Towards a multiparadigm approach to model energy management in WSN for IoT based edge computing applications

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ABSTRACT

Energy management in Wireless Sensor Networks (WSN) is a vastly analyzed, yet still open issue in the scientific literature. Managing energy is of paramount importance when sensors are battery-powered and distributed in large, hardly (or expensively) accessible sites, such as a forest, for environmental or safety monitoring, or a stretch of sea, to counter contraband or drug traffic or other illegal activities, or dangerous scenarios, such as extended fires or areas on which toxic or dangerous chemical agents are insisting as the result of an incident or an attack. As an extended WSN presents a significant complexity in terms of the number, type, heterogeneity and workload of nodes, communications, interactions with the environment and information propagation and management. To deal with this issue, we present here a preliminary feasibility study for a parameterizable modeling framework aiming to investigate energy balancing and management in WSN. To cope with complexity and with the diversity of the problems to be analyzed in the small and in the global scale of a WSN system, and to provide a tool to evaluate and take into account the actual technological stacks available and arbitrary software workloads, we chose a customizable multiparadigm approach, that has been designed within the research agenda of VALERE research project ePassion.

I. INTRODUCTION

The WSN technology has become a commodity and has been adopted in uncountable different contexts to easily deploy monitoring devices over existing scenarios. WSN are used in small scale environments, both indoor spaces like apartments, warehouses, museums or industrial shelters and outdoor spaces like campuses or parking lots, and large scale environments, such as a forest, a stretch of sea, farmland, a forest, a city. Applications span from surveillance, security, smartification of existing facilities, emergency management, Industry 4.0 solutions, smart cities, military support, environmental protection, with a continuous proliferation due to the increasing availability of more and more affordable WSN nodes and sensors, increasing in both capabilities and computing power.

In some scenarios, WSN nodes have to be battery-powered, e.g. if installed in locations that do not allow wiring for historical, practical or cost reasons, or because they must be relocatable, self-moving or just deployed by throwing them in a scenario that is not otherwise practically reachable. In some cases, it is suitable and convenient to adopt technologies that can recharge batteries by harvesting energy from the environment, e.g. by solar panels, tidal waves, mechanical vibrations. However, even when harvesting is possible, a proper and careful design is needed to ensure the correct engineering of both the nodes and the network as deployed. Indeed, to accomplish the mission, a WSN needs to keep undamaged both the environmental coverage and the connection between all nodes: this requires the definition of a proper number of nodes and a location strategy to ensure survivability, also by facing node loss using reconfigurations that, in turn, need tools to model and evaluate with sufficient accuracy energy consumption on nodes as deployed in the scenario.

When dealing with large scale heterogeneous WSN, complexity is significantly increased for various reasons, such as the number of nodes, scenario dimensions, increased complexity in scheduling and routing, diversity of node workloads and battery level dynamics.

In this paper we sketch a modeling strategy designed to evaluate and manage energy usage and balancing in large WSN applications. This modeling framework is still in its preliminary development. This notwithstanding, here we discuss the approach as a case of multiparadigm modeling, with special attention to the heterogeneity of the involved modeling techniques, the different modeling planes, the parameterization of the adoptable modeling techniques and the advantages of

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multiparadigm approaches for dealing with problems characterized by different scales and detail levels.

The paper is organized as follows: Section II analyzes the WSN energy aspects to be modeled; Section III presents the general modeling approach; Section IV presents an instantiation of the methodology with specific modeling formalisms; Section VI points at some relevant literature; conclusions close the paper.

II. ANALYSIS OF WSN CHARACTERISTICS AND REQUIREMENTS

WSN nodes can be considered embedded computers equipped with a radio connection, used to support networking, and a number of different sensors, whose type and characteristics depend on the application. Nodes may be battery operated or connected to the common electrical grid: in the following, we only focus on battery-operated sensors. The software stack running on the nodes can consist of a proprietary solution or open software, either derived from other segments (e.g. Linux distributions or analogous projects) or natively design for WSN. Network support is generally based on standard general-purpose (e.g. based on IPv4 or IPv6 and the TCP/IP protocol suite) or specialized (e.g. ZigBee) network protocols, to ensure interoperability. Costs are one of the main drivers in the design of commodity WSN solutions: this notwithstanding, a node may have enough resources to be able to run applications locally or as part of a distributed environment, also including edge computing solutions.

The nature of the problem, the equipment and the Hardware/Software (HW/SW) architecture are not the only key elements to understand WSN: the other relevant factor is the management of the network and communications. A shared practice is adopting infrastructure-less solutions, that allow WSN to be deployed and self-sufficient by dedicated routing and management techniques (e.g. mesh, ad-hoc networks, MANET for mobile WSN), also providing reconfiguration features. This approach also inherently allows the extension of a WSN to grow up to hundred or thousand of nodes, in principle, introducing scaling problems for the characterization of the WSN as a whole, due to propagation and lack of centralization of management and state of the network.

When dealing with battery operated nodes, both node activities and network dynamics impact on energy consumption.

Modeling energy in WSN nodes specifically targets the general and local optimization of the available energy level to reorganize, periodically or dynamically, the workloads in terms of local computing, the delegation of tasks (if possible) and preferred routing paths, acting simultaneously and synergistically on two aspects: energy supply and energy consumption. Therefore, the modeling approach is intended to support the development of such systems, both guiding the design or the choice of the electronics and the integration of a node and the identification of optimal operating parameters, and analyzing the effects of active use of single nodes and the whole network. The aim is achieving the maximization of the energy available at the sensor nodes and the ratio between service quality and energy consumption, with reference to a specific application scenario. The complexity of the system and the number of possible scenarios and applications suggest the use of multiple coordinated modeling approaches to cope both with the network aspects, by abstract techniques, and the node features with a high level of detail. This allows to minimize the complexity and the analysis time and to keep a high degree of fidelity when dealing with the actual behavior of the used technological stack, and, finally, helps validation. While both analytical and numeric evaluation techniques are precious to model the system on a small scale, soft computing or approximated techniques may help in coping with global analysis while keeping the complexity of the evaluation manageable. For this reason, we chose a multiparadigm approach as evaluating framework, to leverage the benefits of very different modeling techniques inside the same model for different levels of the system.

Modeling a node requires taking into account: a model of the actual hardware configuration with the actual activation scheme of each sensor; a model of the software environment in terms of background activity of the operating system and the activation/sleeping state of the node; a model of the tasks that run on the node and its schedule, that might be non-deterministic; a model of the activities that the node performs on the network according to the generated traffic and the routed traffic depending to its role in the network; and, finally, a model of the harvesting process, if any, depending on the conditions of a specific node in the network and the environment. Using an analytical modeling technique (e.g. a stochastic technique based on Markov chains or Petri nets or queuing networks) provides a good first approximation model but cannot capture all details that would allow a realistic validation. Simulation offers specialized tools that actually mimic the technological stack faithfully, but only allows a limited number of possible configurations and behaviors of the system to be actually simulated to keep feasibility, and has a high level of time and memory complexity if the system has a very high scale.

At the network level, global characteristics of the system are strongly dependent on the specific topology: the topology, even neglecting the technological aspects, affects routing decision and more abstract characteristics of the network, such as robustness and resilience. These two characteristics are an important target, because they are connected to keeping the coverage of the WSN or to a smart degradation of the coverage when nodes start exhausting their batteries. They may be evaluated on an abstract level by means of advanced mathematical descriptions, e.g. borrowed from the statistical physics corpus of knowledge, from the artificial intelligence domain, from the soft computing field. Of course, this abstraction step must be intended as a way to provide a guide for parameter space exploration and high-level dynamics evaluation that must then be validated, e.g. by properly simulating the real scenario.

III. A PROPOSAL OF MODELING METHODOLOGY

The proposed methodology aims at joining the advantages of high-level models and approaches with the realism that may be obtained by using a specific simulation platform, capable of capturing actual events at the desired detail level. The methodology is based on considering the WSN on three different levels: the global level, the simulation level and the node environment level. At the global level, optimization is performed considering a synthetic representation of nodes or node groups, to abstract details and to allow the use of different methods; at the simulation level, a faithful model of nodes and network mechanisms is exploited by means of a specialized, extensible, modular network simulator, to evaluate the actual costs of communications, network organization and configurations in terms of energy, both to obtain synthetic parameters for the global level and to validate the results of the optimization; at the node environment level, a faithful description of the HW/SW configuration of each node is integrated by a model of the harvesting mechanism and a model of the applications to be executed on the node and of their scheduling and reactive behavior.

The methodology leverages a multiparadigm approach [25] to allow maximum flexibility in the choice of the optimization strategy. This allows defining an interface representation of parameters, topology and configuration to integrate the tools used at the global level and the simulation level.

The modeling and evaluation process is articulated in 8 phases, as in Fig. 1. The starting phase (*Requirements elicitation*) is meant to understand the problem the WSN should solve, the general characteristics of the environment, the constraints on available hardware and possible topology. This leads to the *Definition of node architecture*, that includes hardware, configuration, devices and harvesting model, and provides as output the node simulation model. The phase of *Definition of the scenario* allows defining the global information needed to produce the optimization model and the contexts for the generation of the testbeds. The phase of *Definition of exploration testbed* produces a local simulation testbed around single nodes, typical because of their configuration or their position or role in the WSN, or node groups, that is used to generate parameters for the global level model in the *Estimation by exploration testbed* phase. In the *Optimization* phase, the global level model is evaluated, to generate the optimal configuration for the WSN, that is used to generate the simulation model evaluated in the *Validation* phase. If the simulation of the configuration of the optimal configuration confirms the results of the Optimization phase, the overall final configuration for the system is generated; otherwise, in the *Parameter refinement* phase a new set of parameters is generated, and two possible iterations are taken until the Validation phase produces a satisfactory result.

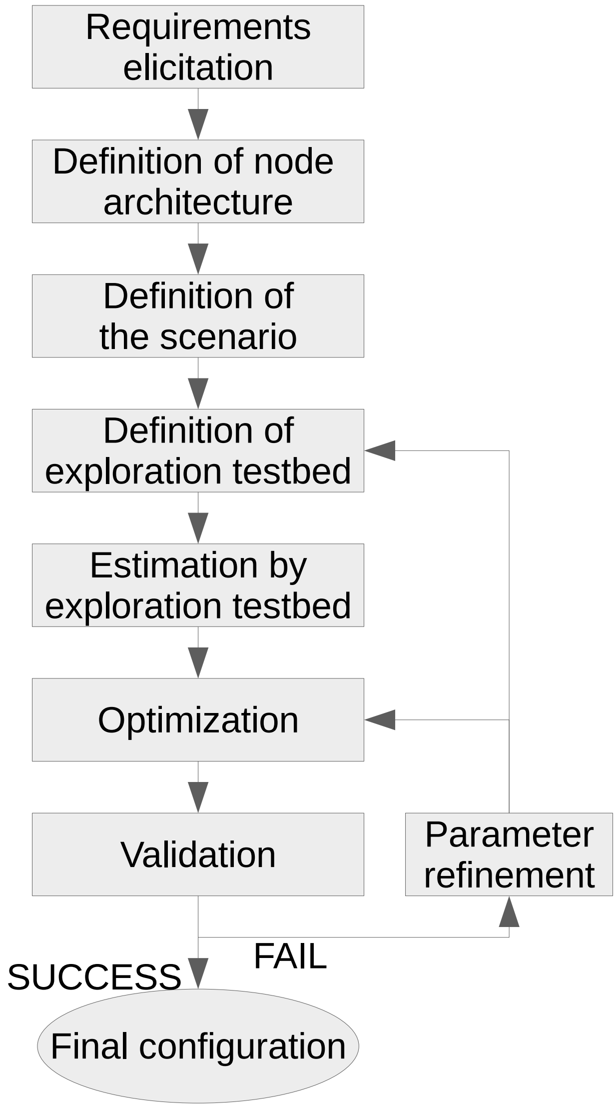

Fig. 1. The simulation methodology

IV. AN INSTANTIATION OF THE METHODOLOGY

To provide an application of the methodology, we defined a framework suitable for the analysis of energy management in large WSN. In this case, the global level is implemented by a modeling and evaluation technique borrowed from statistical physics, namely *percolation theory*; the simulation level is implemented by leveraging a well established network simulator, namely *ns-3*; the node environment level is implemented by a *multiformalism* modeling approach [10] that exploits *Fluid Stochastic Petri Nets* (FSPN), Ordinary Differential Equations (ODE) and again ns-3.

A. The global layer

This level of implementation is focused on the topology of the WSN. More precisely, it assumes that a given number of sensors are distributed in space in fixed space positions. Each sensor dissipates energy to perform different operations, data acquisition, elaboration and transfer and is supplied by a harversting device. As a consequence, there is a finite probability that temporal periods exist in which one or more nodes are inactive. The aim is to find the topology of the links among the different nodes, which maximizes the probability that, at each time step, each node is connected to the external receiver sink. It requires as input information the average energy balance of a single sensor which is provided by the previous analysis for a typical scenario. More precisely, the central quantity is the average value of the dissipated rate for data transfer, as a function of the distance between transmitter and receiver, for data elaboration and data acquisition. At the same time, it depends on the average rate of energy accumulation.

It is quite evident that the larger the number of links incoming and/or outcoming from a single node, the larger is the energy dissipated by that node and, therefore, the larger is the probability for that node to become inactive. As a consequence, the optimization of the link topography corresponds to the minimization of the number of links. This is a typical problem of statistical physics, known as "percolation theory" [23], [1]. Within this framework indicating with p the probability that a link is present between two arbitrary nodes, there exists a critical value p_c such that for $p < p_c$ the network is not connected, i.e. information cannot be conveyed to the external sink. In the case of the WSN, the situation is more complicated for two reasons: i) since the cost for energy transfer depends on the distance between the connected nodes, links are not equivalent, but there are links that are less energy-consuming than others; ii) nodes are not always active, and this information must be included in the optimization procedure. Accordingly, the WSN must be treated as a weighted graph where each node is a vertex to which is assigned a random variable assuming value 1 or 0 if the node is active or inactive, respectively. The problem can be faced by means of advanced mathematical tools developed in the field of graph and information theory, focusing for instance on quantities like entropy, joint entropy, and mutual information. The entropy of a random variable is a function which attempts to characterize its intrinsic "unpredictability". The Joint entropy is the entropy of a joint probability distribution or a multi-valued random variable, and the mutual information is a quantity that measures a relationship between two random variables that are sampled simultaneously. A precise definition of these quantities can be found in the literature [7].

For our specific problem, a key role can be played by the betweenness centrality, a widely used measure in graph theory that captures the role of a node in allowing information to pass from one part of the network to the other [3], [18]. More precisely, to evaluate the betweenness of a node J, for all pairs of nodes, one must identify the shortest paths between those nodes; then one evaluates the fraction of those shortest paths that pass through node J, which provides the betweenness centrality for node J. A node with higher betweenness centrality would have more control over the network because more information will pass through that node. Nodes with the largest betweenness do not automatically correspond to most connected nodes, and a possible optimization procedure corresponds to minimizing the energy consumption of node with large betweenness. This would allow us to stabilize those nodes which are more central in transferring information. The optimization procedure will be implemented by means of typical methods of statistical mechanics, such as Monte Carlo sampling [15] or simulated annealing [13].

B. The simulation level

For the simulation layer ns-3 (www.nsnam.org/) has been chosen, a discrete event simulator that is specialized for computer networks simulation. The choice is motivated by some of its key characteristics. As first, it is designed as open and to be extended according to a modular architecture, that allows the generation of additional components to support our methodology. As second, it is designed to faithfully reproduce all aspects of network protocols, management, hardware, routing, and other details, so that simulation can closely reproduce realistic situations for a given scenario and execution trace. Finally, it is widely used in the scientific community and by practitioners for WSN [5]. The logic of the simulation is based on the generation of events to be scheduled for execution in the temporal order in which they would happen in the real system [20]. ns-3 is supported by a vast community that develops and validates new features and components, and existing components also support energy management. Finally, ns-3 also has a real-time scheduler to implement simulation-in-the-loop and can execute real workloads on the nodes, including virtual machines, thus allowing a very close tracking of the software layer of each node as well. As the authors declare that they aim at enabling the reuse of real-world protocols without specific reimplementations, the level of details possible is only limited by the need of longer wall-clock simulation execution times as much as the simulation is close to reality and the dimension of the simulated network grows. As ns-3 is very popular and widely accepted, we suggest interested readers a systematic literature review of papers dealing with the use of ns-3 in WSN in [5] for further details.

C. The node environment level

Modeling the node environment allows the determination of average node behavior for typical nodes to obtain the initial parameters. As in the considered node model, each node executes software tasks when needed besides normal activities related to data sensing and processing and communications to implement an edge computing platform. A stochastic oriented modeling approach is consequently needed. In addition, harvesting has external influencing factors depending on the environment and exhibits a continuous behavior of battery energy level, that varies for the two opposing factors (usage and harvesting), and differently according to the power state of each node (idle, sensing, processing, high performances). In this isolated model, the contribution of interactions between nodes, as well as routing problems and connected influences on energy levels and contributions of software tasks that are launched as a reaction to events detected on the field in the scenario are not known, but can be taken into account on a probabilistic basis as a first approximation.

Due to these requirements, the chosen modeling technique is a multiformalism approach based on FSPN and ODE, that are used together to evaluate node behavior and parameters and to partially generate the Node simulation model. FSPN are a variant of stochastic Petri nets in which additional places, transitions and arcs exist that deal with continuous marking (i.e., a continuous place is not marked by an integer number of tokens, but by a continuous level, and incoming and outcoming arcs influence its marking by a rate when the enabling conditions hold). They are thus suitable to easily represent energy levels and the power drain due to node activities that happen for a given duration but are activated with a discrete event logic described by the ordinary (non-fluid) elements of the formalism (e.g. a scheduling scheme, reactions to events, guards or activities with stochastic duration): for formalization and details on modeling and analysis with FSPN, interested readers may refer to [11], for an example of application to [8]. ODE well describe the mathematical model of harvesting-related phenomena and are easily comparable with the fluid part of FSPN, so that they can be modeled by a domain expert that is not familiar with the FSPN. However, the reduced semantic distance between the two modeling formalisms may be easily bridged within multiformalism frameworks, like SIMTHESys [2].

V. MODELING AND EVALUATION PROCESS

The modeling and evaluation process is depicted in Fig. 2. The inputs for the process, generated in the Requirements elicitation phase and Definition of node architecture phase, are the Scenario model, the Harvesting analytical model, the Node HW configuration and the Node SW configuration.

The *Scenario model* is an abstract description of the geometry, the characteristics and the configuration of the scenario in which the WSN energy management evaluation has to be performed. This model considers the requirements of the application to be implemented and is used to generate[1] the *Global analytical optimization model*, that is the base of the Global level in this implementation, and the information needed to define the *Parameters exploration testbed*, namely the *Scenario characterization*.

The *Harvesting analytical model* is provided in terms of a parametric ODE description of the harvesting model of a node. It is used to generate the *Harvesting numerical model* as a component of the ns-3 Node simulation model, and, together with the Node HW configuration and Node SW configuration, the *Node environment model*, in turn used to instantiate parameters in the Node simulation model and the Parameters exploration testbed.

The *Node HW configuration* and the *Node SW configuration* are used to generate the Node configuration, that in turn is used to generate the ns-3 Node simulation model.

The *Node simulation model* is used to produce the *Node instances* that are used to compose both the Parameters exploration testbed and the Global WSN model, to be used during the Estimation by exploration testbed phase and the Validation phase, respectively.

Finally, the *Global WSN model*, as configured after the execution of the Global analytical optimization model, is used to simulate the WSN by ns-3 in detail, and the results are compared with the results of the Global analytical optimization model results to decide if an iteration is needed or if the final result is satisfactory.

VI. RELATED WORK

Energy management in WSN has been widely discussed in the literature, focusing the attention on one or more aspects of the problem. For an introduction and a general description of relevant issues, we suggest [29], [16] and [4], that also introduce the main elements needed to define a modeling framework. Modeling approaches can be found in [17] and [27]. Power management methods are examined in [12], [19], while energy saving in protocols and network management is surveyed in [28] and [24]. A survey about energy harvesting and energy management is provided in [26]. Different energy optimization techniques have been applied to WSN, including neural networks [21][14], reinforcement learning [22], game theory [6] and genetic algorithms [9].

VII. CONCLUSIONS AND FUTURE WORKS

In this paper, we presented an experimental modeling methodology for the evaluation and the optimization of energy use in WSN, that may scale to extensive configurations and allows realistic verification by simulation. Future works include the application to real-world case studies and the implementation of automatic mechanisms, where possible, for the evaluation process.

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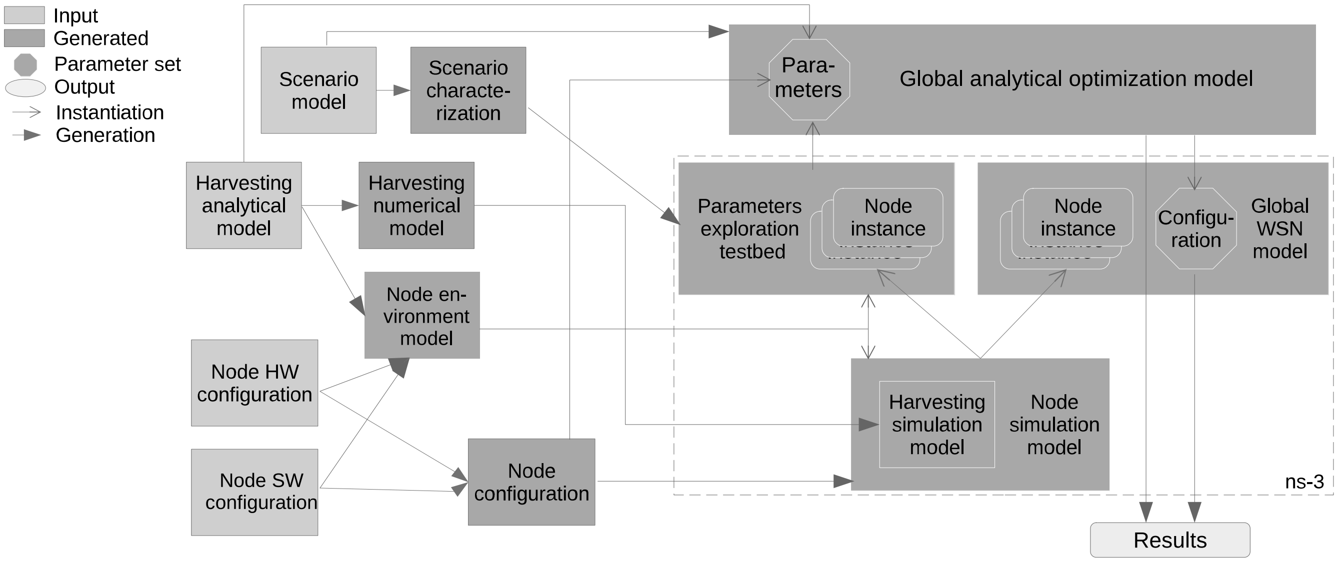

Fig. 2. The modeling and evaluation process

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