Improving Reliability and Fairness of LoRaWAN-based Advanced Metering Infrastructure

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Abstract. Designing a reliable telecommunication network for Advanced Metering Infrastructure (AMI) is crucial. This paper focuses on using LoRaWAN as the network and improving transmission reliability while maintaining fairness among smart meters. The Spreading Factor (SF) of LoRaWAN is used to control Packet Delivery Ratio (PDR) and measure reliability. Higher SFs increase redundancy and reliability, but collisions can occur between Smart Meters (SMs) with the same SF. To optimize SF assignment, an SF assignment problem is solved to maximize the minimum achievable PDR, ensuring fairness. A novel solution called Reliable SF Assignment (RSFA) using a game of learning automata is proposed. Simulation results demonstrate that RSFA outperforms four conventional SF assignment approaches. RSFA improves packet collision rate, PDR, the number of served meters, and fairness index, albeit with a slight increase in transmission delay.

KEYWORDS Advanced Metering Infrastructure; Learning Automata; LoRaWAN; Reliability; Fairness; Spreading Factor.

Introduction

Advanced Metering Infrastructure (AMI), which includes thousands of Smart Meters (SMs) and telecommunication networks, forms the basis of smart grid architecture. Wireless networks are more commonly used for AMI due to their low cost and flexibility in installation and maintenance [1]. Typically, AMI is supported by wireless technologies such as 802.11s (Wi-Fi) and Z-Wave for short-range communication, 802.15.4g (Zigbee Pro) and 802.11ah for medium-range communication, as well as cellular networks (e.g., 3G, LTE) and Low-Power Wide Area Networks (LPWANs) for long-range scenarios [1]-[3]. LPWANs are designed to support many devices with low data rates and low power consumption. Some of the most well-known and commonly used LPWANs include Sigfox, Weightless-P, Long-Range Wide Area Network (LoRaWAN), Narrowband Internet of Things (NB-IoT), and Random Phase Multiple Access (RPMA). Among them, LoRaWAN meets most of the requirements of AMI [4], as it supports many meters, has a wide coverage area, and is compatible with the energy consumption plans of smart grid meters.

The LoRaWAN network architecture usually has a star-of-stars topology. It consists of four components: End-Devices (EDs), Gateways (GWs), Network Server (NS), and Application Server (AS), as shown in Figure 1. EDs broadcast their data so that all GWs can receive uplink packets in the vicinity of EDs. GWs relay packets from EDs to NS. GWs are connected to NS via Ethernet, Wi-Fi, satellite, or cellular networks. NS manages the network by processing the incoming packets, filtering duplicate packets, forwarding packets to AS, and sending responses to EDs through a single designated GW. Finally, AS handles the LoRaWAN application layer.

LoRaWAN deploys a specific parameter known as Spreading Factor (SF), which can be adjusted to affect the coverage, packet transmission time from an ED to a GW, called Time on Air (ToA), and data rate of LoRaWAN, as shown in Table 1 for Semtech SX1272/73 LoRa modem [5]-[8]. Coverage is determined via Received Signal Strength Indicator (RSSI). RSSI is a metric of receiver sensitivity, which is a function of the assigned SF to the ED and LoRa module specification. SF takes values from the set of {7,8,9,10,11,12}. Different SFs are mutually orthogonal, i.e., EDs with different SFs transmit their packets on the same frequency channel at the same time without interfering with each other, and thus they can be received simultaneously by a GW. A GW is in the vicinity of an ED if the received power at the GW is higher than the required RSSI, corresponding to an SF. On the one hand, the higher SF means longer coverage distance and a higher number of accessible GWs in the vicinity of an ED, i.e., a more scalable topology and higher reliability. On the other hand, the higher SF requires a higher ToA. As LoRaWAN relies on Pure Aloha Medium Access Control (MAC) protocol, using higher SFs increases the possibility of collisions between packets concurrently transmitted due to the long-time occupation of the channel, i.e., lower reliability [7].

AMI includes many SMs that transmit sensitive data and require almost the same level of reliability. Therefore, if LoRaWAN is deployed for implementing AMI, the topology design should be scalable and provide fair reliability to all SMs.

Several works have been presented in the literature to improve the reliability and scalability of LoRaWAN. A reliable and fair data rate allocation algorithm called Fair Adaptive Data Rate (FADR) is proposed in [8]. The FADR uses RSSI values in its computations while assigning SFs and allocates transmission powers to maximize the ratio of received packets to transmitted packets over a period of time among all EDs. Some clustering-based fair SF assignment algorithms for large-scale LoRaWAN have been presented in [9]-[11]. These papers consider fairness in scalability, i.e., the EDs at the same distance have the same data rate. To reduce collisions, the authors in [12] propose two heuristic algorithms, EXPLoRa-SF and EXPLoRa-AT. EXPLoRa-SF assigns equal SFs to EDs who have equal RSSI. EXPLoRa-AT sets SFs to balance the ToA of EDs in each SF's group. The simulation results show EXPLoRa-AT outperforms EXPLoRa-SF in terms of reliability. A scheduling scheme for improving reliability and collision avoidance in LoRaWAN is presented in [13]. The scheme assigns SFs in different frequency channels and schedules each ED's transmission time by a GW to reduce packet collisions. In [14], a heuristic SF allocation algorithm is proposed, which considers the impact of channel fading and path-loss. Similarly, a distance-based SF allocation scheme that improves the scalability of LoRaWAN called Exponential Windowing Scheme (EWS) has been proposed in [15]. To improve the reliability and scalability of LoRaWAN networks, several LoRa multi-user receivers have been proposed in [16]-[18]. A parallel interference cancellation LoRa receiver, relying on the differences in carrier frequencies and received powers between users, is introduced in [16]. Similarly, a two-user LoRa detector capable of demodulating two colliding users with the same SF is presented in [17, 18]. To increase reliability in LoRaWAN, an iterative process called RALI is proposed in [19]. In RALI, each ED sends multiple copies of the same packet in the same MAC frame. This process continues as long as all the packets in the frame are successfully decoded in the receiver or when no more packets can be saved. In [20], the author introduces the concept of blindly retransmitting the same packet a fixed number of times, irrespective of its successful reception. This approach aims to enhance network reliability through diversity gain.

So far, most literature algorithms reviewed were limited to single-GW deployments [8]-[20]. At the same time, multi-GW scenarios improve reliability by increasing redundancy, i.e., providing multiple parallel channels between one ED and several GWs. An extended use of the idea of ToA balancing for the multi-GW scenario, called Adaptive Mitigation of the AIr-time pressure in lORa (AD MAIORA), is proposed in [21]. It assigns SF intending to balance the ToA on the different GWs. In [22], to improve the reliability and scalability of LoRaWAN, the EDs are clustered based on their transmission powers, so the number of orthogonal SFs increases in each cluster, simultaneous transmissions grow, and packet collisions are reduced. The conventional approach for improving the reliability of LoRaWAN is Adaptive Data Rate (ADR) implemented by SF assignment and transmission power allocation. In ADR, first, the transmission power steps up upon unsuccessful transmissions. If transmission power improvement is ineffective, SFs rise gradually up to the maximum. Later, ADR utilizes the Signal to Noise Ratio (SNR) of the last 20 transmissions to modify the transmission power and SF to ensure successful transmissions [23]. Instead of SNR, the collision probability metric and ADR, called Collision-Aware ADR(CA-ADR), are deployed in [24] to compute the maximum number of EDs that can use a specific SF. CA-ADR improves reliability significantly. A scheduling process, called FCA-LoRa, which leverages fairness and improves collision avoidance in LoRaWAN, is proposed in [25]. FCA-LoRa combines time division with carrier sensing multiple access mechanisms for transmitting packets.

Although improving LoRaWAN joint reliability and scalability has been studied in the aforementioned literature, maintaining fair reliability is still an open issue. Specifically, as we deal with sensitive data of SMs in AMI, reliability is of great importance when AMI is going to be implemented by LoRaWAN. Moreover, SMs with the same data types should have the same data loss, so we should maintain fair reliability among SMs. In this paper, we solve an SF assignment problem to improve transmission reliability while maintaining fairness among SMs equipped with LoRaWAN cards. The objective of the problem is to maximize the minimum achievable Packet Delivery Ratio (PDR) of every SM. To solve the problem, we propose a novel approach called Reliable SF Assignment (RSFA), which employs a game of learning automata with adaptive penalty and reward coefficients uniquely measured for the specific AMI application for the first time. Furthermore, to increase the search speed for finding the optimal solution, at the beginning of the RSFA activity, the probabilities of actions for each automaton are defined unequally based on the characteristics of LoRaWAN technology. This is contrary to conventional methods that use equal probabilities for actions at the beginning of the game. Overall, the use of a game of learning automata with adaptive penalty and reward coefficients, along with unequal probabilities of actions, provides a unique approach to solving the SF assignment problem.

Simulation results show that RSFA significantly improves the number of collisions, the number of served meters, transmission reliability, scalability, and fairness of LoRaWAN compared to the three other SF assignment approaches, ADR, AD MAIORA, CA-ADR, and EWS, at the expense of higher transmission delay.

The remainder of this paper is organized as follows. Section 2 describes the basic concepts and details of the proposed SF assignment approach. Section 3 presents the simulation results, and Section 4 concludes the paper.

The Proposed Approach

The proposed reliability and scalability improvement approach tunes SF parameters of all SMs by using learning automata. This section first briefly explains the system model and the basics of learning automata. Then, we describe the details of the SF assignment problem and the corresponding solution approach.

1.1. LoRaWAN

LoRaWAN emerged in 2015, developed by Semtech with the participation of a community of large companies such as IBM, Cisco, HP, and Foxconn, called LoRa Alliance [26]. LoRaWAN cards propagate and retrieve low amplitude signals below the noise level. Therefore, SMs equipped with LoRaWAN cards can work with only one battery for years. The operating frequency of LoRaWAN is less than 1 GHz in an unlicensed spectrum band. To reduce interference in this technology, different duty cycles - 0.1%, 1%, and 10% - have been defined, depending on the operating frequency of LoRaWAN. For example, in a 100-second interval, a duty cycle of 1% means that if an ED sends a packet for 1 second, it is not allowed to send any packet in the rest of the interval. In LoRaWAN, the data transfer rate varies from 980 bps to 50 kbps. LoRaWAN allows long-range transmission up to 15 kilometers in rural areas and 1 to 5 kilometers in urban environments [3].

1.2. System model

We consider a LoRaWAN with N SMs and G GWs. The SMs are distributed uniformly in a two-dimensional Euclidean plane. All SMs transmit on the same frequency carrier, f_c,with bandwidth BW. The SMs have six levels of receiver sensitivity corresponding to six SF values. If the corresponding received power at a GW is above the j^{th} receiver sensitivity, then SF_j and above are assigned to the SM. The received power at a GW depends on the transmission power and the losses due to signal attenuation and shadowing. The losses are computed using the log-distance path loss model [27], based on the distance d between the transmitter and receiver as

$$L(d) = L(d_0) + 10n \log \frac{d}{d_0} + X_\sigma \tag{1}$$

where $L(d_0)$ is the mean path loss at a reference distance d_0, n is the path loss exponent, and X_σ is shadow fading represented by s, a zero-mean Gaussian distributed random variable with standard deviation σ.

The SMs produce periodic traffic, i.e., one B-bytes packet every M minutes. The MAC is pure aloha. All SMs transmit their packets regardless of whether the channel status is free or occupied. Generally, a packet collision occurs when SMs with the same SFs transmit their packets simultaneously to a GW on the same frequency channel. A Packet sent by an SM is successfully received at the NS if at least one GW successfully receives it.

1.3. Problem formulation

To improve reliability while maintaining fairness among SMs, we formulate a problem to assign SF parameters to all SMs. SFs that cause a GW to be in the vicinity of the i^{th} SM are called allowable SF, S_i. Our decision variable is f_i^j defined as

$$f_i^j = \begin{cases} 1 & \text{if the } i^{th} \text{SM uses its } j^{th} \text{SF} \in S_i \quad i = 1, ..., N;\ j = 1, 2, ..., |S_i| \\ 0 & otherwise. \end{cases} \tag{2}$$

We define x_i^g as an indicator to specify if the g^{th} GW is in the vicinity of the i^{th} SM:

$$x_i^g = \begin{cases} 1 & \text{if } L_i^g > \sum_{j \in S} f_i^j \times RSSI_j \\ 0 & otherwise, \end{cases} \tag{3}$$

where L_i^g is the path loss between the i^{th} SM and the g^{th} GW, and $RSSI_j$ is the minimum required received power at g^{th} GW of the i^{th} SM, which has been assigned the j^{th} SF. LoRaWAN-based networks operate in a broadcast manner, where each SM transmits data to all GWs within range of the SM, allowing multiple GWs to receive the same data. The notation x_i^g, indicates whether a particular gateway "g" is within the transmission range of a specific SM "i". For example, $x_{100}^2 = 1$ means that the second gateway is within the transmission range of the 100^{th} SM.

The PDR is a performance metric used in LoRaWAN-based networks to evaluate the efficiency of data transmission. PDR values range from 0 to 1, where a PDR of 1 indicates that all available GWs within the vicinity of an SM successfully receive the transmitted packet without any collisions. Conversely, a PDR value between 0 and 1 indicates that some GWs do not receive the packet due to collisions, while a PDR of 0 indicates that none of the available GWs received the packet.

The PDR of the i^{th} SM, PDR_i, is calculated using Equation (3) when a packet is transmitted. The value of N_r^i represents the number of available GWs that successfully receive the packet, while N_t^i is the total number of GWs within the vicinity of the i^{th} SM.

$$PDR_i = \frac{N_r^i}{N_t^i},\ i = 1,\ldots,N. \qquad (4)$$

Our objective function maximizes the minimum PDR_i, i=1, …, N, as represented by (5). Equation (6) ensures that the i^{th} SM is assigned an SF, s_i^j, from its allowable SF S_i. Equation (7) defines the binary SF allocation variables f_i^j. Constraint (8) guarantees that each SM is assigned exactly one SF. Constraint (9) ensures that at least one GW is in the vicinity of each SM. Constraint (10) limits the transmitted power of the i^{th} SM, E_i, to the minimum possible transmission power, e_i^k from the set E, $E = \{2,\ 5,\ 8,\ 11,\ 14\}$. This constraint ensures at least one GW to be in the vicinity of the i^{th} SM with the smallest possible allowable SF. Constraint (11) limits the mean reliability of the network to R, which is required by AMI rules [4],[28]. Finally, Constraint (12) ensures that at least one packet sent by an SM is successfully received at the NS.

$$Max\ (\min(PDR_i\ (f_i^j))),\ \ i = 1,\ldots,N;\ j = 1,2,\ldots,|S_i| \qquad (5)$$

s.t.

$$s_i^j \in S_i \subseteq S = \{7,\ 8,\ 9,\ 10,\ 11,\ 12\},\ i = 1,\ \ldots,\ N \qquad (6)$$

$$f_i^j \in \{0,1\},\ \forall(i,j),\ i = 1,\ \ldots,\ N;\ j \in \{1,\ 2,\ \ldots,\ |S_i|\} \qquad (7)$$

$$\sum_j f_i^j = 1,\ \forall i,\ i = 1,\ \ldots,\ N \qquad (8)$$

$$\sum_{g \in G} x_i^g \geq 1,\ \forall i,\ i = 1,\ \ldots,\ N;\ g = 1,\ldots,\ G \qquad (9)$$

$$E_i = \left\{ e_i^k \in E = \{2,\ 5,\ 8,\ 11,\ 14\} \,\middle|\, \sum_{g \in G} x_i^g \neq 0,\ \forall i\ \&\ \min(S_i) \right\},$$
$$i = 1,\ \ldots,\ N;\ k = 1,\ldots,\ 5 \qquad (10)$$

$$\frac{\sum_{i=1}^{N} PDR_i\ (f_i^j)}{N} \geq R \qquad (11)$$

$$PDR_i\ (f_i^j) > 0,\ \forall(i,j),\ i = 1,\ \ldots,\ N;\ j \in \{1,\ 2,\ \ldots,\ |S_i|\} \qquad (12)$$

To solve the problem, we propose RSFA using a game of learning automata, which is briefly presented here after.

1.4. Learning automaton

A Learning Automaton (LA) is a decision-making unit that learns to select an optimal action from a finite set of feasible actions, S = {s_1,…, s_r}, through repeated interactions with an unknown random environment, i.e., iterations, as shown in Figure 2. At each iteration t, LA selects an action $s_j \in S$, based on an action probability $p_j \in \mathbf{p}$= {p_1,…, p_r}. The environment sends a response $\beta \in \{0,1\}$ to the automaton after evaluating an objective function that shows the effect of s_j on the environment. The response is a reward, $\beta = 1$, if the value of the objective function in iteration t is better than the best one obtained so far. Otherwise, the environment response is a penalty, $\beta = 0$. Then, LA updates its action probability vector by a learning algorithm, **Q** [s_j, β, **p**]. If $\beta = 1$, then p_j is substituted by $p_j + a(1 - p_j)$, and the rest of the action probabilities, p_v; $v = \{1,\ldots,r\}$ and $v \neq j$, are substituted by $(1-a)p_v$. If $\beta = 0$, then p_j is updated by $(1-b)p_j$, and the rest of the action probabilities are substituted by $\frac{b}{1-r} + (1-b)p_v$, where a denotes the reward and b represents the penalty value. According to a and b, three types of learning algorithms exist. If a = b, the learning algorithm is called linear reward-penalty (L_{R-P}) algorithm; if a>>b, the algorithm is called linear reward-epsilon-penalty ($L_{R\varepsilon P}$), and finally, if b = 0, it's called linear reward-inaction (L_{R-I}). By repeating this process, the automaton learns to choose the optimal action [29]. Several automata can be interconnected to exhibit group behavior. This configuration is called a game of learning automata. In a game, *N* automata contribute to the game. However, each automaton can behave independently.

The "game of learning automata" is a probabilistic method for solving complex optimization problems with uncertainty, nonlinearity, and multiple decision variables. It adjusts decision variables based on environmental feedback, converging to the optimal solution. Learning automata can adapt to changing conditions and improve network efficiency.

Learning automata quickly converge to the optimal SF assignment, even in large-scale networks. They adapt to changing network conditions, making them useful in complex, poorly understood, or high-dimensional optimization problems. They have a simple structure, low computational load, and are suitable for real-time applications [30]-[31].

By using the game of learning automata, we can avoid the need for explicit knowledge of the complex optimization problem. This would refer to knowledge of the underlying optimization problem that the automaton is trying to solve, including information such as the problem's structure, objectives to be optimized, and constraints that need to be satisfied.

1.5. SF assignment based on a game of learning automata

We present RSFA based on a game of learning automata to solve the max-min problem given in (5) to (12). First, to set up a game, a set of *N* automata, $A=\{A_1, \ldots, A_N\}$, where automaton A_i corresponds to the i^{th} SM, is generated. Each automaton is identified by the feasible actions set, S_i, and its correspondent action probability vector, $\mathbf{p_i}$, and a learning algorithm, $\mathbf{Q}$. The learning automata game is a repetitive process in which the set of actions for each automaton, S_i, can have different elements. S_i remains constant in all iterations, and only the probability of selecting each action changes based on environmental feedback. The feasible actions set of automaton A_i is a set consisting of the allowable SFs of the i^{th} SM. As different SMs have a different number of allowable SFs, the feasible actions sets of A_i, $i=\{1, \ldots, N\}$, may not have the same number of members. Correspondent to each member of the feasible actions set of A_i, s_i^j where $j=\{1, \ldots, r\}$, action probability p_i^j is defined. At the beginning of the game, the initial values of p_i^j can be adjusted equally or unequally. For faster convergence, unlike most learning automata that use equal p_i^j at the beginning of their operation [31], we define the values of p_i^j unequally based on the normalized ToA of correspondent allowable SFs of each automaton as

$$p_i^{r_i-j+1} = \frac{D_i^j}{\sum D_i^j}, \quad j=1, \ldots, r_i \;;\; i=1, \ldots, N \qquad (13)$$

where D_i^j is the ToA of the j^{th} SF of S_i, s_i^j, and r_i is the number of members of S_i. According to (13), SFs with lower values have higher chances of selection due to using lower values of ToA.

The RSFA based on a game of learning automata tries to find the best value of SF for each SM through the iterative process, which continues until the stop condition of the approach is reached. We consider two stopping criteria for terminating the iterations: the maximum number of pre-defined iterations, *T*, and the non-improving objective function in a certain number of consecutive iterations, *H*. The iterations stop when either of these criteria is met. The updating algorithm $\mathbf{Q}$ is applied as follows: At iteration *t*, each A_i, $i=\{1, \ldots, N\}$, selects an action s_i^j, and uses it on a LoRaWAN as a random environment. Then, the value of $\mathbf{p_i}$ is updated, depending on whether the taken action is desirable, $\beta=1$, or undesirable, $\beta=0$, by LoRaWAN, which is defined in this paper based on two factors: 1) comparison of $min\, PDR_i(f_i^j)$ at the current iteration, called $MP(t)$, with the maximum value of $min\, PDR_i(f_i^j)$ in the previous iterations, 2) comparison of the numbers of SMs with $PDR_i(f_i^j)=0$, called $NZ(t)$, with the ones in the previous iterations at the current iteration. In other words, the action is desirable when 1) $MP(t)$ is not zero and is greater than the maximum value obtained for the $min\; PDR_i(f_i^j)$ in the previous iterations. 2) $MP(t)$ is zero, and $NZ(t)$ is less than the minimum number of SM with $PDR_i(f_i^j)=0$ in the previous iterations. Otherwise, the action is undesirable.

Accordingly, the rewards, $a_i^j(t)$, and penalties, $b_i^j(t)$, are determined dynamically as follows:

$$K(t) = \alpha \times MP(t) + (1-\alpha) \times \left(\frac{N - NZ(t)}{N}\right) \times 0.1, \qquad (14)$$

$$W(t) = \alpha \times (1 - MP(t)) \times 0.1 + (1-\alpha) \times \left(\frac{NZ(t)}{N}\right) \times 0.1, \qquad (15)$$

$$a_i^j(t) = \begin{cases} 3 \times K(t) & PDR_i(f_i^j) = 1 \\ K(t) & otherwise, \end{cases} \quad (16)$$

$$b_i^j(t) = \begin{cases} 0.33 \times W(t) & PDR_i(f_i^j) = 1 \\ W(t) & otherwise, \end{cases} \quad (17)$$

Equations (14) to (17) explain how the reward and penalty coefficients used in each iteration of RSFA are computed. In learning automata, these coefficients can be either constant or adaptive [32]. Our research in this paper shows that using adaptive coefficients increases the search speed of RSFA in finding the optimal solution in comparison to using constant coefficients. As a result, in RSFA, these coefficients are adaptively defined and uniquely measured for the specific AMI application.

In each iteration of RSFA, the base value for the reward (K) or penalty (W) is determined based on equations (14) and (15), respectively. Equations (14) is derived to assign higher rewards to selected actions as $min\ PDR_i(f_i^j)$ at the current iteration, called *MP*(*t*), gets closer to its maximum value (i.e., $min\ PDR_i(f_i^j) = 1$) compared to the maximum value of $min\ PDR_i(f_i^j)$ in the previous iterations. Equations (15) is derived to assign higher penalties to selected actions as *MP*(*t*) gets closer to its minimum value (i.e., $min\ PDR_i(f_i^j) = 0$) compared to the maximum value of $min\ PDR_i(f_i^j)$ in the previous iterations.

During the initial iterations of automata, some SMs may have a PDR value of zero. So, due to lack of variation in $min\ PDR_i(f_i^j)$ in these iteration, the learning automata cannot differentiate between the performance of selected actions to decide whether to reward or penalize the selected actions. To overcome this issue, the increase or decrease in the number of SMs with PDR=0, called *NZ*(t), is considered in equations (14) and (15). Thus, higher rewards are assigned when the *NZ*(t) decreases closer to zero compared with the ones in the previous iterations at the current iteration. The coefficient α deactivates this part of the equations if *NZ*(t)=0. The coefficient α takes on values of 0 or 1. If *MP*(*t*) is not zero, α is equal to 1, and therefore, the amount of reward is proportional, and the amount of penalty is inversely proportional to *MP*(*t*). Similarly, if α equals zero, the reward amount is inversely proportional, and the penalty is proportionate to *NZ*(*t*).

Our investigations have shown that providing higher rewards or lower penalties to SMs with PDR=1 compared to other SMs in the network accelerates the convergence rate in RSFA. By using a trial-and-error method and applying different coefficients for rewards and penalties, we have implemented a 3:1 ratio for increasing rewards and decreasing penalties for SMs with PDR=1, as stated in equations (16) and (17). Therefore, in subsequent iterations, the probability of selecting those SFs for these SMs increases. This approach significantly contributes to achieving faster convergence of the problem.
The coefficients given in (14) to (17) have been determined based on the following three factors and improved by trial and error:

1) The numbers of SMs with $PDR_i = 0$, $i = 1, \ldots, N$, must be kept minimum in each iteration.
2) If the $min\ PDR_i$, $i = 1, \ldots, N$, is not zero. According to the value of β, a higher reward or lower penalty will be considered.
3) $L_{R\varepsilon P}$ learning scheme is chosen because it performs better than L_{R-P} and L_{R-I} in RSFA.

Simulation Results

We evaluate the performance of RSFA through simulations. First, we describe the evaluation metrics, followed by the simulation setup. Then, we demonstrate the performance of RSFA compared with three other conventional approaches: ADR [24], AD MAIORA [21], CA-ADR [24], and EWS [15] which assume perfect orthogonality among SFs. The significant contribution of these approaches is that they have been focused on reducing collision to improve reliability.

1.6. Evaluation Metrics

We utilize several evaluation metrics to represent the reliability, scalability, and fairness performance. These include 1) packet collision rate, 2) PDR evaluation results, and 3) average ToA metrics to assess reliability. The number of served SMs determines scalability. To evaluate fairness, we use Jain's fairness index, defined as follows [8]:

$$J = \frac{\left(\sum_{i=1}^{N} PDR_i\right)^2}{N \sum_{i=1}^{N} PDR_i^2} \quad (18)$$

1.7. Simulation Setup

In the simulated scenario, at most, N=18000 SMs are uniformly distributed in a rectangular 9km×18km area. We consider G=5 GWs regularly located in this area, as shown in Figure 3. Each SM uses the minimum possible transmission power to communicate with the nearest GW, and we calculated the required transmission power based on the large-scale fading, given in (1), around the location of SM and the minimum SF value that ensures at least one GW is visible. The propagation parameters, i.e., n, X_{σ}, and σ, have been derived from [27]. Each SM's packet size, B, is 15 bytes, and we use the Semtech SX1272/73 LoRa module, whose specifications are presented in Table 1. The SMs transmit in the same channel of carrier frequency f_c = 868 MHz, and BW = 125 kHz. The minimum reliability value, R, is set to 99% according to the AMI communication requirement. All simulations were performed using the MATLAB simulator, and the code provided in [33] was modified and updated to support a network with multiple GWs. The stopping criteria values for T and H are set to 200 and 100, respectively, based on trial and error, respectively. It is conventional in AMI to transmit the packets periodically every M =15 minutes, so the simulated time is 15 minutes.

1.8. Evaluation Results

The packet collision rate percentage for different SMs is illustrated in Figure 4. The results show that RSFA causes the lowest collision rate compared to ADR, AD MAIORA, CA-ADR, and EWS approaches. ADR assigns the same SF to all SMs located within a certain distance from a GW, which may cause some selected SF to be overused, leading to collisions. CA-ADR is a more efficient than ADR algorithm. CA-ADR uses an equation to assign the obtained minimum SF to each meter, as long as the number of nodes already assigned that SF value does not exceed the maximum allowed. If the limit is reached, then the algorithm tries to assign a higher SF. Consequently, the probability of having many SMs with the same SF decreases, and the packet collision rate reduces compared to ADR. The collision rate for CA-ADR is approximately close to the AD MAIORA. Both approaches assign SFs based on ToA. However, since they focus on balancing ToA on different GWs, the probability of having many SMs with the same SFs decreases. Hence, the packet collision rate reduces compared to ADR. In the EWS, the SF allocation to the SMs is based on the distance criterion of each meter from the network gateway. Therefore, all SMs within a specific distance range from the gateway are assigned the same SF value. This results in an increased chance of simultaneous reception of multiple data packets with the same SF value in a gateway, leading to network collisions. Moreover, in the EWS method, with an increase in the number of smart meters, more SMs are assigned higher SF values. Since the packet transmission time of SMs with higher SF values is longer than those with lower SF values, this leads to an increase in network collisions. Unlike ADR, AD MAIORA, and CA-ADR, which assign SFs sequentially to SMs and may leave some SFs unused, RSFA deploys all SFs in the assignment and does not leave any SF unused.

In the compared approaches, SF allocation to the SMs is based on either the distance from the gateway or calculating the number of SMs for each SF value. In LoRaWAN technology, SF takes values from the set of {7, 8, 9, 10, 11, 12}. Different SFs are mutually orthogonal, meaning that smart SMs with different SFs can transmit their packets on the same frequency channel at the same time without interfering with each other, and thus they can be received simultaneously by a gateway. Accordingly, receiving data packets simultaneously from at least two SMs with the same SF value and same frequency channel causes collisions. Therefore, SF allocation based on distance or the number of SMs for each SF value increases the probability of collision in the network. This is because in these approaches, the transmission time for each SM's data packet is not taken into account. In the proposed approach, in addition to optimizing the SF allocation between SMs and making maximum use of the orthogonality among different SF values, another influential factor leading to a significant reduction in the collision rate is the innovative use of environmental feedback in allocating SF values to each SM. The use of environmental feedback in evaluating the SF value allocated to each SM towards reducing collisions in the network not only improves the results, but also takes into account the effect of data packet transmission time in the proposed approach.

PDR is one of the most widely used LoRaWAN reliability indicators [34] because PDR reflects the redundancy in the number of wireless transmission paths between an SM and the neighboring GWs. The desirable reliability in AMI is above 99% [4], [28]. Therefore, to illustrate the ideal reliability achievement of the approaches, we divide the PDR value into three parts: PDR=1, 0<PDR<1, and PDR=0. PDR evaluation results measured for 18000 SMs are shown in Table 2. As ADR has the highest packet collision ratio compared to the other approaches, it has the lowest and highest percentage of PDR=1 and PDR=0, respectively. EWS has better collision rate performance compared to ADR, but it has a higher collision rate than the other three approaches. AD MAIORA and CA-ADR have similar packet collision rates, so they have almost the same performance, with the difference in the number of unserved SMs, i.e., PDR=0. RSFA provides the best performance among the other approaches in terms of served and unserved SMs. Furthermore, as the network reliability of ADR, AD MAIORA,CA-ADR, and EWS are less than 99%, they cannot be deployed in AMI, which requires reliability over 99%.

To investigate the tradeoff between reliability and transmission delay, we represent the average ToA of packets to reach the GWs in Figure 5. ADR approach has the lowest average TOA since it assigns the lowest SF to all SMs, resulting in short transmission times. AD MAIORA modifies ADR by assigning higher SF to some SMs located in the congested area to reduce collision. Accordingly, AD MAIORA experiences a higher average ToA than ADR. CA-ADR has a higher average ToA value compared to ADR and AD MAIORA. CA-ADR does not assign higher SFs as long as the number of SMs is lower than a threshold value. By reaching the threshold, ToA increases by increasing SF abruptly, resulting in sharp changes occur in average

ToA. These three approaches start SF assignment by allocating the lowest SF values to SMs, and at the end of the assignment, the higher SF values may remain unused. EWS has improved the average ToA compared to ADR, AD MAIORA, and CA-ADR by using all SF values and allocating more SMs to smaller SF values in low-density environments. However, in this approach, increasing the ratio of SMs with larger SF values proportional to the increase in environmental density has resulted in an increase in the average ToA in the network.

Despite the significant improvement in the collision rate, the proposed approach has increased the average packet transmission time in the network compared to other approaches, as shown in Figure 5. In ADR, AD MAIORA, CA-ADR approaches, and also EWS approach in low-density of SM scenarios, the first priority is to assign smaller SF values to SMs. However in RSFA, we insist on deploying all SFs values to enhance the reliability by having the max orthogonality among SFs. Since the TOA of SMs with larger SF values is much greater than those with smaller SF values, as shown in Table 1, the average ToA increases in RSFA. Nevertheless, the delay requirement of AMI is less than 2000ms [4],[28], and the delay that occurs in RSFA is acceptable. However, with the increase in the density of SMs and the allocation of more S to larger SF values in the EWS approach, the delay of this approach compared to RSFA increases.

The ratio of the number of served SMs to the number of total SMs is illustrated in Figure 6. While the compared approaches, ADR, AD MAIORA, CA-ADR, and EWS show a decreasing ratio trend with an increasing number of total SMs due to the increasing packet collision rate, RSFA has an approximately constant ratio. In other words, RSFA demonstrates outstanding scalability performance because it has a significantly low collision rate in comparison to the evaluated approaches.

Jain's fairness index of all approaches is demonstrated in Figure 7. As the number of SMs increases, the index of ADR, AD MAIORA, CA-ADR, and EWS degrade dramatically due to collisions. However, RSFA maintains an almost constant index, approximately equal to one. RSFA is the fairest approach to providing almost identical reliability for all SMs, as nearly all SMs have PDR=1. In contrast, in the other approaches, the amount of PDR varies between between zero and one. ADR is the least fair approach because it suffers from higher collisions and hence lower PDR.

Regarding the sudden decline in performance of the EWS approach, it is important to note that this approach falls under the category of distance-based approaches. It involves assigning the same SF value to all SMs located within a specific distance range from the network gateway. During the implementation of this approach, the range is divided into three modes for each SF value, depending on the meter density. In regions with lower meter density, a larger proportion of SMs are assigned smaller SF values, whereas in denser areas, a higher percentage of SMs are allocated larger SF values. Due to the utilization of the ALOHA medium access protocol in LoRaWAN technology and the significantly longer ToA for larger SF values compared to smaller SF values, the spatial allocation range for each SF value changes as the meter density increases. This sudden alteration results in a noticeable increase in collision rates during packet transmission, leading to reduced reliability and fairness within the EWS approach.

Conclusion & Future Work

A scalable, fair, and reliable SF assignment approach, called RSFA, has been proposed for AMI implemented by LoRaWAN. RSFA uses the game of learning automata, $L_{R\epsilon P}$, tuned by variable penalty and reward parameters to assign SFs to SMs. The objective of the automata is to maximize the minimum of PDR, i.e., to maintain *max-min* reliability fairness among SMs. We aim to deploy as many SFs as possible in the assignment to take advantage of maximum orthogonality among SMs. We compare the reliability, scalability, and fairness performance of RSFA with four conventional approaches: ADR, AD MAIORA, CA-ADR, and EWS. The simulation results show that RSFA outperforms the other approaches regarding packet collision rate and PDR at the expense of increased transmission delay. However, the delay conforms to the requirement of AMI with a sufficient margin. As the number of SMs increases, the network reliability of ADR, AD MAIORA, CA-ADR, and EWS decreases sharply to less than 99%, which is unacceptable in AMI. In comparison, the network reliability of RSFA is over 99%.

Furthermore, unlike the other approaches, RSFA is scalable since the reduction in the number of served SMs, as the number of SMs increases, is negligible. Jain's fairness index shows that RSFA maintains fairness among SMs even when the number of SMs increases because it provids almost equal reliability for all SMs, while the index decreases sharply in the other approaches. In our future work, we plan to implement RSFA in a practical scenario (case study) and consider the effect of imperfect orthogonality among SMs.

References

[1] Li, Y., Cheng, X., Cao, Y., et al. "Smart choice for the smart grid: Narrowband Internet of Things (NB-IoT)" , *IEEE Internet of Things Journal*, 5(3), pp. 1505-1515 (2017).

[2] Abrahamsen, F. E., Ai, Y., and Cheffena, M. "Communication Technologies for Smart Grid: A Comprehensive Survey" , *Sensors*, 21(23), (2021), doi: https://doi.org/10.3390/s21238087.

[3] Bembe, M., Abu-Mahfouz, A., Masonta, M., et al. "A survey on low-power wide area networks for IoT applications" , Telecommunication Systems, 71(2), pp. 249-274 (2019).

[4] DOE, U. S., "Communications requirements of Smart Grid technologies", Tech. Rep. US Department of Energy, pp. 1-69 (2010), [Online]. Available: https://www.energy.gov/gc/downloads/communications-requirements-smart-grid-technologies.

[5] Babaee, M., and Sharifian, S. "An improved spread factor assignment method for large-scale LoRaWAN deployments in IoT" , In *4th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS)*, pp. 183-187 (2018).
[6] Lin, E.R. "LoRa protocol. Evaluations, limitations and practical test", Ph.D. dissertation. Universitat Politècnica de Catalunya. Escola Tècnica Superior d'Enginyeria de Telecomunicació de Barcelona, 2016.
[7] Fragkopoulos, M., Panagiotakis, S., Kostakis, M., et al. "Experimental Assessment of Common Crucial Factors That Affect LoRaWAN Performance on Suburban and Rural Area Deployments", Sensors, 23(3), 2023.
[8] Abdelfadeel, K. Q., Cionca, V., and Pesch, D. "Fair adaptive data rate allocation and power control in LoRaWAN" , In *IEEE 19th International Symposium on A World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, (2018).
[9] Asad Ullah, M., Iqbal, J., Hoeller, A., et al. "K-means spreading factor allocation for large-scale LoRa networks" , *Sensors*, 19(21), (2019).
[10] Caillouet, C., Heusse, M., and Rousseau, F. "Bringing Fairness in LoRaWAN through SF Allocation Optimization" , In *2020 IEEE Symposium on Computers and Communications (ISCC)*, pp. 1-6 (2020)
[11] Mohammadi, S., and Farahani, G. "Scalability analysis of a LoRa network under inter-SF and Co-SF interference with Poisson point process model" , Journal of Computing and Security, 8(2), pp. 43-57 (2021).
[12] Cuomo, F., Campo, M., Caponi, A., et al. "EXPLoRa: Extending the performance of LoRa by suitable spreading factor allocations" , In *IEEE 13th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, pp. 1-8, (2017)
[13] Triantafyllou, A., Sarigiannidis, P., Lagkas, T., et al. "A Novel LoRaWAN Scheduling Scheme for Improving Reliability and Collision Avoidance" , In *9th International Conference on Modern Circuits and Systems Technologies (MOCAST)*, pp. 1-4, (2020).
[14] Saluja D., Singh, R., Baghel, L. K., et al. "Scalability analysis of LoRa network for SNR-Based SF allocation scheme", *IEEE Transactions on Industrial Informatics*, 17(10), pp. 6709–6719 (2021).
[15] Saluja, D., Singh, R., Gautam, S., et al. "EWS: Exponential windowing scheme to improve LoRa scalability" , *IEEE Transactions on Industrial Informatics*, 18(1), pp. 252–265 (2022).
[16] Shahid, M. O., Philipose, M., Chintalapudi, K., et al. "Concurrent interference cancellation: Decoding multi-packet collisions in LoRa" ,in Proc. ACM SIGCOMM Conf, pp. 503–515 (2021).
[17] Garlisi, D., Mangione, S., Giuliano, F., et al. "Interference cancellation for LoRa gateways and impact on network capacity" , IEEE Access, 9, pp. 128133–128146 (2021).
[18] Tapparel, J., Xhonneux, M., Bol, D., et al. "Enhancing the reliability of dense LoRaWAN networks with multi-user receivers" , IEEE Open Journal of the Communications Society, 2, pp. 2725-2738 (2021).
[19] El Rayess, J., Khawam, K., Lahoud, S., et al. " RALI: Increasing Reliability in LoRaWAN through Repetition and Iteration" , In 2023 IEEE Wireless Communications and Networking Conference (WCNC), pp. 1-6 (2023).
[20] El Rayess, J., Khawam, K., Lahoud, S., et al. "Study of LoRaWAN Networks Reliability" , In IEEE 6th Conference on Cloud and Internet of Things (CIoT),pp. 200-205 (2023).
[21] Cuomo, F., Campo, M., Bassetti, E., et al. "Adaptive mitigation of the Air-Time pressure in LoRa multi-gateway architectures" , In *24th European Wireless Conference*, pp. 1-6, (2018).
[22] Reynders, B., Wang, Q., Tuset-Peiro, P., et al. "Improving reliability and scalability of lorawans through lightweight scheduling" , *IEEE Internet of Things Journal*, 5(3), pp.1830-1842 (2018).
[23] Li, S., Raza, U., and Khan, A. "How agile is the adaptive data rate mechanism of LoRaWAN?" , In *2018 IEEE Global Communications Conference (GLOBECOM)* , pp. 206-212, (2018).
[24] Marini, R., Cerroni, W., and Buratti, C. "A novel collision-aware adaptive data rate algorithm for LoRaWAN networks" , *IEEE Internet of Things Journal*, 8(4), pp. 2670-2680 (2020).
[25] Triantafyllou, A., Sarigiannidis, P., Lagkas, T., et al. "Leveraging fairness in LoRaWAN: A novel scheduling scheme for collision avoidance" , *Computer Networks*, 186, (2021), doi: https://doi.org/10.1016/j.comnet.2020.107735.
[26] Ahmad, A. I., Ray, B., and Chowdhury, M. "Performance evaluation of LoRaWAN for mission-critical IoT networks" , In *International Conference on Future* Network Systems and Security, Springer, Cham, pp. 37-51(2019).
[27] Slabicki, M., Premsankar, G., and Francesco, M. D. "Adaptive configuration of LoRa networks for dense IoT deployments" , In NOMS 2018-2018 IEEE/IFIP Network Operations and Management Symposium, pp. 1-9 (2018).
[28] Azmi, K. H. M., Radzi, N. A. M., Azhar, N. A., et al. (2022). Active Electric Distribution Network: Applications, Challenges, and Opportunities. *IEEE Access*.
[29] Nikhalat-Jahromi, A., Saghiri, A. M., and Meybodi, M. R. "VDHLA: Variable Depth Hybrid Learning Automaton and Its Application to Defense Against the Selfish Mining Attack in Bitcoin" , arXiv preprint arXiv:2302.(2023).
[30] Sarhadi, A., and Torkestani, J. A. "Cost-Effective Scheduling and Load Balancing Algorithms in Cloud Computing Using Learning Automata" , Computing and Informatics, 42(1), pp.37-74 (2023).
[31] Karmakonda, K., Das, M. S., and Ravi, G. "An Energy-Efficient Learning Automata and Cluster-Based Routing Algorithm for Wireless Sensor Networks" , Contemporary Mathematics, pp.488-504 (2023).
[32] He, Z., Chen, L., Li, F., et al. "Congestion Avoidance in Intelligent Transport Networks Based on WSN-IoT through Controlling Data Rate of Zigbee Protocol by Learning Automata" , Electronics, 12(9), (2023).
[33] Lavric, A. " LoRa (long-range) high-density sensors for internet of things", Journal of Sensors (2019).
[34] Liang, R., Zhao, L., and Wang, P. "Performance evaluations of LoRa wireless communication in building environments" , *Sensors*, 20(14), (2020).

Figure 1. LoRaWAN Architecture.
Table 1. Semtech Sx1272/73 Lora Modem Specification [5], [6].
Figure 2. The interaction between a learning automaton and a random environment.
Figure 3. An instance of random distribution of 2000 SMs around the GWs.
Figure 4. Packet collision rate for different numbers of SMs.
Table 2. PDR distribution (%) of ADR, AD MAIORA, EWS, CA-ADR, and RSFA for 18000 SMs.
Figure 5. The average ToA for different numbers of SMs.
Figure 6. The ratio of the number of served SMs against the total numbers of SMs.
Figure 7. Jain's fairness index for different numbers of SMs.

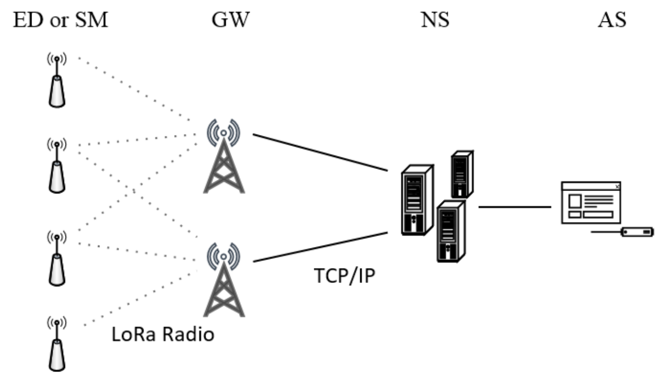
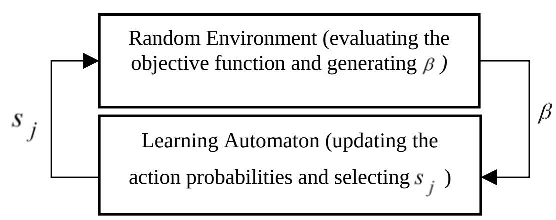


Figure 1. LoRaWAN Architecture, (Abbreviation: SM:Smart Meter; ED: End-Device; GW: Gateway; Ns:Network Server; AS: Application Server; TCP/IP: Transmission Control Protocol/Internet Protocol; LoRa(Long Range)).

Table 1. Semtech Sx1272/73 Lora Modem Specification [5], [6].

SF	Packet Size (bytes)	Bandwidth (kHz)	RSSI (dBm)	ToA (msec)	Data Rates (bps)
7	15	125	-124	44	5469
8	15	125	-127	78	3125
9	15	125	-130	136	1758
10	15	125	-133	272	977
11	15	125	-135	545	537
12	15	125	-137	928	293

Note: SF: Spreading Factor; RSSI: Received Signal Strength Indicator; ToA: Time on Air



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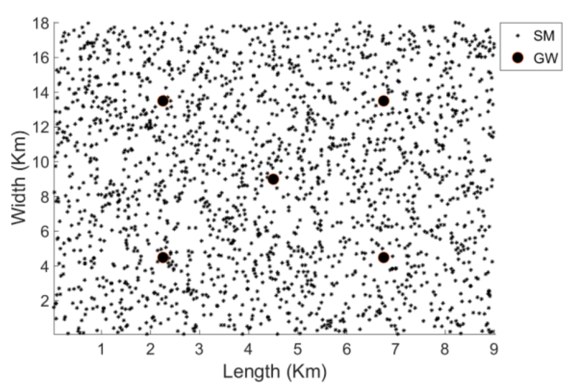


Figure 3. An instance of random distribution of 2000 SMs around the GWs, (Abbreviation: SM:Smart Meter; GW: Gateway).

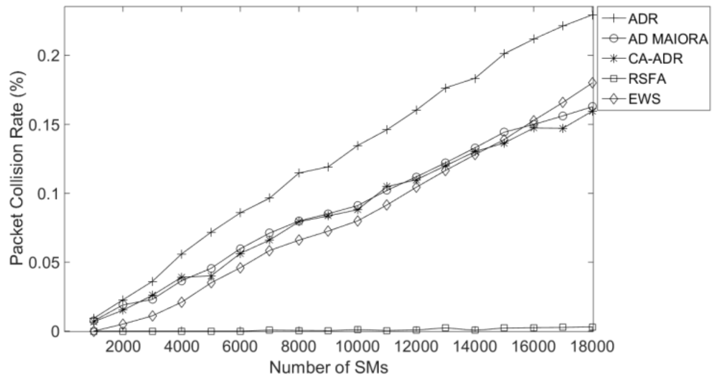


Figure 4. Packet collision rate for different numbers of SMs, (Abbreviation: ADR: Adaptive Data Rate ; AD MAIORA: Adaptive Mitigation of the AIr-time pressure in lORa ; CA-ADR: Collision-Aware ADR ; RSFA: Reliable SF Assignment ; EWS: Exponential Windowing Scheme)

Table 2. PDR distribution (%) of ADR, AD MAIORA, EWS, CA-ADR, and RSFA for 18000 SMs.

Approach	**PDR distribution (%)**		
	PDR=0	0<PDR<1	PDR=1
ADR	22	2	76
AD MAIORA	16	1	83
EWS	19	3	78
CA-ADR	13	4	83
RSFA	0.2	0.25	99.55

Note: PDR: Packet Delivery Ratio; ADR: Adaptive Data Rate ; AD MAIORA: Adaptive Mitigation of the AIr-time pressure in lORa ; CA-ADR: Collision-Aware ADR ; RSFA: Reliable SF Assignment ; EWS: Exponential Windowing Scheme.

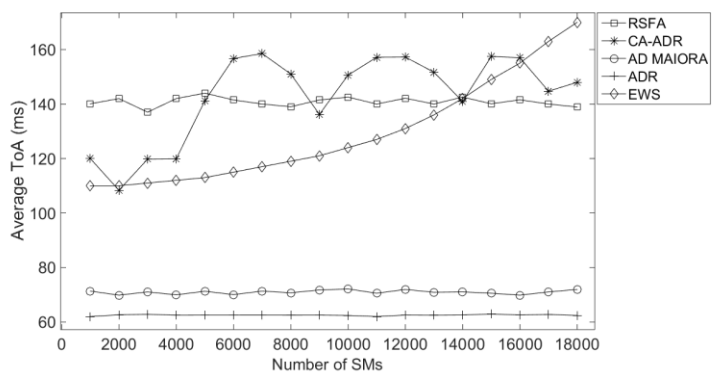
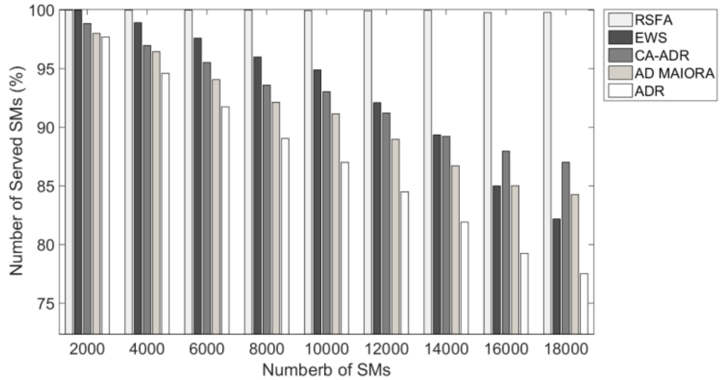


Figure 5. The average ToA for different numbers of SMs, (Abbreviation: ADR: Adaptive Data Rate ; AD MAIORA: Adaptive Mitigation of the AIr-time pressure in lORa ; CA-ADR: Collision-Aware ADR ; RSFA: Reliable SF Assignment ; EWS: Exponential Windowing Scheme; SMs: Smart Meters; ToA: Time on Air).



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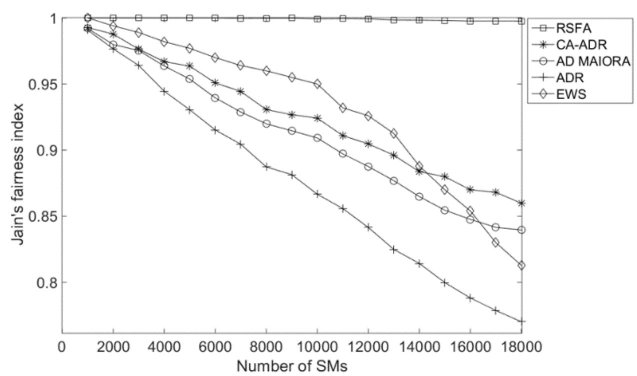

Figure 7. Jain's fairness index for different numbers of SMs, (Abbreviation: ADR: Adaptive Data Rate ; AD MAIORA: Adaptive Mitigation of the AIr-time pressure in lORa ; CA-ADR: Collision-Aware ADR ; RSFA: Reliable SF Assignment ; EWS: Exponential Windowing Scheme; SMs: Smart Meters).

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