Slot-by-slot minimum squared error estimator for tag populations in FSA protocols

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Abstract. Framed Slotted ALOHA (FSA) is an anti-collision technique in the currently most popular standard of RF-ID systems in the UHF domain, the 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 to achieve the highest detection rate possible. Therefore, a lot of effort is spent on the estimation of this parameter and a range of different estimation techniques exist. One of the most promising techniques is the minimum squared error (MSE) estimator for expectation values formulated by Vogt et al. for completely observed frames. This technique has not yet been adapted to an in-frame adjustment of the frame size (i.e. without quitting the interrogation round), as it is favoured in the aforementioned standard. In this work the MSE is reformulated to work on slot-by-slot basis and an efficient algorithm is proposed to exploit the on-the-fly adjustment of the frame size. The results are compared to other common estimation techniques for the tag population with respect to cumulated estimation error and detection rate. Furthermore, it is demonstrated that the performance is approximating the theoretical bound obtained by the maximum likelihood estimator.

Key words: Framed Slotted Aloha, Anti Collision, Minimum Squared Error Estimator, Slot-by-Slot Estimator, RF-ID

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

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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 [9].

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 [8]. 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 lies on the development of an efficient algorithm based on the minimum squared error estimator proposed by Vogt et al. This approach is reformulated to allow for the in-frame adjustment of the frame size, as this feature has only been considered recently by Flörkemeier [2] with an Bayesian belief estimator. Unfortunately, Flörkemeier's approach is only applicable for small tag populations, as a counting problem occurs with an exponentially increasing number of multiplications. All other existing approaches estimate the number of tags depending only 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 suggests a suboptimal setting of the frame size. With this feature it is not necessary to quit the current interrogation round and to retransmit the request. Until now, current standards offer only the Q-algorithm or related techniques to accomplish this task [6].

In the next section the most important related work in the field will be surveyed. Section 3 then introduces terms and definitions necessary for Framed Slotted ALOHA scenarios, the FSA formulation as *occupancy problem*, and the fundamentals of the MSE tag number estimator. In Section 4 an efficient algorithm is designed that reacts on the evidence of partly observed frames and adjusts on-the-fly the size of the remaining frame. Section 5 compares the performance of the MSE estimator with the slot-by-slot based maximum likelihood estimator and other techniques. In the last section, the paper is summarised and its contribution is discussed.

2 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 [8]. The estimated number of clients after a complete frame is then estimated to be $\widehat{n} = 2.39 m_c$, where m_c is the number of observed collisions. Evidently, the observed values for empty slots, m_0, and singleton slots, m_1, are neglected in this scheme, as well as the assumption of the Poisson distribution may not be true in all applications. In this paper its modification to partly observed frames, $\widehat{n}(N) = 2.39 m_c \frac{F}{N}$ is applied, and will be compared to in Section 5.

Vogt [10] introduced the MSE estimator and analysed its behaviour for completely observed frames. As it will be demonstrated by us, his approach can be easily modified towards a partly observed frame, its combination with knowledge from previous complete frames, and the optimal frame size adjustment to powers of two, as it is instructed by current RF-ID standards.

In ISO/IEC CD 18000-6 the so-called Q-algorithm is proposed to adjust the frame size based on the evidence of partly observed frames. 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 frame size. After the slot has been processed, the Q-algorithm calculates the new frame size as follows: $F_{new} = F_{old} \beta^{m_c - m_0}$. As soon as $\lfloor F_{new} \rceil \neq F_{old}$ the frame size is adjusted on-the-fly. The standard does not state how to compute a suitable β, but at least comments on a reasonable range $1.07 \leq \beta \leq 1.41$. Most recently, Lee et al. [6] published an improved Q^+-algorithm with optimised parameters $\beta_1 = 2^{C_c}$ for detected collisions and $\beta_2 = 2^{-C_i}$ for detected empty slots, with $C_c = 0.35$ and $C_i = (e-2)C_c = 0.25$ as optimal ratio. In our paper its performance is compared to the slot-by-slot MSE estimator in Section 5.

Krohn et al. [5] 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. Their estimation performance lies well in the region of the Q^+-algorithm and is therefore not considered as additional benchmark in this work.

Recently, Flörkemeier [2] published a Bayesian slot-by-slot estimator for the tag population. This approach utilises exponential generating functions to create a probability formula for all distinct events $\langle m_0, m_1, m_c \rangle$ under the parameters N observed slots out of F slots in a complete frame and n tags being distributed in them. Unfortunately, he could not find a closed form for the coefficient formula of the exponential generating functions, which avoids to *count* all permutations that generate a given event $\langle m_0, m_1, m_c \rangle$ with n tags. Hence, his approach is only applicable for scenarios, in which the number of tags n and the number of collisions m_c is very low, as the number of required multiplications in this counting problem grows exponentially with both of them.

Most recently, Knerr et al. [4] published the maximum likelihood (ML) estimator for the number of tags for completely and partly observed frames. Avoiding the exponentially growing counting problem introduced by Flörkemeier, a closed form for the probability P of the event $\langle m_0, m_1, m_c\rangle$ under given parameters F, N, n has been found. Via this function that particular $\widehat{n}$ can be identified, which makes the observed event most probable. Although the evaluation of $P(\langle m_0, m_1, m_c\rangle : F, N, n)$ is computationally much less intensive than Flörkemeier's approach, as the number of terms in P grows only linear with m_c, its inner expressions contain powers and faculties of n that can easily cause fractional, overflow, and underflow errors. The proposed MSE estimator proves to be more stable in this respect and is much easier to compute.

3 FSA and MSE Tag Number Estimation

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 anti-collision.

An *interrogator* (or *reader*) is issuing a request to an unknown number of clients. These clients (or *tags* in RF-ID) respond in a controlled manner. The reader's request includes the current frame size, i.e. a time interval subdivided by additional signalling provided by the reader into F slots. 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. It is intended to obtain as many as possible slots with exactly one response contained, since only then the responding tag is identifiable and can be accessed and controlled furthermore. But whenever more than one tag respond in the same slot, a collision occurs and 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 [3] that can be found in a broad range of applications [7]. 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:

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

The expected number of slots $E_r = E\left(\mathcal{X}_r = \mathcal{X}_1\right)$ 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. 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:

$$E_r = E(\mathcal{X}_r^{F,n}) = F B_{n,\frac{1}{F}}(r) \tag{2}$$

By simple calculus it has been shown by Schoute [8] that T is maximised if the frame length F equals the tag population size n. Hence, the estimation of the present population size $\widehat{n}$ from the given evidence $\mathcal{X} = \langle m_0, m_1, m_{\geq 2}\rangle$ has to be as exact as possible to adjust the frame size correctly.
The best applicable estimation technique is the minimum squared error (MSE) estimator by Vogt [10]. Vogt's approach can easily be modified to partly observed frames (N out of F slots seen) and discloses the path to exploit the in-frame adaptability of the frame size enabled by current standards, when the evidence of the currently processed frame suggests that.

$$E_{r,N} = E(\mathcal{X}_r^{F,N,n}) = NB_{n,\frac{1}{F}}(r) \tag{3}$$

The MSE estimator is formulated as follows. 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 (4) 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 (3) for a given parameter n and the observed values m_0, m_1 and m_c in $N = m_0 + m_1 + m_c$ out of F slots. Via this function that particular n is determined for which the distance function $D(\mathcal{X} : N, F, n)$ is minimised.

$$\widehat{n}_{\text{MSE}} = \arg\min_n \underbrace{\left| \begin{pmatrix} E_{0,N} \\ E_{1,N} \\ E_{c,N} \end{pmatrix} - \begin{pmatrix} m_0 \\ m_1 \\ m_c \end{pmatrix} \right|^2}_{D(\mathcal{X}:N,F,n)} \tag{4}$$

In Figure 1 the distance function is plotted for four examples with varying parameters for N and F to illustrate its shape. For instance, the red line depicts the case when $N = 20$ out of $F = 64$ slots have been observed with $m_0 = 2$ empty, $m_1 = 8$ singleton, and $m_c = 10$ collision slots. In that example the minimum (i.e. the MSE estimate of the tag population size) lies at $\widehat{n} = 109$. The figure shall highlight several important observations. The distance function possesses a single minimum for all possible observations except from the case $\langle m_0, m_1, m_c\rangle = \langle 0, 0, N\rangle$ for which the minimum is at $n = \infty$. The slopes towards the minimum become steeper the more of the frame has been observed $N \to F$, or in other words the estimate becomes more reliable the more evidence is present. For $n \to \infty$ the error converges to an evidence specific constant maximum, since then $E_{c,N} \to N$, $E_{0,N} \to 0$, and $E_{1,N} \to 0$.
Hence, we can develop a slot-by-slot tag population estimator by performing a minimum search on the distance function. The task to identify the minimum analytically via $\frac{\delta D(\mathcal{X}:N,F,n)}{\delta n} = 0$ is unfortunately not possible because of its inner term $n(1 - \frac{1}{F})^{n-1}$ in $E_{1,N}$. So, in order to obtain the minimum, either an approximation technique could be utilised to find the zero-crossing or a gradient search over $D(\mathcal{X} : N, F, n)$. In comparison with iterative approximation with Newton's method, which requires an repetitive evaluation of $\frac{\delta^2 D(\mathcal{X}:N,F,n)}{\delta n^2}$, a gradient search is computationally less expensive.
A two staged gradient search initially searches for the first occurrence of a positive gradient with step width $\widehat{n}(i) = (m_1 + 2m_c)\,2^i, i = 1, 2, \ldots$. When the first

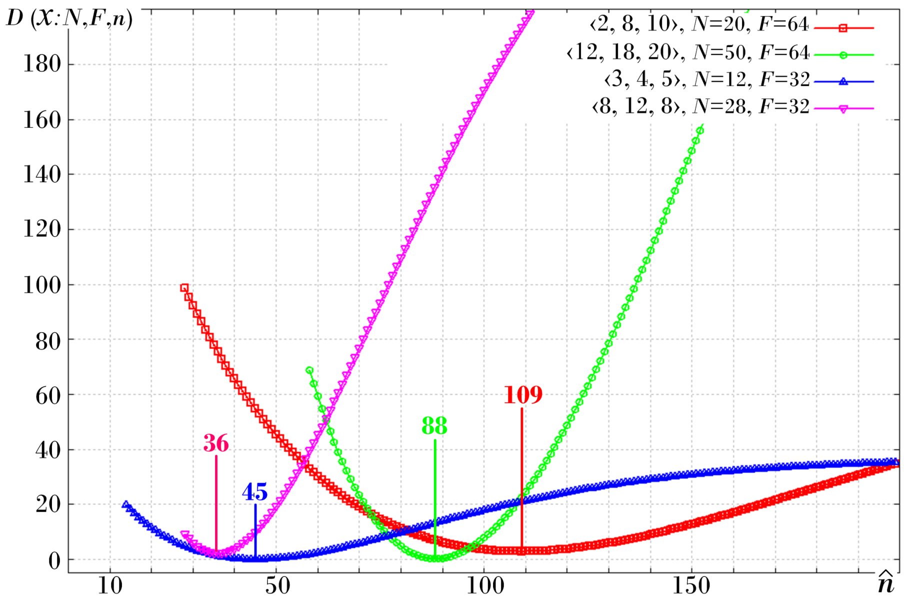

Fig. 1. Squared error functions for four observed events over n.

positive slope is detected at step i, the maximum lies between $\widehat{n}(i-1)$ and $\widehat{n}(i)$. Within this range the second stage of the gradient search analyses the slope over the nested intervals in $\log_2(\widehat{n}(i) - \widehat{n}(i-1))$ steps for the worst case, yielding finally the minimum and thus the estimate $\widehat{n}_{\text{MSE}}$. The estimated number of remaining tags in the field is then $\widehat{n} = \widehat{n}_{\text{MSE}} - m_1$. Eventually, the slot-by-slot minimum squared error estimator for the tag population size in FSA protocols has been formulated.

4 MSE Algorithm for In-Frame Adjustment

A concrete implementation of an MSE based estimation algorithm typically has to incorporate additional standard or application specific information. Although the issue of in-frame adjustment is per se a technique dedicated to fast changing environments, in which the knowledge from the past frames is likely to be obsolete, the incorporation of that knowledge into the MSE estimation technique is easily possible. In (5) the minimisation problem is formulated with the distance functions for the current frame $D_{cur}(\mathcal{X} : N, F, n)$ and for the P past frames $D_p(\mathcal{X} : N = F, n)$:

$$\widehat{n}_{\text{MSE}} = \arg\min_n \left(D_{cur}(\mathcal{X} : N, F, n) + \sum_{p=1}^{P} D_p(\mathcal{X} : N = F, n) \right) \qquad (5)$$

In this case several modifications may come into play, for instance a weighting of the $P+1$ distance functions according to the up-to-dateness of the frames: more recent frames get higher weights than earlier ones, etc. However, in this work the different possible strategies to include many preceding frames are not further analysed, since our focus is put on a fast changing environments for which the in-frame adjustment has been invented. In these scenarios there is either no existing knowledge, then the initial frame size equals $F_0 = 1$, or, if present, the MSE estimate of the very last frame serves as initial frame size.
In the RF-ID standard EPCglobal Class 1 Gen 2 (ISO/IEC 18000-6 D) the frame size can only be adjusted in powers of two to facilitate the random number generation residing in the passively powered tags. Consequently, a relevant

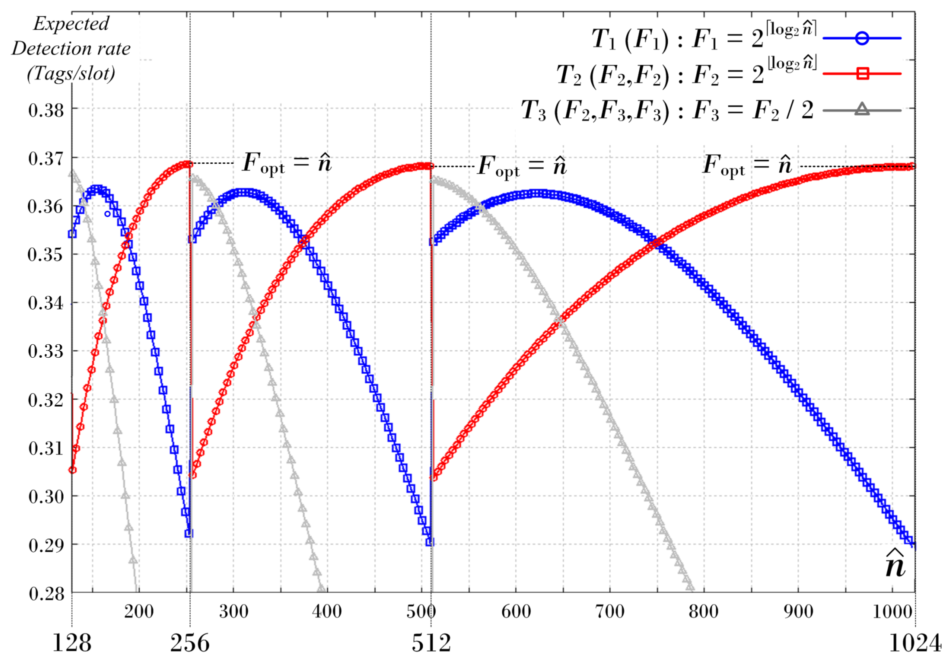

Fig. 2. Throughput functions for optimal adjustment of the new frame size.

implementation aspect is concerned with the decision, which of both possible powers of two for the frame size is actually taken, since the estimated value $\hat{n}$ lies between them in most cases. The property to be maximised by this decision is the throughput T, i.e. the number of correctly detected tags per slot. As already stated before, this value is calculated by the quotient of the expected number of singleton slots and the current frame size $\frac{E(\mathcal{X}_1)}{F}$. For our decision two different throughput functions have to be compared. The first throughput function T_1 follows from the adjustment of the new frame size to the higher one of both powers of two $F_1 = 2^{\lceil \log_2 \widehat{n} \rceil}$ as it is formulated in (6):

$$T_1 = \frac{1}{F_1}\,\widehat{n}\,(1 - \frac{1}{F_1})^{\widehat{n}-1} \tag{6}$$

The first term of the second throughput function T_2 is analogously defined with the lower power of two $F_2 = 2^{\lfloor \log_2 \widehat{n} \rfloor}$. But in T_2 a second term is added to include that expectation value for the remaining tags being distributed over a succeeding number of F_2 slots, since $F_1 = F_2 + F_2$ then represents the same *time* dimension:

$$T_2 = \frac{1}{F_2 + F_2}\left(\underbrace{\widehat{n}\,(1 - \frac{1}{F_2})^{\widehat{n}-1}}_{E_{1,2}} + (\widehat{n} - E_{1,2})\,(1 - \frac{1}{F_2})^{\widehat{n}-E_{1,2}-1}\right) \tag{7}$$

In Figure 2 the throughput functions have been plotted for the interval $\widehat{n} \in [128, 1024]$ to visualise the thresholds. A third curve has been added illustrating the expected throughput T_3 for the frame adjustment to F_2 followed by two frames sizes F_3 with half the size of F_2. This third curve results from the same decision F_2 instead of F_1 as first frame size, but shows how consecutive adjustments (F_3 as second and third frame size instead of a single second F_2) raise the expected throughput curve towards its optimal value again. With these thresholds the following look-up table can be computed to guide the decisions which frame size optimises the throughput in the MSE (or any other) algorithm.

$\widehat{n}$	F
1 ... 1	1
2 ... 3	2
4 ... 5	4
6 ... 11	8
12 ... 23	16
24 ... 46	32
47 ... 93	64
94 ... 187	128
188 ... 374	256
375 ... 749	512
750	1024
etc.	

Tab.1. Frame size thresholds to optimise throughput.

With this knowledge an MSE based algorithm to adjust the frame size can be formulated, as it has been done in Listing 1.1. Initially in Line 1, the frame size F is set to one, when there is no a-priori knowledge available. N is the number of slots already noticed and equals zero, and variable C controls when precisely the MSE estimation shall take place and is set to four. The variable `n_est` ($\widehat{n}$) holds the estimated number of tags in the field and `n_rec` counts the already recognised tags. With the control points C the accuracy can be traded-off against the computational overhead, i.e. the number of MSE evaluations. In Line 3, a loop is entered, in which the current slot is processed and the current slot number is incremented (Line 4). The loop is terminated, when the last frame has been processed completely without any collisions (Line 6). When a control point or end of frame is reached (Line 8), the MSE estimator is invoked returning a new estimate $\widehat{n}$ for the given event $\langle m_0, m_1, m_c \rangle$ (Line 9) under the current parameters F and N. The current evidence is combined with all evidences from earlier estimates within the current frame (typically, the frame size has been adjusted several times). This function takes the completely observed evidence of the current run in from of the m estimates $\widehat{n}_1(F_1, N_1), ..., \widehat{n}_m(F_m, N_m)$ and computes the following weighted average to obtain a global estimate for the initial tag population:

$$\widehat{n} = \frac{\sum_{i=1}^{m} \frac{N_i}{F_i} \widehat{n}_{,i}(F_i, N_i)}{\sum_{i=1}^{m} \frac{N_i}{F_i}} \tag{8}$$

In case the current frame size is not appropriate to detect the remaining tags `n_est-n_rec`, the frame size is updated in Line 14-17. When the frame size is increased, the C is doubled to include more evidence for the next control point (Line 18). When the frame size is decreased, the control point keeps its size restricted to the interval $[4, F/2]$. Hence, it is ensured that with every new frame size adjustment more evidence is taken into account, but at the latest after half the frame a check point is invoked.
Note that the design of this algorithm allows for the replacement of the MSE estimator by any other preferred technique, for instance the maximum likelihood estimator [4] or the classical approach firstly presented by Schoute [8].

Listing 1.1. Pseudocode for an MSE based FSA algorithm

```
 0 MSE_Algorithm() {
 1   F = 1;  N = 0;  C = 4;  n_est = 1;  n_rec = 0;
 2
 3   while (true) {
 4     Event<m0,m1,mc> = processCurrentSlot();  N++;
 5
 6     if (N == F && mc == 0) break; // TERMINATION
 7
 8     if (N == C || N == F) {       // Check point
 9       n_new = MSE_Estimator(Event<m0,m1,mc>,F,N) - m1;
10       n_est = collectEvidence(n_new, N, F, n_rec);
11
12       F_new = ThroughputTable(n_est-n_rec);
13
14       if (F_new != F) {
15         SendQueryAdjust(F_new);  F = F_new;  N = 0;
16         if (F_new > F) C = 2*C;
17       }
18       C = min(C, 1/2*F_new); C = max(4,C);  n_rec += m1;
19     }
20   }
21 }
```

5 Results

Before the feasibility of the MSE based algorithm is evaluated, the general performance of the MSE estimator is analysed. To obtain a clear picture of different techniques to estimate the tag population, the expected error of the estimation functions ($\widehat{n}_x = \widehat{n}_{\mathrm{ML}}$, $\widehat{n}_{\mathrm{MSE}}, \widehat{n}_{\mathrm{Schoute}}$) testifies to the quality of the estimators.

We sum up the errors of the estimation functions over the complete possible event space for a given parameter set and weight the summands by their occurrence probability:

$$\varepsilon_x(F,N,n) = \sum_{\langle m_0,m_1,m_c\rangle} |\widehat{n}_x - n| \; P(\langle m_0,m_1,m_c\rangle : F,N,n) \tag{9}$$

A closed form for the occurrence probability P of an event $\langle m_0,m_1,m_c\rangle$ under the given parameters N,F,n has been recently published by Knerr et al. [4].

In Figure 3 the cumulated errors $\varepsilon_{\mathrm{MSE}}$, $\varepsilon_{\mathrm{ML}}$, and $\varepsilon_{\mathrm{Schoute}}$ have been plotted over the observed $N = 1\ldots F$ slots for the random experiment with $F = 32$, and $n = 20, 50$. Similarly, Figure 4 plots a different scenario with $F = 64$, $n = 50, 100$. Apparently, for all estimators the quality of the result improves the more of the

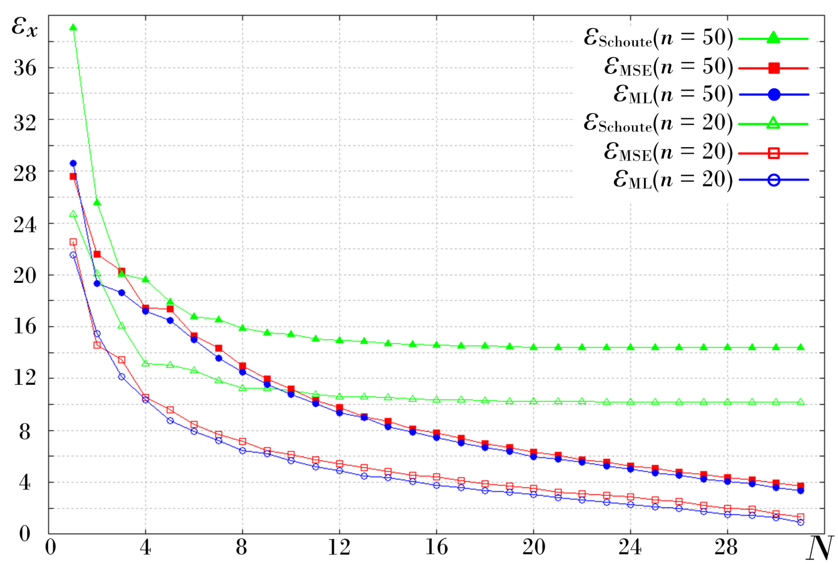

Fig. 3. Cumulated error ε for the MSE, ML and the Schoute estimators for $F = 32$ and $n = 20, 50$.

current frame has been observed ($N \to F$). Note, that for very low values of N, the event $m_c = N$ for which the MSE and the ML estimators cannot apply their gradient search, becomes 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 via Schoute's estimator [8] to be $\widehat{n} = 2.39 m_c \frac{F}{N}$, which has been shown to provide a reasonable estimate, although with a much lower quality than the MSE and ML estimator when compared over the complete event space.

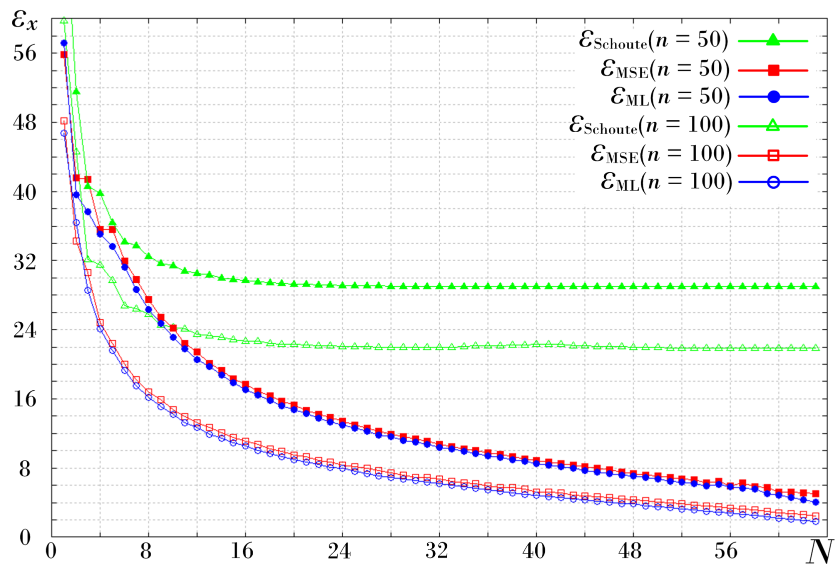

Fig. 4. Cumulated error ε for the MSE, ML and the Schoute estimator for $F = 64$ and $n = 50, 100$.

Hence, the behaviour depicted for $N < 5$ may deviate from this general observation. But more importantly, the MSE estimator reveals a near optimal estimation quality for the full event space for any observed number of slots during frame processing. The ML estimator represents the lower bound for any stochastic estimation technique in this scenario as long as there is no additional knowledge of the tag population available.

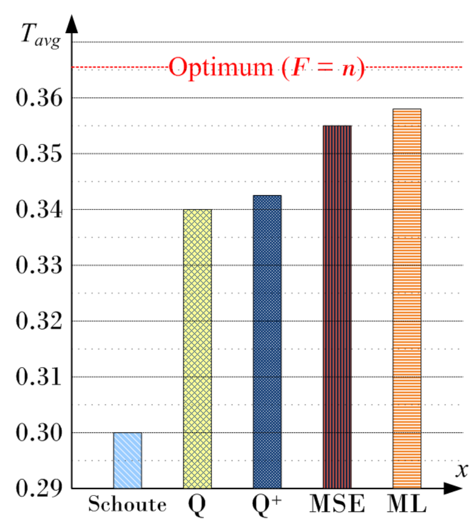

Fig. 5. Measured throughput for all algorithms with in-frame adjustment of F in powers of two.

Finally, the performance of the MSE based algorithm for the on-the-fly adjustment of the frame size is compared to classical Q-algorithm proposed in ISO/IEC 18000-6 D standard and the improved Q^+-extension published recently by Lee et al. [6]. In the first case the constant is set to $1.07 \leq \beta = 2^{0.31} = 1.24 \leq 1.41$, in the second case the parameters are set to $C_c = 0.35$ and $C_i = 0.25$.

The MSE algorithm is applied as outlined in Listing 1.1. Moreover, two further reference values are presented in this comparison: the MSE estimator is either replaced in Listing 1.1 by the ML estimator or by Schoute's estimator yielding two more algorithms.

The bar chart in Figure 5 depicts the achieved throughput in a test scenario, in which in a single run a tag number n is randomly generated between 1 and 512. Any of the aforementioned algorithms is applied and the number of required slots S is counted until all n tags have been recognised, hence yielding a measured throughput of $T(x) = n/S$, with $x \in \{\text{Schoute}, \text{Q}, \text{Q}^+, \text{MSE}, \text{ML}\}$. The results are averaged for $1,000$ runs for any algorithm ($T_{avg}(x) = \frac{1}{1000} \sum_{i=1}^{1000} T_i(x)$), and the initial frame size of all algorithms is set to $F = 16$. The red line indicates the achievable optimum, when the tag number $n \in [1, 512]$ is known and the frame size F can be adjusted to match precisely, instead to match only powers of two. It can be observed that the MSE based algorithm is only second to the maximum likelihood estimator by a very small margin of 0.0031 detected tags per slot. Both the Q and the improved Q$^+$-algorithm perform reasonably well and are very good candidates, when a gradient search over the distance function D as in the MSE based algorithm is already too time-consuming. The maximum likelihood estimator has to undergo a thorough analysis to avoid any fractional, underflow and overflow errors in its new formulation, but reveals naturally the very best estimation performance and therefore the highest throughput.

6 Conclusion

In this paper the minimum squared error estimator for the tag population in FSA anti-collision schemes for partly observed frames has been formulated. Its general near-optimal performance could be demonstrated in comparison with the maximum likelihood estimator. Thorough considerations on how to adjust the frame size optimally in powers of two as demanded by current standards were exhibited and an efficient MSE based algorithm has been proposed that outperforms both the Q and Q$^+$-algorithm without requiring excessive computation.

Future work will concentrate on the implementation of all anti-collision schemes in an existing rapid prototyping environment for the HF and UHF domain [1], in which the real effects of the communication channel between reader and tags onto the anti-collision procedure can be measured and analysed.

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