Energy Management in Wireless Sensor Networks with Energy-hungry Sensors

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Abstract

In recent years, the number of wireless sensor network deployments for real life applications has rapidly increased. Still, the energy problem remains one of the major barrier somehow preventing the complete exploitation of this technology. Sensor nodes are typically powered by batteries with a limited lifetime and, even when additional energy can be harvested from the external environment (e.g., through solar cells or piezo-electric mechanisms), it remains a limited resource to be consumed judiciously. Efficient energy management is thus a key requirement for a credible design of a wireless sensor network.

Most energy management strategies proposed in the literature assume that data acquisition consumes significantly less energy than their transmission. Unfortunately, this assumption does not hold in a number of practical applications where the power consumption of the sensing activity may be comparable or even greater than that of the radio. In this context, effective energy management strategies should include policies for an efficient use of energy-hungry sensors, which become one of the main components affecting the network lifetime. In this paper, we survey the main approaches for efficient energy management in sensor networks with energy-hungry sensors.

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1. Introduction

A wireless sensor network (WSN) consists of a large number of tiny *sensor nodes* deployed over a geographical area also referred as *sensing field*; each node is a low-power device that integrates computing, wireless communication and sensing abilities [1][2][3]. Nodes organize themselves in clusters and networks and cooperate to perform an assigned monitoring (and/or control) task without any human intervention at scales (both spatial and temporal) and resolutions that are difficult, if not impossible, to achieve with traditional techniques. Sensor nodes are thus able to sense physical environmental information (e.g., temperature, humidity, vibration, acceleration or whatever required), process locally the acquired data both at unit and cluster level, and send the outcome –or aggregated features- to the cluster and/or one or more collection points, named *sinks* or *base stations* (Figure 1).

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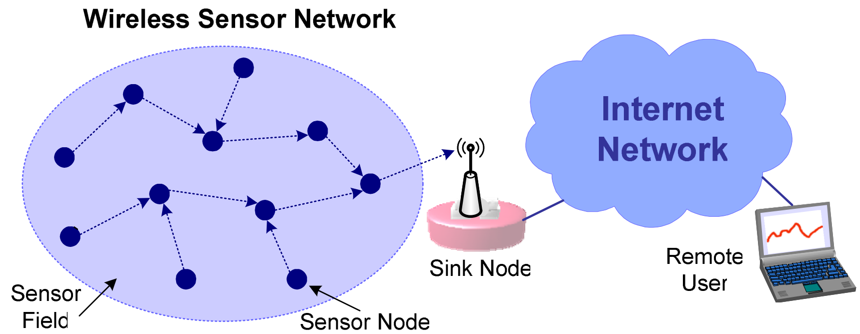

Figure 1. A typical sensor network architecture.

A WSN can thus be viewed as an intelligent distributed measurement technology adequate for many different monitoring and control contexts. In recent years, the number of sensor network deployments for real-life applications e.g., environmental monitoring [4][5][6], agriculture [7][8], production and delivery [9][10], military [11][12], structure monitoring [13] and medical applications [14] has rapidly grown with a trend expected to further increase in the incoming years [15],[16].

However, energy consumption still remains one of the main obstacles to the diffusion of this technology, especially in application scenarios where a long network lifetime and a high quality of service are required. In fact, nodes are generally powered by batteries which have limited capacity and, often, can neither be replaced nor recharged due to environmental constraints. Despite the fact that energy scavenging mechanisms can be adopted to recharge batteries, e.g., through solar panels, piezoelectric or acoustic transducers (the interested reader can refer to [17],[18],[19],[20],[21],[22],[23]), energy is a limited resource and must be used judiciously. Hence, efficient energy management strategies must be devised at sensor nodes (and then at cluster and network level) to prolong the network lifetime as much as possible.

Several energy management schemes have been proposed in the literature (a detailed survey can be found in [24]), most of which assuming that data acquisition and processing have an energy consumption significantly lower than communication; as such, they are targeted at minimizing the radio activity. Only recently, the increasing exploitation of sensor networks for monitoring complex phenomena has highlighted that the above assumption does not hold in many practical application scenarios, mainly due to specific sensors whose power consumption cannot be neglected [25].

Table 1 and Table 2 show the power consumptions of the most popular radio equipments used in sensor nodes and some common off-the-shelf sensors, respectively. If we also consider that acquisition times are typically longer than transmission ones, we can conclude that some sensors may even consume significantly more energy than the radio.

Table 1. Power consumption for some common radios (extending [26])

Radio	Producer	Power Consumption	
		Transmission	Reception
CC2420	Texas Instruments	35 mW (at 0 dBm)	38 mW
CC1000	Texas Instruments	42 mW (at 0 dBm)	29 mW
TR1000	RF Monolithics	36 mW (at 0 dBm)	9 mW
JN-DS- JN513x	Jennic	111mW (at 1 dBm)	111mW

Table 2. Power consumption for some off-the-shelf sensors

Sensor	Producer	Sensing	Power Consumption
STCN75	STM	Temperature	0.4 mW
QST108KT6	STM	Touch	7 mW
SG-LINK (1000Ω)	MicroStrain	Strain gauge	9 mW
SG-LINK (350Ω)	MicroStrain	Strain gauge	24 mW
iMEMS	ADI	Accelerometer (3 axis)	30 mW
2200 Series, 2600 Series	GEMS	Pressure	50 mW
T150	GEFRAN	Humidity	90 mW
LUC-M10	PEPPERL+FUCHS	Level Sensor	300 mW
CP18, VL18, GM60, GLV30	VISOLUX	Proximity	350 mW
TDA0161	STM	Proximity	420 mW
FCS-GL1/2A4-AP8X-H1141	TURCK	Flow Control	1250 mW

Energy management schemes aimed at minimizing the radio activity might be insufficient to fully address the energy savings issue and need to be complemented with (or replaced by) techniques for energy-efficient management at the sensor level. Intuitively, these techniques operate to reduce the number of data acquisitions (i.e., data samples) rather than the number of transmitted messages.

In this paper we classify and review the main approaches proposed for energy management at the sensor level. To complement the approach the interested reader can refer to [24], where strategies for reducing the power consumption acting at the radio level are surveyed. Further energy savings can be obtained by acting at the unit, cluster and network levels, e.g., by considering data compression [27][28] and aggregation [29][30], predictive monitoring [31], topology management [32][33] and adaptive duty cycle [34] to cite the few.

In the next sections we introduce a general framework for energy-efficient data acquisition from sensors. In particular, section 3 provides a taxonomy for adaptive sensing strategies, while sections 4-6 survey the main solutions proposed in the related literature. The concluding section critically discusses the proposed methods and outlines some open research issues.

2. A General Framework for Energy-efficient Sensor Management

Most monitoring applications based on sensor networks rely on a synchronous philosophy where readings are carried out with a given sampling frequency. In such a case two main approaches can be considered to reduce the energy consumed by a sensor, i.e., *duty cycling* and *adaptive sensing*. Duty cycling consists in waking up the sensorial system only for the time needed to acquire a new set of samples and powering it off immediately afterwards. This strategy allows us for optimally managing energy provided that the dynamics of the phenomenon to be monitored are time-invariant and known in advance. Since such hypotheses only partly hold in many applications, periodic sensing is typically considered. Here, the (fixed) sampling rate is computed *a priori*, based on partial available information about the process to be monitored and assuming that the process dynamics are stationary. As a consequence, the sampling rate is larger than necessary (*oversampling*), e.g., 3 to 5 times, inducing, in turn, energy wasting. A better approach would require an adaptive sensing strategy able to dynamically adapt the sensor activity to the real dynamics of the process.

It is obvious that an efficient sensing strategy, by reducing the number of samples, also reduces the amount of data to be processed and -possibly- transmitted to clusters and/or the base station.

Duty cycling and adaptive sensing are complementary approaches that can be used in combination as shown in **Figure 2**.

In detail, the operating system has to provide a set of primitives for powering on and off the sensors to support duty cycle mechanisms. Afterwards, the application uses such primitives to acquire data according to the (adaptive) sensing strategy it implements.

In designing the sensor drivers for the operating system some aspects must be considered to grant an effective handling of the duty-cycle issue: failing in doing that might result in not-valid acquired data, and/or energy dissipation larger than that associated with the always-on mode [35].

In fact, each sensor is characterized by a set of functional characteristics, e.g., *wakeup latency* and *break-even cycle*, impacting on the energy management of the sensor. The wakeup latency is the time required by the sensor to generate a correct value once activated. Clearly, if the sensor reading is performed before the wakeup latency has elapsed, the acquired data is not valid. The break-even cycle is defined as the rate at which the power consumption of a node with a power management policy is equal to that of not power managed node. Such value is in inverse proportion with the power consumption overhead introduced by the non-ideal on/off sensor transition and represents the highest sampling rate for which applying a power management is worth. Moreover, the break-even cycle is not fixed since the energy consumed by the sensor during normal operations and in on-off transitions depends on the supply voltage, which changes over time [35].

Finally, the drivers should be designed by using, at least, information about wakeup latency and break-even cycle for the sensors to provide an effective sensor-specific energy management [35]. Unfortunately, most currently available operating systems for sensor nodes do not follow this philosophy and let the application programmer decide when to power the sensor on and off (manual management). Future operating systems will have to adopt the automated and sensor-specific approach for both relieving the application programmer from manual handling and improving the effectiveness of the duty-cycling mechanism.

The general framework of figure 2 allows the WSN designer for focusing on the selection of the best adaptive sensing strategy leaving low-level duty cycling aspects to the Operating System.

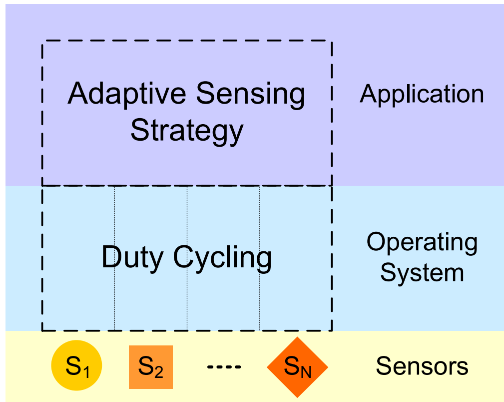

Figure 2. A general framework for sensor energy management.

Survey of the most interesting and novel adaptive sensing strategies will be given in next sections: the philosophy behind each technique is introduced to permit the WSN designer to identify the best adaptive sensing strategy for its application.

3. Taxonomy of Adaptive Sensing Strategies

Figure 3 shows a possible taxonomy, based on the classification given in [25], for the adaptive sensing strategies proposed in the literature.

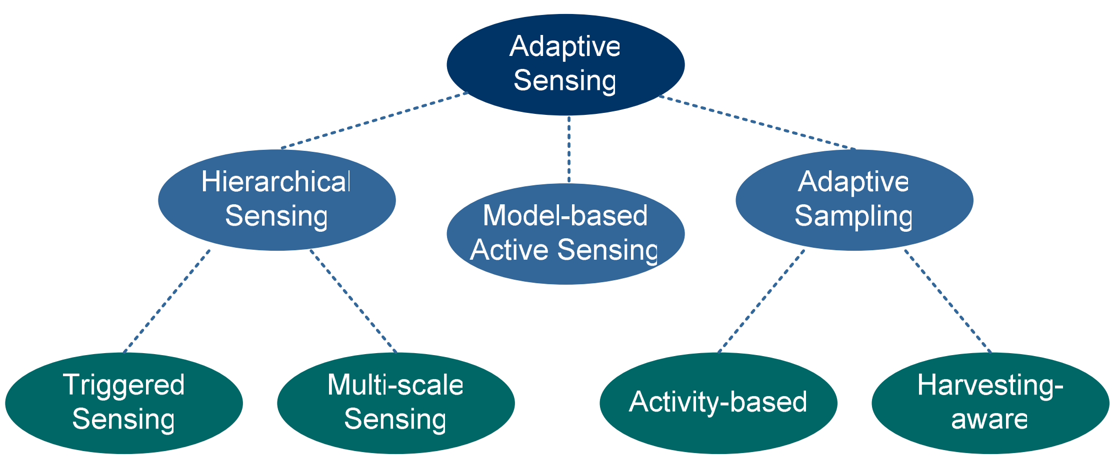

Figure 3. Classification of adaptive sensing strategies.

Adaptive sensing can be implemented by exploiting three different approaches, i.e., *hierarchical sensing*, *adaptive sampling*, and *model-based active sensing*.

- *Hierarchical sensing* requires units equipped with different sensors, each characterized by its own accuracy and power consumption, to measure the same physical quantity. The final measurement is inferred by processing data coming from all sensors. In most cases, simple sensors are energy efficient but provide a very limited resolution. On the other hand, advanced/complex sensors can give a more accurate characterization of the sensed phenomenon at the cost of higher energy consumption. Thus, accuracy can be traded off with energy efficiency. At first, low-power sensors are considered to a provide coarse-grained characterization of the sensing field or trigger an event. Then, accurate -but power hungry- sensors can be activated with measurements used to improve the coarser description.
- *Adaptive sampling* techniques are aimed at dynamically adapting the sampling rate by exploiting correlations among the sensed data and/or information related to the available energy. For instance, if the quantity of interest evolves slowly with time – so that subsequent samples do not differ very much– it is possible to take advantage of the temporal correlation. On the other side, it is very likely that measurements taken by sensor nodes that are spatially close each other do not differ significantly. Spatial correlation can thus be exploited to further reduce the sensing energy consumption. Obviously, both these approaches can be combined to further reduce the number of samples to be acquired. Finally, the sampling rate can be adjusted dynamically depending on the available energy.
- *Model-based active sampling* consists in building a model of the sensed phenomenon on top of an initial set of sampled data. Once the model is available, next data can be predicted by the model instead of sampling the quantity of interest, hence saving the energy consumed for data sensing. Whenever the requested accuracy is no more satisfied, the model needs to be updated, or re-estimated, to adhere to the new dynamics of the physical phenomenon under observation.

In the following sections we survey the main techniques proposed in the literature based on the above classification.

4. Hierarchical sensing

As mentioned above, hierarchical sensing techniques assume that multiple sensors are installed on the sensor nodes and observe the same phenomenon with a different resolution and power consumption (see Fig. 4). The idea behind hierarchical sensing techniques is to dynamically select which of the available sensors must be activated, by trading off accuracy for energy conservation.

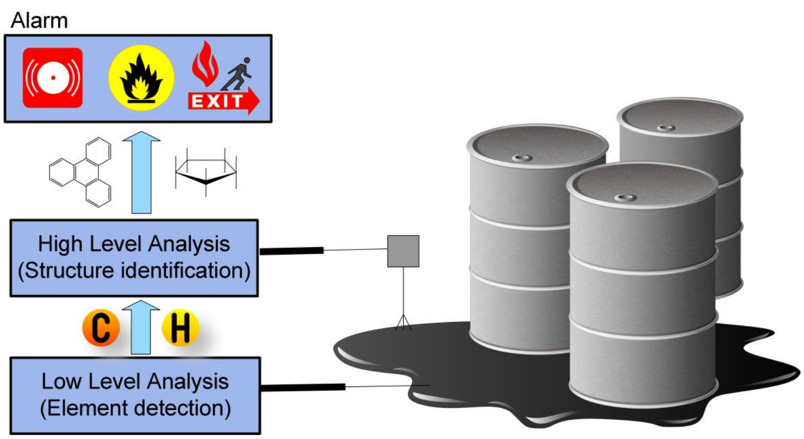

Figure 4 - Hierarchical Sensing: multiple sensors observe the same phenomenon with different resolution and energy consumption.

4.1 Triggered sensing

The activation of the more accurate and power consuming sensors after the low-resolution ones once some activity within the sensed area has been detected is referred to *triggered sensing*.

An example of triggered sensing is presented in [37] for structural health monitoring and damage detection of a civil structure (i.e., a bridge). The structure to be monitored is split into zones instrumented with sensing units capable of detecting two scales of responses: accelerometers (MEMS and piezo-electric) and strain gauges (the three-wire quarter-bridge circuit). A central node, which supervises all the activities of the sensor network, is endowed with a triggering system: sensor units are activated when the passage of isolated, large payload vehicles are detected by an imaging system [38]. Initially, in each sensor unit, only accelerometers are activated to collect data and perform a local assessment of the potential damage. Sensor units detecting a potential damage remain awake and exchange information with their neighbor accelerometers to cross-check their readings, while all other sensor units return to sleep to conserve energy (until the next activation). Whenever a potential danger is detected, strain gauges present in the area are activated to get more accurate information so as to corroborate or dismiss the initial suspicion, while the central node remotely transmits information about the possible alert (e.g., damage localization). Finally, the sensor units return to sleep.

A different triggered approach is presented in [39] where an image-based wireless sensor network for object detection has been deployed. The sensing units are endowed with integrated CMOS camera modules which, to reduce energy consumption, have been configured to provide a coarse-grained acquisition of images. Image processing is then carried out to detect the potential presence of targets. When this occurs, cameras are reconfigured and commute into a fine-grained high quality modality, hence providing images with high resolution; object detection is accomplished on these images. Afterwards, cameras are configured back to the power saving low-resolution modality.

Other examples of triggered sensing can be found in [40], [41].

4.2 Multi-scale sensing

A different use of hierarchical sensing consists in identifying areas within the monitoring field that require a more accurate observation. This is obtained by relying on a coarse-grained description of the field with lower accuracy sensors and activating additional high-resolution ones only in areas where their accurate acquisition are requested. These approaches are referred as *multi-scale sensing* [42].

An example of such a strategy is suggested in [43] for a multi-scale approach to fire emergency management. The sensor field is instrumented with static sensors which monitor the environment. When a given area presents an anomaly – i.e. the sampled temperature is above a given threshold – static nodes ask the base station for a deeper investigation. As a consequence, the base station sends a mobile sensorial unit to visit the potentially critical location which collects data and takes a snapshot of the scene. After having observed the event, the mobile unit goes back to the base station and reports the acquired data.

5. Adaptive sampling

Adaptive sampling strategies dynamically adapt the sensor sampling rate based on the spatial and/or temporal correlation among acquired data (*activity-driven adaptive sampling*) and/or the available energy whenever the sensor node is able to harvest energy from the environment (*harvesting-aware adaptive sampling*) .

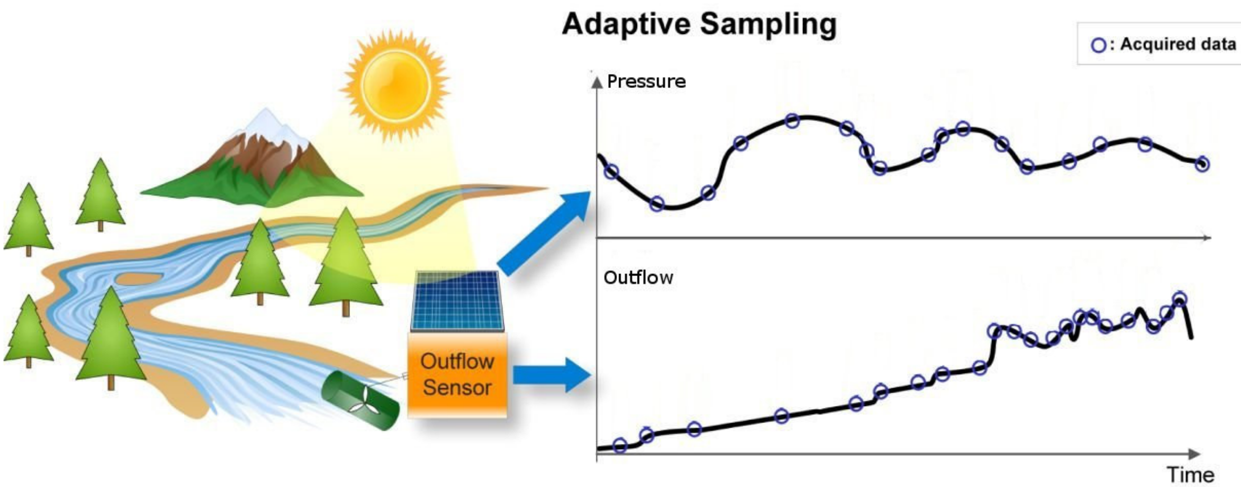

Figure 5 - Activity-driven Adaptive sampling: the sampling rate is adapted to the physical phenomenon under observation.

5.1 Activity-driven adaptive sampling

Activity-driven adaptive sampling exploits the correlation (both temporal and spatial) among the acquired data (See Fig. 5).

Temporal correlation has been considered in [44], where the authors proposed an adaptive sampling algorithm for minimizing the energy consumption of a snow sensor. The suggested algorithm dynamically estimates the current maximum frequency of the signal by using a first set of acquired samples and relies on a modified version of the CUSUM test [45] to detect changes in such a frequency. The change is detected when the current maximum frequency happens to be above or below a threshold (determined with CUSUM) for some consecutive samples. A change in the maximum frequency affects the new sampling frequency which needs to be updated. As the above computational load is high, a centralized approach is taken, i.e., the algorithm is executed at the base station and the estimated sampling rates are notified to each sensor node.

A similar approach has been suggested in [46], where the sampling rate is adapted based on the outcome of a Kalman filter. Unlike the previous case, here authors take a decentralized approach, i.e., the Kalman filter is executed on sensor nodes. Such a solution might not be feasible in sensor networks consisting of tiny devices with limited computational capabilities.

An application-specific approach to adaptive sampling is also proposed in [47] where a flood alerting system (FloodNet) is presented. The system includes a flood predictor which is used to adjust the reporting rate of individual nodes.

A spatial correlation approach has been investigated in [48] where the authors propose the *backcasting* scheme. Here, the main idea is that nodes do not need to sense the field in a uniform way. The philosophy behind is that more nodes should be active in those areas where the variation of the sensed quantity is high or, in other terms, the quantity of information coming from the environmental area is large. In the proposed scheme, the process of activating the required number of sensor is done in two phases. In the first phase –or *preview*- only a subset of nodes are activated, which allows the network for getting a coarse-grained estimate of the spatial distribution of the sensed phenomenon.

This estimation phase is performed in several steps. At first, the sensors activated during the preview phase partition the sensing field in a number of sub-squares with a non-uniform resolution: the smaller the spatial variation of the observed phenomenon the larger the sub-square associated with the location. The resulting tessellation is used to cluster sensor nodes, each managed by a cluster-head. Finally, a preliminary hypothesis on which sensors activate is sent to a fusion center (i.e., the sink).

Based on this initial hypothesis, in the second phase called *refinement*, the fusion center may activate additional sensors in those locations where the spatial correlation is low. This is accomplished with a "backcast" procedure where the fusion center sends an activation message to those cluster-heads residing in the smallest square areas generated in the preview phase.

When the sensing field has no regions with sharp variations of the sensed quantity, the preview phase might suffice in providing accurately data without needing the refinement phase.

Spatial correlation is also exploited in [49] to selectively reduce the number of nodes used to report data to the sink. In detail, a spatial *Correlation-based Collaborative MAC* protocol (CC-MAC) is suggested which regulates medium access and prevents redundant transmissions from closely located sensors. To this end, the *Iterative Node Selection* algorithm computes a correlation radius at the sink based on the maximum distortion tolerable by the application. This information is then broadcasted to sensor nodes during the network setup and it is used during the operational phase. CC-MAC prevents the transmission of redundant information by allowing only a single node within an area determined by the correlation radius to transmit its data towards the sink. All the other nodes whose distance from this representative node is less than the correlation radius must refrain from transmitting.

Finally, the solution proposed in [50] exploits both spatial and temporal correlation within an environmental monitoring application. Authors use an actuation-enabled robotic sensor called *Networked Info-mechanical System* which consists of a mobile node carrying meteorological sensors. The sampling problem is addressed as a combination of different phases. At first, a navigation criterion defining how the mobile sensor has to move along the field is defined based on cost, position information and variation of the phenomenon under measurement. In this way the placement of observations is tailored to the desired error and areas inducing a higher error are sampled more densely. Besides exploiting spatial correlation, the system also incorporates an adaptive parameters selection, so that temporal correlation between samples is exploited as well.

5.2 Harvesting-aware adaptive sampling

The harvesting-aware adaptive sampling techniques (e.g., [51], [52], [53]) exploits knowledge about the residual and the forecasted energy coming from the harvester module to optimize power consumption at the unit level.

The approach requires the development of models able to characterize the evolution over time of energy availability and the energy consumption of sensor units. In this direction [51] focuses on solar radiation as an energy harvesting source and defines a time-varying energy harvesting prediction model P_s computed with a weighted moving average of the energy scavenged in the previous exposition days. Similarly, the energy consumption profile P_c is estimated. The non-ideality of the harvesting system has been modeled by considering both a loss in charging operation due to the non-ideal charging efficiency η and the leakage current ρ_{leak} of the energy storage medium (e.g., batteries or supercapacitors).

This mathematical framework allows the authors for defining the concept of *energy-neutral* operating mode which guarantees that the harvested energy is consumed at an appropriate rate to maximise the lifetime of the units. The available energy is

$$B_0 + \eta . \int_0^T [P_s(t) - P_c(t)]^+ dt - \int_0^T [P_c(t) - P_s(t)]^+ dt - \int_0^T P_{leak}(t)\, dt \geq 0 \qquad \text{with } t=[0,\infty)$$

where B_0 and P_{leak} are the initial stored energy and the leakage power of the energy storage medium, respectively and $[P_s(t) - P_c(t)]^+ = \max(0, P_s(t) - P_c(t))$.

The basic idea of the proposed power management algorithm is to dynamically identify the maximum duty-cycle (which consequently maximize $\int_0^T P_c(t)\, dt$) for energy-neutral operations.

Differently, [52] proposes a physical model-free scheme which makes no assumptions about nature and dynamics of the energy source. There, the energetic problem has been reformulated as a linear-quadratic tracking one solved with a simple ad-hoc control law.

Finally, [53] introduces a decentralized adaptive sampling algorithm developed for predicting the occurrence of floods. Sensor nodes acquire data to reduce the total uncertainty error of information collected at the base-station (expressed in terms of confidence bands about the linear regression line). The adaptive sampling algorithm aims at minimizing the total uncertainty error while minimizing the amount of data acquired by each sensor. Authors formulate the adaptive sampling as linear programming problem which has been solved by using integer programming.

6. Model-based Active Sensing

Model-based active sensing operates by building an abstraction of the sensed phenomenon though a forecasting model (see Fig. 6).

The model predicts the next data the sensor is expected to acquire, hence avoiding the need of sampling at the node level and transmit data; both nodes and sink are in possess of the same model. Of course, the effectiveness of this approach is bounded by the accuracy of the model and the nature of the process to be monitored. If the model is effective in forecasting the incoming data up to time *K-1* then only 1 out of *K* data will be transmitted to the sink. Once a data is received, the model is updated by integrating the incoming information and the parameters broadcast back to the network units. The consequence is that model-based active sensing reduces the energy needed for data acquisition and also the number of information sent to the sink.

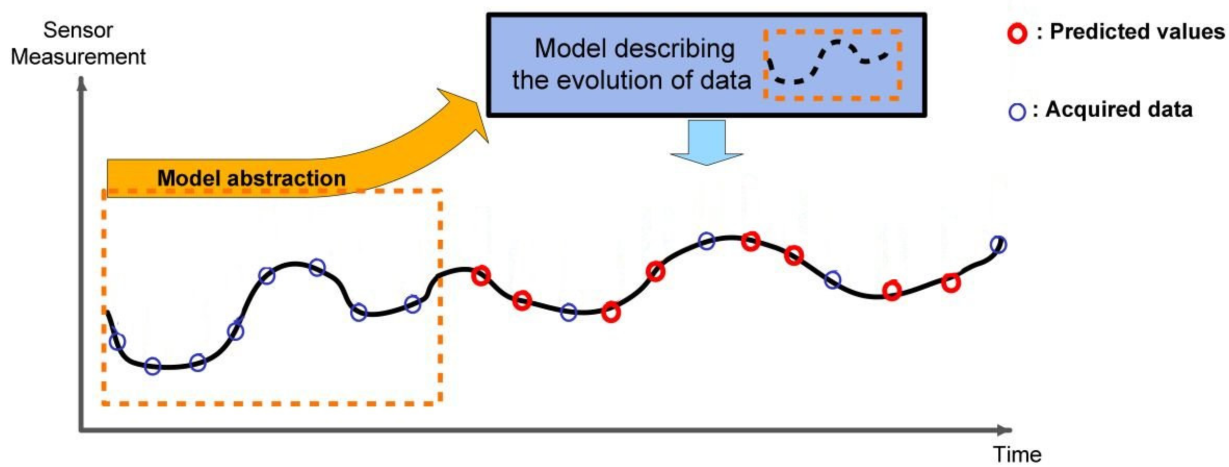

Figure 6 - Model-based Active Sensing allows to create a model of the physical phenomenon under observation and to predict incoming data without the need to acquire them.

Model-based active sensing was first proposed in [54] in the framework of the *Barbie-Q* (*BBQ*) query system. The query system relies on a probabilistic model and a query planner, both present in the sink. Starting from a given number of samples, a probability density function (pdf) over a set of attributes is derived, which can be exploited to obtain spatial and/or temporal correlations. The planner builds a query plan including a list of sensors and the most relevant quantities to get. For example, when an user is interested in the temperature sensed in a given area, the planner chooses the subset of sensors to be contacted and the quantities to be sampled. In fact, the temperature can be measured directly with the dedicated transducer, but it can also be derived from the voltage measured at the destination node (this is an example of correlation between different attributes). In general, a voltage measurement is cheaper than a temperature measurement; as a consequence the planner may choose to get the voltage at some nodes in order to reduce the overall power consumption associated with the query. Upon receiving a query, the planner computes the observation cost by considering both sampling and communication.

Since computing the optimal solution has an exponential complexity, the authors proposed a polynomial-time effective heuristic.

A similar approach has been suggested in [55], where an Adaptive Sampling Approach to Data Collection (ASAP) is proposed. In contrast with BBQ, ASAP splits the network into clusters: a cluster formation phase is performed to elect cluster heads and assign nodes to clusters. The figure of metric used to group nodes within the same cluster include the similarity of sensor readings and the hop count. Not all nodes in the same cluster are requested to sample the environment: the *correlation-based sampler selection* is performed at each cluster head and aims at determining those sampler nodes that capture at the best the spatial and temporal correlations among the other sensor readings. Moreover, probabilistic models for not used nodes are built. Finally, ASAP collects sensor readings from only a subset of nodes (sampler nodes) that have been previously selected. The values of not sampler nodes are predicted using the probabilistic models built in the previous step; clusters are dynamically changed after each predefined schedule update period.

A different approach is taken by [56], where a *Utility-based Sensing and Communication* protocol is presented in the context of glacial-environment monitoring application. In this case, a limited-window linear regression model is used to forecast samples. The algorithm for updating the sampling frequency is running at the network nodes: if the predicted value falls outside the confidence interval, then the sampling frequency is increased to a pre-defined maximum value. This improves the accuracy during the model update. Differently, if the prediction lies within the confidence interval, the sampling frequency is decreased by a given factor, unless a minimum pre-defined frequency is reached.

In addition to the sensing model, the authors also defined a routing protocol which accounts for the energy spent for both sensing and communication; sensors that are not relaying data can perform additional sampling and routes where data is sampled with lower frequency are preferred to routes where nodes spend more energy for sampling.

7. Conclusion and Discussion

The paper surveys the main research directions for extending the lifetime of sensor units encompassing energy-hungry sensors. The general framework for energy-efficient data acquisitions is based on a duty cycle approach requiring the sensing board to be switched off in between two consecutive samples. The hierarchical sampling techniques are actually feasible when the network units are endowed with multiple sensors observing the same phenomenon with a different resolution and power consumption. In particular, triggered sensing, which is particularly suitable for object/event detection systems, exploits low-power coarse-grained sensing units to activate fine-grained (and more power-consuming) sensors that allow for a more effective object/event detection. On the contrary, multi-scale sensing is particularly suitable for environmental monitoring applications since it identifies those areas of interest which require a more accurate observation.

Techniques based on activity-driven adaptive sampling are very promising, as they are quite general and efficient. However, most of the proposed solutions are limited only to a single direction, i.e., they typically exploit either temporal or spatial correlation. A more energy-efficient approach would be obtained by exploiting spatio-temporal correlation.

It should be emphasized that adaptive sampling techniques, by reducing the amount of acquired data, indirectly contribute to reducing the energy consumed for data communication as well. On the other side, when using adaptive sampling, data losses introduced by the sensor network cannot be tolerated any more and a 100% reliability is required in the communication from sensor nodes to the sink. This can be achieved by using retransmissions of missed data, Forward Error Correction, and multi-path routing techniques. All these techniques increase the percentage of data correctly delivered to the sink at the cost of additional energy consumed by the radio. Therefore, when assessing the performance of an adaptive sampling solution, one should consider the total energy consumed by the entire sensor network with and without adaptive sampling. Finally, adaptive sampling techniques are often implemented in a centralized fashion, e.g. because they require rather huge computations. To this end, additional work has still to be done for reducing the complexity of these solutions, so that viable distributed approaches can be afforded as well.

Harvesting-aware adaptive sampling (and, more generally, harvesting-aware power management) is a very interesting approach that promises to prolong the network lifetime to a virtually unlimited time. This is a desirable property for credible deployments of sensor networks in real environments. These techniques have been introduced only recently and, thus, they represent an interesting research field. The main limitation of this approach is that it can only be used when the energy source is predictable.

Model-based active sensing is also very interesting. However, in most cases, solutions based on this approach are computationally expensive, and must be implemented in a centralized way. In this context, model-based techniques should be improved in the direction of deriving distributed algorithms for model computation and diffusion through the network. In addition, selection of the most appropriate model is the key issue in the design of a model-based active sensing strategy. In general, this choice is application specific.

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