Slot-by-slot maximum likelihood estimation of tag populations in framed slotted aloha protocols

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Abstract

Framed Slotted ALOHA (FSA) is an anti-collision technique in current and future standards of RF-ID systems, as in ISO/IEC CD 18000-6. The number of tags present in the field is a crucial parameter to apply FSA algorithms in an optimal manner. Therefore, a lot of effort is spent on the estimation of this parameter and a range of different estimation techniques exist. But until now, a maximum likelihood estimator has not been formulated. In this paper, a closed formula for the probability of any observed event defined by the number of *empty*, *singleton*, and *collision* slots in the observed frame is derived. Since the referred standard allows for the in-frame adjustment of the frame size (without quitting the interrogation round), this formula is then modified to compute the probability for partly observed frames. Finally, a maximum likelihood estimator is formulated to yield the estimated number of tags on a slot-by-slot basis.

1. INTRODUCTION

Any information processing system performs the tasks of acquiring, interpreting, retaining, and distributing data. Whenever the communication channel is shared, the tasks acquisition and distribution face the risk of possible contention of simultaneously transmitted signals and thus degrading the communication and lowering throughput. A special case is the 1-to-n communication, in which the entity that serves as master of the communication link encounters a yet unknown number of n unidentified clients. Under these circumstances stochastic anti-collision techniques can be utilised that enable a time dispersion of responding clients in controlled manner. Radio Frequency Identification (RF-ID) systems are exemplary for this kind of communication scenario and its passive category gained recently enormous interest as it is generally considered to have dramatic effect on economical, social, and intellectual life [8].

For RF-ID systems two stochastic anti-collision methods are commonly used in state-of-the-art standards: binary tree search (e.g. the ISO/IEC 15693, ISO/IEC CD 18000-3, ISO/IEC CD 18000-6 Type B), and Framed Slotted ALOHA in in EPC Global UHF Class 1 Generation 2 and Type A of ISO/IEC CD 18000-6.

In Framed Slotted ALOHA any client that tries to answer a request submitted by the communication master with a data packet chooses at random a time slot of a frame [7]. The frame length, i.e. the number of available slots, is the parameter that determines the achievable throughput of the system. In RF-ID systems the number of clients (or tags) in the powering field is usually unknown and is often subject to a strong fluctuation. Assume a harbour cargo gate through which trucks loaded with tagged objects of differing size and number enter and leave. In such an environment the number of tags in the field may vary from a few dozen in one second to a few thousands in the next. The transmission control strategy has to estimate and adjust the frame size, which determines the broadcast probability of the tags, to the optimal value.

The contribution of this paper is twofold. Although a number of algorithms and techniques exist that estimate the number of tags in the field and dynamically adjust the frame size to the current scenario, a maximum likelihood (ML) estimator has not yet been formulated. In this work this task will be accomplished. Secondly, the in-frame adjustment of the frame size has only been considered recently by Flörkemeier [3] with an Bayesian belief estimator. All other existing approaches estimate the number of tags depending on the past, completely observed, frames, then set the frame size anew and process the current frame accordingly. However, the EPC Global UHF Class Gen 2 standard explicitly favours an in-frame adjustment of the frame size with the `QUERYADJUST` command. Thus, it is possible to observe only a small part of a frame and to react immediately, if the number of collisions or empty slots exceeds a certain value. With this feature it is not necessary to quit the current interrogation round and to retransmit the request. The maximum likelihood formulation is hence modified towards partly observed frames on a slot-by-slot basis.

The next section of this paper introduces necessary terms and definitions used for Framed Slotted ALOHA scenarios and the classical formulation of the ALOHA anti-collision as *occupancy problem*. Section 2. deals with the probability equations and derives a closed formula for the probability of an event for a partly observed frame. In Section 3. the formula is analysed and the maximum likelihood estimator is formulated. Section 4. compares the performance of the new ML estimator with the minimum squared error estimator, which has been modified by us to be applicable to partly observed frames. Related work will be addressed in Section 5. before the paper will be concluded with the last section.

2. PROBABILITIES IN FSA

As RF-ID systems serve as example application due to their outstanding importance at present, we will use expressions typically used in such systems. However, the following considerations are of course true for any system applying FSA.

A request issuing master is named *interrogator* or just the *reader*. The clients responding to this request in a controlled manner are called *tags*. After issuing a request including the current frame size, the reader waits for a specified time interval, i.e. the length of the frame, which is divided into a number of slots separated by additional signalling issued by the reader. At the beginning of the frame any tag in the field randomly generates a number between 1 and the frame size F that determines the slot in which it tries to respond. Whenever more than one tag use the same slot for their responses, a collision occurs and typically the data sent by the involved tags are corrupted. In general, it is not possible to deduce the exact number of tags that caused the collision. The number of present tags in the field, the tag population, is denoted by n.

The allocation of tags to time slots within a frame can be formulated as an occupancy problem [4] that can be found in a broad range of applications [6]. In these problems balls are randomly allocated to a number of bins. Balls correspond to tags as bins correspond to slots.

Having F slots available and n tags in the field, the fill level of r tags in a given slot is described by a binomial distribution:

$$B_{n,\frac{1}{F}}(r) = \binom{n}{r}\left(\frac{1}{F}\right)^{r}\left(1-\frac{1}{F}\right)^{n-r} \quad (1)$$

The expected number of slots $E(\mathcal{X}_r = \mathcal{X}_1)$ with just a single tag response, i.e. fill level $r = 1$, is of major interest to measure the throughput $T = \frac{E(\mathcal{X}_1)}{F}$ of the system. By simple calculus it has been shown by Schoute [7] that T is maximised if the frame length F equals the tag population size n.

The number r of tags in a particular slot is called its *occupancy number*. Since the distribution (1) applies for all slots of a frame, the expected number of slots $\mathcal{X}_r$ with *occupancy number r* is given by:

$$\mathcal{X}_r^{F,N,n} = NB_{n,\frac{1}{F}}(r) = N\binom{n}{r}\left(\frac{1}{F}\right)^{r}\left(1-\frac{1}{F}\right)^{n-r}, \quad (2)$$

where N is the number of observed slots ($N = F$ for a completely observed frame). As already indicated it is only possible to observe for any slot seen, whether it features the fill levels $r = 0, 1, \geq 2$, thus having for N out of F observed slots: m_0 *empty* slots, m_1 *singleton* slots, and $m_{\geq 2} = m_c$ *collision* slots.

$$P(\mathcal{X}_r = m_r : F, n) = \underbrace{\binom{F}{m_r}}_{A}\underbrace{\left[\prod_{l=0}^{m_r-1}\binom{n-lr}{r}\left(\frac{1}{F}\right)^{r}\right]}_{B}$$
$$\sum_{k=0}^{S}(-1)^k\underbrace{\binom{F-m_r}{k}}_{C}\underbrace{\left[\prod_{j=0}^{k-1}\binom{n-rm_r-jr}{r}\left(\frac{1}{F}\right)^{r}\right]}_{D}$$
$$\underbrace{\left(\frac{F-m_r-k}{F}\right)^{n-rm_r-kr}}_{E} \quad (3)$$

Vogt [9] published a closed formula (3) for the probability $P(\mathcal{X}_r)$ for the random variable $\mathcal{X}_r$ of exactly $\mathcal{X}_r = m_r$ slots, where $\mathcal{X}_r$ is the random variable that equals the number of slots being filled with exactly $r = 0, 1, \ldots, n$ tags. Then the distribution of $\mathcal{X}_r$ depends on the probability in (3) with $S = \min\left(\begin{smallmatrix}F-m_r,\\ \lfloor(n-rm_r)/r\rfloor\end{smallmatrix}\right)$.

The underbraces denote the subterms to facilitate later references. It is necessary to thoroughly explain the subtleties of this formula to comprehend the new considerations. In the experiment for (3), n tags shall hit arbitrary m_r out of F slots exactly r times, and the remaining $F - m_r$ slots **not** r times. Term A chooses m_r out of F slots arbitrarily. Term B distributes in any of these slots rm_r arbitrary tags out of n candidates. The large sum is concerned with the distribution of the remaining $n - rm_r$ tags in the S slots. The alternating term represents the *inclusion-exclusion* principle that can be applied here: For $k = 0$ terms C and D are 1 and term E gives the probability of all remaining $n - m_r r$ tags being distributed arbitrarily into the remaining $F - m_r$ slots. Then we have inevitably considered also all possibilities with **at least** one slot having fill level r, which is forbidden as none of the $F - m_r$ should contain exactly r tags. And even more important, term E considers these forbidden events with different permutations of the $n - rm_r$ tags. To successively diminish this error, the forbidden combinations have to be subtracted. For $k = 1$ term C chooses one slot, which is then filled with r tags (term D), and all remaining $n - rm_r - r$ tags are again distributed arbitrarily into the remaining $F - m_r - 1$ slots. Then a part of the former erratically considered possibilities has been corrected (those having exactly one forbidden slot with fill level r). Now the arbitrary distribution of the remaining $n - rm_r - r$ considers too many possibilities for the forbidden slots ≥ 2. For $k = 2$ these are added again. And so forth for $k = 3 \ldots S$ until no tags are available anymore ($S = \lfloor(n - rm_r)/r\rfloor$) or all remaining slots have been considered ($S = F - m_r$). In both cases the *problematic* term E does not introduce an error anymore because it equals 0 when $S = F - m_r$ or 1 when $S = \lfloor (n-m_r)/r \rfloor$.

$$P(\mathcal{X}_0; N,F,n) = \binom{N}{m_0} \sum_{i=0}^{\min\binom{N-m_0,}{n}} (-1)^i \binom{N-m_0}{i} \underbrace{\left(\frac{F-m_0-i}{F}\right)^n}_{E_{m_0}} \tag{4}$$

$$P(\mathcal{X}_1; F,N,n) = \underbrace{\binom{N}{m_1}}_{A_{m_1}} \underbrace{\left[\frac{n!}{(n-m_1)!}\left(\frac{1}{F}\right)^{m_1}\right]}_{B_{m_1}} \sum_{i=0}^{\min\binom{N-m_1,}{n-m_1}} (-1)^i \underbrace{\binom{N-m_1}{i}}_{C_{m_1}} \underbrace{\left[\frac{(n-m_1)!}{(n-m_1-i)!}\left(\frac{1}{F}\right)^i\right]}_{D_{m_1}} \underbrace{\left(\frac{F-m_1-i}{F}\right)^{n-m_1-i}}_{E_{m_1}} \tag{5}$$

This rather complex equation yields for any alleged number of slots with a certain fill level r, how probable the outcome m_r is under a given parameter scenario of n tags being distributed in F slots. We are interested in an event with more information contained. We are looking for the formula yielding the probability $P(\mathcal{X}: F,N,n)$ for the event $\mathcal{X} = \langle m_0, m_1, m_c \rangle$ characterised by "m_0 empty **and** m_1 singleton **and** m_c collision slots" in $N = m_0 + m_1 + m_c$ observed slots with the parameter scenario of n tags being distributed in F slots. Apparently, this event is characterised by the two versions of (3) for $r = 0$ and $r = 1$, with $r \geq 2$ being implicit, since $m_c = N - m_0 - m_1$ is hence predetermined. Equation (4) represents the case $r = 0$ and (5) shows the case $r = 1$. Until here, only minor modifications have been performed to consider only N out of F observed slots.

With Equations (4) and (5) it is possible to develop a new closed formula for the composed event of "m_0 and m_1 and (implicitly) m_c slots". Consider the term E_{m_0} that is concerned with the arbitrary and iteratively erroneous distribution of the remaining n tags. With precisely these tags the event m_1 described in (5) has to be composed. Hence, we replace the term E_{m0} with term $\widehat{E}_{m_0}$ and insert thereafter (5) leading to the Equation (6).

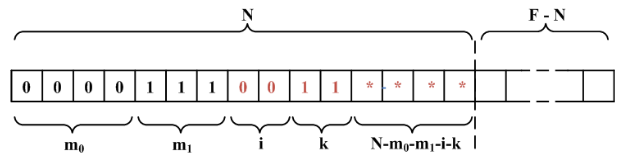

Figure 1. Slots and their fill levels $r = 0, 1, \geq 2$ depicting indices of (6).

For the index transformations and further necessary modifications, consider Figure 1, in which the scenario for a given event has been captured. For clarity the slots with equal fill levels are grouped together in this figure. Instead of distributing all n tags into the remaining $F - m_0 - i$ slots in term E_{m_0}, we have to put aside m_1 tags to be filled into m_1 slots to complete the event. Thus, term $\widehat{E}_{m_0}$ fills only $n - m_1$ tags into $F - m_0 - m_1 - i$ slots. Term $\widehat{A}_{m_1}$ chooses those m_1 slots from the remaining $N - m_0$ slots and fills in each one exactly one tag via term $\widehat{B}_{m_1}$. Here, we enter the second sum originating from (5). This sum distributes precisely one tag into any of k slots out of the now remaining $N - m_0 - i - m_1$ slots (term $\widehat{C}_{m_1}$ and $\widehat{D}_{m_1}$). The last term $\widehat{E}_{m_1}$ is concerned with all remaining tags distributed arbitrarily among the remaining $F - m_0 - i - m_1 - k$ slots. In this large formula there exist two terms that miscount the partial possibilities, $\widehat{E}_{m_0}$ and $\widehat{E}_{m_1}$, hence leading to the cascaded sums in the same manner as described for (3). The correctness of this formula has then been verified empirically.

$$\begin{aligned} &P(\mathcal{X} = \langle m_0, m_1, m_c \rangle; N,F,n) = \\ &\binom{N}{m_0} \sum_{i=0}^{\min\binom{N-m_0-m_1,}{n-m_1}} (-1)^i \binom{N-m_0}{i} \underbrace{\left(\frac{F-m_0-m_1-i}{F}\right)^{n-m_1}}_{\widehat{E}_{m_0}} \underbrace{\binom{N-m_0-i}{m_1}}_{\widehat{A}_{m_1}} \underbrace{\left[\frac{n!}{(n-m_1)!}\left(\frac{1}{F}\right)^{m_1}\right]}_{\widehat{B}_{m_1}} \\ &\left[\sum_{k=0}^{\min\binom{N-m_0-i-m_1,}{n-m_1}} (-1)^k \underbrace{\binom{N-m_0-i-m_1}{k}}_{\widehat{C}_{m_1}} \underbrace{\left[\frac{(n-m_1)!}{(n-m_1-k)!}\left(\frac{1}{F-m_0-i-m_1}\right)^k\right]}_{\widehat{D}_{m_1}} \underbrace{\left(\frac{F-m_0-i-m_1-k}{F-m_0-i-m_1}\right)^{n-m_1-k}}_{\widehat{E}_{m_1}} \right] \end{aligned} \tag{6}$$

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3. MAXIMUM LIKELIHOOD ESTIMATOR FOR FSA

In Figure 2 an example for the developed probability function (6) is depicted over the event plane (m_0, m_1) for the parameters $F = 20, N = 15$ and a given tag population $n = 30$. For any permitted parameter set $(m_0 \neq N \wedge m_c \neq N \wedge n \geq m_1 + 2m_c \wedge F \geq N \geq 1 \wedge m_0 + m_1 + m_c = N)$ this function always reveals a *sugar loaf*-like shape. Since in our scenario the parameter n is not known, but the outcome of this random experiment has been observed, given as event $\mathcal{X} = \langle m_0, m_1, m_c \rangle$, we may assume that the unknown parameter n is that particular n, which makes the observed event most likely. Hence, the probability function for the observed event is analysed over different values of n, looking for that n, which yields maximum probability. The plots in Figure 3 and 4 show the outline

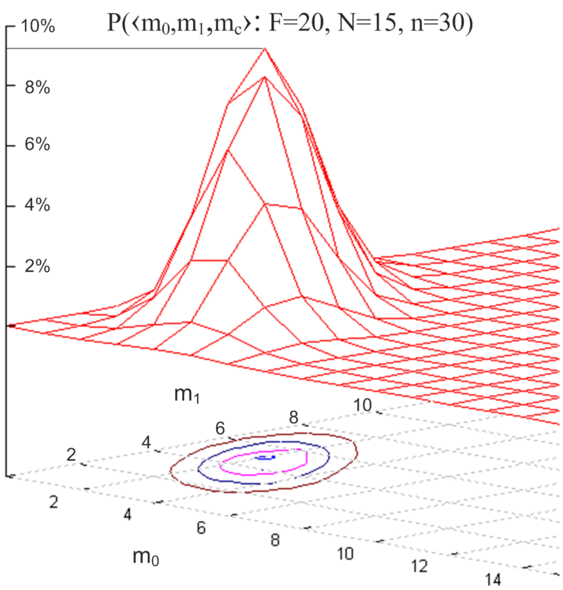

Figure 2. Probabilities over event space (m_0, m_1) for given parameters $F = 20$, $N = 15$, $n = 30$.

of the probability for given events over the parameter n. The plots in Figure 3 are subject to three different events $\mathcal{X} = \langle 2,2,1 \rangle, \langle 0,3,2 \rangle, \langle 1,2,2 \rangle$ for a relative low number of $N = 5$ observed slots out of $F = 32$ slots. The plots in Figure 4 outline the probabilities for a much higher number of observed slots $N = 20$ out of $F = 32$ slots for a different event set, $\mathcal{X} = \langle 4,6,10 \rangle, \langle 8,4,8 \rangle, \langle 1,9,10 \rangle$. It is important to notice the well-behaved shape of this function. Except from the border case $m_c = N$ for which the maximum lies with $n = \infty$, a single well defined maximum can be identified (for $m_0 = N$ lies the maximum with $n = 0$). This maximum indicates, as stated before, that n for which the observed event is most likely. Hence, we can develop a slot-by-slot tag population estimator by performing a maximum search. Unfortunately, the derivation $\frac{\delta P(\mathcal{X}:F,N,n)}{\delta n}$ exhibits an even more complex structure. So, in order to obtain the maximum analytically, an approximation technique would have to be utilised to find the zero-crossing $\frac{\delta P(\mathcal{X}:F,N,n)}{\delta n} = 0$. In comparison with iterative techniques, for instance Newton's method, a gradient search is then still less computationally expensive. A two staged gradient search ini-

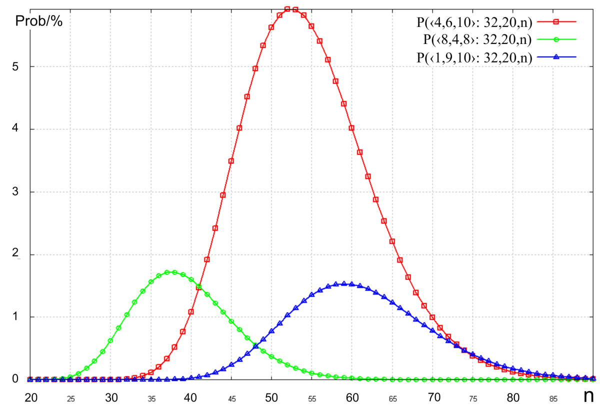

Figure 3. Probability for given events over possible values for the tag population n, $N = 5$, $F = 32$.

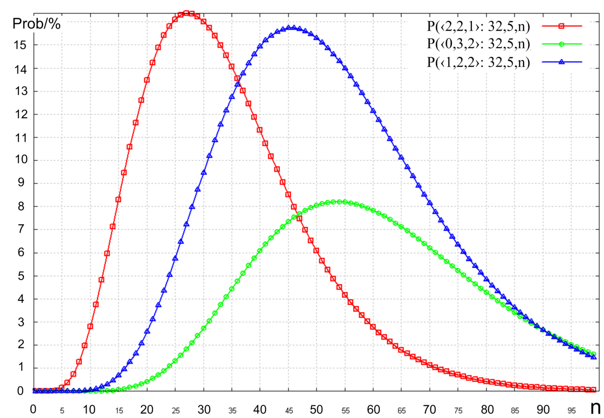

Figure 4. Probability for given events over possible values for tag population n, $N = 20$, $F = 32$.

tially searches for the first occurrence of a negative gradient with step width $n(i) = (m_1 + 2m_c)\,2^i, i = 1, 2, \ldots$. When the first negative slope is detected at step i, the maximum lies between $n(i-1)$ and $n(i)$. Within this range the second stage of the gradient search analyses the slope over the nested intervals in $\log_2(n(i) - n(i-1))$ steps for the worst case. It has to be mentioned that the referred standards momentarily only allow for a frame size adjustment in powers of two to facilitate the tags' computation of random values. In that case the first stage of the gradient search begins with $n(0) = 2^{\lfloor \log_2 2m_c + m1 \rfloor}$ and the second stage of the gradient search is apparently not necessary at all. The decision has then to be made between $n(i)$ and $n(i-1)$ only, for which that n is taken, which yields the higher probability value. Eventually, the maximum likeli-

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hood estimator $\hat{n}_{ml} = \arg\max_n P(\mathcal{X} : F, N, n)$ obtained by gradient search has been formulated.

4. COMPARISON WITH MSE ESTIMATOR

The best estimation technique so far applicable to only partly observed frames in this setting is the minimum squared error estimator [9]. Chebychev's inequality states that the result of a random experiment with random variable $\mathcal{X}$ is most likely near the expected value of $\mathcal{X}$. Hence, a squared error function (7) is defined using the distance between the expected events $\mathcal{X}_0, \mathcal{X}_1$ and $\mathcal{X}_{\geq 2} = \mathcal{X}_c$ out of (2) for a given parameter n and the observed values m_0, m_1 and m_c. Via this function that n is determined for which the distance function is minimised.

$$\hat{n}_{mse} = \arg\min_n \left| \begin{pmatrix} \mathcal{X}_0 \\ \mathcal{X}_1 \\ \mathcal{X}_c \end{pmatrix} - \begin{pmatrix} m_0 \\ m_1 \\ m_c \end{pmatrix} \right|^2 \tag{7}$$

As $m_c = N - m_0 - m_1$ and with some simple calculus this is equivalent to

$$\hat{n}_{mse} = \arg\min_n (\mathcal{X}_0 - m_0)^2 + (\mathcal{X}_1 - m_1)^2 + (\mathcal{X}_0 - m_0)(\mathcal{X}_1 - m_1) \tag{8}$$

The minimisation of this function can be performed in a quite similar manner via a gradient search as, except from the border cases of the parameter set, a single local minimum is formed. Again, although this error function is simpler than (6), an analytical calculation of the minimum is not possible due to the inner terms $\left(1 - \frac{1}{F}\right)^n$ and $n\left(1 - \frac{1}{F}\right)^{n-1}$ in $\mathcal{X}_0$ and $\mathcal{X}_1$, respectively.

To obtain a clear comparison between the tag population estimation techniques, the expected error of the estimation functions ($\hat{n}_x = \hat{n}_{ml}$, $\hat{n}_{mse}$) testifies to the quality of the functions. We sum up the errors of the estimation functions over the possible event space for a given parameter set and weight the summands by their occurrence probability:

$$\varepsilon_x = \sum_{\langle m_0, m_1, m_c \rangle} |\hat{n}_x - n| P(\langle m_0, m_1, m_c \rangle) \tag{9}$$

In Figure 5 the cumulated errors ε_{mse} and ε_{ml} have been plotted over the observed $N = 1 \ldots F$ slots for the random experiment with $F = 32$, and $n = 20, 50$. Similarly, Figure 6 plots a different scenario with $F = 64$, $n = 50, 100$. Apparently, for both estimators the quality of the result improves the more of the current frame has been observed ($N \to F$). Note, that for very low values of N, the event $m_c = N$ for which both estimators cannot apply their gradient search, is very likely. For both a fallback mechanism has been implemented for this case $N = m_c$ to estimate the number of tags in the current frame to be $\hat{n} = 2.39 m_c \frac{F}{N}$, which has been shown by Schoute [7] to provide a reasonable estimate, although with a

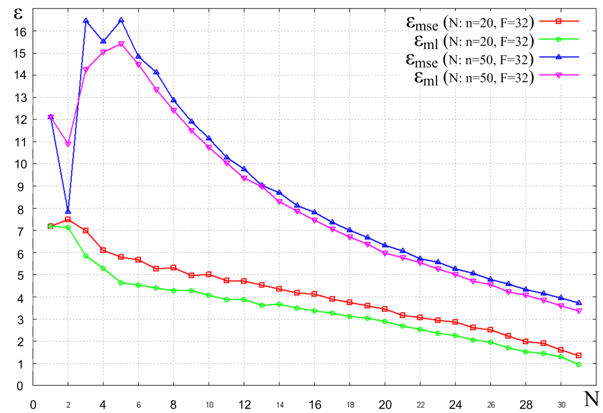

Figure 5. Cumulated error ε for the MSE and the ML estimators.

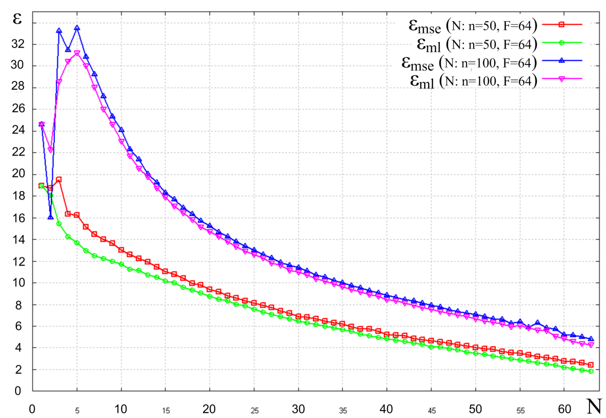

Figure 6. Cumulated error ε for the MSE and the ML estimator.

much lower quality than the MSE estimator when compared over the complete event space [2]. Hence, the behaviour depicted for $N < 5$ may deviate from this general observation. But more importantly, the ML estimator reveals a better quality for the full event space for any observed number of slots during frame processing. A more accurate estimation of the tag population is directly related to a higher throughput, since the frame size can be adjusted more precisely to the true size of the tag population. Moreover, it has to be stated that as long as there is no additional knowledge of the tag population available, which could affect the distribution probability of $P(\mathcal{X} = \langle m_0, m_1, m_c \rangle)$, the maximum likelihood estimator provides a lower bound for (9) to any other stochastic estimation technique.

A disadvantage of the ML estimator lies apparently in its computational overhead. Although the gradient search can be applied in a binary search form, some of the inner terms of (6) are to power of n or factorial of n and divisions between values of very different size occur, thus necessitating a rather complex computation algorithm to prevent the introduction of overflow, underflow or partial fraction errors. In fact, the

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successive slot-by-slot computation of (6), in which only the parameters N and one out of m_0, m_1 or m_c are incremented, offers a lot of potential to diminish this overhead. Similarly, the gradient search can be optimised as well, as only its parameter n is varied from iteration to iteration. Future work will focus on this analysis, and an implementation in an RF-ID testbed is intended [1].

5. RELATED WORK

Under the assumption that the frame size is chosen such, that in case the number of clients that transmit in each frame is Poisson distributed with mean 1, Schoute developed a backlog estimation technique for FSA [7]. As already stated, the estimated number of clients after a complete frame is then estimated to be $\widehat{n} = 2.39 m_c$. Evidently, not the complete observable information is used in this scheme, as well as the assumption of the Poisson distribution may not be true in all applications. And as already stated the simple modification to partly observed frames, $\widehat{n}(N) = 2.39 m_c \frac{F}{N}$, reveals a much worse performance than the MSE estimator as shown by Vogt [9].

Vogt introduced the MSE estimator and analysed its behaviour for completely observed frames. As it has been shown by us, his approach can be easily modified towards partly observed frames and is, as such, a promising candidate for modern RF-ID standards. Moreover, Vogt's work clarifies the superior performance of the MSE estimator in comparison with the Q algorithm defined in ISO/IEC 18000-6 C. This algorithm keeps a representation of the tag number estimation, which is either multiplied by a constant β whenever a collision occurs, or divided by β whenever an empty slot is detected. A singleton slot does not alter the current estimation. After the frame has been processed, the Q algorithm calculates the new frame size as follows: $\widehat{n}_{Q,new} = \widehat{n}_{Q,old} \beta^{m_c - m_0}$. This algorithm does not state how to compute a suitable β, but at least comments on a reasonable range $1.07 \leq \beta \leq 1.41$. This estimation technique could also be applied on a slot-by-slot basis, but as the performance on a frame-by-frame basis has already revealed a lower performance than the MSE estimator, it is not being considered as competitive.

Krohn et al. [5] recently presented an approach which presents a fast technique to estimate approximately the number of tags present in the read range. They state explicitly to optimise rather for fast detection than for accuracy of the estimate and base their work on the assumption that there are empty and occupied slots only. From this perspective, our approach exhibits a contrary objective with the identification of the achievable lower bound for the estimation error.

Most recently, Flörkemeier [3] published a Bayesian slot-by-slot estimator for the tag population. This approach utilises exponential generating functions, for which a closed formula for their coefficients has to be developed. Such a coefficient formula discloses the way to an equation for the probability of distinct events m_0, m_1, m_c under the parameters N, F, n as in our case. A substantial drawback lies in the fact that the coefficient formulas vary with the observed evidence of m_0, m_1, and m_c slots. A recipe to obtain this formula for any possible event, i.e. with m_0, m_1, m_c as parameters, has not yet been published. Hence, an implementation is not possible.

6. CONCLUSIONS

In this work the maximum likelihood estimator for the tag population of Framed Slotted ALOHA protocols has been developed. The exact probability distribution of the observable event space in FSA systems has been determined, thus enabling the ML formulation of a slot-by-slot tag population estimator. This result may serve for future algorithms to close in to the theoretical bound of the achievable throughput in FSA protocols. Especially, for state-of-the-art protocols that allow for an in-frame adjustment of the frame size, as EPC Global UHF/HF Class 1 Generation 2, this method can be applied for an immediate update of the frame size according to the probability level of the current slot-by-slot estimate. This issue will be subject of upcoming research.[1]

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