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PRIORITIZING SENSED DATA TRANSMISSION BY CONSENSUS RELATION IN WIRELESS SENSOR NETWORK

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Abstract: In this work we propose an approach to prioritizing order of transmission of sensed data in wireless sensor network that are very popular in, for example, environmental monitoring. The approach is based on determination of a consensus relation which is in "nearest distance" from all initial rankings shaped by multiple sensors of each network node. Statistically and probabilistically based analytical models useful for assuring network performance and providing reasonable number values $n - k$ and m are proposed and discussed, where $n - k$ is a number of packets transmitted to the sink; n is a number of the network sensor nodes; k is a number of dropped packets due to a congestion; and m is a number of node sensors (or rankings).

Keywords: rankings, consensus relation, sensor data fusion.

1. INTRODUCTION

In addition to the traditional task of providing network access to mobile users, wireless networks have also been increasing deployed in environments where traditional wired network infrastructure cannot be easily deployed due to high cost, ease of deployment and accessibility. These deployments include community wireless networks, construction sites, remote areas and disaster areas etc. Such deployments often exploit the use of multihop mesh connectivity to reduce cost and improve coverage. In these (sensor) networks, data fusion (or data aggregation) technique has been put forward as an essential paradigm for wireless routing shifting the focus from the traditional address-centric approaches for networking to a data-centric approach (see, for example, [1-3]).

In this paper, we focus on the use of wireless mesh networks for monitoring and information collection purposes. Such deployments are increasingly common in industrial monitoring, security and surveillance applications. The important characteristics of these deployments are as follows:

- traffic pattern usually consists of a small number of gateways collecting or disseminating information to the rest of the network;
- uncontrolled and potentially hostile environment;
- need for information aggregation and prioritization due to network bandwidth constraints.

In particular, it would be desirable to investigate the issues of gathering information in a robust way in the presence of large scale node failure. Namely, congestion control is necessary due to large number of node failure. We assume that packet scheduling and buffer management can be enhanced by taking into account usefulness of information gathered from various nodes. One possible technique is the use of ordinal statistics to aggregate and rank information from different sources.

In an emergency event, it is not possible and unrealistic to perform signaling for resource reservation. In addition, it is also not possible for the application to decide in advance how important their packets are since the importance depends on what else is happening in the network. There are correlations and redundancy among events generated. In [4] such an example has been presented where location information is available in the packet header and the goal is to maximize overall network coverage. By themselves, the packets are equally important. However, if a packet from location (x, y, z) has been transmitted recently, then the importance of packets from nearby nodes within some time window would be relatively less important. The objective is thus to generalize the framework of relative importance. Based on correlated events which can be used to compare and rank information gathering by different nodes, the most important packets will be forwarded or buffered.

In Section 2 a problem of prioritizing sensed data transmission in a wireless sensor network is formulated in the form of consensus relation determination. A particular practical example is given. In Section 3 a statistical analytical model of the consensus determination under condition of a congestion and/or loss in the network is proposed and discussed. And in Section 4 a probabilistic analytical model allowing justification of a reasonable number of node sensors or rankings is also proposed and discussed.

2. PRIORITIZING BY CONSENSUS RELATION

Suppose we have m *rankings* on set $A = \{a_1, a_2, ..., a_n\}$ of n *objects*. Then we have the relation set $\Lambda = \{\lambda_1, \lambda_2, ..., \lambda_m\}$, where each of m rankings (preference relations) $\lambda = \{a_1 \succ a_2 \succ ... \sim a_s \sim a_t \succ ... \sim a_n\}$ may include $\succ$, a strict preference relation π, and $\sim$, an equivalence (or indifference) relation ν, so that $\lambda = \pi \cup \nu$. Such a relation λ is generally called a *weak order*. The relation set Λ is titled a *preference profile* for the given m rankings. We can determine a single preference relation that would give an integrative characterization of the objects. Let a subspace Π be a set of all $n!$ linear (strict) order relations $\succ$ on A. Each linear order corresponds to one of permutations of first n natural numbers $\mathbf{N_n}$. We use a permutation $\beta \in \Pi$ of the alternatives $a_1, ..., a_n$ to represent the preference profile Λ and call it *consensus ranking* [5].

Assume now that A is a set of n wireless nodes which are placed in a physical environment, for example over an open area or a building to be monitored. Each wireless node has a number of sensors that measures different attributes. These nodes communicate through a wireless network, for example ZigBee. An example of such a node is the MICAz mote from Crossbow. Sensor nodes can be ranked by m attributes.

The ranking λ can be represented by an $(n \times n)$ *relation matrix* $R = [r_{ij}]$ whose rows and columns are labeled by the objects a and

$$r_{ij} = \begin{cases} 1 \text{ if } a_i \succ a_j \\ 0 \text{ if } a_i \sim a_j \\ -1 \text{ if } a_i \prec a_j \end{cases}. \quad (1)$$

The symmetric difference distance function $d(\lambda_k, \lambda_l)$ (*Kemeny distance*) between two rankings λ_k and λ_l is defined by formula

$$d(\lambda_k, \lambda_l) = \sum_{i<j} | r_{ij}^k - r_{ij}^l | \quad (2)$$

and may be understood as the number of disagreements between two rankings.

On the basis of the distance (2) between the rankings, we can define the distance $D(\beta, \Lambda)$ from β to the profile Λ and then formulate a consensus relation determination problem as

$$\beta = \arg\min_{\lambda \in \Pi} D(\lambda, \Lambda), \quad (3)$$

where $D(\lambda, \Lambda) = \sum_{k=1}^{m} d(\lambda, \lambda_k)$.

Algorithm for finding a solution of the problem (3) is described, for example, in [5].

One of possible application of the problem (3) is the case where a number of sensors collect multiple attributes and all these sensed values are available in a single location. A centralized algorithm can then be applied to determine the consensus relation [6]. An extension of this approach to a networked environment where the sensors are distributed can be done in the following way.

Let these nodes be connected in a tree structure, where all nodes send packets along the tree to a single sink node. However, due to the need to increase the quality of the information and reduce the amount of wireless transmission, the sensed data will be ranked so that only the most important information will be transmitted to the sink first and "unimportant" information may not be forwarded.

Consider Fig. 1 where there are seven wireless nodes and single data sink. The (wireless) network connectivity is such that only certain nodes $\underline{a_i}$ (after [2], we will call them *aggregators*) can communicate with one another. For example, the sink node can only communicate with node $\underline{a_1}$, in its turn $\underline{a_1}$ can receive packets from a_2, a_3, a_4 and so on. For $\underline{a_3}$, it receives data from a_6 and a_7. After ranking all packets, including its own, $\underline{a_3}$ sends packets to a_1 in order of the ranking. The more important packets are sent earlier. Such ranking and prioritization are performed on all nodes, aggregators, that receive packets from other nodes. As a measure to reduce wireless transmission, nodes may be programmed to only transmit a small number of packets.

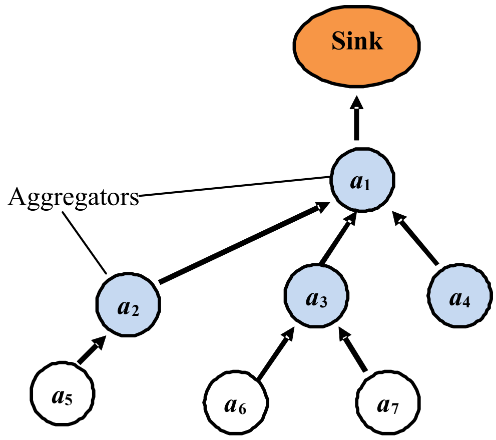

Fig 1. Topology of wireless sensor nodes

A possible performance measure is the following. Assume that the sink can only receive $n - k$ packets, then only the *most important* $n - k$ packets should be transmitted to the sink.

As an illustration, consider an automated building fire alarm system. Sensors collecting different information are placed in different locations in the building. Examples of these information are listed in Table 1. The sensors can be connected using the topology shown in Fig. 1.

Table 1. Example of sensed data (n = 7, m = 6)

Sensor node	λ_1 Location Importance (0-9)	λ_2 Tempe-rature (°C)	λ_3 Rate of Temperature Increase (°C/minute)	λ_4 Smoke Level (0 – 1)	λ_5 Sprinkle Status (0/1)	λ_6 Human Presence (0/1)
a_1	9	26	0	0	0	0
a_2	2	55	3	0.6	1	0
a_3	4	135	20	0.5	1	1
a_4	7	50	1	0.2	1	0
a_5	1	450	10	0.8	0	0
a_6	4	40	15	0.3	1	1
a_7	5	–1	2	0	0	0

In this example, a_5 detects a fire burning with lots of smoke and is spreading to location monitored by a_2. At the same time, the location monitored by a_3 is rapidly heating up. Assuming that the sink can only receive updates from k = 2 sensors, how should each node prioritize packet transmission such that the sink get the two most important updates?

The preference profile obtained from the sensor data (see Table 1) is as follows:

$$\begin{aligned}
&\lambda_1: a_5 \succ a_2 \succ a_3 \succ a_6 \sim a_7 \succ a_4 \succ a_1\\
&\lambda_2: a_5 \succ a_3 \succ a_2 \succ a_4 \succ a_6 \succ a_1 \succ a_7\\
&\lambda_3: a_3 \succ a_6 \succ a_5 \succ a_2 \succ a_7 \succ a_4 \succ a_1\\
&\lambda_4: a_5 \succ a_2 \succ a_3 \succ a_6 \succ a_4 \succ a_1 \succ a_7\\
&\lambda_5: a_2 \sim a_3 \sim a_4 \sim a_6 \succ a_1 \sim a_5 \sim a_7\\
&\lambda_6: a_3 \sim a_6 \succ a_1 \sim a_2 \sim a_4 \sim a_5 \sim a_7
\end{aligned} \tag{4}$$

The solution of the consensus relation determination algorithm is

$$\beta = \{a_5 \succ a_3 \succ a_2 \succ a_4 \succ a_6 \succ a_1 \succ a_7\}. \tag{5}$$

Hence, the packets of the nodes a_5 and a_3 must be received by sink in the first place.

Thus, it seems that the method works well. However, due to *congestion* and/or *loss* in the network, or processing delay in the node, some data are missing and the set of data differs each cycle/second. Say there is a congestion and node a_3 can only send two data packets instead of three (a_3, a_6 and a_7). Which two packets should it send first to ensure a "better" result? The choice seems to be important if say a_2 also has to select to send only a_2 or a_5.

In general, we can consider a case where each aggregator a_i having n_i adjacent (neighboring) source nodes needs to prioritize the data from them if only ($n_i - k_i$) packets can be transmitted in one round. That is, k_i packets are dropped (not transmitted) in this round. In the next round, a new set of data will arrive. Generally, each aggregator has to make this choice and it is not clear which ($n_i - k_i$) data will be available. For example, node a_3 can send only one packet and may have packets from a_3 and a_6 in one round, and a_3 and a_7 in another.

For the complete network we can have $n - k = n - \sum_i k_i$ nodes to be ranked where i are indexes of all aggregators and a final consensus relation β' will be different from β of ideal case.

Our aim is to highlight analytically expressed conditions under which we could manage the negative effect of the network congestion or losses. The possible statistically based solution is given in the next section.

3. COPING WITH CONGESTIONS

To deal with the problem we use the *Kendall rank correlation coefficient* [7] that is a non-parametric statistic used to measure the degree of correspondence between two rankings. Kendall's τ ranges from –1 (no agreement, fully inconsistent rankings) to +1 (complete agreement, fully consistent rankings). If we want to determine a consistency between two consensus relations β_1 and β_2 (recall that the relations are strict orders, i.e. without ties) then τ is defined by formula:

$$\tau = \frac{2}{n(n-1)} \sum_{i<j} r_{ij}^1 r_{ij}^2, \tag{6}$$

where r_{ij}^1 and r_{ij}^2 are elements of relation matrices of the consensus relations β_1 and β_2 correspondingly.

As shown in [8], there is a relationship between the Kendall's rank correlation coefficient (6) and the Kemeny distance (2):

$$\tau(\beta_1, \beta_2) = 1 - \frac{d(\beta_1, \beta_2)}{n(n-1)}. \tag{7}$$

Let us consider two relations β_1 and β_2 for n nodes fixed. The natural requirement is for them to be consistent. Designate the respective level of consistency through τ_1. For $n - k$ nodes where k is number of dropped packets (from k nodes) we will have other two relations β'_1 and β'_2, with consistency τ_2. Evidently, we should save the same level of consistency in both cases. Then

$$\tau_1 = \tau_2 \tag{8}$$

Denoting $d_1 = d(\beta_1, \beta_2)$ for the case where the number of nodes is equal to n and $d_2 = d(\beta'_1, \beta'_2)$ for the case where the number of nodes is equal to $n - k$ we have expressions for corresponding rank correlation coefficients:

$$\tau_1 = 1 - \frac{d_1}{n(n-1)} \text{ and} \tag{9}$$

$$\tau_2 = 1 - \frac{d_2}{(n-k)(n-k-1)}. \tag{10}$$

Taking into account condition (8) and expressions (9) and (10) we have

$$\frac{d_1}{n(n-1)} = \frac{d_2}{(n-k)(n-k-1)}, \tag{11}$$

$$\frac{d_2}{d_1} = \frac{(n-k)(n-k-1)}{n(n-1)}. \tag{12}$$

Define a measure of deviation from the Kemeny distance value in the form of *relative distance change* δ:

$$\delta = \frac{d_1 - d_2}{d_1} = 1 - \frac{d_2}{d_1}. \tag{13}$$

Using expression (12), finally, we have

$$\delta = 1 - \frac{(n-k)(n-k-1)}{n(n-1)}. \tag{14}$$

Knowing some predefined value of δ (see Fig. 2) one can select reasonable value of k dropped packets for suitable values of n. This control mechanism can be applied at both level of group of nodes neighboring some aggregator and level of several such groups or complete network.

Particularly, a random dropping scheme may give reasonable approximation if the ratio of k/n is relatively small. One way to utilize this observation is as follows. For nodes further from the sink, there are less sensor data. Hence, an actually ranking of the local data collected can be performed, and the more important $n - k$ samples are sent. Higher up the tree, with more data, a random dropping scheme may suffice. The parameter to be controlled is k_i where k_i is the number of dropped packet allowed for node i. These k_i needs to be estimated based on the feedback information propagated from nodes closer to the sink. Note that congestion is normally higher closer to the sink.

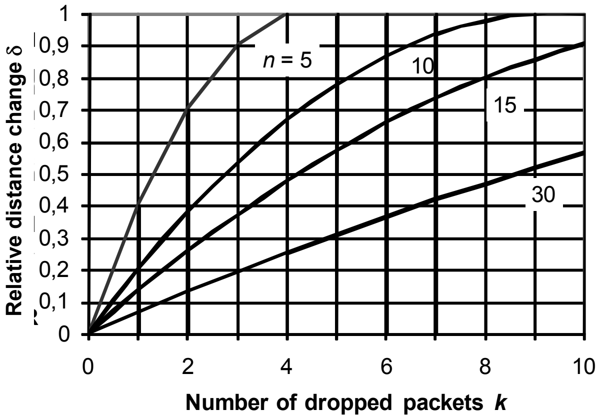

Fig. 2. Graphic presentation of the relative distance change δ depending on number of dropped packets *k* for different values of *n*, see equation (14)

Use of an efficient (possibly heuristic) algorithm that quickly sort the data into two (maybe more) sets such that the elements in one set is likely to be more important than the other set would provide an approximate classification that seems be very useful to enhance performance beyond random dropping.

4. REASONABLE NUMBER OF NODE SENSORS

When planning a surveillance system it is necessary to know a reasonable number m of sensors in each node. By one of the paper authors, for other application area – quality assessing – it was proposed [9] to estimate the value of m using simple probabilistic Bernoulli model that allows to suppose that m must be in the range from 4 to 10 for most of applications.

In this section, we are trying to apply the approach to the sensor network. Thus, we are interested in estimation of an upper bound for the number of sensors (rankings) m. At that, we are aware of absolutely exact estimations for m cannot be determined. So we will search for its approximate values.

4.1. The probabilistic model

We use a probabilistic approach to the problem of calculating number of sensors and as the examination model we also use a situation where m sensors measure m *attributes* of an object under monitoring (see, for example, Table 1).

Let us use the following simple model based on Bernoulli trial. Suppose we have multisensors consisting of m sensors measuring attributes independently of each other. The attribute values also are independent of whether they have been found before.

Let p be the probability of detecting the average attribute by a single "average" sensor (we will call it *elementary probability*).

Then the probability P of that at least one attribute is detected by m sensors is defined as follows:

$$P = 1-(1-p)^m , \qquad (15)$$

On the other hand, the probability P can be determined taking into account its frequency interpretation. Let D_t be the total number of attributes and D_f be the number of attributes that have been detected at least once by m sensors. Then we have

$$P \simeq \frac{D_f}{D_t} , \qquad (16)$$

Finally, having regard to equations (15) and (16), we obtain the following expression for the number of attributes found:

$$D_f \simeq D_t[1-(1-p)^m] , \qquad (17)$$

The similar model (however, referring to Poisson process) has been used in [10] in order to estimate the amount of evaluation required to detect so called usability problems in a user interface design.

Clearly, the number of sensors can be easily obtained from the formula (15), i.e.

$$m = \frac{\ln(1-P)}{\ln(1-p)} . \qquad (18)$$

The graph plotted by formula (15) (see Fig. 3) shows that there is some critical value m_c of m such that any $m > m_c$ does not give an essential increase of number of attributes found. For example, at $p = 0.6$, there is no necessity to have more than 5 sensors as these five sensors have detected practically all attributes.

One more proposition can be made after consideration of Fig. 1: *the more the number of a sensor group participants, the less the probability of a new attribute detecting*.

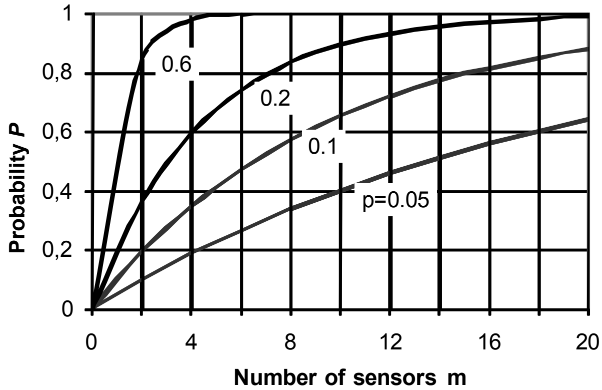

Fig. 3. Probability *P* depending on *m* for different values of *p*, see expression (15)

4.2. Probability of new attributes detecting due to additional sensors

It is interesting to investigate how the probability P will increase after adding one more sensor to the sensor group. The following formula shows how many times the probability $P(m+1) = P_1$ is greater than the probability $P(m) = P$:

$$\frac{P_1}{P} = \frac{1-(1-p)^{m+1}}{1-(1-p)^m} = 1+\frac{p(1-p)}{1-(1-p)^m} . \qquad (19)$$

It can be seen from Fig. 3 that the increase of sensor number by unit results in a minor gain of the probability P of the attributes detecting. This gain becomes especially insignificant for all numbers $m > m_c = 4$. And the more probability p the more this insignificance is.

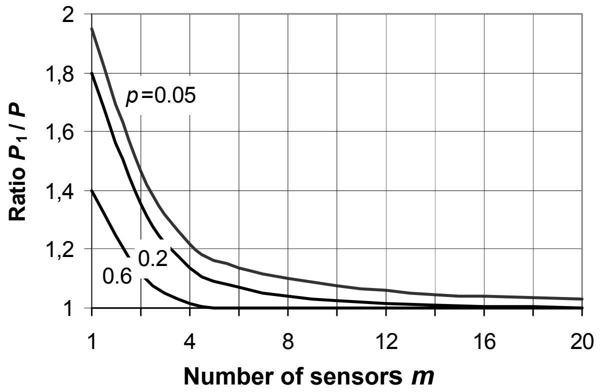

Fig. 4. The ratio P_1/P depending on m for different values of p, see expression (19)

It is worth to estimate this gain in explicit and more general form. Let α be the relative probability growth resulting from inclusion of k additional sensors into the group consisting of m sensors, i.e.

$$\alpha = \frac{P(m+k) - P(m)}{P(m)} = \frac{P_k - P}{P}, \tag{20}$$

where

$$P_k = 1 - (1-p)^m (1-p)^k, \tag{21}$$

From (15), (20) and (21) we have

$$\alpha = (1-p)^m \frac{1-(1-p)^k}{1-(1-p)^m}. \tag{22}$$

Calculations of α are reduced in Table 2 and graphically presented in Fig. 5.

As Table 2 and Fig. 5 indicate an essential gain of probability of revealing new attributes due to attraction of additional k sensors exists only if the elementary probability p is low (see Fig. 5, $p = 0.05$). In this case, the dependency $\alpha(k)$ has almost linear character. However, already at $m = 7$, doubling of found attributes number ($\alpha = 100\%$) happens only where $k = 10$.

At $p = 0.5$, if the sensor group has included 4 sensors, addition of new sensor is useless as it gives out no new data to test a quality of the object. In case of $p > 0.5$, one can see the loss of necessity in new sensors as early as $k = 5$, though the sensor group consists of a single member.

Looking at Table 2 one can see that *it is important in what fashion a sensor group was set up*. Indeed, if $p = 0.05$, $m = 2$ and $k = 8$ give the relative growth $\alpha = 3.11$, whereas $m = 4$ and $k = 6$ produce only $\alpha = 1.16$, and at that the total number of sensors is the same: $m + k = 10$. Thus, a combination of m and k with their fixed sum results in greater growth α, if $m < k$.

Table 2. Values of the relative probability growth α(k) for different numbers m, see expression (22)

	k	$m = 1$	$m = 2$	$m = 4$	$m = 7$
$p = 0.05$	0	0	0	0	0
	1	0.95	0.46	0.21	0.11
	2	1.85	0.90	0.42	0.22
	3	2.71	1.32	0.63	0.33
	4	3.52	1.72	0.81	0.42
	5	4.30	2.09	0.99	0.52
	6	5.03	2.45	1.16	0.61
	7	5.73	2.79	1.32	0.70
	8	6.39	3.11	1.48	0.78
	9	7.02	3.42	1.62	0.86
	10	7.62	3.71	1.76	0.93
$p = 0.5$	0	0	0	0	0
	1	0.5	0.17	0.03	0.004
	2	0.75	0.25	0.05	0.006
	3	0.87	0.29	0.06	0.007
	4	0.94	0.31	0.06	0.007
	5	0.97	0.32	0.06	0.008
	6	0.98	0.33	0.07	0.008
	7	0.99	0.33	0.07	0.008
	8	1.0	0.33	0.07	0.008
	9	1.0	0.33	0.07	0.008
	10	1.0	0.33	0.07	0.008
$p = 0.8$	0	0	0	0	0
	1	0.2	0.03	0.0013	0
	2	0.24	0.04	0.0015	0
	3	0.25	0.04	0.0016	0
	4	0.25	0.04	0.0016	0
	5	0.25	0.04	0.0016	0
	6	0.25	0.04	0.0016	0
	7	0.25	0.04	0.0016	0
	8	0.25	0.04	0.0016	0
	9	0.25	0.04	0.0016	0
	10	0.25	0.04	0.0016	0

The number k can be easily determined in explicit form using expression (21). That is

$$k = \frac{\ln(1-P_k)}{\ln(1-p)} - m = m\frac{\ln(1-P_k)}{\ln(1-P)} - m, \tag{23}$$

In practice, the number k can be calculated on the assumption of desirable or critical value of P_k known. Surely, the elementary probability p should also be given or estimated.

The probability p is usually recommended to be found approximately by results of practical sensor tests. In [10] it was proposed to use the following estimations:

$$D_t \simeq \frac{D_f(1)}{p} \tag{24}$$

and

$$p \simeq 2 - \frac{D_f(2)}{D_f(1)}, \qquad (25)$$

where $D_f(1)$ and $D_f(2)$ are *average* numbers of different attributes (events) detected by a single sensor and a pair of sensors correspondingly. Expressions (24) and (25) are easily derived from (17).

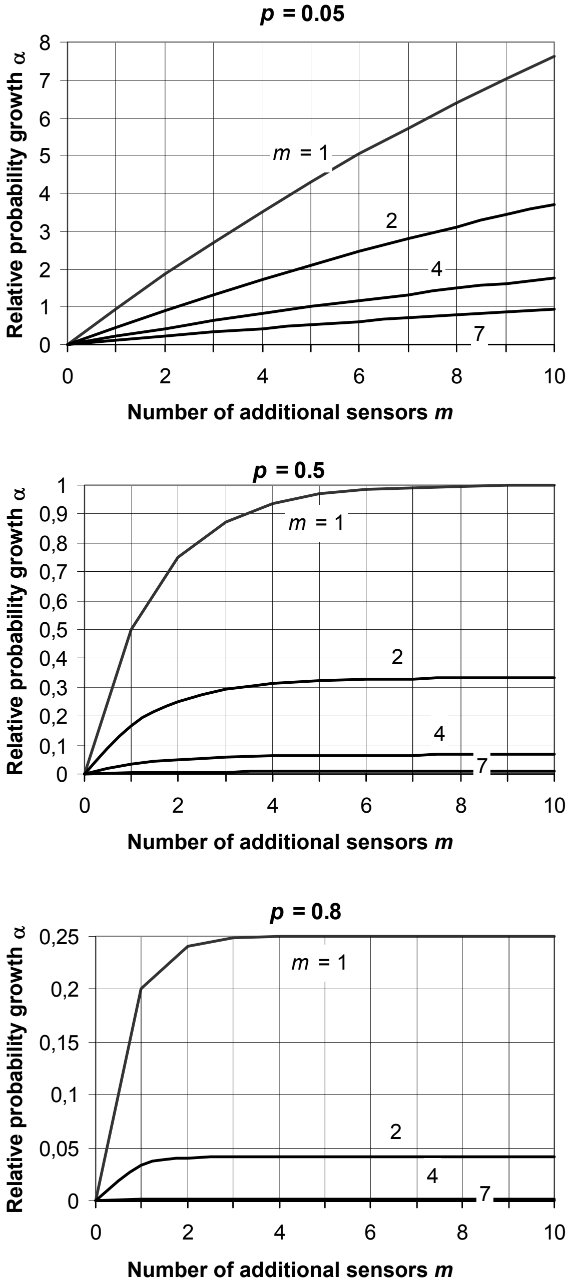

Fig. 5. Graphs (for p = 0.05, 0.5 and 0.8) of the relative probability growth α depending on number of additional evaluators k for different numbers m, see expression (22)

5. CONCLUSION

It would not be out of place to notice that statistical considerations of Section 3 and the probabilistic model discussed in Section 4 are based on assumptions that hardly characterize real situation of the sensor networking. For example, probabilities of different attributes revealing are different and often dependent on each other. In this relation, developments of new models more exactly describing the situations are welcome.

Nevertheless, the discussed models allow to obtain interesting and useful recommendations on assuring wireless sensor network performance.

The proposed in the paper analytical models are ease to use and they can be particularly useful for implementation of mobile agent technology based sensor networks [11].

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