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Improved Linearized Combinatorial Model (ILCM) for Optimal Frame Size Selection in ALOHA-based RFID Systems

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Abstract—**Radio Frequency Identification (RFID) technology became the most important tool for identification of items and tracking. Nowadays, the most popular in terms of best price-performance ratio is passive RFID technology, where tags are both powered-up and communicating using the same radio waves transmitted via reader antenna(s).**

Since the objects with tags are usually moving in and out of range interrogated by the reader, it is crucial to identify all of them as soon as possible. In order to exchange data, reader and tags commonly use Dynamic Frame Slotted ALOHA (DFSA) transmission scheme, where the communication is divided in the time frames, latter divided in time slots. In DFSA system, tags randomly pick the time slot for the response. To increase tag reading rate it is necessary to set DFSA frame size properly. Calculations show that maximum tag reading rate can be achieved if frame size is set to a number of interrogating tags. Since the number of tags is generally unknown, it should be estimated correctly and the frame size set properly.

In this paper we present the state of the art in the tag estimate methods along with performances of Q-Selection algorithm, a simple mechanism for frame size adaptation suggested as the standard in Gen2 RFID system. We introduce a new efficient optimal frame size selection method denoted as Improved Linearized Combinatorial Model (ILCM). Simulations results show that ILCM outperforms Q-Selection.

Index Terms—**Dynamic Frame Slotted ALOHA, Tag Estimate Method, Optimal Frame Size Selection**

I. Introduction

RFID technologies based on the wireless communication between reader and tag, represent the great innovation in the application of items tracking and identification. Such technology provides the edge infrastructure for the Internet of Things (IoT) final implementation. Regarding tags battery presence or absence, RFID technology can be divided into battery-powered active, battery assisted passive (BAP) and battery free (passive) RFID technology [1].

Active RFID enables tag reading ranges up to 100 meters, but due to tag robustness, price of about 100 USD and battery limited lifetime makes active RFID with limited spectra of usage. To reduce tag size and price, but remain with reading distances up to 40 meters, one can consider BAP RFID usage. Battery in BAP tags is used to power tag circuitry, while the communication is same as in the battery free passive RFID, where tags both communicate and power themselves using same RF waves radiated by reader antenna. An overview of advantages and disadvantages of different types of RFID systems can be seen in [2]. Due to size of about 15 centimetres of width and 1 centimetre height, price of about 0.1 USD per tag and reading range of up to 15 meters, passive RFID became the most popular technology in terms of price-performance ratio.

Typical passive RFID system implementation includes the portal equipped with RFID reading antennas, and a pallet of products with passive RFID tags attached and moved through the area. To increase the performance of such typical passive RFID systems it is crucial to increase tag reading rate, i.e. to identify all the tags as soon as possible.

In order to reduce RFID equipment manufacturing costs and make reader-tag communication worldwide available, EPC-global [3] developed set of standards to support reader-tag communication. As a part of of EPCglobal, Gen2 protocol [4] specifies physical and Medium Access Control (MAC) strategies to support Ultra-high frequency (UHF) reader-tag communication. Gen2 generally allows only one tag identification at the time (this excludes capturing effect, where due to greater signal level one of tags can be successfully decoded). Furthermore, to make passive RFID tags work, it is necessary to deliver enough power to energize tags and make them to respond with required information. Energy levels tags can harvest are small and they cannot afford themselves energy inefficient MAC schemes.

Generally, MAC in RFID is random based and can be divided into binary-tree and ALOHA-based protocols [1]. In binary tree protocols [5], [6], reader can through consecutive YES/NO interrogation reach targeted tags in order to identify them, while ALOHA based algorithm initiates information transmission in the time when reader requests. The most used due to its maximum efficiency is Dynamic Framed Slotted ALOHA (DFSA) protocol [7] with RFID style implementation given in Gen2.

To maximize DFSA throughput and identify all tags as soon as possible, it is necessary to correctly estimate the number of interrogating tags and set size of the next frame accordingly. In this paper we describe state of the art methods for the frame size adaptation. Such methods usually include the number of calculations prior tag number estimate. As a consequence, time of its calculus may cause delay for tags identification. Through stated disadvantages of state of the art methods, we provide Improved Linearized Combinatorial Model (ILCM), which uses only modest calculation operations, and can be easily implemented and applied as tag estimate method. To provide its performances we compare our algorithm with Q-

Selection algorithm presented in Gen2 standard.

This paper is structured as follows: in the next section we describe DFSA-based implementation in RFID system and we provide state of the art methods for the frame adaptation. In the Section III. we present our tag estimate method called Improved Linearized Combinatorial Model (ILCM). In the Section IV. we provide results analysis. Section V. gives concluding remarks and directions for the future work.

II. DFSA Random Access in RFID and Related Works

In DFSA, the communication is divided into frames, which are then divided in the time slots. In real RFID DFSA implementation [4], reader announces the size of frame by broadcasting Q, limiting frames to the sizes of 2^Q. When tags receive Q, they set their slot counters to the random value between 0 and 2^Q-1. Tag(s) with slot counter set to 0 respond back to the reader (its time slot is interrogated). As the next step, reader issues command to decrement tags slot counters by 1. Afterwards, tags with slot counter set to 0 respond back to the reader. Number of slot counter decrease commands being broadcast by an reader is 2^Q-1, which interrogates all time slots of the given frame. Regarding time slot occupancy, there are tree possible scenarios:

- There is no response within the slot (empty slot),
- There is single response within the slot (successful slot),
- There is multiple response within the slot (collision slot).

Example of the interrogation frame is given within the Figure 1.

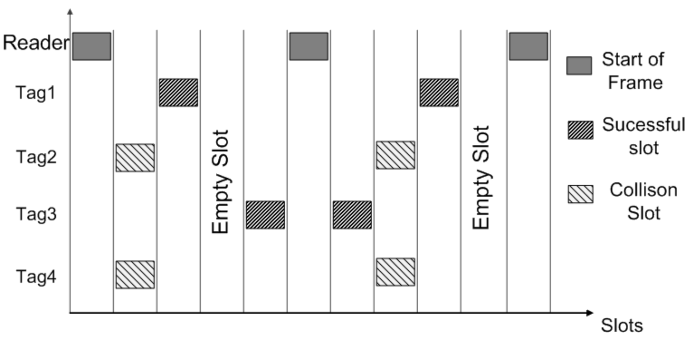

Fig. 1. Example of RFID reader-tag interrogation round with 2 time frame sizes of 4, and with 4 tags in the interrogation area.

DFSA system throughput is given with [8]:

$$U(n,p) = np(1-p)^{(n-1)} \tag{1}$$

where p is the probability of finding a tag within the slot of the frame, given as $1/L$, where frame size is L and n represents total number of tags being interrogated. Maximum throughput is obtained for (1) first derivative equal to 0, which results in:

$$\frac{dU(n,p)}{dp} = n(1-p)^{(n-2)}((1-p)p(n-1)) = 0 \tag{2}$$

Maximum is obtained for $p = 1/n$, i.e. when the number of tags equals frame size ($n = L$). Such case yields maximum throughput of DFSA, given as $1/e = 0.368$. To maximize the throughput, it is necessary to estimate the number of tags ($\hat{n}$) and set the frame size to round($\log_2(\hat{n})$).

In real scenarios, reader can cancel interrogation of given slot if there is no response within, or send another command when collision occur in order to require lost information from collided tags. Such scenarios gives different duration of different timeslots, which means that (1) should be modified accordingly. With aim to simplify frame adaptation model, without of loosing generality, we consider choosing frame size equal to tag estimate ($L = n$).

Many previous works address the issue of estimating correct number of tags, which are mainly based on the information of the number of Empty (E), Successful (S) and Collision (C) slots collected from the previous frame. In the next subsection we provide state of the art tag estimate algorithms.

A. Tag Estimate methods

Vogt's [9] tag estimate describes slot occupancy through binomial distribution, i.e. the probability of finding r tags in one slot is given with:

$$B_{n,1/L}(r) = \binom{n}{r}\left(\frac{1}{L}\right)^r\left(1-\frac{1}{L}\right)^{n-r} \tag{3}$$

where L stands for the frame size, and n for the number of tags. According to (3), empty slot can be described with probability $p_e = B_{n,1/L}(0)$, successful slot with $p_s = B_{n,1/L}(1)$, and probability of collision slot is the given with $p_c = B_{n,1/L}(\geq 2) = 1 - p_e - p_s$. Using p_e, p_s, p_c, associated expect values of number of empty $a_0 = E(B_{n,1/L}(0)) = LB_{n,1/L}(0)$, successful $a_1 = E(B_{n,1/L}(1)) = LB_{n,1/L}(1)$ and collision $a_{\geq 2} = E(B_{n,1/L}(\geq 2)) = LB_{n,1/L}(\geq 2)$ slots can be calculated. If the probabilistic observation is correct, then the expected values should be near its realization. Stated property can be used as

$$\epsilon_{vd} = \min_n \left| \begin{pmatrix} a_0 \\ a_1 \\ a_{\geq 2} \end{pmatrix} - \begin{pmatrix} E \\ S \\ C \end{pmatrix} \right| \tag{4}$$

Given relation is known as the Mean Square Error (MSE) tag estimate.

Chen [10] considers tags in the frame multinomial distributed:

$$P(E,S,C) = \frac{L!}{E!S!C!} p_e^E p_s^S p_c^C \tag{5}$$

To calculate p_e, p_s and p_c Chen used same binomial model (3) as Vogt did. Once the the frame is realized, i.e. the E, S and C is obtained, then *a posteriori* distribution is:

$$\begin{aligned} P(n|E,S,C) = \frac{L!}{E!S!C!} &\times \left[\left(1-\frac{1}{L}\right)^n\right]^E \\ &\times \left[\frac{n}{L}\left(1-\frac{1}{L}\right)^{(n-1)}\right]^S \\ \times \left[1-\left(1-\frac{1}{L}\right)^n - \frac{n}{L}\left(1-\frac{1}{L}\right)^{(n-1)}\right]^C & \end{aligned} \tag{6}$$

When $P(n|E,S,C)$ distribution is calculated, Chen suggests finding maximum of given probability distribution, and set tag estimate to that number, i.e. $\hat{n} = \arg\max_n P(n|E, S, C)$. However, Chen did the mistake in the problem modelling, where he considered independence of the number of E, S and C slots.

Improved Chen version, where the number of different slot types is mutually dependent is provided in [11]. Authors provide correct tag estimate model in closed form formulation given by:

$$P(E, S, C) = \frac{L!}{E!S!C!} P_1(E) P_2(S|E) P_3(C|E, S) \tag{7}$$

where $P_1(E)$, $P_2(S|E)$, and $P_3(C|E, S)$ are given with

$$\begin{aligned} P_1(E) &= (1 - \frac{E}{L})^n \\ P_2(S|E) &= \binom{n}{S} \frac{(L - E - S)^{n-S}}{(L - E)^n} S! \\ P_3(C|E, S) &= \sum_{k=0}^{C} \sum_{v=0}^{C-k} (-1)^{(k+v)} \binom{C}{k} \binom{C - k}{v} \\ &\times \frac{(n - S)!}{(n - S - k)!} \frac{(C - k - v)^{(n-S-k)}}{C^{(n-S)}} \end{aligned} \tag{8}$$

The same model based on used the exponential generating functions counting technique is given by Floerkemeier's frame by frame estimation [8], [12]. Probability of finding n tags in the realized frame is given with:

$$P(E, S, C|n) = \frac{L!}{E!S!C!} \frac{T(E, S, C, n)}{L^n} \tag{9}$$

where $T(E, S, C, n)$ is described with the $x^n/n!$ coefficient within the expansion of exponential generating function:

$$\begin{aligned} G(x) &= \left(\frac{x^2}{2!} + \frac{x^3}{3!} + \frac{x^4}{4!} + ... \right)^C x^s \\ G(x) &= (e^x - (1 + x))^c x^s \end{aligned} \tag{10}$$

The main disadvantage of given algorithms is the number of calculations one have to do before providing tag estimate. Moreover, such calculations often includes factorial operations which can yield very large number required for temporary storage. Such demands for calculation could require specific computer architecture on the reader side.

More efficient way to calculate estimate is provided in [13], due to linear dependence of estimated number of tags and number of S for fixed C within the given frame size L. In such observation one can pre-calculate 4 points and establish C equidistant lines between those points. Pre-calculation of required 4 points can be done through

$$p(E, S, C \mid n) = \frac{\frac{S!}{(n-S)!} \left(e^x - (1 + x)\right)^C \mid_{\frac{x^{(L-S)}}{(L-S)!}} \frac{L!}{E!S!C!}}{L^n} \tag{11}$$

Part $(e^x - (1 + x))^C$ represents exponential generating function used to count all possible ways to distribute tags in collision slots.

The improved version with pre-calculation of all points and extrapolation to multiple frame sizes is given in the [14]:

$$\begin{aligned} k &= (1.0569 + 0.0115L) + (-0.172 + 0.0022L)C \\ &\quad +(0.0441 - 0.0013L)C^2 \\ l &= (-3.8 + 0.2336L) + (0.9633 - 0.0314L)C \\ &\quad +(0.2825 - 0.0053L)C^2 \\ \hat{n} &= kS + l \end{aligned} \tag{12}$$

Presented system involves the error in the estimation due to wrong indexation in modelling and does not cover solutions for the frame size less than 8. In this paper we correct errors, and provide full model describing the more correct interpolation method.

The most simple frame adaptation scheme, today suggested in Gen2 standard is Q-Selection algorithm presented in the next subsection.

B. Q-Selection algorithm

Gen2 RFID standard suggests usage of Q-Selection algorithm shown in the Figure 2. Q-Selection for frame adaptation uses only modest math operations which adds or subtracts constant value C_Q in collision or empty slot scenario. Reader starts the interrogation round by broadcasting $Q = 4$, and at the end updates new value $Q = \text{round}(Q_{fp})$, broadcast to collided tags with aim to identify them. Its main advantage is its simplicity in implementation, while main disadvantage is on the way how to choose constant value C_Q, which is not a part of standard specification. Impact on time delay (shown in the mean number of slots required to identify all tags), while changing C_Q value is shown in the Figure 3. As it can be seen, C_Q should be picked out depending on the number of tags, which is in unknown surrounding unknown information. Some papers have been written with aim to optimize Q-Selection, such as [15], where C_Q can be optimized if number of tags is known, otherwise authors suggest usage two different constants (C_c and C_i). C_c should be picked arbitrarily and added to Q_{fp} in collision scenario, while $C_i = (e - 2) * C_c$ should be added to Q_{fp} in the case of empty slot. Our simulations show that the latter scheme, where tag number is unknown puts a little influence on the tag reading rate, due to pick of C_c which should be different for different tag number (n). In [12], authors compare their developed frame adaptation method with tuned Q-Selection algorithm, where the constant is set to $C_Q = (0.8/\log_2 L)$. Such observation improves tag reading rate in small number of tags, but for large n (over 100) the algorithm misses the frame size and causes great identification delay.

In the following section we describe Improved Linearized Combinatorial Model (ILCM), yielding efficient tag estimate method.

III. Improved Linerized Combinatorial Model (ILCM)

Derivation of ILCM is based on works [13], [14]. For the exact tag estimate we considered calculations of combinatorial model (11). Such calculation can be done using open source

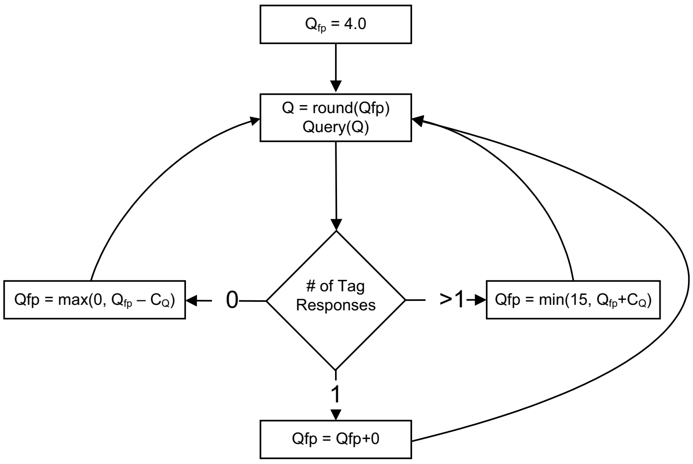

Fig. 2. Q-Selection algorithm suggested for usage in [4], where $0.1 \leq C_Q \leq 0.5$

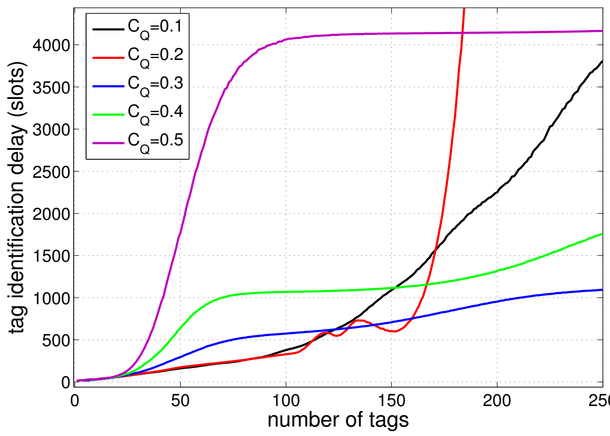

Fig. 3. Q-Selection algorithm performances for different C_Q values.

math tool SAGE (www.sagemath.org). We consider usage of SAGE due to simple handling and operations with generating functions. For example, if we take frame size where $Q = 5$, $L = 2^Q = 32$, we obtain $p(E, S, C \mid n)$ distributions for different realizations of the frame (examples are depicted in the Figure 4). Decision on the expected number of tags $\hat{n}$ is taken where $p(E, S, C \mid n)$ is maximum, i.e.

$$\hat{n} = \arg\max_{n}\{p(E, S, C \mid n)\} \tag{13}$$

Derivation of ILCM is based on linear dependency, where one has to calculate all $p(E, S, C \mid n)$ for fixed frame size, take its maximums and plot it in the way linear property can be seen, i.e. where expected number of tags linearly depends on the number of successful slots for fixed number of collisions. Example of such linearity for the frame $L = 16$ is shown in the Figure 5.

To make the linear model accurate we derived lines from the points obtained from combinatorial model for frames $L = 4$, $L = 8$, $L = 16$, $L = 32$ and $L = 64$. Using calculated estimates and its linear behaviour we provide function which interpolate slopes and $\hat{n}$-intercepts for different frame sizes

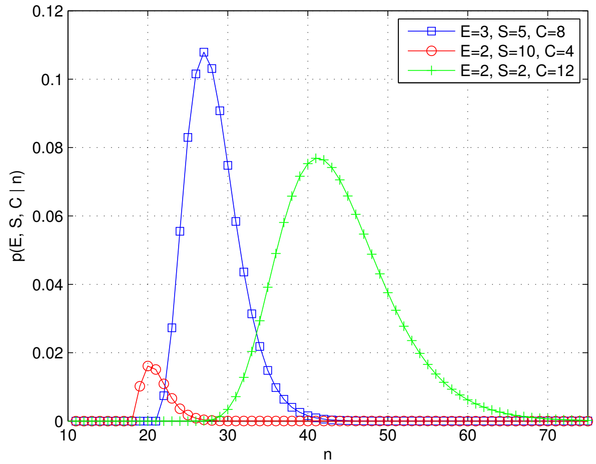

Fig. 4. Examples of $p(E, S, C \mid n)$ distributions, for different frame realizations it its size equals 16. We estimate number of tags as: $\hat{n} = \arg\max_n\{p(E, S, C \mid n)\}$

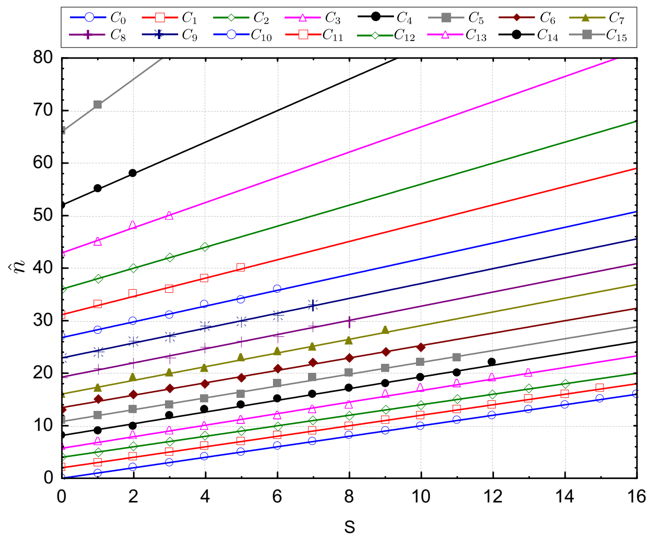

Fig. 5. Linear dependency of estimated number of tags $\hat{n}$ for the number of successful slots S for the fixed number of collisions C in the frame $L = 16$. All points are obtained from combinatorial model (11) given in [13].

as is depicted in Figures 6 and 7. Such interpolation method yields following tag estimate method:

$$\begin{aligned} k &= (1.2592 + 1.513L)\tan(1.234L^{-0.9907}C) \\ l &= \frac{C}{(4.344L - 16.28) + \left(\frac{L}{-2.282-0.273L}\right)C} \\ &\quad +0.2407\ln(L + 42.56) \\ \hat{n} &= kS + l \end{aligned} \tag{14}$$

Further, estimate (14) should be bounded in two cases:

- There are possible negative k's for small frame sizes, i.e. if $k < 0$, it should be set to $k = 0$
- In cases of no collision slots within the frame, its estimate error rises, i.e. if $C = 0$, tag estimate should be set to $\hat{n} = S$

Given method is simple to apply and does not involve the

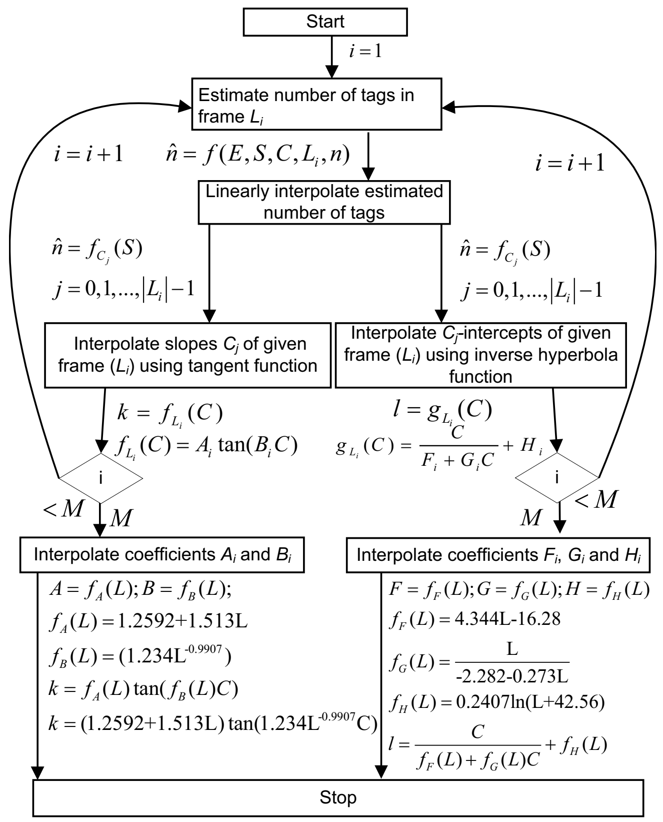

Fig. 6. State diagram for deriving Improved Linearized Combinatorial Model (ILCM). Our frame adaptation scheme given in (14), where $M = 5$ and $L_i = 2^{i+1}$

number of calculations before providing its estimate. In the following section we provide the results obtained from DFSA tag identification simulations.

IV. Simulation Results

The process of identification in Gen2 RFID system works through the rounds containing multiple frames within all tags get identified. After the first frame of the first round is realized, Q value is changed (according to its tag estimate) and broadcasted as an information for the size of next time frame of its round. Current round is not finished until all tags get identified. Once the round is complete, reader begins another round to again identify all tags. Such simulations were conducted through exhaustive Monte-Carlo simulation (10000 random experiments for each number of tags) of Gen2 process of identification, with aim to obtain convergence of results. Described identification process have 2 specific cases to be specified and which we consider in our simulations:

- To sense the environment, the first frame size should be set to some value regarding the nature of the identification process. The impact on choosing correct first frame size is shown in [10]. Larger first frame size for the larger tag number will reduce tag identification time due to reduced number of collisions. But, if there is smaller group of tags to identify, large size of the first frame will cause delay due to large number of empty slots occurred. To follow [4] we set the first frame size to $L = 16$, i.e. set $Q = 4$.

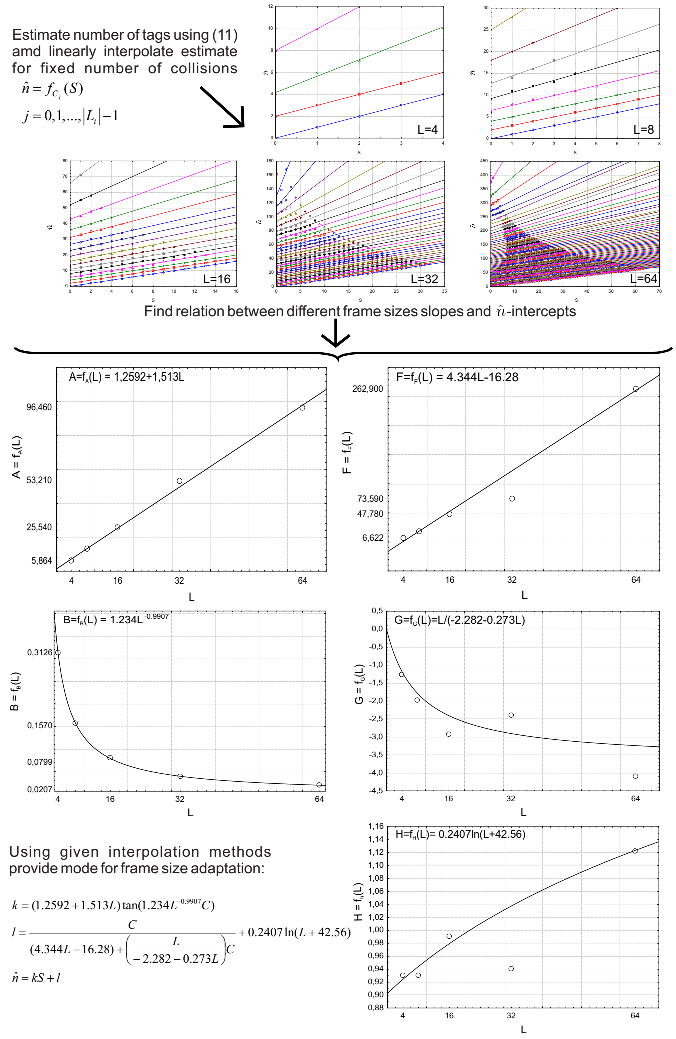

Fig. 7. Interpolation functions used for deriving Improved Linearized Combinatorial Model (ILCM)

- Another issue in the simulation is the all collision scenario. From such scenario, one cannot extract any information (without information about tag distribution in the area of interrogation) there may be any large number of tags causing all collisions. In the case of all collisions we set next frame size as $Q_{new} = Q_{current} + 2$.

In the Figure 8, we present the performance of ILCM algorithm, Q-Selection and perfect tag estimate. Perfect tag estimate sets the frame size to $Q = \log_2(n)$, where n stands for known number of tags being interrogated. For comparison with Q-Selection we used $C_Q = 0.3$, due to smallest delay for the large n as it can be seen in the Figure 3. ILCM provide worse results from Q-Selection if $61 \le n \le 113$ and $C_Q = 0.2$ or $C_Q = 0.1$, where in the worst case Q-selection identifies 106 tags in 130 slots faster than ILCM. This is due to better treatment of all collision scenario for the first $Q = 4$. In such scenarios Q-Selection can be used, but for larger n system would become inefficient.

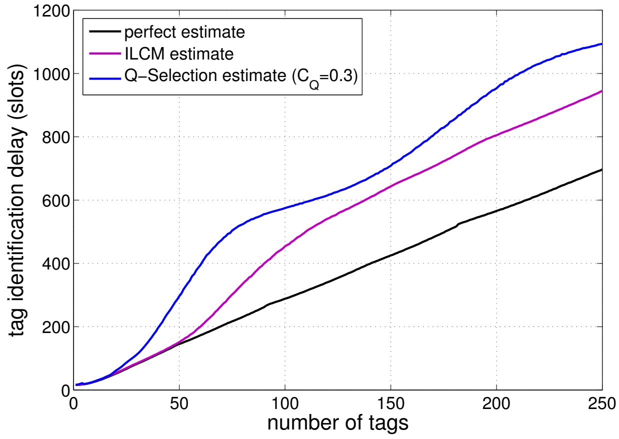

Fig. 8. Mean number of slots required to identify all tags for the perfect tag estimate, where tag number is known, ILCM tag estimate method and Q-Selection tag estimate ($C_Q = 0.3$).

V. Conclusion

In this paper we introduced a new method (ILCM) for optimal frame size selection in Gen2 RFID system. The proposed method provides tag estimate by calculating only 2 variables (k and l) which yields tag estimate for every frame size. Its computing complexity is low compared to state of the art methods. Exhaustive Monte-Carlo simulations in 10000 experiments of tag identification process have been conducted in order to obtain convergence of results. Simulation results show that ILCM significantly outperforms Q-Selection regarding delay in tag identification for any number of tags.

Comparison with the other algorithms as well as the analysis in terms of tag identification time and computational complexity is left for the future research. Further research will also include implementation of proposed algorithm using Software Defined Radio Gen2 application.

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