Entropy-driven analysis of loss-less and energy efficient data aggregation in wireless sensor networks

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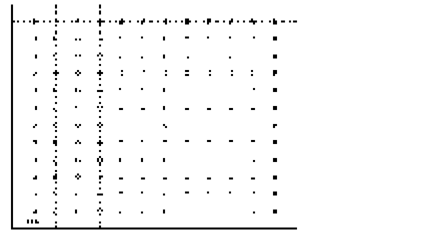
Abstract. Sensor networks are characterized by limited energy and processing capabilities. This becomes crucial in case of event-based sensor networks when multiple close nodes notify the sink about the same event at almost the same time. Propagation of this redundant highly correlated data would be costly for the system and result in energy depletion and network overloading. In the literature data aggregation has been recently regarded as a way to reduce energy consumption and also prevent congestion. In this paper we derive some insight into the data aggregation process. More specifically, we first estimate under which conditions aggregation can be a costly process with respect to non aggregation in a realistic scenario where processing costs related to aggregation of data are taken into account. Also, we consider that aggregation should preserve integrity of data. To this purpose, the entropy of the correlated data sent by sources can be considered in order to both decrease the amount of useless data forwarded to the sink and perform an overall loss-less process. To this target, we develop an analytical framework aimed at evaluating the overall entropy of the joint correlated information. This can be used to figure out a tradeoff between the need to increase data aggregation for energy consumption reduction, and the need to maximize information integrity. Performance results show that the aggregation process can be effectively designed exploiting the possibility to tune the transmission power so as to increase the convenience of performing entropy-driven data aggregation.

Key Words: *Wireless Sensor Networks, Data Aggregation, Entropy, Energy Consumption.*

I. Introduction

Wireless sensor networks are composed of devices characterized by limited battery, processing and storage capabilities [1]. This aspect becomes especially crucial in case of event-based applications, where sensors monitor a given phenomenon and send notifications and measurements back to the sink(s). So, a lot of redundant data, especially in case of high density networks, go back to the sink(s), thus wasting precious bandwidth and energy resources. As an example, in Fig. 1(b) we show the percentage of residual energy in a sensor network where nodes are located according to the topology shown in Fig. 1(a) after 600 s of simulation. In this scenario nodes in the periphery are supposed to send data to the sink to advertise about an anomalous event occurred. It is evident that, due to the so called *funneling effect* [2], the closer a node is to the destination, the more stressed under the perspective of energy efficiency it is. Another problem, usually related to the above one, is congestion which can be met at nodes closer to the sink which are likely to relay a lot of data packets. To this purpose aggregation has been recently regarded as a way to reduce energy consumption [5], [8], [9], and also prevent congestion [3]. When performing aggregation, usually the cost of processing is disregarded. Instead, this could contribute to make the aggregation process even more costly than no aggregation. So an investigation of the conditions under which aggregation can become energetically cheaper with respect to no aggregation is needed. Also one can expect that, the higher the number of packets to be aggregated, the higher the advantage of using aggregation with respect to not using it. However aggregation cannot be increased indefinitely unless precious information are missed. So, much attention should be paid to the way aggregation is pursued. To make aggregation more efficient, in case of event-based applications, spatial correlation of data monitored by nodes in close proximity can be used. More specifically, using entropy considerations, a study on the limit to the maximum amount of data which could be aggregated with no losses, is provided in this paper. Moreover, a tradeoff between aggregation, information integrity, and energy consumption minimization in spite



(a) Area $A(g)$ when $L = 8$.

(b)

Fig. 1. a) Example of a grid network topology b) Percentage of residual energy for the topology shown in (a

of the additional processing required to perform aggregation is identified. Results can be used for designing efficient data aggregation protocols which exploit the possibility to tune the transmission power as available in many sensor commercial devices to make aggregation a successful and cheap process.

The rest of this paper is organized as follows. In Section II we recall some related work in the field. In Section III a power consumption analysis is developed which allows to derive the conditions when aggregation is a costly process with respect to no aggregation. In Sections IV and V the maximum value of the aggregation function which guarantees to preserve data integrity at destination is estimated. In Section VI some performance results are discussed and, finally, in Section VII some conclusions and considerations on future work are drawn.

II. Related Work

Data aggregation has been usually regarded as a way to reduce energy consumption in wireless sensor networks. To this purpose many papers dealing with the problem of constructing data-aggregation trees towards the sink have been proposed in the literature. As an example, in [7] the problem of building optimal aggregation trees has been considered leading to the result that it is NP-hard and so an appropriate delay-energy tradeoff should be considered. In [9] too, an appropriate tradeoff between delay and energy is investigated in the context of a distributed estimation algorithm where the final result depends on the aggregation performed by few nodes. In [6] the impact of nodes' density on energy-efficient aggregation tree construction is also considered. In [8] an analytical study of how partially correlated data affect the performance of clustering algorithms is proposed. Also, in that work rate distortion considerations are used to study energy consumption and lifetime of the network, provided that some correlation among the data is available. Finally, in [10] an analytical model which characterizes the tradeoff between aggregation and topology control in case of trivial aggregation (e.g. min/max, average, etc.) through the use of sleep-active schedules employed to reduce energy consumption is proposed. In that work the authors try to minimize energy consumption, while preserving responsiveness and fidelity in the aggregation process. In this paper, instead, the main focus is on figuring out a tradeoff between need to reduce power consumption through use of aggregation, and fidelity in the aggregation process. More specifically, considering a network where few nodes perform aggregation and assuming that they work independently from each other, we investigate on the tradeoff between aggregation for reduction in the energy consumption and information integrity support. Accordingly a set of conditions under which aggregation can be less expensive than no aggregation are identified. The latter can be used by network designers to appropriately design network protocols so as to tune the transmission power in a way to increase network lifetime and fidelity in data delivery.

III. Power Consumption Analysis

In order to optimize the solution of the aggregation problem, interactions among all network nodes should be considered. However, this would imply an additional overloading of the network through signaling and a consequent waste of resources. Accordingly, in this work we assume that nodes exploit only local information, thus taking independent solutions when aggregating based only on their knowledge of the local topology.

Let us consider an event-based application scenario. In this case nodes are required to monitor unexpected events, e.g. temperature, humidity or degree of contamination exceeding a given threshold and report the monitored information to the sink(s) which disseminated queries through an interest-like approach. As an example in Fig. 2 the reference network is shown. In this figure sensors in the interest area monitor different variables and, accordingly, send different metrics to the sink. In this case an aggregator node should implement different queues per each metric to be delivered to the sink.

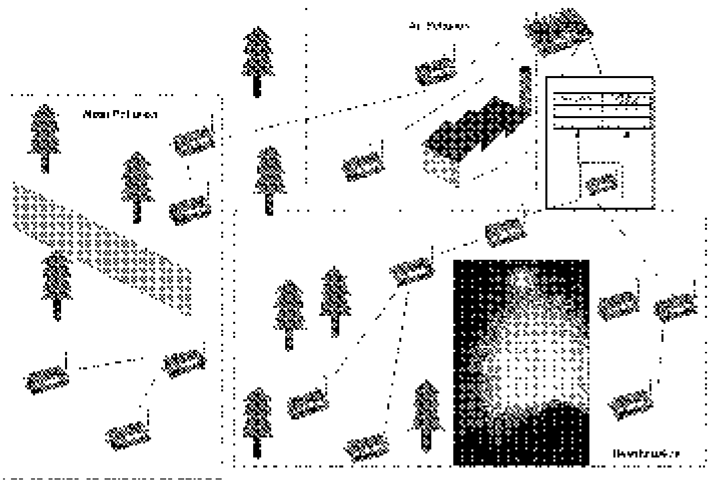


Fig. 2. Event monitoring scenario with an aggregator.

Let us suppose that a node, say k, receives traffic from N_k one-hop neighbor nodes. This traffic needs to be relayed to other nodes towards the destination (sink). In order to reduce energy consumption, thus increasing network lifetime, packets sent by these N_k nodes could be effectively aggregated so as to take advantage of the correlated traffic generated by high density sensor networks when nodes are located in the proximity of each other. In fact, observe that the correlation coefficient between the traffic generated by a pair of nodes is a function of their physical proximity.

If a node k performs aggregation, it will be denoted as *aggregator*.

Aggregation will clearly result in a reduction in the energy which is depleted by relaying redundant data. However, aggregation implies performing more complex operations with respect to simply relaying traffic; this can lead to an increase in the overall energy consumption[1]. Observe that, when different metrics are monitored throughout the network, only homogeneous data will be aggregated. So if an aggregator node like the one shown in Fig. 2 receives two kinds of data we assume it can aggregate only packets carrying the same data, e.g. only pollution notifications.

Let us now evaluate the power consumption, C_k, at node k, comparing both the case when this node acts only as a forwarder, simply relaying other nodes' packets, or as an aggregator. In the first case,

$$C_k = (P_{TX} + P_{RX}) \cdot \sum_{j=1}^{N_k} \mu_j + P_{TX} \cdot r_k \qquad (1)$$

where we denote

- μ_j the packet emission rate at each of the $j-th$ one-hop neighbors of the considered aggregator node, k
- P_{TX} and P_{RX} the packet transmission and reception power, respectively
- r_k the rate of data generated by node k

In the case when node k is an aggregator, the power consumption can be written as follows

$$\begin{aligned} C_k = \left(\tfrac{P_{TX}}{\alpha_k(t)} + P_{Cod}\right) \cdot \left(\textstyle\sum_{j=1}^{N_k} \mu_j + r_k\right) + \\ + P_{RX} \cdot \textstyle\sum_{j=1}^{N_k} \mu_j + P_{Circ} \end{aligned} \qquad (2)$$

where

- P_{Circ} is the power needed to keep on the aggregation circuitry independently of the amount of data to be aggregated
- $\alpha_k(t)$ is the *aggregation function* at node k, where $\alpha_k(t) \geq 1$. The latter represents the number of packets whose information can be aggregated by node k into one packet, at time t. Different choices are possible. On the one hand, $\alpha_k(t)$ could remain constant and be not reactive to network dynamics, i.e. $\alpha_k(t) = \alpha$. On the other hand, $\alpha_k(t)$ could be variable in time according to the current network status and the number of packets which should be delivered to the sink.
- P_{Cod} is the coding power employed for coding and processing a single packet to perform data aggregation.

  In Table III we show the values of the current drain for the different working modes for a MICAZ Crossbow device.

From eqs. (1) and (2) we observe that, when

$$\frac{P_{Cod}}{P_{TX}} < 1 - \frac{1}{\alpha_k(t)} - \frac{P_{Circ}}{P_{TX}} \cdot \frac{1}{r_k + \sum_{j=1}^{N_k} \mu_j} \qquad (3)$$

the process of transmission without aggregation results more costly in terms of energy consumption with respect to the case when aggregation is used.

Let us also consider the total power consumption C_I per each transmitted packet at nodes upstream an aggregator node in the sink direction. Nodes upstream a node k are nodes met along the path going from node k up to the sink. The aggregator node k is supposed to be H hops away from the sink. We consider that a tree-path from each node to the sink is derived and in this

[1]In the following of this work, we disregard delay problems since we assume that data packets can be aggregated only if already available in the aggregator's buffer so that no additional delay, waiting for packets to come, is considered.

Current Drain	Value
Microprocessor	
Full operation	6 mA
Sleep mode	8 μA
RF	
Receive mode	8 mA
Transmit mode	12 mA
Sleep mode	2 μA
Logger	
Write	15 mA
Read	4 mA
Sleep	2 μA
Sensor Board	
Full operation	5 mA
Sleep mode	5 μA

TABLE I

CURRENT DRAIN FOR VARIOUS WORKING MODES FOR A MICAZ CROSSBOW DEVICE.

scenario we take into account both the case when there are no other aggregator nodes upstream along the path to the sink and the case when there are A aggregator nodes. In the first case, the total power consumption per each packet transmitted by k can be evaluated as

$$C_T = (P_{TX} + P_{RX}) \cdot (H - 1) \tag{4}$$

In the second case, instead,

$$\begin{aligned} C_I &= (P_{TX} + P_{RX}) \cdot (H - 1) + A \cdot P_{Cod} + \\ &+ \textstyle\sum_{i=1}^{A} \frac{P_{RX}}{\alpha_i(t)} - A \cdot P_{TX} + A \cdot P_{Dec} \end{aligned} \tag{5}$$

From eqs. (4) and (5) we can figure out that when

$$\frac{P_{Cod}}{P_{TX}} < \left(1 - \frac{1}{A} \cdot \sum_{i=1}^{A} \frac{1}{\alpha_i(t)} - \frac{P_{Dec}}{P_{TX}}\right) \tag{6}$$

i.e. when no other aggregators are met upstream towards the sink, the system results more costly per each transmitted packet than when A aggregators can be found.

Accordingly, based on (3) and (6), if

$$\begin{aligned} \tfrac{P_{Cod}}{P_{TX}} &< min\left\{1 - \tfrac{1}{A} \cdot \textstyle\sum_{i=1}^{A} \tfrac{1}{\alpha_i(t)} - \tfrac{P_{Dec}}{P_{TX}};\right. \\ & \left. 1 - \tfrac{1}{\alpha_k(t)} - \tfrac{P_{Dec}}{P_{TX} \cdot (\mu_k + \sum_{j=1}^{N_k} \mu_j)}\right\} \end{aligned} \tag{7}$$

performing aggregation is more convenient than not aggregating at all. Looking at the above equations, it is evident that the higher is the aggregation function, i.e. the number of packets which are aggregated, the lower is the amount of power needed to perform transmission. However, it is intuitive that high aggregation could be costly in terms of loss of information. Accordingly, in the next section we will analyze in detail to what extent aggregation can be performed without loss of information.

IV. ENTROPY ESTIMATION

In this section we focus on the aggregation process which can be performed at an aggregator node, so as to reduce the data traveling towards the sink, while preserving the integrity of the information.

The information aggregation process we pursue should be such that no information is lost even if reducing the amount of data packets propagated from an aggregator node to the sink. Thus, on the one hand the aggregation process should be loss-less because no information should be lost; on the other hand, the process should be lossy in the sense that useless data packets will not be forwarded.

By using aggregation, we expect that node's k emission rate, $\mu_k(t)$, should be lower than $\sum_{j=1}^{N_k} \mu_j(t)$. To evaluate $\mu_k(t)$ let us model the data generated by each neighbor of node k as a time-continuous random variable X_j.

In order to appropriately design the data aggregation process at a generic node k, we preliminarily evaluate the differential joint entropy of variable $\Gamma = (X_1, \ldots X_{N_k})$, i.e. $h(\Gamma) = h(X_1, \ldots, X_{N_k})$, which differs from the entropy in that the random variables are not required to be discrete but are supposed to be continuous.

As a property of the differential joint entropy, it follows that [4]

$$h(X_1, \ldots X_{N_k}) < \sum_{j=1}^{N_k} h(X_j) \tag{8}$$

Accordingly, in a loss-less process, a rate $r > h(X_1, \ldots X_{N_k})$ is sufficient to accurately reconstruct variables $X_1, X_2, \ldots X_{N_k}$.

Let us estimate the joint probability distribution function (pdf) of variable Γ which can be written as [4]:

$$f_\Gamma(\gamma) = \frac{1}{2\pi^{N_k/2}\sqrt{detV}} \cdot e^{\left[-\frac{(\gamma-m)V^{-1}(\gamma-m)^T}{2}\right]} \quad (9)$$

where m is the array of the average values for each of the N_k random variables, i.e. $m = [m_{X_1}, \dots m_{X_{N_k}}]$, and V is the matrix of the covariances. Matrix V can be written as

$$V = \begin{pmatrix} \sigma^2_{X_1} & \sigma_{X_1,X_2} & \dots & \sigma_{X_1,X_{N_k}} \\ \dots & \dots & \dots & \dots \\ \sigma_{X_{N_k},X_1} & \sigma_{X_{N_k},X_2} & \dots & \sigma^2_{X_{N_k}} \end{pmatrix} \quad (10)$$

where

- σ^2_J is the variance of variable $J \in \{X_1, \dots, X_{N_k}\}$
- σ_{J_1,J_2} is the covariance of variable (J_1, J_2) and is given by $\sigma_{J_1,J_2} = \rho_{J_1,J_2}\sigma_{J_1}\sigma_{J_2}$ with $\rho_{J_1,J_2} \in [-1, 1]$. We assume that the covariance of variable (J_1, J_2) is proportional to the proximity of devices. To this purpose ρ_{J_1,J_2} represents the correlation coefficient between variables J_1 and J_2 and depends on the locations of nodes 1 and 2 who generated variables J_1 and J_2. The highest the nodes proximity, the highest the correlation coefficient and viceversa.

Accordingly, the joint differential entropy can be evaluated as

$$\begin{aligned} h(\gamma) &= \int_{-\infty}^{+\infty} f_\Gamma(\gamma) \cdot log_2\left(\frac{1}{f_\Gamma(\gamma)}\right)d\gamma \\ &= \int_{-\infty}^{+\infty} \frac{1}{(2\pi)^{\frac{N_k}{2}}\sqrt{detV}} \cdot e^{\left[-\frac{(\gamma-m)V^{-1}(\gamma-m)^T}{2}\right]} \cdot \\ &\quad log_2\left(\frac{1}{(2\pi)^{\frac{N_k}{2}}\sqrt{detV}} \cdot e^{\left[-\frac{(\gamma-m)V^{-1}(\gamma-m)^T}{2}\right]}\right)^{-1} d\gamma \end{aligned} \quad (11)$$

V. Aggregation function maximization

The joint differential entropy can be used to estimate the maximum loss-less improvement in terms of reduction in the amount of useless data that have to be transmitted using aggregation with respect to non aggregating. The improvement, θ_K, is given by the ratio between the difference in the data to be relayed by node k when no aggregation is performed and when loss-less aggregation is applied and the total amount of data to be relayed with no aggregation performed. More specifically, the overall improvement achieved using aggregation, can be evaluated as

$$\theta_k = \frac{\sum_{j=1}^{N_k} h(X_j) - h(X_1, X_2 \dots X_{N_k})}{\sum_{j=1}^{N_k} h(X_j)} \quad (12)$$

In order to understand how to use the information on the overall improvement θ to appropriately design the network aggregation process let us consider that, whatever is the choice in the aggregation function, in order not to loose any information, $\alpha_k(t)$ should be such that

$$\alpha_k(t) \leq \frac{1}{1-\theta_k} \quad (13)$$

An increase in $\alpha_k(t)$ beyond this threshold would result in a loss of information. Therefore, in order to be aggressive in the process so as to reduce energy consumption while also preserving integrity of the information, the maximum value of the aggregation function at node k should be such that

$$\alpha_k^{MAX} = \frac{1}{1-\theta_k} \quad (14)$$

Finally, it follows that

$$\mu_k(t) = (1-\theta_k) \cdot \sum_{j=1}^{N_k} \mu_j(t) \quad (15)$$

VI. Case Study

In this section we investigate on the joint differential entropy and consequently the maximum amount of aggregation which can be applied compatibly with the need for minimizing energy consumption while preserving information integrity. To this purpose in Figs. 3 we show the values of the differential joint entropy obtained when considering a node k with a number of one-hop neighbors equal to $N_k = 2$ and $N_k = 3$, respectively. In these figures the mean value of the sensor measurements is denoted as m_X and measurements are assumed to have a standard deviation σ_X, equal for all neighbors. Comparing Figs. 3 (a) and (c) we observe that, as expected, as soon as the number of one-hop neighbors increases, the improvement θ_k increases because the difference between the joint differential entropy and the sum of the single source entropies as a function of the ratio σ_X/μ_X increases. This is also evident looking at Figs. 3 (b) and (d) where the maximum value of the aggregation function is shown.

Those figures have been obtained assuming that the correlation coefficient is a decreasing function of the distance between pairs of nodes, i.e.

$$\rho_{J_1,J_2} = Ae^{-\beta \cdot d^2_{1,2}} \quad (16)$$

As expected, as soon as the number of neighbor nodes increases, a higher aggregation can be applied which allows to reduce the amount of redundant data packets sent by the aggregator node to the sink. Observe that an increase of one in the number of neighbors, allows to almost double the maximum value of the aggregation function as evident comparing Figs. 3 (b) and (d). Once the maximum value of the aggregation function has been derived, in order to test the power consumption cost in Fig. 4 we show the normalized power consumption at node k as a function of the normalized coding power and the number of neighbors, N_k. In this figure, which has been obtained assuming $\mu_j = 2$ pkts/s, $P_{Cod} = P_{Cre}$, $r_k = 1$ pkts/s and $\alpha_k(t) = 2$, we show the region described in eq. (3). More specifically, the region where the light curve overcomes the dark curve is the one where performing aggregation results more costly than not aggregating. This region is met as soon as the ratio P_{Cod}/P_{TX} is approximately above 0.4. This is because when the coding cost becomes comparable to about half the transmission cost, aggregation becomes a costly process. When the aggregation function, $\alpha_k(t)$, increases, the region where aggregation is more convenient than no aggregation increases as well. This figure can be used in conjunction with Fig. 3 for design purposes. In fact, based on the number of neighbors that are currently sending data to node k, the joint differential entropy can be estimated and, consequently, the maximum value of the aggregation function which allows to perform a loss-less process can be calculated. Accordingly, when different values of the transmission power, P_{TX}, can be exploited, the ratio P_{Cod}/P_{TX} can be chosen so as to make aggregation more efficient than no aggregation. On the other hand the above figure allows to understand to what extent, depending on the number of neighbors, N_k, and on the aggregation function, $\alpha_k(t)$, aggregation can be less expensive than no aggregation. For worth of completeness, in Fig. 5 we show the limit condition given in eq. (3) which represents the maximum value of the ratio P_{Cod}/P_{TX} as a function of both the number of neighbors, N_k, and the ratio P_{Cre}/P_{TX}. This curve summarizes the conditions when aggregation is more convenient than no aggregation. Finally, in Fig. 6 we show the result derived in eq. (7) when considering that $\alpha_i(t) = \alpha\ \forall i$, $r_k = 1$ pkts/s, and $\mu_j = 2$ pkts/s $\forall j$. Looking at the above figure we observe that, the higher is the aggregation value α, the higher the ratio $(P_{Cod} + P_{Cre})/P_{TX}$ and, thus, the lower the value of P_{TX} which allows to achieve both energy consumption reduction and decrease in the amount of data traveling throughout the network while preserving integrity of data.

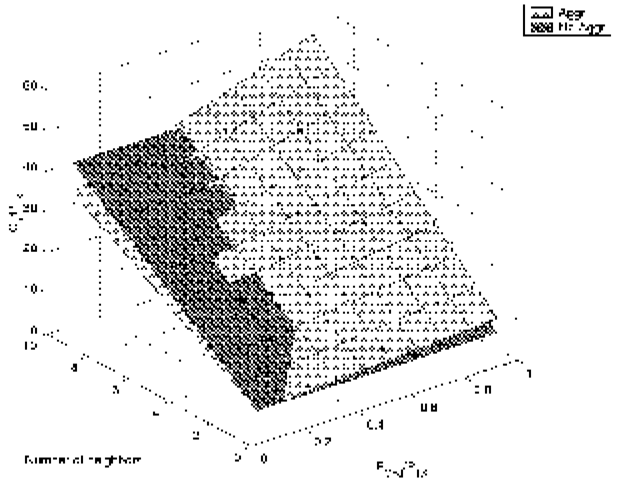


Fig. 4. Normalized power consumption at node k in case of aggregation and no aggregation as a function of the number of neighbors and the normalized coding power when $r_k = 1$ pkts/s, $\mu_j = 2$ pkts/s $\forall j$ and $\alpha_k = 2$ pkts.

VII. Conclusions

In this paper we investigated on the use of data aggregation for improving energy efficiency in high density wireless sensor networks for event-monitoring applications. In this case, nodes are expected to send multiple correlated data to the sink, thus implying propagation of redundant information throughout the network which will lead to both waste of energy resources, bandwidth and increase in network congestion. Aggregation is however a costly mechanism because an additional processing is required which could imply, in certain conditions, higher power consumption with respect to traditional forwarding of data. Also, aggregation should be such that integrity of data is preserved since the higher is the aggregation, the higher is the probability to miss important data. Accordingly, in this paper we have developed some analysis for evaluation of the power cost of the aggregation process with respect to not performing aggregation. Then we estimated the joint entropy of the correlated information sent by different sources; this allowed us to figure out a tradeoff between need to perform energy efficient data aggregation and loss-less aggregation of data packets. Results can be used to design appropriate aggregation processes which both preserve integrity of the information and reduce energy consumption.

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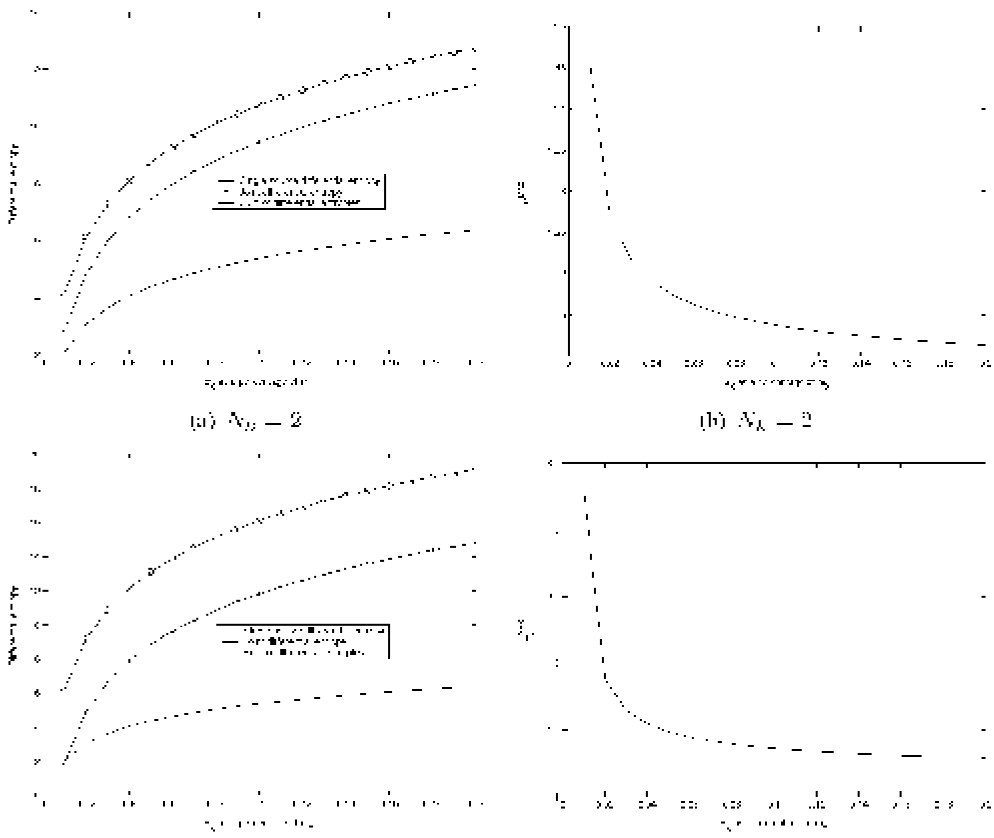

(a) $N_k = 2$ (b) $N_k = 2$

(c) $N_k = 3$ (d) $N_k = 3$

Fig. 3. Differential entropy when node k has two (a) or three (c) neighbors. Maximum value of the aggregation function when node k has two (b) or three (d) neighbors as a function of the ratio between σ_X and m_X.

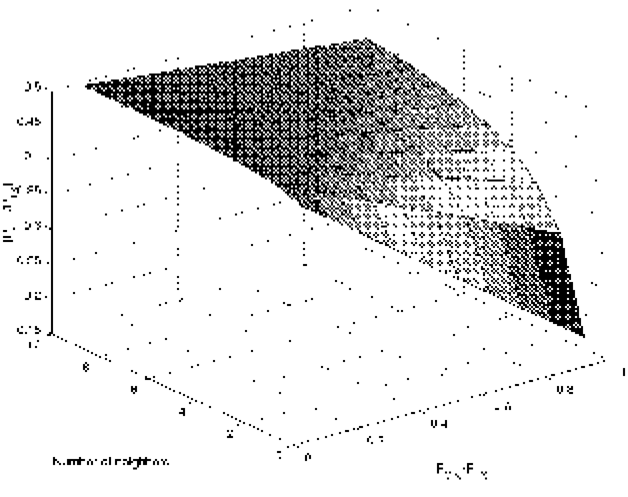

Fig. 5. Maximum value of the ratio P_{CAG}/P_{TX} as a function of the number of neighbors and the ratio P_{CAG}/P_{TX} under which the aggregation process is more convenient than no aggregation.

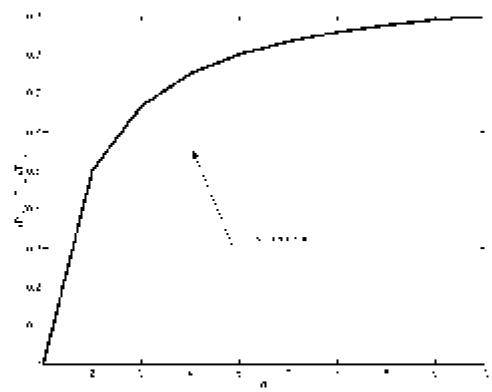

Fig. 6. Ratio $(P_{CAG} + P_{CAG})/P_{TX}$ as a function of the aggregation value, α, assumed constant at all nodes.

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