Accurate Energy-aware Workload Distribution for Wireless Sensor Networks Using a Detailed Communication Energy Cost Model

Yanqiu Huang*, Wanli Yu, and Alberto Garcia-Ortiz

Institute of Electrodynamics and Microelectronics, University of Bremen, 28359, Bremen, Germany
{huang, wyu, agarcia}@ item.uni-bremen.de

* corresponding author: Yanqiu Huang

Address:

W3100, Institute of Electrodynamics and Microelectronics

Building NW1, University of Bremen

Otto-Hahn Allee 1

28359 Bremen, Germany

Office : W3100

Fax : +49 (0)421 218 9862533

Email : huang @ item.uni-bremen.de

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Abstract — *Wireless Sensor Networks (WSNs) have gained a lot of attention from the research and industrial communities. In almost any application involving WSNs, energy efficiency is a primary concern. As the complexity of the motes and the applications increases (e.g. in-network DSP processing, internet-of-the-things), the energy of communication and computation processes have to be considered and optimized simultaneously.*

In this work, we propose an offline workload distribution approach based on integer linear programming (ILP) to reduce the energy consumption and extend the network lifetime for cluster-based WSNs. It takes communication and computation energy into account, employs a novel and detailed model for the communication cost, and provides optimal partitions for both symmetrical and asymmetrical networks.

The experimental results confirm that the novel communication model can be applied to both CDMA and TDMA based MAC protocols with high accuracy. The estimated communication cost (approx. 10% deviation) is more accurate than the one employed in the previous works on partitioning (over 85% deviation). The incorporation of the accurate communication model into the workload distribution problem produces better partition result that reduces the energy cost by 16.8%. The economized execution time (less than 1 second) makes the ILP approach feasible for typical WSN applications and guarantees the optimality of the energy-aware partition.

Keywords* —** *Wireless Sensor Networks (WSNs),** *energy-aware workload partition, scheduling, communication energy, power-macromodel*

1. INTRODUCTION

In the past decades, Wireless Sensor Networks (WSNs) have gained a lot of attention from the research and industrial communities. This key technology enables a wide range of new applications and services including monitoring of physical environments, enhanced industrial control, remote health care, logistic, etc. They typically involve low-cost and low-power devices, which must be operational without battery change for long periods (ranging from several days in the case of long-term health monitoring, months for supply chain management, and years or even decades for applications such as weather monitoring). In almost any application of WSNs, energy efficiency is a primary concern.

As widely recognized by the research community, one of the most energy intensive processes of a sensor node is the wireless communication [1]. In a classical architecture for instance, a single bit transmission requires 1000 times the energy cost of a 32-bit computation [2]. A large body of research exists in communication energy minimization techniques addressing all the abstraction levels from different perspectives. In [3], for example, the authors propose an efficient clustering protocol to reduce the impact of the transmission distance on the communication cost. The reduction of the transmission rate is the target of [4] and [5]; whereas [6] and [7] focus on decreasing the communication volume.

Further on, as the complexity of the motes increases [8][9] and the applications addressed in WSNs become more complex [10][11] (e.g. in-network DSP processing, internet-of-the-things), the processing energy cost cannot be ignored anymore. This computation energy cost can be economized by energy scaling algorithms [12], dedicated low-power processors [13], and energy-aware partitioning among multiple sensor nodes [14][15]. For instance, in [16] the processing operations are distributed among sensor nodes, which are considered as distributed digital signal processors to reduce the energy consumption of the overall network. A hierarchal structure is proposed in [17] to distribute different sub-tasks for sensor nodes by considering the tradeoffs among task execution time, accuracy and the overall energy consumption. In [14], the communication cost between end-users and sensor nodes is reduced with the help of the clustering scheme. At the same time, by exploring partitioning of the computation and dynamic scaling of the voltage for the cluster head and sensor nodes, the network becomes more energy efficient.

Among the existing schemes, a highly efficient solution is the workload distribution as described in [15]. By taking the communication and computation cost into account, the work finds a suitable partition of the workload for the slave and master nodes in a cluster-based WSN. The communication energy cost is assumed to be proportional to the number of communicating bits. It does not consider the overheads of the protocol that can even dominate the whole energy cost in some cases (see e.g.

Sec. 4). In addition, the method to find the partition result is based on a heuristic approach. Although it is faster than the exhaustive method, the partition solutions are suboptimal in some cases. Moreover, the approach is limited to completely symmetrical slave-constellations, which do not reflect a realistic scenario.

To distribute the workload more efficiently, it is of paramount importance to estimate the communication cost of each node in the network realistically. However, previous communication models either lack the analysis of cross-layer interaction [3][18], or aim at finding the whole network communication cost [19] without a detailed description at the mote-level.

The main contribution of this paper is an improved energy-aware partition algorithm for data processing applications, which employs a novel and detailed model for the communication cost and provides optimal partition solutions. The algorithm is expected to be executed offline.

In contrast to previous works, we describe the partition problem as the (0-1) integer linear programming problem for both symmetrical and asymmetrical networks. For the typical WSN applications, the execution time is similar to the previous approaches while returning the optimal partition. In addition, to calculate the communication energy cost accurately, a novel communication energy cost model is proposed. It overcomes the limitations of the previous works by analyzing the energy consumption from different layers including hardware, MAC and application layers. By applying our method to a centralized estimation algorithm, the energy consumption of the network is reduced by over 41%.

The rest of the paper is organized as follows. In Sec. 2, we present the proposed communication cost model. The mathematical description of the energy aware workload distribution approach is provided in Sec.3. In the following section, we verify the validity of the model and evaluate the partition method. Finally, Sec. 5 summarizes our work and presents the future research directions.

2. PROPOSED ENERGY CONSUMPTION MODEL FOR COMMUNICATION

Let us consider the communication cost in WSN. In the real communication process, a sensor node wanting to send or receive data, turns on the radio firstly. Before transmitting the data packet and according to some MAC protocols, the node needs to access the wireless channel and possibly exchange some control packets. After that, the actual transaction commences and once finished, the radio is shut down. During this period, the node may turn on its receiver prior to the actual reception because of the unawareness of the destination active state (it is the so called *idle listening)* and may receive some packets that are not intended for it (namely *overhearing*). Due to collision, the packets may not be transmitted or received successfully which causes retransmission and extra energy cost.

Thus, the total communication energy consumption of a node (from the radio startup to shutdown) can be described with the following terms:

$$E_{cmn} = E_{startup} + E_{channe\,l\_access} + E_{control} + E_{turnaround} + E_{idle\_listening} + E_{over\,hearing} + E_{collision} + E_{data}$$

corresponding to the energy cost of radio startup, channel accessing, control packets, turnaround, idle listening, overhearing, collision and data packets transmission.

In order to calculate the cost of each part, we divide the above-mentioned process into seven different states as listed in Tab. I.

TABLE I
SEVEN DIFFERENT STATES OF A NODE DURING COMMUNICATION PROCESS

State	Definition
ST	The radio is turned on
CC	The node tries to access the wireless channel
IL	The node turns on its receiver prior to receiving
OH	The node receives some packets that are not intended to it
RX	The node receives the packets
TX	The node transmits the packets
TA	The node switches between RX and TX

Using the number of cycles, exchanging bits and the duration in each state (see Tab. II for details), the communication energy cost can be expressed as:

$$E_{cmn} = N_{st} \cdot e_{st} + P_{cc} \cdot t_{cc} + (e_{rx} \cdot k_{cr} + e_{tx} \cdot k_{ct}) + N_{ta} \cdot e_{ta} + P_{il} \cdot t_{il} + e_{oh} \cdot k_{oh} + E_{cl} + e_{tx/rx} \cdot k_d$$

The collision energy cost E_{cl} is affected by several parameters, e.g., the collision probability p_{cl}, the channel accessing failure probability p_{cc}, etc. It is convenient to calculate the average communication energy cost for each packet by introducing the average transmission times $N(p_{cc}, p_{cl})$ as proposed in [20][21]:

$$E_{cmn} = N_{st} \cdot e_{st} + N(p_{cc}, p_{cl}) \cdot \left[P_{cc} \cdot t_{cc}(p_{cc}) + (e_{rx} \cdot k_{cr} + e_{tx} \cdot k_{ct}) + N_{ta} \cdot e_{ta} + P_{il} \cdot t_{il}(p_{cc}) + e_{oh} \cdot k_{oh}(p_{cc}) + e_{tx/rx} \cdot k_d\right]$$

It is important to note the different nature of the parameters used by the model. They are either constant (independent of the transmission pattern) or variable (associated with the communication scenario). Furthermore, they are determined by the hardware (HW), the MAC protocol, the application layer (APP) or their combination as listed in Tab. II.

Constant parameters are the number of control packets, the radio startup and turnaround times (specified in the MAC protocol) as well as the energy consumption of each state (determined by the HW platform).

The transmission energy cost e_{tx} is a function of ***d*** as indicated below:

$$e_{tx}(d) = P_{tx}(d) \cdot t_{unit} = \left(P_{T0} + \frac{P_{Tout}(d)}{\eta}\right) \cdot t_{unit} = \left(P_{T0} + 10^{\left(\frac{L(d)+P_{rin\_dBm}}{10}\right)}/\eta\right) \cdot t_{unit} \tag{1}$$

where $L(d)$ is the path loss and η is the drain efficiency of the power amplifier.

Given a required receiver sensitivity P_{rin_dBm} and an efficient path loss model $L(d)$ of the wireless channel, the transmission power P_{tx} in the specific distance ***d*** could be obtained by equation (1). The detailed information about the power model can be found in [18].

TABLE II
PARAMETERS IN THE COMMUNICATION ENERGY CONSUMPTION MODEL

Constant	**HW**	e_{st}	The energy cost of radio startup
		P_{cc}	The power cost of accessing channel
		$e_{tx}(d)$	The energy cost of transmitting one bit (as a function of the distance ***d***)
		e_{rx}	The energy cost of receiving one bit
		e_{ta}	The energy cost of turnaround
		P_{il}	Idle listening power cost
		e_{oh}	The energy cost of overhearing one bit
	MAC	k_{cr}	Receiving bits in control packets
		k_{ct}	Transmitting bits in control packets
		N_{ta}	The number of turnaround times
		N_{st}	The number of radio startup times
Variable	**APP**	k_d	Transmitting bits in data packets
		T_{schd}	The duration of a scheduling period
	APP&MAC	$N(p_{cc}, p_{cl})$	The average number of transmission times for each packet (as a function of p_{cc} and p_{cl})
		p_{cc}	Clear channel assessment (CCA) failure probability
		p_{cl}	Collision probability
		$t_{cc}(p_{cc})$	Mean access channel time
		$t_{il}(p_{cc})$	Mean idle listening time
		$k_{oh}(p_{cc})$	The mean number of overhearing bits

Variable parameters are the number of transmitting bits k_d and the scheduling period T_{schd}, which depend on the application layer. In addition, all the parameters related to the channel condition are variable as well. They depend on which MAC protocol the device uses, the number of contending nodes and the communication frequency stated by the application layer.

The variable parameters determined by the MAC protocols can simply be obtained in TDMA based approaches as illustrated in Sec.4.3. Without loss of generality and for illustration purpose, we focus on CSMA/CA based protocols to obtain them for this model. In this case, the successfully accessing probability is $(1 - p_{cc}{}^{MaxNB+1})$ with p_{cc} as the probability of channel access failure. In each transmission, the collision probability is assumed to be p_{cl}. Then, the average transmission times for each packet as described in [20] can be approximated as:

$$N(p_{cc}, p_{cl}) = \sum_{i=0}^{Maxretry} (1 - p_{cc}{}^{MaxNB+1})^{i+1} \cdot p_{cl}{}^{i} \tag{2}$$

where $Maxretry$ and $MaxNB$ are the maximum retransmission times and backoff repetitions specified in the MAC protocol, and an analytical formula to calculate p_{cc} and p_{cl} as functions of the number of contention nodes can be found in [21].

Following this average concept, a node would perform on average $\sum_{i=0}^{MaxNB} p_{cc}{}^{i}$ CSMA trials during a packet transmission attempt. In each trial, the node would wait on average $\frac{1}{2} \cdot \left(2^{\min(\mathrm{MinBE}+\mathrm{i},\ \mathrm{MaxBE})} - 1\right) \cdot \mathrm{t_{bk}}$ backoff duration and then executes the CCA procedure in the following t_{cca} period. Thus, the average channel access time for each transmission is:

$$t_{cc}(p_{cc}) = \sum_{i=0}^{MaxNB} p_{cc}{}^{i} \cdot \left[\frac{1}{2} \cdot \left(2^{min(MinBE+i,\ MaxBE)} - 1\right) \cdot t_{bk} + t_{cca}\right] \tag{3}$$

where $MinBE$, $MaxBE$, t_{bk} and t_{cca} are constant values specified in the MAC protocols. On this basis, the idle listening time $t_{il}(p_{cc})$ is related to the $t_{cc}(p_{cc})$ as described in the following examples and it affects the number of overhearing bits $k_{oh}(p_{cc})$.

In addition, depending on the MAC protocols, the radio is either started once and kept active until the end of successful transmission, or it is turned off and restarted again with each retransmission. In other words, the radio startup times are either one or the average transmission times.

$$N_{st} = \begin{cases} 1 \\ N(p_{cc}, p_{cl}) \end{cases}$$

From the above analysis, given a specific p_{cc} and p_{cl} according to the application layer, it is possible to estimate the average energy consumption of the communication. Combining related terms, the communication energy cost and time cost can be modeled as:

$$E_{cmn} = N_{st} \cdot e_{st} + N(p_{cc}, p_{cl}) \cdot \left(e_o + e_{tx/rx} \cdot k_d\right) \tag{4}$$

$$T_{cmn} = N_{st} \cdot t_{st} + N(p_{cc}, p_{cl}) \cdot \left(t_{\mathrm{o}} + t_{tx/rx} \cdot k_d\right) \tag{5}$$

where $t_{tx/rx}$ is the time cost of transmitting/receiving one bit and t_{st} is the radio startup time. The overhead energy cost e_o and time cost t_o (with t_{ta} as the turnaround time and t_{oh} as the time cost by overhearing one bit) are given by:

$$e_o = P_{cc} \cdot t_{cc}(p_{cc}) + (e_{rx} \cdot k_{cr} + e_{tx} \cdot k_{ct}) + N_{ta} \cdot e_{ta} + P_{il} \cdot t_{il}(p_{cc}) + e_{oh} \cdot k_{oh}(p_{cc})$$

$$t_o = t_{cc}(p_{cc}) + (t_{rx} \cdot k_{cr} + t_{tx} \cdot k_{ct}) + N_{ta} \cdot t_{ta} + t_{il}(p_{cc}) + t_{oh} \cdot k_{oh}(p_{cc})$$

The model applies to both CDMA and TDMA based MAC protocols by simply adjusting related parameters as illustrated in Sec.4.1 and Sec.4.3.

3. ENERGY EFFICIENT WORKLOAD DISTRIBUTION METHOD

In a cluster-based WSN as depicted in Fig.1, each cluster consists of several slave nodes and a master node. Usually, the master is in charge of receiving data from the slave nodes, processing them and transmitting the request data by one-hop or multi-hop procedure to the sink node. These operations typically cause the master node overburdened. In order to balance the energy consumption of the cluster and to extend the network life, it is necessary to efficiently distribute the workload for the master and slave nodes. In this section, we incorporate the novel communication model into the energy-aware workload distribution problem for cluster-based WSNs and formulate the distributing problem as the (0-1) integer linear programming problem.

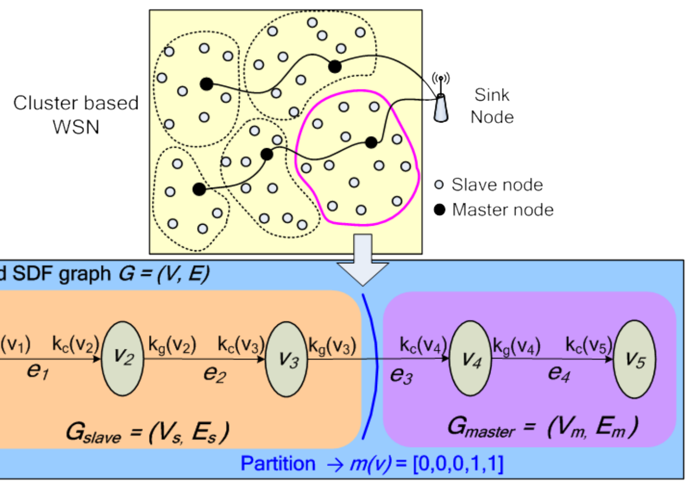

Figure 1. Schematic diagram of workload distribution for a cluster in a cluster based WSN

Following the idea of [15], the workload of a WSN can be described as a synchronous dataflow (SDF) graph $G = (V, E)$ as shown in Fig.1. In such a graph, each actor $v \in V$ is a data processing task. It generates and consumes constant data (tokens), $k_g(v)$ and $k_c(v)$. Each edge $e \in E$ is a buffer for actors to store and fetch tokens. Distributing the workload for the master and the slave is equivalent to divide the modeled workload graph $G = (V, E)$ into two subgraphs $G_{slave} = (V_s, E_s)$ and $G_{master} = (V_m, E_m)$ with a partition.

In order to find the best partition that minimizes the energy cost, thereby maximizing the network lifetime, all of the existing energy cost of slave and master nodes, including processing, communicating and sleeping energy cost, need to be taken into account. By introducing a Boolean parameter $m(v)$ to indicate whether an actor v belongs to the master or the slave node, the total energy consumption of each node can be calculated as a linear function of $m(v)$. Correspondingly, the partition problem is modeled as a (0-1) integer linear programming (ILP) problem. The optimal $m(v)$ obtained by the ILP is the best workload distribution partition for slave and master nodes.

$$m(v) = \begin{cases} 0 & v \in G_{slave} \\ 1 & v \in G_{master} \end{cases}$$

TABLE III
PARAMETERS FOR THE INTEGER LINEAR PROGRAMMING METHOD

APP	NoV	The number of actors (tasks) in the SDF graph
	$q(v)$	The number of execution times for each actor $\boldsymbol{v}$ during one schedule period
	$k_g(v)$,$k_c(v)$	The number of tokens generated and consumed by actor $\boldsymbol{v}$ during each invocation period
	NoS	The number of slave nodes
HW	$P_s(v)$, $P_m(v)$	Mean processing power dissipation of actor v when executed in slave and master nodes
	$t_s(v)$, $t_m(v)$	Mean processing time dissipation of actor v when executed in slave and master nodes during each invocation
	$P_s(e)$, $P_m(e)$	Mean power dissipation of fetching (or storing) one token from (or into) edge $\boldsymbol{e}$ in each sub graph
	$t_s(e)$, $t_m(e)$	Mean time dissipation of fetching (or storing) one token from (or into) edge $\boldsymbol{e}$ in each sub graph
	$t_{prc\_s}(v)$, $t_{prc\_m}(v)$	Processing time cost of actor v when executed in slave and master nodes.
	P_{slp_s}, P_{slp_m}	Sleeping power consumption of slave and master nodes

The parameters required for estimating the processing, communication and sleep energy cost during one schedule period are listed in Tab.III.

The processing cost during one schedule period involves the energy cost of each actor in three aspects: fetching tokens from its input edges, processing tokens, and storing tokens onto its output edges as given by:

$$\begin{aligned} E_{prc\_s} &= \sum_{v \in V} E_{prc\_s}(v) \cdot (1 - m(v)) \\ &= \sum_{v \in V} q(v) \cdot [P_s(v) \cdot t_s(v) + k_g(v) \cdot P_s(e) \cdot t_s(e) + k_c(v) \cdot P_s(e) \cdot t_s(e)] \cdot (1 - m(v)) \end{aligned}$$

$$\begin{aligned} E_{prc\_m} &= \sum_{v \in V} E_{prc\_m}(v) \cdot m(v) \\ &= \sum_{v \in V} q(v) \cdot [P_m(v) \cdot t_m(v) + k_g(v) \cdot P_m(e) \cdot t_m(e) + k_c(v) \cdot P_m(e) \cdot t_m(e)] \cdot m(v) \end{aligned}$$

Therefore, the time spent on processing of slave and master nodes are:

$$T_{prc\_s} = \sum_{v \in V} t_{prc\_s}(v) \cdot \left(1 - m(v)\right) = \sum_{v \in V} q(v) \cdot \left[t_s(v) + k_g(v) \cdot t_s(e) + k_c(v) \cdot t_s(e)\right] \cdot \left(1 - m(v)\right)$$

$$T_{prc\_m} = \sum_{v \in V} t_{prc\_m}(v) \cdot m(v) = \sum_{v \in V} q(v) \cdot \left[t_m(v) + k_g(v) \cdot t_m(e) + k_c(v) \cdot t_m(e)\right] \cdot m(v)$$

The communication cost of the slave and master nodes can be calculated by equation (4), while the communication data k_d varies with the change of the partition. We introduce a constant parameter $K(v)$ as the net consumed tokens of each actor. It is the difference between the consumed and generated tokens:

$$K(v) = q(v) \cdot \left(k_c(v) - k_g(v)\right)$$

On the edge of a SDF graph, the total number of tokens generated by the source actor $q(v_{source}) \cdot k_g(v_{source})$ equals the tokens consumed by the sink actor $q(v_{sink}) \cdot k_c(v_{sink})$. Thus, k_d is a linear function of $m(v)$: it is the summation of net consumed (generated) tokens $K(v)$ of each actor in the master (slave) node during a schedule period:

$$k_d = \sum_{v \in V} K(v) \cdot m(v) = \sum_{v \in V} K(v) \cdot (m(v) - 1)$$

Combining equation (4), the communication energy cost of the slave and master nodes are:

$$E_{cmn\_s} = N_{st} \cdot e_{st} + N(p_{cc}, p_{cl}) \cdot \left(e_{o\_s} + e_{tx} \cdot \sum_{v \in V} K(v) \cdot (m(v) - 1)\right)$$
$$E_{cmn\_m} = N_{st} \cdot e_{st} + N(p_{cc}, p_{cl}) \cdot \left(e_{o\_m} + e_{rx} \cdot \sum_{v \in V} K(v) \cdot m(v)\right)$$

From equation (5), the relative time spent in communicating are:

$$T_{cmn\_s} = N_{st} \cdot t_{st} + N(p_{cc}, p_{cl}) \cdot \left(t_{o\_s} + t_{tx} \cdot \sum_{v \in V} K(v) \cdot (m(v) - 1)\right)$$

$$T_{cmn\_m} = N_{st} \cdot t_{st} + N(p_{cc}, p_{cl}) \cdot \left(t_{o\_m} + t_{rx} \cdot \sum_{v \in V} K(v) \cdot m(v)\right)$$

Upon completion of processing and communication, the node typically enters into sleep mode. If there are NoS slave nodes in the network, the master needs to iterate NoS times to receive and process the values before sleeping. This factor NoS may not affect some of the time and energy cost during the communication process. That depends on a specific scenario. Here for generalization and conciseness, all the cost of the master are formulated as a function of NoS.

Thus, during a schedule period, the sleep time T_{slp} of the slave and master nodes are:

$$T_{slp\_s} = T_{schd} - T_{prc\_s} - T_{cmn\_s}, \qquad T_{slp\_m} = T_{schd} - NoS \cdot (T_{prc\_m} + T_{cmn\_m})$$

Accordingly, the sleep energy cost of the slave and master nodes could be easily obtained as:

$$E_{slp\_s} = P_{slp\_s} \cdot T_{slp\_s}\,, \qquad E_{slp\_m} = P_{slp\_m} \cdot T_{slp\_m}$$

The total energy cost for the slave and the master nodes during a schedule period as linear functions of $m(v)$ are provided by equation (6) and (7) respectively.

$$E_{slave} = E_{prc\_s} + E_{cmn\_s} + E_{slp\_s} = P_{slp\_s} \cdot T_{schd} + E_{a\_s} + \sum_{v \in V} E_{b\_s}(v) \cdot \big(1 - m(v)\big) \tag{6}$$

$$E_{master} = NoS \cdot \big(E_{prc\_m} + E_{cmn\_m}\big) + E_{slp\_m} = P_{slp\_m} \cdot T_{schd} + NoS \cdot \left[E_{a\_m} + \sum_{v \in V} E_{b\_m}(v) \cdot m(v)\right] \tag{7}$$

where E_{a_s}, E_{b_s}, E_{a_m}, and E_{b_m} are constant values for a given SDF graph and a communication protocol as given by:

$$\begin{aligned}
E_{a_s} &= N_{st} \cdot e_{st} + N(p_{cc}, p_{cl}) \cdot e_{o_s} - P_{slp_s} \cdot \big(N_{st} \cdot t_{st} + N(p_{cc}, p_{cl}) \cdot t_{o_s}\big)\\
E_{b_s} &= E_{prc_s}(v) - P_{slp_s} \cdot t_{prc_s}(v) - N(p_{cc}, p_{cl}) \cdot K(v) \cdot \big(e_{tx} - P_{slp_s} \cdot t_{tx}\big)\\
E_{a_m} &= N_{st} \cdot e_{st} + N(p_{cc}, p_{cl}) \cdot e_{o_m} - P_{slp_m} \cdot \big(N_{st} \cdot t_{st} + N(p_{cc}, p_{cl}) \cdot t_{o_m}\big)\\
E_{b_m} &= E_{prc_m}(v) - P_{slp_m} \cdot t_{prc_m}(v) + N(p_{cc}, p_{cl}) \cdot K(v) \cdot \big(e_{rx} - P_{slp_m} \cdot t_{rx}\big)
\end{aligned}$$

Initially, we consider that the nodes have the same battery resources E_{bat} and that the network elapses when the first node runs out of energy, i.e., $T_{net} = min(T_{master}, T_{slave})$ as assumed in [15]. Thus, maximizing the network lifetime is equivalent to find the appropriate $m(v)$ that $maximize\left\{min\left(\frac{E_{bat}}{E_{slave}} \cdot T_{schd}, \frac{E_{bat}}{E_{master}} \cdot T_{schd}\right)\right\}$ with several constraints: *a)* neither the master nodes can finish the whole application tasks (total $\boldsymbol{NoV}$ actors of the SDF graph) *b)* nor the slave node; *c)* the cyclic dependencies in the SDF graphs should be forbidden. In addition, the latency of the algorithm is considered. **Scheme I** summarizes the formal definition of the problem.

In a realistic scenario, the network is not completely symmetrical, e.g., the slave and master nodes may have different energy resources; the distances between them are not exactly equivalent and so on. That requires the partitioning algorithm to supply individual solutions for different nodes in the asymmetrical network. In other words, for each slave node i, there exists an optimal partition $m_i(v)$ which maximizes the node's lifetime thereby extending the whole network lifetime.

We formulate the network lifetime as $T_{net} = min\left(\frac{E_{bat\_s}}{E_{slave\ i}} \cdot T_{schd}, \frac{E_{bat\_m}}{E_{master}} \cdot T_{schd}\right)$. In this case, the energy consumption of each slave node is formulated in (8) as a function of $m_i(v)$. Correspondingly, the energy consumption of the master is the summation of the cost with different partitions as shown in (9). By finding different $m_i(v)$ with the help of the **Scheme II** for each slave node, the network lifetime could be extended more efficiently.

$$E_{slave_i} = P_{slp\_s} \cdot T_{schd} + E_{a\_s} + \sum_{v \in V} E_{b\_s}(v) \cdot \left(1 - m_i(v)\right) \tag{8}$$

$$E_{master}\,(m_i(v)) = P_{slp\_m} \cdot T_{schd} + \sum_{i=1}^{Nos} \left[E_{a\_m} + \sum_{v \in V} E_{b\_m}(v) \cdot m_i(v)\right] \tag{9}$$

Considering the impact of the distance on the transmission energy cost as formulated in equation (1), the slave nodes with different transmission distances should execute different processing tasks. To balance the problem complexity and the algorithm accuracy, we divide the slave nodes into several groups to find different partitions. For each group, the partition result is obtained by arbitrarily selecting one slave node to execute **Scheme II**.

$$\underset{m(v)}{arg\_min}\{max(E_{slave}, E_{master})\}$$

$$\begin{aligned} Subject\ to{:}\ a)&\ \sum_{v \epsilon V} m(v) \le NoV - 1 \\ b)&\ -\sum_{v \epsilon V} m(v) \le -1 \\ c)&\ m(v_{source}) - m(v_{sink}) \le 0 \end{aligned}$$

Scheme I. Symmetrical network

$$\underset{m_i(v)}{arg\_min}\left\{max\left(\frac{E_{master}\,(m_i(v))}{E_{bat\_m}}, \frac{E_{slave_i}}{E_{bat\_s}}\right)\right\}, i \in [1, NoS]$$

$$\begin{aligned} Subject\ to{:}\ a)&\ \sum_{v \epsilon V} m_i(v) \le NoV - 1 \\ b)&\ -\sum_{v \epsilon V} m_i(v) \le -1 \\ c)&\ m_i(v_{source}) - m_i(v_{sink}) \le 0 \end{aligned}$$

Scheme II. Symmetrical & asymmetrical network

4. EXPERIMENT RESULTS

In this section, we aim at verifying the validity of the proposed communication energy cost model and analyzing the performance and exactness of the energy efficient integer linear programming method.

4.1 Evaluation of the proposed communication model

In order to verify the validity of the proposed energy cost model, we analyze the energy consumption for the typical motes and compare it with the reported measurements in previous works [22] and [23]. In the two tests, different hardware components (CC2530, CC2430) and protocol modes (non-beacon and beacon modes) are used to assess the flexibility of the model.

4.1.1 Example 1: CC2530 + IEEE 802.15.4 nonbeacon-enabled mode

In non-beacon-enabled networks, the master typically turns on its receiver continuously, while the slave nodes only wake up according to the application requirement. In this case, the communication process is always initiated by the slave node. When it wants to receive data from the master, it first transmits a request command using unslotted CSMA-CA. The master responses with an acknowledge frame and indicates whether there is pending data for it. The process and the state diagram of a slave node contacting the master without pending data are depicted in Fig. 2.

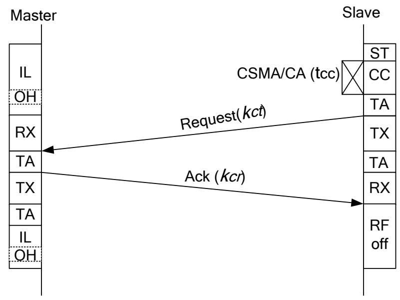

Figure 2. State diagram corresponding to a slave node contacting the master without pending data in a nonbeacon-enabled PAN

To model and calculate the energy consumption in this process, we refer to the simplest application in [22], with only one slave node (CC2530) and one master (CC2530). The application related parameters are easily obtained (see lower part of Tab. IV). The slave node accesses the channel successfully at the first time and transmits without collision, hence $N(p_{cc}, p_{cl})$ equals one. According to equation (3), $t_{cc}(p_{cc})$ is about 1.25ms. From the communication process we obtain the idle listening time of the master $t_{il}(p_{cc}) \approx 3.7$ ms.

TABLE IV
PARAMETERS FOR CC2530 WITH IEEE 802.15.4 NONBEACON-ENABLED MODE

HW	e_{st}	50 uJ	Under different test conditions, the values vary. This is taken from the measurement.
	P_{cc}	61.5 mW	Receive sensibility is -50 dBm
	e_{tx}	0.3444 uJ	Radio in TX mode, 1 dBm output power, CPU idle, 28.7 mA
	e_{rx}	0.246 uJ	Radio in RX mode, -50 dBm input power, CPU idle, 20.5 mA
	e_{ta}	8.64 uJ	Assuming 15 mA as the turnaround power
	P_{il}	61.5 mW	Radio in RX mode, -50 dBm input power, CPU idle
	e_{oh}	0.3444 uJ	Radio in RX mode, -50 dBm input power, CPU idle
MAC	k_{ct}	18 bytes	The control packet transmitted by the slave
	k_{cr}	11 bytes	The control packet received by the slave
	N_{ta}	2-4	Depends on the scenario
	N_{st}	1	Only startup once
APP	k_d	0	Without data
	T_{schd}	5 ms	We define this period
APP & MAC	$N(p_{cc}, p_{cl})$	1	Transmit only once
	p_{cc}	0	No channel access failure
	p_{cl}	0	No collision
	$t_{cc}(p_{cc})$	1.25 ms	The first access average time
	$t_{il}(p_{cc})$	3.7 ms	Idle listening time
	$k_{oh}(p_{cc})$	0	No overhearing

In addition, the hardware and the MAC parameters required by the model listed in the upper portion of Tab. IV, are set according to [22][24] and IEEE 802.15.4 nonbeacon-enabled mode [25].

Using equation (4), we obtain that the average energy consumption of the slave node is about 0.22 mJ, which is close to the measurement result of 0.25 mJ. The deviation is due to the slightly different transmitting and receiving power in our analysis and their experiments. The simple communication model in [15] would estimate a communication cost of zero (since no user data is transmitted).

4.1.2. Example 2: CC2430 + IEEE 802.15.4 beacon-enabled mode

In beacon-enabled networks, the master will periodically wake up to broadcast a beacon that specifies the superframe structure and keep active during this superframe duration (SD). When a slave node wants to transfer data to the master in a beacon-enabled PAN, it first listens for the network beacon. When the beacon is found, the node transmits its data frame, using slotted CSMA-CA, to the master. The master can send an optional acknowledgement to confirm the successful reception. The sequence is summarized in Fig. 3.

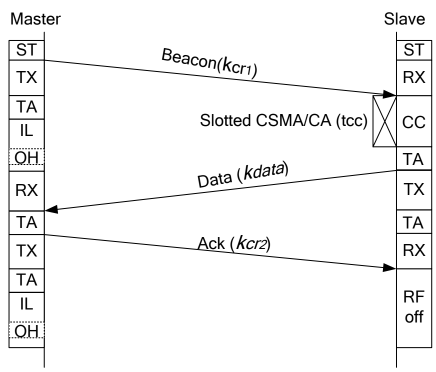

Figure 3. State diagram corresponding to a slave node transmitting data to the master in a beacon-enabled PAN.

To measure the energy consumption for both of them in a beacon-enabled IEEE 802.15.4 network, the experiment in [23] sets up a simple scenario with only one CC2430 slave node and one master. In this case, the SD of the master is 15.36 ms; the beacon and the data frame are 26 bytes and 50 bytes separately. As in the last example, $N(p_{cc}, p_{cl}) = 1$ and $t_{cc}(p_{cc}) \approx 1.25$ ms. During one SD, the idle listening time of the master is $t_{il}(p_{cc}) \approx 11.66$ ms. Finally, the hardware and the MAC parameters are set according to [26], [27] and IEEE 802.15.4 beacon-enabled mode [25]; they are listed in Tab. V.

The average energy consumption of the master calculated by equation (4) is about 1.284 mJ, while the measurement result is 1.368 mJ; the estimated and the measured cost for the slave are 0.53 mJ and 0.91 mJ respectively. The deviation is due to the uncertainty of the synchronization process that causes 0.32 mJ additional energy cost in the slave node and a small additional processing energy that we do not consider.

TABLE V
PARAMETERS FOR CC2430 WITH IEEE 802.15.4 BEACON-ENABLED MODE

HW	e_{st}	$e_{st\_m} = 95uJ$ $e_{st\_s} = 185uJ$	Under different test conditions, the values vary. These are taken from the measurement.
	P_{cc}	80.1 mW	Receive sensibility is -50dBm
	e_{tx}	0.3228 uJ	Radio in TX mode, 0 dBm output power, low MCU activity(26.9 mA)
	e_{rx}	0.3204 uJ	Radio in RX mode, -50 dBm input power, low MCU activity (26.7 mA)
	e_{ta}	10.368 uJ	Assuming 18 mA as the turnaround power[an053]
	P_{il}	80.1 mW	Radio in RX mode, -50 dBm input power, low MCU activity
	e_{oh}	0.3204 uJ	Radio in RX mode, -50 dBm input power, low MCU activity
MAC	k_{cr}	37 bytes	The control packet received by the slave node
	k_{ct}	0	The control packet transmitted by the slave node
	N_{ta}	2 or 3	The number of turnaround times is 2 and 3 for the slave and the master respectively.
	N_{st}	1	Only startup once
APP	k_d	50 bytes	Data length
	T_{schd}	15.36 ms	One superframe duration
APP & MAC	$N(p_{cc}, p_{cl})$	1	Transaction only happens once
	p_{cc}	0	No channel access failure
	p_{cl}	0	No collision happen
	$t_{cc}(p_{cc})$	1.25 ms	The average channel access duration
	$t_{il}(p_{cc})$	11.66 ms	The idle listening time during SD
	$k_{oh}(p_{cc})$	0	No overhearing

As a comparison, the estimated communication energy costs in the slave and master nodes employing the model in [15] are 0.129 mJ and 0.128 mJ respectively, which are very inaccurate.

4.2 Evaluation of the integer linear programming method

In this part, we first estimate the feasibility of the linear partition method for WSNs applications by measuring its execution time and comparing it with previous approaches; then we verify that its partition solutions are exact and optimal by comparing them to the previous work (assuming a simple communication model). At last, we incorporate our novel communication model into the linear programming method to find the impact on the partition result.

In order to evaluate the feasibility of our linear programming method, we use a series of synthetic SDF graphs as in [15] and the parameters of CC2430 device for both master and slave nodes. All the algorithms are implemented in Matlab to provide a fair comparison. Fig. 4 summarizes the execution time of the exhaustive, the heuristic [15] and our linear methods. As the complexity of the application increases, the exhaustive method requires an exponentially increasing execution time while the time of the heuristic and our linear approach are not dramatically affected: they are very close and less than one second. It is apparent that our approach is feasible for SDF graphs found in typical WSN applications.

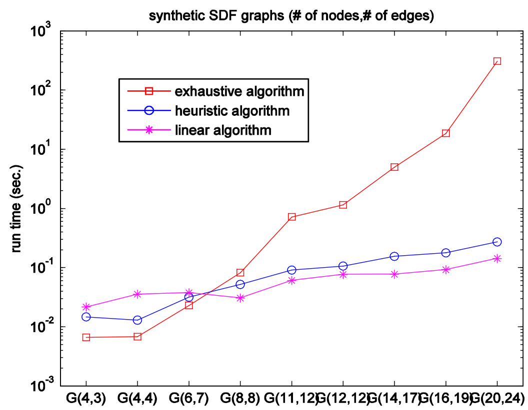

Figure 4. Execution time comparison based on synthetic SDF graphs

To evaluate the efficiency of the different methods, we use the *network energy cost* metric. It is defined as the maximum energy consumption among slave and master nodes during one schedule period, namely, $E_{net} = max(E_{slave}, E_{master})$.

We consider a scenario with eight slave nodes and one master in each cluster which execute a typical SDF graph (maximum entropy spectrum computation, MEPS) as depicted in Fig. 5. The execution time of each actor in this graph corresponding to a CC2430 device is listed in Tab.VI, the communication MAC protocol between the slave and master nodes is IEEE 802.15.4 non-beacon enabled mode as depicted in Fig. 3.

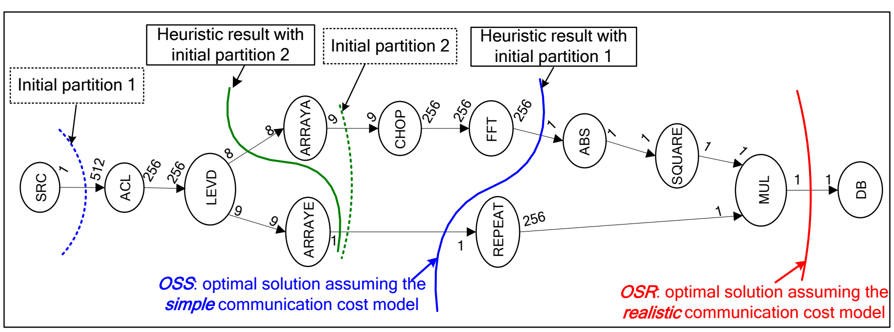

Figure 5. Our ILP method overcomes the suboptimal partition limitation. By using our new communication cost model, the optimal partition result is affected.

First, we employ the simple communication model in [15] to verify that the partition solutions of the linear programming method are optimal. The partition result of our linear approach, named ***OSS***, achieves the minimal energy cost of 95.3312 mJ, whereas the result of the heuristic algorithm depends on the initial partition as shown in Fig. 5. With the initial partition 1, it matches our optimal solution; while with the initial partition 2 its result is suboptimal: the network energy cost is 105.76

mJ. The energy consumption of ILP, exhaustive and heuristic approach using the simple model are listed in Tab.VII.

TABLE VI
EXECUTION TIME OF ACTORS IN A TYPICAL SDF GRAPH WITH CC2430 DEVICE

Actors	**SRC**	**ACL**	**LEVD**	**ARRAYA**	**ARRAYE**	**REPEAT**
time (sec.)	7.92e-5	1.65	0.56	6.83e-5	1.01e-5	8.77e-4
Actors	**CHOP**	**FFT**	**ABS**	**SQUARE**	**MUL**	**DB**
time (sec.)	1.24e-3	0.23	4.46e-5	1.5e-5	1.93e-5	2.26e-5

TABLE VII
THE ENERGY CONSUMPTION OF THE ALGORITHMS
USING THE SIMPLE COMMUNICATION COST MODEL

Algorithm	**Network Energy Cost (mJ)**
ILP	95.3312
Exhaustive	95.3312
Heuristic with initial partition 1	95.3312
Heuristic with initial partition 2	105.7560

In the next experiment, our novel communication model is incorporated into the linear programming method to determine the impact of the communication energy cost on the partition result.

We start to obtain the value of the parameters to initiate our model. When the number of slave nodes is eight, as predicted in [20], p_{cc} and p_{cl} are 0.82 and 0.61 respectively. By equation (2), the average transmission time of each packet $N(p_{cc}, p_{cl})$ is approx. 1. The time spent on accessing the channel of each slave node t_{cc} is about 11.85ms from equation (3). Assuming one schedule period is 1.5 s, the idle listening time of the master node is a function of $m(v)$. Besides, as measured in [23], the slave node spends 4 ms on idle listening (t_{il}) to wait for the beacon from the master. The other constant parameters decided by the hardware and MAC protocol can be acquired from Tab.V. Using equation (4), (5), (6) and (7), we obtain the optimal solution, namely ***OSR***. Because of the different communication cost, the solution is different from ***OSS***. This result is reasonable because as the communication cost increases, the slave node should implement less computation tasks.

Tab. VIII summarizes the energy consumption of the two solutions. The partition result obtained by the workload distribution algorithm using the simple communication model, *OSS*, is suboptimal. It consumes more energy than the one using our detailed model, *OSR*.

TABLE VIII
THE ENERGY COST COMPARISON OF ILP
USING THE SIMPLE AND THE DETAILED COMMUNICATION COST MODEL

Algorithm	**Network Energy Cost (mJ)**
OSR	126.33
OSS	151.92

4.3. Application on Centralized Estimation Algorithm

In the centralized processing applications, every slave node forwards the raw data to the master for processing. The overburdened master node exhausts quickly. This problem can be improved by executing part of the computation tasks in the slave nodes before transmission; it is the so called in-network processing. For these applications, we aim at finding the best workload partition that reduces the network energy consumption thereby extending the network life cycle.

In this section, we present a simple centralized estimation algorithm. All the nodes in the cluster sense the same source signal and each node transmits its observation vector X_s and the disturbance matrix H_s to the master. After receiving these values, the master node calculates the final optimized estimation Y using equation (10) by combining its own value X_m and H_m. The SDF graph for this application is depicted in Fig. 6.

$$Y = (H_m^T \cdot H_m + \sum_{s=1}^{NoS} H_s^T \cdot H_s)^{-1} \cdot (H_m^T \cdot X_m + \sum_{s=1}^{NoS} H_s^T \cdot X_s) \tag{10}$$

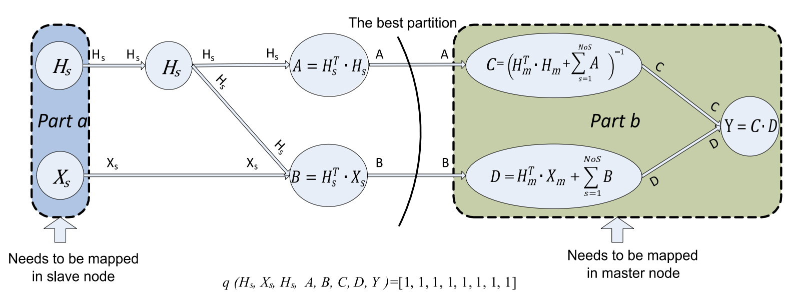

Figure 6. The partition result for a centralized estimation algorithm

In this experiment, we assume that a TDMA MAC protocol is applied in the CC2430 device. There are one master and five slave nodes in the network and they have already synchronized. Then the number of radio startup times N_{st} and the average transmission times $N(p_{cc}, p_{cl})$ are one and the overhead energy cost E_o equals zero. The processing energy requirement can be derived by calculating the energy cost of each operation including addition, subtraction, multiplication and division from the CC2430 datasheet. As in [28], we consider that the observation and disturbance matrices are 5×1 and 5×2 respectively, and each element of them is 16 bits wide. Then all of the parameters in equation (6) and equation (7) are acquired to find the optimal workload distribution solution.

The final partition result is $m(v) = [0,0,0,0,0,1,1,1]$; it is that the actors $\{H_s, X_s, H_s, A, B\}$ belongs to the slave nodes. With the help of the efficient linear partition method, the energy consumption of the network is reduced about 41% (as shown in Fig.7). The network lifetime is extended approx. 1.7 times.

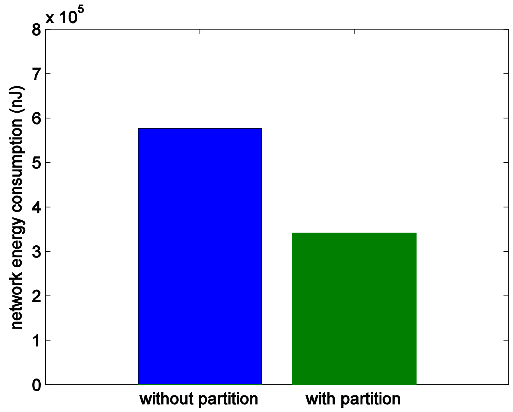

Figure 7. The network energy reduction for the centralized estimation algorithm by the linear partition method

V CONCLUSION AND FUTURE WORK

To reduce the energy consumption of the nodes thereby extending the network life, we propose an improved energy-aware partitioning algorithm for cluster-based WSNs. The partition problem is described as the (0-1) integer linear programming problem for both symmetrical and asymmetrical networks. By employing a novel and detailed model for the communication cost calculation, our linear partition method provides optimal partition solutions. The economized execution time (less than 1 second) makes it feasible for typical WSN applications.

Our experimental results demonstrate that by simply adjusting the related parameters, the communication model applies to both CDMA and TDMA based MAC protocols. Compared to the reported measurements, the estimation of the communication energy cost using our communication model is more accurate (around 10% deviation) than with the previous model used for workload distribution (over 85% deviation). The ILP method requires similar execution time as the previous works while supplying the optimal partition solutions and reducing by 16.8% the energy consumption. By incorporating the accurate communication model into our linear partition method, the estimation of the node's energy consumption is more realistic which produces more reasonable partition results. For a centralized estimation algorithm, it extends the network lifetime approx. 1.7 times with 41% network energy cost reduction. Our experimental code is available online.

In the future, we plan to further reduce the energy consumption of the sensor nodes by incorporating compression and dynamic voltage and frequency scaling (DFVS) into the partitioning problem.

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BIOGRAPHIES

Yanqiu Huang received the B. S. degree in Information Engineering from China University of Mining and Technology, Xuzhou, China, in 2009 and the M.S. degree in Communication and Information System from China University of Mining and Technology, Xuzhou, China, in 2012. She is currently working towards the Ph. D degree in Institute of Electrodynamics and Microelectronics, University of Bremen, Germany.

Her current research interests are Wireless Sensor Networks (WSN), energy efficient hardware architecture for WSN, low-power wireless communication solutions and energy efficient algorithm for WSN.

Wanli Yu received the B. S. degree in Information Engineering from China University of Mining and Technology, Xuzhou, China, in 2009 and the M.S. degree in Signal and Information Processing from China University of Mining and Technology, Xuzhou, China, in 2012. He is currently working towards the Ph. D degree in Institute of Electrodynamics and Microelectronics, University of Bremen, Germany.

His current research interests are Wireless Sensor Networks (WSN), energy management strategies for WSN, and energy efficient algorithm for WSN

Alberto Garcia-Oritz obtained the diploma degree in Telecommunication Systems from the Polytechnic University of Valencia (Spain) in 1998. After working for two years at Newlogic in Austria, he started the Ph.D. at the Institute of Microelectronic Systems, Darmstadt University of Technology, Germany. In 2003, he received from the Department of Electrical Engineering and Information Technology of the university the Ph.D. degree with “summa cum laude.” From 2003 to

2005, he worked as a Senior Hardware Design Engineer at IBM Deutschland Development and Research in Böblingen. After that he joint the start-up AnaFocus (Spain), where he was responsible for the design and integration of AnaFocus' next generation Vision Systems-on-Chip. He is currently full professor for the chair of integrated digital systems at the university of Bremen.

Dr. Garcia-Ortiz received the "Outstanding dissertation award" in 2004 from the European Design and Automation Association. In 2005, he received from IBM an innovation award for contributions to leakage estimation. Two patents are issued with that work. He serves as editor of JOLPE and is reviewer of several conferences, journals, and European projects.

His interests include low-power design and estimation, communication-centric design, SoC integration, and variations-aware design.