

## 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 numbers  $n$  of sensor nodes and  $m$  of node sensors are proposed and discussed.

**Keywords:** rankings, consensus relation, sensor data fusion.

### 1. INTRODUCTION

Infrastructure based single-hop wireless networks such as cellular networks and public access networks, such as Wireless@SG, are playing increasing important roles in our daily life. However, in addition to the traditional task of providing network access to mobile users, wireless networks have also been increasingly deployed in environments where traditional wired network infrastructure cannot be easily deployed due to reasons like 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 (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.

### 2. PRIORITIZING BY CONSENSUS RELATION

Suppose we have  $m$  rankings on set  $A = \{a_1, a_2, \dots, a_n\}$  of  $n$  objects. Then we have the relation set  $\Lambda = \{\lambda_1, \lambda_2, \dots, \lambda_m\}$ , where each of  $m$  rankings (preference relations)  $\lambda = \{a_1 \succ a_2 \succ \dots \sim a_s \sim a_t \succ \dots \sim a_n\}$  may include  $\succ$ , a strict preference relation  $\pi$ , and  $\sim$ , an equivalence (or indifference) relation  $\nu$ , so that  $\lambda = \pi \cup \nu$ . Such a relation  $\lambda$  is generally called a *weak order*. The relation set  $\Lambda$  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  $\Pi$  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  $a_1, \dots, a_n$  to represent the preference profile  $\Lambda$  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  $\lambda$  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  $\lambda_k$  and  $\lambda_l$  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  $\beta$  to the profile  $\Lambda$  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  $a_j$  (after [2], we will call them *aggregators*) can communicate with one another. For example, the sink node can only communicate with node  $a_1$ , in its turn  $a_1$  can receive packets from  $a_2, a_3, a_4$  and so on. For  $a_3$ , it receives data from  $a_6$  and  $a_7$ . After ranking all packets, including its own,  $a_3$  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.

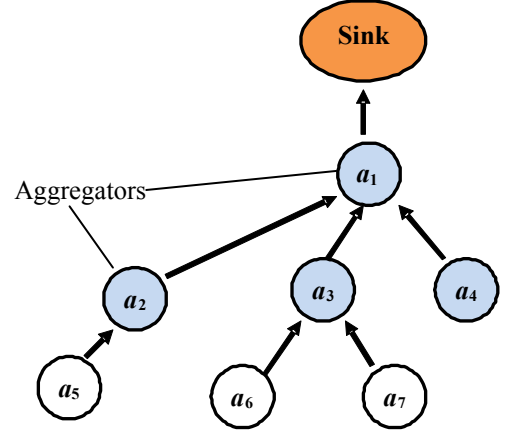


Fig 1. Topology of wireless sensor nodes

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

Sensor node	$\lambda_1$	$\lambda_2$	$\lambda_3$	$\lambda_4$	$\lambda_5$	$\lambda_6$
	Location Importance (0-9)	Temperature (°C)	Rate of Temperature Increase (°C/minute)	Smoke Level (0-1)	Sprinkle Status (0/1)	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:

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

The solution of the consensus relation determination algorithm is

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

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, if due to *congestion* and/or *loss* in the network, or processing delay in the node, some data is 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  $\beta'$  will be different from  $\beta$  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  $\tau$  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  $\beta_1$  and  $\beta_2$  (recall that the relations are strict orders, i.e. without ties) then  $\tau$  is defined by formula:

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

where  $r_{ij}^1$  and  $r_{ij}^2$  are elements of relation matrices, of the consensus relations  $\beta_1$  and  $\beta_2$  correspondingly.

As shown in [8], there is a relationship between the Kendall's rank correlation coefficient (4) and Kemeny distance (2):

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

Let us consider two relations  $\beta_1$  and  $\beta_2$  for  $n$  nodes fixed. The natural requirement is for them to be consistent. Designate the respective level of consistency through  $\tau_1$ . For  $n - k$  nodes where  $k$  is number of dropped packets (from  $k$  nodes) we will have other two relations  $\beta'_1$  and  $\beta'_2$ , with

consistency  $\tau_2$ . Evidently, we should save the same level of consistency in both cases. Then

$$\tau_1 = \tau_2 \quad (8)$$

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:

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

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

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

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

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

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

$$\delta = \frac{d_1 - d_2}{d_1} = 1 - \frac{d_2}{d_1}. \quad (13)$$

Using expression (12), finally, we have

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

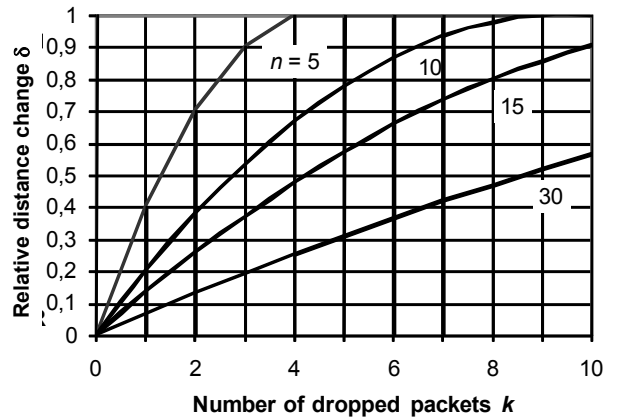


Fig. 2. Graphic presentation of the relative distance change  $\delta$  depending on number of dropped packets  $k$  for different values of  $n$ , see equation (14)

Knowing some predefined value of  $\delta$  (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.

### 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:

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

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 found at least once by  $m$  sensors. Then we have

$$P \approx \frac{D_f}{D_t}, \quad (16)$$

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

$$D_f \approx D_t [1 - (1 - p)^m], \quad (17)$$

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.

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

The graph constructed 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 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.*

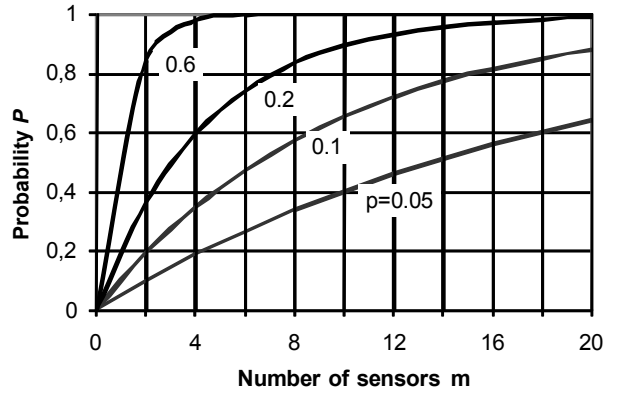


Fig. 3. Probability  $P$  depending on  $m$  for different values of  $p$ , see expression (15)

#### 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  $P(m) = P$ :

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

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.

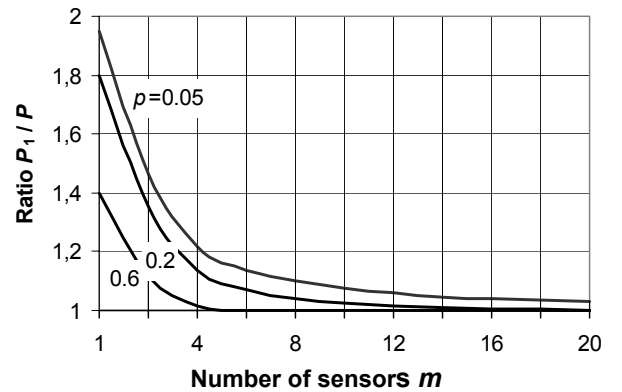


Fig. 4. The ratio  $P_1/P$  depending on  $m$  for different values of  $p$ , see expression (19)

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

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

where

$$P_k = 1 - (1-p)^m (1-p)^k, \quad (21)$$

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

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

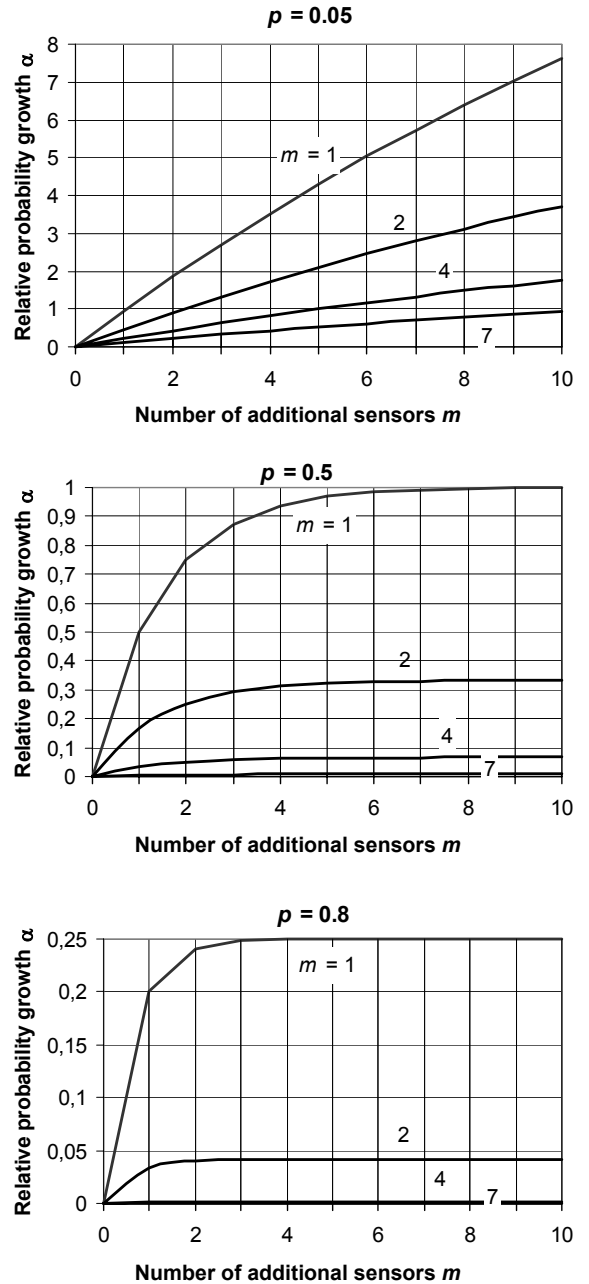
Calculations of  $\alpha$  are reduced in Table 2 and graphically presented in Fig. 4.

**Table 2. Values of the relative probability growth  $\alpha(k)$  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

As Table 2 and Fig. 4 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. 4,  $p = 0.05$ ). 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. If  $p > 0.5$ , one can see the loss of necessity in new sensors as early as  $k = 5$ , though the sensor group consists of a single member.



**Fig. 4. Graphs (for  $p = 0.05, 0.5$  and  $0.8$ ) of the relative probability growth  $\alpha$  depending on number of additional evaluators  $k$  for different numbers  $m$ , see expression (22)**

Looking at Table 1 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  $\alpha$ , if  $m < k$ .

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

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

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:

$$D_t \approx \frac{D_f(1)}{p} \quad (24)$$

and

$$p \approx 2 - \frac{D_f(2)}{D_f(1)}, \quad (25)$$

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

## 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. In fact, probabilities of different attributes revealing are different and often dependent on each other. In this relation, developments of new models more exactly describing the situation are welcome.

Nevertheless, the discussed model allows to obtain interesting and useful recommendations on selection of number of an sensor group members when measuring quality.

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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