Energy Estimator for Weather Forecasts Dynamic Power Management of Wireless Sensor Networks

Nicolas Ferry[1], Sylvain Ducloyer[1], Nathalie Julien[1], and Dominique Jutel[2]

[1] Lab-STICC, Centre de Recherche, Rue Saint Maudé,
56100 Lorient, France
{nicolas.ferry,sylvain.ducloyer,nathalie.julien}@univ-ubs.fr
[2] ERYMA Security System, Z.I. La Montagne du Salut,
56600 Lanester, France
{dominique.jutel}@eryma.com

Abstract. Emerging Wireless Sensor Networks (WSN) consist of spatially distributed autonomous sensors. Although an embedded battery has limited autonomy, most WSNs outperform this drawback by harvesting ambient energy from the environment. Nevertheless, this external energy is very variable and mainly depends on weather evolution. Therefore, including weather at design stage and weather forecasts at runtime is essential for autonomy management. This paper presents a Power Estimator to simulate node autonomy for various weather conditions and locations. This work also addresses the integration of Weather Forecasts in the Dynamic Power Management policy (WF-DPM). These two contributions significantly improve the system scaling and the energy availability prediction to help to achieve better node autonomy duration. Experimental results compared various locations to study the weather impact on the system autonomy.

Keywords: Wireless Sensor Networks, Weather Forecasts, Dynamic Power Management, Design Tools.

1 Introduction

Wireless Sensor Networks (WSNs) are distributed communicating embedded systems. With constant technological progress in thinness and wireless communication, nodes are given increasingly improved features, thus leading to their deployment in more wide-range of environments. As stand-alone equipment, they must be autonomous in energy. Most embedded systems integrate cells, but they keep a limited autonomy. To overcome this drawback, some WSN harvest ambient energy directly or recharge an energy storage system. These WSN have a self-recharge feature that increases the autonomy for a limited amount or for a complete recharge. From the other side, the WSN application scenario depletes the energy resource. Thus, the problem is to estimate the node autonomy as the recharge factor can be highly variable. To handle this point, environment must be take into account; and most criteria like solar, wind, and temperature depend more precisely on weather. Thus, the difficulty is to find relatively

J.L. Ayala et al. (Eds.): PATMOS 2011, LNCS 6951, pp. 122–132, 2011.

good environment estimators to predict this variability. And currently, the best weather estimator we have is given by forecasters.

In this article, our contribution is to propose a Power Estimator design tool able to integrate Weather Forecasts (WF) into a Dynamic Power Management (DPM) to simulate the system autonomy for specific weather environment, scenario, hardware configuration, RF activity, and DPM algorithm. The Power Estimator (PE) goal is to identify at design level the power consumption hot-spots, and thus, to scale accordingly the system in term of harvesters, low power components, battery capacity, and DPM strategy.

This research contribute to the CAPNET project which joins industrial and laboratory partners to equip fire services brigades. In this project, a linear WSN demonstrator must be realize to monitor gas spread and person intrusions in firemen secure area.

This paper is organized as follows: section 2 provides a state-of-the-art on WSN design tools. In section 3, we present available weather forecast models. WF-DPM with QoS strategies is described in section 4, while section 5 focuses on the Power Estimator and the experimental results before concluding.

2 States-of-the-Art

Low Power Design [1] advancement has recently moved onto a higher level with algorithmic dedicated implementation, and operating system advancement with power down modes, DVFS, and power-aware scheduling. Thus, power reduction can be applied all along the co-design process [2] by respecting a low power design methodology [3].

The emerging wireless sensor network domain has existed for a few years, however an increasing number of projects have been referenced [4]. Technology integration improves and nodes tend to achieve lower size like Smartdust and the Picocube project [5] which is a 1 cm3 sensor node powered by harvested energy. In this part, we focus mainly on new prototypes for which harvested energy is provided by the weather environment.

Some interesting rechargeable WSN are Heliomote [6] which uses a voluminous solar panel directly connected to a two AA Ni-MH battery through a diode. Prometheus [7] uses a solar panel directly hardwired to a 22F supercapacitor which directly supplies power to the system or charges a secondary Li-Polymer battery. Like Heliomote, it does not harvest energy efficiency with an MPPT. Everlast [8] only has a solar panel and a supercapacitor, but no battery. For optimal power harvesting, it uses a MPPT approach that charges a 100F supercapacitor. However, it requires MCU to perform the MPPT algorithm calculation. PUMA [9] has multiple power sources. It uses a power routing technique to harvest simultaneous multiple power sources. The high energy harvesting is achieved with a combination of MPPT and power defragmentation. However, it requires MCU control based on input from light and wind sensors. AmbiMax [10] is a multiple harvester system with solar and wind experiments. It includes MPPT tracking using an hysteresis comparator coupled with an additional sensor to hardware calculated MPPT. The harvested power is sent to a boost regulator before charging a Li-Polymer battery.

We have noted that these systems embed energy harvesters, but none of them, except Duranode with its current solar policy, has sought to predict the potential energy harvested for energy management.

In the WSN domain, CMOS circuit power consumption repartition evolves so that clock and leakage are no longer the main drawbacks against RF transceivers and heavy industry sensors. Thus, concentrating the analysis only on the MCU or the operating systems is not a complete approach. It is recommended that the tool supports a power estimation of the whole system.

In that domain, power estimation tools work at specific levels. At physical level, SPICE is a general-purposes circuit estimator. It is well defined for transistor and PCB simulations, but requires an enormous amount of work to model the whole system. At instruction levels, there are many MCU simulators: Simbed for the Motorola M-CORE, Skyeye for the MIPS platform, eSimu for the ARM9 and EMSIM for the strongARM platform. SoftExplorer is a CPU Power Estimation tool which estimates power consumption of C or ASM languages for a modeled CPU. Specific FPGA cards rely directly on Xilinxs, Altera or Intel manufacturers, but all of these simulators are accurate for the particular specific chip for which it is intended to work. Nevertheless in WSN, MCU is definitely not the most consuming resource. This is particularly true, that in our project MCU consumes no more than 2% of the whole system. At the architectural level, prototyping work includes PowerOpt from ChipVision, which is a low-power synthesis C/SystemC to verilogRTL tool. Or Interconnect Explorer which studies bus interconnexion power consumption. These tools are useful for design optimization at their level, but here again a global vision with less precision could be more pertinent for our needs. At the OS level, Softwatt analyses power dissipation for Embra, Mipsy, and MXS platforms. One interesting tool is powerTOSSIM which is a TinyOS Simulator mainly for the Mica2 node. Finally, new research projects are trying to model the WSN in the whole by using macromodeling, or components modeling like CAT which is the nearest whole system simulator. However, they do not model the external environment which impacts weather and rechargeable energy.

Thus, we underline the lack of a global view simulator, which may be less accurate than dedicated separate tools but which can integrate the entire components and the weather environment. So, what models can be used to predict weather environment?

3 Weather Forecasts

Meteorology is the science which studies atmospheric phenomena mainly in the first 31 km of the atmosphere. The meteorologist Lorenz discovered the chaos theory [11] showing that the atmosphere cannot be entirely determinist. Small variations in the initial states can result in huge consequences in the final results: this phenomenon is known as the "Butterfly Effect". Therefore, the final interpretation is left to human interpretation to formulate the weather forecasts. A new predictive approach consists in evaluating a set of different runs. Each run slightly modifies an initial parameter corresponding to a well-chosen particular error/perturbation. Therefore, the standard deviation can be exploited to give a trusted indicator for the predictions.

Multiple Meteorology centers use home or different meteorology models. We could cite many: WRF, GFS, ECMWF, UKMO, JMA, ARPEGE, and AROME... Among these different models, the Global Forecast System (GFS) is an American numerical weather forecast model. This model divides the Earth into a mid-meshing grid of squares of 30 km and the atmosphere into 64 altitude layers. A model computation is called "a run" and predicts up to 16 days forward. The main advantage of this model is the output which is freely available and in real-time after generation. We reuse information given by the Meteociel website [12] which digests the GFS information in a vector. Each piece of interesting information is collected to supply the simulated harvested external energy potential. However, solar information is only given as a variable icon representation. To translate this information, we rely on another website to convert solar potential into a sunset irradiance in W/m2.

The European JRC - Photovoltaic Geographical Information System (PVGIS) is a website [13] for photovoltaic technology. For Europe and Africa, the system can give a photovoltaic estimation of the solar potential during an entire typical day of a specific month. PVGIS gives three sunset indicators: IR global clear-sky sunset, IR global real-sky sunset, IR diffuse real-sky sunset as a time function. IR global clear-sky is the maximal sunset irradiance expected with no nebulosity. IR global real-sky is the standard sunset irradiance for the average cloud-covered sky in a month. IR diffuse real-sky is the expected sunset irradiance by diffuse luminosity which can be translated as the minimum irradiance that can be harvested even by a heavily clouded sky. All these information must be merged to provide the weather coefficients.

Since meteorology data are now widely available through multiple sources, they can be extracted directly from Internet websites. Weather coefficients can be combined together to produce an energy function prediction over time. In the Power Estimator, the scenario builder works as follows for the meteorology part. It can connect to specific meteorology Internet websites, from which the weather data is downloaded in HTML string syntax. The next step consists in parsing and extracting the weather data from the page. Of course, this module is generic and is implementation depends on the target website. Weather Data are presented in a vector structure where each column represents a weather component (Sunset irradiance, Wind speed, Temperature...) and the row increments in the time dimension. As most websites do not give the sunset irradiance, we must combine various website data.

Depending on your world position (Latitude, Longitude) on the globe, and the month in which the simulation must run, PVGIS gives you sunset measurements: IR clear-sky sunset, IR med sunset, IR diffuse sunset. These values are extracted for each month once at start up. The time granularity is given every 15 minutes.

Weather data are interpolated according to a Lagrange Law, while PVGIS data are interpolated as well, and finally they are combined into a two dimensional vector of the simulation resolution. The result is a data file that can be exploited in the simulator to reproduce the weather parameters. However, we tested the Runge interpolation error that forced us to fallback to a Spline or Hermite cubic interpolation. Since energy is scavenged from the environment, the node model must include a model for each power source type. Currently, CAPNET focuses only on solar, wind, and thermal power sources. The meteorology context is constructed with the Weather-Builder integrated into the simulator. The context can be created manually, scanned from a website, or extracted from a meteorology file recorded day after day.

Then, when the DPM replays a scenario, the weather state is updated and provides the weather data for the simulation. Finally, the simulator converts them into power depending on the physical installed hardware.

However, we must keep in mind that despite WF models continuously evolved and offered better accuracy; WFs suffer from interpretation errors and/or inaccuracies.

Currently, most WF models can predict 1-day up to 3-days forward with relatively good accuracy but a complete week with more uncertainty. The WF theory limit is announced to a maximal of a two-week forward window.

4 Dynamic Power Management

Dynamic Power Management (DPM) policy controls the different power states enabled for the system. This model is not directly the microprocessor program, but rather a subset of the global power states view. The DPM has been modeled as a Finite State Machine (FSM) composed of a set of states $\{S_i\}$ and transitions $\{T_i\}$. Each state represents a particular system power consumption state $\{Pt_i\}$, and has a variable duration $\{Tt_i\}$. The DPM commands the behaviors of the system, entering special power modes or monitoring power supply. A Sequence is a set of one to many states linked together and form a path to produce a service.

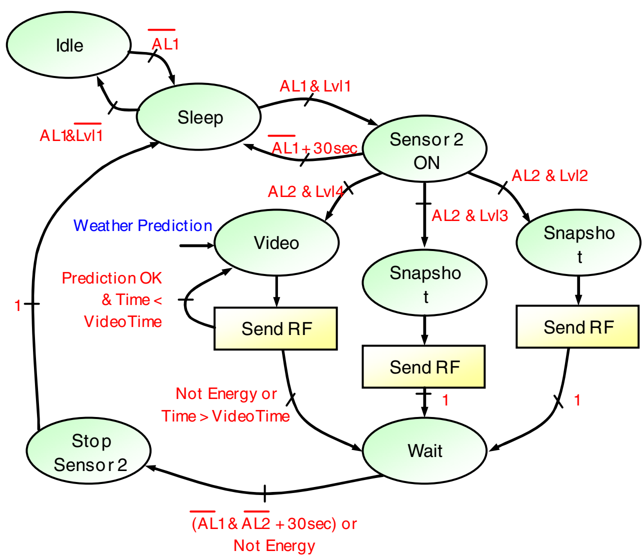

Fig. 1. A WF-DPM example using weather forecasts results to make low power decisions

The WF-DPM model introduces the capacity to exploit the meteorological WF coefficients. WFs can be used for various applications like power switch policies to determine which power harvesting source will probably have the highest energy availability. For CAPNET application, WFs is computed on the supervisor which transfer only the indicator to stay or not in waiting states.

In CAPNET, the intrusion detection service is defined by the DPM shown in figure 1. The system uses two sensors for detection except when there is not enough energy; the node directly sends an alarm and enters an IDLE waiting state. When the sensor 1 detection flag is raised, Sensor 2 is activated to verify the intrusion. If both are raised, the node sends an alarm to the supervisor. With lot of energy, the system sends a video for a variable duration. Or it sends a snapshot in high or low resolution depending on the energy level. Then, the DPM waits for the two sensor releases before stopping sensor 2 and returning to Sleep State. Video time duration depends on a maximal timing and the energy prediction function.

We define an energy function based on a real energy state of charge (SOC) and the WFs. With WFs, we have prediction data for each ambient microsource: the sunset irradiance potential in W/m2, the wind speed potential in Km/h, the thermal temperature potential in °C. Due to specific models built for each microsource, we can determine the equivalent power produced. This gives us a power representation in Watt and, for a one-second resolution, the energy in Joules. Each microsource power potential is cumulated to provide the Potential Ambient Energy Value (PAEV), which is a total amount of external energy expected in the near future. We can quantify the harvested energy by expressing the PAEV as:

$$PAEV = \sum_{i=1}^{n} E_i . \mathrm{Re}\, s \tag{1}$$

Where i is the index in seconds in the WF forward moving windows, n its length size, Ei the cumulated energy of each harvester and Res is the resolution in seconds. Thus, if we define the battery State Of Charge in Joules, we can express the battery charging duration as:

$$SOC + \sum_{i=1}^{n} E_i . \mathrm{Re}\, s \leq SOC_{Full} \tag{2}$$

The DPM has several states, each having its own level of power consumption. A sequence is a set of states realized to perform a typical task, but the calculation can apply to multiple sequences. If we know the duration of each state, we can calculate the Required Energy value for a sequence.

We can express the total Required Energy (RE) for a sequence as:

$$RE = \sum_{j=1}^{nbT} Pt_j . Tt_j \tag{3}$$

Thus, if we define the battery State Of Charge in Joules, we express the maximal sequence duration as:

$$SOC - \sum_{j=1}^{nbT} Pt_j . Tt_j \geq SOC_{LowLevel} \tag{4}$$

We have to validate that the conditional expression (5) is always true for all values:

$$SOC + \sum_{i=1}^{n} E_i \cdot \mathrm{Re}\, s - \sum_{j=1}^{nbT} Pt_j . Tt_j \geq SOC_{LowLevel} \tag{5}$$

The Energy function result can be one of the two cases: if true the sequence has potentially enough energy to be executed, otherwise the sequence will probably fail due to a lack of energy.

As batteries have special behaviors [14], modeling battery charging with only a sum/minus operator is a simplification. In fact, we have built a battery model that supports both discharging and charging in order to handle these behaviors. Such a model has been developed based on previous work done by [15]. The model enables us to estimate efficiently the battery capacity to handle service. From this point, we can explore multiple solutions to adapt the quality of service.

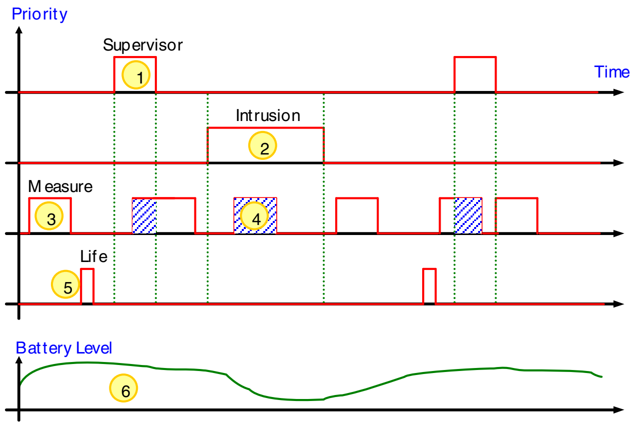

Fig. 2. Service scheduling ordered by priority levels. (1) The supervisor request has the highest priority; it masks all other low priority services. (2) When an intrusion has occurred, it runs the DPM shown in figure 1. (3) Task Measures acquire gas and temperature data. (4) Measure task can be masked by a higher priority task. (5) Life indicator is sent periodically. (6) The battery SOC can be used to redefine task priority.

By using a WF-DPM, we want to explore QoS techniques to reduce power consumption dynamically. We reference various techniques: service choice, service variable quality rating, service priority, service delay, and service delegation.

- Service Choice: at runtime, the DPM dynamically chosen which service is active or not. This can be used to select conditionally a service between two or more. A service choice example is the three branches to select video quality in the figure 1.
- Service Variable Quality Rating: this technique defines a variable criterion on a device or on a feature. For multimedia streams one can adjust the bandwidth and the calculation to decrease power consumption. In figure 1, the video mode adapts the bandwidth depending on the battery level.
- Service Priority: in such systems, each active service has a priority which defines the task ordering during power modes. Higher priority levels mask lower services. It can be combined with the service delay technique.

Figure 2 gives an example of service priority handling defined by the energy level.

- Service Delay: when not enough energy is available for a service, it is delayed in time until having the requested energy. In figure 2, a life packet is sent periodically, but it cannot be emitted while in low battery state.
- Service Delegation: when the service does not have enough energy, it can be delegated to another node which can accept or refuse to handle the job. This can typically occur when a device jams.

These techniques can be implemented in the DPM or a DVFS scheduler. Nevertheless, we underline the need to utilize these QoS techniques at a more global view, not only at CPU level. We have not quantified here the potential gain for each technique, but the result seems to be strongly application dependant.

5 Experimental Results

We have built a Power Estimator (PE) to simulate the whole node power/energy consumption. The PE is built with Labview from National Instruments. The complete PE description and the simulation process are detailed in [16]. Each component model is characterized from physical measures by applying the FLPA methodology [17].

For this experiment, we measure the relevance of a prototype deployment, by estimating its autonomy in various towns. We use a nominal scenario from the CAPNET project. The scenario is called “Fire Services - Container Boilover”. It integrates toxic gas spread detection and human intrusion in the secure perimeter.

The scenario hypotheses for a 7 day duration are:

- Intrusion (both) Sensors: 20 activation each day, duration: 120 seconds, 140 total.
- Gas Sensor OLTC 50 activity: every 15 minutes, 15 second duration, 2016 total.
- Gas Sensor OLTC 80 activity: every 15 minutes, 15 second duration, 2016 total.
- WFs enhancements disabled (static weather – no predictive DPM).
- Weather data in winter from February 09 2011 10:00 GMT to February 17 2011 01:00 GMT for nine cities of France: {Brest, Lorient, Rennes, Dunkerque, Lille, Metz, Strasbourg, Aurillac, and Nice}.

The PE is setup with components listed in Table 1, and the local weather. Then, the simulation is run. Table 1 shows the energy and power consumption results independently from recharge. Results are grouped by components. The average total power consumption is 716 mW, battery duration is near 1.18 days for the 2Ah battery.

Table 1. CAPNET Node Power Consumption

Components	Type	Min (mW)	Max (mW)	Avg. (mW)	%
Concertina	Sensor 1	355.66	393.38	368.84	51.54
Miwi 1	Radio 1	115.5	181.5	115.92	16.2
OLTC 50	Gas sensor 1	0	1074.6	72.458	10.13
OLTC 80	Gas sensor 2	0	884.51	58.216	8.135
MT48T35AV	RAM	0	150	26.326	3.679
LM3100	DCDC	25.84	55.03	25.928	3.623
Mygale	Sensor 2	0	583.49	19.268	2.693
MAX618	DCDC	0	93.446	10.822	1.512
PIC24F	CPU	0	52.8	9.2664	1.295
LM3100	DCDC	0	84.023	6.0276	0.8423
LM3100	DCDC	0	12.627	2.2161	0.3097
µCAM	Video	0	305	0.21	0.029
Miwi 2	Radio 2	0	181.5	0.0834	0.0116
Total Sensors				519	72.58
Total Radios				116	16.23
Total DCDC				45	6.3
Total RAM				26	3.63
Total CPU				9	1.26

By studying Table 1, we can find the blocking elements. In this WSN application, the first surprise comes from the PIC which should not impact the consumption with **1.26%**. We have also noticed that the RAM should have a low **3.63%** consumption due to their idle mode. The DC/DC converters have a high efficiency ratio so their impact depends more on the connected devices. They are proportionally constant with **6.3%**. The Radio1 is not negligible here: it affects **16.23%** of the consumption due to permanent listening. The radio analysis part is left to a partner laboratory, thus we do not go into detail here. The highest consuming element (i) is the professional Sensor 1 with **369mW**, besides all sensors cumulated reach **72.58%** of the total consumption. This is explained by analysis of the DPM whose Sensor1 runtime is permanently on. This limitation cannot be addressed easily because the monitoring requires constant listening and depends more on manufacturer technology. Currently, some manufacturers do not provide low power equipment; however it would be of interest to encourage most of them to follow this direction.

The next simulation runs are executed sequentially for each city. In Table 2, we report the battery autonomy results in days.

Table 2. Deployment in various localizations

Localization	No Recharge Reference	Autonomy with Solar energy	Autonomy with Wind energy	Autonomy Solar + wind
Brest	1.18	7	7	7
Lorient	1.18	7	7	7
Rennes	1.18	6.71	7	7
Dunkerque	1.18	5.78	7	7
Lille	1.18	5.5	6.8	7
Metz	1.18	4.74	4.05	7
Strasbourg	1.18	7	1.18	7
Aurillac	1.18	6.65	1.18	6.65
Nice	1.18	7	1.24	7

By examining the results, we remarked that with the nominal 2Ah battery, the node autonomy is 1.18 days without any recharge (ii). With the Solar-10W harvester, we expect sunset exposure which nearly depends on latitudes like those given by PVGIS. However here, Strasbourg is the exception which proves the rule. Finally, the solar harvesting approach even without too much irradiance greatly extends the autonomy beyond the worst reference case (iii).

The results of the Rutland 504 wind harvester particularly correlate with the average dominant wind speed expected in these regions. Detailed battery curves clearly show that recharge is very fast. This is particularly true because of the Rutland is over-scaled for the needs (iii) and really suffers from the minimal speed start point.

When cumulating both solar and wind harvesters, all the cities, except Aurillac, recharge for the required 7 days of simulation. Thus, finally the PE certifies the battery autonomy of 2Ah will be sufficient for the deployment location (iv).

Finally for the CAPNET project, the PE has helped to identify power limitations:

(i) the highest power consumption components.
(ii) the worst-case autonomy duration.
(iii) the harvesters scale for the energy demand.
(iv) the battery autonomy for a given scenario and location.

Thus, the PE has provided clues to validate the battery scaling depending on weather condition and location.

6 Conclusion

In this paper, we have underlined the lack of a design tool which provides a global power consumption view during the design stage. It is essential for validating WSN designs to study the weather availability impact in the deployed location. To do that, we have proposed a simulator able to integrate Weather Forecasts DPM in order to provide better energy management.

Experimental results show that the Power Estimator has been able to identify the most power consuming hot-spots, and it helps to calibrate the WSN to fit its requirements in terms of system scaling and autonomy. This contribution improves WSN design and can be reuse for other WSN. We conclude in the interest to focus at design dynamically over the blocking element. For example MCU power consumption still not required to be more optimized compared to some industrial sensors.

As future work, we will want to experiment more deeply the WF-DPM to evaluate the predictive WF energy gain.

Acknowledgments. We would like to thank the CAPNET project partners. Fire Service partners: SDIS29 (Service Départemental d'Incendie et de Secours du Finistère). Industrial partners: ERYMA Security Systems (Leader), DeltaDore, AtlanticRF. Academics partners: I.E.T.R Rennes, Lab-STICC Lorient. Financial pole: "Pôle Image et Réseaux", "Conseil Général du Morbihan", "Région Bretagne", and "Ministère Français de l'Economie de l'Industrie et de l'Emploi". Proofreader: Joanna Ropers.

References

1. Chandrakasan, A.P., Brodersen, R.W.: Low Power Digital CMOS Design. Kluwer Academic Publishers, Dordrecht (1995) ISBN, 0-7923-9576-X
2. Schmitz, M.T., Al-Hashimi, B.M., Eles, P.: System-Level Design Techniques for Energy-Efficient Embedded Systems. Kluwer Academic Publishers, Dordrecht (2004) ISBN, 1-4020-7750-5
3. Pedram, M., Rabaey, J.: Power-Aware Design Methodologies. Kluwer Academic Publishers, Dordrecht (2002) ISBN, 1-4020-7152-3
4. http://en.wikipedia.org/wiki/List_of_wireless_sensor_nodes
5. Chee, Y., Koplow, M., Mark, M., Pletcher, N., Seeman, M., Burghardt, F., Steingart, D., Rabaey, J., Wright, P., Sanders, S.: PicoCube: A 1cm3 Sensor Node Powered by Harvested Energy. In: DAC (2008)
6. Raghunathan, V., Kansal, A., Hsu, J., Friedman, J., Srivastava, M.: Design Considerations for Solar Energy Harvesting Wireless. In: IPSN (2005)
7. Jiang, X., Polastre, J., Culler, D.: Perpetual Environmentally Powered Sensor Networks. In: IPSN (2005)
8. Simjee, F.I., Chou, P.H.: Everlast: Longlife Supercapacitor-operated wireless Sensor Node. In: ISLPED (2006)
9. Chen, M., Rincón-Mora, G.A.: Single Inductor, Multiple Input, Multiple Output (SIMIMO) Power Mixer-Charger-Supply System. In: ISLPED (2007)

10. Park, C., Chou, P.H.: AmbiMax: Autonomous Energy Harvesting Platform for Multi-Supply Wireless Sensor Node. In: IEEE SECON (2006)
11. http://www.meteociel.fr/ (last visited May 25, 2011)
12. http://re.jrc.ec.europa.eu/pvgis/ (last visited May 25, 2011)
13. Lorentz, E.: The essence of chaos. The Jessie and John Danz Lecture Series. University of Washington Press (1993) ISBN 0-295 97514-8
14. Benini, L., Bruni, D., Macii, A., Macii, E., Poncino, M.: Discharge Current Steering for Battery Lifetime Optimization. IEEE Transactions on Computers 52(8) (2003)
15. Erdinc, O., Vural, B., Uzunoglu, M.: A dynamic lithium-ion battery model considering the effects of temperature and capacity fading. In: International Conference on Clean Electrical Power, p. 383 (2009)
16. Ferry, N., Ducloyer, S., Julien, N., Jutel, D.: Power/Energy Estimator for Designing WSN Nodes with Ambient Energy Harvesting Feature. EURASIP Journal on Embedded Systems 2011 (2011)
17. Laurent, J., Senn, E., Julien, N., Martin, E.: Functional Level Power Analysis: An Efficient Approach for Modeling the Power Consumption of Complex Processors. In: DATE (2004)