Power-Efficient Software Allocation in Wireless Sensor Networks

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Abstract
The present work concentrates on the formulation of a model and an heuristic for generating, respectively, optimal and sub-optimal software allocations to maximize the lifetime of Wireless Sensor Networks. This is achieved by minimizing and balancing the energy consumption, while preserving the completeness of the application and the resilience against nodes’ faults.
In the considered scenario a node can schedule and execute multiple functions, either stored on its Flash memory or dynamically retrieved from the base station or the cluster head, through a dynamic reprogramming mechanism. Execution is guaranteed by a distributed scheduling mechanism, capable of orchestrating the execution of a given function among all the nodes on which that function is run, so that its execution frequency is guaranteed and the overall energy consumption minimized by exploiting parallelism among nodes. Both the model and the heuristic include constraints on the available memory and the desired execution frequency of functions, as well as routing and overhearing issues.
The main result of the proposed work is a framework to efficiently define the software allocation on a WSN under power-consumption constraints, encompassing also more evolved architectures, equipped with a dynamic reprogramming mechanism, multitasking nodes and a distributed scheduler.
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Abstract
While designing the applicable domain of a Wireless Sensor Network, minimizing the energy consumption is crucial to maximize its overall lifetime. We propose a model and an heuristic for determining an optimal and fast sub-optimal functional allocation, guaranteeing applicative completeness and availability, under both functional and non-functional constraints.

ILP Model & Optimization Goal
We model a WSN as composed by:
• A set of N nodes \(N = \{n_1, ..., n_N\}\)
• A set of F functions \(F = \{f_1, ..., f_F\}\)
Functions may statically resides on the node memory or dynamically be loaded from the base station or the cluster head, to cope with memory bounds. Nodes and functions are characterized by the parameters listed in Table 1 and Table 2. Most real applications rely on a hierarchical routing tree with cluster-based topology. We thus define:
• Clusters as partitions on the set of nodes
• Tasks as set of functions

The optimization goal can be expressed as:

\[
\min q \in \mathbb{Q} \left\{ \frac{E_{com.d}}{E_i} \right\} \quad \forall i \in \{1, N\}
\]

where:

\[
E_{com.d} = E_{sta,j} + E_{dyn,j} + E_{route} + E_{obj}
\]

\[
E_{sta,j} = \sum_{i=1}^{F} \sum_{j=1}^{F} \phi_{ij} \quad \forall i \in \{1, N\}
\]

\[
E_{dyn,j} = \sum_{i=1}^{F} (E_{sta,i} + E_{d_i}) \cdot \phi_{ij} \quad \forall i \in \{1, N\}
\]

\[
E_{route} = \sum_{i=1}^{F} \sum_{j=1}^{F} \phi_{ij} \quad \forall j \in \{1, N\}
\]

\[
E_{obj,j} = \sum_{i=1}^{F} \phi_{ij} \quad \forall j \in \{1, N\}
\]

The contribution have the following meanings:
• \(E_{sta,j}\): Energy for running the functions statically or dynamically allocated to node \(i\).
• \(E_{route}\): Energy for forwarding a dynamic function to node \(i\).
• \(E_{obj}\): Energy associated to neighboring nodes over-hearing.

The output of the problem is described by the variables \(\phi_{ij}\), indicating the execution frequency of each function on node \(i\).

ILP Model Constraints
Several constraints need to be imposed for the model to be correct and significant. First of all, the energy consumed by each node must not exceed the available energy:

\[
E_{com.d} \leq E_i
\]

To implement fault resilience we require that some functions are statically allocated with a minimum redundancy:

\[
\sum_{i=1}^{F} S_j \geq R_j \quad \forall j \in \{1, F\}
\]

Memory constraints must also be met. This means that the sum of the size of all statically allocated functions and that of the biggest dynamically allocated function (in the pessimistic hypothesis of downloading each dynamic function on-the-fly) must not exceed the available memory:

\[
d_{sta} + \sum_{j=1}^{F} S_j \leq M_i \quad \forall i \in \{1, N\}
\]

The completeness of the task is then required, to assure that all functions are allocated at least once, either statically or dynamically:

\[
\sum_{j=1}^{F} S_j + d_{sta} \geq 1 \quad \forall j \in \{1, F\}
\]

The correctness of the task functionality must be guaranteed by ensuring that the sum of distributed frequencies \(\phi_{ij}\) for each function corresponds to the required frequency imposed by the designer:

\[
\sum_{j=1}^{F} \phi_{ij} = \Phi_j \quad \forall j \in \{1, F\}
\]

Finally, some additional constraints are required to enforce non-negativity, frequency upper bounds, mutual exclusion between a static and a dynamic allocation of a given function, for each node:

\[
\sum_{j=1}^{F} \phi_{ij} = 0 \quad \forall j \in \{1, F\}
\]

Results
A complete and integrated optimization flow has been implemented using GNU Octave, GLPSOL and custom tools developed on purpose. It is divided in three main phases:
1. Generation of random test instances
2. Execution of the ILP model solver and the heuristic algorithm
3. Verification of feasibility of the solution found

Test instances are generated drawing data from a real dataset, obtained in a previous work. All the energy consumption parameters have been estimated combining the methodology in [1], with devices characterization figures found in [2]. The results obtained demonstrated very good results in balancing energy, since the gap between the node with more remaining energy and the one with less, is always less than 3% for the ILP model and under the 7% for the heuristic.

The heuristic, in particular, proved to be very fast and accurate if compared to the optimal solution:
• It runs 6 order of magnitude faster than ILP
• It produces results with a relative error less than 3.3% w.r.t. the ILP solution.

References