MAC Layer RFID Protocol for Low Cost Object Identification

Shweta Singh
Wipro Technologies,Bangalore,India
shweta.singh@wipro.com

***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 there by 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-2Protocols 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.

Based on "Low Cost Object Identification in RFID via Dynamic Markov Chain and Two Time Scale SPSA" published in SAINT - 2006", by Shweta Singh which appeared in the Proceedings of the IEEE International Symposium on Application and Internet on January-2006, Phoenix, Arizona,USA Jan 2006. © 2006 IEEE.

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

III. BASIC SIMULATION MODEL

Mathematical Model has been designed by the combination of the Markov model to read tags with two time scale SPSA so as to reduce the cost and increase the throughput. Assuming that all the messages involved in the collision are destroyed hence not taking into consideration the 'capture effect'. Employing a variant of 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< ∞ .

A. Tag Reading As Dynamic Markov Chain

Assume that each backlogged node retransmits with some fixed probability qr 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 ≥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_r. 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 λ/m, the probability of no arrivals is e-λ/m, thus, the Probability that an unbacklogged node transmits a packet in the given slot is q_a =1- e-λ/m. Then we obtain 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

$$Q_a(i,n) = \text{prob } i \text{ unbacklogged nodes transmitted}$$
$$= \binom{m-n}{i}(1-q_a)^{m-n-i} q_a^i \text{..............................} (1)$$
$$Q_r(i,n) = \text{prob } i \text{ backlogged nodes transmitted}$$
$$= \binom{n}{i} q_r^i (1-q_r)^{n-i} \text{..} (2)$$

And the transition probabilities can be defined as under:

$$P_{n,n+i} = \begin{cases} Q_a(i,n) & 2 \le i \le (m.-n) \\ Q_a(1,n)[1-Q_r(0,n)] & i=1 \\ Q_a(1,n)Q_r(0,n)+Q_a(0,n)[1-Q_r(1,n)] & i=0 \\ Q_a(0,n)Q_r(1,n) & i=\text{-}1 \end{cases} \quad (3)$$

B. Performance Analysis

We define the *drift* in state *n* (D_n) as the expect 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*) q_a] 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_{succ}. (Appendix B). Thus, where on finding the gradient of success twice to find the maximised value of P_{succ} . Hence the value of q_a and q_r such that P_{succ} is maximized is $(m-n)q_a = 1-nq_r$ or in other words

$$q_a = \frac{1-nq_r}{(m-n)} \text{.......................................} (4)$$

IV.ALGORITHM DESCRIPTION

A. The Optimization Problem

The process that we seek to optimize is a $Z^+ \cup \{0\}$ valued parameterized with parameter $q_r \in [0.01,1]$ 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(●) denotes the cost function (assumed bounded),then the goal here is to find $q_r^* \in (0,1]$ that minimizes

$$J(q_r) = \lim_{n\to\infty} \frac{1}{n} E\left[\sum_{i=0}^{n-1} R(x_i)\right] \text{............................} (5)$$

In particular lets take q_r the values in the set [0.01, 1] (for any given q_r). In particular lets take q_r 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_θ (X, Y), represents the transition probability of {X (J}.Our aim is to find a 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 $\Pi(x) \stackrel{\Delta}{=} \min(\max(0.01,x),(1))$ denote the point closest to x∈ R in the interval [0.01,1].Then $\Pi(\theta)$ is a projection of θ ∈ 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)= $i^{-\alpha}$,i ≥ 1 with ½< α <1. In our experiments we have taken the value of α as 2/3. Then clearly

$$\frac{a(n+1)}{a(n)}, \frac{b(n+1)}{b(n)} \text{ as } n \to \infty \ldots \ \ldots\ldots\ldots\ldots \quad (6)$$

$$\sum_n a(n) = \sum_n b(n) = \infty \text{ ....} \quad (7)$$

$$\sum_n a(n)^2 \text{ , } \sum_n b(n)^2 < \infty \text{, a (n) =o (b (n)) ....} \quad (8)$$

Now let {X^- (l)} and {X^+(l)} be the parallel simulation. It depend on parameter sequences { q_r(n) + $\delta\Delta(n)$ }and q_r(n)-$\delta\Delta(n)$ }respectively, in the manner defined below. Let L$\geq$1 is a given fixed integer. We extract double sequence {$\bar{X}_m$ (n)} and {X^+_m (n)}, n$\geq$0, m=0, 1 ...L-1, from the parallel simulations in the following manner. Write l as l=nL+m where n$\geq$0 and m$\in$ {0,1,….L-1} .Now set $\bar{X}_m(n) \stackrel{\Delta}{=} \bar{X}$(nL+m) and $X^+_m(n) \stackrel{\Delta}{=} X^+$(nL+m) respectively. Now for m=0,1…..L-1 {$\bar{X}_m$ (n)} is governed by the parameter { q_r(n)- $\delta\Delta(n)$ }.Similarly for m=0, 1…..L-1 {X^+_m (n)} is governed by the parameter { q_r(n)+ $\delta\Delta(n)$ }. Finally the algorithm can be described as

$$qr(n+1) = \prod \left(qr(n) + a(n)\left(\frac{v_0^1(n) - v_0^2(n)}{2\delta\Delta\ (n)}\right)\right) \text{ ... (9)}$$

Also define two double sequences

$$V^1_{m+1}(n) = V^1_m(n) + b(n)\big(R(X^-_m(n) - V^1_m(n)\big). \quad (10)$$

$$V^2_{m+1}(n) = V^2_m(n) + b(n)\big(R(X^+_m(n) - V^2_m(n)\big) \text{...(11).}$$

For m=0, 1 …L-1.Also $V_i^1(0) = V_i^2(0) = 0$ $\forall$ i $\in$ {0, 1 ….L-1}Using these two sequences we can show that $V^1_n \to J(q^*_r - \delta\Delta^*\ )$ and $V^2_n \to J(q^*_r + \delta\Delta^*)$ the purpose of the above two sequences (also known as the faster time scale recursion) is to average the cost function, corresponding to perturbed parameter updates { $q_r(n)$ - $\delta\Delta(n)$ } and { $q_r(n) + \delta\Delta(n)$ } 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)- $\delta\Delta(n)$) and J (q_r(n) + $\delta\Delta(n)$) respectively for any given value of q_r and Δ.Now all one needs to do is to substitute these values in the slower timescale recursion to obtain the equivalent recursion.

Algorithm

1. Compute qr by the formula qr=(1-(m-n)qa)/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)- $\delta\Delta(n)$ } and { q_r(n)+ $\delta\Delta(n)$ }
3. Compute $V^1_{m+1}(n) = V^1_m(n) + b(n)\big(R(X^-_m(n) - V^1_m(n)\big)$ & $V^2_{m+1}(n) = V^2_m(n) + b(n)\big(R(X^+_m(n) - V^2_m(n)\big)$
4. Substituting the above obtained values to find $qr(n+1) = \prod \left(qr(n) + a(n)\left(\frac{v_0^1(n) - v_0^2(n)}{2\delta\Delta\ (n)}\right)\right)$
5. Find the Converged Value of qr in order to get argmin J (θ^*)= q_r^*

$$qr(n+1) = \prod \left(qr(n) + a(n)\left(\frac{J(q_r(n) - \delta\Delta(n)) - J\{q_r(n) + \delta\Delta(n))}{2\delta\Delta(n)}\right)\right)$$
……… .. . (12)

So we can say that equation (12) is analogous to $qr(n+1) = \prod \big(q_r(n) + a(n)(-\nabla J(q_r(n)) + o(\delta))\big)$(13) (Appendix C). The last corresponds to a gradient descent algorithm that asymptotically tracks the trajectories of the ordinary differential equation (ODE)

$$\dot{q}_r = \tilde{\Pi}(-\nabla J(q_r)) \text{ ………………… …….. .. (14)}$$

In the limit as $\delta \to 0$ where $\tilde{\Pi}$ (.) is defined as

$$\prod (v(x)) = \frac{\lim_{n \downarrow o} (\Pi\,(x + \eta v\ (x)) - x)}{\eta} \text{ .. …...} \quad (15)$$

For bounded continuous function $v(\bullet)$, let K=$\{\theta(\tilde{\Pi}(\nabla J(\theta)) = 0\}$ 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 θ, $\{X_n\}$ 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…….m. Here our goal is to find $\theta^* \in [0, 1] \times [0, 1]$, such that the long run expected cost (J (θ^*)is minimized. Or

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

Here x^i depends on θ. Note that in general

$$\lim_{n\to\infty} \frac{1}{n} E\left[\sum_{i=1}^{n} R(x_i) \mid x_0 = 0\right] \neq \lim_{n\to\infty} E\left[\frac{1}{n} \sum_{i=1}^{n} R(x_i) \mid x_0 = 0\right]$$
(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 θ^* =argminJ (θ) 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 (θ) 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 θ^* =argmin J (θ) 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 δ 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 argmin J (θ^*)= 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 $K^{\eta} = \{\nu \in C \mid \exists \nu \in K \text{ s.t.} \| \theta - \nu \| < \eta \}$ denotes the set of all points that are within a distance η from the set K.

APPENDIX B-P-SUCC.

$$P_{succ} = Q_a(1,n)Q_r(0,n) + Q_a(0,n)Q_r(1,n).$$

$$D_n = (m-n)q_a - P_{succ}$$

$$= [(m-n)(1-q_a)^{m-n-1}q_a](1-q_r)^n + (1-q_a)^{m-n}[n(1-q_r)^{n-1}q_r].$$

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

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 $\dfrac{J(q_r(n) - \delta\Delta(n)) - J\{q_r(n) + \delta\Delta(n))}{2\delta\Delta(n)}$

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

APPENDIX D-TABLE-1

Optimal	Heuristically Changed
qr: 0.845363 Avg cost: 0.30302 Mean Succ Tx: 0.31016 Prob of collision: 0.42725 Channel Idling: 0.26259	qr: 0.494678 Avg cost:1.76711 Mean Succ Tx:0.16559 Prob of collision:0.60805 Channel Idling: . 22636
Heuristically Changed	**Heuristically Changed**
qr: 0.194678 Avg cost: 0.38342 Mean Succ Tx: 0.28619 Prob of collision: 0.46742 Channel Idling: 0. 24639	qr: 0.94678 Avg cost: 1.33308 Mean Succ Tx: 0.30347 Prob of collision: 0.44073 Channel Idling: 0.25580

(Optimal qr vs. Heuristically changed qr)

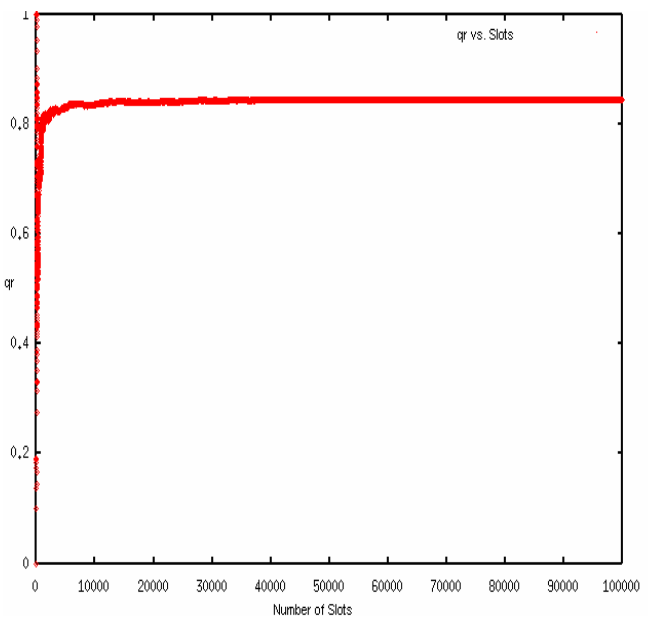
APPENDIX D-TABLE-2
(Arrival rate vs. qr)

Arrival Rate 0.24	
qr:	0.805543
Average cost:	1.22486
Mean Successful Transmission:	0.34493
Probability of collision:	0.16424
Channel Idling:	0.49083

Arrival Rate 0.20	Arrival Rate 0.16
qr: 0.563151 **Avg cost: 1.23079** **Mean Succ Tx 0.34475** **Prob of collision: 0.16520** **Channel Idling: 0.49005**	**qr: 0. 524961** **Avg cost: 1. 27126** **Mean Succ Tx: 0.322214** **Prob of collision: 0. 21336** **Channel Idling: 0. 46443**
Arrival Rate 0.28	**Arrival Rate 0.32**
qr: 0. 336978 Avg cost: 1. 20109 Mean Succ Tx: 0. 35841 Prob of collision: 0.13400 Channel Idling: 0. 50759	qr: 0. 729803 Avg cost: 1.24476 Mean Succ Tx: 0.32395 Prob of collision: 0.28907 Channel Idling: 0.38698

APPENDIX E (GRAPH)

Fig-1(q_r vs. slots)



REFERENCES

[1] Klaus Finkenzeller. RFID *–Handbook: Radio Frequency Identification Fundamentals and Applications,*John willey &sons.

[2] Dimitri Bertsekas,Robert Gallager *Data networks* - Prentice Hall, second edition. Pages 275-281

[3] Harald vogt-.*Efficient object identification with passive RFID tags*. In international conference on pervasive computing,LNCS.Springer-Verlag,2002.

[4] Bhatnagar, Fu, Marcus ,Bhatnagar-Two time scale algorithms for simulation optimization of hidden markov model IIE Transactions (Pritsker special issue on simulation), Vol.3, pp.245-258, 2001.

[5] James C.Spall-*stochastic optimization and simultaneous perturbation method*

[6] Ross Anderson and Markus Kuhn. Low Cost Attacks on Tamper Resistant Devices. In *IWSP: International Workshop on Security Protocols, LNCS*, 1997.

[7] Stephen A. Weis, Sanjay E.Sarma, Ronald L. Rivest, Daniel W.Engles: *Security and privacy aspects of low cost RFID systems* accepted for publication to the First International Conference on Security in Pervasive Computing (SPC 2003), March 12-14, 2003.

[8] Jeffrey Hoffstein, Jill Pipher, and Joseph H. Silverman. NTRU: A Ring-Based Public Key Cryptosystem. *Lecture Notes in Computer Science*, 1423:267–, 1998.

[9] Suresh Chari, Charanjit Jutla, Josyula R. Rao, and Pankaj Rohatgi. A Cautionary Note Regarding Evaluation of AESCandidates on Smart-Cards. In *Second Advanced Encryption Standard (AES) Candidate Conference*, Rome, Italy,1999.

[10] H. Vogt. Multiple object identification with passive RFID tags. In *IEEE International Conference on Systems,*

[11] *Man and Cybernetics, SMC'02*, volume 3, pages 6 – 9, October 2002.

[12] Law, K. Lee, and K. Siu. Efficient memoryless protocol for tag identification. In *4th International Workshop on Discrete Algorithms and Methods for Mobile Computing and Communications, ACM*, pages 75–84, August 2000.

[13] J.R. Tuttle. Traditional and emerging technologies and applications in the radio frequency identification (RFID) industry.In *IEEE Radio Frequency Integrated Circuits (RFIC) Symposium*, pages 5–8, June 1997.

[14] J. Weiseltheir, A. Ephremides, and M. Larry. An exact analysis and performance evaluation of framed ALOHA with capture. *IEEE Transactions on Communications*, 37-2:125–136, February 1989.

[15] W. Szpankowski. Packet switching in mutiple radio channels : Analysis and stability of radio access system. *ComputerNetworks*, Vol. 7:17–26, 1983.

[16] Junius Ho,Daniel W. Engles,Sanjay E.Sarma : HiQ: A Hierarchical Q-Learning Algorithm to Solve the Reader Collision Problem, International Symposium on Applications and the Internet Workshops (SAINTW'06) pp. 88-91

[17] I-Jeng Wang and Edwin K. P. Chong: A Deterministic Analysis of Stochastic Approximation with Randomized Directions, IEEE Transaction on Automatic Control Vol 43No 12 December 1998.

Shweta Singh (MIEEE)

Shweta was born on September 17th 1983 in India. She has done her Bachelors in Computer Science from HBTI Kanpur,India in 2004 and is currently a Master's Computer Science Student. Her major field of study and interest is Computer Networks, Wireless Adhoc and Sensor Networks. She is working as a Software Engineer for Wireless Networks and Devices (Centre Of Excellence) at Wipro Technologies, Bangalore. INDIA She is not only a Young Bright and Dynamic researcher but has also presented published and reviewed papers for IEEE journals conferences and Magazines. She has been selected as Session Co-chair for IEEE-ITNG-06 Sensor Network Track and has set up a landmark by being the youngest researcher who represented India among 19 nations for IEEE-SAINT-06. She is an invited speaker in Design and Developer's Forum at IEEE-GlobeCom 2006. She is a member of IEEE society also.