The Optimal Reading Strategy for EPC Gen-2 RFID Anti-Collision Systems

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***Abstract*—The anti-collision mechanism is an important part in Radio-frequency Identification (RFID) technology. Recently, many anti-collision algorithms were designed based on the EPCglobal standards. These works mainly focused on the tag population estimation. But they chose frame size based on the classical results of Random Access (RA) systems. We show that a new theory is needed for the optimization of the RFID systems as they have characteristics very different from the RA systems. We model the reading process as a Markov Chain and derive the optimal reading strategy through first-passage-time analysis. We show that the optimal strategy can be easily incorporated into the EPCglobal standards to give significant performance improvement.**

***Index Terms*—RFID anti-collision systems, algorithms, optimization methods, communcation system performance.**

I. Introduction

In Radio-frequency Identification (RFID) systems, tags share a common communication channel. Therefore, if multiple tags transmit at the same time, their packets will collide and get lost [1]. Passive tags have bare-bone functionality and no embedded power supply. They cannot sense the media or cooperate with one another. The RFID reader needs to coordinate their transmissions to avoid collisions. Depending on working principles, RFID anti-collision algorithms in literature can be divided into three main classes: Tree based algorithms [5][6], Framed Aloha (FA) based algorithms [8-16] and Interval based algorithms [7]. Among these, only FA based algorithms are widely used in RFID communication standards [2-4] for their simplicity and robustness.

In different literature, there are variations on the working mechanisms of FA based RFID systems, but not all of them are used in real applications. Up to now, the most popular RFID system is the one defined in the EPCglobal Class 1 Generation 2 standards [2]. We summarize its anti-collision mechanism as follows:

1) The reader starts a frame by broadcasting a special command 'QueryAdjust' with a parameter L[1]. Each tag chooses a random value from 0 to $L-1$ as its transmission delay. Those generating '0' contend the channel immediately.
2) The reader uses the 'QueryRep' command to ask tags to decrement their counters by 1. Tags contend the channel when their counters reach 0.
3) When contending the channel, the tag only sends a short packet containing its temporary ID. In EPCglobal standards, this 'ID' is named 'RN16' (random number 16 bits). If only one tag replies, the reader can receive this short packet successfully.
4) The reader has a set of *operation* commands: reading data, writing new data, changing password, etc. After receiving a temporary ID, the reader can select a particular tag by including its ID in the operation commands.
5) The reader can send a *silence* command[2] to a selected tag. Silenced tags will not contend the channel in future frames.
6) The reader can use the 'QueryAdjust' command again even before all tags' counters reach 0. When hearing this command, unsilenced tags regenerate their counter values according to the new frame size.

RFID systems satisfying the above properties are called **Gen-2 RFID systems**, or EPCglobal RFID systems. One feature of this system is the 3-way handshaking mechanism. (The reader sends a *query*; tags reply their temporary ID; the reader sends the temporary ID back in operation commands.) Conventionally the time from the point that the reader sends out a *query* to the point that the tags finish replying their temporary IDs is called a *contention time slot*, or just *slot* for short. Since the communication after the 3-way handshaking is collision-free, the time involved does not depend on the anti-collision strategy. Therefore, the performance of anti-collision algorithms is conventionally compared by their average contention time measured by the number of contention slots. Another feature is frame cancellation. The reader can initiate a new frame using the *'QueryAdjust'* command whenever the current frame size is found unsuitable. So a Gen-2 algorithm should specify how to choose frame size and when to cancel a running frame.

The goal of algorithm design is to minimize the average contention time T. Unfortunately, T cannot be expressed explicitly as a function of L. So previous research [8-15] uses the expected instantaneous throughput U as the optimization objective instead. In Random Access theory, a classical formula to calculate the throughput U with terminal population N and frame size L is given in [10] as:

$$U(N,L)=\frac{N}{L}\left(1-\frac{1}{L}\right)^{N-1}. \tag{1}$$

In (1), U can be optimized by setting the frame size equal to the terminal number, or $L=N$. Based on this, previous

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[1]In EPCglobal standards, the frame sizes are limited to 2^Q, where $Q=0,1,\ldots,15$. In this paper, we consider both this special case and the general case where $L\in\mathbb{Z}_{++}$.

[2]In some literature, this command is also referred to as *Kill* command. In EPCglobe standards, it corresponds to the *Select* command, which have other uses besides silencing a tag.

algorithms [8-15] either directly set the frame size L equal to $E[N]$ or try to find an optimal L to maximize U for a given probability distribution of N. However, these approaches are not suitable because maximizing U in every frame will not necessarily minimize the average contention time. As we will show later, optimizing L based on (1) will only yield a frame-local optimal result, and the concatenation of locally optimal results are usually far from the globally optimal one.

In this paper, we model the reading process as a Markov Chain and derive the optimal reading strategy through first-passage-time analysis. To the best of our knowledge, it is the first time that the performance bound of the Gen-2 RFID system is rigorously derived. We show that the optimal strategy can be easily incorporated into the EPCglobal standards to give significant performance improvement with minimum increase of the system complexity.

In section II, we give a survey of the traditional algorithms and show why a new theory is needed. In section III, we derive the optimal reading strategy for the precise estimation case. In section IV, we generalize the strategy to the imprecise estimation case and show the simple use of it in EPCglobal standards.

II. A Survey of Previous Works

In real applications, the number of tags are unknown before identification. So a proper FA algorithm always contains two parts: **Population Estimation** part and **Reading Strategy Determination** part. The first part is for estimating the tag population based on tags' replies while the second part is for adjusting the parameter, such as the frame size, using the estimation. Based on the difference in the Estimation part, algorithms can be divided into: the max-likelihood approach and the probability distribution approach.

A. The Max-likelihood Approach

Schoute [10] noticed that when N is large and L suitably chosen (say $L \approx N$), the number of tags contending each slot has a Poisson distribution with mean 1. So in the *Population Estimation* part, his algorithm uses $\hat{N} = \text{round}(2.39 s_c)$, where s_c is the number of collided slots in the last frame. Based on this, in the *Reading Strategy Determination* part, the frame size is set as

$$L = \hat{N}. \tag{2}$$

This choice is based on (1). It tries to maximize the instantaneous throughput by setting the frame size equal to the expected terminal number.

Vogt [11] improved the *Population Estimation* strategy of Schoute's algorithm by using the statistics of empty slots s_e and singleton slots s_s in addition. Tag population is estimated to be the value $\hat{N}$ that minimizes the error between the observed values of s_e, s_s, s_c and their expected values using $\hat{N}$. In the *Reading Strategy Determination* part, it also uses (2).

Kodialam [16] proposed an new *Population Estimation* strategy based on the Central Limit Theorem. That is when the number of contending tags is large enough, the number of collision slots and empty slots in a frame should obey the Normal distribution. Thus using his method, one may obtain the estimation accuracy as well as the max-likelihood tag population. But after deriving $\hat{N}$, it also sets $L = \hat{N}$.

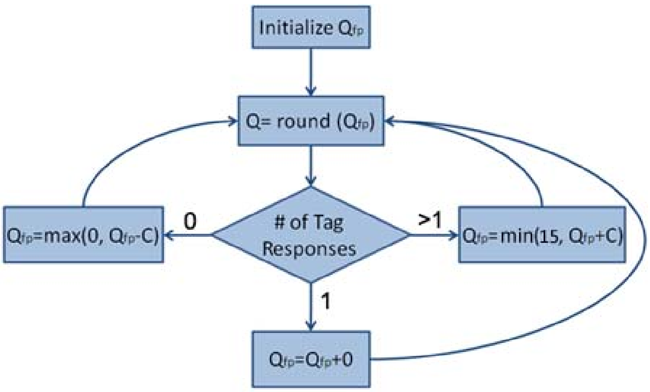

Fig. 1. The tag population estimation strategy of the Q algorithm.

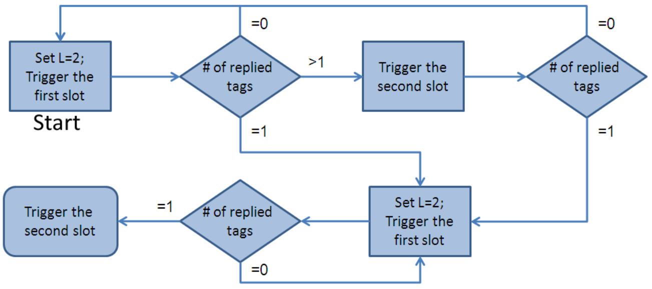

Fig. 2. The optimal strategy to read three tags.

Another example is the Q algorithm in EPCglobal standards [2]. As shown in Figure 1, the RFID reader maintains a floating-point variable Q_{fp}. It decreases a typical value C when no tag replies, increases C when multiple tags reply and stays unchanged when only 1 tag replies.[3] The tag population is estimated as $\text{round}(2^{Q_{fp}})$ while the frame size is set to 2^Q, where $Q = \text{round}(Q_{fp})$. In [13][14], the efficiency of the Q algorithm was obtained with different choices of C and Q_{fp} and some methods to improve the estimation strategy were proposed.

In summary, algorithms of this type compute the maximum-likelihood tag population $\hat{N}$ based on the reading results and set $L = \hat{N}$ as the frame size. The advantage is simplicity. In Q algorithm, the reader only needs to perform the '*add*' operation once every time slot.

B. The Distribution Approach

Floerkemeier [12][15] assumes that a rough estimation of the target group size is always available in the form of a distribution $\Pr\{N = n\}$. As a new *Population Estimation* strategy, it updates the population distribution by Bayesian method based on tags' replies. In the *Reading Strategy Determination* part, the frame size is chosen as

$$L^* = \left\{ L : \max_{L \in \Upsilon} \sum_{n=0}^{N_{max}} U(N = n, L) \Pr\{N = n\} \right\}, \tag{3}$$

[3]In EPCglobe standards, it is recommended that $0.2 \le C \le 0.5$ and the initial $Q_{fp} = 4$

where Υ is the set of possible frame sizes while $U(N, L)$ is calculated by (1). A running frame will be canceled when the updated distribution prefers another value of L^* according to (3).

This approach can track the value of N more accurately. The tradeoff is complexity. In every time slot, the reader needs to do Bayesian update N times and optimize L according to (3).

C. The Need for a New Model

As we can see from this review, previous work focused on the *Population Estimation*. On the other hand, the *Reading Strategy Determination* part is underdeveloped. All the algorithms in literature use (1) for calculating throughput. As we mentioned before, (1) is obtained from the theory of Random Access (RA) system. Since a terminal in RA system would still attempts the channel after a successful transmission, the 'contending group' can be assumed unchange during a long enough period. The long-term throughput of an RA system is therefore equal to the expected instantaneous throughput U calculated by (1). However, in RFID systems, identified tags are silenced by the reader, leading to tag population decrease during the reading process. When the frames are not identical, a concatenation of locally optimal solutions is not globally optimal. As an example, suppose the target group contains exactly 3 tags. From (1), the suitable frame size should be $L = 3$ and the efficiency is $U = 0.44$. However, if we choose $L = 2$ and follow the strategy in Figure 2, the efficiency can achieve 0.6.

In this paper, we focus on the *Reading Strategy Determination* part. Based on a given $\hat{N}$, no matter which estimation method is used[4], we derive the *Optimal Reading Strategy* that can minimize the expected contention time.

III. Optimal Reading Strategy with Precise Population Estimation

To derive the optimal reading strategy, we first assume the estimated tag population $\hat{N}$ is precise, or $\hat{N} = N$. This assumption will be removed in section IV. In subsection A, we derive the **System State** for the optimal reading strategy. In subsection B, we model the reading process by a Markov Chain and derive the **System Equation** which establishes the functional relationship between the System State and the expected contention time. In subsection C and D, the System Equation is solved analytically and numerically.

A. System State

Figure 3 shows an intermediate step of the reading process. Let L denote the frame size and N denote the unresolved tag population at the beginning of a frame. For ease of referencing, we list the major variables used in the analysis in Table 1. In this section, we assume N is precisely available from the estimation. With this assumption, we can focus on the reading strategy part. Further let S_E, S_S and S_C denote the number

TABLE I
TABLE 1: MAJOR VARIABLES

L	the current frame size
N	the tag population at the beginning of the current frame
S_E	the number of empty slots in the current frame
S_S	the number of singleton slots in the current frame
S_C	the number of collided slots in the current frame
S_R	the number of remaining (untriggered) slots in the current frame $S_R = L - S_E - S_S - S_C$
N_R	the number of tags in the remaining slots
N_U	the number of unresolved (unsilenced) tags $N_U = N - S_S$
r_e	the probability that the next slot is empty
r_s	the probability that the next slot is singleton
r_c	the probability that the next slot is collided

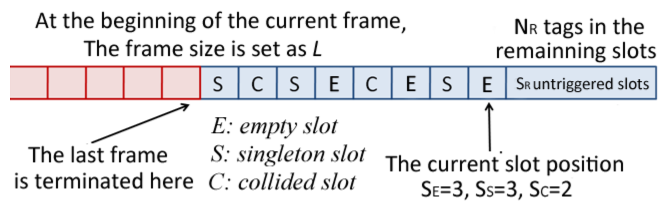

Fig. 3. The reading process of Gen-2 algorithms.

of empty slots, singleton slots and collided slots up to the current slot in the current frame. To illustrate, the current slot position in Figure 3 is 8 and the current reading result is $(S_E = 3,\ S_S = 3,\ S_C = 2)$. Suppose $L > 8$. Then the reader has two options: 1) continue this frame and trigger the next slot, or 2) terminate this frame and start a new one.[5] The decision is made according to the **Cancellation Strategy** of an algorithm.

Let S_R be the number of Remaining (untriggered) slots in the current frame and N_R be the number of tags in these slots. Ideally, the reader should choose option 1 when $S_R \approx N_R$ and choose option 2 otherwise. Although S_R can be obtained as $S_R = L - S_E - S_S - S_C$, the precise value of N_R is usually unavailable when some slots are collided. Let $\mathrm{B}el(N_R)$ denote the *belief* of N_R, or the conditional distribution of N_R based on all the information we know [18]. Due to the memoryless property of passive tags, $Bel(N_R)$ is independent of all the previous frames given L and N. Thus we have $Bel(N_R) = \Pr\{N_R | S_S, S_C, S_R, N, L\}$.

Lemma 1: $Bel(N_R)$ is a function of N_U, S_R and S_C only, where $N_U = N - S_S$ is the unresolved tag population.

Proof: By definition,

$$Bel(N_R) = \Pr\{N_R \,|\, S_S,\, S_C,\, S_E,\, N,\, L\}.$$

Since $S_R = L - S_S - S_C - S_E$, S_E can be replaced by S_R as a condition. With this substitution, we use Bayes rule to obtain:

[4]The choice of population estimation method depends on hardware capability of the reader. Often, very elaborate statistical estimation methods are not suitable due to real-time requirement.

[5]If the current frame is terminated, the tag population N will be updated as $N^{(new)} = N - S_S$. The variables S_E, S_S and S_C will be reset to track the reading results of the new frame.

$$
\begin{aligned}
Bel(N_R) &= \Pr\{N_R \,|\, S_S,\, S_C,\, S_R,\, N,\, L\} \\
&= \Pr\{S_S,\, S_C \,|\, N_R,\, S_R,\, N,\, L\} \Pr\{N_R \,|S_R,\, N,\, L\} Z^{-1} \quad (4)
\end{aligned}
$$

where

$$
\begin{aligned}
Z &= \sum_{n_r=0}^{N} \Pr\{S_S,\, S_C \,|\, N_R = n_r,\, S_R,\, N,\, L\} \\
&\quad \Pr\{N_R = n_r \,|S_R,\, N,\, L\}
\end{aligned}
$$

is the normalization constant. The first term in (4) can be derived by drawing analogy to the urn problem [17]. Specifically, when putting $N - N_R$ balls into $L - S_R$ urns, the probability that S_S urns contain exactly 1 ball, S_C urns contain more than 1 balls and the others are empty is:

$$
\begin{aligned}
&\Pr\{S_S = s_s,\, S_C = s_c \,|\, N_R = n_r,\, S_R = s_r,\, N = n,\, L = l\} = \\
&\binom{l - s_r}{s_s, s_c, l - s_r - s_s - s_c} \frac{(n - n_r)!}{(n - n_r - s_s)!(l - s_r)^{n - n_r}} \\
&* \sum_{\substack{m_1, m_2, \ldots, m_{sc} \geq 2, \\ m_1 + m_2 + \ldots + m_{sc} = n - n_r - s_s}} \binom{n - n_r - s_s}{m_1, m_2, \ldots, m_{sc}}, \quad (5)
\end{aligned}
$$

where $m_1, m_2, \ldots, m_{sc}$ denote the numbers of tags in the s_c collided slots. Similarly, the second term in (4) is the probability that the last S_R urns contain N_R balls when N balls are randomly put into L urns, or

$$
\begin{aligned}
&\Pr\{N_R = n_r \,|\, S_R = s_r, N = n, L = l\} \\
&= \binom{n}{n_r} \left(\frac{s_r}{l}\right)^{n_r} \left(1 - \frac{s_r}{l}\right)^{n - n_r}. \quad (6)
\end{aligned}
$$

Substituting (5) and (6) into (4), we obtain:

$$
\begin{aligned}
&Bel(N_R) \\
&= \Pr\{N_R = n_r | S_S = s_s, S_C = s_c, S_R = s_r, N = n, L = l\} \\
&= \frac{1}{Z} \frac{s_r^{n_r}}{n_r!(n_u - n_r)!} \\
&* \sum_{\substack{m_1, m_2, \ldots, m_{sc} \geq 2, \\ m_1 + m_2 + \ldots + m_{sc} = n_u - n_r}} \binom{n_u - n_r}{m_1, m_2, \ldots, m_{sc}}, \quad (7)
\end{aligned}
$$

where $n_u = n - s_s$ is the number of unresolved tags.

From (7), it is clear that $Bel(N_R)$ depends only on N_U, S_R and S_C. □

When the RFID system is treated as an intelligent system [18], The initial information (N, L) and the evidence (S_E, S_S, S_C) together cover all the information in the system and are sufficient for the optimal decision. But some information is redundant, a smaller sufficient set can be obtained.

Let $V = (N_U, S_C, S_R)$. For an N-tag group, $V = (N, 0, 0)$ before identification. It changes slot by slot during the reading process. Let $\mathscr{V}_N$ be a set of V that the process may visit starting from (N,0,0). Then we have $\mathscr{V}_N = \left\{(N_U, S_C, S_R) \,\middle|\, N_U, S_C, S_R \in \mathbb{Z}_+,\ N_U \leq N,\ S_C \leq \frac{N_U}{2},\ S_C + S_R \leq L_N^*\right\}$, where L_N^* is the optimal frame size for N tags. Since the value of L_N^* is around N, or $L_N^* \sim \mathcal{O}(N)$, we have $|\mathscr{V}_N| \sim \mathcal{O}(N^3)$. This shows that $\mathscr{V}_N$ is a finite set.

Theorem 1: When the tag population is precisely estimated, the optimal cancellation strategy depends only on $V = (N_U, S_C, S_R)$.

Proof: Let $\mathcal{T}(N)$ denote the expected contention time for N tags using the optimal strategy when this N is precisely estimated. Although the value of $\mathcal{T}(N)$ is not available yet, it should be exact and depends only on N. We prove the theorem by mathematical induction as follows.

The first case is $V \in \mathcal{V}_1$, where $\mathcal{V}_1 = \{(N_U, S_C, S_R) \in \mathscr{V}_N : S_R = 1\}$, or there is only 1 remaining slot in the current frame. If the current frame is canceled, the expected finishing time for the N_U unresolved tags should be $T_1 = \mathcal{T}(N_U)$. Otherwise, if the reader triggers the last slot, the expected finishing time can be obtained by averaging the different outcomes of the last slot as

$$
\begin{aligned}
T_2 &= 1 + \Pr\{\text{The last slot is singleton}\}\, \mathcal{T}(N_U - 1) \\
&\quad + \Pr\{\text{The last slot is empty or collided}\}\, \mathcal{T}(N_U) \\
&= 1 + r_s\, \mathcal{T}(N_U - 1) + (1 - r_s)\, \mathcal{T}(N_U).
\end{aligned}
$$

In this case, $r_s = Bel(N_R = 1)$, because there is only 1 slot left. By Lemma 1, $Bel(N_R)$ is a function of N_U, S_C and S_R. Thus T_2 depends only on V. Obviously, the frame will be canceled when $T_1 < T_2$. So the cancellation strategy depends only on V. Without loss of generality, we let $\mathcal{T}_F^{(1)}(V) = \min\{T_1, T_2\}$ denote the mapping from V to the expected finishing time when $V \in \mathcal{V}_1$.

We assume the theorem still holds when $V \in \mathcal{V}_k$, where $\mathcal{V}_k = \{(N_U, S_C, S_R) \in \mathscr{V}_N : S_R = k\}$ $(k \geq 1)$, or the expected finishing time for V can be obtained from $T = \mathcal{T}_F^{(k)}(V)$. Then for the case that $V \in \mathcal{V}_{k+1}$, where $\mathcal{V}_{k+1}$ is similarly defined, we have

1) If the current frame is canceled, the expected finishing time is $T_1 = \mathcal{T}(N_U)$.

2) If the next slot is triggered, only k slots left. Let v_e, v_s and v_c denote the triples when the triggered slot is empty, singleton and collided respectively. We have $v_e,\, v_s,\, v_c \in \mathcal{V}_k$. Then the expected reading time is

$$
T_2 = 1 + r_e\, \mathcal{T}_F^{(k)}(v_e) + r_s\, \mathcal{T}_F^{(k)}(v_s) + r_c\, \mathcal{T}_F^{(k)}(v_c),
$$

where r_e, r_s and r_c denote the probability that the next slot contains 0, 1 and multiple tags respectively, which can be obtained from $Bel(N_R)$ as

$$
\begin{aligned}
r_e &= \sum_{i=0}^{N_U} \left(1 - \frac{1}{S_R}\right)^i Bel(N_R = i); \quad (8) \\
r_s &= \sum_{i=1}^{N_U} \frac{i}{S_R} \left(1 - \frac{1}{S_R}\right)^{i-1} Bel(N_R = i); \quad (9) \\
r_c &= 1 - r_e - r_s. \quad (10)
\end{aligned}
$$

Similar to Case 1, T_2 depends only on V. As the frame will be canceled when $T_1 < T_2$, the theorem still holds. By mathematical induction, we can claim for any $V \in \mathscr{V}_N$, the optimal cancellation rule depends only on V. □

From Theorem 1, V is the system state which determines the reading strategy. Let $\mathcal{C}(V)$ be the optimal *Cancellation Rule* defined on $V \in \mathscr{V}_N$, i.e. $\mathcal{C}(V) = 1$ when the current frame should be canceled and $\mathcal{C}(V) = 0$ otherwise.

B. The Markov Chain

Let $V_j = (N_U, S_C, S_R)$ denote the state of the reading process in time slot j. For N tags to identify, let $V_0 = (N, 0, 0)$ be the initial state and $\mathcal{U}_T = \{(N_U, S_C, S_R) \in \mathscr{V}_N : N_U = 0\}$ be the set of terminal states. Since a new frame starts as soon as S_R reaches 0, we have $(N, 0, 0) = (N, 0, L_N^*)$. As proved in Theorem 1, although the optimal frame size L_N^* is not available yet, it is fixed and depends only on N.

Theorem 2: When the initial tag population is known, the states $V_0 V_1 V_2 \ldots$ following the optimal reading strategy form a Markov Chain.

Proof: For a given state $V_j = (n_u, s_c, s_r)$,[6] if the next slot is empty and the current frame is not canceled, the next state is $V_{j+1} = (n_u, s_c, s_r - 1)$; but if the frame is canceled, the next state becomes $V_{j+1} = (n_u, 0, 0)$. Combining these two cases, V_{j+1} has probability $r_e[1 - \mathcal{C}(n_u, s_c, s_r - 1)]$ to be $(n_u, s_c, s_r - 1)$ and probability $r_e \mathcal{C}(n_u, s_c, s_r - 1)$ to be $(n_u, 0, 0)$. Similarly for the singleton and collided cases, the transition probability from a particular state $V_j = (n_u, s_c, s_r)$ to V_{j+1} is therefore:

$$\Pr\{V_{j+1} \,\big|\, V_j V_{j-1} \ldots V_0\} = \begin{cases} r_e \mathcal{C}(n_u, s_c, s_r - 1) & , \quad V_{j+1} = (n_u, 0, 0) \\ r_s \mathcal{C}(n_u - 1, s_c, s_r - 1) & , \quad V_{j+1} = (n_u - 1, 0, 0) \\ r_c \mathcal{C}(n_u, s_c + 1, s_r - 1) & , \quad V_{j+1} = (n_u, 0, 0) \\ r_e \left[1 - \mathcal{C}(n_u, s_c, s_r - 1)\right] & , \quad V_{j+1} = (n_u, s_c, s_r - 1) \\ r_s \left[1 - \mathcal{C}(n_u - 1, s_c, s_r - 1)\right] & , \quad V_{j+1} = (n_u - 1, s_c, s_r - 1) \\ r_c \left[1 - \mathcal{C}(n_u, s_c + 1, s_r - 1)\right] & , \quad V_{j+1} = (n_u, s_c + 1, s_r - 1) \\ 0 & , \quad \text{others} \end{cases}$$

From (8) $\sim$ (10), r_e, r_s and r_c depends on V_j only. Hence $\Pr\{V_{j+1} \,|\, V_j V_{j-1} \ldots V_0\} = \Pr\{V_{j+1} \,|\, V_j\}$, and the evolution of V_j following the optimal reading strategy is a Markov Chain. □

For all $V \in \{(N_U, S_C, S_R) \in \mathscr{V}_N : N_U > 0\}$, let $\mathcal{T}_F(V)$ denote the expected first passage time from V to $\mathcal{U}_T$. Then we have the following equations from Markov Chain theory as

$$\begin{aligned} \mathcal{T}_F(V_j) &= 1 + \sum_{V_{j+1} \in \mathscr{V}_N} \Pr\{V_{j+1} | V_j\}\, \mathcal{T}_F(V_{j+1}) \\ &= 1 + r_e \mathcal{T}_F\left(V_{j+1}^{(e)}\right) + r_s \mathcal{T}_F\left(V_{j+1}^{(s)}\right) + r_c \mathcal{T}_F\left(V_{j+1}^{(c)}\right), \end{aligned} \tag{11}$$

where

$$\begin{aligned} V_{j+1}^{(e)} &= \underset{V \in \{(n_u, s_c, s_r - 1),\, (n_u, 0, 0)\}}{\arg\min} \mathcal{T}_F(V), \\ V_{j+1}^{(s)} &= \underset{V \in \{(n_u - 1, s_c, s_r - 1), (n_u - 1, 0, 0)\}}{\arg\min} \mathcal{T}_F(V), \\ V_{j+1}^{(c)} &= \underset{V \in \{(n_u, s_c + 1, s_r - 1),\, (n_u, 0, 0)\}}{\arg\min} \mathcal{T}_F(V). \end{aligned}$$

For the special cases $V_j = (n, 0, 0)$ (the beginning of a frame), since the optimal frame size L_n^* is not available yet, (11) becomes

$$\begin{aligned} \mathcal{T}_F(V_j) &= \mathcal{T}(n) \\ &= \min_l \left\{ 1 + r_e \mathcal{T}_F\left(V_{j+1}^{(e)}\right) + r_s \mathcal{T}_F\left(V_{j+1}^{(s)}\right) + r_c \mathcal{T}_F\left(V_{j+1}^{(c)}\right) \right\}, \end{aligned} \tag{12}$$

where

$$\begin{aligned} V_{j+1}^{(e)} &= \underset{V \in \{(n, 0, l - 1),\, (n, 0, 0)\}}{\arg\min} \mathcal{T}_F(V), \\ V_{j+1}^{(s)} &= \underset{V \in \{(n - 1, 0, l - 1),\, (n - 1, 0, 0)\}}{\arg\min} \mathcal{T}_F(V), \\ V_{j+1}^{(c)} &= \underset{V \in \{(n, 1, l - 1),\, (n, 0, 0)\}}{\arg\min} \mathcal{T}_F(V). \end{aligned}$$

(11) and (12) are the **System Equations** of the optimal strategy for Gen-2 RFID systems, which establishes the functional relationship between the expected contention time and system state. The optimal frame size L^* and the cancellation rule $\mathcal{C}(V)$ can be obtained by solving the system Equations.

C. Analytical Solution of the System Equation

The system equations can be recursively solved from $\mathscr{V}_1$. Here we use some simple cases to illustrate the derivation.

Case 1: $V \in \mathscr{V}_1$, or there is only one tag to be identified. Obviously, $L_1^* = 1$ and $\mathcal{T}(1) = 1$.

Case 2: $V \in \mathscr{V}_2$. As defined in subsection A, $\mathscr{V}_2$ is a set of all the possible combinations of (N_U, S_C, S_R) beginning from $N = 2$. Thus $N_U \in \{1, 2\}$, $S_C \in \{0, 1\}$ and $S_R \in \{1, 2, 3, \ldots, L_2^* - 1\}$. Although L_N^* is not available yet, it cannot be much larger than N. In our derivation, we assume $L_N^* \leq \lceil 1.5N \rceil$. Combining with other constraints like $S_C \leq \lfloor \frac{N_U}{2} \rfloor$ and $S_R + S_C \leq L^*$, we have $\mathscr{V}_2 \subseteq \hat{\mathscr{V}}_2 = \{(1, 0, 1),\ (2, 0, 1),\ (2, 1, 1),\ (1, 0, 2),\ (2, 0, 2),\ (2, 1, 2),\ (1, 0, 3),\ (2, 0, 3)\}$. Substituting this into (11), we have

$$\begin{cases} \mathcal{T}_F(1, 0, 1) = 1 \\ \mathcal{T}_F(2, 0, 1) = 1 + \mathcal{T}(2) \\ \mathcal{T}_F(2, 1, 1) = 1 + \mathcal{T}(2) \\ \mathcal{T}_F(1, 0, 2) = 1 + \frac{1}{2} \min\{\mathcal{T}_F(1, 0, 1),\ \mathcal{T}(1)\} \\ \mathcal{T}_F(2, 0, 2) = 1 + \frac{1}{4} \min\{\mathcal{T}_F(2, 0, 1),\ \mathcal{T}(1)\} \\ \qquad\qquad\qquad + \frac{1}{2} \min\{\mathcal{T}_F(1, 0, 1),\ \mathcal{T}(1)\} \\ \qquad\qquad\qquad + \frac{1}{4} \min\{\mathcal{T}_F(2, 1, 1),\ \mathcal{T}(2)\} \\ \mathcal{T}_F(2, 1, 2) = 1 + \min\{\mathcal{T}_F(2, 1, 1),\ \mathcal{T}(2)\} \\ \mathcal{T}_F(1, 0, 3) = 1 + \frac{2}{3} \min\{\mathcal{T}_F(1, 0, 2),\ \mathcal{T}(1)\} \\ \mathcal{T}_F(2, 0, 3) = 1 + \frac{4}{9} \min\{\mathcal{T}_F(2, 0, 2),\ \mathcal{T}(2)\} \\ \qquad\qquad\qquad + \frac{4}{9} \min\{\mathcal{T}_F(1, 0, 2),\ \mathcal{T}(1)\} \\ \qquad\qquad\qquad + \frac{1}{9} \min\{\mathcal{T}_F(2, 1, 2),\ \mathcal{T}(2)\} \end{cases} \tag{13}$$

Since $\mathcal{T}(1) = 1$ and $\mathcal{T}(2) = \mathcal{T}_F(2, 0, L_2^*) \leq \mathcal{T}_F(2, 0, L)$ for all $L \geq 0$. (13) becomes

$$\begin{cases} \mathcal{T}_F(1, 0, 1) = 1 \\ \mathcal{T}_F(2, 0, 1) = 1 + \mathcal{T}(2) \\ \mathcal{T}_F(2, 1, 1) = 1 + \mathcal{T}(2) \\ \mathcal{T}_F(1, 0, 2) = 1.5 \\ \mathcal{T}_F(2, 0, 2) = 1.75 + \frac{1}{4}\mathcal{T}(2) \\ \mathcal{T}_F(2, 1, 2) = 1 + \mathcal{T}(2) \\ \mathcal{T}_F(1, 0, 3) = 1.67 \\ \mathcal{T}_F(2, 0, 3) = 1.44 + \frac{5}{9}\mathcal{T}(2) \end{cases} \tag{14}$$

As a special case, $\mathcal{T}(2)$ can be obtained from (12) as

$$\begin{aligned} \mathcal{T}(2) = \min_L \Bigg\{ & 1 + \left(\frac{L-1}{L}\right)^2 \min\left\{\mathcal{T}_F(2, 0, L-1),\ \mathcal{T}(2)\right\} \\ & + \frac{2(L-1)}{L^2} \min\left\{\mathcal{T}_F(1, 0, L-1),\ \mathcal{T}(1)\right\} \\ & + \frac{1}{L^2} \min\left\{\mathcal{T}_F(2, 1, L-1),\ \mathcal{T}(2)\right\} \Bigg\} \end{aligned} \tag{15}$$

By substituting (14) into (15), we have

[6] If $s_r = 0$, $V_j = (n_u, 0, L_{n_u}^*)$.

$$\mathcal{T}(2) = \min_{L} \left\{ 1 + \left(\frac{L-1}{L}\right)^2 \mathcal{T}(2) + \frac{2(L-1)}{L^2} + \frac{1}{L^2}\mathcal{T}(2) \right\} \tag{16}$$

(16) can be solved to obtain $L_2^* = 2$ and $\mathcal{T}(2) = 3$. Substituting $\mathcal{T}(2)$ into (14), we get the expected finishing time $\mathcal{T}_F(V)$ for $V \in \hat{\mathscr{V}}_2$ as

$$\begin{aligned} &\mathcal{T}_F(1,0,1) = 1, \;\; \mathcal{T}_F(1,0,2) = 1.5, \;\; \mathcal{T}_F(1,0,3) = 1.67, \\ &\mathcal{T}_F(2,0,1) = 4, \;\; \mathcal{T}_F(2,0,2) = 3, \;\;\;\;\; \mathcal{T}_F(2,0,3) = 3.11, \\ &\mathcal{T}_F(2,1,1) = 4, \;\; \mathcal{T}_F(2,1,2) = 4. \end{aligned}$$

The optimal cancellation rule is obtained by comparing $\mathcal{T}_F(V)$ with $\mathcal{T}(N)$. For example, beginning with the state $V_0 = (2,0,2)$, we have $V_1 = (2,0,1)$ when the first slot is empty. At this time, the current frame should be canceled, as continuing reading needs on average 4 slots while resetting $L = 2$ needs on average 3 slots.

D. *Numerical Solution of the System Equation*

In this subsection, we provide an iterative program to solve the system equations.

The system equation can be iteratively solved. As an example, consider (14) and (15) in the last subsection. We first set initial value for $\mathcal{T}(2)$ and substitute it into (14). After calculating $\mathcal{T}_F(V)$, we substitute $\mathcal{T}_F(V)$ and $\mathcal{T}(2)$ into the right-hand side of (15) and update the value of $\mathcal{T}(2)$. Next, we substitute the new $\mathcal{T}(2)$ back into (14) and continue. As we will prove later, this iteration is guaranteed to converge. After obtaining $\mathcal{T}(2)$, we can also iteratively solve the system equations for $V \in \mathscr{V}_3$ by setting any initial value for $\mathcal{T}(3)$. As a general case, starting from $\mathcal{T}(1) = 1$, we design an iterative program to calculate $\mathcal{T}(N)$ and $\mathcal{T}_F(V)$ for $V \in \mathscr{V}_N$ as follows:

Algorithm 1

For n=2:N
1) Let $\mathcal{T}(n) = \mathcal{T}(n-1) + 2.71818$ as the initial value.
2) For $s_r = 1 : \lceil 1.5n \rceil$
    For $s_c = 0 : \min(2n - s_r, \lfloor n/2 \rfloor)$
      Update $\mathcal{T}_F(n, s_c, s_r)$ from (11);
    End For
  End For
3) Update $\mathcal{T}(n)$ using (12). Repeat step 2 if the difference of old and new values of $\mathcal{T}(n)$ exceeds a threshold.

End For

The convergence of this iterative program is proved in Appendix I. In our experiment, the difference converges to 0.001 within several loops.

By running the iterative program, we obtain the following results for $\Upsilon = \mathbb{Z}_{++}$ as

- The optimal frame size is shown in Figure 4 by marks 'o'. For n ($n > 2$) tags to be read, the optimal frame size L_n^* is found to be a little less than n. This serves as a correction to the results in [11][12][15].

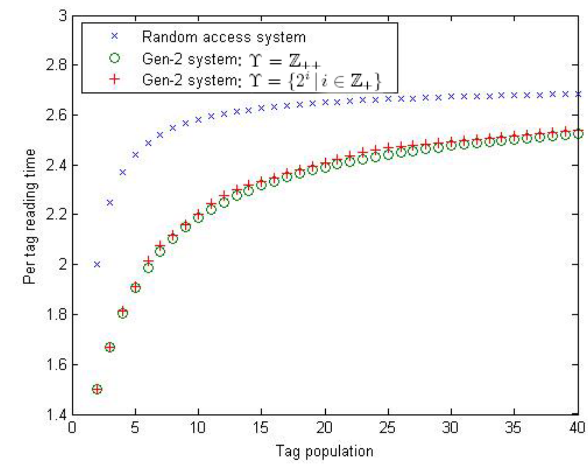

Fig. 4. The average contention time per tag using the optimal reading strategy.

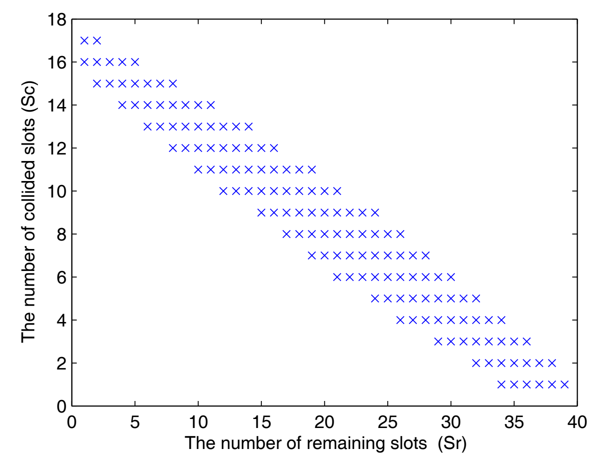

Fig. 5. The cancelation rule for $N_U = 40$, $\Upsilon = \mathbb{Z}_{++}$.

- For $N \leq 40$, the performance of the optimal strategy is shown in Figure 5 by marks 'o'. We can see that the average contention time per tag of the Gen-2 RFID system is always below the bound of Random Access systems [10].
- Figure 6 shows the optimal cancellation rule for $N_U = 40$. The current frame should be terminated whenever the state wanders outside the permitted region marked by $\times$. For other values of N_U, similar permitted regions can be found.

The results for $\Upsilon = \{2^i | i \in \mathbb{Z}_+\}$ are similarly obtained by running the iterative program with limited choice of L:

- The optimal frame size is shown in Figure 4 by marks $'+'$. We see that they are just the quantized values of the previous case.
- The performance is shown in Figure 5 by marks $'+'$. We observe that although the choices of frame size are severely limited, the performance loss is very small.
- The cancellation rule for $N_U = 40$ is shown in Figure 7. Compared with the case where L can be any positive value, the permitted region is larger. As a result, frame

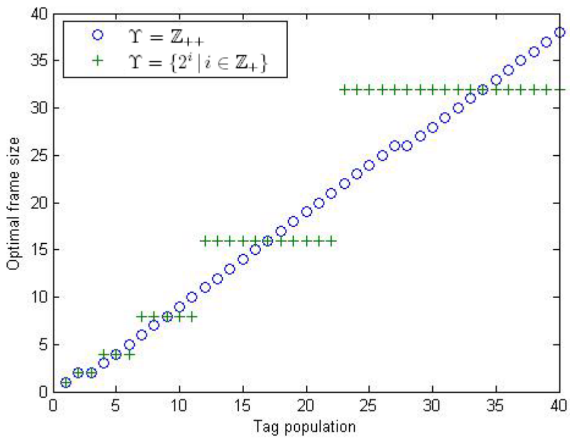

Fig. 6. The optimal frame size.

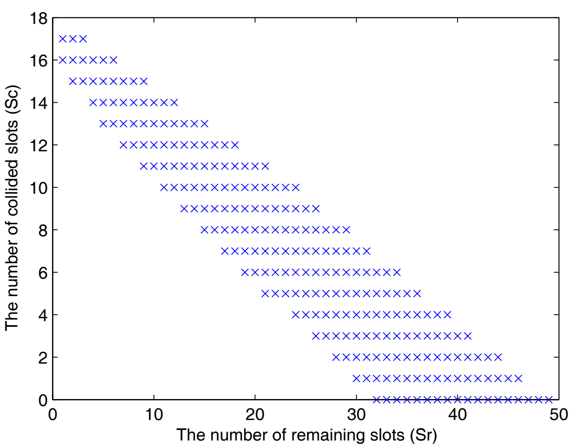

Fig. 7. The cancelation rule for $N_U = 40$, $\Upsilon = \{2^i \mid i \in \mathbb{Z}_+\}$.

cancellation is significantly less than that of the previous case.

IV. Generalization to Imprecise Population Estimation

In this section, we remove the assumption that the estimated tag population is precise. As mentioned in Section III, most FA algorithms adopt the maximum-likelihood approach for simplicity concern. We show significant improvement can be obtained when the optimal reading strategy is used in maximum-likelihood estimation algorithms.

In Section II, we showed many estimation strategies. But not all of them can be used in a real RFID system due to hardware constraints, software constraints, robustness requirement and the real-time operation requirement. In the EPCglobal Gen-2 system, the Q-method as shown in Figure 1 is used for tag population estimation. Although minor modification is allowed by the standards, such as changing the initial values of Q_{pf} and C, adopting advanced methods like the Bayesian estimation is certainly out of question. In this paper, we focus on the optimal reading strategy part and allow different estimation strategies to be used. When the precise value of N is replaced by $\hat{N}$, two new problems arise:

1) What is the optimal frame size for $\hat{N}$?

Previous maximum-likelihood algorithms choose frame size $L = \hat{N}$. This is reasonable, as $\hat{N}$ is the only knowledge using maximum-likelihood estimation. When a suitable estimation method is used, the estimation becomes more and more accurate as reading proceeds. In Q algorithm, $\hat{N}$ is very close to N for most of the time. Thus choosing the frame size as $L^*_{\hat{N}}$ is the best we can do.

2) Should the current frame be canceled when $\hat{N}$ changes?

In EPCglobal standards, the Q algorithm cancels the current frame whenever round(Q_{fp}) changes. This action is improper as although the frame size is wrongly chosen, the number of remaining slots may still be suitable for the remaining tags. Our analysis show that the cancellation decision is determined by $V = (N_U, S_C, S_R)$ instead of the frame size. For an estimated tag population $\hat{N}$, the whole theory can be similarly proved. Therefore we can simply replace N_U by $\hat{N}$ and check whether V satisfies the cancellation rule.

We now show how to adapt the optimal reading strategy into the Q algorithm to obtained the Improved Q algorithm, or IQ algorithm for short.

Q algorithm: (From the EPCglobal standards)

1) Set the initial value for Q_{fp} and C.
2) Set the frame size $L = 2^Q$, where $Q = \text{round}(Q_{fp})$.
3) During the reading process, maintain a variable S_R to track the number of remaining slots and another float-point variable Q_{fp} as

$$Q_{fp} = \begin{cases} Q_{fp} + C, & \text{collided reply} \\ Q_{fp} + 0, & \text{singleton reply} \\ Q_{fp} - C, & \text{no reply} \end{cases}$$

4) Cancel the current frame when $Q = \text{round}(Q_{fp})$ changes and set the new frame size as $L = 2^Q$.

IQ algorithm:

1) Set the initial value for Q_{fp} and C.
2) Let $\hat{N} = \text{round}(2^{Q_{fp}})$ and set the frame size as $L = L^*_{\hat{N}}$.
3) During the reading process, track variables S_R and S_C and maintain another float-point variable Q_{fp} as

$$Q_{fp} = \begin{cases} Q_{fp} + C, & \text{collided reply} \\ \log_2\left(2^{Q_{fp}} - 1\right), & \text{singleton reply} \\ Q_{fp} - C, & \text{no reply} \end{cases}$$

4) Cancel the current frame when the state $(\hat{N}, S_C, S_R)$ satisfies the cancellation rule and set the new frame size as $L = L^*_{\hat{N}}$.

The optimal frame size $L^*_{\hat{N}}$ and the cancellation rule can be precalculated and stored in the reader. Therefore the IQ algorithm only requires one more table-lookup in every time slot, which barely increases the system complexity. Further, the IQ algorithm does not change the working mechanism of the Q algorithm. Thus the good properties, such as robustness, are still preserved. Figure 8 shows the simulation results of

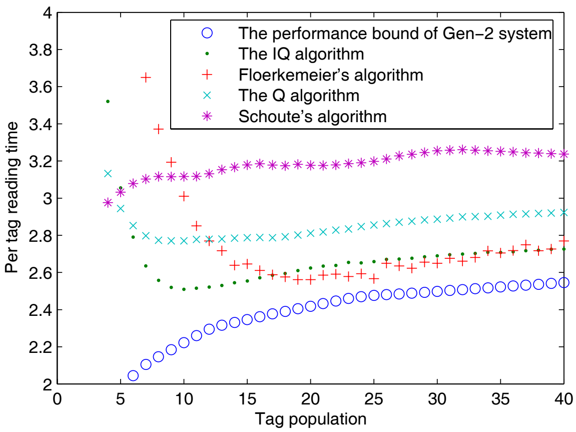

Fig. 8. The performance of different algorithms.

different algorithms.[7] We observe,

1) Schoute's algorithm needs the longest reading time; but it is also the simplest one, which does not need the frame cancellation.

2) The Q algorithm gives around 10% improvement by introducing the frame cancellation.

3) The IQ algorithm is around 8% better than the Q algorithm with minimum increase of system complexity.

4) Floerkemeier's algorithm and the IQ algorithm have similar performance for large N. The reason is that Floerkemeier's algorithm uses the Bayesian estimation method but chooses unsuitable frame sizes while the IQ algorithm uses the optimal reading strategy but adopts a rough estimation method. Although the combination of Bayesian estimation method and the optimal reading strategy can yield even better performance, it is not practical because the Bayesian estimation is heavily computation intensive, particularly for large N.

5) The performance of Floerkemeier¡¯s algorithm depends on the initial estimation. In this case, the highest efficiency is obtained around 20, because the initial estimation we use, as mentioned in footnote 6, is a uniform distribution from 1 to 40 (20 is the mean). On the other hand, the performance of IQ algorithm is more stable for large N. That is why the curve of Floerkemeier¡¯s algorithm intertwines with the IQ algorithm.

The gap between the performance of IQ algorithm and the bound is caused by the population estimation error. Simulation result shows that a better choice of Q_{fp} and C can narrow this gap. In the best case, when $Q_{fp} = \log_2 N$ and $C \to 0$, IQ algorithm achieves the optimal performance. Optimizing C and Q_{fp} to derive a more accurate $\hat{N}$ belongs to the Population Estimation part.

V. Summary

In this paper, we optimized reading strategy for Gen-2 RFID systems. The optimal frame length and cancellation rule can be obtained by running an iterative program and can easily be adopted in different RFID anti-collision algorithms. Simulation results show significant improvement.

[7] $\Upsilon = \{2^i \,|\, i \in Z_+\}$ for all algorithm. In Q and IQ algorithms, $C = 0.3$ while the initial $Q_{fp} = 4$ as recommended by the standards. In Floerkemeier's algorithm, the initial distribution of tag population is uniform between 1 and 40.

Appendix A

For a function $f(x)$ from $M \subseteq \mathbb{R}$ to itself, let x_0 denote the only stationary point of $f(x)$, or $x_0 = f(x_0)$. If there is some real value $0 < k < 1$ such that, for all $x \in M$, $|f(x_0) - f(x)| \le k|x_0 - x|$. Then $f(x)$ is a contraction mapping [19]. Starting from any $x \in M$, we can obtain x_0 iteratively.

Theorem: When the values of $\mathcal{T}(n-1)$ and $\mathcal{T}_F(V)$ for $V \in \mathscr{V}_{n-1}$ are available, (11) and (12) together form a contraction mapping for $\mathcal{T}(n)$.

Proof: Let t_n be the exact value of $\mathcal{T}(n)$ and $\hat{t}_n$ be any positive value. Further let $\Delta = |\hat{t}_n - t_n|$ be the distance between $\hat{t}_n$ and t_n. We use $\hat{t}_n$ as the initial value of $\mathcal{T}(n)$ and substitute $\hat{t}_n$ into (11) to obtain $\hat{\mathcal{T}}_F(V)$; then we substitute $\hat{\mathcal{T}}_F(V)$ and $\hat{t}_n$ back to (12) to update $\mathcal{T}(n)$ as $\hat{t}'_n$. Thus $\hat{t}'_n$ is the image of $\hat{t}_n$ by (11) and (12). Here we will prove there is some real value $0 < k < 1$ such that, for all $\hat{t}_n > 0$, $|\hat{t}'_n - t_n| \le k|\hat{t}_n - t_n|$.

For $V \in \{(N_U, S_C, S_R) \in \mathscr{V}_n : S_R = 1, N_U = n\}$, from (11), we have $\mathcal{T}_F(V) = 1 + r_e\mathcal{T}(n) + r_s\mathcal{T}(n-1) + r_c\mathcal{T}(n)$. Thus, using $\hat{t}_n$ to substitute $\mathcal{T}(n)$, we have $\hat{\mathcal{T}}_F(V) = 1 + r_e\hat{t}_n + r_s\mathcal{T}(n-1) + r_c\hat{t}_n$. Since $\mathcal{T}(n-1)$ is given as our precondition, we have the distance between $\mathcal{T}_F(V)$ and $\hat{\mathcal{T}}_F(V)$ as

$$|\hat{\mathcal{T}}_F(V) - \mathcal{T}_F(V)| = (r_e + r_c)|\hat{t}_n - t_n| = (r_e + r_c)\Delta \le \Delta.$$

For $V \in \{(N_U, S_C, S_R) \in \mathscr{V}_n : S_R = k, N_U = n\}$, Suppose $|\hat{\mathcal{T}}_F(V) - \mathcal{T}_F(V)| \le \Delta$ still holds. Then for any $V \in \mathscr{V}_n \cap \{(N_U, S_C, S_R) \,|\, S_R = k+1, N_U = n\}$, from (11) we have

$$\begin{aligned} \mathcal{T}_F(V) = \; & 1 + r_e \min\{\mathcal{T}_F(n, s_c, k), \mathcal{T}(n)\} \\ & + r_s \min\{\mathcal{T}_F(n-1, s_c, k), \mathcal{T}(n-1)\} \\ & + r_c \min\{\mathcal{T}_F(n, s_c+1, k), \mathcal{T}(n)\} \end{aligned} \quad (17)$$

Since $\mathcal{T}_F(n-1, s_c, k)$ and $\mathcal{T}(n-1)$ are known as our precondition, we have $\hat{\mathcal{T}}_F(V)$ by using $\hat{t}_n$ as

$$\begin{aligned} \hat{\mathcal{T}}_F(V) = \; & 1 + r_e \min\{\hat{\mathcal{T}}_F(n, s_c, k), \hat{t}_n\} \\ & + r_s \min\{\mathcal{T}_F(n-1, s_c, k), \mathcal{T}(n-1)\} \\ & + r_c \min\{\hat{\mathcal{T}}_F(n, s_c+1, k), \hat{t}_n\} \end{aligned} \quad (18)$$

Comparing (17) and (18), the distance between $\hat{\mathcal{T}}_F(V)$ and $\mathcal{T}_F(V)$ is obtained as (19).

Then we conclude by mathematical induction that, for all $V \in \{(N_U, S_C, S_R) \in \mathscr{V}_n : N_U = n\}$, $|\hat{\mathcal{T}}_F(V) - \mathcal{T}_F(V)| \le \Delta$ always holds. Next we substitute $\hat{\mathcal{T}}_F(V)$ back to (12) to get the image of $\hat{t}_n$ as

$$\begin{aligned} \hat{t}'_n = \; & \min_L \Big\{ 1 + r_e \min\{\hat{\mathcal{T}}_F(n, 0, L-1), \hat{t}_n\} \\ & + r_s \min\{\mathcal{T}_F(n-1, 0, L-1), \mathcal{T}(n-1)\} \\ & + r_c \min\{\hat{\mathcal{T}}_F(n, 1, L-1), \hat{t}_n\} \Big\}. \end{aligned}$$

Comparing this with t_n, we obtain the following by the similar derivation as in (19):

$$|\hat{t}'_n - t_n| \le (r_e + r_c)\Delta = (r_e + r_c)|\hat{t}_n - t_n|.$$

In the first slot, the probability of singleton is positive, so $r_e + r_c = 1 - r_s < 1$. Thus we conclude that (11) and (12) together

$$
\begin{aligned}
&|\hat{\mathcal{T}}_F(V) - \mathcal{T}_F(V)| \\
&= \Big| r_e \min\{\hat{\mathcal{T}}_F(n, s_c, k), \hat{t}_n\} + r_c \min\{\hat{\mathcal{T}}_F(n, s_c+1, k), \hat{t}_n\} \\
&\quad - r_e \min\{\mathcal{T}_F(n, s_c, k), \mathcal{T}(n)\} - r_c \min\{\mathcal{T}_F(n, s_c+1, k), \mathcal{T}(n)\} \Big| \\
&= \Big| r_e \Big(\min\{\hat{\mathcal{T}}_F(n, s_c, k), \hat{t}_n\} - \min\{\mathcal{T}_F(n, s_c, k), t_n\} \Big) \\
&\quad + r_c \Big(\min\{\hat{\mathcal{T}}_F(n, s_c+1, k), \hat{t}_n\} \\
&\quad - \min\{\mathcal{T}_F(n, s_c+1, k), t_n\} \Big) \Big| \\
&\leq r_e \Big| \min\{\hat{\mathcal{T}}_F(n, s_c, k), \hat{t}_n\} - \min\{\mathcal{T}_F(n, s_c, k), t_n\} \Big| \\
&\quad + r_c \Big| \min\{\hat{\mathcal{T}}_F(n, s_c+1, k), \hat{t}_n\} - \min\{\mathcal{T}_F(n, s_c+1, k), t_n\} \Big| \\
&\leq r_e \max\Big\{ \Big| \hat{\mathcal{T}}_F(n, s_c, k) - \mathcal{T}_F(n, s_c, k) \Big|, \ \Big| \hat{t}_n - t_n \Big| \Big\} \\
&\quad + r_c \max\Big\{ \Big| \hat{\mathcal{T}}_F(n, s_c+1, k) - \mathcal{T}_F(n, s_c+1, k) \Big|, \ \Big| \hat{t}_n - t_n \Big| \Big\} \\
&\leq r_e \Delta + r_c \Delta \leq \Delta
\end{aligned} \tag{19}
$$

form a contraction mapping for $\mathcal{T}(n)$, given the values of $\mathcal{T}(n-1)$ and $\mathcal{T}_F(V)$ for $V \in \mathscr{V}_{n-1}$.

In Section III.D, the program calculate $\mathcal{T}(n)$ and $\mathcal{T}_F(V)$ recursively from $n = 1$. Since $\mathcal{T}(1) = 1$ is given, the precondition of Theorem 3 is satisfied in the program. Thus it will surely converge.

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