The effect of RF unit breakdowns in sensor communication networks

Tamás Bérczes, Béla Almási, János Sztrik, Attila Kuki

***Abstract*—In this paper the wireless transmission problem in sensor networks is investigated. The server (RF unit) is assumed to be subject to random breakdowns both in busy and idle states. The sensors of the networks are grouped in two classes. The first one is the "Emergency" class, which performs the notification of special emergency situations (eg. fire alarms). The second one is the "Normal" class, which measures and transmits environmental data (eg. temperature). The novelty of investigations is the inclusion of the non-reliability of the server. Our main interest is to give the main steady-state performance measures of the system computed by the help of the MOSEL tool. Several Figures illustrate the effect of the failure and repair rates of the server on the mean queue lengths and on the probability of server's breakdowns.**

I. Introduction

Wireless sensor networks are widely used to implement low cost non-attend monitoring of different environments. Baronti et al. [1] showed that the technology limits are far beyond the current usage. Chiany [2] represented the wireless sensor networks as a system containing three main components see Figure 1. Buchmann [3] showed that the operation mechanisms depending on the vendor implementations can be totally different, but also common features are observable. For example, power saving is a standard requirement to achieve long time operation of the wireless nodes. Similarly, a common feature that the wireless data transmission can appear as a bottleneck in the operation.

Retrial queues have been widely investigated and used to model many problems arising in telephone switching systems, telecommunication networks, computer networks, optical networks and most recently sensor networks, etc. The main characteristic of a retrial queue is that a customer who finds the service facility busy upon arrival is obliged to leave the service area, but some time later he comes back to re-initiate his demand. Between trials a customer is said to be in orbit. The literature on retrial queueing systems is very extensive. For a recent account, readers may refer to the recent books of Falin and Templeton [4], Artalejo and Gomez-Corral [5] that summarize the main models and methods. For some recent results on retrial queues with applications the interested reader is referred to, for example see papers of Tien Van Do [6] and references therein.

Using wireless sensor networks, see [7], [8] one of the biggest problem is the lifetime of the sensor. Most of the

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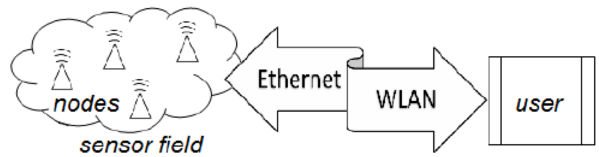

Fig. 1. Wireless sensor network.

time it is very hard to change or repair the RF Unit of the sensors. Because these facts, the reliability of the RF Unit is very important. The lifetime of the sensor determine the lifetime of the network too.

In this paper we introduce a finite-source retrial queueing model to investigate the performance characteristics of the wireless transmission problem in the sensor networks. We divide the sensors into two classes. The first one is the "Emergency" class, which performs the notification of special emergency situations (eg. fire alarms). The second one is the "Normal" class, which measures and transmits environmental data (eg. temperature).

The emergency class has priority over the normal class in the operation. For the performance evaluation of the wireless transmission we study and compare two cases: In the first model the RF transmission possibility will be available randomly for the sensor nodes (Non-Controlled case). In the second model the RF transmission requests coming from the emergency class will access the wireless channel immediately (Controlled case).

The main purpose of the present paper is to generalize the sensor network model (see. Bérczes et al. [9], [10]) using a more realistic case when the RF unit is subject to breakdowns during its operations. Our aim is to illustrate graphically the effect of the non-reliability of the RF unit on the steady-state system measures.

Because of the fact, that the state space of the describing Markov chain is very large, it is rather difficult to calculate the system measures in the traditional way of writing down and solving the underlying steady-state equations. To simplify this procedure we used the software tool MOSEL (Modeling, Specification and Evaluation Language), see Begail et al. [11], to formulate the model and to obtain the performance measures.

The rest of this paper is organized as follows. In Section 2 we present the corresponding queueing model. Numerical results and their discussion are provided in Section 3. Finally,

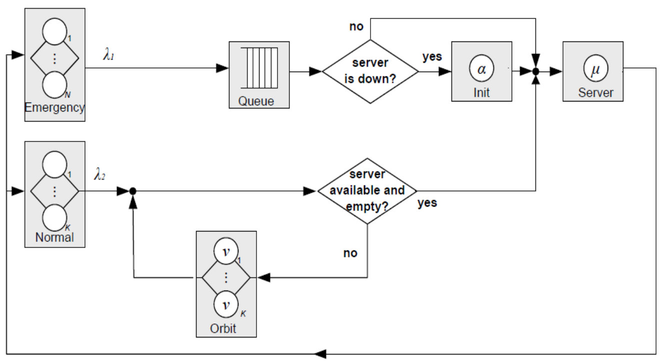

Fig. 2. A retrial queue with components

Section 4 concludes the paper.

II. System Model

Let us consider a single server queue with two classes of finite-sources which represent the sensors. The first class of sensors correspond to the emergency case (eg. fire alarms), the second class refers to the normal case (eg. temperature, humidity measurement). The number of sensors of the first class is denoted by N, and the number of sensors of the second class is denoted by K. Each sensor generates a new service request (ie. to send the measured value through the radio interface), according to an exponentially distributed time with parameter λ_1 for the emergency sensors and with parameter λ_2 for the normal class, respectively.

The server, which refers to the radio transmission in the model, can be in three states:

- *available(idle) state:* If the server is available it can start serving the arriving requests.
- *sleeping state:* The server can be in sleeping state (for power saving purposes).
- *failed state:* If the server is in failed state, it can not start serving any arriving requests until it is repaired.

The server is busy, when the server is in available state and at least one requests are in the service area. The server is idle, when the server is in available state and there is no requests in the service area.

The server can fail during the interval $(t, t+dt)$ with probability $\delta dt + o(dt)$ if it is in idle or in busy state. If the server is in sleeping state it can not be failed. If the server fails in a busy state, the interrupted request returns to the sources. The repair time is assumed to be exponentially distributed with a finite mean $1/\tau$. If the server is failed, two different cases can be treated. The first one is blocked sources case when all the operations are stopped, that is no new calls are generated. The second one is the unblocked sources case, when only service is interrupted but all the other operations are continued. In this paper we investigate only the unblocked sources case.

The server starts with a listening period. The time of this listening period is assumed to be exponentially distributed with parameter α. If no customer arrives during this period, the server will enter into the sleeping state. The time of the sleeping period is supposed to exponentially distributed with parameter β.

When the sleeping period is terminated, then the server wakes up. If there are emergency requests waiting in the queue the server begins to serve them. In the opposite case, when there is no emergency request waiting in the queue, the server remains in the available state, it will start a listening period.

Until the listening period finished, the requests arriving to the server can access to its service. If the listening period expires without any arrivals the server will enter into the sleeping mode.

A request of the emergency class goes directly to a FIFO queue waiting to be served (ie. transmitted through the radio interface).

If an emergency request arrives to the server we consider four operation possibilities:

- If the server is available, it starts the service of the emergency request.
- If the server is busy, the emergency request goes to the FIFO queue, waiting to be served.
- If the server is in sleeping state the request wakes up the server, which will start the service after an exponentially distributed initialization time with parameter γ.
- If the server is failed, the emergency request goes to the FIFO queue.

If a request from the second class finds the server busy or in sleeping state or the server is failed then the requests goes to the orbit. These requests waiting in the orbit retry to find the server idle according to a Poisson flow with retrial rate ν. We assume that emergency requests have non-preemptive priority over normal requests.

The service times for each request coming from both classes are assumed to be exponentially distributed with parameter μ.

The operational dynamics of the system can be seen in the corresponding queueing model, see Fig. 2.

We introduce the following notations (see the summary of the model parameters in Table I):

- $k_1(t)$ is the number of active sensors in the emergency source at time t,
- $k_2(t)$ is the number of active sensors in the normal source at time t,
- $q(t)$ denotes the number of emergency requests in the queue at time t,
- $o(t)$ is the number of jobs in the orbit at time t.
- $y(t) = 0$ if there is no job in the server and the server is available, $y(t) = 1$ if the server is busy with a job coming from the emergency class, $y(t) = 2$ when the server is busy with a job coming from the normal sensor class, $y(t) = 3$ if the server is in sleeping state at time t and $y(t) = 4$ if the server is failed at time t
- $c(t) = 1$ when the server is in sleeping state at time t and one emergency request has started the initialization procedure, $c(t) = 0$ in the other cases.

It is ease to see that:

$$k_1(t)+k_2(t) = \begin{cases} K+N-q(t)-o(t), & y(t)=0,4 \\ K+N-q(t)-o(t)-1, & y(t)=1,2 \\ K+N-q(t)-o(t)-c(t), & y(t)=3 \end{cases}$$

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TABLE I
OVERVIEW OF MODEL PARAMETERS

Parameter	Maximum	Value at t
Active imergency sensors	N (population size)	$k_1(t)$
Active normal sensors	K (population size)	$k_2(t)$
Emergency generation rate		λ_1
Normal generation rate		λ_2
Total gen. rate	$\lambda_1 N + \lambda_2 K$	$\lambda_1 k_1(t) + \lambda_2 k_2(t)$
Requests in queue	N	$q(t)$
Service rate		μ
Busy servers	1 (number of servers)	$c(t)$
Cust. in service area	$N+1$	$c(t)+q(t)$
Requests in Orbit	K (orbit size)	$o(t)$
Retrial rate		ν
Server's failure rate		δ
Server's repair rate		τ

To maintain theoretical manageability, the distributions of inter-event times (i.e., request generation time, service time, retrial time, available state time, sleeping state time, failed state time) presented in the network are by assumption exponential and totally independent. The state of the network at a time t corresponds to a Continuous Time Markov Chain (CTMC) with 4 dimensions:

$$X(t) = (y(t); c(t); q(t); o(t))$$

The steady-state distributions are denoted by

$$P(y,c,q,o) = \lim_{t\to\infty} P(y(t)=y, c(t)=c, q(t)=q, o(t)=o)$$

Note, that the state space of this Continuous Time Markovian Chain is finite, so the steady-state probabilities surely exist. For computing the steady-state probabilities and the system characteristics, we use the MOSEL software tool in this paper. These computations are described in papers of Bolch and Wüchner et al. [12], [13].

As soon as we have calculated the distributions defined above, the most important steady-state system characteristics can be obtained in the following way:

- *Utilization of the server*

$$U_S = \sum_{y=1}^{2}\sum_{q=0}^{N}\sum_{o=0}^{K} P(y,0,q,o)$$

- *Availability of the server*

$$A_S = \sum_{y=0}^{2}\sum_{q=0}^{N}\sum_{o=0}^{K} P(y,0,q,o)$$

- *Average number of jobs in the orbit*

$$\begin{aligned}\overline{O} &= E(o(t)) = \\ &= \sum_{y=0}^{2}\sum_{q=0}^{N}\sum_{o=0}^{K} oP(y,0,q,o) \\ &+ \sum_{y=3}^{4}\sum_{c=0}^{1}\sum_{q=0}^{N}\sum_{o=0}^{K} oP(y,c,q,o)\end{aligned}$$

- *Average number of jobs in FIFO*

$$\begin{aligned}\overline{Q} &= E(q(t)) = \\ &= \sum_{y=0}^{2}\sum_{q=0}^{N}\sum_{o=0}^{K} qP(y,0,q,o) \\ &+ \sum_{y=3}^{4}\sum_{c=0}^{1}\sum_{q=0}^{N}\sum_{o=0}^{K} qP(y,c,q,o)\end{aligned}$$

- *Average number of jobs in the network*

$$\begin{aligned}\overline{M} &= \overline{O} + \overline{Q} + \\ &+ \sum_{y=1}^{2}\sum_{q=0}^{N}\sum_{o=0}^{K} P(y,0,q,o) + \\ &+ \sum_{q=0}^{N}\sum_{o=0}^{K} P(3,1,q,o)\end{aligned}$$

- *Average number of active emergency sensors*

$$\overline{\Lambda_1} = N - \overline{Q} - \sum_{q=0}^{N-1}\sum_{o=0}^{K} P(1,0,q,o)$$

- *Average number of active normal sensors*

$$\overline{\Lambda_2} = K - \overline{O} - \sum_{q=0}^{N}\sum_{o=0}^{K-1} P(2,0,q,o)$$

- *Average generation rate of emergency sensors:*

$$\overline{\lambda_1} = \lambda_1 \overline{\Lambda_1}$$

- *Average generation rate of normal sensors:*

$$\overline{\lambda_2} = \lambda_2 \overline{\Lambda_2}$$

III. Numerical Results

In this section, we present some numerical results in order to illustrate graphically the effect of the server's breakdown on some of the most important measures in sensor networks. The corresponding parameters are summarized in Table II. numerous interactions of parameters were investigated. The most interesting results are displayed in the following figures. In each Figure the blue lines (dotted with circles) represent the case when $\lambda = 0.5$ and the red lines (dotted with triangles) represent the case when $\lambda = 2.5$.

In Figure 3 one can see the effect of the server's failure rate on the mean queue length of emergency request in the FIFO. The length is increasing in both cases, but at higher generation rate this increase is faster.

Figure 4 shows how orbit fills up at different failure rates and request generation rates. It can be seen, that at high value of the generation rates the server's failure rate has almost no effect on the orbit size. At lower generation rate the orbit size significantly increases when the failure rate has large values.

Figure 5 illustrates the probability of the idle state of the server. In natural way, this idle state probability is much higher at large generation rates than at low ones. If we investigate the effect of the failure rate of the radio unit, a decrease of this probability can be observed. The speed of this decrease is much faster at the low generation rates.

In Figure 6 the probability of the failed state of the server is calculated, where the server initially was in idle state. It means, that there is no loss of requests here. Requests arriving during this failed period will be forwarded to queue or to orbit, depending on their priorities.

At low request generation rates the idle periods are longer than at higher rates, so the failed periods are more likely. With higher failure rates the probability of down periods increases, faster at low load and lower at high load of requests.

Figure 7 shows the same probability, but in this case the server breakdown occurs in busy state, ie. there was a request under servicing. The service terminates and the request is transmitted to the source. In the physical environment it means, that the signal of the sensor has been lost. Important result, because at relatively high failure rate the probability of lost request is significantly high, and it hardly depends on the generation rate.

It should be underlined that because the terminated requests under servicing return to the source without service, there is no sense to investigate response and waiting times.

Figure 8 illustrates the probability that the server fails in an idle state as a function of repair rates. It means, that there is no loss of requests in this case. As one can see increasing the repair rate, the probability of the failure decreases. For all repair rates we get smaller probabilities by using higher generation rate.

Figure 9 shows the probability that the server's breakdown occurs in busy state, ie. there is a request under servicing. The service terminates and the request returns to the source without service. In this case using higher generation rate we get higher probabilities because the server's busy periods last longer than using smaller generation rate.

IV. Conclusion

In this paper we have investigated a finite-source retrial queueing model with non-preemptive priorities and repeated vacations with non-reliable server. The MOSEL tool was used to formulate and solve the problem, and the main performance and reliability measures were derived and illustrated graphically. The main goal of the evaluation of the proposed system was to show how the of server's failure rate influences the performance of the system. To the best knowledge of the authors, this is the first proposal for the use of the theory of retrial queues to model sensor networks with priority finite-source with orbit, state dependent vacation times and a non-

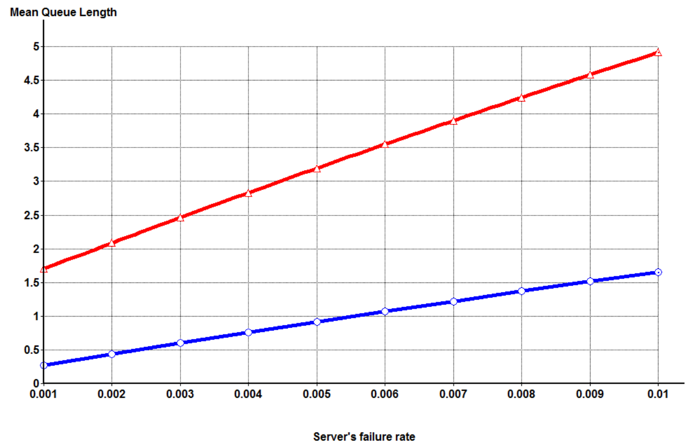

Fig. 3. Mean queue length vs Server's failure rate, repair rate = 0.1

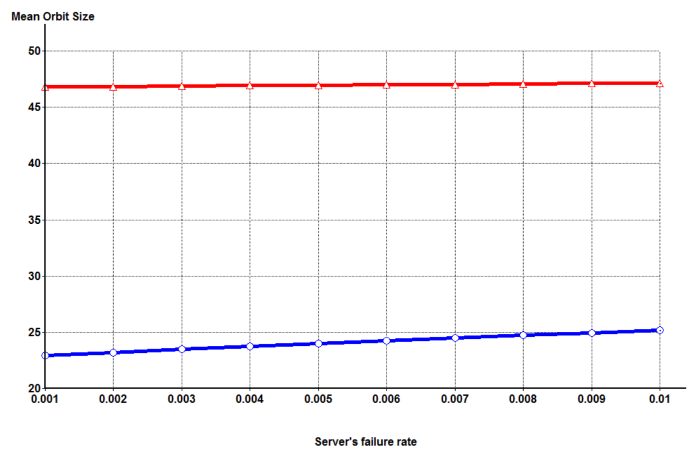

Fig. 4. Mean orbit size vs Server's failure rate, repair rate = 0.1

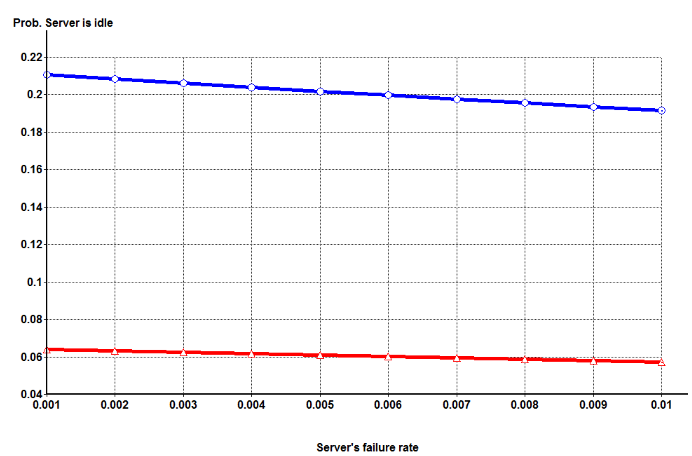

Fig. 5. Probability that the server is in idle state vs Server's failure rate, repair rate = 0.1

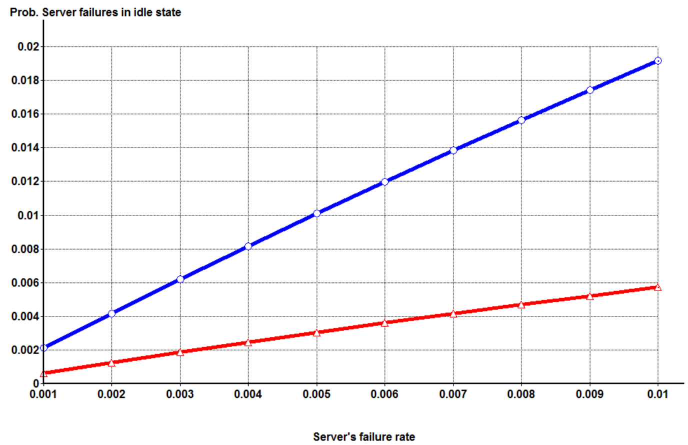

Fig. 6. Probability that the server failures in idle state vs Server's failure rate, repair rate = 0.1

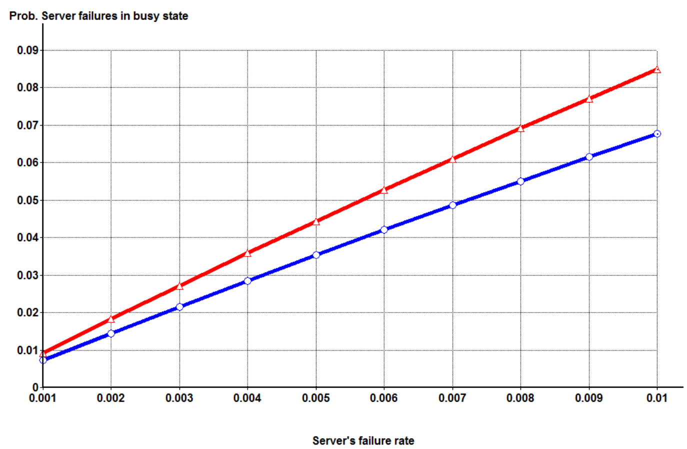

Fig. 7. Probability that the server failures in busy state vs Server's failure rate, repair rate = 0.1

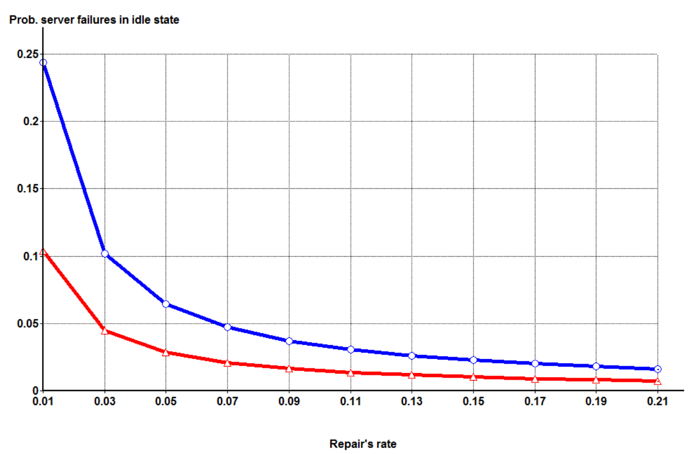

Fig. 8. Probability that the server failures in idle state vs Server's repair rate, failure rate = 0.005

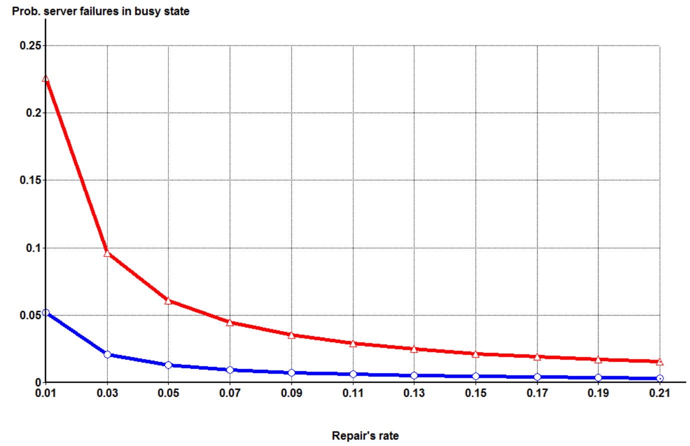

Fig. 9. Probability that the server failures in busy state vs Server's repair rate, failure rate = 0.005

TABLE II
NUMERICAL VALUES OF MODEL PARAMETERS

Parameter	Symbol	Value
Overall generation rate	λ	0.5,2.5
Emergency generation rate	$\lambda_1 = \frac{\lambda}{10}$	[0.05,0.25]
Normal generation rate	$\lambda_2 = \frac{9}{10}\lambda$	[0.45,2.25]
Number of Emergency sensors	N	50
Number of Normal sensors	K	50
Retrial rate	ν	2
Service rate	μ	20
Server's failure rate	δ	[0.001..0.01]
Server's repair rate	τ	[0.01..0.21]
Initialization rate	γ	10
Mean time of sleeping period	$\frac{1}{\beta}$	2.5
Mean time of listening period	$\frac{1}{\alpha}$	1.5

reliable server. In the future work we would like to investigate more complex sensor models by using finite-source queueing models.

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