Supervised Learning based Arrival Prediction and Dynamic Preamble Allocation for Bursty Traffic

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Abstract - Achieving ultra-reliable low latency communications (URLLC) in massive machine type communication networks requires novel medium access mechanisms to accommodate a huge number of traffic arrivals. Random access based on LTE-A suffers from collisions and long latency when two or more devices select the same preamble to initiate channel access simultaneously and this problem becomes severe in mMTC networks. In this paper, we propose a machine learning based scheme that allows an eNB to predict the number of arrivals at each random access slot and allocate preambles accordingly. We demonstrate that, by combining arrival prediction with group based dynamic preamble reservation, the grouped devices are able to achieve URLLC under bursty traffic conditions and meanwhile the performance of non-grouped devices is also improved.

C.1 Introduction

Driven by various novel application scenarios, the development of 5G mobile and wireless communication standards is focusing on three main technological directions, i.e., enhanced mobile broadband (eMBB), massive machine type communications (mMTC), and ultra-reliable low latency communications (URLLC). While mMTC is expected to accommodate 1+ million connections per square kilometer, URLLC is targeted at providing ultra-reliability levels with very low latency for certain types of, e.g., mission-critical, services. When the number of devices attempting to access the network is large, it often results in access congestion due to competitions among devices for scarce resources and thereby deteriorating their performance. This situation becomes even more challenging for bursty traffic. Therefore, such problems need to be addressed to a satisfactory degree in order to achieve URLLC for mMTC. However, the long-term evolution advanced (LTE-A) based random access (RA) process is not designed to facilitate a very large number of devices due to its limited number of available preambles. This limitation may increase collision probability and lead to long latency.

In [2], the 3rd generation partnership project (3GPP) specifies several possible solutions to address LTE RA congestion. One popular solution is access class barring (ACB) based schemes according to which devices are classified into access categories with different access probabilities and barring times. Moreover, approaches like dynamic resource allocation, MTC specific backoff, slotted RA, and pull based (i.e., eNB initiated) access procedures were also considered in [2]. In addition to 3GPP based solutions, there exist also other approaches proposed to reduce RA congestion (see e.g., [2] and the references therein). Moreover, group based access schemes have also been proposed to reduce collision probabilities [3]. However, while these solutions contribute towards reducing random access channel (RACH) congestion, they do not adequately address the URLLC requirements. Consequently, these solutions often provide high levels of reliability at the cost of long latency. For URLLC, the tradeoff between reliability and latency needs to be addressed.

To estimate traffic arrivals at an eNB is one potential technique that can be utilized to prevent the occurrence of congestion at an early stage which leads to reduced latency. For ACB based random access, there exist some studies which focus on estimating random access load and then adjusting ACB parameters using different methods. For example, [4] proposed a congestion-aware admission control mechanism in which MTC signaling traffic is rejected at the radio access network with a probability p that represents the level of congestion. It utilizes a proportional integrative derivative controller to derive the value of p. A Markov chain based traffic load estimation scheme was proposed in [5]. As a machine learning based effort, [6] proposed a reinforcement learning based approach to dynamically adjust the ACB barring rate. While most of these solutions focused on parameter tuning for the ACB scheme, it is imperative to investigate how the observed data at an eNB can be combined with machine learning techniques to achieve real-time predictions of arrivals data which enables URLLC.

In this paper, we propose a supervised learning based random access scheme which first predicts bursty traffic arrivals at an eNB and then allocates preambles for group based access. The prediction is based on the detected number of preambles at the eNB. According to its prediction, the eNB is able to dynamically evaluate traffic arrival conditions and allocate preamble resources to different types of user groups. By combining a group based access phase along with bursty traffic prediction, the eNB is able to provide URLLC services to a set of mMTC devices.

The remainder of this paper is organized as follows. Sec. C.2 provides the background information and problem statement for this study. Thereafter, Sec. C.3 presents a machine learning based approach for predicting the number of arrivals, followed by Sec. C.4 which proposes one scheme for achieving URLLC based on arrival predictions. The numerical results are provided in Sec. C.5. Finally, the paper is concluded in Sec. D.6.

C.2 Background and Problem Statement

In this section, we first present some related background for this study and then introduce the problem statement.

C.2.1 LTE-A RACH Process

Consider that multiple MTC end user devices are covered by the same eNB. When an uplink communication is required, an LTE-A device needs to follow a 4-step random access procedure [7], as illustrated in Fig. C.1. Each device needs to randomly select a preamble from a set of R available preambles which are periodically advertised by the eNB. These R preambles are orthogonal to each other and the selected preambles are transmitted in the next available RA slot which appears every fifth subframe [7]. If two or more devices select the same preamble to transmit in the same RA slot, a collision of preambles may be

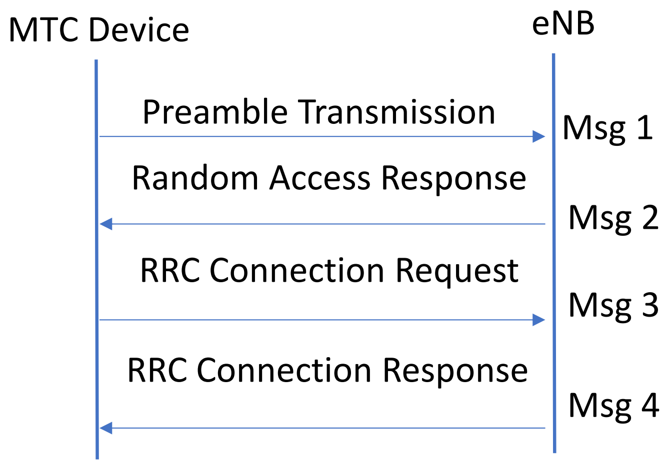

Figure C.1: 4-step LTE-A random access for MTC devices.

detected and the collided devices will not receive a Msg 2, i.e., a random access response (RAR) message, from the eNB. If no Msg 2 is received within a timeout period, the devices will retransmit Msg 1 up to a maximum number of times, N_{max}. A retransmission follows the same procedure as mentioned above but happens after a backoff time selected randomly from the range of $[0, W_{BO} - 1]$, where W_{BO} is the backoff window size.

If a preamble is successfully received at the eNB, it will reply with Msg 2 in Fig. C.1. If two or more devices select the same preamble and transmit within the same RA slot but the eNB cannot detect a collision at Step 1, then Msg 3 and Msg 4 will be exchanged to resolve the contention.

C.2.2 RACH Limitations

A main constraint of the LTE-A RA process is the limited number of preambles available for a cell. According to [7], 64 preambles can be allocated for a particular cell and out of these a certain amount, typically 10, is reserved for non-contention based transmissions like handover traffic. The rest are considered to be available for the competing devices for random channel access.

When a large number of devices attempt to access the channel at the same time, the preamble collision probability increases. Additionally, this will result in longer latency for successfully accessed devices. This problem is even more serious for mMTC scenarios where the number of competing devices could be much larger. To demonstrate this effect, we illustrate in Fig. C.2 the access success probability for a bursty mMTC traffic scenario with an increasing number of devices based on the analysis in [8] and the simulations we performed. It can be observed that when the number of devices is very large, i.e., 30000 or more, the access success probability decreases sharply to an unsatisfactory level.

Generally, traffic arrivals for periodic data reporting are considered to follow an uniform arrival process. On the other hand, event-driven data reporting which often leads to bursty traffic arrivals is assumed to follow a Beta distribution based arrival function as expressed below

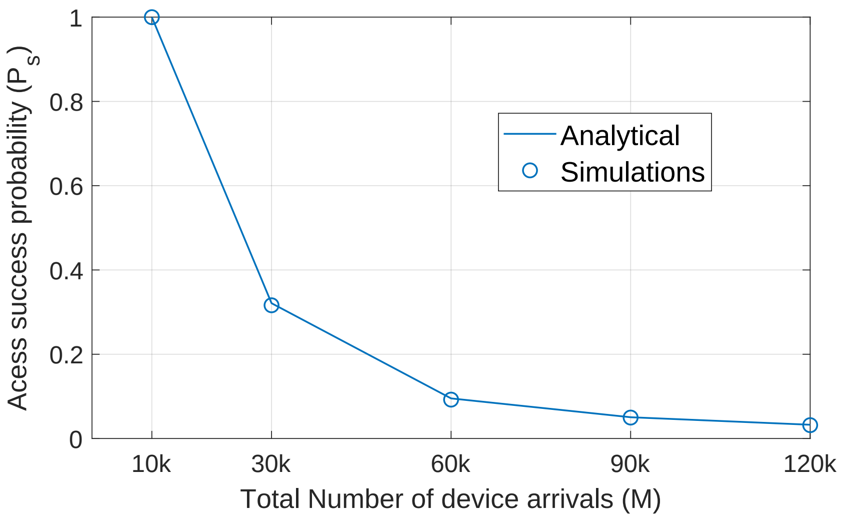

Figure C.2: Access success probability for a varying number of total devices.

$$A(i) = M \int_{t_i}^{t_{i+1}} p(t)dt, \tag{C.33}$$

where $A(i)$ represents the access intensity for a total number of M devices accessing an RA slot i between time t_i and t_{i+1}. In (C.33), $p(t) = (t^{\alpha-1}(T-t)^{\beta-1})/(T^{\alpha+\beta-1}Beta(\alpha,\beta))$ with $Beta(\alpha,\beta)$ being the Beta function with $\alpha = 3$ and $\beta = 4$. T is the total observation time for traffic arrivals [2].

C.2.3 Problem Statement

Considering the drawback in the LTE-A RA process as discussed above, it is imperative to introduce novel solutions to enable URLLC based applications. Since an eNB does not have sufficient information on the number of devices attempting random access at a particular time, it is difficult to implement real-time dynamic preamble allocation based solutions which satisfy the needs of URLLC.

Assuming that a preamble is correctly received by the eNB, collision detection at the eNB depends on several factors like the delay spread and the signal strength received from the competing devices. The eNB may detect a preamble even though multiple devices are transmitting the same preamble, if the devices are separated sufficiently far away from each other. On the other hand, when multiple devices are closer to each other, the preamble transmissions overlap with each other and the eNB cannot distinguish whether there are two or more users transmitting using the same preamble. Hence, Msgs 3 and 4 are needed to resolve the collision. Generally, it is difficult to use the previous collision data to predict the future MTC arrivals accurately.

In this work, we resolve this issue by proposing an arrival prediction based preamble allocation (APPA) scheme which consists of two phases. 1) We first propose a machine learning based technique to predict the number of arrivals in a given RA slot based on the number of successful detections at the eNB; and 2) we then propose dynamic preamble allocation to achieve URLLC based on the estimated arrivals. In the following two sections, we present these two phases in details.

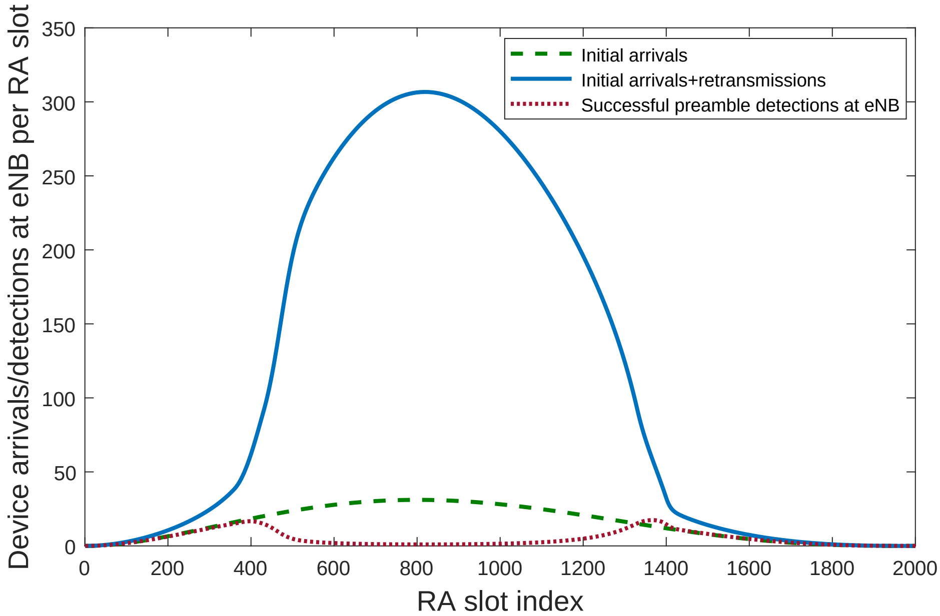

Figure C.3: Number of arrivals and detections in LTE-A random access for 30000 devices with 54 preambles following a bursty arrival process.

C.3 APPA Phase 1: Arrivals Prediction

In this section, the proposed machine learning based prediction technique is presented. It corresponds to the first phase of APPA as shown in Algorithm 1.

C.3.1 Arrivals versus Successful Access: A Dilemma

For a given RA slot, the total number of arrivals consists of new arrivals and the retransmissions from previously failed devices. Due to collisions and detection failures, only a few number of such arrivals are correctly decoded at the eNB. In some cases, not all the detected devices will receive Msg 2 due to the limit on the number of devices that can be responded in a given RAR message.

A substantial distinction between the numbers of arrivals and detections within an RA slot under a bursty traffic scenario can be observed in Fig. C.3, which is obtained based on 30000 devices in a period of 10 sec with $R = 54$ preambles. The numerical results presented in this figure are generated following the LTE-A RA process [2] and the analytical model proposed in [8]. It is evident that the actual number of arrivals consisting of the initial arrivals and the retransmissions is much higher than the initial arrivals itself. Hence, the number of retransmissions caused by collisions is a major cause for further collisions. Furthermore, it is observed that the number of successfully detected preambles initially increases with the increasing number of arrivals and then decreases to a lower value as the arrival traffic reaches its peak around the 850^{th} RA slot. Thereafter, the success rate increases when the number of arrivals decreases, and then it reaches null corresponding to zero arrivals.

In reality, not all the information illustrated in Fig. C.3 is available at the eNB. Instead, the eNB has only knowledge on how many preambles are successfully detected at each RA slot. From the above observations, we argue that there is a clear relationship

Algorithm 1 Algorithm for arrival prediction and group based dynamic preamble allocation

Input for Phase 1: Training data including Detections, Arrivals, and Current arrival type; Validation data including Number of detected preambles (real time); Bursty arrival threshold;

Input for Phase 2: Initial arrival type; Number of levels (L); Priority level for each group (l); Number of groups per level (N_l); Device population M; Number of available preambles at eNB R; Number of priority levels (L); Assigned priority level l for each group; Number of groups with priority level l (N_l), priority level l group threshold η.

Output: Predicated number of arrivals at each RA slot; Dynamic preamble allocation and group enabling

Phase 1: Prediction of Arrivals:

1: **Training:** Smooth input data via Savitzky-Golay filtering;
2: Train the model using smoothed training data;
3: Select the model with minimum RMSE.
4: **Prediction:** Input real detection data at each RA slot and current arrival type to the trained model.
5: **if** predicted arrivals > Bursty arrival threshold, **then**
6:     current arrival type = Bursty
7: **else**
8:     current arrival type = Normal
9: **end if**

Phase 2: Dynamic Group Preamble Allocation:

10: **if** predicted arrivals > priority level l group threshold **then**
11:     Upgrade N_l groups in level l to highest priority
12:     Reserve preambles for N_l groups in priority level l
13:     Inform NGDs about preamble reservation
14:     Update device population and number of available preambles for next prediction and preamble allocation.
15: **else**
16:     Go to Line 4 **Prediction**.
17: **end if**

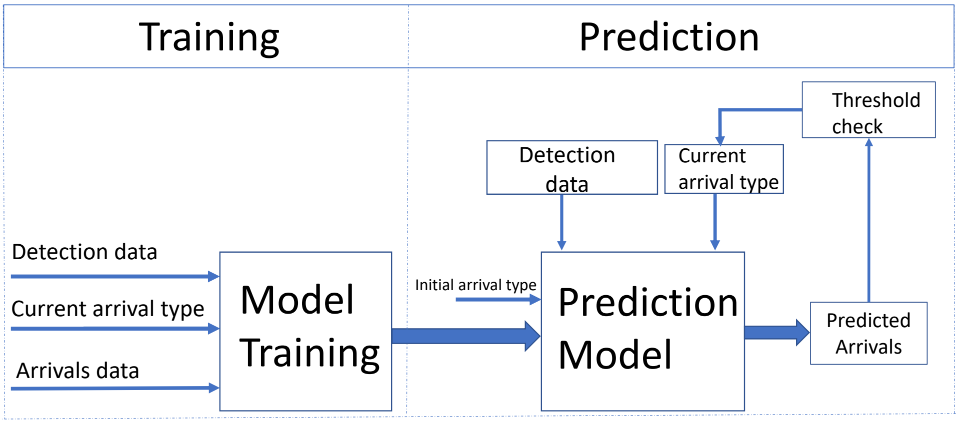

Figure C.4: A machine learning based prediction model.

between the number of detections and the corresponding number of arrivals for a given device population attempting to access the same channel. If the eNB is able to predict the number of arrivals based on the local available information, i.e., the detected preamble, it would be helpful to allocate on the fly a number of preambles to reduce RA congestion. In the following, we propose a machine learning based arrival prediction technique that utilizes the detected data to predict the number of arrivals at each RA slot.

C.3.2 Arrival Prediction using Supervised Learning

Supervised learning is one type of machine learning algorithms that maps an input to an output based on labeled training input-output data pairs. It is a widely used technique that can be utilized for various regression and classification tasks. In this work, we aim at applying supervised learning to predict the number of arrivals at the eNB.

Fig. C.4 denotes a block diagram which illustrates the main idea of the proposed model for arrival prediction. The input data available at the eNB is the number of successful detections at each RA slot. The eNB has also information about the initial arrival type, i.e, the traffic type is bursty or normal. These two features and the corresponding arrival data are used as input to train the model to predict the number of arrivals. The trained model is then validated with the test data. For arrival prediction, we are interested in identifying the point at which the predicted level of arrivals crosses a certain pre-defined threshold. This criterion is evaluated with each new data arrival and the result is fed back to the model to update its information about the current status of the traffic arrivals. In what follows, we further elaborate the aforementioned process.

C.3.2.1 Input data preparation

For model training, a simulation based data set following the LTE-A RA process is generated. For initial training, a burst of arrivals with $M = 30000$ devices for a duration of 10 sec is considered. These devices compete for 54 RA available preambles following the RA process described in Subsec. C.2.1. The losses due to channel impairment are represented using a detection probability p_n, where the preamble detection probability of the n^{th} preamble transmission is given by $p_n = 1 - 1/e^n$. In order to increase the accuracy of learning, the input data is filtered to smooth out any abrupt changes. This

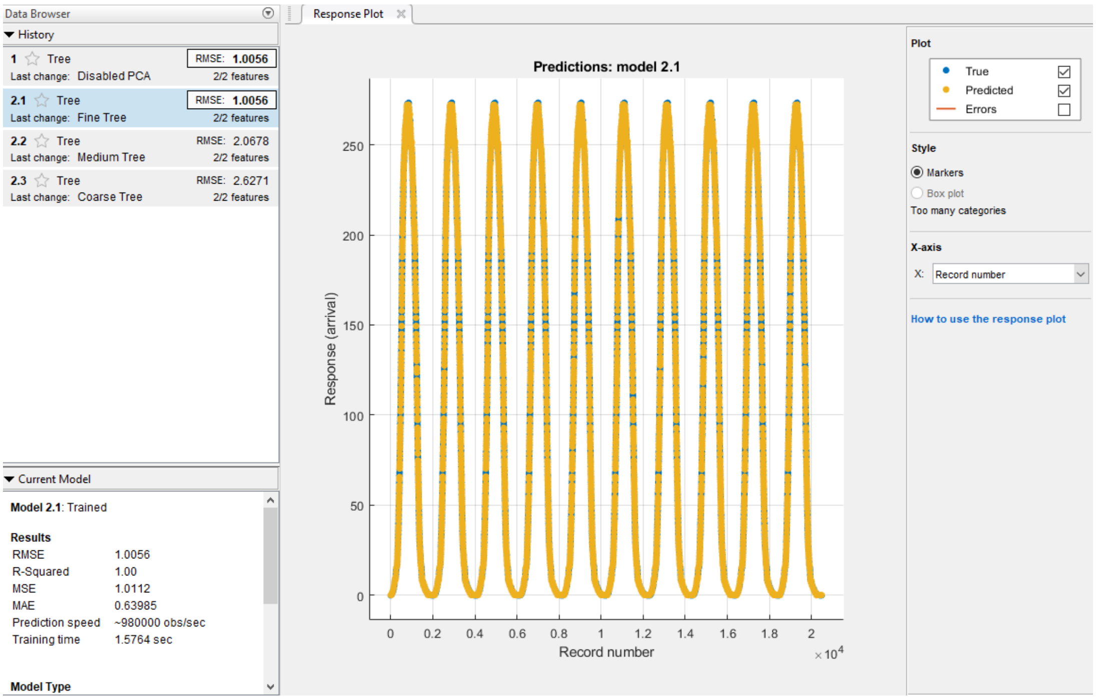

Figure C.5: Responses from the learning model with RMSE.

is achieved using the Savitzky-Golay (SG) filtering method which enables to increase the signal-to-noise ratio without significantly distorting the signal. The SG method achieves this by minimizing the least-square errors in fitting a polynomial to frames of noisy data.

C.3.2.2 Model training

The model training process is carried out through a 5-fold cross validation procedure that ensures protection against over fitting by partitioning the data set into different folds and estimating the accuracy of each fold. Different models are evaluated based on root mean square errors (RMSE) which indicate how close the observed data points are with respect to the values predicted by the model. Among the models available in the simulation tool, the tree based models generate the minimum RMSE error. Therefore, the fine tree model with RMSE ≈ 1.0 is selected for our validation. In Fig. C.5, we illustrate the response plots based on the fine tree model. It reveals that the predicted values (in yellow) match the real values (in blue which are largely overlapping with the yellow curve) precisely. In Fig. C.6, we demonstrate the accuracy of the training model by plotting the real response and the prediction response in the x- and y-axis respectively. With both sets fitting the diagonal line, the accuracy of the trained model is verified.

C.3.2.3 Prediction model

To validate the training model, another set of simulation data that represents a traffic arrival burst is generated. The initial traffic arrival type is considered to be normal and we assume that the eNB can detect the transmitted preambles successfully at each RA slot. The eNB performs live data detection and relies on the trained model to predict new arrivals. The data detection result from the current RA slot is added to the existing

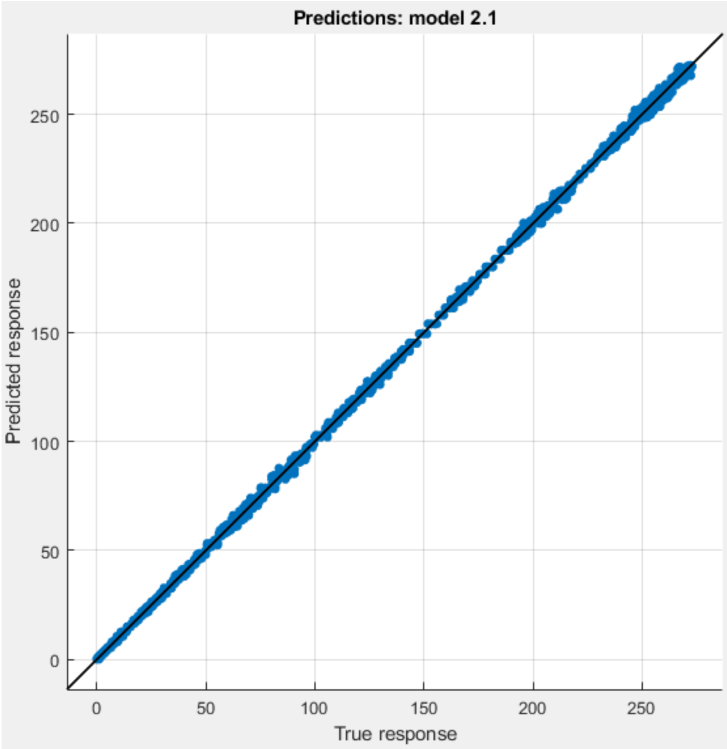

Figure C.6: Responses from the learning model.

data to predict arrivals in the next slot.

When the predicted number of arrivals within an RA slot exceeds the bursty arrival threshold, the traffic type is assessed to having changed from normal to bursty. Furthermore, different thresholds are configured to measure the bursty level of traffic arrivals. We will further elaborate this procedure in Sec. C.4. On the other hand, when the predicted arrival intensity drops below a certain threshold, the traffic type is considered to having changed back to normal traffic.

Moreover, providing a higher number of training data samples results in a lower RMSE in the training model. Hence, several iterations of bursty traffic with the same 10 sec duration are provided for training. Recall that the detection data alone may not provide sufficient information for accurate arrival prediction. Therefore, we assume that the traffic type is known initially. With the knowledge on both traffic type and detection data, precise arrival prediction can be achieved at the eNB.

C.4 APPA Phase 2: Preamble Allocation

The knowledge on the number of arrivals can be exploited in several ways for URLLC applications. In this section, we present two group based preamble allocation schemes, one static which serves as a baseline scheme and another one dynamic which is based on arrival prediction presented above.

C.4.1 Static Group based Preamble Allocation (SGPA)

In this scheme, MTC devices are grouped based on their URLLC priority levels, location, and applications. Devices with URLLC access requirements, e.g., those for monitoring mission-critical information in smart grids or industrial processes, belong to grouped devices (GDs). Other MTC devices which are covered by the same eNB are regarded as non-grouped devices (NGDs).

Each group has a dedicated preamble managed by the group leader which has higher processing and memory capability in comparison with its members. The eNB stores information about group members and their leaders during the initial registration process. When a triggering event occurs, the group devices establish an uplink communication with their associated eNB through a collision-free preamble transmission initiated by their group leader. By decoding the dedicated preamble, the eNB identifies the group and its members based on the stored information during the initial registration process. Then, the eNB will allocate an appropriate amount of radio resources for all the devices in that particular group. For NGDs, the access process follows the standard RA procedure as explained in Subsection II-A. However, for a given device population, allocating a suitable number of preamble to NGDs is not an easy task, especially for bursty traffic. With static preamble allocation without real-time traffic intensity awareness, the performance of GDs and/or NGDs may be deteriorated.

C.4.2 Arrival Prediction based Preamble Allocation

In the APPA scheme, we consider that GDs have L different priority levels based on their URLLC requirements, denoted as $1, 2, ..., L$ in an descending priority order. The devices belonging to a higher priority level have more stringent latency requirements than those in a lower level group. Regardless of the arrival traffic type, the highest priority, i.e., level-1, GDs always have their dedicated preambles reserved for communication with the eNB. Under *normal* traffic conditions, other priority level group members follow the legacy LTE-A RA process the same as NGDs. However, when a traffic burst is observed in the first phase of APPA, the eNB will dynamically allocate more preambles as dedicated to a lower level GDs. In this way, more devices will experience collision-free transmissions based on dynamic preamble allocation.

Whenever a group belonging to a certain priority level is upgraded to the level with dedicated preambles, its member devices will be able to enjoy collision-free preamble transmissions through their group leaders. We assume that the eNB transmits the updated reservation information immediately to all devices. With this information, these GDs will not compete with the NGDs using the common RA preambles. Accordingly, the number of preambles available for the NGDs is reduced. Meanwhile, the number of competing devices is also reduced. Recall, however, that such a preamble allocation update is performed dynamically based on the predicted traffic arrival. Hence, in comparison with the SGPA scheme, the preamble utilization efficiency is improved in APPA.

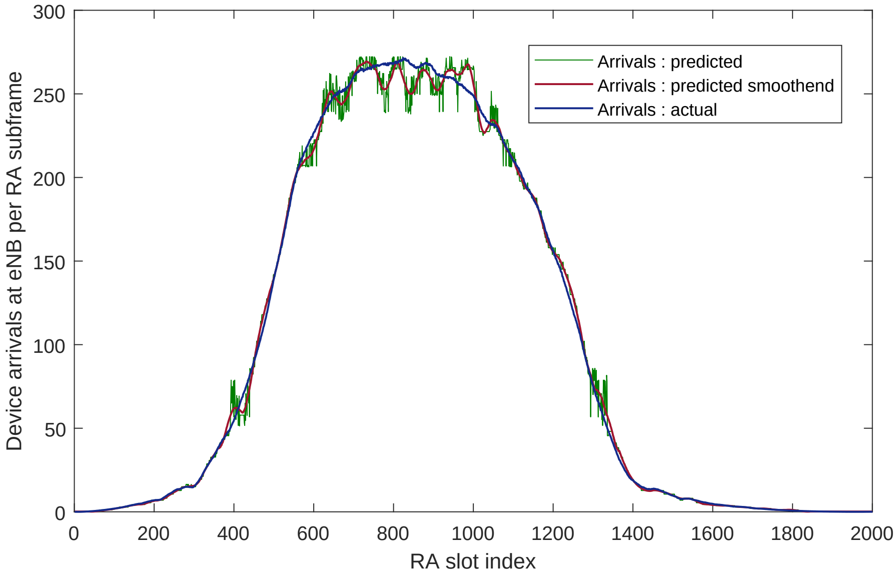

Figure C.7: Bursty traffic arrivals: Prediction versus actual.

C.5 Simulations and Numerical Results

To evaluate the performance of the proposed schemes, we perform extensive simulations in MATLAB. Consider a cell with $M = 30000$ devices and a traffic burst in a period of 10 sec. The devices are categorized into GDs (with 40% of M devices) and NGDs (with 60% of M devices). These GDs are further classified into $L = 3$ levels, as 10%, 10%, and 20% of M devices for level-1, -2, and -3 respectively. For each level, there are multiple groups each with a number of member devices. As mentioned earlier, each group has only one dedicated preamble which is managed by the group leader.

For performance comparison, three schemes are studied, i.e., 1) preamble allocation without grouping (PAWG), 2) SGPA, and 3) APPA. The following three metrics recommended by 3GPP [2] are used for our performance evaluation.

- Collision probability, P_c, defined as the ratio between the number of occurrences when two or more devices transmit the same preamble during the same RA slot and the overall number of RA opportunities within this slot.
- Access success probability, P_s, defined as the probability that a device successfully completes the RA procedure within $N_{max} + 1$ transmissions.
- Average delay for successfully accessed devices, D_a, calculated from the first preamble transmission attempt to the successful completion of the access process.

C.5.1 Validation of the APPA Scheme

To assess the performance of the proposed APPA scheme, we plot two figures to illustrate the results obtained based on the two phases of APPA, i.e., Fig. C.7 for Phase 1 and Fig. C.8 for Phase 2, respectively.

In Fig. C.7, we illustrate both the actual traffic arrivals generated by simulations and the predicted number of arrivals which is obtained based on the supervised learning

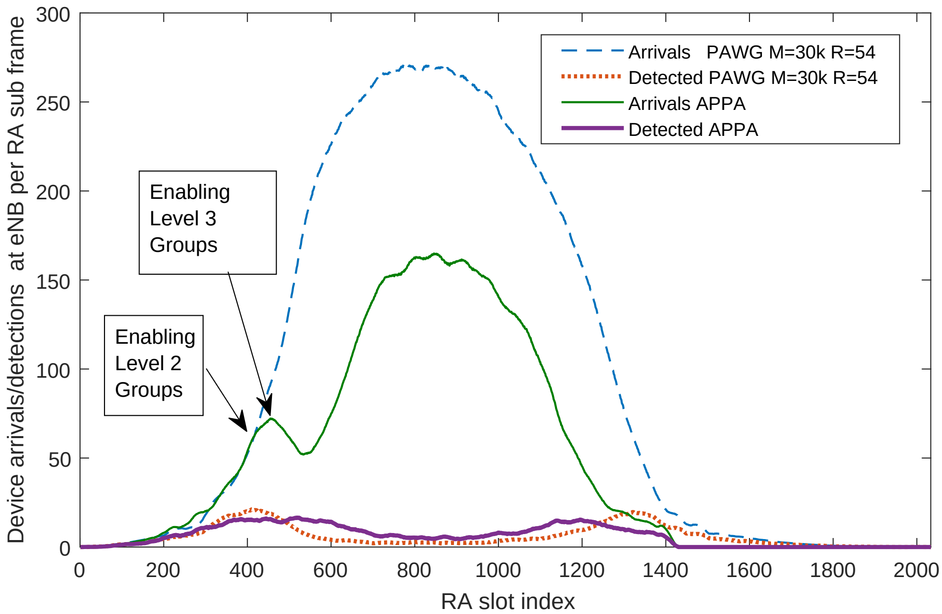

Figure C.8: Enabling dynamic grouping according to traffic arrival prediction.

algorithm presented in Subsection III-B. It is evident that, despite the sparks occurred in simulated arrivals, the predicted number of arrivals represents closely the actual data arrivals.

Let us now explain how the second phase of APPA works using Fig. C.8 which illustrates how to allocate the number of dedicated preambles based on the predicted number of arrivals per RA slot. Following the LTE-A RA process, there are $R = 54$ preambles which are available for all $M = 30000$ devices. However, how to allocate these preambles depends on the adopted scheme. In PAWG, all devices follow the standard process based on 54 preambles. In SGPA, certain number of preambles are allocated to GDs beforehand but the eNB is not aware of traffic arrival patterns.

When APPA is employed, we initially enable only level-1 groups with dedicated preambles. In other words, there are 27k devices, including NGDs and level-2 and -3 GDs, competing for 51 preambles. At around the 407^{th} RA slot, the number of predicted arrivals exceeds the threshold, which is 50 according our network configuration. Then level-2 groups are upgraded with contention-free preambles. Correspondingly, the total number of competing devices is reduced to 24k while the number of preambles reduces to 48. At the 466^{th} RA slot, the predicted arrivals exceed the second threshold, which is 75. Immediately, the level-3 groups are upgraded with contention-free preambles. This causes a greater reduction of the number of competing devices to 18k, competing for 44 preambles.

At each stage when more GDs are allocated with dedicated preambles, the number of NGD arrivals decreases significantly since only leaders generate preambles on behalf of each group. This behavior can be observed in the figure when comparing the original arrival curve based on PAWG in which all 30k devices compete for these 54 available preambles. Accordingly, the RA performance could be improved as presented below.

Table C.5: Performance evaluation of grouped and non-grouped devices

SchemeMetric	P_c	P_s	D_a
GDs	0	1	11.0
NGDs with PAWG	0.4288	0.3153	67.35
NGDs with SGPA	0.2909	0.5875	67.0144
NGDs with APPA	0.2684	0.6816	73.5183

C.5.2 Performance Comparison of PAWG, SGPA, and APPA

Table C.5 illustrates the numerical results for the studied three schemes. For grouped devices with dedicated preambles, denoted as GDs in the table, the collision probability is zero and the access success probability equals to one. The delay associated with these devices is calculated to be approximately 11 subframes. In comparison with the other results shown in the same table, this means that for GDs ultra reliability is achieved together with very low access delay.

For NGDs, as well as level-2 and/or -3 GDs that do not yet have a dedicated preamble, all denoted as NGDs in Table C.5, we investigate the benefits brought by APPA based on the performance metrics defined earlier. It is evident that APPA outperforms SGPA and APPA in terms of P_s and P_c. This is because in APPA preamble resources are dynamically allocated depending on the predicted traffic arrivals. Compared with the significant improvements for P_s and P_c, the extra delay cost introduced by APPA is low.

C.5.3 Further Discussions

The delay results shown in Table C.5 have a unit as the duration of a subframe which is 1 ms in LTE-A. In 5G new radio (NR), the transmission time interval (TTI) is shortened down to 125 μs or even 62.5 μs. Accordingly, much shorter delay can be achieved, meeting the requirements for URLLC.

Another potential application of the proposed APPA scheme Phase 1 is to apply it for dynamic frame structure configuration as suggested in [9]. If a flexible 5G NR frame structure is implemented, where the TTI size is configurable on a per-user basis according to its specific service requirement, different TTI sizes can be configured on the fly depending on the predicted traffic arrival load at eNB. When traffic load is predicted to be light, a short TTI appears to be more pragmatic for achieving low latency, and vice versa.

C.6 Conclusions

In this paper, we have proposed a machine learning based traffic prediction and preamble allocation scheme which encompasses two phases. The first phase relies on local information available at the eNB to estimate the number of arrivals within one RA slot. Based on the prediction, dynamic allocations of preamble resources are performed to enable URLLC applications. By combining group based preamble reservation with the proposed traffic prediction and preamble allocation scheme, we demonstrate, through extensive simulations, that URLLC for grouped devices can be achieved while improving the performance of non-grouped devices.

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