MAC Layer RFID Protocol for Low Cost Object Identification

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Abstract— In this paper, we introduce a novel medium access control (MAC) protocol for Radio Frequency Identification (RFID) systems. This protocol exploits the Markov Chain Model of Slotted Aloha and thereby tries to come up with a more efficient model so as to significantly improve the total read time performance along with the lesser tag collision. The protocol design has been extended so as to address the problem of cost reduction in RFID. This is done by combining the of Markov Chain Slotted Aloha model for MAC Layer along with Two Time Scale SPSA (Simultaneous Perturbation Stochastic Approximation). The so designed protocol is programmatically simulated and mathematically the results have been derived to prove its enhanced performance along with lowered cost involved in object identification.

Index Terms—RFID, SPSA, Cost, MAC layer, Slotted Aloha

I. INTRODUCTION

Motivation of the paper is identifying ‘cost’ as a prime barrier in making RFID as a complete success. Several ways of cost reduction are proposed of which one of them is making use of passive tags. Of the major challenges involved in RFID are cost, security and privacy issue, standardization and last but not the least failed tag read problem. Most of the communication models between the reader and tag propose a Slotted Aloha based scheme. Also to note here is that in this model the problem of failed tag read comes into picture. A mathematical model is designed to enhance the communication between the reader and tag. This proposed protocol finds its space in the MAC layer of the Generation-2 Protocols (Gen-2 Protocols also has a MAC Protocol which use a variant of Slotted Aloha) This is done by developing a Markov chain model for slotted aloha and designing a two time scale SPSA models for the same.

A. MAC LAYER PROTOCOL DESIGN

Motivation behind the efficient MAC protocols for RFID systems is to improve the total read time performance of the presently available models. The performance degrades due to impact of excessive collisions in random multi-access communications. Indeed, tag collisions, which occur when multiple tags simultaneously transmit information in the same channel severely, limit the performance of RFID systems. Now the focus here is that intelligence is being provided to the protocol that is sufficient to alleviate this limitation via intelligent MAC design. By the fundamental nature of Dynamic Markov Chain the probability of the next state depends only on the current state and not on the past stages and this happens to be the soul of this protocol design. The more recently proposed Class 1 - Generation 2 also has a MAC protocol based on time-slotted ALOHA. The proposed protocol exploits a variant of Aloha named framed Slotted-ALOHA and then it utilizes the statistical information related to the tag population inherently collected at the reader in each round (frame) in order to decide the next tag transmission. The statistical information primarily consists of the number of failed and successful transmission in each round of transmission. This strategy aims at reducing the probability of tag collisions while simultaneously expediting the identification of RFID tags.

B. ALTERNATE DESIGN METHODOLOGIES

Reader Collision problem can also be addressed by learning the collision patterns of the readers and then by effectively assigning frequencies over time to ensure neighboring readers do not experience collisions from one another. This approach also has somewhat similar expectations to the one which have been adopted in this paper to minimize the tag collision. This approach could also be taken as an alternate design technique so as to minimize the failed reads and thereby also reduce the cost involved in tag collision.

We have taken two time Scale SPSA as a technique to assign cost to the failed and the read tags correspondingly. This approach can further be enhanced by using a Deterministic Analysis of Stochastic Approximation with Randomized Directions. This will help in providing even better Convergence of the SPSA algorithm.
C. RELATED WORK

Much work has been going to come up with a better and suitable RFID MAC layer protocol. Research is also going on to reduce the tag/reader collision problem faced during the reader tag communication of RFID. Professors of MIT (Massachusetts Institute of Technology), Dr. Sanjay Sarma, Daniel W. Engles have come up with HIQ algorithms which is a hierarchical, online learning algorithm that finds dynamic solutions to the Reader Collision Problem in RFID systems[16]. Also much work has been done at the Pennsylvania State University to come up with an Adaptive Slotted ALOHA Protocol (ASAP), This is a medium access control (MAC) protocol for Radio Frequency Identification (RFID) systems which exploits the statistical information collected at the reader.

D. WORK DIFFERENT FROM THE PREVIOUS PUBLISHED WORK.

This work is different from the previously published work as the earlier work deals with the protocol design (Markov Model of Slotted Aloha) and correspondingly its possible combination with two time scale SPSA, so as to come up with optimal cost of object identification with minimum tag collisions. In this work initiative has been taken up so a to fit in the so designed protocol in the possible MAC layer so as to have a proper protocol stack for the algorithm to fit in! Apart from this alternate design methodologies along with ongoing research in the same field has also been depicted.

II. MAJOR CHALLENGES INVOLVED IN RFID

Following are the few major challenges involved in RFID
- Failed RFID tag reads
- Cost – full blown RFID systems are not cost effective.

A. Failed RFID Tag Reads and Their Causes

Failure to detect tags that are present in the read range of a reader can be due to a variety of causes including collisions on the air interface, tag detuning, tag misalignment, and metal and water in the vicinity of the RFID system.

A. Tag collisions:
When multiple tags respond simultaneously to a reader’s signal, their communication signals can interfere with one another. This interference is referred to as a collision and typically results in a failed transmission. In order for a reader to communicate with multiple tags, a method for collision free tag communication must be employed. These methods are referred to as anti-collision methods. An anti-collision method must be employed if an application will typically have more than one tag communicating with a reader at the same time. Anti-collision methods, or algorithms, in tags have similarities to anti-collision algorithms in networking. Unlike standard networking however, RFID tags pose a number of problems that arise from the very limited resources that they are provided with. First, they can afford only limited computation power. Second, state information, such as what portion of the tags identifier has already been read, may be unreliable. Third, collisions may be difficult to detect due to widely varying signal strengths from the tags. Finally, as in most wireless networks, transponders cannot be assumed to be able to hear one another. A common classification of anti-collision algorithms, either probabilistic or deterministic, is based upon how the tags respond during the anti-collision algorithm. In probabilistic algorithms, the tags respond at randomly generated times. There are several variations of probabilistic protocols depending on the amount of control the reader has over the tags. Many probabilistic algorithms are based on the Aloha scheme in networking. The times at which readers can respond can be slotted or continuous. The ISO 15693 protocol, for example, supports a slotted Aloha mode of anti-collision. Deterministic schemes are those in which the reader sorts through tags based on their unique identification number. The simplest deterministic scheme is the binary tree-walking scheme, in which the reader traverses the tree of all possible identification numbers. At each node in the tree, the reader checks for responses. Only tags whose identifier is a child of the checked node respond. The lack of a response implies that the sub-tree is empty. The presence of a response gives the reader an indication as to where to search next.

B. The Cost Issue
Passive RFID systems are the most promising to provide low-cost ubiquitous tagging capability with adequate performance for most supply chain management applications. These low-cost RFID systems are, of necessity very resource limited, and the extreme cost pressures make the design of RFID systems a highly coupled problem with sensitive trade-offs. Unlike other computation systems where it is possible to abstract functionality and think modularly, almost every aspect of an RFID system affects every other aspect. Primarily the question of low cost approach comes into picture when we are more concerned with using this technique as a simple identity information collector, embedding it into the existing IT system with minimum disruption. Our proposed scheme is that cost can be brought down if the cost involved in tag collision can be reduced by adopting the so designed model of communication which is basically the combination of dynamic markov chain model of slotted aloha and two time scale SPSA.
slotted Aloha for access to shared communication medium, known as framed Aloha. Also we assume that during reader tag communication there are no buffers at any node. Thus a packet arriving at a backlogged node or at a node that is currently transmitting is not admitted into the system and is hence lost. A packet arriving at an unbacklogged node is transmitted immediately in the next slot. The total number of nodes in the system is $m < \infty$.

A. Tag Reading As Dynamic Markov Chain

Assume that each backlogged node retransmits with some fixed probability $q_r$ in each successive slot until a successful transmission occurs. In other words, the number of slots from a collision until a given node involved in collision retransmits in a geometric random variable having value $i \geq 1$ with probability $q_r = q_r(1 - q_r)^{i-1}$. The behavior of slotted Aloha can now be described as a discrete-time Markov chain. Let $n$ be the number of backlogged node at the beginning of a given slot. Each of these nodes will transmit a packet in the given slot, independently of each other, with probability $q_a$. Each of the $m-n$ other node will transmit a packet in the given slot if one (or more) such packets arrived during the previous slot. Since such arrivals are Poisson distributed with mean $\lambda/m$, the probability of no arrivals is $e^{-\lambda/m}$, thus, the Probability that an unbacklogged node transmits a packet in the given slot is $q_a = 1 - e^{-\lambda/m}$. Then we obtain probability of no arrivals is $e^{-\lambda/m}$ as the transition probability of the backlogged node.$q_a = 1 - e^{-\lambda/m}$.

\[ P_{a,n} = \begin{cases} 
Q_a(i,n) & 2 \leq i \leq (m-n) \\
Q_a(1,n)[1 - Q_a(0,n)] & i = 1 \\
Q_a(1,n)Q_a(0,n) + Q_a(1,n)[1 - Q_a(1,n)] & i = 0 \\
Q_a(0,n)Q_a(1,n) & i = -1 \end{cases} \tag{3} \]

B. Performance Analysis

We define the drift in state $n$ ($D_n$) as the expected change in backlog over one slot time[2], starting in state $n$. Thus, $D_n$ is the expected number of new arrivals accepted into the system i.e. $[m-n]$ less the expected number of successful transmissions in the slot. The expected number of successful transmissions is just the probability of a successful transmission, defined as $P_{\text{succ}}$ (Appendix B). Thus, where on finding the gradient of success twice to find the maximised value of $P_{\text{succ}}$. Hence the value of $q_a$ and $q_r$ such that $P_{\text{succ}}$ is maximized is $(m-n)q_a = 1 - nq_r$, or in other words

\[ q_a = \frac{1 - nq_r}{(m-n)} \tag{4} \]

IV. ALGORITHM DESCRIPTION

A. The Optimization Problem

The process that we seek to optimize is a $Z^+ \cup \{0\}$ valued parameterized with parameter $q_r \in [0, 1]$ Markov process. Here $\{X(N)\}$ is a markov chain where $X(n)$ number of backlogged tags in the slot $n$ depends on parameter $q_r$. Suppose $R(\bullet)$ denotes the cost function (assumed bounded), then the goal here is to find $q_r \in (0, 1]$ that minimizes

\[ J(q_r) = \lim_{n \to \infty} \frac{1}{n} \sum_{i=0}^{n-1} R(x_i) \tag{5} \]

In particular let $q_r$ be the values in the set $[0.01, 1]$ (for any given $q_r$). In particular let $q_r$ be the values in the set $[0.01, 1]$, now we develop an algorithm that tunes $q_r$ in order to minimize $J(q_r)$. Also let $P_\theta$ is the transition probability of $\{X(J)\}$. Our aim is to find $q_r$ IN THE SET $C = [0.01, 1]$ that minimizes the average cost $J(q_r)$ as defined above.

B. Two Time Scale SPSA Algorithm

The SPSA (Simultaneous Perturbation Stochastic Approximation) algorithm has proven to be an effective stochastic optimization method. Its primary virtues are (i) relative ease of implementation and lack of need of loss function (ii) theoretical and experimental support for relative efficiency (iii) robustness to noise in the loss measurement and (iv) empirical evidence to ability to find a global minimum when multiple (local and global) minima exist [5]. Detailed description of SPSA can be found in [4]. The so defined algorithm is called two time scale SPSA as it is governed by two step size sequences (or timescales) $\{a(n)\}$ and $\{b(n)\}$ defined below. Before proceeding let us define some basic notations. Let $\delta > 0$ be a fixed constant. Let

\[ \Pi(\lambda(x) = \min(max(0,0.01), \lambda(x))) \] denote the point closest to $x \in R$ in the interval $[0.01, 1]$, Then $\Pi(\lambda(\theta))$ is a projection of $\theta \in R$ onto the set $C$. Define sequences $\{a(n)\}$ and $\{b(n)\}$ as follows, $a(0) = b(0) = 1$, $a(i) = i^{-1}$ and $b(i) = i^{-\alpha}$, $\alpha \geq 1$ with $1/2 < \alpha < 1$. In our experiments we have taken the value of $\alpha$ as 2/3. Then clearly

\[ a(n+1), b(n+1) \quad \text{as} \quad n \to \infty \quad \ldots \quad \ldots \quad \ldots \tag{6} \]
\[ \sum_{n} a(n) = \sum_{n} b(n) = \infty \]  
\[ \sum_{n} a(n)^2, \sum_{n} b(n)^2 < \infty, a(n) = o(b(n)) \]  
\[ \sum_{n} a(n)^2 = \sum_{n} b(n)^2 < \infty, a(n) = o(b(n)) \]

Now let \( \{X^-(l)\} \) and \( \{X^+(l)\} \) be the parallel simulation. It depend on parameter sequences \( \{q_r(n) + \Delta \theta(n)\} \) and \( \{q_r(n) - \Delta \theta(n)\} \) respectively, in the manner defined below. Let \( L \geq 1 \) is a given fixed integer. We extract double sequence \( \{X^- (n)\} \) and \( \{X^+ (n)\} \), \( n \geq 0 \) and \( m = 0, 1, \ldots, L - 1 \) from the parallel simulations in the following manner. Write \( l = nL + m \) where \( n \geq 0 \) and \( m \in \{0, 1, \ldots, L - 1\} \). Now set \( X^- (n) \equiv X \left( nL + m \right) \) for \( n \geq 0 \) and \( m \in \{0, 1, \ldots, L - 1\} \). Now set \( X^+(n) \equiv X \left( nL + m \right) \) for \( n \geq 0 \) and \( m \in \{0, 1, \ldots, L - 1\} \). Finally we take \( \delta \) and \( \Delta \) numbers taking values +1 or -1 with probability 0.5.

Also define two double sequences
\[ V_{m+1}^1(n) = V_{m}^1(n) + b(n) \left( R(X^-_{m}(n) - V^\circ_{m}(n)) \right) \]  
\[ V_{m+1}^2(n) = V_{m}^2(n) + b(n) \left( R(X^+_{m}(n) - V^\circ_{m}(n)) \right) \]

For \( m = 0, 1, \ldots, L - 1 \). Also \( V_i^1(0) = V_i^2(0) = 0 \) \( \forall i \in \{0, 1, \ldots, L - 1\} \). Using these two sequences we can show that \( V^1 \rightarrow J(q^*_r - \Delta \theta^*) \) and \( V^2 \rightarrow J(q^*_r + \Delta \theta^*) \) the purpose of the above two sequences (also known as the faster scale recursion) is to average the cost function, corresponding to perturbed parameter updates \( \{q_r(n) - \Delta \theta(n)\} \) and \( \{q_r(n) + \Delta \theta(n)\} \) respectively. Here \( \Delta(n) \) are independently generated Bernoulli random numbers taking values +1 or -1 with probability 0.5.

### V. CONVERGENCE ANALYSIS OF SPSA

As shown in [4], the faster scale recursions converge to \( J(q_r(n) + \Delta \theta(n)) \) and \( J(q_r(n) - \Delta \theta(n)) \) respectively for any given value of \( q_r \) and \( \Delta \). Now all one needs to do is to substitute these values in the slower timescale recursion to obtain the equivalent recursion.

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**Algorithm**

1. Compute \( q_r \) by the formula \( q_r = (1 - (m-n)q_a)/n \) where \( n \) is the number of backlogged sources
2. Let there be two parallel simulations such that for simulation the each of them is governed by the following \( \{q_r(n) - \Delta \theta(n)\} \) and \( \{q_r(n) + \Delta \theta(n)\} \)
3. Compute
   \[ V_{m+1}^1(n) = V_{m}^1(n) + b(n) \left( R(X^-_{m}(n) - V^\circ_{m}(n)) \right) \]
   \[ V_{m+1}^2(n) = V_{m}^2(n) + b(n) \left( R(X^+_{m}(n) - V^\circ_{m}(n)) \right) \]
4. Substituting the above obtained values to find
   \[ q_r(n+1) = \prod (q_r(n) + a(n) \left( \frac{V^1_r(n) - V^2_r(n)}{2\Delta \theta(n)} \right)) \]
5. Find the Converged Value of \( q_r \) in order to get
   \[ \arg \min J(\theta^*) = q^*_r \]

So we can say that equation (12) is analogous to
\[ q_r(n+1) = \prod (q_r(n) + a(n) \left( \frac{J(q_r(n) - \Delta \theta(n)) - J(q_r(n) + \Delta \theta(n))}{2\Delta \theta(n)} \right)) \]

In the limit as \( \Delta \rightarrow 0 \) where \( \prod \) is defined as
\[ \prod \left( v(x) \right) = \lim_{\eta \rightarrow \infty} \left( \left( \prod (x + \eta v(x)) - x \right) \right) \]

For bounded continuous function \( v(x) \), let \( K = \{ (\theta \in \mathbb{R} | (\prod v(\theta)) = 0) \} \) denote the set of all asymptotically stable fixed points of the ODE. We thus have the theorem (Appendix A).

### VI. NUMERICAL RESULTS

In this section we demonstrate the cost analysis of the Dynamic markov chain model of slotted aloha via two time scale SPSA models. Cost as taken in our case is in the following manner; cost assigned will be one less than the number of packets transmitted in a slot. For example if the number of packets transmitted is two then the cost is one in a particular slot. Or in a more general form the cost is \( n-1 \) if the number of packets is \( n \). Also to note that
the cost will be two if there are zero packets because in this case though there is no collision yet no throughput. Hence our goal is not only to reduce the collision but also to increase the throughput. Now describing the cost function, let \( \{ X_n \} \) be the parameterized process. \( \{ X_n \} \equiv \) Number of packets at time \( n \). Now for a given value of \( \theta^* \), \( \{ X_n \} \) is a Markov chain. Also there is an associated cost \( R(x) \) where \( X_n = x \) at a given time \( n \) where \( x=0, 1, 2, \ldots, m \). Here our goal is to find \( \theta^* \in [0, 1] \times [0, 1] \), such that the long run expected cost \( J (\theta^*) \) is minimized. Or

\[
\min_{\theta} \lim_{n \to \infty} \frac{1}{n} E \left[ \sum_{i=1}^{n^*} R(x_i) \mid x_0 = 0 \right] \quad \ldots \ldots \quad (16)
\]

Here \( x^i \) depends on \( \theta \). Note that in general

\[
\lim_{n \to \infty} \frac{1}{n} E \left[ \sum_{i=1}^{n^*} R(x_i) \mid x_0 = 0 \right] = \lim_{n \to \infty} E \left[ \frac{1}{n} \sum_{i=1}^{n^*} R(x_i) \mid x_0 = 0 \right]
\]

(17)

The key to note here is that the Expectation is taken first and then the limit as \( n \to \infty \). Also to note that if \( \theta^* = \arg\min J (\theta) \), where \( \theta^* \in [0, 1] \times [0, 1] \) then our goal will be the standard procedure to evaluate \( \nabla J (\theta) = 0 \). Now as \( J (\theta) \) is not an analytical function we have used the two time scale SPSA to find its value.

As we have shown that \( q_r \to q_r^* \), such that \( \theta^* = \arg\min J (\theta) \) consequently we have shown that the cost obtained by the so designed model is optimal as compared against all the heuristically changed values of \( q_r \). (Appendix D-Table-1). Here the arrival rate taken for all the five sources is 0.24 and the value of \( \delta \) is taken as 0.05. The next set of our experiment (Appendix D-Table-2) shows the change in the value of \( q_r \) as against the change in arrival rate for all the five sources. The trend which has generated here implies that with the decrease of arrival rate the converged value of \( q_r \) is lower than the optimal one and similarly with the increase of arrival rate the converged value of \( q_r \) is higher than the optimal value. (Appendix E- Fig (1)) shows \( q_r \) against \( n \) (number of slots). The simulation has been run for over 100000 slots and the converged value of \( q_r \) is found to be 0.83. Hence \( \arg\min J (\theta^*) = q_r^* \) is found to be 0.83 from the simulations.

VII. CONCLUSION

We have adopted a two time scale Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm for optimizing the retransmission probabilities of backlogged nodes in a slotted aloha model for reader tag communication. We have also shown the convergence analysis of this model. With the help of numerical analysis and experimentation (programmatically simulating the model) it has been proved that the so designed model not only helps to minimize the tag collision but also gives the optimal cost with increased throughput. Approach has also been depicted for the possible MAC layer integration of the algorithm along with alternate design approaches.
APPENDIX A-FOR BOUNDED FUNCTIONS

Given $\eta > 0$, there exist $\delta_0 > 0$ such that for all $\delta \in (0, \delta_0]$, $\theta(n) \to K^\eta$ as $\eta \to \infty$. In the above $K^\eta = \{ \nu \in C \mid \exists \nu \in K \text{ s.t.} \| \theta - \nu \| \leq \eta \}$ denotes the set of all points that are within a distance $\eta$ from the set $K$.

APPENDIX B-P-SUCC.

$$P_{\text{succ}} = Q_r(1.\eta)Q_r(0.n) + Q_r(0.n)Q_r(1.\eta).$$

$$D_\delta = (m-n)q_r - P_{\text{succ}}.$$

$$\left[ (m-n)(1-q_r)^{n-1} + (1-q_r)^{n-1} \right].$$

$$\left[ (m-n)q_r + \frac{nq_r}{1-q_r} \right] - \left[ (1-q_r)^{n-1} \right].$$

APPENDIX C-TAYLOR EXPANSION

$$J(q_r(n) - \delta \Delta(n)) = J(q_r(n) - \delta \Delta(n) \nabla J(q_r(n)) + o(\delta)$$

& $$J(q_r(n) + \delta \Delta(n)) = J(q_r(n) + \delta \Delta(n) \nabla J(q_r(n)) + o(\delta)$$. Hence

$$\frac{J(q_r(n) - \delta \Delta(n)) - J(q_r(n) + \delta \Delta(n))}{2\delta \Delta(n)} = - \nabla J(q_r(n)) + o(\delta)$$

APPENDIX D-TABLE-1

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<th>Arrival Rate 0.24</th>
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<th>Arrival Rate 0.28</th>
<th>Arrival Rate 0.32</th>
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<td>Avg cost: 1.27126</td>
<td>Avg cost: 1.33308</td>
<td>Avg cost: 1.24476</td>
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<tr>
<td>Mean Succ Tx: 0.34493</td>
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<td>Mean Succ Tx: 0.32214</td>
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<td>Prob of collision: 0.21336</td>
<td>Prob of collision: 0.13400</td>
<td>Prob of collision: 0.28907</td>
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<td>Channel Idling: 0.46443</td>
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APPENDIX D-TABLE-2

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APPENDIX E (GRAPH)

Fig-1( qr vs. slots)
REFERENCES


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