ACKNOWLEDGMENT

We would like to thank the editor and the anonymous referees for the constructive comments to help us improve the quality and the presentation of the manuscript.

REFERENCES

[1] J. Rivoir, "Parallel test reduces cost of test more effectively than just a cheap tester," in *Proc. IEEE/CPMT/SEMI 29th Int. Electron. Manuf. Technol. Symp.*, 2004, pp. 263–272.
[2] C.-F. Chien and J.-Z. Wu, "Analyzing repair decisions in the site imbalance problem of semiconductor test machines," *IEEE Trans. Semicond. Manuf.*, vol. 16, pp. 704–711, 2003.
[3] X. Yao, E. Fernadez-Gaucherand, M. Fu, and S. Marcus, "Optimal preventive maintenance scheduling in semiconductor manufacturing," *IEEE Trans. Semicond. Manuf.*, vol. 17, pp. 345–356, Aug. 2004.
[4] P. H. Tag and M. T. Zhang, "eManufacturing in the semiconductor industry: A case study on intelligent preventive maintenance," *IEEE Robot. Autom. Mag.*, pp. 25–32, Dec. 2006.
[5] D. Babbs and R. Gaskins, "Effect of reduced equipment downtime variability on cycle time in a conventional 300 mm Fab," in *Proc. IEEE/SEMI Adv. Semicond. Manuf. Conf.*, 2008, pp. 237–242.
[6] M. J. Lopez and S. C. Wood, "Systems of multiple cluster tools: Configurations, reliability, and performance," *IEEE Trans. Semicond. Manuf.*, vol. 16, pp. 170–178, 2003.
[7] P. B. Luh, D. Yu, S. Soorapanth, A. Khibnik, and R. Rajamani, "A Lagrangian relaxation based approach to schedule asset overhaul and repair services," *IEEE Trans. Autom. Sci. Eng.*, vol. 2, no. 2, pp. 145–157, 2005.
[8] S. A. Mosley, T. Teyner, and R. M. Uzsoy, "Maintenance scheduling and staffing policies in a wafer fabrication facility," *IEEE Trans. Semicond. Manuf.*, vol. 11, no. 2, pp. 316–323, 1998.
[9] T. K. Das and S. Sarkar, "Optimal preventive maintenance in a production inventory system," *IIE Trans. Qual. Reliab. Eng.*, vol. 31, no. 6, pp. 537–551, 1999.
[10] H. Wang, "A survey of maintenance policies of deteriorating systems," *Eur. J. Oper. Res.*, vol. 139, no. 3, pp. 469–489, 2002.
[11] L. Lopez, "Advanced electronic prognostics through system telemetry and pattern recognition methods," *Microelectron. Reliability*, vol. 47, no. 12, pp. 1865–1873, 2007.
[12] N. Vichare and M. Pecht, "Prognostics and health management of electronics," *IEEE Trans. Compon. Packag. Technol.*, vol. 29, pp. 222–229, 2006.
[13] W.-Y. Chang, T.-C. Wang, and Y.-P. Shin, "Real-time fault detection and condition monitoring system for chiller," in *Proc. Semicond. Manuf. Technol. Workshop*, 2004, pp. 160–165.
[14] Y.-C. Su, F.-T. Cheng, M.-H. Hung, Y.-C. Lin, and R.-C. Lin, "Design and implementation of an intelligent prognostics system," in *Proc. IEEE Int. Conf. Autom. Sci. Eng.*, 2005, pp. 273–278.
[15] K. M. Goh, B. Tjahjono, T. Baines, and S. Subramaniam, "A review of research in manufacturing prognostics," in *Proc. IEEE Int. Conf. Ind. Informat.*, 2006, pp. 417–422.
[16] T. Jin and Y. Yu, "Production loss based maintenance with uncertain failure service times," in *Proc. 2009 Int. Conf. Reliab., Maintainability, and Safety Symp.*, 2009, pp. 32–37.
[17] N. Gebraeel, A. Elwany, and J. Pan, "Residual life predictions in the absence of prior degradation knowledge," *IEEE Trans. Rel.*, vol. 58, pp. 106–117, 2009.
[18] A. H. Christer and W. Wang, "A model of condition monitoring of a production plant," *Int. J. Prod. Res.*, vol. 30, no. 9, pp. 2199–2211, 1992.
[19] C. Lu and W. Meeker, "Using degradation measures to estimate a time-to-failure distribution," *Technometrics*, vol. 35, no. 2, pp. 161–174, 1993.
[20] T. Jin, P. Wang, and Q. Huang, "A practical MTBF estimate for PCB design considering component and non-component failures," in *Proc. Annu. Reliab. Maintainability Symp.*, 2006, pp. 604–610.
[21] A. Urmanov, "Electronic prognostics for computer servers," in *Proc. Reliab. Maintainability Symp.*, 2007, pp. 65–70.
[22] C. Park and W. J. Padgett, "Stochastic degradation models with several accelerating variables," *IEEE Trans. Rel.*, vol. 55, pp. 379–390, 2006.
[23] W. J. Padgett and M. A. Tomlinson, "Inference from accelerated degradation and failure data based on Gaussian process models," *Lifetime Data Anal.*, vol. 10, pp. 191–206, 2004.
[24] D. Montgomery, *Design and Analysis of Experiment*, 7th ed. New York: Wiley, 2009, ch. 2, pp. 47–48.

Bayesian Tag Estimate and Optimal Frame Length for Anti-Collision Aloha RFID System

Haifeng Wu and Yu Zeng

***Abstract*—In a dynamic framed slotted aloha RFID system, the key technique can be divided into two parts: precisely estimating tag quantity and determining an optimal frame length. For estimating tag quantity, this paper uses three risk functions to propose three Bayesian estimates, and improves the estimates to reduce computational complexity. For determining an optimal frame length, this paper derives an optimal frame length, which can make the system achieve maximum channel usage efficiency under the condition that the durations of an idle, a collision and a successful slot are not identical. In our simulations, comparison with several conventional tag estimates shows that the proposed Bayesian tag estimates have less error. In addition, the improved estimates have lower computational complexity and their estimate performance is not reduced. The simulations results also indicate that the derived optimal frame length guarantees the maximum channel usage efficiency.**

***Note to Practitioners*—Tag estimates proposed in this paper are capable of precisely estimating tag quantity in a dynamic framed aloha RFID system. The main advantage of the proposed estimates is to present a method to reduce computational complexity of estimating tag quantity. Since estimating tag quantity is generally processed at a reader, the presented method can help engineers to improve the reader's running speed and reduce the reader's memory usage. In current RFID standards such as ISO-18000-6 and EPC C1 Gen2, the durations of an idle, a collision and a successful slot are set to being different to improve identification efficiency. Under such condition of the slot duration, the published frame length schemes would not guarantee maximum channel usage efficiency. Since setting frame length is not specified in these standards, engineers can reduce the time of identifying tags by applying an optimal frame length derived in this paper to these standards. The maximum channel usage efficiency of the derived frame length surpasses that of the published schemes.**

***Index Terms*—Anti-collision, framed aloha, frame length, RFID, tag estimate.**

I. INTRODUCTION

One of radio frequency identification (RFID) advantages over traditional bar code is that RFID can support simultaneous multi-tag identification, and hence offer higher identification efficiency. The multi-tag identification is actually a multi-access communication system. When the multiple tags simultaneously transmit their signals to the reader, collisions will happen. Now, many conventional anti-collision algorithms for multi-access systems have been applied to the RFID tag anti-collision system. These algorithms can be grouped into two broad categories: tree-based algorithms [1]–[9] and aloha-based algorithms [10]–[19]. Aloha-based algorithms randomize access times of tags to reduce collisions and are suitable for systems with limited capabilities mobile nodes and a powerful base station or a reader. In an RFID system, a reader dominates the multiple-access procedure and tags are, in general, passive devices and have very limited power.

Manuscript received January 15, 2009; revised May 26, 2009. First published March 11, 2010; current version published October 06, 2010. This paper was recommended for publication by Associate Editor B. Sai and Editor V. Kumar upon evaluation of the reviewers' comments. This work was supported by National Natural Science Foundation of China (60963026) and open foundation of Key Laboratory of Wireless Sensor Network Technology of Yunnan Province (09ZK04).

H. Wu is with the School of Electrical and Information Technology, Yunnan University of Nationalities, Kunming 650500, R.O.C. (e-mail: whf5469@gmail.com).

Y. Zeng is with the School of Electrical and Information Technology, Yunnan University of Nationalities, Kunming 650500, R.O.C. (e-mail: yv.zeng@gmail.com).

Digital Object Identifier 10.1109/TASE.2010.2042957

Hence, aloha-based algorithms are very suitable for the RFID system. Aloha-based algorithms can be categorized into pure aloha, slotted aloha and dynamic framed slotted aloha. Since the dynamic framed slotted aloha can dynamically adjust the frame length in the subsequent round (frame) to improve system throughput, the dynamic framed slotted have higher identification efficiency than the pure aloha and the slotted aloha. However, the frame length's adjustment is according to tag population, which is generally unknown to the reader. Therefore, in order to improve the performance of the dynamic framed slotted aloha, we should consider two problems: precisely estimating the tag population and determining the optimal frame length.

Among conventional tag estimates, the simpler ones are lower bound estimate [11]–[14], Schoute estimate [10], [13]–[15] and idle slot estimate [18]. However, these three estimates are not applied to aloha-based systems now because their estimate results are not accurate. Vogt estimate [11], [12], [16], [17] and maximum *a posteriori* (MAP) estimate [19] have less error than those three estimates. Vogt estimates tag quantity by searching the minimal distance between the real results of idle slot, successful slot and collision slot quantity and the expected ones. MAP estimates tag quantity also by searching maximum *a posteriori* probability. In these two methods, one obvious concern is a tag quantity range over which the minimal distance or the maximum probability needs to be searched. If the range is wide, the estimates' computational complexity will be high.

To improve the performance of dynamic framed slotted aloha, another problem, the frame length determination according to tag quantity also needs to be taken into consideration. References [10], [13], [15], [19] all propose that the RFID system would achieve maximum channel usage efficiency when the frame length, i.e., the time slot quantity in a frame, is equal to the tag quantity. However, this proposition is based on the assumption that the durations of an idle, a collision and a successful slot are identical. In fact, the channel usage efficiency can be enhanced if these three durations are set to being different. In some current RFID standards such as ISO 18000-6 [20], [21] and EPC C1 Gen2 [22], the durations are different. Therefore, the scheme that the frame length is equal to the tag quantity is not suitable for the systems in these standards.

Application of Bayes' rule to a multi-access system is not new. Rivest proposes a Bayesian transmission strategy for a slotted aloha broadcast system [23]. Based on Rivest's work, Floerkemeier also applies the Bayesian transmission strategy to a framed aloha RFID system in [13], [14], [24]. Theses works mainly concern about how to control system transmission, such as using Bayesian rule to update the probability distribution of tag quantity and computing an optimal frame size. On the other hand, the tag estimate method has not been discussed in these references. In fact, Bayesian tag estimate is very suitable for estimation under few observation samples [25]. Since a reader in an RFID system usually reads tags only once in a frame and could not collect enough observations, Bayesian could also be used for the tag quantity estimate.

Using different risk functions, this paper proposes three Bayesian tag estimates: Bayesian mean-square, Bayesian absolute-error and Bayesian posterior-probability estimate. By narrowing the search range of tag quantity, this paper also improve several tag estimates to reduce their computational complexity. Besides, we derive an optimal frame length scheme, which can achieve maximum channel usage efficiency under the condition that the durations of an idle, a collision and a successful slot are different. This paper is organized as follows. Section II presents a dynamic framed slotted aloha RFID system model and Section III proposes several tag estimates. In Section IV, we derive an optimal frame length scheme. Section V provides simulations to demonstrate the performance of the proposed estimate and the derived frame length scheme. Finally, conclusions are drawn in Section VI.

II. Dynamic Framed Slotted Aloha RFID System

A dynamic framed slotted aloha RFID system configures a read process with some continuous frames that consist of slots. Each tag responds at a randomly selected slot and only once in a frame. For a given time slot, there are only three possible outcomes: idle slot, collision slot and successful slot, which means no tags, only one tag and at least two tags response in a slot, respectively. The dynamic framed slotted aloha system can adjust a frame length in the subsequent frame to reduce the idle slot and collision slot, and hence has better performance than the fixed framed aloha. Now, we give the following properties for the dynamic aloha system.

Consider a dynamic framed slotted aloha system with n tags to be read and a read cycle with a frame length of L time slots. The probability of idle, successful and collision slot is given by [11], [12], [15]–[17], [19]

$$p_0 = (1 - 1/L)^n \tag{1-a}$$
$$p_1 = (n/L)(1 - 1/L)^{n-1} \tag{1-b}$$
$$p_\kappa = 1 - (1 - 1/L)^n - (n/L)(1 - 1/L)^{n-1} \tag{1-c}$$

Thus, the expected number of idle, collision and successful slots in a frame can be given by

$$a_0(L, n) = L(1 - 1/L)^n \tag{2-a}$$
$$a_1(L, n) = n(1 - 1/L)^{n-1} \tag{2-b}$$
$$a_\kappa(L, n) = L[1 - (1 - 1/L)^n - (n/L)(1 - 1/L)^{n-1}] \tag{2-c}$$

In addition, according to (2), we can also obtain the probability that there are c_0 idle slots, c_1 successful slots and c_κ collision slots in a frame of length L, which is shown as [19]

$$p(n \mid c) = \frac{L!}{c_0! c_1! c_\kappa!} p_0^{c_0} p_1^{c_1} p_\kappa^{c_\kappa} \tag{3}$$

where c is observation of a frame read result, which is shown by the triple

$$c = \langle c_0, c_1, c_\kappa \rangle. \tag{4}$$

III. Tag Estimate

To achieve higher identification efficiency, the dynamic framed slotted ALOHA RFID system needs to dynamically adjust a frame length. Compared with tag quantity, a smaller frame length may produce excessive collisions, while a much larger frame length would lead to underutilization of channels. These both result in long tag identification delay and low throughput. Therefore, the frame length adjustment should be according to the tag quantity, which is, however, usually unknown to a reader. In general, we can utilize read results collected at the reader to estimate the tag quantity, such as idle slot, collision slot and successful slot quantity in a frame [11], [12].

A. Bayesian Tag Estimate

In the dynamic framed slotted aloha RFID system, let $\mathbf{c} = [c(0), c(1), \ldots c(M-1)]^{\mathrm{T}}$ be M past observations of read results, idle slot, collision slot and successful slot quantity in a frame. Some statistical theories, such as frequency probability methods [25] consider $\mathbf{c}$ as random variable and tag quantity n as unknown deterministic one. Hence, $\mathbf{c}$ obeys a probability distribution of n and $\mathbf{c}, \mathbf{c} \sim p(\mathbf{c}, n)$, and then the tag quantity n can be estimated using $p(\mathbf{c}, n)$. The estimate accuracy, however, is guaranteed only under large numbers of observations, i.e., M is very large. However, a reader in an RFID system usually reads the tags only once in a frame and hence could not collect enough observations. Therefore, the frequency probability methods would not be reliable when $M = 1$. Bayesian estimate considers n as a random variable, not a deterministic one, and updates the prior distribution of n by the posterior distribution $p(n|\mathbf{c})$. Therefore, Bayesian estimate has better performance even under only one observation and is very suitable for the tag estimate in an RFID system. The tag quantity of Bayesian estimate can be shown as

$$\hat{n} = \arg\min_{\tilde{n}\in\Omega} \sum_{n=1}^{+\infty} J(\tilde{n}, n) p(n|c) \tag{5}$$

where $J(\tilde{n}, n)$ is a risk function and $p(n|c)$ is probability of n, given event c. Since there are at least two contending tags in a collision slot, lower bound of $\tilde{n}$ can be determined. Thus, the search tag range, set Ω can be expressed as [11]–[14]

$$\Omega = \{\tilde{n} \mid c_1 + 2c_\kappa \le \tilde{n} \le N\} \tag{6}$$

where we suppose that N is maximum number of tags that an RFID system can read. Bayesian estimate is actually to find the minimum conditional expectation of risk function $J(\tilde{n}, n)$. Different Bayesian estimates will have different risk functions. Next, we give the following estimates using three kinds of risk functions:

Bayesian mean-square estimate's risk function is denoted by [25]

$$J(\tilde{n}, n) = (\tilde{n} - n)^2. \tag{7}$$

Substituting (7) into (5) and computing extremum, we will have

$$\hat{n} == \sum_{n=1}^{N} n\bar{p}(n \mid c) \tag{8}$$

where we let p be normalized $\bar{p}$ which can make $\sum_{n=1}^{N} \bar{p}(n \mid c) = 1$.

Bayesian absolute-error estimate's risk function is denoted by [25]

$$J(\tilde{n}, n) = |\tilde{n} - n|. \tag{9}$$

Hence, the corresponding Bayesian estimate is

$$\hat{n} = \arg\min_{\tilde{n}\in\Omega} \left(\sum_{n=1}^{\tilde{n}} p(n \mid c) - \sum_{n=\tilde{n}}^{N} p(n \mid c) \right). \tag{10}$$

Bayesian posterior-probability estimate's risk function is denoted by [25]

$$J(\tilde{n}, n) = \begin{cases} 1 & |\tilde{n} - n| \ge \Delta/2 \\ 0 & |\tilde{n} - n| \le \Delta/2 \end{cases} \tag{11}$$

where Δ is a parameter with small value. Hence, the corresponding Bayesian estimate is

$$\hat{n} = \arg\max_{\tilde{n}\in\Omega} p(\tilde{n} \mid c). \tag{12}$$

Bayesian posterior-probability estimate in (12) is actually MAP estimate, which is the same form as the estimate in [19].

B. Tag Estimate With Low Computational Complexity

To find extremum, Bayesian estimates (10) and (12) need to search $N - c_1 + 2c_\kappa$ times in the range of $\tilde{n}, \Omega$. In fact, by narrowing Ω, we can reduce the search times and hence reduce the Bayesian estimates computational complexity.

Let expectation of idle slots quantity in a frame a_0 be replaced by observation c_0. Then, according to (2-a), we have [18]

$$\bar{n} = \frac{\ln(c_0/L)}{\ln(1 - 1/L)}. \tag{13}$$

Since we use only the information of idle slot quantity, the estimate $\bar{n}$ in (13) is not accuracy and could not be consider as a final estimate result. In Bayesian absolute-error estimate (10), let

$$\delta(\tilde{n}) = \sum_{n=1}^{\tilde{n}} p(n \mid c) - \sum_{n=\tilde{n}}^{N} p(n \mid c). \tag{14}$$

From many simulations of computing $\delta(\tilde{n})$, we have the following results. For a given L and $c, \delta(\tilde{n})$ has a unique minimum and it will be monotonically decreasing for $\tilde{n} < \hat{n}$ and monotonically increasing for $\tilde{n} > \hat{n}$. Therefore, $\delta(\tilde{n})$ is actually a V curve with respect to $\tilde{n}$. Substituting $\bar{n}, \bar{n} + 1$ into (14), we can obtain $\delta(\bar{n}), \delta(\bar{n} + 1)$ and compare them. If $\delta(\bar{n}) \ge \delta(\bar{n} + 1)$, then $\delta(\tilde{n})$ will be monotonically decreasing for $\bar{n} \le \tilde{n} \le \hat{n}$. The search for $\hat{n}$ can be stopped when $\delta(\tilde{n})$ begins to increase, for increasing $\tilde{n}$. That is, once $\delta(\tilde{n} = n_x) < \delta(n_x + 1)$, the increment of $\tilde{n}$ will be stopped and n_x is the solution of estimate $\hat{n}$. Likewise, if $\delta(\bar{n}) \le \delta(\bar{n} + 1), \delta$ will be monotonically increasing for $\hat{n} \le \tilde{n} \le \bar{n}$. Once $\delta(\tilde{n} = n_x) < \delta(n_x - 1)$, the decrement of $\tilde{n}$ will be stopped and n_x is the solution of estimate $\hat{n}$. Therefore, tag quantity of Bayesian absolute-error estimate over $\tilde{n} \in \Omega$ is equivalent over $\tilde{n} \in \Psi$, where

$$\Psi = \delta(\bar{n}) \ge \delta(\bar{n} + 1)?\Psi_1 : \Psi_2 \tag{15}$$
$$\Psi_1 = \{\tilde{n} \mid \bar{n} \le \tilde{n} \le \hat{n}\} \tag{16}$$
$$\Psi_2 = \{\tilde{n} \mid \hat{n} \le \tilde{n} \le \bar{n}\} \tag{17}$$

in which $x?a : b$ defines a conditional expression which returns a if x is true, but b otherwise. Since conditional probability $p(n \mid c)$ has a unique maximum, whose curve is actually a Λ curve with respect to n, we could process Bayesian posterior-probability estimate similar to (15) to (17). Therefore, tag quantity of Bayesian absolute-error estimate over $\tilde{n} \in \Omega$ is equivalent over $\tilde{n} \in \Gamma$, where

$$\Gamma = p(\bar{n} \mid c) \le p(\bar{n} + 1 \mid c)?\Gamma_1 : \Gamma_2 \tag{18}$$
$$\Gamma_1 = \{\tilde{n} \mid \bar{n} \le \tilde{n} \le \hat{n}\} \tag{19}$$
$$\Gamma_2 = \{\tilde{n} \mid \hat{n} \le \tilde{n} \le \bar{n}\}. \tag{20}$$

Vogt estimate is denoted by [11], [12], [16], [17]

$$\hat{n} = \arg\min_{\tilde{n}\in\Omega} \|\mathbf{A}(\tilde{n}) - \mathbf{C}\|^2 \tag{21}$$

where $\|\bullet\|$ is Euclidean norm and

$$\mathbf{C} = [c_0, c_1, c_\kappa]^{\mathrm{T}}$$
$$\mathbf{A}(\tilde{n}) = [a_0(L, \tilde{n}), a_1(L, \tilde{n}), a_\kappa(L, \tilde{n})]^{\mathrm{T}}.$$

Let

$$\delta'(\tilde{n}) = \|\mathbf{A}(\tilde{n}) - \mathbf{C}\|^2. \tag{22}$$

Similar to $\delta(\tilde{n})$, the function δ' has also a unique minimum. We could also use (15) to (17) to narrow Ω. Therefore, tag quantity of Vogt estimate over $\tilde{n} \in \Omega$ is equivalent over $\tilde{n} \in \Psi$.

TABLE I
COMPUTATIONAL COMPLEXITY

Estimate	Computational Complexity
Bayesian mean-square estimate	$O(N\text{-}c_1\text{-}2c_k+1)$
Bayesian absolute-error estimate	$O(2N\text{-}c_1\text{-}2c_k+1)$
Bayesian posterior-probability estimate	$O(N\text{-}c_1\text{-}2c_k+1)$
Vogt estimate	$O(N\text{-}c_1\text{-}2c_k+1)$
Improved absolute-error estimate	$O(N+\|\hat{n}-\overline{n}\|+2)$
Improved posterior-probability estimate	$O(\|\hat{n}-\overline{n}\|+2)$
Improved Vogt estimate	$O(\|\hat{n}-\overline{n}\|+2)$

C. Computational Complexity Analysis

To obtain the sum of conditional probability $p(n|c)$ from $n = 1$ to $n = N$, Bayesian mean-square estimate needs to enumerate the conditional probability N times. Bayesian absolute-error estimate not only enumerates the probability N times but also searches $N - c_1 - 2c_\kappa + 1$ times over Ω to find minimum. Similar to Bayesian absolute-error estimate, Bayesian posterior-probability and Vogt estimate both need to search $N - c_1 - 2c_\kappa + 1$ times over Ω to find extremum. The improved estimates: Bayesian absolute-error, posterior- probability and Vogt estimate with low computational complexity narrow the search range. Hence, these improved estimates all needs to search only $|\hat{n} - \bar{n}| + 2$ times. The computational complexity of the estimates above is listed in Table I.

IV. FRAME LENGTH

A. Channel Usage Efficiency

The frame length in the dynamic framed aloha RFID should be related to the tag quantity. Some frame length expressions with respect to the tag quantity is derived in [10], [13], [15], [16], [18], [19], which assume that the durations of an idle, a collision and a successful slot are identical [10], [13], [15], [16], [19] or the durations of a collision and a successful slot are identical [18]. To improve identification efficiency, however, these durations can be different. In current RFID standards such as ISO 18000-6 [20], [21] and EPC C1 Gen2 [22], an idle, a collision and a successful slot duration have been set to being different. In these systems, a responding tag will firstly transmits its 16-bit random or pseudo-random numbers (RN16) to a reader in a slot. There are three possible outcomes: terminating a slot ahead for no RN16 information received at the reader, transmitting the tag's 64-bit electronic product code (EPC) after the RN16 correctly received, and not needing to transmit 64-bit EPC for the RN16 colliding with others. Therefore, durations of the slots ranges from the most to the least as follows: the successful, collision and idle slot.

Here, we analyze that the maximum channel usage efficiency could be enhanced under the condition that an idle, a collision and a successful slot duration are not identical. Suppose that t_0, t_κ and t_1 is an idle, a collision and a successful slot duration, respectively. Then, channel usage efficiency can be shown as [10], [15]–[19]

$$P_s = \frac{a_1(L,n)t_1}{a_0(L,n)t_0 + a_1(L,n)t_1 + a_\kappa(L,n)t_\kappa}. \tag{23}$$

We consider a linear model which assumes that L be linearly related to $n, L = kn$. Then, when number of tags n is very large, we can obtain

$$\left(1 - \frac{1}{kn}\right) \approx e^{-\frac{1}{k}}. \tag{24}$$

Let $\alpha = t_0/t_1, \beta = t_\kappa/t_1$, and substitute (24) and (2) into (23). This yields

$$P_s \approx \frac{1}{k\beta e^{\frac{1}{k}} + k(\alpha - \beta) + 1 - \beta}. \tag{25}$$

From (25), we have

$$P_s^*|_{\alpha<\beta<1} > P_s^*|_{\alpha<1,\beta=1} > P_s^*|_{\alpha=\beta=1} \tag{26}$$

where $P_s^*|_{\alpha<\beta<1}, P_s^*|_{\alpha<1,\beta=1}$ and $P_s^*|_{\alpha=\beta=1}$ is the maximum channel usage efficiency under $\alpha < \beta < 1, \alpha < \beta = 1$ and $\alpha = \beta = 1$, respectively. Formula (26) indicates that the maximum channel usage efficiency can be enhanced by lessening an idle or a collision slot duration. In fact, when $L = n$, substituting $k = 1$ into (26) can yield $P_s^*|_{\alpha<\beta<1} > P_s^*|_{\alpha=\beta=1} = 1/e = 0.368$, which means that the maximum channel usage efficiency under $t_0 < t_\kappa < t_1$ can surpass the value, 0.368 under $t_0 = t_\kappa = t_1$.

B. Optimal Frame Length

In the dynamic framed slotted aloha RFID system, [10], [13], [15], [19] all propose that the channel usage efficiency achieve maximum at $L = n$. However, this proposition assumes $t_0 = t_\kappa = t_1$. Computing derivative of P_s in (23) respect to L and substituting $L = n$ will yield

$$\left.\frac{dP_s}{dL}\right|_{L=n} = 0 \Leftrightarrow \alpha = \beta. \tag{27}$$

Formula (27) indicates that the frame length scheme $L = n$ in [10], [13], [15], [19] could not guarantee the maximum channel usage efficiency if $t_0 \neq t_\kappa$. Reference [18] defines $t_0 \neq t_\kappa$ and $t_\kappa = t_1$, under which the maximum channel usage efficiency is simply that in (25) when $\beta = 1$.

Next, we will define our optimal frame length scheme, which allows the channel usage efficiency to achieve its maximum. Suppose that P_s in (25) achieve maximum at $k = k^*$, and consider a linear model that L is linearly related to n. Thus, the optimal frame length can be denoted by

$$L = \lfloor k^* n \rfloor. \tag{28}$$

where $\lfloor \bullet \rfloor$ is the floor integer function. The key point of (28) is how to obtain the solution of k^*, i.e., to find the maximum of P_s in (25). The solution of k^* is a complicated concavity problem. To simplify it, we consider another policy. For a given RFID system, α and β in (25) could not be time-variable, so k^* do not require being obtained time-variably. We can find k^* beforehand and store it in memory. Additionally, since the frame length $L = \lfloor k^* n \rfloor$ is an integer, k^* may not be accurate enough. Therefore, we can find k^* by graphics. For example, we draw some curves of P_s with respect to k under different α and β in Fig. 1, where P_s achieves the maximum at $k = 1.7$ when $\alpha = 0.125, \beta = 0.5$. Thus, we have $k^* \approx 1.7$. Likewise, we can obtain that k^* is approximately 1.0 and 2.3 when $\alpha = 0.125, \beta = 0.125$ and $\alpha = 0.125, \beta = 1$, respectively.

V. COMPUTER SIMULATION RESULTS

Computer simulations were performed to check and extend the analytical results of the previous section. Frame length was set to L slots and tags quantity, n were put into the L time slots. After each experiment, we obtained a triple c and then performed the proposed method. Finally, we obtained the average results after completing 500 experiments.

A. Tag Estimate

Frame length was set to $L = 128$ slots in our simulations of this subsection. Fig. 2 presents tag estimate error against number of tags

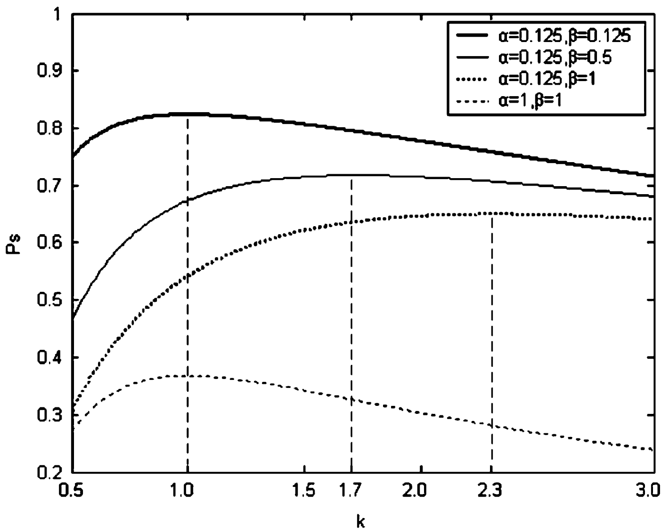

Fig. 1. Channel usage efficiency Tag P_s against k.

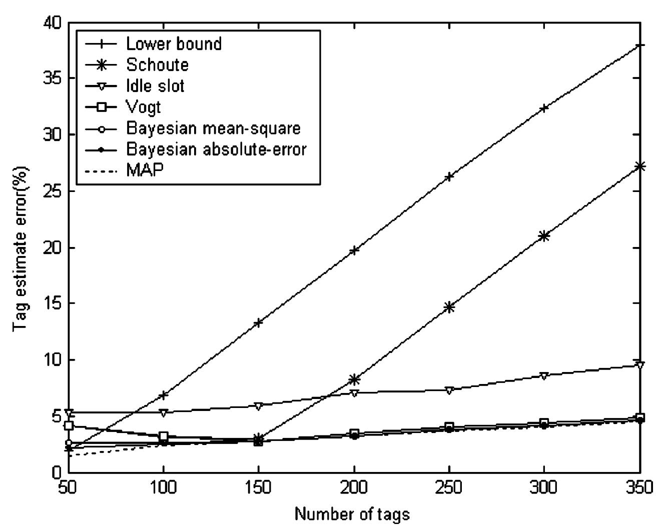

Fig. 2. Simulation results for tag estimate error.

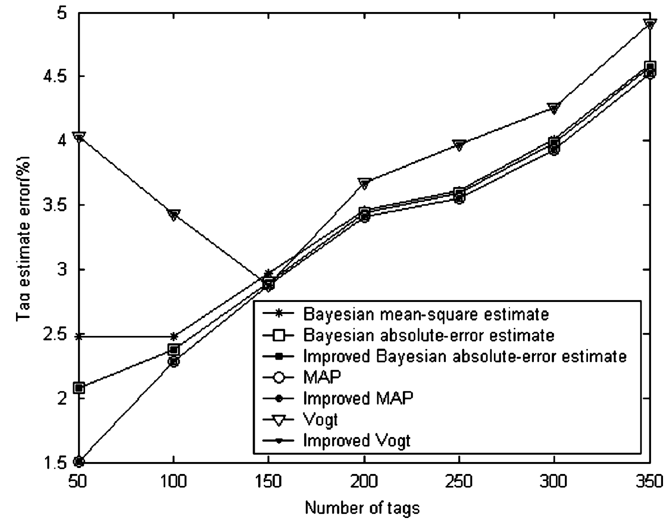

Fig. 3. Simulations results for low complexity tag estimate error.

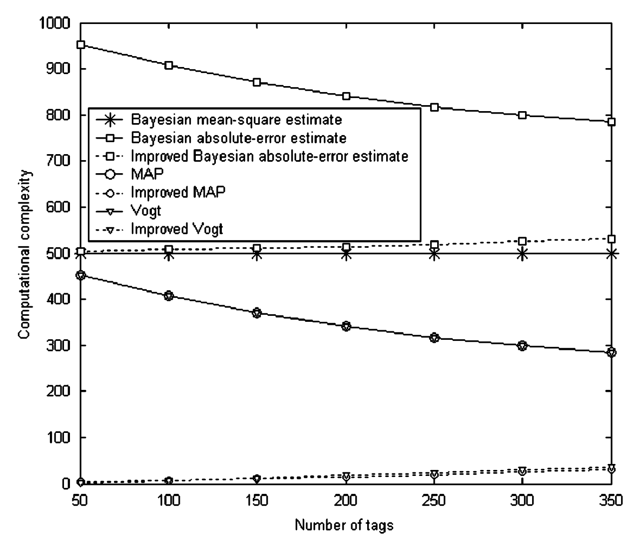

Fig. 4. Simulation results for estimate computational complexity.

for lower bound [11]–[14], Schoute [10], [13]–[15], idle slot [18], Vogt [11], [12], [16], [17], MAP estimate [19], Bayesian mean-square estimate in (8), and Bayesian absolute-error estimate in (10). We define the estimate error ε as

$$\varepsilon = \frac{\hat{n} - n}{n} \times 100\%. \tag{29}$$

Note that for Bayesian posterior-probability estimate in (12), since it is actually MAP estimate [19] and has the same results as MAP, we do not give Bayesian posterior-probability estimate results in our simulations. Fig. 2 shows that the proposed Bayesian mean-square and Bayesian absolute-error estimate errors are both no more than 4%, a little less than Vogt estimate. And the two Bayesian estimates have the similar curves to MAP, while the other three estimates: lower bound, Schoute and idle slot estimate error is much more than 4% when $n > 200$.

The estimate error for the improved estimates with low computational complexity and the unimproved estimates is shown in Fig. 3, where the improved ones are denoted by black-point lines and the unimproved ones by white-point lines. Fig. 3 shows that the black-point lines are superposed on the white-point ones. In addition, the estimate error loss of Vogt estimate from the Bayesian estimates is 0.3% when $n > 150$, while the loss is more than 2% when $n = 50$. The two Bayesian estimates and MAP have the similar curves, where the loss among them is no more than 0.1% when $n > 100$.

Fig. 4 shows computational complexity for the improved and unimproved estimates, where the computational complexity can also be seen in Table I. The improved estimates are denoted by dashed lines and the unimproved ones by solid lines. Compared with the solid lines, the computational complexity for the dashed lines is reduced more than 300 times.

B. Frame Length

Tag quantity was set to $n = 100$ in our simulations of this subsection. An idle, collision and successful slot duration are listed in Table II. Fig. 5 shows four channel usage efficiency cures under different α and β. The maximum channel usage efficiency of the four cures ranges from the highest to the lowest as follows: 0.8, 0.7, 0.6 and 0.4, which have the same results as (25)'s theoretical curves in Fig. 1. The results indicate that when an idle or collision slot duration is less than a successful slot, the channel usage efficiency can be enhanced. In addition, these four curves achieve the maximum channel usage efficiency at $n = 100, 170, 230$ and 100, respectively. Substituting these values of n into (28) yields $k^* = 1.0, 1.7, 2.3$ and 1.0, respectively. These

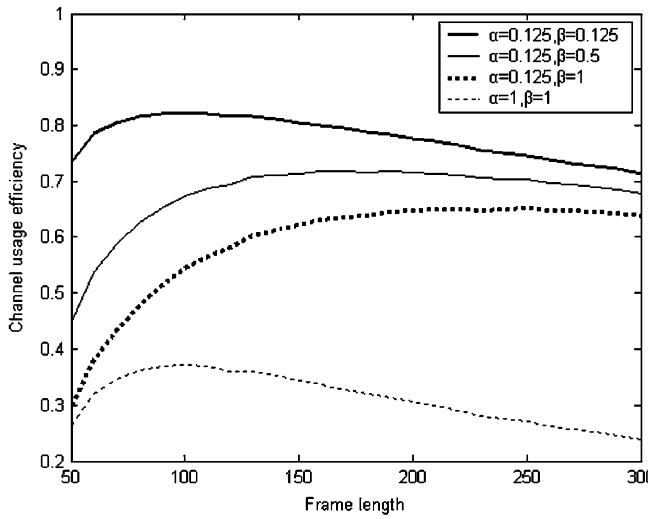

Fig. 5. Simulation results for Channel usage efficiency.

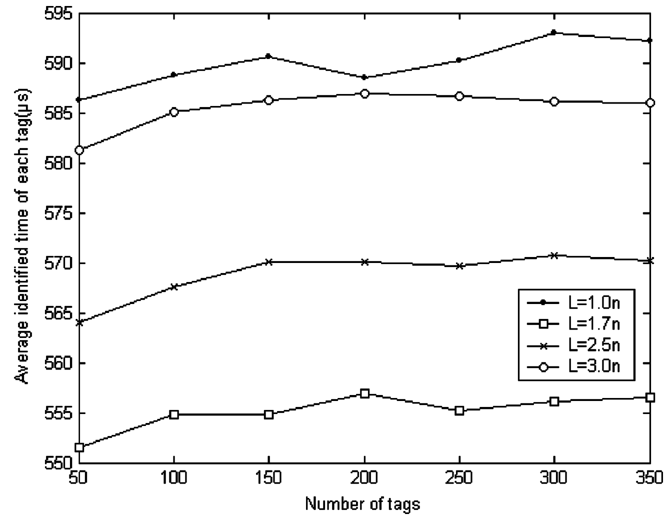

Fig. 6. Average tag identified time of each tag for frame length.

TABLE II
TIME FOR α AND β

Time (μ s)	t_0	t_1	t_κ
α=0.125, β=0.125	50	50	400
α=0.125, β=0. 5	50	200	400
α=0.125, β=1	50	400	400
α=1, β=1	400	400	400

values of k^* are the same as the theoretical values in Fig. 1. Furthermore, we can see from Fig. 1 that the curves of $\alpha = 0.125, \beta = 0.5$ and $\alpha = 0.125, \beta = 1$ do not achieve the maximum channel usage efficiency at $L = n = 100$.

Fig. 6 shows that the average identified time of each tag, where the average identified time is defined as

$$\bar{t} = \frac{\sum_{i=1}^{I} c_0^i t_0 + c_1^i t_1 + c_\kappa^i t_\kappa}{n} \tag{30}$$

where identifying all tags needs I frame, and t_0, t_1 and t_κ are 50, 200 and 400 μs, respectively, thus $\alpha = 0.125, \beta = 0.5$. It is seen from Fig. 6 that the time of $L = 1.7n$ is the least and about from 550 to 555 μs, while the other three curves are about from 565 to 595 μs. Based on the theoretical curves in Fig. 1, we know that the channel usage efficiency achieves the maximum at $k = 1.7$. Therefore, Fig. 6 can indicate that, the frame length which guarantees the maximum channel efficiency can have the least identified time.

VI. CONCLUSION

In this paper, we propose three Bayesian tag estimates for a dynamic framed slotted aloha RFID system, and improve several estimates to reduce computational complexity. Besides, we derive an optimal frame length scheme, which allows channel usage efficiency achieve maximum. From our theoretical derivation and simulation results, we draw the conclusions as follows.

The three proposed Bayesian estimates, Bayesian mean-square, Bayesian absolute-error and posterior- probability estimate have much better estimate performance than lower bound estimate, Schoute estimate and idle slot estimate, a little better than Vogt estimate and similar to MAP estimate. The improved Bayesian absolute-error estimate, MAP estimate and Vogt estimate have less computational complexity than the unimproved one, but do not reduce estimate performance.

The maximum channel usage efficiency under the condition that an idle slot duration is less than a collision slot and the collision slot duration is less than a successful slot, is larger than that under the condition that the durations of an idle, a collision and a successful slot are identical or the durations of an collision and a successful slot are identical. If the durations of an idle, a collision and a successful slot are not identical, the conventional scheme that the frame length is set to be the tag quantity would not guarantee the maximum channel usage efficiency. However, the derived frame length scheme in this paper may guarantee the maximum one, and have less tags' identified time than the conventional frame length scheme.

REFERENCES

[1] K. Finkenzeller, *RFID Handbook: Radio-Frequency Identification Fundamentals and Applications*, 2nd ed. New York: Wiley, 2003.
[2] D. H. Shin, P. L. Sun, D. C. Yen, and S. M. Huang, "Taxonomy and survey of RFID anti-collision protocols," *Comput. Commun.*, vol. 29, no. 11, pp. 2150–2166, 2006.
[3] J. I. Capetanakis, "Tree algorithms for packet broadcast channels," *IEEE Trans. Inf. Theory*, vol. 25, no. 5, pp. 505–515, 1979.
[4] D. R. Hush and C. Wood, "Analysis of tree algorithm for RFID arbitration," in *Proc. IEEE Int. Symp. Inf. Theory*, Cambridge, U.K., 1998, p. 107.
[5] C. Law, K. Lee, and K. S. Siu, "Efficient memoryless protocol for tag identification," in *Proc. 4th ACM Int. Workshop on Discrete Algorithms and Methods for Mobile Computing and Commun.*, Boston, MA, 2000, pp. 75–84.
[6] M. Jihoon, L. Wonjun, and J. Srivastava, "Adaptive binary splitting for efficient RFID tag anti-collision," *IEEE Commun. Lett.*, vol. 10, no. 3, pp. 144–146, 2006.
[7] J. Myung, W. Lee, and T. K. Shih, "An adaptive memoryless protocol for RFID tag collision arbitration," *IEEE Trans. Multimedia*, vol. 8, no. 5, pp. 1096–1101, 2006.
[8] J. Myung, W. Lee, J. Srivastava, and T. K. Shih, "Tag-Splitting: Adaptive collision arbitration protocols for RFID tag identification," *IEEE Trans. Parallel Distrib. Syst.*, vol. 18, no. 6, pp. 763–775, 2007.
[9] Y. C. Lai and C. C. Lin, "A pair-resolution blocking algorithm on adaptive binary splitting for RFID tag identification," *IEEE Commun. Lett.*, vol. 12, no. 6, pp. 432–434, 2008.
[10] F. C. Schoute, "Dynamic frame length aloha," *IEEE Trans. Commun.*, vol. Com-31, no. 4, pp. 565–568, 1983.
[11] H. Vogt, "Multiple object identification with passive RFID tags," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, Hammamet, Tunisia, 2002, pp. 1–6.

[12] H. Vogt, "Efficient object identification with passive RFID tags," in *Proc. Int. Conf. Pervasive Computing*, Zurich, 2002, pp. 98–113.
[13] C. Floerkemeier, "Transmission control scheme for fast RFID object identification," in *Proc. IEEE PerCom Workshop on Pervasive Wireless Networking*, Italy, 2006, pp. 1–6.
[14] C. Floerkemeier and M. Wille, "Comparison of transmission schemes for framed ALOHA based RFID protocols," in *Proc. Int. Symp. Appl. Internet Workshops*, 2006, pp. 92–97.
[15] J. R. Cha and J. H. Kim, "Novel anti-collision algorithms for fast object identification in RFID system," in *Proc. Int. Conf. Parallel Distrib. Syst. Comput.*, Japan, 2005, pp. 63–67.
[16] S. R. Lee, S. D. Joo, and C. W. Lee, "An enhanced dynamic framed ALOHA algorithm for RFID tag identification," in *Proc. Int. Conf. Mobile and Ubiquitous Systems: Networking and Services*, 2005, pp. 166–174.
[17] M. A. Bonuccelli, F. Lonetti, and F. Martelli, "Tree slotted ALOHA: A new protocol for tag identification in RFID networks," in *Proc. Int. Symp. World of Wireless, Mobile and Multimedia Networks*, 2006, pp. 603–608.
[18] G. Khandelwal, A. Yener, K. Lee, and S. Serbetli, "ASAP: A MAC protocol for dense and time constrained RFID systems," in *Proc. IEEE Int. Conf. Commun.*, Istanbul, Turkey, 2006, pp. 4028–4033.
[19] W. T. Chen, "An accurate tag estimate method for improving the performance of an RFID anticollision algorithm based on dynamic frame length ALOHA," *IEEE Trans. Autom. Sci. Eng.*, vol. 6, no. 1, pp. 9–15, 2009.
[20] *Information Technology—Radio Frequency Identification (RFID) for Item Management—Part 6: Parameters for Air Interface Communications at 860 MHz to 960 MHz*, International Standard ISO/IEC 18000-6, 2004.
[21] *Information Technology—Radio Frequency Identification (RFID) for Item Management—Part 6: Parameters for Air Interface Communications at 860 MHz to 960 MHz, Amendment 1: Extension With Type C and Update of Types A and B*, International Standard ISO/IEC 18000-6, 2006.
[22] EPC Radio-Frequency Identification Protocols Class-1 Generation-2 UHF RFID Protocol for Communications at 860 MHz–960 MHz Version 1.1.0 Draft 1. EPCglobal Inc. 2005.
[23] R. L. Rivest, "Network control by bayesian broadcast," *IEEE Trans. Inf. Theory*, vol. IT-33, no. 3, pp. 323–328, 1987.
[24] C. Floerkemeier, "Bayesian transmission strategy for framed ALOHA based RFID protocols," in *Proc. IEEE Int. Conf. RFID*, TX, 2007, pp. 228–235.
[25] J. O. Berger, *Statistical Decision Theory and Bayesian Analysis*, 2nd ed. New York: Springer-Verlag, 1985.

Long-Term Scheduling for Cascaded Hydro Energy Systems With Annual Water Consumption and Release Constraints

Yanjia Zhao, *Student Member, IEEE*, Xi Chen, *Member, IEEE*, Qing-Shan Jia, *Member, IEEE*, Xiaohong Guan, *Fellow, IEEE*, Shuanghu Zhang, and Yunzhong Jiang

***Abstract*—Long-term scheduling for cascaded hydro energy systems is very important for low carbon energy production. It aims at determining the water release over a planning horizon to meet water resource requirements and the system demands for electric power. The problem is challenging in view of the complicated and stochastic system dynamics, nonlinear marginal cost, coupled hydraulic constraints, and the large problem size. In this paper we formulate the long-term scheduling problem of cascaded hydro energy systems with annual consumption and release constraints as a finite horizon constrained Markov decision process (CMDP), and develop a new rollout algorithm to optimize the policies. Numerical results demonstrate the effectiveness and the efficiency of the formulation and the new algorithm.**

***Note to Practitioners*—Long-term scheduling of cascaded hydro energy systems is an important planning activity in the reservoir management and electric industry. This paper formulates a long-term scheduling problem for cascaded hydro energy systems with annual water consumption and release constraints as a finite horizon CMDP, and develops a new rollout algorithm to deal with the large problem size. Motivated by a practical project on Yellow River in north China, this work has extended applicability since the new algorithm can start with any feasible policies currently used in practical systems and improve their performance. Numerical results demonstrate the effectiveness and efficiency of the formulation and the new algorithm.**

***Index Terms*—Cascaded hydro energy systems, constrained Markov decision process (CMDP), long-term scheduling, rollout algorithm.**

I. Introduction

Long-term scheduling for cascaded hydro energy systems is very important for low carbon energy production [8], [16]. It aims at determining the water release over a planning horizon to meet water resource requirements and the system demands for electric power. Its goal is to minimize the total energy production cost. Typically, the planning horizon is one year, and the decision stage is week or bi-weeks.

The long-term scheduling for cascaded hydro energy systems has been an active research area over the past decades due to its significant economic impact [8], [16]. It is generally a very difficult

Manuscript received September 09, 2009; accepted March 07, 2010. Date of publication June 01, 2010; date of current version October 06, 2010. This paper was recommended for publication by Associate Editor S. G. Poonambalam and Editor Y. Narahari upon evaluation of the reviewers' comments. This work is supported in part by NSFC (60736027, 60704008, 60921003, 90924001), in part by the 111 International Collaboration Project of China (B06002), and in part by the National New Faculty Funding for Universities with Doctoral Program (20070003110).

Y. Zhao, X. Chen, and Q.-S. Jia are with the Center for Intelligent and Networked Systems, Department of Automation, TNList, Tsinghua University, Beijing 100084, China (e-mail: zhaoyj@mails.tsinghua.edu.cn; bjchenxi@tsinghua.edu.cn; jiaqs@tsinghua.edu.cn).

X. Guan is with the Center for Intelligent and Networked Systems, Department of Automation, TNList, Tsinghua University, Beijing 100084, China, and also with SKLMS Laboratory and MOE KLINNS Laboratory, Xian Jiaotong University, Xian, Shaanxi 710049, China (e-mail: xhguan@tsinghua.edu.cn).

S. Zhang and Y. Jiang are with the Chinese Institute of Water Resources and Hydropower Research, Beijing 100038, China (e-mail: sxslzsh@163.com; lark@iwhr.com).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TASE.2010.2050139