Green Wireless Networks through Exploitation of Correlations
(Invited Paper)

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Abstract. Energy-efficient wireless networks are essential to reduce the effect of global warming and to minimize the operational costs of future networks. In this paper we investigate approaches exploiting spatial correlations that offer a high potential to significantly decrease the total energy consumption thus enabling "green" wireless networks. In particular, we analyze the impact of distributed compression and optimized node deployments on the energy-efficiency of networks. Furthermore, we present results on the operational lifetime of networks which is often a major performance criterion from applications' perspective.

Keywords: green networking, energy consumption, spatial correlation, distributed compression, deployment strategies.

1 Introduction

Information and communication technologies (ICTs) are a contributor to the global energy consumption. Increasing demands of energy is foreseen in future since intensified use and extended availability of ICTs is expected. Power generation through regenerative but also fossil technologies causes greenhouse gas emissions. Climatologists determined that primarily accumulated carbon dioxide (CO_2) forms a shield in the earth's atmosphere that prevents heat radiated away from earth [1]. Thus, carbon dioxide advances the global warming that beyond doubt will have strong negative impact on the societies world-wide. It has been estimated that ICTs contribute around 2-2.5 % of global greenhouse gas emissions already in the year 2007 with a strong trend to increase [2].

Although wireless networks are responsible for only a minor share of CO_2 emissions they have shown exponentially increasing energy consumption figures, doubling almost every four years. In addition, providing communication services on a world-wide scale would consume about 40 % of the current global power generation capabilities if western standards are targeted [3]. In addition to minimizing the environmental impact of industry, network operators show strong interest for economical reasons since the expenses for energy tend to increase,

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while the revenues in bandwidth tend to decrease. Furthermore, energy conservation can also lead to improved performance in terms of operational lifetime of networks if those consist of nodes that are battery-operated.

Within the communications and networking sector a trend towards improved energy-efficiency, thus reducing the CO_2 footprint, has been identified. The most common energy reduction approaches target the hardware components and the power management of nodes and entire networks. Additionally, significant energy savings can be achieved if two other concepts are taken into account. First, improvements are possible if the amount of data to be communicated between nodes is reduced [4–7]. Second, gains can be achieved through optimisation of the applied node deployment strategies [8–11]. Both concepts considered in this work rely on the energy-efficient exploitation of spatial correlations and are complementary. Although we focus on the spatial domain, in principle also the temporal domain offers great potential. Spatial correlations are often inherent to networking scenarios taken from the wide field of data gathering applications. For example, for monitoring and surveillance purposes various correlation properties in the phenomenon under observation can be assumed.

Previous works often seek to decrease energy consumption either by trading off communication vs. signal processing costs or shifting computational complexity between transmitter and receiver. However, not all works thoroughly take into account the overall net energy balance including entire signal processing costs, see, for example, [6, 7, 11–13]. It is therefore of strong interest to minimize the *total energy* consumed, which includes the energy consumed in terms of communication as well as the energy sacrificed for the extra signal processing. Those additional costs occur due to the use of data reduction techniques offering the actual benefits.

In this study we present results on the analysis of the total energy consumed by a clustered wireless network. We consider lossless distributed compression on the lowest level in the hierarchy of nodes since we can make use of synergy effects if most of the data is reduced where it is originated. In addition, the net energy balance of our proposed approach is provided. Furthermore, different node deployment strategies are evaluated since the location of nodes has a strong impact on the energy consumption and operational lifetime of the network.

The remainder of the paper is structured as follows. In Section 2 we explain the lossless distributed compression scheme in detail. Section 3 briefly describes the system model including the node deployment models used for topology generation. In Section 4 we present the net energy balance taking into account the total energy consumed. Section 5 provides extensive simulations results and the energy-efficiency analysis of the considered wireless networks. Network lifetime is investigated in Section 6 since it is often a major performance criterion in the case of battery-operated networks. Finally, Section 7 draws conclusions.

2 Distributed Compression

In wireless networks observations of neighbouring nodes can be seen as spatially correlated discrete sources. The source information consists of blocks of v

symbols (bits) that are compressed into the same number of blocks of u symbols each, with $u < v$. Thus, the packet sizes are reduced prior to the transmission while the overall number of packets is kept constant. We denote the probability density function of the random source X by $p(x)$. Let $H(X)$ denote the information entropy which is the measure of the uncertainty associated to the source X. The Shannon source coding theorem states the limits on the achievable code rate R_x for lossless data compression described by $R_x \equiv \frac{u}{v} \geq H(X)$, where v and u denote the block lengths of the information word and of the code word, respectively.

One way of exploiting the spatial correlation of, for example, two neighboring nodes X and Y is through joint compression based on inter-node information exchange. If the nodes are allowed to communicate with each other, they could avoid the transmission of any redundant information, leading to the total compression rate R equal to the joint entropy $H(X,Y)$ [14]. The strong drawback is that this comes at the expense of energy and substantial communication overhead. The traditional way for separate encoding avoiding any inter-node communication is to compress at the total rate $R = H(X) + H(Y)$. Since we assume spatial correlation, $H(X) + H(Y)$ is always greater than $H(X,Y)$ and thus this approach is suboptimal and not considered further. Hence, the question arises what we will loose in compression efficiency if the costly inter-node communication is not allowed. This question has been answered by the fundamental information-theoretic result obtained by Slepian and Wolf [15]. The theorem states that there is theoretically no loss in performance if the joint distribution quantifying the node correlation structure is known. The Slepian-Wolf theorem defines the achievable rate regions for two sources and is given by

$$\begin{aligned} R_x &\geq H(X|Y), \\ R_y &\geq H(Y|X), \\ R = R_x + R_y &\geq H(X,Y), \end{aligned} \tag{1a}$$

where $H(\cdot|\cdot)$ and $H(\cdot,\cdot)$ are the conditional entropy and the joint entropy, respectively.

The source nodes do not communicate with each other and directly send their compressed observations to a central node (such as cluster head or gateway) which performs joint decoding. Hence, we actually reduce computational complexity of the source nodes and increase the computational complexity of the usually more powerful central node without sacrificing performance. Distributed compression can save energy by compression while preserving accuracy [16]. Furthermore, this approach is independent on the modality of the observed data.

We implement the source encoder as simple and energy-efficient matrix multiplication. The entropy tracking algorithm estimates the underlying joint probability density function $p(x,y)$ of the observations obtained by the source nodes which describes the correlation structure. Based on $p(x,y)$ we can determine the conditional information entropy

$$H(X|Y) = -\sum \sum p(x,y) \log p(x|y). \tag{2}$$

The previous works follow rather idealistic assumptions in terms of communication and network topology. Furthermore, the energy consideration is often highly abstracted and does not consider practical issues at sufficient depth. In this work, we study various effects on the performance of distributed compression in more realistic topologies. A sophisticated phenomenon model flexibly generating sensed phenomena with widely varying correlation structure is applied. For thorough and realistic evaluation we make use of a detailed framework that includes a Gilbert-Elliot error model and an energy model allowing even bit-level evaluation. Our network analysis considers the signal processing costs associated with distributed compression including entropy tracking capability and packet header overhead. The evaluation of more realistic deployment models leads to the identification of the best fitting deployment strategy in relation to the characteristics of the phenomena under study.

3 System Model

3.1 Phenomenon Model and Spatial Correlations

In this study we make use of synthetically generated and spatially correlated data fields $h(x, y)$ [17]. The model used is independent on the node density, the number of nodes or the topology. Any correlation structure can be taken into account by varying the parameters controlling the statistical structure of $h(x, y)$ which gives great flexibility. One important parameter that can be varied is the correlation distance $r_{\max}$. If the distance between data elements of the phenomena is more than $r_{\max}$, then they cannot be directly derived from each other. The generated data sampled from the model shows good correspondence when statistically compared with experimental data. It assumes an underlying stationary process that has any unique first-order distribution. This model is more general and more realistic than the commonly used jointly Gaussian model which makes it a suitable choice for our purposes.

3.2 Deployment Model

The node deployment model consists of the specification of the total number of nodes N, and the coordinates $(x_i, y_i)_{i=1}^{N}$ of the individual nodes. We assume a fixed region A with area $|A|$ and that the coordinates are defined by a *random point process* (PP) [18]. The simplest example of such a PP is the (homogeneous) Poisson PP for which the coordinates are distributed uniformly and independently on the region under study, and N is a Poisson random variable with parameter $\lambda|A|$. Here λ is called the *intensity* of the process, with units of points per unit area. The Poisson assumption might be convenient but unfortunately a rather unrealistic one. Hence, the need arises to develop and apply improved and more realistic models to make more reliable statements about real wireless networks. For more details on enhanced deployment models the reader is referred to [9]. In order to study the effects of different network realisations we have chosen three suitable deployment models. The first model we study is the Poisson PP for comparison purposes. The second and third are clustered models called the Thomas PP and the Matern PP.

The Thomas process [19] is based on a Poisson PP of intensity λ_T which is used to generate *cluster centers*. Then each parent or cluster center point is replaced by a cluster of points. The number of points in each cluster l_i is a Poisson distributed random variable with mean value μ_T,

$$\mathrm{Prob}_{l_i}(l_i) = \frac{{\mu_T}^{l_i}}{l_i!} e^{-\mu_T}. \tag{3}$$

The locations of nodes (x, y) in each cluster are sampled from a two-dimensional (symmetric) normal distribution with variance σ_T^2 and the mean located at the cluster center,

$$\mathrm{p}_{x,y}(x, y) = \frac{1}{2\pi\sigma_T^2} \exp\left(-\frac{x^2 + y^2}{2\sigma_T^2}\right). \tag{4}$$

Another example of a cluster process is the Matern point process. As for the Thomas PP, the number of parent points are distributed according to a Poisson process with intensity λ_M. The number of cluster members in each cluster is also sampled from a Poisson distribution with mean μ_M. The only difference lies in how the cluster points themselves are distributed. While for the Thomas PP a normal distribution is used, the cluster points of a Matern PP are uniformly distributed over a disc of radius R_M with the respective parent point as the center. Again, the parent points do not occur in the resulting realisation of the point process.

All introduced models can be conveniently described by up to three parameters. These parameters can easily be adjusted in order to create different models of the same class of point processes. For comparison reasons we have to ensure that all deployment models exhibit the same overall area density λ_A. Hence, the condition $\lambda_A = \lambda = \lambda_T \cdot \mu_T = \lambda_M \cdot \mu_M = \text{const.}$ needs to be always fulfilled.

3.3 Communication Model

In terms of communication we assume that each node has an omni-directional transmission range and utilizes erroneous links. For modeling error characteristics a widely used model is the "Gilbert-Elliot bit error model" [?, 20, 21]. This model is fundamentally based on a two-state Markov model that takes bit error bursts into account. In the case of packet errors, generated by this model, at maximum three retransmissions are initiated. In our simulations we observe an overall average packet error rate of ≈ 0.1 per scenario. We apply practical distributed compression achieving high energy-efficiency through exploitation of spatial correlations in the phenomena under study [4,5,8]. Here distributed compression is performed clusterwise and based on node pairs where the compressing node is a cluster member and the reference node is its cluster head. In terms of mobility the nodes are quasi-stationary at known positions and the overall network density is constant in all cases. In our simulations we focus on the closest-to-center of gravity scheme meaning that the cluster member with the minimum

Euclidean distance to the cluster center is selected as cluster head. For analysis of further cluster head selection schemes, see, for example, [5]. Throughout the scenarios the shortest path multihop routing protocol is applied.

4 Derivation of the Net Energy Balance

Let T_{x} and R_{x} denote the transmission and reception energies per bit, respectively. For the derivation of the net energy balance we also take into account the packet header overhead and the additional energy consumption due to the compression-related signal processing such as encoding, joint decoding and entropy tracking. While E_c accounts for the energy consumed for encoding, E_d stands for the decoding energy. The entropy tracking algorithm is executed each observation cycle once and consumes the energy denoted as E_t.

Let $D(i)$ denote the set of all descendent nodes of node i that belong to the same cluster. Furthermore, let $D_h(i)$ denote the set of all descendent nodes of node i that are cluster members belonging to any other cluster. Using the indicator function $\mathbf{1}_m(i)$ that is set to 1 if node i is a cluster member and 0 otherwise, we can define the energy consumption of a node i as follows:

$$
\begin{aligned}
e_i = \mathbf{1}_m(i)\Big[k\mathrm{E}_c + (kc_in+p)T_{\mathrm{x}} + (T_{\mathrm{x}}+R_{\mathrm{x}})\sum_{j\in D(i)}(kc_jn+p)\Big] \\
+ \big(1-\mathbf{1}_m(i)\big)\Big[\mathrm{E}_t + |D(i)|k\mathrm{E}_d + R_{\mathrm{x}}\sum_{j\in D(i)}(kc_jn+p) \\
+ (kn+p)\Big[|D(i)|T_{\mathrm{x}} + |D_h(i)|(T_{\mathrm{x}}+R_{\mathrm{x}})\Big]\Big],
\end{aligned}
\tag{5}
$$

where n is the number of uncompressed bits and c being the used code rate which is always equal to the conditional information entropy $c = H(X|Y)$ of the considered node pair. The number of compressed bits thus becomes $c\cdot n$. Additionally, each packet consists of a constant number of packet header bits denoted by p and a payload consisting of a number of compressed or uncompressed phenomena observations k.

In order to analyse the energy consumption behaviour of cluster members and cluster heads in the distributed compression case vs. the conventional case we derive the energy balance as follows. For the worst case we assume a cluster member node i in the distributed compression case that may relay only uncompressed (i.e., $c = 1$) packets so that its energy balance is not inequitable improved over the conventional case. Thus, due to

$$\sum_{j\in D(i)} kc_jn = |D(i)|kn \tag{6}$$

we can neglect the relay part in our consideration and find

$$(kn+p)T_{\mathrm{x}} = k\mathrm{E}_c + (kc_in+p)T_{\mathrm{x}}. \tag{7}$$

This leads to the condition

$$c_i \leq 1 - \frac{\mathrm{E}_c}{nT_{\mathrm{x}}}, \tag{8}$$

which has to be always fulfilled if a cluster member node i saves energy. Hence, we define the *break-even* point determined by the code rate $c_i = 1 - \frac{\mathrm{E}_c}{nT_{\mathrm{x}}}$. Only if the code rates reach the break-even point we automatically switch from the distributed compression scheme to the conventional scheme (i.e., no compression applied).

In case node i is a cluster head, we can ignore the transmission and relay energies in the balance since those are identical in both the distributed compression case and the conventional case. Using

$$|D(i)|R_{\mathrm{x}}(kn + p) = \mathrm{E}_t + |D(i)|k\mathrm{E}_d + R_{\mathrm{x}} \sum_{j \in D(i)} (kc_j n + p), \tag{9}$$

we find the condition for the cluster head to be

$$\sum_{j \in D(i)} c_j \leq |D(i)|(1 - \frac{\mathrm{E}_d}{R_{\mathrm{x}} n}) - \frac{\mathrm{E}_t}{R_{\mathrm{x}} kn}. \tag{10}$$

Since $\mathrm{E}_d/(R_{\mathrm{x}} n) > 1$ for our energy model and $c_j \geq 0$ is always valid, no energy savings can be achieved at the cluster head. This is not surprising due to the distributed compression principle of shifting the computational complexity from the cluster members to the cluster head. This is the trade-off we face so that the more resource-constrained cluster members, being the majority of the nodes, can conserve significant amounts of energy. For more details the reader is referred to [8]. However, in order to achieve reduced total energy consumption the cluster member level needs to at least compensate the inherent losses on cluster head level. In the following we show that indeed strong total energy savings can be achieved by our proposed approach.

5 Energy-Efficiency Analysis

Applying the presented energy model, see equation (5), we investigate both the impact of distributed compression and the impact of the deployment strategy on the energy-efficiency behaviour of wireless networks.

5.1 Impact of Distributed Compression

For comparison of the compression scheme and the conventional scheme we consider the total energy savings through distributed compression according to different parameters. Figure 1 shows the total energy savings in relation to the correlation distance parameter $r_{\max}$. From the figure we can observe that the topology types behave very similar to each other and that the energy savings are strongly dependent on the correlation properties. From our quantitative results

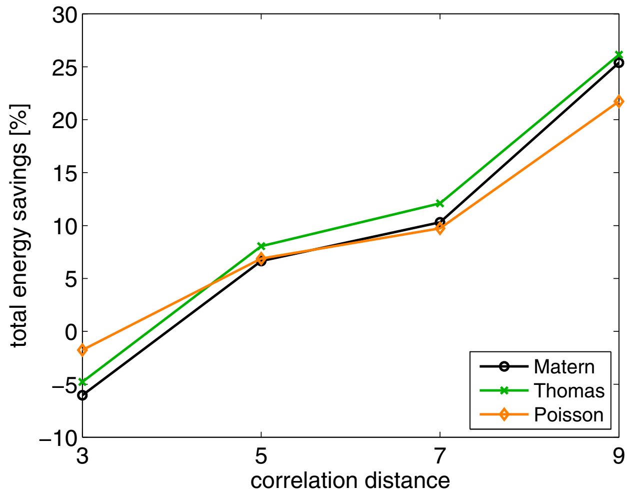

Fig. 1. Total energy savings vs. correlation distance for three topology types; 2000 simulation runs

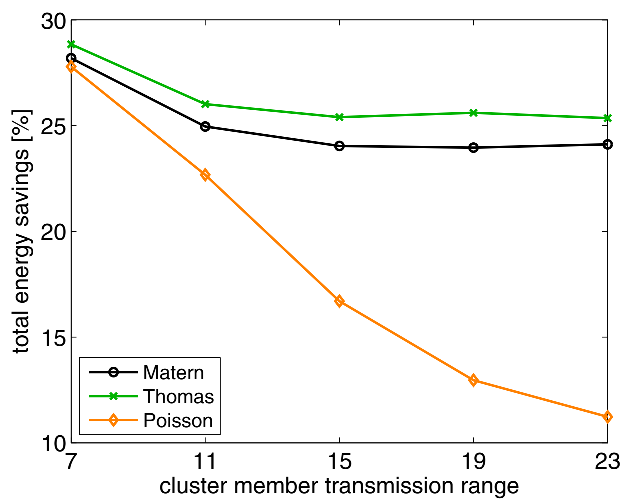

Fig. 2. Total energy savings vs. cluster member transmission range for three topology types; $r_{\max} = 9$, 2000 simulation runs

it follows that the savings can differ up to 31 % between phenomena that exhibit weak or strong spatial correlations. Since distributed compression seeks to exploit the correlation in the phenomena data the results confirm the intuition that the stronger the phenomenon is correlated the stronger the energy savings will be. Only for very weak correlations ($r_{\max} = 3$) small negative values can be observed. In this case the distributed compression gains on cluster member level cannot compensate for the loss on cluster head level. In addition, for moderate to stronger correlations total energy savings of up to 26 % at $r_{\max} = 9$ can be realized by distributed compression. Figure 2 shows the total energy savings according to the transmission range of the cluster members. The transmission range is increased from 7 to 23 units with a constant step size of 4. We can observe that the savings of cluster PP topologies are overall independent on the transmission range. Only at very small transmission ranges the cluster PP topologies exhibit slightly higher energy savings. For the Poisson topology savings significantly increase while decreasing transmission range. The reason for improved savings at reduced transmission ranges in all cases lies in the resulting topologies having increased graph depth. While the node depth is defined as the number of edges that are traversed from the root node to the chosen node, the graph depth is defined as the maximum appearing node depth. Restricting the transmission range leads to cluster members that cannot be directly connected to the respective cluster head. It follows that intermediate nodes are used in order to create a path between such cluster members and the cluster head using the shortest path routing protocol. The intermediate nodes participate in the energy savings since gains can be achieved through multi-hop communication of compressed packets. We see only little improvement in energy savings for cluster PP topologies in contrast to the Poisson topology. The probability that cluster members cannot be directly connected to the cluster head is much lower for the considered cluster PP topologies since nodes are grouped together more closely. It is noteworthy that the transmission range effects the total energy savings of a given topology dependent on the cluster spread parameter of the chosen deployment strategy.

From Figure 3 we can see the relation between total energy savings and the payload size included during packet formation. The number of observations being the payload is increased from 10 to 200. Increasing the payload size leads to less relative header costs per packet and results in improvements independent on the topology type.

Overall we can see from Figure 1 to Figure 3 that independent on the parameter varied the distributed compression gains for cluster PP topologies are superior to those for Poisson PP in all cases. Furthermore, the Thomas PP topology outperforms all other topologies and achieves significant total energy savings through distributed compression of $\approx 26\,\%$ in the reference case.

5.2 Impact of Deployment Strategies

For evaluation of different deployment strategies we focus on the total energy consumption of wireless networks as the performance criterion. Because of the significant total energy savings achieved by distributed compression we focus on wireless networks applying this powerful technique.

Figure 4 and Figure 5 compare the deployment strategies considering the parameters correlation distance and number of clusters, respectively. The total en-

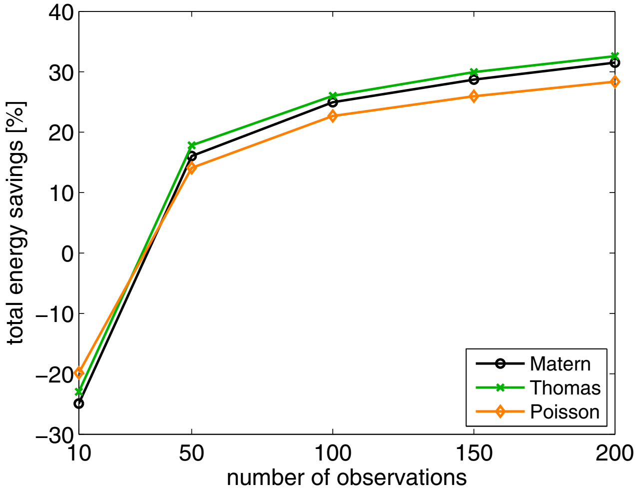

Fig. 3. Total energy savings vs. number of observations per packet payload for three topology types; $r_{\max} = 9$, 2000 simulation runs

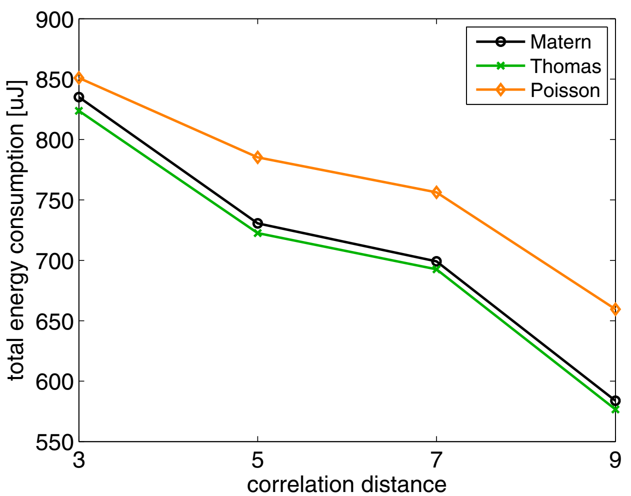

Fig. 4. Total energy consumption vs. correlation distance for three topology types; compression scheme applied; 2000 simulation runs

ergy consumption shows similar behaviour and reaches its minimum for Thomas PP topologies. Taking into account the parameters number of observations and cluster member transmission range confirms this result. Hence, the Thomas deployment is our suggested node deployment strategy since it outperforms the other approaches for all phenomena under study.

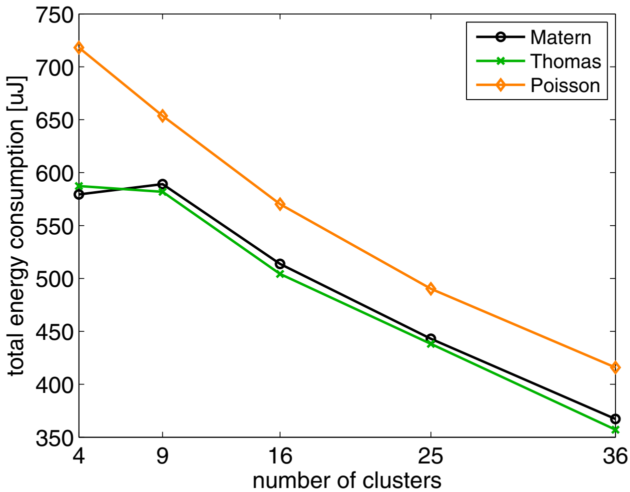

Fig. 5. Total energy consumption vs. number of clusters for three topology types; compression scheme applied; $r_{\max} = 9$, 2000 simulation runs

It is noteworthy that the data points at the minimum number of clusters = 4 in Figure 5 are not fully reliable. The corresponding node connectivity is decreased by $\approx 20\,\%$ for cluster topologies and even $\approx 40\,\%$ for Poisson topologies compared to all other data points. Low number of clusters result in large cluster sizes. This implies inter-node distances exceeding the given transmission range of cluster members thus generating disconnected nodes. Not connected nodes are omitted in the energy consideration which leads to artificially lower values in energy consumption.

We have shown that significant total energy savings can be achiy distribute compression in realistic environments. In addition, optimized deployment strategies lead to strongly reduced total energy consumption of wireless networks. Those candidate approaches thus have high potential to make future wireless networks "green".

6 Network Lifetime Analysis

Operational network lifetime is a major performance criterion for networks also from applications' perspective. Hence, we continue our analysis considering lifetime focusing on cluster members, being the majority of the nodes, since those are typically more resource-constrained than cluster heads. In our studies network lifetime is defined as the number of data gathering cycles elapsed until the first node in the network depletes its energy. After that it is considered to be "dead".

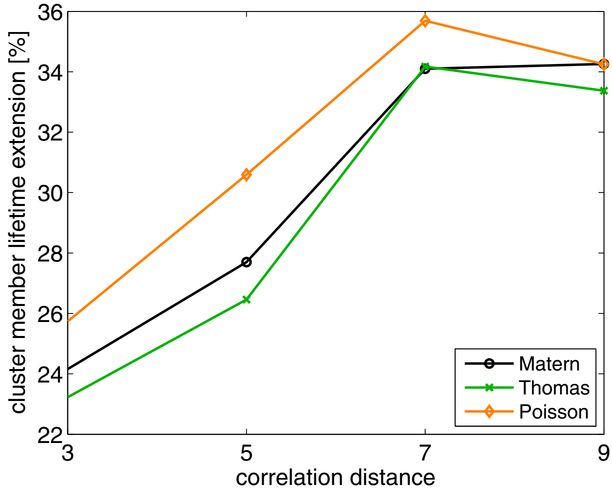

Fig. 6. Lifetime extensions of cluster members vs. the correlation distance for three topology types; 2000 simulation runs

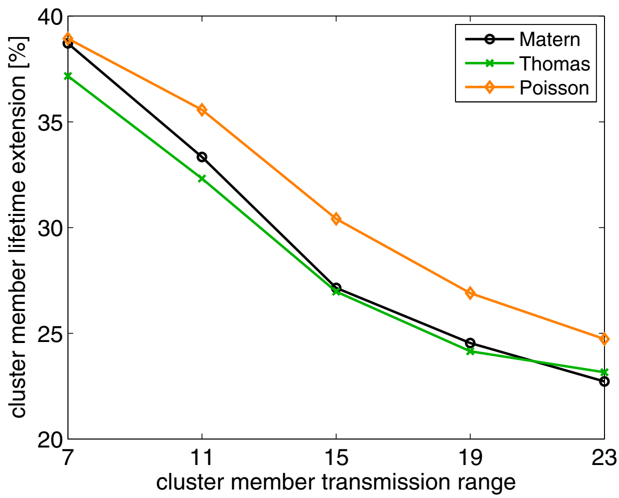

Fig. 7. Lifetime extensions of cluster members vs. the cluster member transmission range for three topology types; $r_{\max} = 9$, 2000 simulation runs

Figure 6 and Figure 7 depict the lifetime extensions on cluster member level in relation to the correlation distance and the cluster member transmission range for three topology types. Overall we can observe from those figures that the Poisson PP topology is superior to all other topology types in terms of cluster member lifetime extension. Other parameters are omitted since corresponding

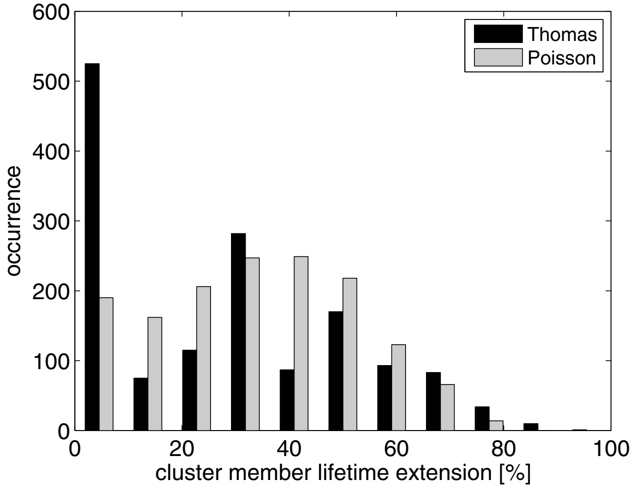

Fig. 8. Histograms of the lifetime extension of cluster members for the Thomas PP and Poisson PP topology; $r_{\max} = 9$, 1500 simulation runs

results show similar behaviour. As we have seen this result is contrary to the energy-efficiency analysis. In the following we provide an explanation for this behaviour using the comparison of Thomas PP topology and the Poisson PP topology exemplarily.

Higher cluster member lifetime extensions for the Poisson PP topology compared to the cluster PP topologies are obtained. Reason is that there is on average less reduction in the *maximum* energy consumption of cluster members through distributed compression in the case of the cluster PP topologies. Independent on the topology type some nodes experience high conditional entropy values determined based on the phenomena values observed by the node pairs. Those entropy values can be higher than the break point, thus switching to the conventional scheme for such nodes since no energy savings can be achieved if distributed compression is applied in this particular case. This implies that a certain number of cluster members cannot improve their node lifetime. The overall number of nodes having no lifetime extension is higher for the cluster PP topology than for the Poisson PP topology. Figure 8 compares the histograms of the cluster member lifetime for the Thomas PP topology and the Poisson PP topology. From the figure we observe that the first bin representing no network lifetime extension has ≈ 3 times higher occurrences in the Thomas case than in the Poisson case, while the remaining part of the histograms does not show severe discrepancy.

The strong difference in occurrences of the first bin influences the overall network lifetime defined as the average value over the histogram. The resulting average network lifetime extension is 33.3 % in the Thomas case and 35.6 % in the Poisson case.

The rationale for very different occurrences of the first bin lies in the different probabilities of leaf nodes that are dependent on the topology type. A leaf node is defined as a cluster member that does not have any descendent nodes. The leaf node probability for the cluster PP topology is higher than for the Poisson PP topology. Nodes are located on average closer to the respective cluster head, forming often (albeit not always) direct connections due to the applied shortest path routing protocol. The Poisson PP topology inherently has thus less leaf nodes and more relaying cluster members at the same time. It is noteworthy that this effect is dependent on the cluster member transmission range and the cluster spread parameter since, for example, the Thomas PP topology with extremely large cluster spread can be seen as Poisson PP topology.

In contrast to leaf nodes, relaying cluster members experiencing high conditional entropies can improve their node lifetime. In fact this happens only when relay nodes benefit from their descendent nodes through relaying of compressed packets towards the sink. Required is at least a single descendent node experiencing entropy values below the break-point. Hence, even if relaying nodes face high entropy values their node lifetime can be improved by the help of other nodes.

As a result, considering energy consumption is not sufficient to make reliable statements on lifetime. We have shown that reduced total energy consumption does *not* directly imply extended operational lifetime as indicated in previous works, for example, [13, 22]. However, solutions minimizing total energy consumption can be used as a starting point towards maximizing network lifetime.

7 Conclusions

In this paper we have shown how "green" wireless networks with minimized operational costs can be realized. The two concepts proposed rely on the exploitation of spatial correlations inherent to both the phenomenon under study and the location of the nodes. In particular, we have investigated the distributed compression scheme and optimized node deployment strategies. The application of the candidate solutions show significantly reduced total energy consumption of wireless networks. Furthermore, we provided the analysis of the network lifetime being often a major performance criterion from applications' perspective. As a result, we found that reduced total energy consumption does not always directly imply extended operational lifetime of networks contrary to assumptions made.

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