An MDP model-based initial strategy prediction method for LoRaWAN

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***Abstract*—As one of the technologies in the wide-area network category, LoRaWAN provides a wireless network with a large capacity of end devices (ED) in long-range. With a pure Aloha protocol implemented into its MAC layer, LoRaWAN can reduce its power consumption. Besides, some orthogonal transmission parameters give LoRaWAN capability to avoid collision and packet loss. Thus, allocating transmission parameters to increase the network performance becomes a challenging issue for LoRaWAN. Some dynamic Spreading Factor (SF) allocation strategies are studied in this paper. A distributed Markov Decision Process (MDP) model is constructed for the uplink transmission of the class-A device in LoRaWAN. The model is also solved and implemented to the algorithms for the initial strategy prediction. Analytical results show that the MDP model increases the performance of the studied algorithms on the transmission of the packet.**

***Index Terms*—LoRaWAN, reinforcement learning, Markov Decision Process**

I. Introduction

LoRa (Long Range) is wireless communication technology. It aims to provide end-to-end, energy-efficient communications [1]. EDs with LoRa chips can communicate in a star-of-star topology using its spread spectrum radio technique. LoRaWAN operates on the free-use ISM frequency band (e.g., 868 MHz in Europe).

However, LoRaWAN has some challenges. Firstly, having a MAC protocol based on the Aloha mechanism, LoRaWAN faces an issue of the packet loss rate and collision [2]. Moreover, most LoRaWAN EDs are called Class-A devices to save energy consumption. These EDs spend most of their time in sleep mode and only wake up when they send an uplink packet. For downlink transmission, Class-A devices only listen to downlink messages in two receive windows once an uplink packet is sent [3], which limits the network throughput. Thus, LoRaWAN is now primarily implemented on the Internet of Things (IoT) and Machine To Machine (M2M) applications with low data rates such as smart city monitoring [4] and air quality monitoring [5].

Facing the challenge of collision and packet loss, LoRaWAN adopts near-orthogonal transmission parameters to improve network performance. Among the orthogonal parameters, the Spreading Factor (SF) is one of the most important. A lower SF often can get a higher data rate and less air-time, but it will also reduce the communication range and increase packet loss probability. On the contrary, a higher SF can reduce the probability of lost packets but leads to a lower transmission speed, which will waste radio resources [6]. Thus, the parameters allocation becomes a vital issue of the performance in LoRaWAN.

In order to solve this issue, some dynamic approaches are proposed. In these methods, EDs are considered dynamic nodes that can change the parameter's choice during transmission. The reinforcement learning idea is also studied and implemented into some research works and positively impacts the network. However, reinforcement learning algorithms often face the challenge of convergence. Among the many factors that affect the convergence speed of the algorithm, the choice of the initial strategy is a critical factor [7]. Thus, in this study, an initial strategy prediction method based on the Markov Decision Process (MDP) model is constructed for the class-A devices' uplink transmission and implemented to the chosen reinforcement learning method. This model is distributed, which means it can easily be implemented into the network without making a significant change. By solving this method, a prediction of the initial strategy is given to the algorithm. Analytical results show that the MDP model increases the performance of the studied algorithms.

The remainder of this paper is organized as follows. Section II presents the related works of dynamic parameter allocation in LoRaWAN. Section III presents the reinforcement learning algorithm whose name is STEPS. The model proposition and theoretical calculation are given in Section IV. The analytical results and performance evaluation are given in Section V. Finally, the main contribution of this study and perspectives are given in Section VI.

II. Related Works

Many research works proposed their dynamic methods for the parameters' allocation problem. These methods allow EDs to change their transmission parameters during the transmission. In [8] and [9], Semtech Corporation, the developer of LoRa, have proposed ADR (Adaptive Data Rate). This method allows the network server to detect the transmission quality and adjust EDs' data rate by sending a downlink MAC frame. However, this dynamic method is not flexible enough. Even in different network environments, EDs will still use the same allocation strategy, which will lead to lower efficiency. Therefore, studies based on reinforcement learning have become a research hotspot.

In [10] and [11], authors modeled the LoRaWAN transmission procedures with the Markov chain. With their models, the authors evaluated the network performance. However, [10] focuses on the join process of EDs and [11] studied the downlink transmission of class-B devices, which are not the common transmission modes of LoRaWAN. For the normal reliable uplink transmission of class-A devices in LoRaWAN, authors in [12] built up a Markov chain model to study the network performance. However, these research works modeled the transmission but did not propose the behavior of EDs. Thus, the EDs and the network will stay the same.

In [13], a Q-learning algorithm is implemented to the nodes by the author to avoid collision dynamically. However, this algorithm is used for the scheduling and the transmission probability rather than the parameter allocation. For parameter allocation, authors in [14] proposed a Markov Decision Process (MDP) model to dynamically change EDs' parameters during the transmission and trained the MDP model by a neuronal network in [15]. The authors in [16] also proposed MDP and Q-learning algorithms for data rate allocation. However, all the adjustment methods above are centralized and triggered by the network server. The control message loss will quickly block the network's adjustment and waste resources and energy. Thus, the distributed decision methods by EDs are more suitable for the LoRaWAN network.

The authors in [17], [18], and [19] modeled a Multi-Armed Bandit (MAB) problem for distributed parameter allocation. In [17], the authors assumed an uni-SF LoRaWAN network. In [18], the authors ignored the capture effect and assumed a uniform ED distribution. However, these assumptions are impractical in a real LoRaWAN network. The author of [19] used the EXP3.S algorithm to solve the MAB problem for SF allocation. However, these methods are in lack of punishment. EDs will stick in the same strategy when a transmission fails. Furthermore, the equally likely initialization will also lead to slow convergence and reduce the transmission efficiency.

In our previous work [20], we proposed another reinforcement learning-based approach to improve the network performance. We designed a distributed approach that allows EDs to update and choose their parameter allocation strategy based on a score table. We also implemented a punishment mechanism to improve our method's performance further. However, in [20], the score table and strategy are initialized as the method in [21] which are not flexible.

In order to further improve the performance of the network, a distributed Markov Decision Process (MDP) model is constructed. By is solving the MDP, EDs can predict the allocation strategy before transmission and initialize their strategy. In the following part of this study, we choose the method in [20] as the research object and implement the MDP model. Analytical results will also be given to prove the improvement of network performance.

III. Prediction Method for Collision Reduction

Based on the reinforcement learning concepts, we proposed the STEPS method in [20]. It is a Score Table based Evaluation and Parameters Surfing approach of LoRaWAN. Nodes with the STEPS method will make a transmission, evaluation-update, and surfing approach instead of the traditional transmission approach with a score table that aims to provide more transmission experience for the nodes to decide. What is more, the transmission in STEPS still follows the Aloha protocol of LoRaWAN, which makes STEPS easy to be implemented.

Unlike the proposed methods in [19], in the evaluation-update phase, STEPS uses three coefficients of updating which are: The ACK reward c_a, the only-receive punishment c_r and the fail punishment c_f. When the node does not receive the ACK message, it will first estimate the probability that the message is received or not. Furthermore, STEPS also uses a ”further punishment” mechanism to avoid a long punishment process when a previous strategy is no longer applicable to the current network for some sudden reasons. Then, based on the probability estimated, the node will choose the corresponded coefficient and update the score table.

Although the simulation results in [20] show that STEPS brings the LoRaWAN network a remarkable improvement for bi-directional transmission, the original STEPS has some shortcomings. The nodes initialize their SF and the score table by the distance between the node and the base station. Therefore, the node is likely to choose a bad initial strategy, wasting transmission resources and affecting network performance.

To get a better initial strategy, an MDP model is built for the uplink transmission procedure of class-A devices in LoRaWAN. By solving this MDP model, nodes with STEPS can predict the initial strategy.

IV. The MDP Model

A. Overview of MDP

In this study, a Markovian Decision Process (MDP) is modeled for uplink transmission of the class-A device in LoRaWAN. It is a mathematical model of sequential decision, which is used to simulate the randomness strategies and rewards that can be achieved by the agent in an environment where the system state has Markov properties. The overview of the MDP is shown as in Fig. 1. It can be described as a tuple $M =< S, A, P, R >$ where: S is the finite set of states which includes:

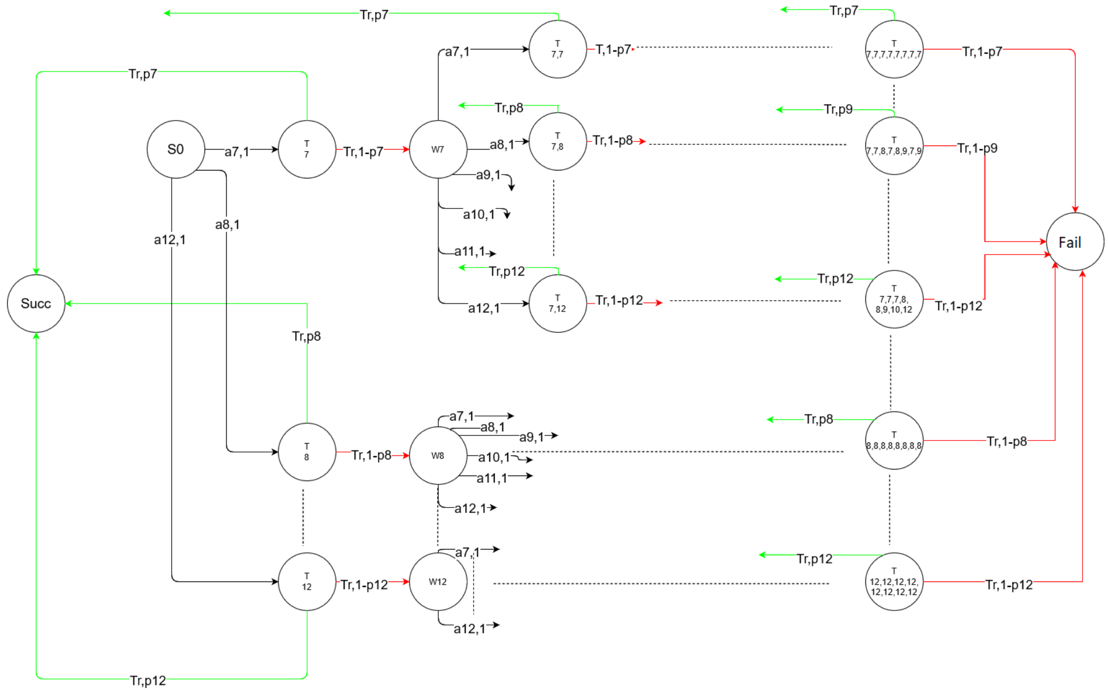


Fig. 1. Structure of MDP.

- The initial state $S0$. This state is the beginning of the packet transmission.
- The Transmit subset T. The states $s \in T$ represent that the node is prepared to transmit. The state s for the k-th attempt is described as $T/\{sf_i\}_k$ where $\{sf_i\}_k$ is a k-elements sequence and $1 \leq k \leq 8$ in LoRaWAN. The elements sf_i represent the SF chosen at the i-th transmission. For example, $T/\{7, 8, 10\}$ means the node fails in the two previous attempts using SF7 and SF8 and will make the third time attempt with SF10.
- The Waiting subset W. The states $s \in W$ is described as $W/\{sf_i\}_k$ means that the node is waiting after the k-th transmission attempt failed. $\{sf_i\}_k$ is a k-elements sequence of previous attempts parameter, in LoRaWAN, $1 \leq k \leq 7$. For example, $W/\{9, 11\}$ means the node fails in the two previous attempts using SF9 and SF11 and will make the choice of SF for next transmission.
- Two final states $\{Succ, Fail\}$. For the states $s \in T$, the node will go into state $Succ$ if the transmission succeeds. Otherwise, if a node fails its last attempt (i.e., $s = T/\{sf_i\}_8$), the packet transmission is failed, and the node will go into state $Fail$.

$A = \{Tr, a7, a8, ..., a12\}$ is the set of actions. The action Tr is transmit action that nodes will take at state $s \in T$. The actions a_{sf} represent that the node in waiting state $s \in W$ takes sf as its SF for the next transmission.

$P : S \times A \times S$ is the matrix of transitions between states. The elements in P are the probabilities of transitions denoted as $\mathbb{P}(s, a, s')$, which represent the probabilities of reaching state $s' \in S$ from state $s \in S$ by the action $a \in A$. The calculation of $\mathbb{P}(s, a, s')$ will be given in the following parts. In the MDP, there are 4 types of transition(s, a, s'):

1) $s \in T, a = Tr, s' = Succ$. This transition means the transmission is successful, and the node will transmit a new packet. (e.g. $T/\{7\} \rightarrow Succ$ in Figure 1 means transmission succeed at the first attempt with SF7 and $T/\{8, 10\} \rightarrow Succ$ means after failing in the first attempt with SF8, the transmission succeed at the second attempt with SF10).
2) $s = T/\{sf_i\}_k \in T, a = Tr, s' = W/\{sf_i\}_k \in W$. This transition means the transmission is failed but the maximum attempt limit is not exceeded. The node will retransmit the packet (e.g. $T/\{7\} \rightarrow W/\{7\}$ in Figure 1 means first attempt with SF7 failed and $T/\{7, 9\} \rightarrow W/\{7, 9\}$ means after failing in the first attpempt with SF7, the second attempt with SF9 is also failed).
3) $s' = W/\{sf_i\}_k \in W, a = a_{sf}, sf \in [\![7, 12]\!], s' = T/\{sf_i, sf\}_{k+1} \in T$. This transition means the node chooses sf as its next SF and retransmit the packet(e.g. $W/\{7\} \rightarrow T/\{7, 8\}$ in Figure 1 means after failing in the first attempt with SF7, the node choses SF8 as its next transmission SF).
4) $s \in T, a = Tr, s' = Fail$. This transition means the transmission is failed and the maximum attempt limit is exceeded. The node will abandon the packet and transmit a new packet (e.g., $T/\{7, 7, 7, 8, 9, 10, 11, 12\} \rightarrow Fail$ in Figure 1 means after failing in the 8-th attempt with SF12, the packet transmission is failed with the SFs used as sequence $\{7, 7, 7, 8, 9, 10, 11, 12\}$).

B. Probabilities of transition

The transition probabilities can be divided into two cases. The first one is $s \in W$, in this case, $\mathbb{P}(s, a, s') = 1$ since the node will transmit the message after choosing an SF. Another case is when $s \in T$, the node will have a success probability p_i of transmission with chosen sf i. An estimation of success probability is calculated as follows.

C. Estimation of Success Probability

Due to limitations in computing performance and energy consumption, nodes in LoRaWAN cannot predict general network information or whether the gateway can send ACK messages correctly. Therefore, the node can only assume that all uplink messages sent successfully can be answered. Based on the above assumption, a successful transmission must meet two conditions [22]: 1. The message is not lost. 2. The message does not enter in collisions.

1) Probability of Not Lost:

In LoRaWAN transmission, an uplink message is not lost only when the received signal-to-noise ratio (SNR) is greater than the threshold q_{SF}. Thus, the probability $H_i(SF)$ that the packet sent by node i at the distance d_i with SF is not lost can be expressed as equation: $H_i(SF) = \mathbb{P}[SNR \geq q_{SF}|d_i]$ [23]. In [22] and [23], the authors give a theoretical calculation of $H_i(SF)$. Assuming that the channel gain modeled as an exponential random variable as $h_i \sim exp(1)$, the probability $H_i(SF)$ that the uplink packet sent by node i is not lost can be expressed as: $H_i(SF, d_i) = exp\left(-\frac{\mathcal{N} q_{SF}}{P_i g(d_i)}\right)$

where $\mathcal{N} = -174 + NF + 10\log_{10}(Bandwidth)$ dBm, NF is the receiver noise, which is assumed to be 6 dB.

However, this calculation is based on the Friis transmission equation, which is modeled for free space. Even though the authors have modified the formula, there is still a physical dimension inconsistency.

Thus, the MDP uses Log-distance path loss model for the SNR calculation [24]. By calculating the SNR with the formula in [24], the probability of H_i can be written as (1).

$$H_i(SF, d_i) = \mathbb{P}[SNR \geq q_{SF}|d_i] = \frac{1}{2}\left(1 - erf\left(\frac{q_{SF} + \mathcal{N} - P_{tx} + PL_0 + 10\eta\log_{10}\left(\frac{d_i}{d_0}\right)}{\sigma\sqrt{2}}\right)\right) \quad (1)$$

where P_{tx} is the transmit power, PL_0 is the distance path loss at d_0, η is the loss exponent and X_σ is the flat fading attenuation modeled with $X_\sigma \sim N(\mu, \sigma^2)$ with $\mu = 0$.

2) Probability of No Collision:

If two packets i and k have a collision, they must satisfy all 4 of the following conditions [2]:

1) $Freq_i = Freq_k$
2) $SF_i = SF_k$
3) $P_{rx_i} - P_{rx_k} < 6$ where P_{rx} is the receive power
4) $t_{pream_i} - t_{fin_k} < t_c$ where t_{pream_i} is the processing time for the preamble of i, t_{fin_k} is the processing time for k and t_c is the minimum duration which is the processing time for 5 preamble symbols

Thus, the probability of no collision for i and k is defined as (2):

$$Q_i(k) = 1 - \left(\chi_{SF_i}(SF_k)\,\chi_{freq_i}(freq_k)\,\mathbb{P}_k(cond3|i)\,\mathbb{P}_k(cond4|i)\right) \quad (2)$$

where $\chi_a(x) = 1 \; if \; a = x, \; 0 \; else$.

By noting $F_{X_{\sqrt{2}\sigma}}(z)$ as the CDF of $X_{\sqrt{2}\sigma} \sim N(0, 2\sigma^2)$, $\mathbb{P}_k(cond3|i)$ can be calculated as:

$$\mathbb{P}_k(cond3|i) = F_{X_{\sqrt{2}\sigma}}\left(6 + 10\eta\log_{10}\left(\frac{d_i}{d_k}\right)\right) \quad (3)$$

For condition 4), assuming that all nodes transmit in a time which obeys an exponential distribution of time mean τ. That is, $T_{tr} \sim exp(1/\tau)$. The probability of $\mathbb{P}_k(cond4|i)$ can be calculated in (4)

$$\mathbb{P}_k(cond4|i) = F_{X_k}(Tc) = 1 - e^{-\frac{2T_{rec} - T_{6pream}}{\tau}} \quad (4)$$

where T_{rec}, T_{6pream} are given by [2] represent the processing time of the packet and 6 symbols of the preamble.

With (3) and (4), the probability of no collision for i can be calculated as:

$$Q_i = \prod_{\substack{k != i \\ SF_k = SF_i \\ freq_k = freq_i}} \left(1 - \mathbb{P}_k(cond4|i)\,\mathbb{P}_k(cond3|i)\right) \quad (5)$$

With estimation above, the probabilities of transition of $s \in T$ can be calculated as:

$$\begin{aligned} &\forall s = T/\{sf_i\}_k \in T, i \in [\![7, 12]\!] \\ &\mathbb{P}(s, a, succ) = p_i \\ &\mathbb{P}(s, a, s') = 1 - p_i \;\; s' = Fail \; if \; k{=}8, s' \in W \; if \; not \\ &where \; p_i = H_i Q_i \end{aligned} \quad (6)$$

Note that the calculation of Q_i requires the assumption of distribution of nodes, SFs, and frequencies. In certain cases, the assumption of uni-distribution can be used. In the case of three channels available, the calculation of Q_i can be:

$$Q_i = \prod_{k != i} \left(1 - \frac{1}{3} * \frac{1}{6}\mathbb{P}_k(cond4|i)\,\mathbb{P}_k(cond3|i)\right) \quad (7)$$

D. Cost and Rewards

$R : S \times A \times S$ in tuple $M =< S, A, P, R >$ is the reward matrix. The elements in R are denoted as $R(s, a, s')$ which is the expected reward of reaching state $s' \in S$ from the state $s \in S$ with action $a \in A$.

Although a higher SF brings a higher success rate, it brings also a higher energy consumption. Thus, it is necessary to consider the energy consumption for the reward R and encourage the nodes to choose the lowest SF possible while ensuring the transmission. Therefore, for $i \in [\![7, 12]\!], s \in T, a = Tr$, the reward of success is defined as (8)

$$R(s, Tr, Success) = V(i) \quad (8)$$

TABLE I
SIMULATION ENVIRONMENT

Parameters	Value
Channels	3 bi-directional ISM 868 Mhz band with 1% duty-cycle, 1 channel with 10% duty-cycle for only downlink
Bandwidth	125 kHz
Coding Rate	4/5
Payload Length	20 bytes
Node number	50
Packet rate	every exp(5 [mins])
Simulation Time	2 hours
Path Loss Model [24]	$\overline{Lpl(d0)} = 128.95dB \ d0 = 1000m, \gamma = 2.32, \sigma = 7.8$
Receiver sensitivities	See [25]
Transmission power	14dB
Collision Model	full collision model in [2]

where $V(i)$ is a decreasing function related to the transmission energy at $SF = i$.

For the failure punishment, the node should avoid repeating bad strategies chosen before. Thus, with the $V(i)$ defined above, for $i \in SFs, s \in T/\{sf_i\}_k \in T, a = Tr, \ s' = Fail \ if k = 8, s' \in W \ if \ not$, the failure punishment is defined as (9)

$$R(s, Tr, s') = -\alpha n(i)V(i) \tag{9}$$

where $n(i)$ is the number of uses of the SF during previous attempts.

E. MDP Resolve

For solution of the MDP modeled above, the iteration of Bellman's equations are implemented to maximize $V(s)$ for $s \in S, a = Tr$. The iteration of $V(s)$ is calculated as follows:

$$V^i(s) = \max_{a \in A} \left(\sum_{s'} \mathbb{P}(s, a, s')R(s, Tr, s') + \gamma V^{i-1}(s') \right) \tag{10}$$

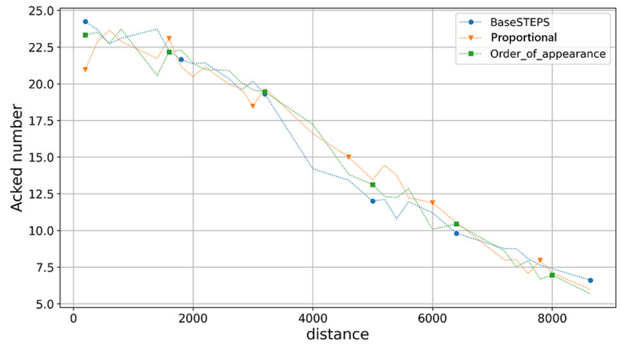
Once the iteration is finished, by taking the optimal path of $V(s)$, a series with eight attempts is built up which be used for the initial strategy prediction. The analytical results of the MDP will be given in the following section.

V. ANALYTICAL RESULTS

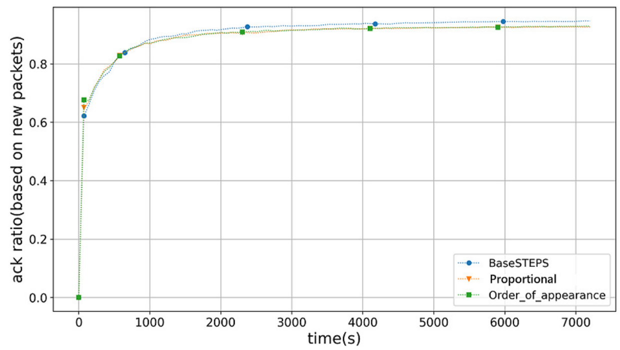
To evaluate the performance of MDP proposed above, the simulation is carried out. Table I shows the simulation environment parameters.

With the optimal path obtained by the MDP, the simulation and comparison are made between the following types of nodes:

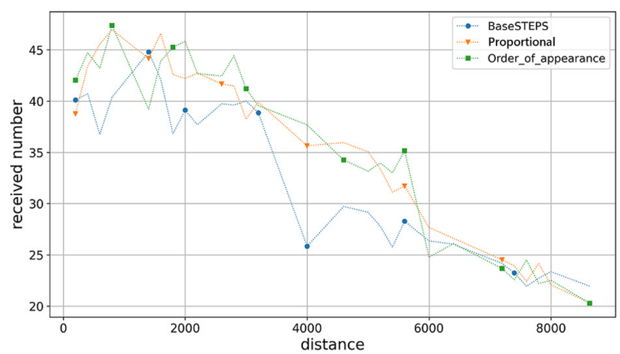
- **BaseSTEPS**: The nodes will use the original version of STEPS in [20].
- **Proportional** : The node will take the occurrence frequency of each SF in the optimal path as the initial score.
- **Order of appearance** : The node will take the 1-normalized sum of occurrence order of each SF in the optimal path as the initial score.



(a) ack number



(b) ack ratio



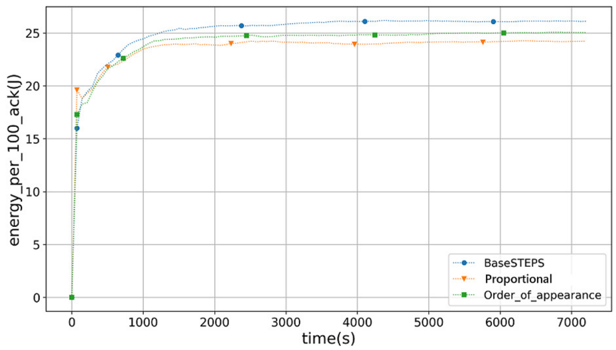
(c) received number

Fig. 2. Performance of MDP Prediction for STEPS.

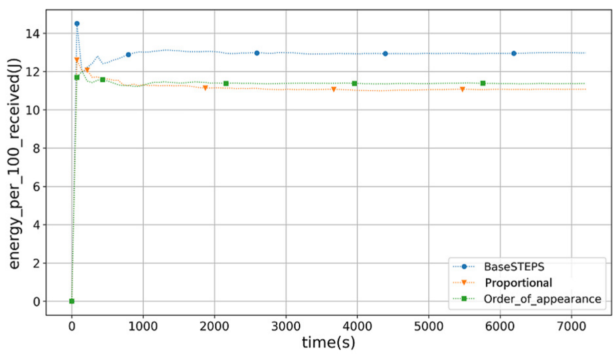
For proportional and order of appearance methods, the initial SF will be the smallest SF where $H_i(SF, d_i) \geq 0.75$. The simulation results are shown in Figure 2.

Fig. 2(a) and Fig. 2(b) show that the MDP keeps the high performance of STEPS in bi-directional transmission with an acknowledgment ratio of 90%. It can be seen in Fig. 2(b) that the acknowledgment ratio of MDP nodes is slightly lower than the original STEPS. This is due to the duty cycle limitation of the base station. As shown in Fig. 2(c), the nodes that use MDP prediction initialization method has a higher number of received packet thus the base station capacity for acknowledgment reaches the upper limit. These results also prove that the MDP prediction initialization increases the uplink performance of the LoRaWAN network.

For the transmission energy consumption, the simulation



(a) energy consumption per 100 acked packet



(b) energy consumption per 100 received packet

Fig. 3. Transmission Energy Consumption of MDP Prediction for STEPS.

results are show as in Fig. 3. It can be seen in Fig. 3(a) that for bi-directional transmission, the nodes using MDP predicted initial strategy for STEPS consume $10\% - 15\%$ less energy than the original STEPS. And for uplink transmission in Fig. 3(b), the MDP predicted initial strategy also decreases 15% of energy consumption than the original STEPS.

VI. Conclusion

In this study, the distributed reinforcement learning-based parameter allocation methods of LoRaWAN are investigated. An MDP model is constructed to describe the transmission approach of LoRaWAN. For the transition functions, an estimation method for transmission success probability is proposed. By choosing STEPS as the target method, the iteration solutions of MDP are implemented for initial strategy prediction. The analytical results show that the MDP prediction method decreases the transmission energy consumption while keeping the high performance as STEPS. For the future, it is planned to make a probabilistic model checking for the MDP model. Furthermore, a prototype is planned to be built up to verify the performance in a real LoRaWAN testbed.

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