Impact of Energy Models on Energy Efficient Sensor Network Routing

Barbara Staehle and Dirk Staehle
University of Würzburg, Institute of Computer Science, Würzburg Germany,
{bstaehle, dstaehle}@informatik.uni-wuerzburg.de

Abstract

Models and proposals for capturing the energy consumption of sensor nodes are plentiful. The majority of those approaches roughly agree about the energy consumed in the states of the sensor node duty cycle, but the costs of radio operations are abstracted very differently. In our work, we establish a general framework whose modular structure allows to compare existing abstractions and to investigate which factors are crucial for the modeling of transmission costs. We analyze the influence of typical assumptions on the creation of energy efficient routing topologies. For this purpose the resulting routing trees are not only compared by topological characteristics, but also by estimating radio related energy consumptions, a metric which changes strongly with the MAC layer efficiency.

1 Introduction

For any large scale wireless sensor network (WSN) deployment, energy is the most critical topic: To maximize the network survivability and hence the quality and quantity of the assembled data, the network has to be designed in the most energy efficient manner as possible. Much work has been dedicated to the design of highly efficient MAC and routing algorithms, therefore the network topology and functionality can be adapted specific to the desired functionality. More optimization potential lies in the sensor node duty cycle, the spatial distribution of the sensor nodes and the number and positions of sink nodes where data has to be delivered to. Due to the large design space, it is therefore vital to rate the reasonableness of an intended deployment *before* actually bringing out the nodes, as any setting which already shows weaknesses on the drawing-board, won't perform better under harsh environment conditions. For this purpose, realistic simulations for determining energy consumptions and the lifetimes of battery operated nodes would yield the most accurate results, but they require a highly detailed model of the sensor nodes and their behavior. As those fine grained models are computationally expensive and time intense, analytical methods are preferable, especially, if a quick estimation is required, or if large scale deployments have to be analyzed.

1-4244-1455-5/07/$25.00 © 2007 IEEE

Obviously, any analytical approach for predicting the energy consumption in sensor networks has to find adequate abstractions for the sensor node behavior. The possibilities for abstractions are countless, we therefore want to identify the critical parameters describing the communication costs which have to be modeled with special care. For this purpose, we chose two exemplary approaches for modeling radio operation costs and investigate in how far the decision between the two different link cost metrics is influencing analytically made energy efficient routing decisions. To compare the resulting topologies not only due to graph theoretic metrics, we estimate the arising radio related energy consumptions which we find to be heavily influenced by the efficiency of the MAC layer. Our findings show that the mapping of transmission output power to transmission distance and power consumptions influence the energy costs most heavily. Thus, the distance related transceiver electronic power consumptions and the transmission channel have to be modeled with care, whereas constant factors have no significant influence.

The structure of this work is as follows: In Section 2 we review different approaches for energy consumption estimations and energy efficient routing proposals in WSNs. Section 3 describes the analytical framework, we use to compare the effect of energy model design choices on routing decisions. This section contains also our proposal for estimating the energy consumptions of a sensor node under the consideration of the MAC and routing layers. We present numerical results of the application of different energy metrics for energy efficient routing in Section 4, before we conclude our work in Section 5.

2 Related Work

The most widely used energy model for analyzing radio operations in sensor networks has been proposed by Heinzelman et al. [4]. The amount of energy necessary for a transmission over a distance d is modeled as the sum of a constant and of the required transmission power. The latter scales with a power of d, accounting for the path loss, the first represents the energy consumptions of the transmitter electronics. Additionally, they include one more constant addend to account for reception costs.

As an energy efficient topology organization is a simple possibility for optimizing a wireless sensor network, many works have proposed reasonable opportunities for prolonging the network lifetime. So do Chang and Tassiulas [1] who demonstrated, that establishing a Minimum Total Energy (MTE) routing tree in order to minimize transmission and receptions costs for each routing path is not suitable for battery operated networks. They propose a new routing algorithm, which minimizes communication costs computed according to the metric from [4], but additionally accounts for limited per node energies by considering the residual energies of the forwarding nodes. Other examples for analytical routing topology establishment and sensor network analysis which base on [4] are [7], [5], [2], or [8].

Landsiedel et al. [6] analyzed the current consumptions of Crossbows' Mica2 mote and found that the transmission costs in terms of current draw are *not* exponentially increasing with the required transmission power as assumed by [4]. The application of the analytically obtained result using this model to a real world sensor network deployment has thus do be done very carefully. For a more hardware oriented approach, the authors of [6] attack the problem of energy consumption modeling by creating a sensor network emulator which is able to predict the energy consumptions of specific applications. A similar approach is proposed by Polastre et al. [10] who estimate sensor node lifetimes by computing the node energy consumptions as the sum of the energy needed for transmitting, receiving, sleeping, channel scanning, and sampling data. Wang et al. [12] extend this hardware oriented approach and consider varying transmission output powers. They find, that the drain efficiency of the power amplifier of the sensor node radio chip, i.e. the ratio of transmission output power and the consumed DC input power, is neither constant nor linear, but increasing with the output power. Based on this fact and under the use of a simple free space path loss model, they present novel insights in the establishment of energy efficient routing topologies.

More general insights on routing in multihop wireless networks are presented by Haenggi [3]. In his work, he gives twelve reasons why long hops should be preferred over short hops. His argumentation is based on a detailed physical layer model, considers end-to-end reliability, channel coding, routing overhead and many other factors and concludes with the statement, that all sensor nodes should always transmit as far as possible. However, in a situation where energy resources are not restrained, as all nodes are e.g. able to gather energy from the environment, the establishment of a MTE routing tree is nevertheless of interest. Moreover, this problem has been well studied in the literature, we therefore use it to illustrate the influence of energy modeling on sensor network analysis.

3 Analytical Framework

3.1 Radio Operation Costs

To illustrate the importance of correct transmission energy consumption modeling for sensor network optimization, we establish a general framework. Simplifying, we do not consider the energy required by the other components of the sensor board, or data handling, topology maintenance or medium access control costs, but focus on the radio unit. Following [4] and [12], the energy for transmitting one bit over a distance d can be expressed as

$$E(d) = E_0 + \frac{T(c,d)}{\eta(c,d)} + E_{rx}. \tag{1}$$

In the above formula, all variables are given per bit. E_0 represents the power consumption in the transmitters' signal processing and front-end circuits. This term is constant for transmissions over all distances. $T(c,d)$, the required transmission output power, is increasing with the distance d and depends furthermore on the channel characteristics. These are represented by c and capture the radio propagation model and the receiver sensitivity. While this notation for transmission power seems somewhat artificial, it allows to compare different channel modeling approaches. $\eta(c,d)$ denotes the drain efficiency of the power amplifier, which is the ratio of transmission output power to DC input power [12]. For most transceivers it is varying with the output power T [12], depends thus also on c and d. E_{rx} finally, represents the constant reception power consumptions.

For parameterizing Eq. (1), we describe two different energy consumption models in the following: A *Theoretical Model (TM)* which is based on the work of Heinzelman et al. [4] and a *Hardware oriented Model (HM)*, which is inspired by the insights presented by Wang et al. [12]. The latter approach tries to capture the characteristics of a typical sensor node transceiver, Chipcon's CC1000 transmitting in the 868 MHz band as it is used in Mica2.

3.1.1 The Theoretical Model (TM)

For this model, we adopt all parameters from [4]. This results in $E_0 = E_{rx} = 50$ nJ/bit and

$$T(c,d) = \begin{cases} c_1 d^2 & \text{if } d < d_0 \\ c_2 d^4 & \text{if } d \geq d_0 \end{cases} \tag{2}$$

with $c_1 = 10$ pJ/bit/m^2 and $c_2 = 0.0013$ pJ/bit/m^4 models receiver sensitivity and free space or multipath signal propagation respectively. As no numerical value for d_0 is given, we obtain the point after which the model predicts a higher path loss as $d_0 = \sqrt{\frac{c_1}{c_2}} = 87.71$ m from Eq. (2). Moreover, the authors assume a direct relation of transmission power and energy consumptions, we therefore adopt a distance independent $\eta(c, d) \equiv 1$.

3.1.2 The Hardware oriented Model (HM)

According to [12], the non-distance related power consumptions in the transmission circuit are slightly smaller than the power amplifier consumptions for the smallest transmission output power. Using this approximation and CC1000's data sheet [11], we obtain $E_0 = 671.875$ nJ/bit $E_{rx} = 750$ nJ/bit. Note that these constant costs are nearly ten times higher than under TM. The transmission output power T required to span a distance d is obtained using the empirical ground plain channel model proposed in [9]. This model translates to

$$T(c, d) = \begin{cases} c_1 d^{2.35} & \text{if } d < d_0 \\ c_2 d^{3.6} & \text{if } d \geq d_0 \end{cases} \qquad (3)$$

where $d_0 = 6.2$ m, $c_1 = 0.0152$ pJ/bit/m$^{2.35}$ and $c_2 = 0.0016$ pJ/bit/m$^{3.6}$.

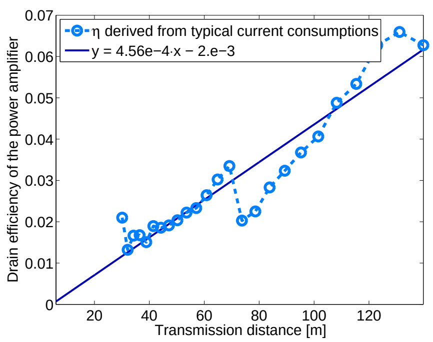

Figure 1. Drain Efficiency of CC1000

For HM, we use a distant dependent η, which we depict in Fig. 1 for the considered transceiver. To obtain the interdependency between d and η, we used the channel characteristics from [9]. We show empirical values for η obtained from typical current consumptions given [11] and a simple linear fit. Keep in mind that while the precise behavior of η depends strongly on the specific chip, the trend of increasing with the transmission distance is observable for most existing transceivers and corresponds to an indirect relation between transmission distance and transmission costs.

3.2 Estimating Energy Consumptions

To approximate the radio related energy consumption of a sensor node, we propose to use a rough abstraction of the radio unit state cycle, similar to the approach presented by [10]: We assume that the radio unit of sensor node i is either transmitting, receiving data, listening for incoming packets or sleeping. In order to listen to the channel, the sensor node transceiver has to be in the receive state, listening therefore consumes the same amount as receiving data. The considered simplified duty cycle therefore reduces to receiving (rx), listening (tx) and sleeping (s). We focus furthermore on situations, were all nodes operate at a regular schedule, i.e. node i has the same duties during all time units. The mentioned state cycle translates thus to the following partition of a time unit u:

$$u = t_i^{tx} + t_i^{rx} + t_i^{s}. \qquad (4)$$

We assume, that each node in the set of all nodes N is equipped with the same radio unit having thus the same typical power consumptions $P^{tx}(T)$, P^{rx} and P^{s} for transmissions with an output power T, receptions and sleeping respectively, the electrical energy, node i needs for radio activities during one time unit u can thus be calculated as

$$E_i^{radio} = t_i^{tx} P^{tx}(T_i) + t_i^{rx} P^{rx} + t_i^{s} P^{s}. \qquad (5)$$

The time each sensor node spends in transmit, receive or sleep state depends on several factors. One is of course the radio's data rate which determines how fast packets are transmitted. Another factor influencing the part of the time a node spends sending and receiving data is its load which is given by the routing topology. To account for this, we need to know the number of measurement packets, each node creates and sends to the sink per time unit. For now, we assume, that all nodes create exactly λ packets during u.

The number of packets S_i, sent by node i during one time unit u, is also influenced by the number of nodes, which use i as a relay towards the sink. S_i could be a random variable, if packet losses, collisions or data aggregation are modeled and increases if acknowledgments and retransmissions are considered. We assume for this analysis, that this is not the case, S_i is thus just the sum of the number of measurement data packets generated by i and its children in the routing tree: $S_i = \lambda(c_i + 1)$, where c_i represents the number of children, node i has. If i is not relaying data, $c_i = 0$. We assume all data packets to have the same size, they can thus be sent and received within t_{dat}. The part of u, node i is busy with sending is thus given by

$$t_i^{tx} = S_i t_{dat} = \lambda(c_i + 1) t_{dat}. \qquad (6)$$

To simplify our model, we neglect protocol overhead and assume that all transmissions succeed. However, we investigate one aspect of wireless networks more deeply. Due to the broadcast nature of wireless communication, sensor nodes in the radio range of a sending node are forced to overhear this transmission unless their radio is in sleep state. This phenomenon can e.g. influence the sensor node duty cycle if a wake on radio policy with periodic channel polling is deployed. The costs for discarding such unwanted packets depend strongly on the deployed protocol. A worst case approximation will however be the simple strategy of allowing the radio unit of a not addressed sensor node to return to sleep state after heaving read the address field of the packet i.e. an amount of time t_{disc}. To model the effectiveness of the MAC protocol, we introduce the variable $\epsilon \in [0, 1]$ which gives the fraction of unwanted transmissions a sensor node could theoretically receive, the node actually *has* to receive and to discard. $\epsilon = 0$ describes the ideal situation, where no sensor node overhears unwanted transmissions of its neighbors. Let $R_i = \lambda c_i$ be the number of data packets, i receives per time unit. Then, we obtain the part of a time unit, i is busy with receiving as

$$\begin{aligned} t_i^{rx}(\epsilon) &= R_i t_{dat} + \epsilon \sum_{j \in N} S_j \vartheta_{ji} t_{disc} \\ &= \lambda [c_i t_{dat} + \epsilon \sum_{j \in N} (c_j + 1) \vartheta_{ji} t_{disc}] \quad (7) \end{aligned}$$

The boolean variable ϑ_{ji} expresses, whether the messages, j sends to its next hop k are overheard by i: $\vartheta_{ji} = 1$, if i overhears transmissions of j and it is 0 otherwise. Note that an energy consumption analysis ignoring the broadcast nature of wireless transmissions would assume $\epsilon \equiv 0$ and hence ignore the second term in Eq. (7) which represents the time, i needs for receiving and discarding unwanted packets. Obviously, the main influence factor on this term is the node's position with respect to the sink: If i could theoretically overhear all transmissions from and to s, its unnecessary reception time will increase, as all data packets generated in the entire sensor network have to be forwarded to its vicinity. Moreover, this time will increase with the network density and the transmission output power, which increase both the number of nodes which are within a the range of a sending node.

Finally, the maximal time, the radio unit of node i can spend in sleep state, is given by

$$t_i^s(\varepsilon) = u - (t_i^{rx}(\varepsilon) + t_i^{tx}). \quad (8)$$

Evaluating Eq. (5) - (8) for a specific routing tree in a given network topology clearly yields only in an absolute lower bound for the total energy consumptions of the sensor nodes: This model does not include factors like energy consumptions required for data sensing, processing or other purposes, or does account for battery discharge characteristics, retransmissions due to collisions or packet losses are also not considered. However, our simple model allows to roughly capture the energy consumptions of the radio unit, and we therefore consider it appropriate for comparing the effects of energy modeling parameter choices on routing topologies.

4 Numerical Results

4.1 Comparison of Transmission Costs

To examine the influence of modeling decisions concerning the constant transmission costs, the reception costs, the channel model and the characteristics of the power amplifier, i.e. parameterizations of E_0, E_{rx}, c and η respectively, we compare variations of the models described in Section 3.1. For both the Theoretical and the Hardware Oriented Model, we evaluate Eq. (1), but with one the four parameters set according to the other metric. Additionally, we investigate variations with $E_{rx} = 0$, as this is also sometimes done during analyzes. As an example: for the variation denoted as "TM, c HM", we compute the transmission costs for d under TM, but use the channel characteristics given by HM. Thus, $E_0 = E_{rx} = 50$ nJ/bit, $\eta(c, d) \equiv 1$, $c_1 = 0.0152$ pJ/bit/m$^{2.35}$ and $c_2 = 0.0016$ pJ/bit/m$^{3.6}$. As most parameter choices result in only slight variations of the energy required for receiving and transmitting one bit in dependence of the transmission distance, we depict only some examples in Fig. 2 and Fig. 3. The channel model from [9] predicts a maximal transmission distance of 139.8 m for the considered chip, we thus only show costs for distances up to this border.

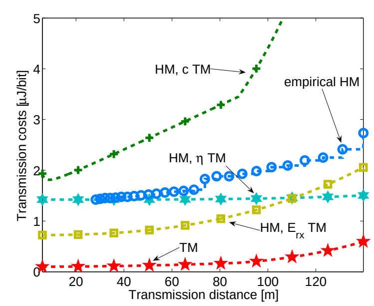

Figure 2. Costs for variations of HM

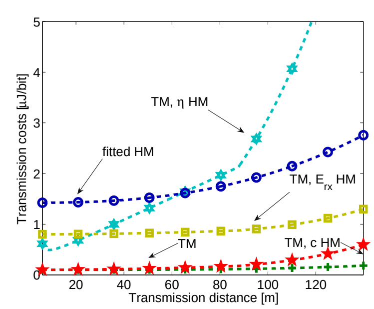

Figure 3. Costs for variations of TM

In both figures, we depict the costs resulting from the pure HM and TM metrics. Fig. 3, we represent the transmission costs for HM using a fit of the empirical η (cf. Fig. 1). Note that due to the nonlinear nature of the drain efficiency, this curve is much smoother than the one for the transmission costs obtained using the empirical values for η shown in Fig. 2, but does not differ much otherwise. We therefore use this fit for computing the costs resulting for variations in the following. For variations of both metrics, changes in the channel model and in the mapping of transmission output power to transmission costs, i.e. the parameters c and η affect the costs most significantly. Curves representing those variants differ thus most dramatically from the pure metric. The curves resulting from a variation of the constant costs, i.e. E_{rx} and E_0 result in mere linear variations of the pure metric. In Fig. 3, the cost curve for "TM, E_{rx} HM" is thus constantly 0.7μ J/bit (the difference between recection costs under both metrics) higher than the curve representing the original TM.

The impact of the channel characteristics and the drain efficiency is however more severe: In both figures, the most heavily increasing curve depicts the combination of the channel characteristics proposed by TM and the output power dependent drain efficiency model proposed by HM, i.e. "HM, c TM" and "TM, η HM" respectively. These large cost variations are due to higher transmission powers resulting from the channel model with a path loss exponent of 4 proposed in TM, resulting in significantly higher energy consumptions, if the influence of the drain efficiency (which makes long transmissions more expensive) is taken into account.

In contrast, the combination of the channel model from HM and a direct mapping of transmission output power to necessary DC input powers, i.e. "TM, c HM" and "HM, η TM" yields to seemingly distance independent transmission costs compared to the other cost metrics. This is however not the case, as the costs for this metric do also increase exponentially, but the use of $\eta \equiv 1$ results in by a factor in the range of 15 to 45 smaller costs. This difference is thus not visible any more, if the corresponding curves are compared with the curves resulting from the other metrics.

All in all it gets clear, that the model of the channel characteristics has a major influence on the analysis of transmission related energy consumptions. Moreover, the parametrization of η, i.e. the mapping of transmission output power to consumed DC input power has to be done carefully, as this parameter has an major influence, too. These insights are quite natural and have already been mentioned in the literature, e.g. [12], [3], but to our knowledge, nobody has examined the practical impact of those different transmission costs on sensor network analysis. Using the example of energy minimizing topologies, we will illustrate in the following, that the abstraction of transmission costs has a huge influence on analytical work.

4.2 Comparison of MTE routing trees

To obtain insights in the impact of energy consumption modeling on sensor network design, we take a well known, widely studied problem as an example for the various optimization problems existing in sensor network research: We assume that all nodes are mains powered or are able to gather energy from the environment. To make optimal use of the resources, a MTE has to be set up which minimizes the per path energy consumptions, i.e. which minimizes the energy required for collecting the measurement data. For a numerical evaluation, we assume that a set of identical sensor nodes is randomly deployed in a quadratic area of size l^2 according to a spatial Poisson process with density ϱ and periodically send measurement data to one sink s.

We use Monte Carlo simulation technique to examine different network snapshots. Using the Dijkstra algorithm, we are able to obtain the MTE for TM, HM and their previously discussed variations for each network snapshot. For an efficient real world realization of such a theoretically established MTE, the deployed sensor nodes have to be able to adapt their transmission output powers to the smallest value required for reaching their next hop. As this may not always be feasible in reality and for comparison purposes, we additionally consider two minimum hop topologies, where all nodes operate with transmission output powers fixed to the minimum or maximum possible value. For the CC1000, these are -20 and 5 dBm respectively, which translates to maximal reachable distances of 28.25 and 139.8 m [9].

We examined scenarios with varying l and ϱ and varying sink positions for which we obtained results showing the same trend. In the following, we present results for topologies obtained in the setting with $l = 400$ m and $\varrho = 0.02$ and the sink placed in the upper left corner, which are representative for all other settings.

4.2.1 Path Lengths

One good metric for comparing routing topologies is the length of the routing paths, as the number of hops each piece of measurement data has to travel to the sink allows to compare the routing delays which determine the freshness of the data. Moreover, we consider a very simple setting, where no data is aggregated, thus an increase in hops means an increase of consumed bandwidth and hence both the times required for sending and receiving data and the risks of collisions and data losses are growing. Furthermore, the relaying load of the nodes within one hop distance of the sink is growing if paths with longer hops are on the majority. To analyze the path length distributions in the considered MTE topologies, we compare the cumulative probability density function (CDF) in Fig. 4 and Fig. 5.

We observed that the CDF of the path length obtained by using the fitted and the discrete values for η for HM are identical to the CDF of the path lengths in the MH topology for fixed transmission power of 5 dBm. If the transmission output power is fixed to $T = -20$ dBm, the data paths grow significantly longer than in all other adaptive topologies, as up to 25 hops are necessary to reach the sink node. This is illustrated in Fig. 5, where the CDF representing this topology is clearly below all other CDFs.

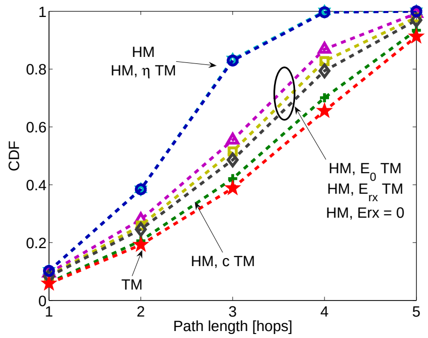

Figure 4. Variations of HM

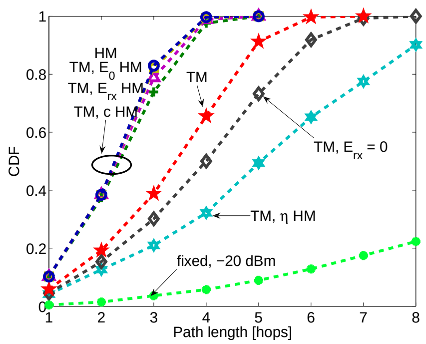

Figure 5. Variations of TM

The CDFs visualized in Fig. 4 demonstrate, that the variation of η is the only parameter of HM which does not influence the distribution of the path length. This is due to the dominance of the constant per hop costs, i.e. E_{rx} and E_0 in comparison to the distance dependent costs. Decreasing the constant costs or using a higher path loss coefficient (i.e. varying c, E_{rx} or E_0) makes several shorter hops more energy efficient than one long hop and leads to topologies with more hops. However, the number of hops in the MTE resulting from the pure TM is never reached.

Fig. 5 reveals that TM is more sensitive to changes: The curves representing “TM, η HM” and “TM, $E_{rx} = 0$” illustrate that the number of hops increase, if distance related transmission costs are higher, or the reception costs are neglected respectively. Both makes more shorter hops more efficient, while increasing the constant costs, i.e. E_{rx} and E_0 and decreasing the path loss coefficient, i.e. changing c, makes less longer hops more favorable. This results in path length distributions very similar to the one of HM.

4.2.2 Relaying load

The analysis of the path length distribution allows to rate the load on the nodes which are responsible for relaying data: It is obvious that more hops result in a higher relaying load. We illustrate this statement by visualizing the CDFs of the size of the child set, each node has in the routing tree, c_i. Recall that $c_i = 0$, if the node does not have to relay data for other nodes. Fig. 6 shows the CDFs of c_i in routing trees resulting from minimum energy routing with adaptive output power with respect to pure TM and HM. This time, we distinguish between topologies obtained from the use of a fitted η and the empirical η. We also show the CDF for minimum hop trees for fixed output power for -20 and 5 dBm.

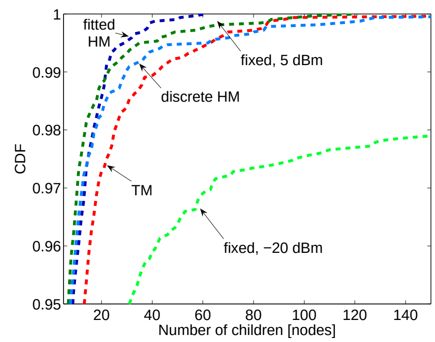

Figure 6. Adaptive and fixed output power

The distributions of the path length in the topologies resulting from the use of the fitted and the empirical η could not be distinguished from the situation of fixed maximal output power. Due to the nature of the cost metrics used with the Dijkstra algorithm, the distributions of c_i differ. Discrete metrics (hop count and typical current consumptions for a limited number of output powers) were used for fixed output powers and the empirical η under HM. In contrast, for the creation of an energy minimizing topology using HM with the fitted η, the continuous metric shown in Fig. 1 was used. The CDFs shown in Fig. 6 demonstrate, that for load balancing purposes, a continuous cost metric like fitted HM seems to be better suited, since it yields in a more homogeneous forwarding load distribution. The latter predicts not achievable link costs, as not programmable transmission output powers would have to be used, but it seems better suited for breaking ties.

Another fact illustrated by this figure is, that longer hops result in an increased number and load of relaying nodes. In the case of battery operation, those nodes will be the first ones to run out of battery. Especially in the minimum hop topology for the small output power, the number of heavily charged nodes is high compared to the number of non-relaying nodes, the network is thus very heterogeneously charged which could lead to a shortened data delivery period.

4.2.3 Link Lengths

In the case, where minimum energy trees are established, we assume perfect power control, i.e. we consider an idealistic scenario where the nodes are able to adjust their transmission power to the minimal value required to reach their next hop. Thus, the comparison of the distribution of the link lengths in the resulting topologies is another criterion to differentiate the routing topologies. In Fig. 7, we therefore show the probability distribution of the link length, i.e. the distance between one sensor node and its next hop on the path towards the sink. To illustrate the capabilities of the radio chip, we indicate the transmission distances corresponding to the different possible transmission output powers of CC1000 by vertical dotted lines.

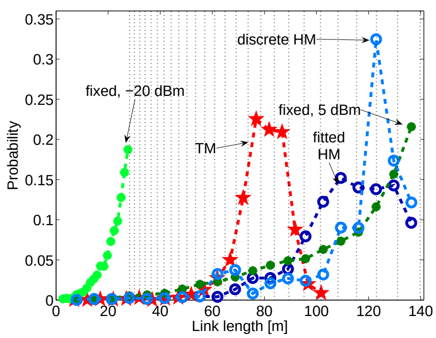

Figure 7. Adaptive and fixed output power

It can be nicely seen, that for a transmission output power fixed to -20 dBm all links are shorter than 28 m which corresponds to the maximal achievable distance with this power. In the case, where all nodes use the maximal power, over 20 % of all links have the maximal feasible length of 139.8 m. Shorter links exist only between nodes which are closer to the sink than this threshold. The comparison between the PDFs representing the topologies generated according to HM and TM yields the same results illustrated earlier: due to the higher path loss exponent and the low reception costs under TM, shorter hops are preferred. The discrepancy between the representation of the topologies created according to HM using the fitted and the empirical η, is explained by studying the characteristics of the empirical η and its fit, depicted in Fig. 1: in general, the linear fit is roughly capturing the values obtained from typical current consumptions, but the curve representing the empirical values is not monotonically increasing, which results in the peaks in the probability distribution of the link length for the empirical HM.

4.2.4 Transmission Output Powers

Next, we compare the transmission output powers which would be required by sensor nodes using the CC1000 in the 868 MHz band to build the MTE trees for adaptive power. That is, we determine for each node the minimal transmission output power which would be necessary for Mica2 nodes to reach its next hop. The resulting probability distributions are shown in Fig. 8 and Fig. 9. Varying E_{rx} and E_0 for HM resulted in similar distributions of T, in Fig. 8, the curve "HM, E_{tx} TM" represents also variants of E_0. We do also not show the transmission output power distribution for "HM, η TM", as it is identical to the pure HM. All not shown variants of TM in Fig. 9 result in link length distributions similar to HM.

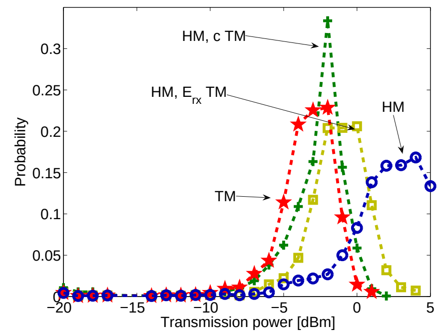

Figure 8. Variations of HM

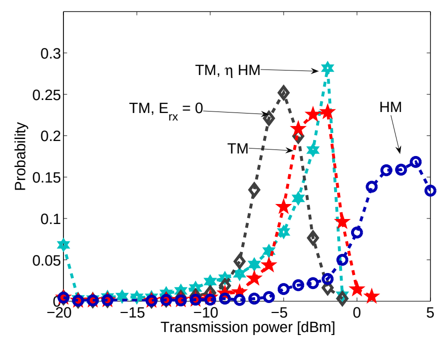

Figure 9. Variations of TM

We saw earlier that the MTE established for TM, yields longer paths and shorter hops. The distribution of the output transmission power for TM in both Fig. 8 and Fig. 9 shows the dominance of smaller transmission powers compared to the topology emerging from the use of HM. Comparing both figures demonstrates moreover, that altering components of HM always results in less or equal transmission powers, whereas only assuming $E_{rx} = 0$, causes the same effect for TM. All other changes make higher transmission output powers more likely. This can e.g. be observed by considering the representation of "TM η HM" in Fig. 9. It shows that this variation results in topologies with highly variant transmission output power distributions: while over 25 % of all nodes are using rather high powers, the percentag of nodes which operate at the smallest possible power is significantly higher than in the other MTE topologies.

4.3 Daily Energy Consumptions

The last three figures in this paper are dedicated to the analysis of the energy efficiency of the created topologies. To obtain numerical results, we assume sensor nodes that have Mica2's characteristics, i.e. need 0.6 μW in sleep state, 28.8 mW for receiving and between 25.8 and 76.2 mW for transmissions in the 868 MHz band, if a voltage of 3 V is assumed. Per u = 1 minute, each node has to create and send $\lambda = 1$ measurement packet towards the sink node. All transmitted data packets carry 10 byte of measurement data, 4 byte are needed for addressing purposes. To illustrate the influence of the MAC efficiency, we depict results for an idealistic MAC protocol, where no sensor node overhears foreign transmissions and for the case, where everything is overheard, i.e. $\epsilon = 0$ and $\epsilon = 1$ respectively. Abstracting any reasonable MAC protocol will result in a value somewhere in between, we therefore use the extreme values for a demonstration of the impact of this factor. In the case, where the node receives a packet which it is not addressed to it, it can return to sleep state, after having read the address field.

In the following, we compare the estimated daily radio related energy consumptions, E_i^{radio} obtained from the model presented in Section 3.2. For presentation purposes, we do not show distributions but the average consumptions of all nodes in the topology. Obviously, E_i^{radio} is varying strongly within the network, but the mean value for one routing topology is suitable for cross-metric comparisons.

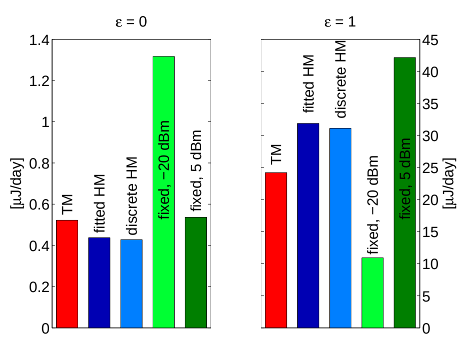

Figure 10. Adaptive and fixed output power

In Fig. 10, we consider MTEs created with respect to the pure HM and TM for adaptive output powers and minimum hop trees for fixed output power. The left figure describes the ideal situation of $\epsilon = 0$ and illustrates, that higher transmission output powers result in smaller per node energy consumptions, if overhearing effects are neglected. This is mainly due to the smaller amount of consumed bandwidth and has been observed earlier [3]. In the case, where all transmissions have to be overheard, depicted on the right, the estimated energy consumptions are in general nearly ten times higher. Next, the relation between the average energy consumption is reversed for $\epsilon = 1$, as topologies with smaller transmission output power seem more favorable now. This is explained by the structure of Eq. (7): the number of potentially overheard messages increases with the transmission power. If all messages are overheard, i.e. $\epsilon = 1$, this leads to a significant reduction of sleep time and hence an increase of energy consumptions.

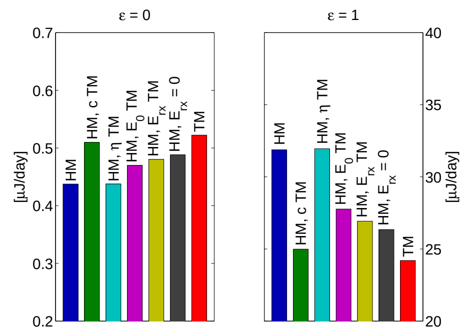

Figure 11. Variations of HM

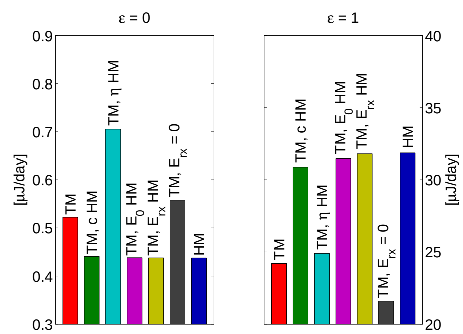

Figure 12. Variations of TM

In Fig. 11 and Fig. 12 where the average estimated daily per node energy consumptions for MTEs created according to variations of HM and TM and are shown, the same observations can be made as in this entire section: the topologies resulting from variations of HM do not vary strongly, the energy consumptions are thus rather similar, if $\epsilon = 0$ is assumed. The right figure of Fig. 10 demonstrates however, that the differences get more striking, if overhearing is taken into account. Again, the statements reverse: "HM, c TM" which had been the least favorable variation of HM for the idealistic case promises the smallest average per node energy consumption, if overhearing is considered.

In Fig. 12, this effect is also observable. If $\epsilon = 0$, the topology created with a path loss exponent of 4 and the distance dependent drain efficiency, "TM, η HM", for instance, results in the highest average per node energy consumptions, as the percentage of nodes operating with a high transmission output power is larger than under all other variations (cf. Fig. 9). If $\epsilon = 1$ is assumed, this topology seems much less favorable.

Note, that our model allows only a very rough estimation of the daily radio related energy consumptions. Especially, the influence of the MAC layer efficiency is only roughly abstracted. The results shown in the last three figures nevertheless demonstrate, that the consideration of mere transmission and reception costs leads to totally different conclusions than the ones obtained including overhearing costs.

5 Conclusion and Outlook

For any analytical work, one model out of the countless existing energy consumption abstractions has to be chosen. To compare the impact of the different energy models, we chose a well known analytical problem and investigated, in how far the shape of analytically designed energy efficient routing trees for a large sensor network deployment varies with the used energy consumption metric. To examine the influence of different modeling assumptions, we built a modular framework and identified four components of the transmission costs. Our findings illustrated that the abstractions of channel characteristics and the mapping of transmission output power to required DC input power influence the analysis of transmission energy consumptions heavily. The precise value of constant reception and transmission costs, as long as they are not neglected, have a minor influence.

We furthermore estimated the energy consumptions in the created topologies and found that the per node energy consumptions vary strongly with the influence of the MAC protocol, i.e. the number of unwanted transmissions a sensor node is forced to overhear. This often neglected factor is also responsible for a possibly wrong estimation of energy consumptions: if an ideal MAC protocol is assumed, i.e. no node is forced to overhear foreign transmissions, topologies which favor a few long hops over several short hops for multihop paths, are rated to be by far more energy efficient than topologies which contain more short hops. This statement does not hold any more if the effect of overhearing is considered, as for larger transmission ranges, more energy may be consumed for discarding unwanted messages. Thus, for any statement concerning per node energy consumptions, the consideration of the MAC layer and the structure of the routing topology is vital.

All in all, our findings illustrate, that energy models used for the design and analysis of real world sensor network deployments have to be chosen with care and with respect of the used hardware, as a bad design choice may lead to incorrect routing decisions.

Our future work will be dedicated to the deeper investigation of physical and medium access layer effects and their influence on energy modeling. We plan to extend our energy consumption estimation model by a more detailed analysis of lower layer overhead to investigate the impact of various factors on typical problems of sensor network analysis.

References

[1] J. Chang and L. Tassiulas. Maximum Lifetime Routing in Wireless Sensor Networks. *IEEE/ACM Transactions on Networking*, 12(4), August 2004.

[2] C. Chiasserini and M. Garetto. Modeling the Performance of Wireless Sensor Networks. In *InfoCom'04*, Hong Kong, China, March 2004.

[3] M. Haenggi. Twelve Reasons not to Route over Many Short Hops. In *VTC2004-Fall*, 2004.

[4] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan. An Application-Specific Protocol Architecture for Wireless Microsensor Networks. *IEEE Transactions on Wireless Communications*, 1(4), 2002.

[5] M. Khan, G. Pandurangan, and B.Bhargava. Energy-Efficient Routing Schemes for Wireless Sensor Networks. Technical Report CSD TR 03-013, Dept. of Computer Science, Purdue University, West Lafayette, IN, USA, 2003.

[6] O. Landsiedel, K. Wehrle, and S. Götz. Accurate Prediction of Power Consumption in Sensor Networks. In *EmNetS-II*, Sydney, Australia, May 2005.

[7] S. Lindsey and C. Raghavendra. PEGASIS: Power-Efficient Gathering in Sensor Information Systems. In *IEEE Aerospace Conference*, Big Sky, MT, USA, March 2002.

[8] T. Melodia, D. Pompili, and I. Akyildiz. On the Interdependence of Distributed Topology Control and Geographical Routing in Ad Hoc and Sensor Networks. *IEEE Journal on Selected Areas in Communications*, 23(3), March 2005.

[9] J. Molina-Garcia-Pardo, A. Martinez-Sala, M. Bueno-Delgado, E. Egea-Lopez, L. Juan-Llacer, and J. Garca-Haro. Channel Model at 868 MHz for Wireless Sensor Networks in Outdoor Scenarios. In *IWWAN 2005*, London, UK, May 2005.

[10] J. Polastre, J. Hill, and D. Culler. Versatile Low Power Media Access for Wireless Sensor Networks. In *SenSys '04*, Baltimore, MD, USA, 2004.

[11] Texas Instruments. CC1000 Single Chip Very Low Power FRF Transceiver. Data sheet.

[12] Q. Wang, M. Hempstead, and W. Yang. A Realistic Power Consumption Model for Wireless Sensor Network Devices. In *SECON 2006*, Reston, VA, USA, September 2006.