Estimation of the Tag Population with Physical Layer Collision Recovery

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Abstract **- In passive RFID systems, tags are arbitrated on the Medium Access Control layer by the Framed Slotted Aloha protocol. Tags select an arbitrary slot to send their information, such that the reader receives slots with no responses, single tag responses or multiple tag responses, generating empty, singleton and collision slots, respectively. In order to maximize the system throughput, precise knowledge of the tag population competing in the read range of the reader is required. Normally, a reader does not have that information and needs to estimate it in every identification round from the statistical information collected: empty, singleton and collision slots. However, this estimate is poor since conventional readers are not capable of determining how many tags actually respond simultaneously when a collision slot occurs. In this work, we use a physical layer reader architectures to extract the *exact* number of tags participating in a collision. We employ this additional information and a technique that permits to successfully extract tag signals from collision slots. This establishes a much more accurate Maximum Likelihood estimator which outperforms other estimators studied in depth in previous works.**

I. Introduction

In passive Radio Frequency Identification (RFID) systems, tag responses are scheduled on the Medium Access Control (MAC) layer, either applying the Framed Slotted Aloha (FSA) or binary tree protocol [1]. While in this paper we focus on FSA as defined in the widely accepted standards of EPCglobal [2] in the Ultra High Frequency (UHF) band, an extension of this work to the binary tree protocol is straightforward.

In FSA based systems, the reader starts an identification round (also called frame) sending a *Query* command. This command announces the frame length, where the tags will send their identifiers. The frame is divided into K slots, and the standard EPCglobal Class-1 Gen-2 (*aka* EPC-C1G2) restricts to K=2^Q, $Q \in [0, ..., 15]$. Upon reception of the *Query* command, tags in coverage select one of the K slots for communication with the reader. Every slot can be selected by no tag, that is an empty slot (e), or by only one tag, that is a singleton slot (s) or by several tags, being a collision slot (c). At the end of every frame, some tags will be successfully identified and collision tags will have to compete in the following frames (see Figure 1). Then, having K slots in a frame and N tags competing, the fill level of z tags in a slot is is given by the binomial distribution function:

$$Pr(z) = \binom{N}{z}\left(\frac{1}{K}\right)^{z}\left(1-\frac{1}{K}\right)^{(N-z)} \quad (1)$$

The expected number of slots filled with exactly z tags is given by $E(z)$=$K \cdot Pr(z)$, and the theoretical throughput (Ω) of FSA (rate of tags identified per time unit) is calculated as follows:

$$\Omega = \frac{E(z=1)}{K} = \frac{N}{K}\left(1-\frac{1}{K}\right)^{(N-1)} \quad (2)$$

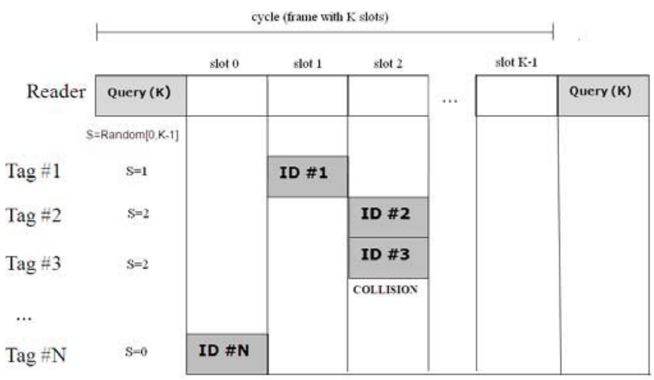

Figure 1 - FSA procedure based on EPC-C1G2.

Its theoretical maximum throughput is reached when the number of slots per frame K equals the number of tags competing N in that frame, resulting in $\Omega \approx 0.36$ [3]. However, in FSA based mechanisms, N is typically unknown, and the reader has to estimate it before starting a new frame, for adjusting the new frame length to K=N (dynamic frame length procedure based on FSA, Dynamic FSA). Conventional readers manage the information collected at MAC layer $\{e, id, c\}$ for estimating the number of tags competing N. However, as we stated in [4], this set of data is not enough for giving an accurate estimate, since conventional readers do not work with the *exact* number of tags colliding in every collision slot, undistinguishing between data of a collision with two, three or more tags data.

Recently, some authors proposed physical layer receivers that estimate the *exact* number of tags R generating a collision, as long as the number of tags R is below the maximum detection parameter M of the reader. This means, that such a reader can determine the exact number of tags generating a collision as long as $R \leq M$. If $R > M$ the reader detects a collision slot, with the only information that more than R tags participated in the collision, but without any further information. The scope of this paper is, to manage this additional physical layer information in order to enhance the tag estimator Multi-Frame Maximum-Likelihood Dynamic FSA (MFML-DFSA), presented in [5].

The rest of the paper is organized as follows: Section II. introduces related work, physical layer receivers for estimating the number of tags generating a collision and tag population estimators. Section III. presents our proposed estimator. Section IV. comments on the optimal settings of the Q parameter. The performance of the proposal is shown in Section V., and the last section finally concludes the paper.

II. Related Work

Tag population estimators in RFID have been extensively studied over the last years. There are several types of estimators: from those based on heuristic algorithms like in [6], to more complex algorithms based on Minimum Square Error like in [7] and [8], the Bayesian Interfere algorithm in [9] or Maximum Likelihood estimators like in [10] and [11]. These mechanisms accurate the estimate of N taking partial or total information from MAC layer: number of empty (e), singleton (*id*) and/or collisions (c) from one (Single-Frame) or several past frames (Multi-Frame). These mechanisms where extensively studied by the authors in [4], where they pointed out that the key for getting the best strategy is to take the whole info from MAC layer, to use a Maximum Likelihood procedure and to take info from several past frames. Taking into account previous considerations new estimators were suggested by the authors, as those proposed in [5] and [11], that outperformed the studied in [4]. However, the use of physical layer information to improve the tag estimation was not explored.

Recently, physical layer techniques have been proposed, that add information to the tag estimation: Khasgiwale et al. [12] and Shen et al. [13] propose reader receiver architectures for passive RFID systems to extract the number of tags R participating in a collision slot by analyzing the baseband receive signal in the I/Q plane. They discovered, that the I/Q constellation in a collision slot depends on the number of tags participating in the collision. The signal at the reader receiver is composed of a leaking carrier signal from the transmitter to the receiver of the reader, and the colliding tag modulation signals (compare with the exemplary constellation of a collision of two tags in Figure 2). If a singleton slot is received, two states are identified due to the applied backscatter modulation: one, if the tag absorbs energy, and a second when it reflects energy. If R=2 tags generate a collision, the constellation consists of up to four states: first, the state $S^{(a,a)}$ where both tags absorb energy; second, the state $S^{(a,r)}$ where tag one absorbs energy while tag two reflects; third, the vice versa situation, where tag one reflects while tag two absorbs energy ($S^{(r,a)}$), and finally, the constellation point $S^{(r,r)}$ where both tags reflect energy simultaneously. An exemplary constellation of such a collision slot with R=2 is depicted in Figure 2. Proceeding to slots with even more tags generating the collision, one in general detects up to 2^R constellation points. If the reader manages to detect and identify these constellation points, it can forward the information to the MAC layer, which then knows the *exact* number of tags R that participated in a collision slot. Moreover, Yu et al. [14, 15] propose to apply multiple antennas and beamforming with RFID to separate the tag population into sectors. However, they do not try to estimate the number of tags that actually generated the collision. Lee et al. [16] identify the potential performance increase by combining smart antennas with binary tree and Slotted Aloha (SA) anti-collision algorithms, but neither they target advanced tag population estimation with physical layer information. Teoh et al. [17] propose a simple tag population estimator for a collision recovery MIMO scheme, based on the number of collision slots at the end of each frame.

III. PHY-MAC-MFML ESTIMATOR

In [5] the Multi-Frame Maximum-Likelihood Dynamic FSA (MFML-DFSA) estimator algorithm was proposed as a reader mechanism which computes the (best guess) number of competing tags at the beginning of every new identification frame. The statistical information $\{e, id, s\}$ collected at MAC layer from the previous frames (Multi-Frame) is used in a Maximum-Likelihood estimator, which permits to estimate the number of competing tags (unidentified tags) at the beginning of a new frame. After that, the frame length is accordingly set to K=N to maximize throughput in next frame.

The MFML-DFSA estimator is improved in this work, proposing the PHY-MAC-MFML estimator, which uses information, not only from the MAC layer, but also from the physical layer to improve the estimate. The information obtained from the physical layer is the number of tags generating a collision in every slot, which is achieved as follows: The reader downconverts the receive signals to the baseband, using I/Q demodulators (see Figure 2). The number of different states realized in the I/Q plane indicates the number of tags colliding. We

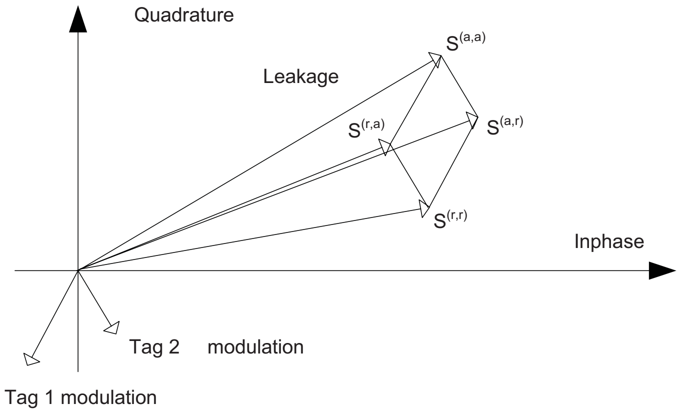

FIGURE 2 - EXEMPLARY READER BASEBAND I/Q DIAGRAM OF COLLISION OF TWO TAGS: THE FOUR GENERATED STATES DEPEND ON THE EXTENT OF THE CARRIER LEAKAGE FROM THE TRANSMITTER TO THE RECEIVER AND THE TAG RECEIVE SIGNALS.

consider a reader that is able to detect and distinguish between collisions slots with exactly two tags [18] ($M = 2$), denoted as (d), and collision slots with more than two tags, renamed (c). Additionally, we assume that the reader allows to recover both tag's data from collision slots with two tags, and that the reader also manages to acknowledge both tags. Then, the throughput in a slot with two tag responses is equal to two, leading to a maximum achievable throughput of 0.834 tags/slot in the Frame Slotted Aloha framework (compare with Figure 3). Note, that a recovery of two tag's data from one collision slot only requires slight modifications of EPC-C1G2 identification procedure [2], or a modification of reader transmitters to communicate with spatially separated tags simultaneously by means of multiple antenna transmit precoding.

3.1 Collision detection and recovery

In [18,19] we proposed architectures to recover from collision of R=2 tags on a physical layer employing a single [19] or multiple receive antennas [18], respectively. In the baseband of the y'th reader receive antenna path, the reader receives the collided signal $s_y(t)$ of both tags (compare with Figure 2):

$$s_y(t) = h_{1,y}(t)a_1(t) + h_{2,y}(t)a_2(t) + n_y(t). \tag{3}$$

Here, $h_{x,y}$ denotes the complex-valued channel coefficient from tag x to antenna y. Furthermore, $a_x(t)$ is the modulation signal of tag x, which is encoded according to an FM0 or Miller line encoding and $n_y(t)$ is the baseband noise. As the backscatter modulation only realises two states (one for the chip mainly absorbing energy and the other for mainly reflecting energy), we model the modulation as an on/off keying, which consists of the (real-valued) levels '0' and '1'. Note, that due to the real-valued modulation signal $a_x(t)$, the receive signal of each antenna y can be split into two independent equations:

$$\Re\{s_y(t)\} = \Re\{h_{1,y}(t)a_1(t) + h_{2,y}(t)a_2(t) + n_y(t)\}, \tag{4}$$
$$\Im\{s_y(t)\} = \Im\{h_{1,y}(t)a_1(t) + h_{2,y}(t)a_2(t) + n_y(t)\}, \tag{5}$$

where $\Re\{\cdot\}$ and $\Im\{\cdot\}$ select the real and imaginary part, respectively. Thus, with y receive antennas, we have $2y$ independent equations. Therefore, up to x=$2y$ tag modulation signals $a_x(t)$ can be resolved successfully. However, the channel estimation method we propose in [19] is restricted to a collision of two tags, such that the technique is restricted to a physical layer collision recovery of x=2 colliding tags. Hence, collisions can only be distinguished for x=2 tags from collisions with $x > 2$ tags.

3.2 Algorithm procedure

Let n be the number of tags within the identification area. In our model we assume all tags remain in the identification area at least until their identities are correctly received, and that no new tags enter during the reading process. The goal is to identify the n tags in the shortest time (equivalently in as few slots as possible). The identification process requires a series of consecutive reading frames (i=1, 2, ...) until all tags are identified. Let us denote n_i as the number of tags competing on frame i, and K_i=2^{Q_i} as the frame length i.

According to the above description, in any arbitrary frame i, the mechanism proposed will work as follows:

- At the end of every slot j of frame i, the reader detects if there is an empty slot (e_{i_j}), singleton slot (id_{i_j}), collision slot with two tags (d_{i_j}) or collision slot with more than two tags (c_{i_j}).

- When the frame i finishes, the reader takes the information collected: $\{e_i, id_i, c_i, d_i\}$ = $\{\sum_{j=1}^{K_i} e_{i_j}, \sum_{j=1}^{K_i} id_{i_j}, \sum_{j=1}^{K_i} c_{i_j}, \sum_{j=1}^{K_i} d_{i_j}\}$ and computes the most likely number of unidentified tags $\hat{n}$ at the beginning of the identification procedure (tags competing in frame i=0 as a function of the set $\{(K_u, e_u, id_u, c_u, d_u); u$=1,..., i$\}$. The estimation is addressed by means of the Maximum Likelihood estimator introduced in Section 3.3.

- Then, the most likely number of tags that compete in the next frame (i+1) is $n_{i+1} = \hat{n}_i - \sum_{v=1}^{i} id_v - 2d_v$, that is, the total number of tags estimated ($\hat{n}$) minus those tags already identified in the previous frames.

- Then, K_{i+1}=$2^{Q_{i+1}}$ is accordingly selected to maximize the expected throughput at frame i+1 (see Section IV.).

3.3 Computation of $\widehat{n}$

Let us denote $P(n, K, e, id, c, d)$ as the probability of obtaining a sample of e with no tag responses, id slots filled with exactly one reply, c slots with a collision of three or more tags and d slots with collision of exactly to tags, if n tags compete for identification in K slots. To compute the probability $P(n, K, e, id, c, d)$, we apply a slight modification of the technique proposed in [20], where the author addresses the derivation of a joint occupancy distribution of urns (in this case slots) and balls (in this case tags) via a bivariate inclusion and exclusion formula (Equation 6): we consider a supply of n tags randomly distributed into K distinguishable slots. The number X of tags distributed into any specific slot is a random variable with probability function q_x=$P(X = x)$, x=$0, 1, \ldots$. The joint probability function and binomial moments of the number W_z of slots occupied by z tags each and the number W_v of slots occupied by v tags each, $z \neq v$, given that a total of S_K=n tags are distributed into the K slots, is derived in terms of convolutions of q_x, x=$0, 1, \ldots$ and their finite differences.

$$\begin{aligned} P(N, K, e, id, c) &= p_{e,id}(n, K; z = 0, v = 1) = \\ &= P(W_z = e, W_v = id | S_K = n) = \frac{\binom{K}{e,id}\binom{n-K+e-1}{n-2K+2e+id}}{\binom{K+n-1}{n}} \end{aligned} \quad (6)$$

The above technique is applied for problems with exactly two states (binomial distributions), that is, number of empty slots and number of single responses, as the estimator in [5]. However, the computation of $\widehat{n}$ in this new estimator involves three states: slots with empty tag responses (e), slots with single response (id) and slots with exactly two responses (d). Hence, the modification of the above technique involves to consider trinomial distributions instead of binomial ones, obtaining:

$$\begin{aligned} P(n, K, e, id, c, d) &= p_{e,id,d}(n, K; i = 0, j = 1, z = 2) = \\ &= P(K_0 = e, K_1 = id, K_2 = d | S_K = n) = \\ &= \frac{K!}{id!e!d!(n - id - e - d)!} \cdot \\ &\cdot \binom{K + n - 1}{n} \binom{n - id - 2(n - id - e - d) - 2d - 1}{n - id - 3(n - id - e - d) - 2d}. \end{aligned} \quad (7)$$

Since n-id-d-e=c, Equation 7 can be simplified as follows:

$$\begin{aligned} &P(n, K, e, id, c, d) = \\ &= \frac{K!}{id!e!d!c!} \cdot \binom{K + n - 1}{n} \binom{n - id - 2c - 2d - 1}{n - id - 3c - 2d} = \\ &= \frac{K}{e!id!d!c!} \prod_{z=0}^{K-1} (k + n - 1 - z) \prod_{y=0}^{c-1} \frac{(n - id - 2c - 2d - 1 - y)}{(c - 1 - y)}. \end{aligned} \quad (8)$$

Equation (8) is computed for $n \geq id + 2d + 3c$, since n is, at least, the sum of the tags identified plus those colliding tags signals recovered from collision slots with only two tags plus colliding tags (at least 3 per collision).

After the first frame of the identification process, the probability of the event $\{(K_1, e_1, id_1, c_1, d_1)\}$ if n tags content is:

$$P(K_1, e_1, id_1, c_1, d_1) = P(n, 2^{Q_1}, e_1, id_1, c_1, d_1) \quad (9)$$

After the second cycle:

$$\begin{aligned} &prob\{(K_1, e_1, id_1, c_1, d_1), (K_2, e_2, id_2, c_2, d_2)\} = \\ &= P(n, 2^{Q_1}, e_1, id_1, c_1, d_1) P(n - id_1 - 2d_1, 2^{Q_2}, e_2, id_2, c_2, d_2) \end{aligned} \quad (10)$$

Note that reading frames are independent, and thus the probability of the observed events. Then, after i frames, if the initial number of tags is n, the probability of a given set of events $\{(K_v, id_v, c_v, e_v) : v = 1, \ldots, i\}$ is calculated as

$$\hat{n} = \underset{\{n \geq \max_{v=1,\ldots,i} n_v\}}{\text{argmax}} \prod_{v=1}^{i} P\left(n - f_v, 2^{Q_v}, e_v, id_v, c_v, d_v\right) \quad (11)$$

being $f_v = \sum_{u=1}^{v} id_{u-1} + 2d_{u-1}$ and n_v denoting the minimum number of competing tags known at frame v, $n_v = 3c_v + \sum_{l=1}^{v} id_l + 2d_l$, and id_0=d_0=0 for consistency.

3.4 Implementation issues

The algorithm implementation feasibility is addressed by an iterative method which is based on the fact that maximizing probability in Equation (11) is equivalent to maximizing its logarithm. To speed up computations, we assume the RFID reader keeps an array with predefined computations of $\sum_{z=1}^{n} log(z)$ for $n = 1, \ldots, 2^{15} + n_{max}$. Let A_z be the z-th position of this array, let us initialize an all-zero array B_n with n_{max} positions, and let n_{min} =1. Then, just at the end of cycle i, it is necessary to:

1. Update n_{min}, n_{min} = $\max\{n_{min}, 2d_i + 3c_i + \sum_{j=1}^{i} id_j\}$
2. Compute the logarithm of Equation (11) for $n = n_{min}, \ldots, n_{max}$. The products of Equation (8) are expressed as a sum of logarithms as follows:

$$\begin{aligned} &log(P(n, K, e, id, c, d)) = K - A_{e_i} - A_{id_i} - A_{c_i} - A_{d_i} + \\ &+ \sum_{z=0}^{K-1} A_{K+n-1-z} - \sum_{y=0}^{c-1} (A_{n-id-2c-2d-1-y} - A_{c-1-y}) \end{aligned} \quad (12)$$

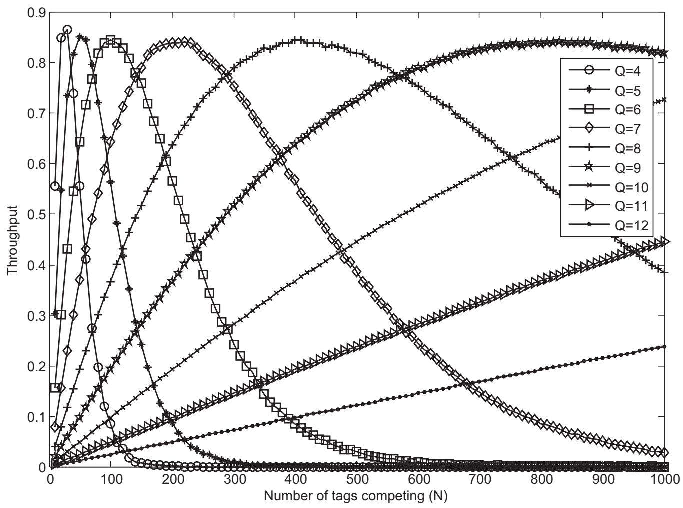

FIGURE 3 - THROUGHPUT EXPECTED FOR DIFFERENT TAG POPULATIONS AND FRAME LENGTH (Q) CONFIGURATIONS

3. Then, the sum of logarithmic probabilities is updated, $B_n = B_n + log(P(n - \sum_{j=1}^{i} id_{j-1} + 2d_{j-1}, 2^{Q_i}, e_i, id_i, c_i, d_i))$, and the index -belonging to $[n_{min}, n_{max}]$- with the largest component in the array minus $\sum_{j=1}^{i} id_j + 2d_j$ is returned as N_{i+1}. This step requires n_{max} sums and comparisons.

4. Finally, the best value of Q_{i+1} is selected as a function of N_{i+1} following the procedure addressed in Section IV.

IV. Q CALCULATION

In typical FSA mechanisms, once the expected number of competing tags N_{i+1} in frame $(i+1)$ is calculated, the frame-length K_{i+1} is adjusted to the value that maximizes the throughput, which maximum value is reached when N_{i+1}=K_{i+1}, being Ω_{i+1}=e^{-1} ≈0.36 [3]. However, the RFID system proposed in this work does not reach the maximum throughput as in FSA because:

- The reader works under the worldwide standard EPCglobal procedure [2]. It restricts the number of slots per frame in $\{K = 2^Q : Q = 0, \ldots, 15\}$.
- The reader implements the detection and recovery collision procedure that permits to recover successful identifications from collision slots with only two tags colliding. Hence, the expected throughput is not given by Equation (2) but,

$$\begin{aligned}\Omega_{i+1} &= \frac{E(z=1)}{K_{i+1}} + 2\frac{E(z=2)}{K_{i+1}} = \\ &= \binom{N_{i+1}}{1}\frac{1}{2^{Q_{i+1}}}\left(1 - \frac{1}{2^{Q_{i+1}}}\right)^{N_{i+1}-1} + \\ &+ 2\binom{N_{i+1}}{2}\left(\frac{1}{2^{Q_{i+1}}}\right)^2\left(1 - \frac{1}{2^{Q_{i+1}}}\right)^{N_{i+1}-2}\end{aligned} \tag{13}$$

The first summand in the above equation belongs to the throughput in slots with a single tag (id), while the second summand results from the throughput of collision slots with two tags (d). Thus, at the end of every frame, when the number of competing tags N in the next frame is estimated, the reader takes Equation (13) and calculates for every Q, the value that maximizes the expected throughput.

Q_i	N_i range
0	$0 < N_i \leq 2$
1	$2 < N_i \leq 5$
2	$5 < N_i \leq 10$
3	$10 < N_i \leq 19$
4	$19 < N_i \leq 36$
5	$36 < N_i \leq 72$
6	$72 < N_i \leq 142$
7	$142 < N_i \leq 286$
8	$286 < N_i \leq 574$
9	$574 < N_i \leq 1155$
10	$1155 < N_i \leq 2350$
11	$2350 < N_i \leq 4733$
12	$4733 < N_i \leq 9624$
13	$9624 < N_i \leq 20017$
14	$20017 < N_i \leq 41136$
15	$41136 < N_i$

TABLE 1 - OPTIMAL Q_i VERSUS N_i RANGE

With the aim of minimizing computation per frame in the reader, we have computed, for each Q, the set of values of N, for which the throughput per frame is maximum. These sets have the form $[N_{min}(Q), \ldots, 2^Q, \ldots, N_{max}(Q)]$. The procedure to compute the optimal Q-value is the same as in [5]. Figure 3 shows the expected throughput with different Q-values and tag populations N. As it can be seen, the maximum throughput is close to the theoretical maximum throughput (0.834) for a given set $\{Q, N\}$. For instance, if the estimator computes that 400 tags will compete in next frame, the frame-length must be set to Q=8 for obtaining the theoretical maximum throughput. Table 1 summarizes all the results for an arbitrary frame *i*. This table permits reader to check quickly the best Q value for every tag population estimated.

V. RESULTS / PERFORMANCE EVALUATION

The performance of PHY-MAC-MFML estimator is compared with the the MFML estimator suggested in [5] (*aka* MAC-MFML), which only uses information from the MAC layer. The estimators have been evaluated by means of a discrete-event simulator. The scenario evaluated consists of a single reader, which is continuously transmitting signals, creating a coverage area, in which tags enter and are identified. When n tags enter the reader coverage area, they remain in it at least until the whole tag population is identified successfully. No new tags enter during the reading process. The goal is to compute the mean identification time for identifying different tag populations with different initial Q configurations. Note that the first frame is not estimated and it must be set in the reader before starting the identification procedure. The physical configuration parameters from the commercial Alien 8800 system [21] at 868 MHz are used. The simulator was previously validated by means of laboratory test beds based on this system in [22].

Figure 4 shows the mean identification delay for both estimators starting with an initial Q_1=4 and Q_1=8. The optimal frame length in the next frames is calculated following the estimator procedure and Q computation explained above. As a reference, we also depict the performance of the ideal algorithms: OPTIMAL-MAC-MFML and OPTIMAL-PHY-MAC-MFML. They have a perfect knowledge of the competing tags at each frame (they do not estimate) and adjust the frame length following data in Table 1. Note that other estimators are not considered in this evaluation because in [5] results demonstrated, under the same simulation conditions, that MAC-MFML outperformed the most relevant estimators based on MAC layer information. The results in Figure 4 demonstrate PHY-MAC-MFML algorithm outperforms previous one, independently the initial frame length considered. PHY-MAC-MFML performs better than other configura-

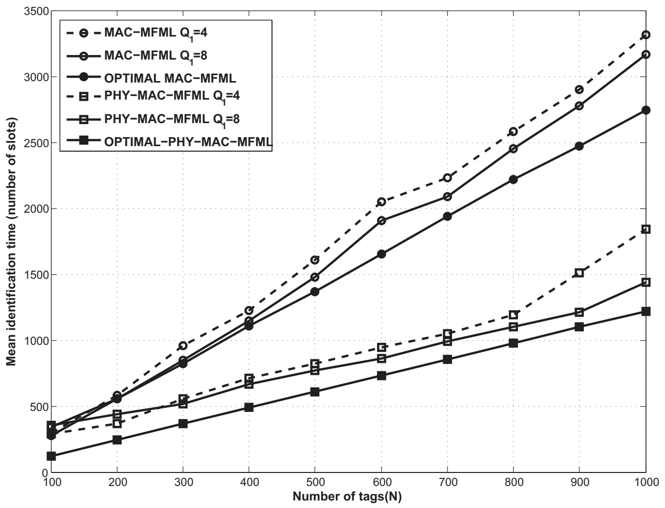

FIGURE 4 - AVERAGE NUMBER OF SLOTS REQUIRED TO IDENTIFY N TAGS FOR DIFFERENT INITIAL FRAME LENGTH CONFIGURATIONS

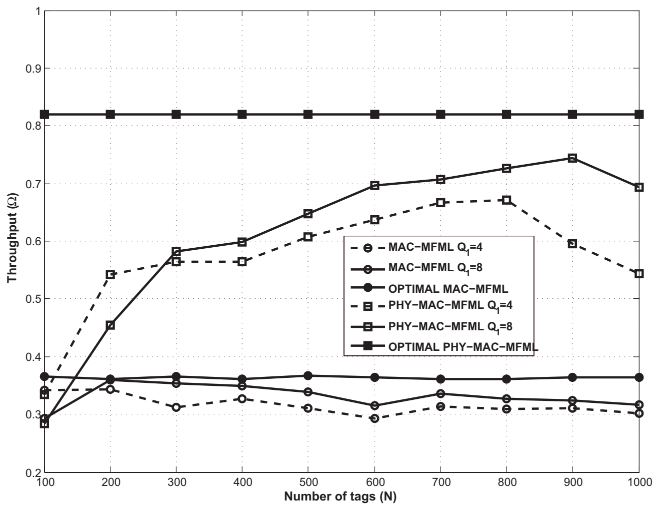

FIGURE 5 - THROUGHPUT FOR DIFFERENT N TAGS AND INITIAL FRAME LENGTH CONFIGURATIONS

tions when $N \leq 270$ and $Q_1 = 4$, lying very close to the optimal bound. Setting Q_1=8, PHY-MAC-MFML has a better performance when $N \geq$270. In both cases, PHY-MAC-MFML outperforms MAC-MFML: *e.g.* setting N=1000, PHY-MAC-MFML with Q_1=4 saves more than 2000 slots and more than 1900 when Q_1=8. Considering the typical length of a EPC-C1G2 slot (slot-duration=2.5 ms) [22], we point out that the identification time is decreased up to 5 seconds with PHY-MAC-MFML and $\{N = 1000, Q_1 = 4\}$ and 4.75 seconds with the same estimator and $\{N = 1000, Q_1 = 8\}$.

Figure 5 shows the throughput achieved for each estimator and configurations. Note that this is not the throughput per frame, but the throughput measured in the whole identification time, that is, the ratio of the tags in coverage and the mean identification delay for that tag population. As it can be seen, the estimator based only on info from MAC layer has the worst response. The OPTIMAL-MAC-MFML reaches its maximum possible throughput, Ω $\approx$0.36. The other MAC-MFML configurations show a worse response, although not far from the optimal. With Q_1=4, the best throughput is reached up to $N \leq 190$. For greater values, Q_1=8 shows the best response.

Obviously, throughput with MAC-MFML strategy is worse than PHY-MAC-MFML. As Figure 5 shows, OPTIMAL PHY-MAC-MFML reaches the maximum value, close to the theoretical maximum ($\Omega \approx 0.834$). From the different PHY-MAC-MFML configurations, with $Q_1 = 4$ PHY-MAC-MFML reaches the maximum throughput up to $N \leq$270, being far from the OPTIMAL PHY-MAC-MFML results when $N \leq$500. When $N \geq 270$, PHY-MAC-MFML with Q_1=8 reaches the best throughput, close to the optimal. From these results we conclude that the initial Q has a strong influence on the performance and, as we pointed out for MAC-MFML in [5], for different initial Q configurations, we can extract the minimum and maximum tags population for which the throughput is maximum.

VI. CONCLUSIONS

Conventional RFID tag estimation procedures only take statistical information from MAC layer (number of empty, singleton and collision slots) to estimate the number of tags competing in a frame. One of those estimation procedures was proposed by the authors in a previous work [5], the MAC-MFML estimator. The results demonstrated that MAC-MFML outperformed most relevant estimators based on MAC layer. However, the set of data used by MAC-MFML for estimating tags was not enough, since the reader could not extract the number of tags colliding in an arbitrary collision slot. Therefore, we concluded that the estimation could improve if this information is available with any procedure. In other previous works we proposed different physical layer reader architectures that permit us to extract successful tag signals from collision slots. In this work, we improved the MAC-MFML estimator by these physical layer techniques and introduce the PHY-MAC-MFML. The MAC-MFML estimator has been modified to take into consideration those slots with exactly two tags colliding, as well as the fact that two tags can be successfully identified when their signals collide in the same slot. Results show the PHY-MAC-MFML estimator improves the estimate, as well as increases the system throughput. Finally, as a future work we aim at taking results under Capture Effect assumption, also including in the identification time results the computation time for estimating tags as well as the applicability of new MFML in Dense Reader Environments.

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