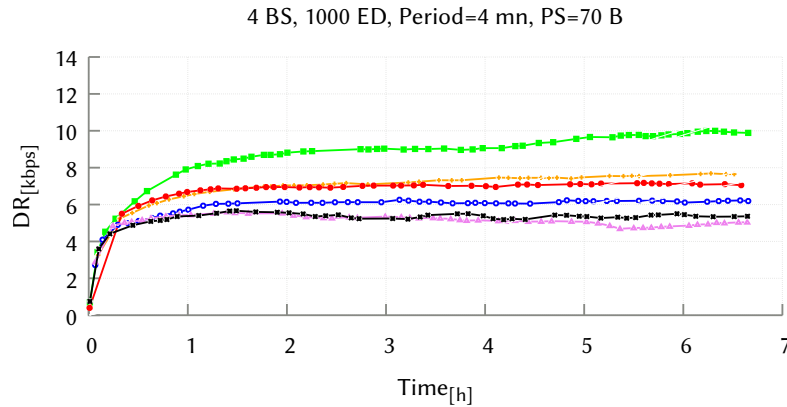


Figure 5.14. DR of all algorithms in the second scenario.

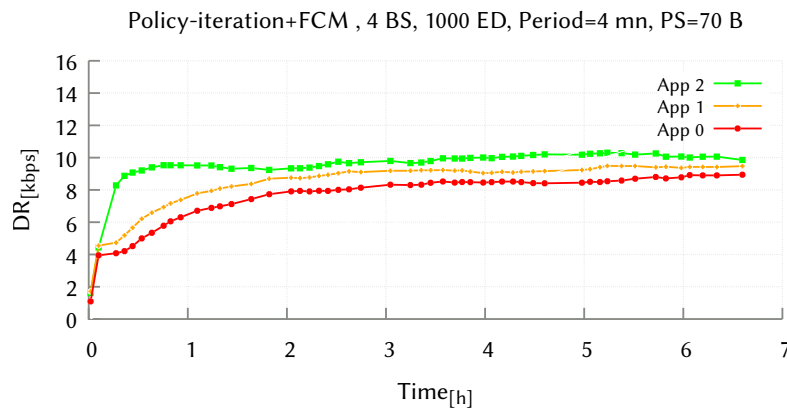


Figure 5.15. Data rate convergence over time in the second scenario.

hibit devices running different applications to converge to the same transmission setting reducing this way interferences that could occur. The data rate with 1000 EDs remains higher than 9 kbps using our solution during the learning process. This highlight the performance of the policy iteration algorithm and FCM to maximize the DR even in a dense network. EXP3 and EXPLoRaTS get a lower DR (less than 7 kbps) when ADR and random algorithms get the worst DR between 4.5 and 5 kbps.

When we look at the difference between the average data rate of the subtraffics generated by the three applications in the second scenario (see Fig. 5.15), we observe the same behavior even if we increased the number of devices from 100 to 1K. The traffic generated by App 2 which requires the highest data rate has the highest data rate during all the learning process. In addition, we observe also that the traffics achieve their highest data rate after only 4 hours. Through this figure, the advantage of clustering transmission settings before even starting the learning process appears clearly and validate our assumption to use of membership degrees as state transition probabilities.

The main advantage of LPWAN is their range but also their low energy consumption that comes with. To highlight this advantage, Fig. 5.16 shows the average energy consumption per packet and per device running three different applications. As increasing the DR fosters the selection of lower SFs that consume less energy, the traffic generated by App 2 has slightly the lowest energy consumption compared to other traffics. Further-

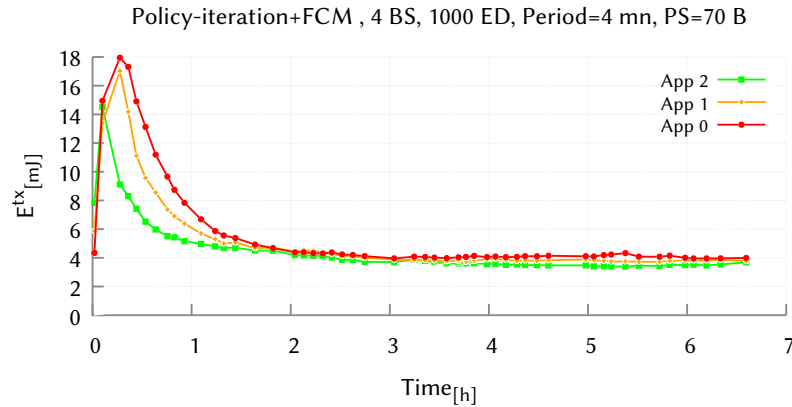


Figure 5.16. Data rate convergence over time in the second scenario.

more, it converges faster than other traffics to the lowest energy consumption since the path to the best uplink state is shortened by following the highest transitions probabilities to that state.

Through the measured metrics in the second scenario, the data rate of all traffics remains better than the state of the art and fits well the required data rate of the three applications even in a dense network. This highlights the high adaptability of our solution to cope with different scenarios while offering the required data rate to applications.

6 Conclusion

We addressed in this chapter the problem of adapting Long Range (LoRa) transmission settings to the requirements of Internet of things (IoT) applications. We introduced a new solution to make these applications use the same physical channel and the same network server but with different Quality of Service (QoS) levels. We proposed a traffic differentiation solution with LoRa technology by making each device target the transmission settings that belong to the cluster that matches the requirements of the application that it runs. Thanks to the Fuzzy C-Means (FCM) algorithm, the prior knowledge about the quality of each transmission setting was built and fed to the policy-iteration algorithm to converge faster and better to the set of transmission settings that best fit IoT applications' needs. Our results show that the policy iteration algorithm of the policy-iteration algorithm improves the efficiency of LoRa transmissions in terms of energy consumption, Packet Delivery Ratio (PDR) and Time on Air (ToA) regarding their Data Rate (DR).

6 | Conclusion

Quotation

The important thing is not what they have made to us, but what we make with what they have made to us. - Jean-Paul Sartre

L'important n'est pas ce qu'on a fait de nous, mais ce que nous faisons nous-même de ce qu'on a fait de nous. - Jean-Paul Sartre

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1 Conclusion

During the few past years, Low Power and Wide Area Networks (LPWAN) networks have gained the interest of research communities and Internet of things (IoT) manufacturers. In fact, many industries, nowadays, require more and more devices with wireless communication technologies to increase their productivity. This has led to the increase of the size of data flowing through such networks that are characterized by their heterogeneity and the diversification of IoT applications that use them. Transmitting the data to the cloud with a high reliability and performance still present a very challenging issue due to the low data rate of LPWAN networks and their random access to the channel. In addition, to offer reliable and accurate services to LPWAN network users, the collected data should be transmitted according to application requirements and the quality of the link should meet their service level agreements. For this reason, we propose in this thesis to exploit the power of machine learning techniques to overcome the encountered challenges and dynamically adjust network settings without human intervention. Hence, we deal in this thesis with three main aspects: i) patterns recognition of wireless transmission settings, ii) online Reinforcement Learning (RL) and iii) contextual wireless transmission based on these patterns. In the first contribution, we propose to cluster the transmission settings using unsupervised learning algorithms to split all the combinations of parameters to three main clusters to see whether they are able to recognize the quality level of each setting. Whereas, in the second contribution, we exploit the outcomes of the clustering process to enhance the uplink traffic quality and to maximize the data rate of IoT devices. Finally, the third contribution exploits in depth the recognized patterns to not only enhance the overall data rate of IoT devices but also to offer a customized data rate regarding the need of each IoT application.

To achieve these goals, we firstly devote our interest to study all available tools to recognize different patterns in different datasets in the literature. This drives us to review many unsupervised learning algorithms and particularly the fuzzy clustering algorithm that is able to split a set of items to many subsets with the same properties. Afterward,

we propose to apply the fuzzy clustering solution in our work to recognize the quality levels (patterns) of Long Range (LoRa) transmission settings (items). The advantage of such solution is its ability to map all transmission settings to three quality levels based on their membership degrees to each cluster. This means that we can recognize from the clustering outputs at which quality level LoRa transmission settings could lead based on their memberships to different clusters. The purpose behind this process is to acquire an initial knowledge that will speed up the learning process by exploiting directly the best transmission settings without exploring more settings. Based on our findings, Fuzzy C-Means (FCM) is able to recognize the quality level of each transmission setting and map each of them to the right cluster. This means that it is able to generate three clusters with three distinguished quality levels based on the Signal to Noise Ratio (SNR), Time on Air (ToA), Bit Error Rate (BER) and the Data Rate (DR) of LoRa transmission settings.

In the second contribution, we propose a new online reconfiguration scheme based on Q-learning which maximize the overall data rate of the network without caring about the requirements of IoT applications. This contribution relies on the output of FCM to know at which state each action (transmission setting) could lead by knowing at which cluster each setting belongs more. The learning process is based on the interaction between end-devices and the gateways to evaluate the uplink traffic by measuring the Quality of Service (QoS) metrics of transmissions. Then, based on the measured reward and the cluster at which transmission settings belong, we update the policy that drive to select better settings.

In the third contribution, we propose to adapt LoRa transmission settings to different IoT applications' requirements. We propose a new solution to make these applications use the same physical channel and the same network server but with different QoS levels. To achieve this goal, We introduce a new traffic separation solution by maximizing the DR of each sub-traffic. Thanks to the knowledge provided by FCM, a prior knowledge about the quality of each transmission setting was built and fed to the policy-iteration algorithm to converge faster and better to the set of transmission settings that best fit IoT applications needs. The advantage of the policy-iteration algorithm compared to Q-learning is its ability to update its policy based on the state transition matrix that discloses the probability $P(s_1|a), \dots, P(s_n|a)$ with which action a will makes wireless transmissions jump to s_1, \dots, s_n . Since FCM is able to generate the membership degrees $M(c_1, a), \dots, M(c_n, a)$ of each transmission setting a to clusters c_1, \dots, c_n , we propose to initialize the state transition matrix $P(s | a)$ of the policy-iteration algorithm by the membership degrees matrix $M(c, a)$ of FCM. Results show that the policy-iteration algorithm and FCM improve the efficiency of LoRa transmissions in terms of energy consumption, Packet Delivery Ratio (PDR) and ToA with regard to the DR of each sub-traffic.

Through these three contributions, we believe that we achieved our main goals by providing new solutions while considering Long Range Wireless Access Network (LoRaWAN) alliance specifications. Our work is open to possible extensions to explore other research issues and face new emerging challenges. Hence, possible enhancements will be the purpose of our future work that we describe in the next section.

2 Perspectives

To highlight our new research perspectives and possible direct applications of our contributions during this thesis, we propose in this section several new ideas that we believe that they can further extend our work in some manners. First, regarding our patterns

recognition in chapter 3. We aim to find a new solution to split the set of transmission settings to get 3 subsets of network settings with delay, reliability and energy sensitivity like eMBB, URLLC and mMTC in 5G network. For this reason, we seek, as a first attempt, to manually divide our dataset using fuzzy logic algorithms to generate 3 subsets of transmission settings: delay, reliability and energy sensitive subsets.

Further enhancements are also planned to use several contextual Multi-Armed Bandit (MAB) algorithms to see whether they are able to consider the new clustering scheme and adapt their training accordingly. This can be done by using several contextual MAB algorithms already proposed by machine learning community to satisfy Internet of things (IoT) users based on their applications requirements.

A | Appendix: LoRa frame and LoRaWAN specification

Quotation

If you see two people fighting, observe well and you will always find a third one that is rubbing his hands – Unknown

Si vous voyez deux personnes qui se bagarrent, regardez bien, vous verrez toujours une troisième qui se frote les mains – Inconnu

Characteristics	CF _[Hz]	6LoWPAN	LoRaWAN	SigFox	NB-IoT	INGENU	TELENSA
Modulation	2.4G 915M 868M	O-QPSK BPSK BPSK	- LoRa LoRa/GFSK	- BPSK↑,GFSK↓ BPSK↑,GFSK↓	QSPSK↓ QSPSK n-tone↑ π/4-QPSK 1-tone	RPMA↑, CDMA↓	2-FSK 2-FSK 2-FSK
Channels	2.4G 915M 868M	16 10 1	- 64+8↑, 8↓ 10	- X 360+40	- X X	40 X X	X X X
CF_[MHz]	2.4G 915M 868M	X 902-929 868-868.6	- 902-928 863-870 and 780	- 902 868.18-868.22	- X X	X X X	ISM 915M 868M/430M
BW_[Hz]	2.4G 915M 868M	5M 2M 600M	- 125k-500k 125k-250k	- X 0.1k-1.2k	200k X X	1M X X	X X X
DR_[kbps]	2.4G 915M 868M	250M 40M 20M	- 980-22k LoRa:37.5k	- X 0.1k↑,0.6k↓	- 234.7↓, 204.8↑ X	78k↑, 19,5k↓ X X	X X 62.5↑, 500↓
Range_{km}	868M	0.01-0.1	5-15	10-50	1	15-?	1-?
Handover	868M	X	Multi BS	Multi BS	X	X	X
msg/day	868M	X	Unlimited	140↑,4↓	Unlimited	X	X
PS_[B]	868M	X	51 - 243	12↑,8↓	1.6k	10k	X
Spreading	868M	DSSS	CSS	UNB	X	DSSS	UNB
Proprietary	868M	X	X	✓	X	X	X
Topology	868M	X	Star, Stars	Star	X	Star, Tree	Star
ADR	868M	X	✓	X	X	✓	X
Security	868M	X	AES 128b	X	X	AES 256B	X
Battery_[years]	868M	1-2	<10	<10	<10		
Cost	868M	Free	35e	25e	1020e		
Standar	868M	IETF	LoRa Alliance		3GPP		
Mobility	868M	High	High,Simple	High,Simple	High,complex	Low	Low
Latency	868M	Low	Low	Low	High (1.6-10s)	High	Medium
E_[dBm]^{tx}	868M		+14/+20		20 -> 23		
Real-Time	868M		Class C	X	X	✓	X
Scalability	868M		1M↑, 100k↓		55 k		

Table A.1. LPWAN Characteristics [93] [104] [32] [100].

Bibliography

Quotation

A quote in a speech, article or book is like a gun in the hands of a soldier. It speaks with authority. - Brendan Francis Brown

Une citation dans un discours, un article ou un livre est comme une arme dans les mains d'un soldat. Elle fait autorité - Brendan Francis Brown

Application layer

- [1] Aloßs Augustin et al. [A Study of LoRa: Long Range Low Power Networks for the Internet of Things](#). In: *Sensors*. Evaluation of Lora 16.9 (Sept. 9, 2016), p. 1466.
- [2] Pape Abdoulaye Barro. [A LoRaWAN Coverage testBed and a Multi-Optional Communication Architecture for Smart City Feasibility in Developing Countries](#). In: (2019), p. 12.
- [3] Pape Abdoulaye Barro, Marco Zennaro, and Ermanno Pietrosemoli. [TLTN extendash The Local Things Network: On the Design of a LoRaWAN Gateway with Autonomous Servers for Disconnected Communities](#). In: *2019 Wireless Days (WD)*. 2019 Wireless Days (WD). Manchester, United Kingdom: IEEE, Apr. 2019, pp. 1–4.
- [4] Pape Barro et al. [A Smart Cities LoRaWAN Network Based on Autonomous Base Stations \(BS\) for Some Countries with Limited Internet Access](#). In: *Future Internet* 11.4 (Apr. 8, 2019), p. 93.
- [5] Pape Barro et al. [Towards Smart and Sustainable Future Cities Based on Internet of Things for Developing Countries: What Approach for Africa?](#) In: *EAI Endorsed Transactions on Internet of Things* 4.13 (Sept. 2018), p. 155481.
- [6] Carlo Alberto Boano, Marco Cattani, and Kay Römer. [Impact of Temperature Variations on the Reliability of LoRa - An Experimental Evaluation](#): in: *Proceedings of the 7th International Conference on Sensor Networks*. 7th International Conference on Sensor Networks. Funchal, Madeira, Portugal: SCITEPRESS - Science and Technology Publications, 2018, pp. 39–50.
- [7] Tonghao Chen, Derek Eager, and Dwight Makaroff. [Efficient Image Transmission Using LoRa Technology In Agricultural Monitoring IoT Systems](#). In: *2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData). Atlanta, GA, USA: IEEE, July 2019, pp. 937–944.
- [8] Adwait Dongare et al. [OpenChirp: A Low-Power Wide-Area Networking Architecture](#). In: *2017 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*. 2017 IEEE International Conference on Pervasive Computing and Communications: Workshops (PerCom Workshops). Kona, HI: IEEE, Mar. 2017, pp. 569–574.

- [9] Mohammad Mohammadi Erbat, Gregor Schiele, and Gerd Batke. [Analysis of LoRaWAN Technology in an Outdoor and an Indoor Scenario in Duisburg-Germany](#). In: *2018 3rd International Conference on Computer and Communication Systems (ICCCS)*. 2018 3rd International Conference on Computer and Communication Systems (ICCCS). Nagoya: IEEE, Apr. 2018, pp. 273–277.
- [10] Joakim Eriksson and Jonas Skog Andersen. [Investigating the Practical Performance of the LoRaWAN Technology](#). In: (2017), p. 61.
- [11] Arshad Farhad, Dae-Ho Kim, and Jae-Young Pyun. [Scalability of LoRaWAN in an Urban Environment: A Simulation Study](#). In: *2019 Eleventh International Conference on Ubiquitous and Future Networks (ICUFN)*. 2019 Eleventh International Conference on Ubiquitous and Future Networks (ICUFN). Zagreb, Croatia: IEEE, July 2019, pp. 677–681.
- [12] Luca Feltrin et al. [LoRaWAN: Evaluation of Link- and System-Level Performance](#). In: *IEEE Internet of Things Journal* 5.3 (June 2018), pp. 2249–2258.
- [13] Jetmir Haxhibeqiri et al. [LoRa Indoor Coverage and Performance in an Industrial Environment: Case Study](#). In: *2017 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*. 2017 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA). Limassol: IEEE, Sept. 2017, pp. 1–8.
- [14] Yik Him Ho, Chi Ho Pun, and Wing Chun Kung. [Vehicle Enabled Big Data Platform](#). In: (2016), p. 12.
- [15] Arliones Hoeller et al. [Analysis and Performance Optimization of LoRa Networks With Time and Antenna Diversity](#). In: *IEEE Access* 6 (2018), pp. 32820–32829.
- [16] Oana Iova et al. [LoRa from the City to the Mountains: Exploration of Hardware and Environmental Factors](#). In: Feb. 20, 2017.
- [17] Yun Seong Jang et al. [Swapped Huffman tree coding application for low-power wide-area network \(LPWAN\)](#). In: *2016 International Conference on Smart Green Technology in Electrical and Information Systems (ICSGTEIS)*. 2016 International Conference on Smart Green Technology in Electrical and Information Systems (ICSGTEIS). swapped Huffman tree (SHT). Denpasar, Indonesia: IEEE, Oct. 2016, pp. 53–58.
- [18] Dong-Hoon Kim, Eun-Kyu Lee, and Jibum Kim. [Experiencing LoRa Network Establishment on a Smart Energy Campus Testbed](#). In: *Sustainability*. Mlijijj 11.7 (Mar. 30, 2019), p. 1917.
- [19] Lingling Li, Jiuchun Ren, and Qian Zhu. [On the Application of LoRa LPWAN Technology in Sailing Monitoring System](#). In: *2017 13th Annual Conference on Wireless On-Demand Network Systems and Services (WONS)*. 2017 13th Annual Conference on Wireless On-Demand Network Systems and Services (WONS). Jackson, WY, USA: IEEE, Feb. 2017, pp. 77–80.
- [20] Davide Magrin, Marco Centenaro, and Lorenzo Vangelista. [Performance Evaluation of LoRa Networks in a Smart City Scenario](#). In: *2017 IEEE International Conference on Communications (ICC)*. ICC 2017 - 2017 IEEE International Conference on Communications. Paris, France: IEEE, May 2017, pp. 1–7.
- [21] Jaco M. Marais, Reza Malekian, and Adnan M. Abu-Mahfouz. [LoRa and LoRaWAN Testbeds: A Review](#). In: *2017 IEEE AFRICON*. 2017 IEEE AFRICON. Cape Town: IEEE, Sept. 2017, pp. 1496–1501.
- [22] Jaco Morne Marais, Reza Malekian, and Adnan M. Abu-Mahfouz. [Evaluating the LoRaWAN Protocol Using a Permanent Outdoor Testbed](#). In: *IEEE Sensors Journal* 19.12 (June 15, 2019), pp. 4726–4733.
- [23] Marco Cattani, Carlo Boano, and Kay Römer. [An Experimental Evaluation of the Reliability of LoRa Long-Range Low-Power Wireless Communication](#). In: *Journal of Sensor and Actuator Networks* 6.2 (June 15, 2017), p. 7.

- [24] Kais Mekki et al. [A Comparative Study of LPWAN Technologies for Large-Scale IoT Deployment](#). In: *ICT Express* 5.1 (Mar. 2019), pp. 1–7.
- [25] Konstantin Mikhaylov, Juha Petäjäjärvi, and Janne Janhunen. [On LoRaWAN Scalability: Empirical Evaluation of Susceptibility to Inter-Network Interference](#). In: *2017 European Conference on Networks and Communications (EuCNC)*. 2017 European Conference on Networks and Communications (EuCNC). Oulu, Finland: IEEE, June 2017, pp. 1–6.
- [26] Jorge Navarro-Ortiz et al. [Integration of LoRaWAN and 4G/5G for the Industrial Internet of Things](#). In: *IEEE Communications Magazine* 56.2 (Feb. 2018), pp. 60–67.
- [27] Pierre Neumann, Julien Montavont, and Thomas Noel. [Indoor Deployment of Low-Power Wide Area Networks \(LPWAN\): A LoRaWAN Case Study](#). In: *2016 IEEE 12th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. 2016 IEEE 12th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). New York, NY: IEEE, Oct. 2016, pp. 1–8.
- [28] Keith E. Nolan, Wael Guibene, and Mark Y. Kelly. [An Evaluation of Low Power Wide Area Network Technologies for the Internet of Things](#). In: *2016 International Wireless Communications and Mobile Computing Conference (IWCMC)*. 2016 International Wireless Communications and Mobile Computing Conference (IWCMC). Paphos, Cyprus: IEEE, Sept. 2016, pp. 439–444.
- [29] Ruben Oliveira, Lucas Guardalben, and Susana Sargento. [Long Range Communications in Urban and Rural Environments](#). In: *2017 IEEE Symposium on Computers and Communications (ISCC)*. 2017 IEEE Symposium on Computers and Communications (ISCC). Heraklion, Greece: IEEE, July 2017, pp. 810–817.
- [30] Francesco Orfei, Chiara Benedetta Mezzetti, and Francesco Cottone. [Vibrations Powered LoRa Sensor: An Electromechanical Energy Harvester Working on a Real Bridge](#). In: *2016 IEEE SENSORS*. 2016 IEEE SENSORS. Oct. 2016, pp. 1–3.
- [31] Jose Paredes-Parra et al. [An Alternative Internet-of-Things Solution Based on LoRa for PV Power Plants: Data Monitoring and Management](#). In: *Energies* 12 (Mar. 2019), p. 881.
- [32] Felisberto Pereira et al. [Using Compact LoRa Devices for In-Building Communications](#). In: (2019).
- [33] Juha Petäjäjärvi et al. [Evaluation of LoRa LPWAN Technology for Indoor Remote Health and Wellbeing Monitoring](#). In: *International Journal of Wireless Information Networks* 24.2 (June 2017), pp. 153–165.
- [34] Juha Petäjäjärvi et al. [Performance of a Low-Power Wide-Area Network Based on LoRa Technology: Doppler Robustness, Scalability, and Coverage](#). In: *International Journal of Distributed Sensor Networks* 13.3 (Mar. 2017), p. 155014771769941.
- [35] Tara Petric et al. [Measurements, Performance and Analysis of LoRa FABIAN, a Real-World Implementation of LPWAN](#). In: *2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*. 2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC). Valencia, Spain: IEEE, Sept. 2016, pp. 1–7.
- [36] Congduc Pham. [Deploying a Pool of Long-Range Wireless Image Sensor with Shared Activity Time](#). In: *2015 IEEE 11th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. 2015 IEEE 11th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). Oct. 2015, pp. 667–674.
- [37] Wimol San-Um et al. [A long-range low-power wireless sensor network based on U-LoRa technology for tactical troops tracking systems](#). In: *2017 Third Asian Conference on Defence Technology (ACDT)*. IEEE, Jan. 2017.

- [38] Ramon Sanchez-Iborra et al. [Performance Evaluation of LoRa Considering Scenario Conditions](#). In: 18.3 (Mar. 2018), p. 772.
- [39] Francisco Helder C. dos Santos Filho et al. [Performance of LoRaWAN for Handling Telemetry and Alarm Messages in Industrial Applications](#). In: *Sensors* 20.11 (11 Jan. 2020), p. 3061.
- [40] Davide Sartori and Davide Brunelli. [A Smart Sensor for Precision Agriculture Powered by Microbial Fuel Cells](#). In: *2016 IEEE Sensors Applications Symposium (SAS)*. 2016 IEEE Sensors Applications Symposium (SAS). Catania, Italy: IEEE, Apr. 2016, pp. 1–6.
- [41] Luca Sciuillo, Angelo Trotta, and Marco Di Felice. [Design and Performance Evaluation of a LoRa-Based Mobile Emergency Management System \(LOCATE\)](#). In: *Ad Hoc Networks* 96 (Jan. 2020), p. 101993.
- [42] Tuyen Truong, Bernard Pottier, and Hiep Huynh. [Cellular Simulation for Distributed Sensing over Complex Terrains](#). In: *Sensors* 18.7 (July 17, 2018), p. 2323.
- [43] Lorenzo Vangelista, Andrea Zanella, and Michele Zorzi. [Long-Range IoT Technologies: The Dawn of LoRa extrademark](#). In: *Future Access Enablers for Ubiquitous and Intelligent Infrastructures*. Ed. by Vladimir Atanasovski and Alberto Leon-Garcia. Vol. 159. Survey. Cham: Springer International Publishing, 2015, pp. 51–58.
- [44] Nadège Varsier and Jean Schwoerer. [Capacity Limits of LoRaWAN Technology for Smart Metering Applications](#). In: *2017 IEEE International Conference on Communications (ICC)* (2017).
- [45] Shie-Yuan Wang et al. [Performance of LoRa-Based IoT Applications on Campus](#). In: *2017 IEEE 86th Vehicular Technology Conference (VTC-Fall)*. 2017 IEEE 86th Vehicular Technology Conference (VTC-Fall). Toronto, ON: IEEE, Sept. 2017, pp. 1–6.
- [46] Andrew J Wixted et al. [Evaluation of LoRa and LoRaWAN for Wireless Sensor Networks](#). In: *2016 IEEE SENSORS*. 2016 IEEE SENSORS. Orlando, FL, USA: IEEE, Oct. 2016, pp. 1–3.
- [47] Guangxiang Yang and Hua Liang. [A Smart Wireless Paging Sensor Network for Elderly Care Application Using LoRaWAN](#). In: *IEEE Sensors Journal* 18.22 (Nov. 15, 2018), pp. 9441–9448.

Artificial Neural Network (ANN)

- [48] Shaohan Feng et al. [Joint Service Pricing and Cooperative Relay Communication for Federated Learning](#). In: *2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData). Atlanta, GA, USA: IEEE, July 2019, pp. 815–820.
- [49] Fengxiao Tang et al. [An Intelligent Traffic Load Prediction-Based Adaptive Channel Assignment Algorithm in SDN-IoT: A Deep Learning Approach](#). In: *IEEE Internet of Things Journal* 5.6 (Dec. 2018), pp. 5141–5154.
- [50] Ge Wang et al. [LRA-3C: Learning Based Resource Allocation for Communication-Computing-Caching Systems](#). In: *2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData). Atlanta, GA, USA: IEEE, July 2019, pp. 828–833.

Channel access layer

- [51] Khaled Q. Abdelfadeel, Victor Cionca, and Dirk Pesch. LSCHC: Layered Static Context Header Compression for LPWANs. Aug. 17, 2017. URL: <http://arxiv.org/abs/1708.05209> (visited on 03/03/2020).
- [52] Floris Van den Abeele et al. [Scalability Analysis of Large-Scale LoRaWAN Networks in Ns-3](#). In: May 16, 2017.
- [53] Ferran Adelantado et al. [Understanding the Limits of LoRaWAN](#). In: Feb. 13, 2017.
- [54] Farzad Azizi et al. [MIX-MAB: Reinforcement Learning-based Resource Allocation Algorithm for LoRaWAN](#). June 7, 2022.
- [55] Norhane Benkahla et al. [Enhanced Dynamic Duty Cycle in LoRaWAN Network](#). In: *Ad-Hoc, Mobile, and Wireless Networks*. Ed. by Nicolas Montavont and Georgios Z. Papadopoulos. Vol. 11104. Cham: Springer International Publishing, 2018, pp. 147–162.
- [56] Martina Capuzzo, Davide Magrin, and Andrea Zanella. [Confirmed Traffic in LoRaWAN: Pitfalls and Countermeasures](#). In: *2018 17th Annual Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net)*. 2018 17th Annual Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net). Capri: IEEE, June 2018, pp. 1–7.
- [57] Jiaming James Chen et al. [A Viable LoRa Framework for Smart Cities](#). In: (2018), p. 16.
- [58] Phui San Cheong et al. [Comparison of LoRaWAN Classes and Their Power Consumption](#). In: *2017 IEEE Symposium on Communications and Vehicular Technology (SCVT)*. 2017 IEEE Symposium on Communications and Vehicular Technology (SCVT). Leuven: IEEE, Nov. 2017, pp. 1–6.
- [59] Francesca Cuomo et al. [EXPLoRa: Extending the Performance of LoRa by Suitable Spreading Factor Allocations](#). In: *2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. 2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). Rome: IEEE, Oct. 2017, pp. 1–8.
- [60] Francois Delobel, Nancy El Rachkidy, and Alexandre Guitton. [Analysis of the Delay of Confirmed Downlink Frames in Class B of LoRaWAN](#). In: *2017 IEEE 85th Vehicular Technology Conference (VTC Spring)*. 2017 IEEE 85th Vehicular Technology Conference (VTC Spring). Sydney, NSW: IEEE, June 2017, pp. 1–6.
- [61] Aghiles Djoudi et al. [Do IoT LoRa Networks Support Emergency Evacuation Systems ?](#) In: *2019 International Conference on Information and Communication Technologies for Disaster Management (ICT-DM)*. 2019 International Conference on Information and Communication Technologies for Disaster Management (ICT-DM). Dec. 2019, pp. 1–2.
- [62] Aghiles Djoudi et al. [Genetic Algorithm For LoRa Transmission Parameter Selection](#). In: *The Fourteenth International Conference on Systems and Networks Communications (2019)*, p. 2.
- [63] Aghiles Djoudi et al. [Reconfiguration of LoRa Networks Parameters Using Fuzzy C-Means Clustering](#). In: *2020 International Symposium on Networks, Computers and Communications (ISNCC)*. 2020 International Symposium on Networks, Computers and Communications (ISNCC). Oct. 2020, pp. 1–6.
- [64] Arshad Farhad and Jae-Young Pyun. [HADR: A Hybrid Adaptive Data Rate in LoRaWAN for Internet of Things](#). In: *ICT Express* 8.2 (June 2022), pp. 283–289.
- [65] Muhammad Omer Farooq and Dirk Pesch. [A Search into a Suitable Channel Access Control Protocol for LoRa-Based Networks](#). In: *2018 IEEE 43rd Conference on Local Computer Networks (LCN)*. 2018 IEEE 43rd Conference on Local Computer Networks (LCN). Chicago, IL, USA: IEEE, Oct. 2018, pp. 283–286.

- [66] Claire Goursaud and Yuqi Mo. [Random unslotted time-frequency ALOHA: Theory and application to IoT UNB networks](#). In: *2016 23rd International Conference on Telecommunications (ICT)*. 2016 23rd International Conference on Telecommunications (ICT). Aloha for UNB. Thessaloniki, Greece: IEEE, May 2016, pp. 1–5.
- [67] Haiyan Hu and Hui Yan. [Study on ALOHA Anti-Collision Algorithm Based on LoRa for Internet of Things](#). In: *2018 3rd International Conference on Smart City and Systems Engineering (ICSCSE)*. 2018 3rd International Conference on Smart City and Systems Engineering (ICSCSE). Xiamen, China: IEEE, Dec. 2018, pp. 652–654.
- [68] Byoungwook Kim and Kwang-il Hwang. [Cooperative Downlink Listening for Low-Power Long-Range Wide-Area Network](#). In: *Sustainability* 9.4 (Apr. 17, 2017), p. 627.
- [69] Nikos Kouvelas, Vijay Rao, and R. R. Venkatesha Prasad. [Employing P-CSMA on a LoRa Network Simulator](#). May 30, 2018. URL: <http://arxiv.org/abs/1805.12263> (visited on 11/20/2019).
- [70] Alexandru Lavric and Valentin Popa. [Performance Evaluation of LoRaWAN Communication Scalability in Large-Scale Wireless Sensor Networks](#). In: *Wireless Communications and Mobile Computing* 2018 (June 28, 2018), pp. 1–9.
- [71] LoRa-Alliance. [LorawanTM 1.1 specification](#), April 2018. URL: <https://loro-alliance.org/lorawan-for-developers> (visited on 01/22/2021).
- [72] Davide Magrin, Martina Capuzzo, and Andrea Zanella. [A Thorough Study of LoRaWAN Performance Under Different Parameter Settings](#). June 12, 2019. URL: <http://arxiv.org/abs/1906.05083> (visited on 11/20/2019).
- [73] P. J. Marcelis, V. Rao, and R. V. Prasad. [DaRe: Data Recovery through Application Layer Coding for LoRaWAN](#). In: *Proceedings of the Second International Conference on Internet-of-Things Design and Implementation - IoTDI '17*. The Second International Conference. Pittsburgh, PA, USA: ACM Press, 2017, pp. 97–108.
- [74] Riccardo Marini et al. [LoRaWANSim: A Flexible Simulator for LoRaWAN Networks](#). In: *Sensors* 21.3 (3 Jan. 2021), p. 695.
- [75] Ivan Martinez, Philippe Tanguy, and Fabienne Nouvel. [On the Performance Evaluation of LoRaWAN under Jamming](#). In: *2019 12th IFIP Wireless and Mobile Networking Conference (WMNC)*. 2019 12th IFIP Wireless and Mobile Networking Conference (WMNC). Paris, France: IEEE, Sept. 2019, pp. 141–145.
- [76] Congduc Pham. [QoS for Long-Range Wireless Sensors Under Duty-Cycle Regulations with Shared Activity Time Usage](#). In: *ACM Transactions on Sensor Networks* 12.4 (Sept. 22, 2016), pp. 1–31.
- [77] Rajeev Piyare et al. [On-Demand TDMA for Energy Efficient Data Collection with LoRa and Wake-up Receiver](#). In: *2018 14th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. 2018 14th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). Limassol: IEEE, Oct. 2018, pp. 1–4.
- [78] Tommaso Polonelli et al. [Slotted ALOHA on LoRaWAN-Design, Analysis, and Deployment](#). In: *Sensors* 19.4 (Feb. 18, 2019), p. 838.
- [79] Alexandru-Ioan Pop et al. [Does Bidirectional Traffic Do More Harm Than Good in LoRaWAN Based LPWA Networks?](#) Dec. 14, 2017. URL: <http://arxiv.org/abs/1704.04174> (visited on 11/20/2019).
- [80] Zhijin Qin and Julie A. McCann. [Resource Efficiency in Low-Power Wide-Area Networks for IoT Applications](#). In: *GLOBECOM 2017 - 2017 IEEE Global Communications Conference*. 2017 IEEE Global Communications Conference (GLOBECOM 2017). Singapore: IEEE, Dec. 2017, pp. 1–7.

- [81] Brecht Reynders, Qing Wang, and Sofie Pollin. [A LoRaWAN Module for Ns-3: Implementation and Evaluation](#). In: *Proceedings of the 10th Workshop on Ns-3 - WNS3 '18*. The 10th Workshop. Surathkal, India: ACM Press, 2018, pp. 61–68.
- [82] Brecht Reynders et al. [Improving Reliability and Scalability of LoRaWANs Through Lightweight Scheduling](#). In: *IEEE Internet of Things Journal* 5.3 (June 2018), pp. 1830–1842.
- [83] Mattia Rizzi et al. [Evaluation of the IoT LoRaWAN Solution for Distributed Measurement Applications](#). In: *IEEE Transactions on Instrumentation and Measurement* 66.12 (Dec. 2017), pp. 3340–3349.
- [84] Qipeng Song, Xavier Lagrange, and Loutfi Nuaymi. [Evaluation of Macro Diversity Gain in Long Range ALOHA Networks](#). In: *IEEE Communications Letters* 21.11 (Nov. 2017), pp. 2472–2475.
- [85] R. B. Sørensen et al. [Analysis of Latency and MAC-Layer Performance for Class A LoRaWAN](#). In: *IEEE Wireless Communications Letters* 6.5 (Oct. 2017), pp. 566–569.
- [86] Wenshu Sui et al. [Energy-Efficient Resource Allocation with Flexible Frame Structure for Heterogeneous Services](#). In: *2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData). Atlanta, GA, USA: IEEE, July 2019, pp. 749–755.
- [87] Thanh-Hai To and Andrzej Duda. [Simulation of LoRa in NS-3: Improving LoRa Performance with CSMA](#). In: *2018 IEEE International Conference on Communications (ICC)*. 2018 IEEE International Conference on Communications (ICC 2018). Kansas City, MO: IEEE, May 2018, pp. 1–7.
- [88] Qihao Zhou et al. A Novel Rate and Channel Control Scheme Based on Data Extraction Rate for LoRa Networks. Feb. 12, 2019. URL: <http://arxiv.org/abs/1902.04383> (visited on 11/20/2019).
- [89] Rafik Zitouni et al. [IoT-Based Urban Traffic-Light Control: Modelling, Prototyping and Evaluation of MQTT Protocol](#). In: *2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. 1. July 2019, pp. 182–189.

Discussion

- [90] Abdullahi Aden Hassan and Rasmus Karlsson Källqvist. [Evaluating LoRa Physical as a Radio Link Technology for Use in a Remote-Controlled Electric Switch System for a Network Bridge Radio-Node](#). 2019.
- [91] Ala I. Al-Fuqaha et al. [Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications](#). In: *IEEE Commun. Surv. Tutorials* 17.4 (2015), pp. 2347–2376.
- [92] Khokhi Alonso. [LoRaWAN In an Environment Transmission Rate According to the Network Server, and The Initial Transmit Power Allocation Scheme](#). 2018.
- [93] Wael Ayoub et al. [Internet of Mobile Things: Overview of LoRaWAN, DASH7, and NB-IoT in LPWANs Standards and Supported Mobility](#). In: 21.2 (2019), pp. 1561–1581.
- [94] Mncedisi Bembe et al. [A Survey on Low-Power Wide Area Networks for IoT Applications](#). In: *Telecommunication Systems* 71.2 (June 2019), pp. 249–274.

- [95] Alexandros-Apostolos A. Boulogeorgos, Panagiotis D. Diamantoulakis, and George K. Karagiannidis. [Low Power Wide Area Networks \(LPWANs\) for Internet of Things \(IoT\) Applications: Research Challenges and Future Trends](#). In: *CoRR* abs/1611.07449 (2016).
- [96] Raouf Boutaba et al. [A Comprehensive Survey on Machine Learning for Networking: Evolution, Applications and Research Opportunities](#). In: *Journal of Internet Services and Applications* 9.1 (Dec. 2018), p. 16.
- [97] Charlmers. [Exploring LoRa and LoRaWAN](#). 2017.
- [98] Mehmet Ali Ert urk et al. [A Survey on LoRaWAN Architecture, Protocol and Technologies](#). In: *Future Internet* 11.10 (Oct. 17, 2019), p. 216.
- [99] Cort es Eva Jurado. [Expanding a LoRaWAN Network for Cost Efficiency Improvement](#). 2018.
- [100] [Low-Power Wide Area Network \(LPWAN\) Overview](#). Tech. rep. May 2018.
- [101] Joseph Finnegan and Stephen Brown. A Comparative Survey of LPWA Networking. Feb. 12, 2018. URL: <http://arxiv.org/abs/1802.04222> (visited on 11/27/2019).
- [102] C. Goursaud and J. M. Gorce. [Dedicated networks for IoT: PHY / MAC state of the art and challenges](#). In: *EAI Endorsed Transactions on Internet of Things*. Survey 1.1 (Oct. 26, 2015), p. 150597.
- [103] Jetmir Haxhibeqiri et al. [A Survey of LoRaWAN for IoT: From Technology to Application](#). In: *Sensors* 18.11 (Nov. 16, 2018), p. 3995.
- [104] H. A. A. Al-Kashoash and Andrew H. Kemp. [Comparison of 6LoWPAN and LPWAN for the Internet of Things](#). In: 13.4 (Oct. 2016), pp. 268–274.
- [105] Oratile Khutsoane, Bassey Isong, and Adnan M. Abu-Mahfouz. [IoT Devices and Applications Based on LoRa/LoRaWAN](#). In: *IECON 2017 - 43rd Annual Conference of the IEEE Industrial Electronics Society*. IECON 2017 - 43rd Annual Conference of the IEEE Industrial Electronics Society. Beijing: IEEE, Oct. 2017, pp. 6107–6112.
- [106] Rachel Kufakunesu, Gerhard P. Hancke, and Adnan M. Abu-Mahfouz. [A Survey on Adaptive Data Rate Optimization in LoRaWAN: Recent Solutions and Major Challenges](#). In: *Sensors* 20.18 (Sept. 2020), p. 5044.
- [107] Tor Lattimore and Csaba Szepesv ari. [Bandit Algorithms](#). 1st ed. Cambridge University Press, July 31, 2020.
- [108] Davide Magrin. [Network Level Performances of a LoRa System](#). In: *Master thesis* (2017).
- [109] Esteban Pablo. [Evaluaci n Del Rango de Transmisi n de LoRa Para Redes de Sensores Inal mbricas Con LoRaWAN En Ambientes Forestales](#). 2017.
- [110] Rashmi Sharan Sinha, Yiqiao Wei, and Seung-Hoon Hwang. [A Survey on LPWA Technology: LoRa and NB-IoT](#). In: *ICT Express* 3.1 (Mar. 2017), pp. 14–21.
- [111] Aleksandrs Slivkins. Introduction to Multi-Armed Bandits. Sept. 29, 2019. URL: <http://arxiv.org/abs/1904.07272> (visited on 02/03/2021).
- [112] Yonghua Song et al. [An Internet of Energy Things Based on Wireless LPWAN](#). In: *Engineering* 3.4 (Aug. 2017), pp. 460–466.
- [113] Richard S. Sutton and Andrew G. Barto. [Reinforcement Learning: An Introduction](#). Second edition. Adaptive Computation and Machine Learning Series. Cambridge, Massachusetts: The MIT Press, 2018. 526 pp.
- [114] Csaba Szepesv ari. [Algorithms for Reinforcement Learning](#). In: *Synthesis Lectures on Artificial Intelligence and Machine Learning* 4.1 (Jan. 2010), pp. 1–103.
- [115] El-Ghazali Talbi. [Metaheuristics: From Design to Implementation](#). Hoboken, N.J: John Wiley & Sons, 2009. 593 pp.

- [116] Junfeng Xie et al. [A Survey of Machine Learning Techniques Applied to Software Defined Networking \(SDN\): Research Issues and Challenges](#). In: *IEEE Communications Surveys & Tutorials* PP (Aug. 23, 2018), pp. 1–1.
- [117] Raoul Zamble, Narcisse Dakouri Dogba, and Auguste Ndrin Hugues. [IMPLEMENTING AND TESTING OF A MOBILE JAMMER AT ESATIC](#). In: *International Journal of Advanced Research* 8.8 (Aug. 2020), pp. 141–150.

Heuristic optimizations

- [118] Khaled Q. Abdelfadeel, Victor Cionca, and Dirk Pesch. Fair Adaptive Data Rate Allocation and Power Control in LoRaWAN. Feb. 28, 2018. URL: <http://arxiv.org/abs/1802.10338> (visited on 11/20/2019).
- [119] James C. Bezdek, Robert Ehrlich, and William Full. [FCM: The fuzzy c-means clustering algorithm](#). In: *Computers & Geosciences*. FCM 10.2-3 (Jan. 1984), pp. 191–203.
- [120] Martin Bor and Utz Roedig. [LoRa Transmission Parameter Selection](#). In: *2017 13th International Conference on Distributed Computing in Sensor Systems (DCOSS)*. 2017 13th International Conference on Distributed Computing in Sensor Systems (DCOSS). Ottawa, ON: IEEE, June 2017, pp. 27–34.
- [121] Xi Chen, Prateek Gangwal, and Daji Qiao. [RAM: Rate Adaptation in Mobile Environments](#). In: *IEEE Transactions on Mobile Computing*. RAM, 11.3 (Mar. 2012), pp. 464–477.
- [122] Francesca Cuomo et al. [Towards traffic-oriented spreading factor allocations in LoRaWAN systems](#). In: *2018 17th Annual Mediterranean Ad Hoc Networking Workshop (Med-Hoc-Net)*. 2018, pp. 1–8.
- [123] Samir Dawaliby, Abbas Bradai, and Yannis Pousset. [Adaptive Dynamic Network Slicing in LoRa Networks](#). In: *Future Generation Computer Systems* 98 (Sept. 2019), pp. 697–707.
- [124] Lara Deek et al. [Joint rate and channel width adaptation for 802.11 MIMO wireless networks](#). In: *2013 IEEE International Conference on Sensing, Communications and Networking (SECON)*. 2013 10th Annual IEEE Communications Society Conference on Sensing and Communication in Wireless Networks (SECON). ARAMIS. New Orleans, LA, USA: IEEE, June 2013, pp. 167–175.
- [125] Kai-Ten Feng, Po-Tai Lin, and Wen-Jiunn Liu. [Frame-Aggregated Link Adaptation Protocol for Next Generation Wireless Local Area Networks](#). In: *EURASIP Journal on Wireless Communications and Networking*. FALA 2010.1 (Dec. 2010), p. 164651.
- [126] G. Gan, J. Wu, and Z. Yang. [A genetic fuzzy k-Modes algorithm for clustering categorical data](#). In: *Expert Systems with Applications*. genetic fuzzy k-Modes algorithm 36.2 (Mar. 2009), pp. 1615–1620.
- [127] Vojtech Hauser and Tomas Hegr. [Proposal of Adaptive Data Rate Algorithm for LoRaWAN-Based Infrastructure](#). In: *2017 IEEE 5th International Conference on Future Internet of Things and Cloud (FiCloud)*. 2017 IEEE 5th International Conference on Future Internet of Things and Cloud (FiCloud). Prague: IEEE, Aug. 2017, pp. 85–90.
- [128] T. Jayasri and M. Hemalatha. [Link Quality Estimation for Adaptive Data Streaming in WSN](#). In: *Wireless Personal Communications* 94.3 (June 2017), pp. 1543–1562.
- [129] Shahbaz Khan. [A Survey of Rate-Adaptation Schemes for IEEE 802.11 Compliant WLANs](#). In: *KSII Transactions on Internet and Information Systems*. Survey 7.3 (Mar. 31, 2013), pp. 425–445.
- [130] Dae-Young Kim et al. [Adaptive Data Rate Control in Low Power Wide Area Networks for Long Range IoT Services](#). In: *Journal of Computational Science* 22 (Sept. 2017), pp. 171–178.

- [131] Sungryul Kim and Younghwan Yoo. [Contention-Aware Adaptive Data Rate for Throughput Optimization in LoRaWAN](#). In: *Sensors* 18.6 (May 25, 2018), p. 1716.
- [132] Soung-Yue Liew et al. [A Fast, Adaptive, and Energy-Efficient Data Collection Protocol in Multi-Channel-Multi-Path Wireless Sensor Networks](#). In: *IEEE Computational Intelligence Magazine* 13.1 (Feb. 2018), pp. 30–40.
- [133] Shan Lin et al. [ATPC: adaptive transmission power control for wireless sensor networks](#). In: *Proceedings of the 4th international conference on Embedded networked sensor systems - SenSys '06*. the 4th international conference. ATPC. Boulder, Colorado, USA: ACM Press, 2006, p. 223.
- [134] Moshe T. Masonta et al. [Adaptive spectrum decision framework for heterogeneous dynamic spectrum access networks](#). In: *AFRICON 2015*. IEEE AFRICON 2015. ASDF Addis Ababa, Ethiopia: IEEE, Sept. 2015, pp. 1–5.
- [135] Michael K. Ng and Joyce C. Wong. [Clustering Categorical Data Sets Using Tabu Search Techniques](#). In: *Pattern Recognition* 35.12 (Dec. 2002), pp. 2783–2790.
- [136] Duy Nguyen and J. J. Garcia-Luna-Aceves. [A practical approach to rate adaptation for multi-antenna systems](#). In: *2011 19th IEEE International Conference on Network Protocols*. 2011 19th IEEE International Conference on Network Protocols (ICNP). RAMAS. Vancouver, AB, Canada: IEEE, Oct. 2011, pp. 331–340.
- [137] Moises Nunez Ochoa et al. [Evaluating LoRa Energy Efficiency for Adaptive Networks: From Star to Mesh Topologies](#). In: *2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. 2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). Rome: IEEE, Oct. 2017, pp. 1–8.
- [138] Ioannis Pefkianakis et al. [Window-based Rate Adaptation in 802.11n Wireless Networks](#). In: *Mobile Networks and Applications*. WRA 18.1 (Feb. 2013), pp. 156–169.
- [139] S. K. Sathya Lakshmi Preeth et al. [An Adaptive Fuzzy Rule Based Energy Efficient Clustering and Immune-Inspired Routing Protocol for WSN-Assisted IoT System](#). In: *Journal of Ambient Intelligence and Humanized Computing* (Dec. 17, 2018).
- [140] Brecht Reynders, Wannes Meert, and Sofie Pollin. [Power and spreading factor control in low power wide area networks](#). In: IEEE, May 2017.
- [141] Enrique H. Ruspini, James C. Bezdek, and James M. Keller. [Fuzzy Clustering: A Historical Perspective](#). In: *IEEE Computational Intelligence Magazine* 14.1 (Feb. 2019), pp. 45–55.
- [142] Mariusz Slabicki, Gopika Premsankar, and Mario Di Francesco. [Adaptive Configuration of Lora Networks for Dense IoT Deployments](#). In: *NOMS 2018 - 2018 IEEE/IFIP Network Operations and Management Symposium*. NOMS 2018 - 2018 IEEE/IFIP Network Operations and Management Symposium. Taipei, Taiwan: IEEE, Apr. 2018, pp. 1–9.
- [143] Guozhi Song et al. [Improved Energy Efficient Adaptive Clustering Routing Algorithm for WSN](#). In: *Wireless Sensor Networks*. Ed. by Jianzhong Li et al. Vol. 812. Communications in Computer and Information Science. Singapore: Springer Singapore, 2018, pp. 74–85.
- [144] Autanan Wannachai and Paskorn Champrasert. [Adaptive Transmission Range Based on Event Detection for WSNs](#). In: *2015 IEEE Tenth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP)*. 2015 IEEE Tenth International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP). A-TRED. Singapore: IEEE, Apr. 2015, pp. 1–6.

Markovian Decision Process (MDP)

- [145] Naoki Aihara et al. [Q-Learning Aided Resource Allocation and Environment Recognition in LoRaWAN With CSMA/CA](#). In: *IEEE Access* 7 (2019), pp. 152126–152137.
- [146] Adnan Aijaz. [Hap-SliceR: A Radio Resource Slicing Framework for 5G Networks With Haptic Communications](#). In: *IEEE Systems Journal* 12.3 (Sept. 2018), pp. 2285–2296.
- [147] Haider Daami R. Albonda and J. Pérez-Romero. [Reinforcement Learning-Based Radio Access Network Slicing for a 5G System with Support for Cellular V2X](#). In: *Cognitive Radio-Oriented Wireless Networks*. Ed. by Adrian Kliks et al. Vol. 291. Cham: Springer International Publishing, 2019, pp. 262–276.
- [148] Salman A. AlQahtani and Waseem A. Alhomiqani. [A Multi-Stage Analysis of Network Slicing Architecture for 5G Mobile Networks](#). In: *Telecommunication Systems* (Aug. 29, 2019).
- [149] H.R. Berenji. [Fuzzy Q-Learning: A New Approach for Fuzzy Dynamic Programming](#). In: *Proceedings of 1994 IEEE 3rd International Fuzzy Systems Conference*. 1994 IEEE 3rd International Fuzzy Systems Conference. Orlando, FL, USA: IEEE, 1994, pp. 486–491.
- [150] Inaam Ilahi et al. [LoRaDRL: Deep Reinforcement Learning Based Adaptive PHY Layer Transmission Parameters Selection for LoRaWAN](#). In: (Nov. 2020).
- [151] Pooyan Jamshidi et al. [Self-Learning Cloud Controllers: Fuzzy Q-Learning for Knowledge Evolution](#). July 2, 2015. URL: <http://arxiv.org/abs/1507.00567> (visited on 06/28/2020).
- [152] Raja Karmakar, Samiran Chattopadhyay, and Sandip Chakraborty. [Linkcon: Adaptive Link Configuration over SDN Controlled Wireless Access Networks](#). In: *Proceedings of the ACM Workshop on Distributed Information Processing in Wireless Networks - DIPWN'17*. The ACM Workshop. Chennai, India: ACM Press, 2017, pp. 1–6.
- [153] Raja Karmakar, Samiran Chattopadhyay, and Sandip Chakraborty. [SmartLA: Reinforcement Learning-Based Link Adaptation for High Throughput Wireless Access Networks](#). In: *Computer Communications* 110 (Sept. 2017), pp. 1–25.
- [154] Petar Kochovski, Pavel D. Drobintsev, and Vlado Stankovski. [Formal Quality of Service Assurances, Ranking and Verification of Cloud Deployment Options with a Probabilistic Model Checking Method](#). In: *Information and Software Technology* 109 (May 2019), pp. 14–25.
- [155] Cheng-Jian Lin. [Reinforcement Evolutionary Learning for Neuro-Fuzzy Controller Design](#). In: *Reinforcement Learning*. I-Tech Education and Publishing, Jan. 2008.
- [156] Ling Li, Shancang Li, and Shanshan Zhao. [QoS-Aware Scheduling of Services-Oriented Internet of Things](#). In: *IEEE Transactions on Industrial Informatics*. Optimization 10.2 (May 2014), pp. 1497–1505.
- [157] D. M. Roijers et al. [A Survey of Multi-Objective Sequential Decision-Making](#). In: *Journal of Artificial Intelligence Research* 48 (Oct. 18, 2013), pp. 67–113.
- [158] Ruben M. Sandoval, Antonio-Javier Garcia-Sanchez, and Joan Garcia-Haro. [Optimizing and Updating LoRa Communication Parameters: A Machine Learning Approach](#). In: *IEEE Transactions on Network and Service Management* 16.3 (Sept. 2019), pp. 884–895.
- [159] Ruben M. Sandoval et al. [Optimal Policy Derivation for Transmission Duty-Cycle Constrained LPWAN](#). In: *IEEE Internet of Things Journal* 5.4 (Aug. 2018), pp. 3114–3125.
- [160] Yao Sun et al. [Distributed Learning Based Handoff Mechanism for Radio Access Network Slicing with Data Sharing](#). In: *ICC 2019 - 2019 IEEE International Conference on Communications (ICC)*. ICC 2019 - 2019 IEEE International Conference on Communications (ICC). Shanghai, China: IEEE, May 2019, pp. 1–6.

- [161] Joel Toussaint, Nancy El Rachkidy, and Alexandre Guitton. [Performance Analysis of the On-the-Air Activation in LoRaWAN](#). In: *2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*. 2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON). Vancouver, BC, Canada: IEEE, Oct. 2016, pp. 1–7.
- [162] Haozhe Wang et al. [Data-Driven Dynamic Resource Scheduling for Network Slicing: A Deep Reinforcement Learning Approach](#). In: *Information Sciences* 498 (Sept. 2019), pp. 106–116.
- [163] Christopher J.C.H. Watkins and Peter Dayan. [Technical Note: Q-Learning](#). In: *Machine Learning* 8.3 (1992), pp. 279–292.
- [164] H.W.M. Witlox. [The HEGADAS model for ground-level heavy-gas dispersion II. Time-dependent model](#). In: *Atmospheric Environment* 28.18 (Oct. 1994), pp. 2933–2946.
- [165] Yi Yu et al. [Multi-Agent Q-Learning Algorithm for Dynamic Power and Rate Allocation in LoRa Networks](#). In: (Aug. 2020).
- [166] Xi Zhang, Jingqing Wang, and Qixuan Zhu. [Q-Learning Based Energy Harvesting for Heterogeneous Statistical QoS Provisioning over Multihop Big-Data Relay Networks](#). In: *2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData). Atlanta, GA, USA: IEEE, July 2019, pp. 807–814.

Multi Armed Bandit (MAB)

- [167] Robin Allesiardo and Raphael Feraud. [EXP3 with drift detection for the switching bandit problem](#). In: *2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA)*. 2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA). EXP3,UCB. Campus des Cordeliers, Paris, France: IEEE, Oct. 2015, pp. 1–7.
- [168] Amin Azari and Cicek Cavdar. [Self-Organized Low-Power IoT Networks: A Distributed Learning Approach](#). In: *2018 IEEE Global Communications Conference (GLOBECOM)*. IEEE, Dec. 2018.
- [169] Rémi Bonnefoi, Christophe Moy, and Jacques Palicot. [Improvement of the LPWAN AMI Backhaul's Latency Thanks to Reinforcement Learning Algorithms](#). In: *EURASIP Journal on Wireless Communications and Networking* 2018.1 (Dec. 2018), p. 34.
- [170] Rémi Bonnefoi et al. [Multi-Armed Bandit Learning in IoT Networks: Learning Helps Even in Non-Stationary Settings](#). In: *Cognitive Radio Oriented Wireless Networks*. Ed. by Paulo Marques et al. Vol. 228. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering. Cham: Springer International Publishing, 2018, pp. 173–185.
- [171] Djallel Bouneffouf and Irina Rish. A Survey on Practical Applications of Multi-Armed and Contextual Bandits. Apr. 2, 2019. URL: <http://arxiv.org/abs/1904.10040> (visited on 05/07/2020).
- [172] Djallel Bouneffouf et al. [Contextual Bandit for Active Learning: Active Thompson Sampling](#). In: *Neural Information Processing*. Springer International Publishing, 2014, pp. 405–412.
- [173] Yann Braouezec. [Stochastic Adaptive Dynamics of a Simple Market as a Non-Stationary Multi-Armed Bandit Problem](#). In: *SSRN Electronic Journal* (2008).

- [174] Sébastien Bubeck. [Regret Analysis of Stochastic and Nonstochastic Multi-armed Bandit Problems](#). now Publishers Inc, 2012.
- [175] John Chia. [Contextual and Linear Bandits](#). In: (July 2020), pp. 191–192.
- [176] Sumit J. Darak, Christophe Moy, and Jacques Palicot. [Proof-of-Concept System for Opportunistic Spectrum Access in Multi-user Decentralized Networks](#). In: *EAI Endorsed Transactions on Cognitive Communications 2.7* (Sept. 2016), p. 151647.
- [177] R. Devanand and P. Kumar. [Empirical study of Thompson sampling: Tuning the posterior parameters](#). In: Author(s), 2017.
- [178] Pratik Gajane. [Les menages agricoles avec un migrant de retour sont plus susceptibles de posséder une entreprise non agricole dans certains pays](#). In: (June 2017).
- [179] Raouf Kerkouche et al. [Node-Based Optimization of LoRa Transmissions with Multi-Armed Bandit Algorithms](#). In: *2018 25th International Conference on Telecommunications (ICT)*. 2018 25th International Conference on Telecommunications (ICT). St. Malo: IEEE, June 2018, pp. 521–526.
- [180] Lihong Li et al. [A contextual-bandit approach to personalized news article recommendation](#). In: *Proceedings of the 19th international conference on World wide web - WWW extquotesingle10*. ACM Press, 2010.
- [181] P. Meyer. [Algorithmes et incontinence urinaire des séniors : évaluations, traitements, recommandations et niveaux de preuve](#). *Revue de la littérature*. In: *Progrès en Urologie 27.3* (Mar. 2017), pp. 111–145.
- [182] Duc-Tuyen Ta et al. [LoRa-MAB: A Flexible Simulator for Decentralized Learning Resource Allocation in IoT Networks](#). In: *2019 12th IFIP Wireless and Mobile Networking Conference (WMNC)*. 2019 12th IFIP Wireless and Mobile Networking Conference (WMNC). Sept. 2019, pp. 55–62.
- [183] Cem Tekin and Eralp Turgay. [Multi-Objective contextual bandits with a dominant objective](#). In: *2017 IEEE 27th International Workshop on Machine Learning for Signal Processing (MLSP)*. IEEE, Sept. 2017.
- [184] Cem Tekin and Eralp Turgay. [Multi-objective Contextual Multi-armed Bandit With a Dominant Objective](#). In: *IEEE Transactions on Signal Processing 66.14* (July 2018), pp. 3799–3813.
- [185] Viktor Toldov. [Adaptive MAC Layer for Interference Limited WSN](#). In: (2017), p. 148.
- [186] Viktor Toldov et al. [A Thompson sampling approach to channel exploration-exploitation problem in multihop cognitive radio networks](#). In: *2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*. IEEE, Sept. 2016.
- [187] Nirandika Wanigasekara et al. [Learning Multi-Objective Rewards and User Utility Function in Contextual Bandits for Personalized Ranking](#). In: *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence*. International Joint Conferences on Artificial Intelligence Organization, Aug. 2019.
- [188] Li Zhou. A Survey on Contextual Multi-Armed Bandits. Feb. 1, 2016. URL: <http://arxiv.org/abs/1508.03326> (visited on 04/28/2020).

Network layer

- [189] Dmitry Bankov, Evgeny Khorov, and Andrey Lyakhov. [On the Limits of LoRaWAN Channel Access](#). In: (2016), p. 5.
- [190] Martin Bor, John Vidler, and Utz Roedig. [LoRa for the Internet of Things](#). In: *EWSN* (Feb. 2016), pp. 361–366.

- [191] Hsiang-Yu Huang et al. [A LoRa-Based Optimal Path Routing Algorithm for Smart Grid](#). In: *2018 12th International Conference on Sensing Technology (ICST)*. 2018 12th International Conference on Sensing Technology (ICST). Limerick: IEEE, Dec. 2018, pp. 71–76.
- [192] Kai-Hsiang Ke et al. [A LoRa Wireless Mesh Networking Module for Campus-Scale Monitoring: Demo Abstract](#). In: *Proceedings of the 16th ACM/IEEE International Conference on Information Processing in Sensor Networks - IPSN '17*. The 16th ACM/IEEE International Conference. Pittsburgh, Pennsylvania: ACM Press, 2017, pp. 259–260.
- [193] Huang-Chen Lee and Kai-Hsiang Ke. [Monitoring of Large-Area IoT Sensors Using a LoRa Wireless Mesh Network System: Design and Evaluation](#). In: *IEEE Transactions on Instrumentation and Measurement* 67.9 (Sept. 2018), pp. 2177–2187.
- [194] Chun-Hao Liao et al. [Multi-Hop LoRa Networks Enabled by Concurrent Transmission](#). In: *IEEE Access* 5 (2017), pp. 21430–21446.
- [195] Daniel Lundell et al. [A Routing Protocol for LoRA Mesh Networks](#). In: *2018 IEEE 19th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM)*. 2018 IEEE 19th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM). Chania, Greece: IEEE, June 2018, pp. 14–19.
- [196] Tie Qiu et al. [ERGIT: An Efficient Routing Protocol for Emergency Response Internet of Things](#). In: *Journal of Network and Computer Applications* 72 (Sept. 2016), pp. 104–112.
- [197] Benjamin Sartori et al. [Enabling RPL Multihop Communications Based on LoRa](#). In: *2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. 2017 IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). Rome: IEEE, Oct. 2017, pp. 1–8.
- [198] Patrick Weber et al. [IPv6 over LoRaWAN extrademark](#). In: *2016 3rd International Symposium on Wireless Systems within the Conferences on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS-SWS)*. 2016 3rd International Symposium on Wireless Systems within the Conferences on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS-SWS). Offenburg, Germany: IEEE, Sept. 2016, pp. 75–79.
- [199] Guibing Zhu et al. [Improving the Capacity of a Mesh LoRa Network by Spreading-Factor-Based Network Clustering](#). In: *IEEE Access* 7 (2019), pp. 21584–21596.

Physical layer

- [200] L. Angrisani et al. [LoRa Protocol Performance Assessment in Critical Noise Conditions](#). In: *2017 IEEE 3rd International Forum on Research and Technologies for Society and Industry (RTSI)*. 2017 IEEE 3rd International Forum on Research and Technologies for Society and Industry - Innovation to Shape the Future for Society and Industry (RTSI). Modena, Italy: IEEE, Sept. 2017, pp. 1–5.
- [201] Mohamed Aref and Axel Sikora. [Free space range measurements with Semtech Lora technology](#). In: *2014 2nd International Symposium on Wireless Systems within the Conferences on Intelligent Data Acquisition and Advanced Computing Systems*. 2014 2nd International Symposium on Wireless Systems within the Conferences on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS-SWS). Measurement. Odessa, Ukraine: IEEE, Sept. 2014, pp. 19–23.
- [202] Dmitry Bankov, Evgeny Khorov, and Andrey Lyakhov. [Mathematical Model of LoRaWAN Channel Access with Capture Effect](#). In: *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*. 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC). Montreal, QC: IEEE, Oct. 2017, pp. 1–5.

- [203] Norbert Blenn and Fernando Kuipers. LoRaWAN in the Wild: Measurements from The Things Network. June 9, 2017. URL: <http://arxiv.org/abs/1706.03086> (visited on 11/20/2019).
- [204] Martin C. Bor et al. [Do LoRa Low-Power Wide-Area Networks Scale?](#) In: *Proceedings of the 19th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems - MSWiM '16*. the 19th ACM International Conference. Evaluation. Malta, Malta: ACM Press, 2016, pp. 59–67.
- [205] Gilles Callebaut, Geoffrey Ottoy, and Liesbet Van der Perre. Cross-Layer Framework and Optimization for Efficient Use of the Energy Budget of IoT Nodes. June 22, 2018. URL: <http://arxiv.org/abs/1806.08624> (visited on 11/20/2019).
- [206] Martina Capuzzo, Davide Magrin, and Andrea Zanella. [Mathematical Modeling of LoRa WAN Performance with Bi-Directional Traffic](#). In: *2018 IEEE Global Communications Conference (GLOBECOM)*. GLOBECOM 2018 - 2018 IEEE Global Communications Conference. Abu Dhabi, United Arab Emirates: IEEE, Dec. 2018, pp. 206–212.
- [207] Daniel Costa et al. [A Fuzzy-Based Approach for Sensing, Coding and Transmission Configuration of Visual Sensors in Smart City Applications](#). In: *Sensors* 17.1 (Jan. 5, 2017), p. 93.
- [208] Daniele Croce et al. [Impact of LoRa Imperfect Orthogonality: Analysis of Link-Level Performance](#). In: *IEEE Communications Letters* 22.4 (Apr. 2018), pp. 796–799.
- [209] Daniele Croce et al. [Impact of Spreading Factor Imperfect Orthogonality in LoRa Communications](#). In: *Digital Communication. Towards a Smart and Secure Future Internet*. Ed. by Alessandro Piva, Ilenia Tinnirello, and Simone Morosi. Vol. 766. Cham: Springer International Publishing, 2017, pp. 165–179.
- [210] Yousri Daldoul, Djamel-Eddine Meddour, and Adlen Ksentini. [IEEE 802.11n/Ac Data Rates under Power Constraints](#). In: *2018 IEEE International Conference on Communications (ICC)* (2018).
- [211] Benjamin Dix-Matthews, Rachel Cardell-Oliver, and Christof Hübner. [LoRa Parameter Choice for Minimal Energy Usage](#). In: Nov. 2018, pp. 37–42.
- [212] Nour El Hoda Djidi et al. [Opportunistic Cluster Heads for Heterogeneous Networks Combining LoRa and Wake-up Radio](#). In: (2018), p. 6.
- [213] Abdurrahman Elmaghbub and Bechir Hamdaoui. [LoRa Device Fingerprinting in the Wild: Disclosing RF Data-Driven Fingerprint Sensitivity to Deployment Variability](#). In: *IEEE Access* 9 (2021), pp. 142893–142909.
- [214] Guillaume Ferre. [Collision and Packet Loss Analysis in a LoRaWAN Network](#). In: *2017 25th European Signal Processing Conference (EUSIPCO)*. 2017 25th European Signal Processing Conference (EUSIPCO). Kos, Greece: IEEE, Aug. 2017, pp. 2586–2590.
- [215] Orestis Georgiou and Usman Raza. [Low Power Wide Area Network Analysis: Can LoRa Scale?](#) In: *IEEE Wireless Communications Letters* 6.2 (Apr. 2017), pp. 162–165.
- [216] Vinay Gupta et al. [Modelling of IoT Traffic and Its Impact on LoRaWAN](#). In: *GLOBECOM 2017 - 2017 IEEE Global Communications Conference*. 2017 IEEE Global Communications Conference (GLOBECOM 2017). Singapore: IEEE, Dec. 2017, pp. 1–6.
- [217] Arliones Hoeller et al. [Exploiting Time Diversity of LoRa Networks Through Optimum Message Replication](#). In: *2018 15th International Symposium on Wireless Communication Systems (ISWCS)*. 2018 15th International Symposium on Wireless Communication Systems (ISWCS). Lisbon: IEEE, Aug. 2018, pp. 1–5.
- [218] Luis Irio and Rodolfo Oliveira. [Modeling the Interference Caused to a LoRaWAN Gateway Due to Uplink Transmissions](#). In: *2019 Eleventh International Conference on Ubiquitous and Future Networks (ICUFN)*. 2019 Eleventh International Conference on Ubiquitous and Future Networks (ICUFN). Zagreb, Croatia: IEEE, July 2019, pp. 336–340.

- [219] Jetmir Haxhibeqiri et al. [LoRa Scalability: A Simulation Model Based on Interference Measurements](#). In: *Sensors* 17.6 (May 23, 2017), p. 1193.
- [220] Pascal Jorke et al. [Urban Channel Models for Smart City IoT-Networks Based on Empirical Measurements of LoRa-Links at 433 and 868 MHz](#). In: *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*. 2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC). Montreal, QC: IEEE, Oct. 2017, pp. 1–6.
- [221] Jaehyu Kim and JooSeok Song. [A Secure Device-to-Device Link Establishment Scheme for LoRaWAN](#). In: *IEEE Sensors Journal* 18.5 (Mar. 1, 2018), pp. 2153–2160.
- [222] Matthew Knight and Balint Seeber. [Decoding LoRa: Realizing a Modern LPWAN with SDR](#). In: *Proceedings of the GNU Radio Conference* 1.1 (1 Sept. 6, 2016).
- [223] Lito Kriara and Mahesh K. Marina. [SampleLite: A Hybrid Approach to 802.11n Link Adaptation](#). In: *ACM SIGCOMM Computer Communication Review* 45.2 (Apr. 22, 2015), pp. 4–13.
- [224] Lukas Krupka, Lukas Vojtech, and Marek Neruda. [The Issue of LPWAN Technology Coexistence in IoT Environment](#). In: (2017), p. 8.
- [225] Jin-Taek Lim and Youngnam Han. [Spreading Factor Allocation for Massive Connectivity in LoRa Systems](#). In: *IEEE Communications Letters*. BER, ToA, PER 22.4 (Apr. 2018), pp. 800–803.
- [226] Michele Magno et al. [WULoRa: An Energy Efficient IoT End-Node for Energy Harvesting and Heterogeneous Communication](#). In: *Design, Automation & Test in Europe Conference & Exhibition (DATE), 2017*. 2017 Design, Automation & Test in Europe Conference & Exhibition (DATE). Lausanne, Switzerland: IEEE, Mar. 2017, pp. 1528–1533.
- [227] Aamir Mahmood et al. [Scalability Analysis of a LoRa Network Under Imperfect Orthogonality](#). In: *IEEE Transactions on Industrial Informatics* 15.3 (Mar. 2019), pp. 1425–1436.
- [228] Yuqi Mo et al. [Optimization of the Predefined Number of Replications in a Ultra Narrow Band Based IoT Network](#). In: *2016 Wireless Days (WD)*. 2016 Wireless Days (WD). Toulouse, France: IEEE, Mar. 2016, pp. 1–6.
- [229] Moises Nunez Ochoa et al. [Large Scale LoRa Networks: From Homogeneous to Heterogeneous Deployments](#). In: *2018 14th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. 2018 14th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob). Limassol: IEEE, Oct. 2018, pp. 192–199.
- [230] Juha Petajarvi et al. [On the coverage of LPWANs: range evaluation and channel attenuation model for LoRa technology](#). In: *2015 14th International Conference on ITS Telecommunications (ITST)*. 2015 14th International Conference on ITS Telecommunications (ITST). Evaluation. Copenhagen, Denmark: IEEE, Dec. 2015, pp. 55–59.
- [231] Congduc Pham et al. [Radio channel access challenges in LoRa low-power wide-area networks](#). In: *LPWAN Technologies for IoT and M2M Applications*. Elsevier, 2020, pp. 65–102.
- [232] P. J. Radcliffe et al. [Usability of LoRaWAN Technology in a Central Business District](#). In: *2017 IEEE 85th Vehicular Technology Conference (VTC Spring)*. 2017 IEEE 85th Vehicular Technology Conference (VTC Spring). Sydney, NSW: IEEE, June 2017, pp. 1–5.
- [233] Brecht Reynders, Wannas Meert, and Sofie Pollin. [Range and Coexistence Analysis of Long Range Unlicensed Communication](#). In: *2016 23rd International Conference on Telecommunications (ICT)*. 2016 23rd International Conference on Telecommunications (ICT). Thessaloniki, Greece: IEEE, May 2016, pp. 1–6.

- [234] Brecht Reynders and Sofie Pollin. [Chirp Spread Spectrum as a Modulation Technique for Long Range Communication](#). In: *2016 Symposium on Communications and Vehicular Technologies (SCVT)*. 2016 Symposium on Communications and Vehicular Technologies (SCVT). Mons, Belgium: IEEE, Nov. 2016, pp. 1–5.
- [235] Semtech. Semtech LoRa Technology Overview: Designers Guide. URL: https://www.openhacks.com/uploads/productos/loradesignguide_std.pdf (visited on 01/30/2023).
- [236] Semtech. Semtech LoRa Technology Overview: Designers Guide. URL: https://www.openhacks.com/uploads/productos/loradesignguide_std.pdf (visited on 01/30/2023).
- [237] Valentin Alexandru Stan, Radu Serban Timnea, and Razvan Andrei Gheorghiu. [Overview of High Reliable Radio Data Infrastructures for Public Automation Applications: LoRa Networks](#). In: *2016 8th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*. 2016 8th International Conference on Electronics, Computers and Artificial Intelligence (ECAI). Ploiesti, Romania: IEEE, June 2016, pp. 1–4.
- [238] Lorenzo Vangelista. [Frequency Shift Chirp Modulation: The LoRa Modulation](#). In: *IEEE Signal Processing Letters* 24.12 (Dec. 2017), pp. 1818–1821.
- [239] Thiemo Voigt et al. Mitigating Inter-Network Interference in LoRa Networks. Nov. 2, 2016. URL: <http://arxiv.org/abs/1611.00688> (visited on 11/25/2019).
- [240] Waspnote. [Waspnote LoRa 868MHz 915MHz SX1272](#). 2017.
- [241] Dimitrios Zorbas et al. [Improving LoRa Network Capacity Using Multiple Spreading Factor Configurations](#). In: *2018 25th International Conference on Telecommunications (ICT)*. 2018 25th International Conference on Telecommunications (ICT). St. Malo: IEEE, June 2018, pp. 516–520.

Others

- [242] Aghiles Djoudi and Guy Pujolle. [Social Privacy Score Through Vulnerability Contagion Process](#). In: *2019 Fifth Conference on Mobile and Secure Services (MobiSecServ)*. 2019 Fifth Conference on Mobile and Secure Services (MobiSecServ). 1. Mar. 2019, pp. 1–6.
- [243] Aghiles Djoudi et al. Differentiated services for LoRaWAN with Markov Decision Process and Fuzzy C-Means Clustering. In: *2023 IEEE Wireless Communications and Mobile Computing (IWCMC)*.
- [244] Aghiles Djoudi et al. [LoRa network reconfiguration with Markov Decision Process and Fuzzy C-Means clustering](#). In: *Computer Communications* 196 (2022), pp. 129–140.
- [245] Yonatan Gur, Assaf Zeevi, and Omar Besbes. Stochastic Multi-Armed-Bandit Problem with Non-Stationary Rewards. In: (2014), p. 9.
- [246] MADWIFI. URL: https://sourceforge.net/p/madwifi/svn/HEAD/tree/madwifi/trunk/ath_rate/minstrel/minstrel.txt (visited on 01/31/2020).
- [247] Alaa Muqattash and Marwan Krunz. [A single-channel solution for transmission power control in wireless ad hoc networks](#). In: *Proceedings of the 5th ACM international symposium on Mobile ad hoc networking and computing - MobiHoc '04*. the 5th ACM international symposium. POWMAC. Roppongi Hills, Tokyo, Japan: ACM Press, 2004, p. 210.
- [248] K Ramachandran et al. [Symphony: Synchronous Two-Phase Rate and Power Control in 802.11 WLANs](#). In: *IEEE/ACM Transactions on Networking*. Symphony, RRAA+ 18.4 (Aug. 2010), pp. 1289–1302.
- [249] Herbert Robbins. [Some aspects of the sequential design of experiments](#). In: *Bulletin of the American Mathematical Society* 58.5 (Sept. 1952), pp. 527–536.

- [250] The Things Network. URL: <https://thethingsnetwork.org/> (visited on 04/29/2020).
- [251] V. Prasanna Venkatesan, C. Punitha Devi, and M. Sivaranjani. [Design of a Smart Gateway Solution Based on the Exploration of Specific Challenges in IoT](#). In: *2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)*. 2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC). Palladam, Tamilnadu, India: IEEE, Feb. 2017, pp. 22–31.
- [252] Starsky H. Y. Wong et al. [Robust rate adaptation for 802.11 wireless networks](#). In: *Proceedings of the 12th annual international conference on Mobile computing and networking - MobiCom '06*. the 12th annual international conference. RRAA,ARE,AARF. Los Angeles, CA, USA: ACM Press, 2006, p. 146.
- [253] R.D. Yates. [A framework for uplink power control in cellular radio systems](#). In: *IEEE Journal on Selected Areas in Communications* 13.7 (1995), pp. 1341–1347.
- [254] Wei Yin, Peizhao Hu, and Jadwiga Indulska. [Rate control in the mac80211 framework: Overview, evaluation and improvements](#). In: *Computer Networks* 81 (Apr. 2015), pp. 289–307.
- [255] B. Zurita Ares et al. [On power control for wireless sensor networks: System model, middleware component and experimental evaluation](#). In: *2007 European Control Conference (ECC)*. European Control Conference 2007 (ECC). MIAD, Marcov. Kos: IEEE, July 2007, pp. 4293–4300.