



Dynamic Power Management in a Wireless Sensor Network using Predictive Control

Olesia Mokrenko, Suzanne Lesecq, Warody Lombardi, Diego Puschini,
Carolina Albea-Sanchez, Olivier Debicki

► To cite this version:

Olesia Mokrenko, Suzanne Lesecq, Warody Lombardi, Diego Puschini, Carolina Albea-Sanchez, et al..
Dynamic Power Management in a Wireless Sensor Network using Predictive Control. 40th Annual
Conference of the IEEE Industrial Electronics Society, Oct 2014, Dallas, United States. hal-01089234

HAL Id: hal-01089234

<https://hal.science/hal-01089234>

Submitted on 1 Dec 2014

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Dynamic Power Management in a Wireless Sensor Network using Predictive Control

Olesia Mokrenko¹, Suzanne Lesecq¹, Warody Lombardi¹, Diego Puschini¹, Carolina Albea²
and Olivier Debicki¹

Abstract—Technological advances have made wireless sensor nodes cheap and reliable enough to be brought into various application domains. These nodes are powered by battery, thus they have a limited lifespan which is a major drawback for their acceptance. This paper addresses a power consumption control problem of wireless nodes equipped with batteries. Dynamic power management is used to dynamically re-configure the set of sensor nodes in order to provide given service and performance levels with a minimum number of active nodes and/or a minimum load on such components. The power control formulation is based on model predictive control with constraints and binary optimization variables, leading to a mixed integer quadratic programming problem. Simulations are performed to demonstrate the efficiency of the proposed control method.

I. INTRODUCTION

Wireless sensor networks (WSN) are usually made of low-power, low-cost, and energy-constrained sensor nodes (SNs) that are deployed to sense a physical phenomenon of interest. The data are collected by access points. From the collected data, an application is built to monitor and/or control the physical world. In both situations, the nodes can be dedicated to specific roles, namely, sensing, actuation and control, or to any combination of the three main roles. Whatever the assigned functionality is, the node embeds processing capability associated with memory capacity, both possibly limited.

In the literature, the SNs are typically split in four main subsystems (SSs) [1] (see Fig. 1):

- the *communication subsystem* connects the sensor node (SN) to the global architecture in order to send/receive information;
- the *computing subsystem* contains a processing element (for example, a micro-controller unit (MCU)) together with its associated memory;
- the *sensing subsystem* senses physical variables. It can contains several sensors with their adapter (for example, a analog-to-digital converter (ADC)) (when mandatory);
- the *power supply subsystem* that contains the battery used by all the subsystems described above.

Most of the wireless SNs are powered by batteries. This is very convenient from a deployment point of view because no

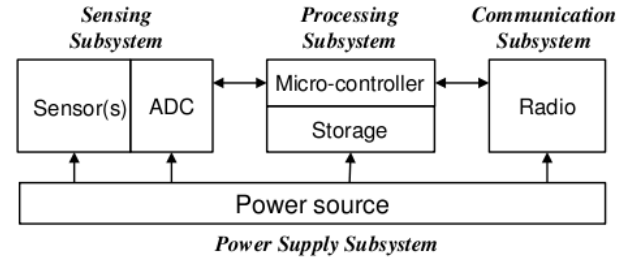


Fig. 1: Functional subsystems of a wireless sensor node

plug is needed by the node. However, the limited available energy makes the node lifespan a tremendous drawback of the wireless node technologies. Moreover, this limited energy may influence the robustness and/or reliability of the monitoring and/or control application built on top of the WSN. As a consequence, nodes have to be designed with stringent power/energy consumption constraints [1] in order to increase the node lifespan. [2] proposes a survey of various approaches that can be implemented in order to increase the WSN lifespan. The authors consider the sensing and communication subsystems. They split the possible approaches in three families, namely: duty cycling, data driven and mobility, for the node energy conservation. The experiment is conducted using TelosB [3] nodes.

Even if each subsystem in the sensor node is designed with power efficiency objectives, their association does not necessarily lead to a low-power SN. Consequently, a power/energy management policy for the whole SN is mandatory.

The ability to enable and disable SNs as well as to adapt their performance to the workload, is key to achieve energy efficient functioning of the whole sensor network. Dynamic Power Management (DPM) is proposed here to dynamically re-configure a WSN in order to provide the requested services and performance levels with a minimum number of active SNs and/or a minimum load on the nodes. DPM is used in the System-on-Chip (SoC) area. It encompasses a set of techniques that achieve energy-efficient computation by selectively turning off or reducing the performance of the system components when they are idle (or partially unexploited). The fundamental premise for the DPM applicability is that systems (and their components) experience non-uniform workloads during the operation time. This assumption is valid for most systems, both when considered in isolation (e.g. SoC platform) and when connected via a network (e.g. a set of SNs). A second assumption of

¹O. Mokrenko, S. Lesecq, W. Lombardi, D. Puschini and O. Debicki are with Univ. Grenoble Alpes, F-38000 Grenoble, France and CEA, LETI, MINATEC Campus, F-38054 Grenoble, France {FirstName.LastName}@cea.fr

²C. Albea is with CNRS, LAAS, 7 avenue du Colonel Roche, F-31400 Toulouse, France and Univ. of Toulouse, UPS, LAAS, F-31400, Toulouse, France calbea@laas.fr

DPM is that it is possible to predict, with a certain degree of confidence, the workload fluctuations. Note that when “energy-hungry” sensors [4] are embedded in the nodes, an efficient DPM must be implemented in order to have an optimal overall energy. This global power management policy is certainly a more complex problem than the one dedicated to a single node because, in essence, the WSN is spatially distributed, usually with a clock frequency in each node that is not (properly) synchronized with the other ones.

The present paper addresses DPM at the WSN level. The objective is to provide for the WSN a given service (hereafter named “mission”) while the lifespan is extended, the power consumption within the network being minimized. The mission is expressed as a set of constraints on the different functioning modes of each SN.

Related work

Power management at the WSN level has already been addressed in the literature in order to increase the node lifespan, see for instance [5], [1]. This latter shows that trade-off mechanisms that give the end-user the option of prolonging the network lifetime at the cost of lower throughput or higher transmission delay, can be implemented. The kinds of mechanisms are not discussed in the present paper, but they might be added to the proposed control. There, Model Predictive Control (MPC) seems an appropriate technique, as it is based on an optimal control policy applied by predicting the behavior of the system over a receding horizon [6]. Due to its characteristics, MPC can handle constraints [7] during the design phase while being applied to linear Single-Input-Single-Output (SISO) and Multiple-Input-Multiple-Output (MIMO) systems [8], [9], nonlinear [10], [11] and hybrid systems [12], [13]. This last class of systems can describe continuous (and sampled) states (real-set variables), discrete and state-machine states (integer-set variables) and logic rules (binary-set variables) [14]. It is solved as a *mixed integer program* (MIP).

A similar problem is considered in the literature using the Fault-Tolerant Control (FTC) paradigm [15]. In this present paper, MPC can handle FTC schemes by changing the constraints or by considering different models in a switched framework. Fault Detection and Isolation (FDI) can be used in a receding horizon strategy, in order to identify parameters and thus determine if the data obtained is consistent with the established model. In this sense, FDI involves deciding if the system works as expected, i.e. if all the components (sensors, actuators, controllers) behave satisfactorily. This decision is generally taken by processing input/output data, and FDI strategies should be able to detect a fault and eventually isolate it. Once the fault is detected, a control reconfiguration can occur in order to guarantee stability and avoid performance degradation.

Power control in a WSN using multiple-description coding is addressed in [16] whose main contribution is to investigate the role of dynamic power control and coding when state estimation is considered. The control objective is to counteract the channel variability (i.e. ensure Quality of Service (QoS))

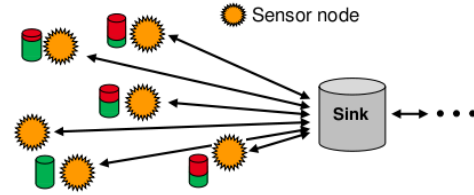


Fig. 2: Single-hop heterogeneous sensor network architecture

and achieve a compromise between the battery use and the estimation accuracy. The controller is located in a gateway. It decides upon the transmission power level and the coding scheme to be used by each node. However, satisfying the QoS does not guarantee that the “mission”, as defined here, is satisfied.

The paper is organized as follows. Section II is first dedicated to the system modeling. Then the control objectives are provided. The control design is developed in section III. It is based on Constrained Predictive Control techniques, with bounded states, equality and inequality constraints and binary control values. Section IV implements the proposed control on a realistic benchmark. Conclusion and future work are provided in section V.

II. SYSTEM MODELING AND CONTROL OBJECTIVES

Consider a WSN that contains $n \in \mathbb{N}$ nodes S_i , $i = 1, \dots, n$, powered by batteries. The nodes are supposed heterogeneous, i.e. their hardware can differ, some nodes possibly embedding more computational capabilities than other ones, leading to different roles in the network. Moreover, their battery characteristics can be different. The communication is supposed to be single-hop clustered [17]: each SN sends its data to a specific node called “sink” which is responsible for the monitoring and control of the area connected by the SNs and/or for interconnecting to a Wide Area Network such as the Internet. This sink chooses the working mode of the nodes thanks to a strategy presented hereafter. The topology considered is depicted in Fig. 2.

Each SN can be placed in different functioning modes M_j , $j = 1, \dots, m$, $m \in \mathbb{N}$, which are related to the states (on, sleep, off, etc.) of each SN subsystem, characterized by a known average power consumption for a given period of time. Here, the nodes are supposed to provide redundant information. Therefore, in order to achieve a given service, only a subset of the SNs is absolutely mandatory. Thus, if one selects properly the mode of the nodes, power savings can be achieved. In other words, most of the devices can be placed in sleep mode, while the other ones are active (i.e. sending and/or transmitting information).

In order to control energy savings in the WSN, the remaining energy in the nodes is modeled with a discrete-time linear time-invariant (LTI) state-space system:

$$x_{k+1} = Ax_k + Bu_k \quad (1)$$

where $x_k \in \mathbb{R}^{n,+}$ is the remaining energy in the battery of node S_i , $i = 1, \dots, n$, at instant k . Bu_k represents the

TABLE I: Average energy consumption for each SN S_i in the different modes M_j over the certain time period T_{PW}

Sensor node	Mode M_1	Mode M_2	...	Mode M_m	
S_1	b_{11}	b_{12}	...	b_{1m}	$= B_1$
\vdots	\vdots	\vdots	\ddots	\vdots	\vdots
S_n	b_{n1}	b_{n2}	...	b_{nm}	$= B_n$

averaged energy that will be used during the time interval $[T_{PW}k, T_{PW}(k+1)]$, where T_{PW} is the decision period (i.e. the time period when the power control is run). The battery has a bounded capacity. Thus, for node S_i :

$$0 \leq x^i \leq X_{max}^i \quad (2)$$

The initial battery charge (i.e. at instant $k = 0$) for S_i is denoted X_0^i . The state matrix $A \in \mathbb{R}^{n \times n}$ is equal to the identity matrix \mathbf{I}_n while $u_k = [u_1^T, \dots, u_n^T]^T \in \{0, 1\}^{nm}$ is the control with $u_i\{j\} \in \{0, 1\}$. Each sub-vector u_i represents the mode of S_i .

The SN S_i has a unique working mode at instant k . Therefore, for $i = 1, \dots, n$, a set of constraints has to be defined at each instant k :

$$\sum_{j=1}^m u_i\{j\} = 1 \quad (3)$$

Matrix $B = \text{diag}[-B_1, \dots, -B_n] \in \mathbb{R}^{n \times nm}$ in Eq. (1) is interpreted as the control matrix. Each component b_{ij} represents the amount of energy averaged over T_{PW} consumed by the SN S_i , when it works in mode M_j during the time interval $[T_{PW}k, T_{PW}(k+1)]$ (see Table I). Note that a change from one mode to another has an extra energy cost that is supposed to be integrated in b_{ij} in this paper.

In order to fulfill a "mission" while decreasing the power consumption, a subset of $d_j \in \mathbb{N}$ SNs is assigned to a given mode M_j . Thus an extra set of constraints is defined:

$$\sum_{i=1}^n u_i\{j\} = d_j \quad (4)$$

Control objectives

A dynamic energy saving control policy has to be implemented at the WSN level in order to increase its lifespan while guaranteeing adequate performance levels expressed as a *mission*. The capability to fulfill a *mission* is related to the WSN QoS. However, it imposes extra functional constraints to the WSN. As indicated above, the control variable u_k takes its values in $\{0, 1\}$. It fixes the functioning mode of each node under constraints (3) (meaning that each mode is in a unique mode) and (4) that are used to define the *mission*. For instance, in a network of n SNs that deliver strongly correlated information, the whole system power consumption can be decreased if the nodes are properly managed in order to provide just enough information for the application to be performed "properly". Broadly speaking, this means that the application requires $N_{on} < N$ nodes that communicate while $N - N_{on}$ nodes can be set in the *Sleep* mode that consumes less energy than the *On* mode.

III. CONTROL DESIGN

The power consumption minimization of (1) can be presented as a Quadratic Programming (QP) problem. Constrained Predictive Control implies the resolution of this problem via the minimization of a cost function using a finite number of finite-dimensional positive definite Quadratic Problems. The constrained QP does not feature the undesirable mismatch between the open-loop and closed-loop nominal system trajectories, which is presented in the other popular forms of MPC that can be implemented with a finite QP algorithm.

Recently, the interest in using MPC for controlling systems that involve a mix of real-valued dynamics and logical rules has arisen [12], [14]. Unfortunately, when this problem is formulated as an optimization one, the resulting description is no longer a QP problem but a Mixed-Integer Quadratic Programming (MIQP) problem. This latter involves optimization variables that can be real values, but also integer values or even binary values, which makes the problem harder to solve than an ordinary QP problem.

It is assumed throughout the rest of the paper that the pair (A, B) of (1) is stabilizable. At each sampling time (i.e. decision time as defined above), the current state (assumed to be available) $x_k = x_{k|k}$ can be used to find the optimal control sequence $\mathbf{u}^* = [u_{k|k}^T, \dots, u_{k+N_p-1|k}^T]^T$ by means of the following minimization problem:

$$\begin{aligned} \mathbf{u}^* = \arg \min_{\mathbf{u}} & \sum_{i=0}^{N_p-1} x_{k+i|k}^T Q x_{k+i|k} + \sum_{i=0}^{N_u-1} u_{k+i|k}^T R u_{k+i|k} \\ \text{subject to:} & \begin{cases} x_{k+i+1|k} = A x_{k+i|k} + B u_{k+i|k}, & i = 1, \dots, N_p - 1 \\ u_{k+i|k} = 0, & i = N_u, N_u + 1, \dots, N_p - 1 \\ u_{k+i|k} \in \{0, 1\} \\ X_{min} \leq x_{k+i|k} \leq X_{max}, & i = 1, \dots, N_p - 1 \end{cases} \end{aligned} \quad (5)$$

where $Q = Q^T \geq 0$ and $R = R^T > 0$ are weighting matrices, X_{min} and X_{max} are the lower and upper bounds on the state $x_{k+i|k}$, and the pair $(Q^{1/2}, A)$ is detectable. The prediction horizon N_p , the control horizon $N_u \leq N_p$ together with matrices Q and R are the degrees of freedom of the control design methodology.

By compacting the states involved in the optimization problem (5) as $\mathbf{x} = [x_{k+1|k}^T, \dots, x_{k+N_p|k}^T]^T$ and denoting $x_{k|k} = x$, the cost function is rewritten in a matrix form as:

$$\begin{aligned} \arg \min_{\mathbf{u}} & \mathbf{x}^T \bar{Q} \mathbf{x} + \mathbf{u}^T \bar{R} \mathbf{u} \\ \text{subject to:} & \begin{cases} \mathbf{u} \in \{0, 1\} \\ \bar{F}_{in_x} \mathbf{x} \leq \bar{G}_{in_x} \\ \bar{F}_{eq_u} \mathbf{u} = \bar{G}_{eq_u} \end{cases} \end{aligned} \quad (6)$$

where $\bar{Q} = \text{diag}[Q, \dots, Q]$, $\bar{R} = \text{diag}[R, \dots, R]$. The inequality and equality constraints are fully described by $\bar{F}_{in_x} \in \mathbb{R}^{s \times n}$, $\bar{G}_{in_x} \in \mathbb{R}^s$, $\bar{F}_{eq_u} \in \mathbb{R}^{p \times r}$ and $\bar{G}_{eq_u} \in \mathbb{R}^p$, $p = (N_p - N_u)nm$, $r = N_pnm$, $s = N_pq$ that express the constraints (2), (3) and (4) on $x_{k|k}$ and $u_{k|k} \forall k$, respectively.

System (1) can now be extended in a compact matrix form:

$$\mathbf{x} = \Phi \mathbf{x} + \Gamma \mathbf{u}$$

$$\Phi = \begin{bmatrix} A \\ A^2 \\ \vdots \\ A^{N_p} \end{bmatrix}, \Gamma = \begin{bmatrix} B & 0 & \cdots & 0 \\ AB & B & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{N_p-1} & A^{N_p-2} & \cdots & A^{N_p-N_u} \end{bmatrix} \quad (7)$$

Then (6) is given as a MIQP (see e.g. [9])

$$\arg \min_{\mathbf{u}} \mathbf{u}^T H \mathbf{u} + 2\mathbf{u}^T F x$$

$$\text{subject to: } \begin{cases} \mathbf{u} \in \{0, 1\} \\ \bar{F}_{in_x} \Gamma \mathbf{u} \leq \bar{G}_{in_x} - \bar{F}_{in_x} \Phi x \\ \bar{F}_{equ} \mathbf{u} = \bar{G}_{equ} \end{cases} \quad (8)$$

where

$$H = \Gamma^T \bar{Q} \Gamma + \bar{R}, F = \Gamma \bar{Q} \Phi \quad (9)$$

It is worth mentioning that the the control designer has to choose of the weighting matrices Q and R and the prediction N_p and control N_u horizon.

IV. APPLICATION

To show the effectiveness of the proposed strategy, a benchmark with $n = 6$ SNs S_i and one sink is considered in simulation¹. At instant k , the SN S_i , $i = 1, \dots, 6$, can be in a unique mode among 3 possible ones M_j , $j = 1, \dots, 3$ (see Table II):

- M_1 is the standard *On* mode. In this mode, the node acquires measurements. It has transmission/reception capabilities. It can also process data and it monitors its battery. Fig. 3 shows the typical current consumption of a SN working in M_1 mode. The waveform corresponds to a wireless SN application cycle: the node awakes from the Sleep state. Then, it goes to Rx state, waiting for a beacon. It collects data and prepares the data packets to be transmitted. Then, the packet is sent to the sink. On the figure, one can see the dependence of the current consumption on the state of each node subsystem. Channels number one and two correspond to the transmission and reception current consumption of the Communication SS, respectively. The fourth channel represents the MCU/Sensor(s) current consumption (Processing and Sensing SSs). The third channel corresponds to the total SN current consumption;
- M_2 corresponds to a *Sleep* mode. In this mode, the SN uses the internal oscillator for lower power consumption (Real Time Clock). When the node awakes the clock is switched to a high frequency oscillator for faster operations but also with a higher power consumption;
- M_3 corresponds to the SN in the *total Switch off* state. In practice, this mode is equivalent to a faulty situation, e.g. the node battery is completely drained, the sink cannot reach the node, etc. Note that the node can exit M_3 for instance when it has enough energy to be placed in M_1 , or when the sink can access it again.

TABLE II: Functioning modes for sensor node S_i

Modes	Processing SS	Communication SS	Sensing SS
M_1	Active	Tx / Rx	On
M_2	Sleep	Off	Off
M_3	Off	Off	Off

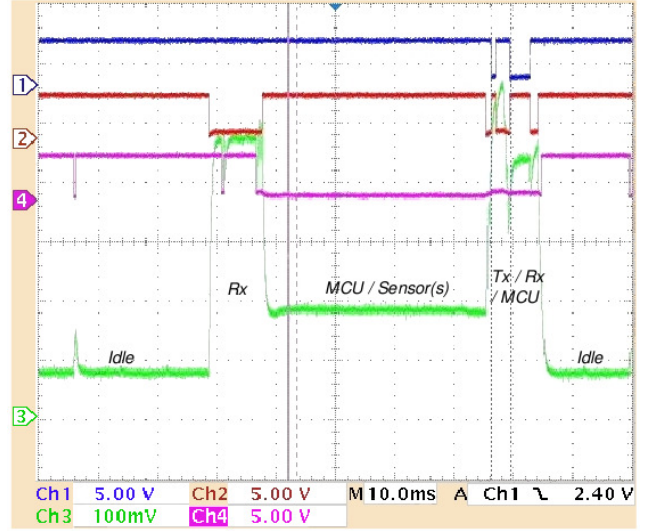


Fig. 3: Excerpt of the waveforms of a typical cycle for a wireless sensor node working in mode M_1 (current consumption)

In the present scenario, the mission is split in two phases corresponding respectively to daytime and night period of time. Therefore, the constraints that define the mission have to be dynamically changed, depending on the time schedule and two constraints (4) define the *dynamic mission*:

$$\begin{aligned} \text{day (8am - 6pm)} : d_1 &= 3 \quad (3 \text{ nodes in } M_1) \\ \text{night (6pm - 8am)} : d_1 &= 1 \quad (\text{a unique node in } M_1) \end{aligned} \quad (10)$$

The sampling period associated to the SNs is $T_s = 60s$. Thus, data collected from sensors in M_1 are every minute. Note that the nodes in mode M_1 perform the reception, measurement, computing and transmission functionalities every minute. The SNs that are not in mode M_1 are placed in M_2 . All the SNs in mode M_2 have to wake up every hour. This latter corresponds to the period $T_{mb} = 1h$ associated with the monitoring of the battery remaining capacity. The remaining energy is sent to the sink. Note that this is in fact a measurement phase with $y_k = x_k$. M_3 corresponds to a faulty situation is imposed when $\frac{X_0^i}{X_{max}^i} \leq \delta$. This corresponds to the situation when the node battery is nearly fully drained.

Assume at k_0 , the node batteries have enough energy so that any node S_i can fulfill the *mission* (i.e. being in M_1). Therefore, during the day (resp. night) period, three (resp. one) nodes are placed in mode M_1 while the 3 (resp. 5) other nodes are placed in M_2 . As soon as the battery capacity of a SN, say sensor S_f , is lower than δ , S_f falls

¹Note the control approach has been developed for $n \in \mathbb{N}$ nodes, see the previous section.

TABLE III: Average current consumption ($mA \cdot h$) of sensor node S_i in the functioning mode M_j over the period T_{mb}

Sensor node	Mode M_1	Mode M_2	Mode M_3
S_1	6.56	0.92	0
S_2	8.72	1.11	0
S_3	7.75	1.08	0
S_4	9.43	1.26	0
S_5	7.54	1.29	0
S_6	7.20	1.03	0

TABLE IV: Sensor node battery characteristics (each sensor node embeds two AA batteries)

Sensor node	Battery Type	Nominal Voltage [V]	Battery capacity $X_{max}^i/2$ [mA·h]	Initial battery capacity $\frac{X_0^i}{X_{max}^i}$
S_1	NiCd	1.2	1100	1
S_2	NiCd	1.2	1100	0.8
S_3	NiMH	1.2	2500	1
S_4	NiMH	1.2	2500	0.7
S_5	Li-ion	3.7	740	0.9
S_6	Li-ion	3.7	740	1

in mode M_3 . Then, the control law assigns a new mode to the remaining nodes in order to meet the dynamic mission while minimizing the energy consumption of the sensor network. Actually, the set of constraints is modified because $u_f(3) = 1$. Hereafter, $\delta = 0.1$ is chosen.

For the system (1), $A = \mathbf{I}_6$ while the components of matrix B are calculated from the values given in Table III, multiplied by battery nominal voltage value of the corresponding SN (see Table IV where the battery characteristics associated to each node are provided). Note that the numerical values are derived from [18]. Table IV also provides the initial capacity of the batteries associated with each SN. These latter numerical values are obtained from [19].

The weighting matrices Q and R that appear in the definitions of \bar{Q} and \bar{R} in (9) are chosen equal to:

$$Q = \mathbf{0}_{6 \times 6}; \quad R = B^T B \quad (11)$$

where $\mathbf{0}$ is the null matrix with appropriate dimension. The choice $Q = \mathbf{0}_{6 \times 6}$ roots in the fact that the state dynamics should evolve as slowly as possible [20]. The choice of R implies that the nodes with bigger energy consumption are more penalized.

From (2), the inequality constraints become:

$$\underbrace{\begin{bmatrix} \mathbf{I}_6 \\ -\mathbf{I}_6 \end{bmatrix}}_{F_{in_x}} \begin{bmatrix} x_1 \\ \vdots \\ x_6 \end{bmatrix} \leq \underbrace{\begin{bmatrix} X_{max}^1 & \cdots & X_{max}^6 & 0 & \cdots & 0 \end{bmatrix}^T}_{G_{in_x}} \quad (12)$$

while the equality constraints (3) and (4) are defined as:

$$\underbrace{\begin{bmatrix} 1 & 1 & 1 & \cdots & 0 \\ \vdots & \ddots & \vdots & & \\ 0 & \cdots & 1 & 1 & 1 \end{bmatrix}}_{F_{equ}^1} \begin{bmatrix} u_1\{j\} \\ \vdots \\ u_6\{j\} \end{bmatrix} = \underbrace{\begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix}}_{G_{equ}^1} \quad (13)$$

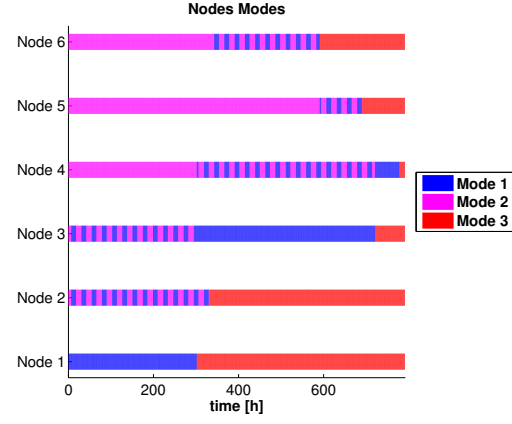


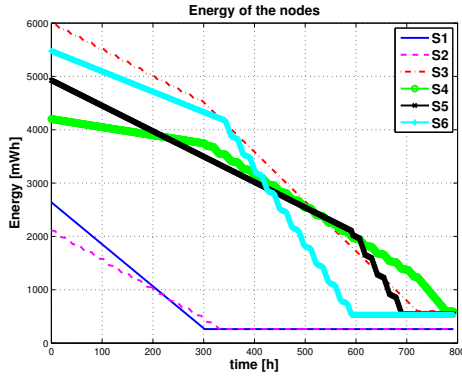
Fig. 4: Functioning modes of sensor nodes vs. time with DPM (simulation started at midnight)

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 & \cdots & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & \cdots & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & \cdots & 0 & 0 & 1 \end{bmatrix}}_{F_{equ}^2} \begin{bmatrix} u_1\{j\} \\ \vdots \\ u_6\{j\} \end{bmatrix} = \underbrace{\begin{bmatrix} a \\ b \\ c \end{bmatrix}}_{G_{equ}^2} \quad (14)$$

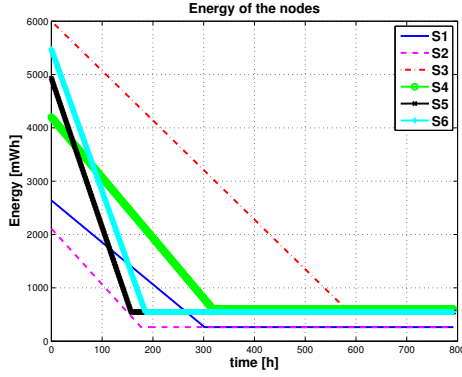
where a and b correspond to the number of nodes in modes M_1 and M_2 , respectively. During daytime $a = 3$ and at night $a = 1$ (see (10)). c corresponds to the number of nodes fallen in mode M_3 with $c = n - a - b$. The other matrices are defined as follows: $F_{equ} = [F_{equ}^1 \ F_{equ}^2]^T$; $G_{equ} = [G_{equ}^1 \ G_{equ}^2]^T$; $\bar{F}_{equ} = \text{diag}[F_{equ}, \dots, F_{equ}]$; $\bar{G}_{equ} = \text{diag}[G_{equ}, \dots, G_{equ}]$; $\bar{F}_{in_x} = \text{diag}[F_{in_x}, \dots, F_{in_x}]$; $\bar{G}_{in_x} = \text{diag}[G_{in_x}, \dots, G_{in_x}]$. The prediction horizon is chosen $N_p = 5$ and the control horizon is $N_u = 1$. As the considered system presents slow dynamics, this horizon seems sufficient enough. The decision period (i.e. the time period when the power control is run) is $T_{PW} = T_{mb} = 1h$. Thus, the MIQP problem is solved on-line at each decision time $T_{PW}k$.

The power control of the SNs at network level is simulated in the MATLAB environment. The MIQP problem is solved with Yalmip [21]. Fig. 4 provides simulation results. One can see the evolution of the number of SNs: it depends on the daytime/night condition and on the battery conditions.

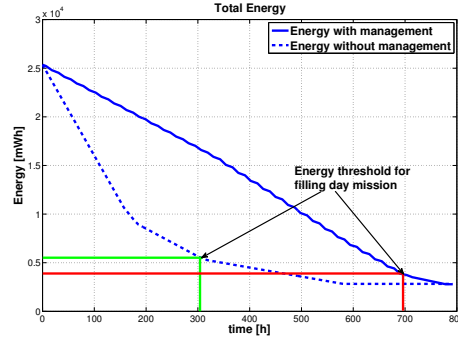
The battery energy state of the SNs is shown when the control of the whole network is implemented in Fig. 5a. Fig. 5b shows the energy in the battery nodes in the usual situation, i.e. when all nodes are in the *On* state during the whole period of simulation. Note that in the first situation with “daytime/night” conditions, the mission can be extended up to 691 hours. This lifespan is highly extended more than 2x because un-useful nodes are in sleep mode. In the case the Dynamic Power Management at network level is not implemented, the network lifespan is equal to 302 hours. This means that, for this particular scenario, the proposed management method doubles the lifespan. Fig. 5c compares the total energy consumption in both situations (i.e. with and without DPM).



(a) Sensor node energy evolution with DPM



(b) Sensor node energy evolution without DPM



(c) Total energy evolution comparison (with and without DPM)

Fig. 5: Results of the system simulation

V. CONCLUSIONS AND FUTURE WORK

In this paper, dynamic power management of SNs at network level via MPC has been proposed. The energy in the SN batteries is modeled using a state-space representation. The control is solved using a MIQP approach. The objectives for the dynamic power control are expressed as a *mission* that defines a minimum number of active SNs to attain performance levels. In this way, only the sensors that are mandatory to fulfill the mission are in *On* mode while the other ones are placed in *Sleep* mode. In this way, the lifespan of WSN is extended. Experiments in simulation for $n = 6$ SNs have been conducted. The results are promising and

can be extended to a larger number of SNs depending the complexity of the MIQP problem to be solved. The DPM method is currently under implementation on a test-bench in order to evaluate in real-life conditions the capability of the proposed control method at network level.

ACKNOWLEDGMENT

This work has been partly funded by the Artemis AR-ROWHEAD project under grant agreement nb. 332987 and by the FP7 SCUBA project under grant agreement nb. 288079.

REFERENCES

- [1] Ian F Akyildiz, Weilian Su, Yogesh Sankarasubramaniam, and Erdal Cayirci. Wireless sensor networks: a survey. *Computer networks*, 2002.
- [2] Giuseppe Anastasi, Marco Conti, Mario Di Francesco, and Andrea Passarella. Energy conservation in wireless sensor networks: A survey. *Ad Hoc Networks*, 2009.
- [3] <http://www.memsic.com>.
- [4] Cesare Alippi, Giuseppe Anastasi, Mario Di Francesco, and Manuel Roveri. Energy management in wireless sensor networks with energy-hungry sensors. *Instrumentation & Measurement Magazine, IEEE*, 2009.
- [5] Jiming Chen, Weiqiang Xu, Shibo He, Youxian Sun, Preetha Thulasiraman, and Xuemin Shen. Utility-based asynchronous flow control algorithm for wireless sensor networks. *Selected Areas in Communications, IEEE Journal on*, 2010.
- [6] María M Seron, Graham C Goodwin, and José A Doná. Characterisation of receding horizon control for constrained linear systems. *Asian Journal of Control*, 2003.
- [7] David Q Mayne, James B Rawlings, Christopher V Rao, and Pierre OM Scokaert. Constrained model predictive control: Stability and optimality. *Automatica*, 2000.
- [8] Eduardo F Camacho and Carlos Bordons Alba. *Model predictive control*. Springer, 2013.
- [9] Jan Marian Maciejowski. *Predictive control: with constraints*. Pearson education, 2002.
- [10] Frank Allgöwer and Alex Zheng. *Nonlinear model predictive control*. Birkhäuser Basel, 2000.
- [11] Frank Allgöwer, Thomas A Badgwell, Joe S Qin, James B Rawlings, and Steven J Wright. Nonlinear predictive control and moving horizon estimation—an introductory overview. In *Advances in control*. 1999.
- [12] Alberto Bemporad and Manfred Morari. Predictive control of constrained hybrid systems. In *Nonlinear model predictive control*. 2000.
- [13] Mircea Lazar. Model predictive control of hybrid systems: Stability and robustness, 2006.
- [14] Alberto Bemporad and Manfred Morari. Control of systems integrating logic, dynamics, and constraints. *Automatica*, 1999.
- [15] Eduardo F Camacho, Teodoro Alamo, and David Muñoz de la Pena. Fault-tolerant model predictive control. In *Emerging Technologies and Factory Automation (ETFA), 2010 IEEE Conference on*.
- [16] Daniel E Quevedo, Jan Ostergaard, and Anders Ahlen. Power control and coding formulation for state estimation with wireless sensors. 2013.
- [17] Vivek Mhatre and Catherine Rosenberg. Homogeneous vs heterogeneous clustered sensor networks: a comparative study. In *IEEE International Conference on Communications*, 2004.
- [18] Nicolas Fourty, Adrien Van Den Bossche, and Thierry Val. An advanced study of energy consumption in an ieee 802.15. 4 based network: Everything but the truth on 802.15. 4 node lifetime. *Computer Communications*, 2012.
- [19] Sujesha Sudevalayam and Purushottam Kulkarni. Energy harvesting sensor nodes: Survey and implications. *Communications Surveys & Tutorials, IEEE*, 2011.
- [20] Robert L Williams, Douglas A Lawrence, et al. *Linear state-space control systems*. John Wiley & Sons, 2007.
- [21] J. Löfberg. Yalmip : A toolbox for modeling and optimization in MATLAB. In *Proceedings of the CACSD Conference*, 2004.