Energy Management in Wireless Sensor Networks with Energy-Hungry Sensors

Cesare Alippi, Giuseppe Anastasi, Mario Di Francesco, and Manuel Roveri

The energy problem in wireless sensor networks remains one of the major barriers 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, it remains a limited resource to be consumed judiciously. Efficient energy management is thus a key requirement, with most strategies assuming that data acquisition consumes significantly less energy than data transmission. When this assumption does not hold, effective energy management strategies should include policies for an efficient use of energy-hungry sensors.

Introduction

A wireless sensor network (WSN) consists of a large number of tiny *sensor nodes* deployed over a geographical area, also referred to as a *sensing field*; each node is a low-power device that integrates computing, wireless communication, and sensing abilities. Nodes are organized in clusters and networks and cooperate to perform an assigned monitoring (and/or control) task. There is no human intervention, and the spatial and temporal scales and resolutions are difficult, if not impossible, to achieve with traditional techniques. Sensor nodes are able to sense physical environmental information (e.g., temperature, humidity, vibration, acceleration, etc.), process the acquired data locally both at the unit and cluster level, and send the outcome—or aggregated features—to the cluster and to one or more collection points, named *sinks* or *base stations* (Figure 1). 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 has rapidly grown, a trend expected to further increase in the coming years.

Energy consumption is one of the main obstacles to the universal application of WSNs. In applications for which a long network lifetime and high quality of service are required, the batteries that power the nodes need to be replaced or recharged because of environmental constraints, and that is not possible in all cases. Even though energy-scavenging mechanisms can be adopted to recharge batteries through solar panels, piezoelectric or acoustic transducers, energy is a limited resource and must be used judiciously [1]. Sensor networks use energy

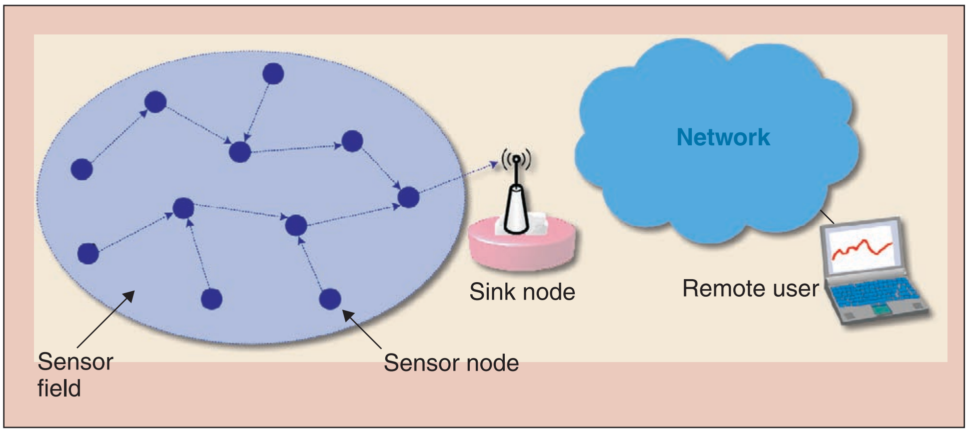

Fig. 1. A typical sensor network architecture.

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Table 1—Power consumption for some common radios

Radio	Producer	Power consumption	
		Transmission	Reception
JN-DS-JN513x	Jennic	111 mW (at 1 dBm)	111 mW
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

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 (three-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	1,250 mW

in monitoring complex phenomena and in communicating the data. Efficient energy management strategies must be devised at sensor nodes and then at cluster and network levels to prolong the network lifetime as much as possible. Only recently have the sensors used more energy for acquiring the data than for communication of that data. This is mainly due to specific sensors used in the network [2].

Several energy management schemes have been proposed for reducing the power consumption acting at the radio level. A detailed survey is found in [3].

Table 1 shows power consumptions of the most popular radio equipment used by sensor nodes, and Table 2 lists some common off-the-shelf sensors. If acquisition times are longer than transmission times, we can conclude that some sensors may even consume significantly more energy than the radio.

Energy management schemes aimed at minimizing the radio activity need to be complemented with (or replaced by) techniques for energy-efficient management at the sensor level, to reduce the number of data acquisitions (i.e., data samples) rather than the number of transmitted messages. At the unit, cluster, and network levels, data compression and aggregation can be considered. Most of the management schemes assume that data acquisition and processing consume significantly less energy than does communication and thus they minimize radio activity.

In this paper we classify and review the main approaches proposed for energy management at the sensor level. We introduce a general framework for energy-efficient data acquisition from sensors, provide a framework for adaptive sensing strategies, survey the main solutions proposed in the related literature, and discuss the proposed methods and some open research issues.

A General Framework for Energy-Efficient Sensor Management

Most monitoring applications based on sensor networks rely on a synchronous philosophy by which readings are carried out with a given sampling frequency. In this case, two main approaches can be considered to reduce the energy consumed by a sensor, *duty cycling* and *adaptive sensing*. *Duty cycling* consists of "waking up" the sensor system only for the time needed to acquire a new set of samples and then powering it off immediately afterwards. Duty cycling plans for optimal energy management, provided that the properties of the event being monitored are time-invariant and known in advance. Periodic sensing is another method of sampling. Here, the (fixed) sampling rate is computed a priori, based on partial available information about the event to be monitored and assuming that the event properties are stationary. With this method, the sampling rate is larger than necessary, resulting in *oversampling*, and more energy is consumed.

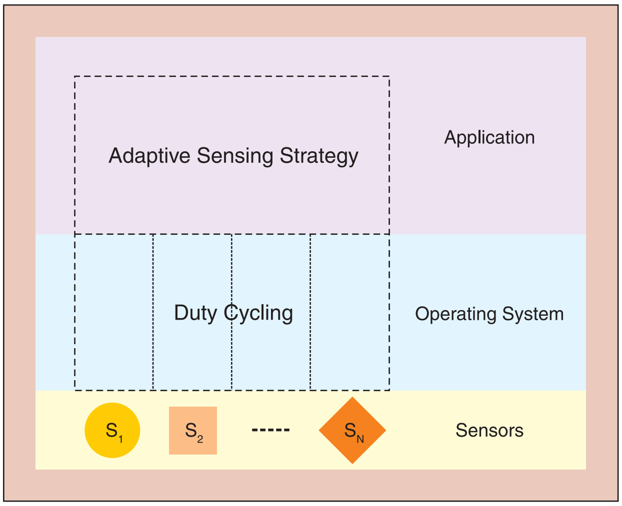

Fig. 2. A general framework for sensor energy management.

An *adaptive sensing* strategy is able to dynamically change the sensor activity to the real dynamics of the process. An efficient adaptive sensing strategy reduces the number of samples, which in turn reduces the amount of data to be processed and transmitted. Duty cycling and adaptive sensing are complementary approaches and can be used in combination (Figure

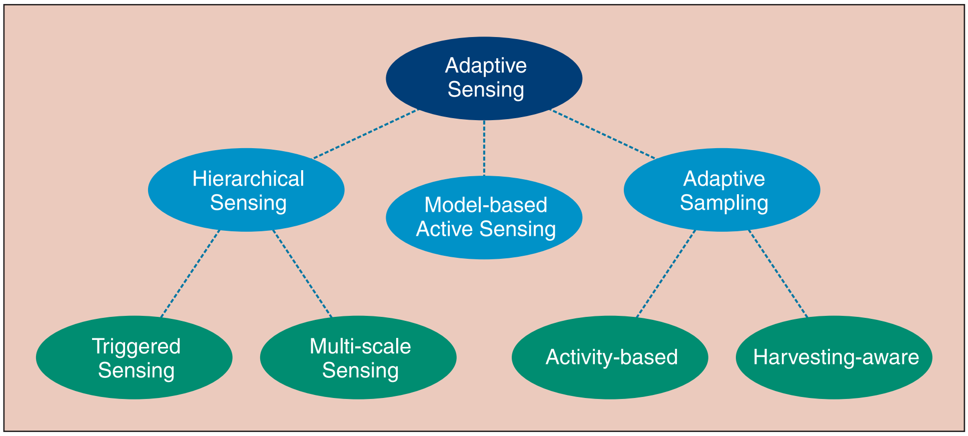

Fig. 3. Organization of adaptive sensing strategies.

2). The operating system provides a set of commands to power the sensors on and off (the duty cycle part); then it implements an adaptive sensing strategy and the sensors acquire data.

In designing the sensor drivers for this operating system, the duty cycle must be carefully constructed around the sensors' *wake-up latency* and *break-even cycle* or the sensor system may return invalid acquired data or may have energy dissipation larger than that associated with the always-on mode [4]. The *wake-up latency* is the time required by the sensor to generate a correct value once activated. If the sensor reading is performed before the wake-up 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 one with no power management. This value is in inverse proportion to the power consumption overhead introduced by the non-ideal, on/off sensor transition and it represents the highest sampling rate possible using power management. Each sensor has a set of functional characteristics that include wake-up latency and a break-even cycle that impact the energy management of the sensor. Also, 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 [4].

Unfortunately, most currently available operating systems for sensor nodes do not follow this philosophy and instead 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 to relieve the manual management and to improve the effectiveness of the duty-cycling mechanism. The general framework of Figure 2 allows the WSN designer to focus on the selection of the best adaptive sensing strategy, leaving low-level duty cycling aspects to the operating system.

Organization of Adaptive Sensing Strategies

Figure 3 shows an organization of the adaptive sensing strategies based on the classification given in [3]. Adaptive sensing can be implemented using three different approaches: hierarchical sensing, adaptive sampling, and model-based active sensing.

Hierarchical Sensing Techniques

These techniques assume that multiple sensors are installed on the sensor nodes and observe the same event with a different resolution and power consumption (Figure 4). In most cases, simple sensors are energy efficient and provide low-resolution readings or trigger an event. Advanced, more complex sensors give more accurate readings of the physical property at the cost of greater energy consumption. The more advanced, accurate, but power-hungry sensors can be activated to make more measurements to improve the low-resolution readings. 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. The resultant measurement is inferred by processing data coming from all of the sensors.

Triggered sensing is when more accurate and power-consuming sensors are activated after the low-resolution sensors detect some activity within the sensed area. An example of triggered sensing is presented in [5] for structural health monitoring and damage detection of a bridge. The bridge is split into zones and instrumented with sensing units capable of detecting two scales of responses: for large structural movement using accelerometers (MEMS and piezoelectric) and stress on materials using strain gauges (the three-wire quarter-bridge circuit). A central node supervises all the activities of the sensor network and has a triggering system: sensor units are activated when isolated; large payload vehicles are detected on the bridge by an imaging system. Initially, in each sensor unit, only accelerometers are activated to collect data and perform a local assessment of potential damage. If sensor units detect possible damage, they 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. Whenever possible damage is detected, strain gauges present in the area are activated to get more accurate information to corroborate or dismiss the initial suspicion. The central node transmits alert information about the possible damage localization to the base station, and then the sensor units return to sleep.

A different triggered approach is presented in [6] for an image-based wireless sensor network for object detection. The sensing units have integrated CMOS camera modules that are configured to provide low-resolution images to reduce energy consumption. Image processing detects the potential presence of targets. If targets are detected, cameras are reconfigured into a fine-grained, high-quality image and provide images with high resolution. Object detection is verified by these images.

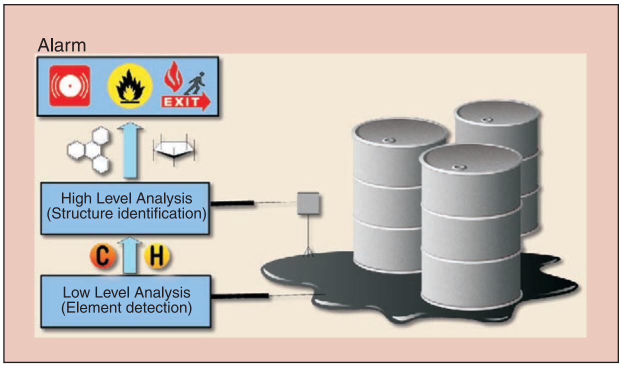

Fig. 4. Hierarchical sensing: multiple sensors observe the same phenomenon with different resolution and energy consumption.

The cameras are then reconfigured to the power-saving low-resolution modality.

Multi-scale sensing is a different use of hierarchical sensing. It identifies areas within the monitoring field that require a more accurate observation. This is obtained by relying on low-resolution data from sensors in the field and activating additional high-resolution sensors only in areas where their accurate acquisitions are requested [7].

An example of multi-scale sensing involves fire emergency management [8]. The sensor field is instrumented with static sensors which monitor the environment. When a given area presents an anomaly (e.g. the sampled temperature is above a given threshold), static nodes ask the base station for more specific data. As a consequence, the base station sends a mobile sensor unit to visit the potentially critical location; the sensor unit collects data and takes a snapshot of the scene. The mobile unit then goes back to the base station and reports the acquired data.

Adaptive sampling

Adaptive sampling techniques change the sampling rate by making correlations between the sensed data and information related to the available energy. If the quantity of interest evolves slowly with time so that subsequent samples do not differ very much it is possible to reduce the sampling rate based on this temporal correlation. It is also very likely that measurements taken by sensor nodes that are spatially close to each other do not differ significantly. If so, then this spatial correlation can be used to reduce the energy-sensing consumption. *Activity-driven adaptive sampling* combines both of these approaches to further reduce the number of samples to be acquired. The sampling rate can also be adjusted dynamically with *harvest-aware adaptive sampling* that depends on the available energy, including when the sensor node is able to harvest energy from the environment. It is important to note that when using adaptive sampling, data losses introduced by the sensor network cannot be tolerated, and 100% reliability is required in the communication from sensor nodes to the sink. This can be achieved by using re-transmissions 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.

Activity-based adaptive sampling

This technique uses the temporal and spatial correlation from the acquired data (Figure 5).

Temporal correlation was used in an adaptive sampling algorithm for minimizing the energy consumption of a snow sensor [9]. The 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 cumulative sum (CUSUM) test to detect changes in this frequency. A change is identified when the current maximum frequency is above or below a threshold that is determined with CUSUM for some consecutive samples. A change then affects the new sampling frequency, so an update is needed. The computational load is high, so the algorithm is executed at the base station and the new estimated sampling rates are sent to each sensor node—a centralized approach.

A similar approach has been suggested in [10], where the sampling rate is adapted based on the outcome of a Kalman filter. The Kalman filter is executed on sensor nodes. This solution might not be feasible in sensor networks consisting of tiny devices with limited computational capabilities—a decentralized approach.

Adaptive sampling is also proposed in [11], in which a flood alerting system (FloodNet) is presented. The system includes a flood predictor that is used to adjust the reporting rate of individual nodes—an application-specific approach.

A spatial correlation approach with a *backcasting* scheme has been investigated [12]. The main idea is that more nodes should be active in areas in which there is a large difference in the data from nodes situated close together. In the first phase, or *preview,* only a subset of the total number of nodes are activated, which allows the network to get a low-resolution estimate by the spatial distribution in the sensor field. The nodes also partition the sensing field into a number of subsquares of nonuniform size. Large subsquares are formed when there is little variation between data sent from nodes in that area. Small subsquares are partitioned when there is a large difference between the data coming from the nodes. Small subsquares generate a preliminary hypothesis that is sent to a fusion center, the sink. It suggests additional sensors to activate in order to obtain more data. In the *refinement phase*, the additional sensors are activated, and each node is managed by a cluster head. The "backcast" procedure occurs when the fusion center sends an activation message to those cluster-heads residing in the smallest square areas. If the sensing field has no small subsquares, the preview phase provides accurate data and the refinement phase is not necessary.

Spatial correlation is also used to selectively reduce the number of nodes used to send data to the sink [13]. In detail, a spatial *Correlation-Based Collaborative MAC* protocol (CC-MAC) is suggested, which regulates access and prevents redundant transmissions from close sensors. An *Iterative Node Selection* algorithm computes a correlation radius at the sink based on the maximum distortion tolerable by the application. This information is then broadcast to sensor nodes during the network setup and is used during the operational phase. CC-

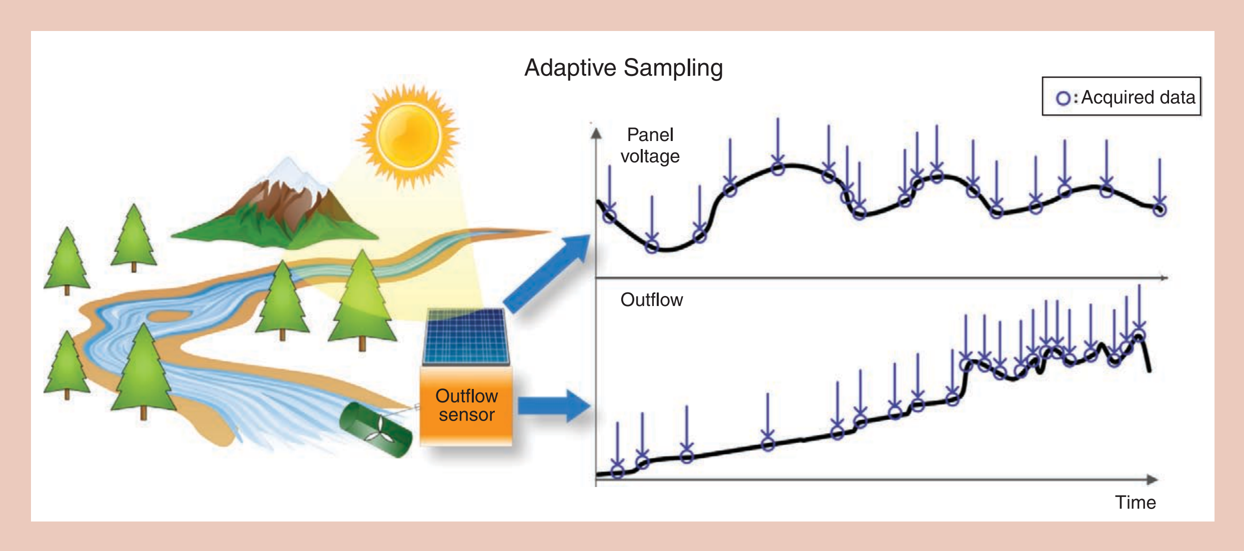

Fig. 5. Activity-driven adaptive sampling: the sampling rate is adapted to the physical phenomenon under observation.

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 to the sink. All the other nodes whose distance from this representative node is less than the correlation radius do not transmit.

The final solution uses both spatial and temporal correlation within an environmental monitoring application [14]. It uses an actuation-enabled robotic sensor called the *Networked Info-Mechanical System*, which is a mobile node carrying meteorological sensors. Sampling is initiated in a combination of different phases. At first, a navigation criterion defines how the mobile sensor has to move along the field based on cost, position information, and variation of the phenomenon under measurement. In this way, the location of the sensors is tailored to the desired error, and areas inducing a higher error are sampled more densely. Besides spatial correlation, the system also incorporates an adaptive parameters selection, so that temporal correlation between samples is also used.

Harvesting-Aware Adaptive Sampling

The harvesting-aware adaptive sampling techniques optimize power consumption at the unit level by using the known remaining battery energy and the forecasted energy coming from a harvester module. This technique is also called harvesting-aware power management. It develops models that characterize energy availability and the energy consumption of sensor units over time. Kansal et al. [15] focus on solar radiation as an energy harvesting source and define a time-varying energy harvesting prediction model, P_s, computed with a weighted-moving-average of the energy scavenged in previous days, and the energy consumption profile, P_c, is estimated. The non-ideality of the harvesting system is modeled by considering both a loss in charging operation due to the non-ideal charging efficiency, η, and the leakage power P_{leak}, of the energy storage medium (e.g., batteries or supercapacitors).

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

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

with $T \in [0, \infty)$, where B_0 is the initial stored energy 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 maximizes $\int_0^T P_c(t)dt$, for energy-neutral operations. Vigorito, Ganesan, and Barto [16] propose a different physical model-free scheme that makes no assumptions about the nature and dynamics of the energy source. In their work the energetic problem has been reformulated as a linear-quadratic tracking problem, one solved with a simple ad-hoc control law.

Finally, [17] 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 minimizes the total uncertainty error while minimizing the amount of data acquired by each sensor. The authors formulate the adaptive sampling as a linear programming problem, which is solved by using integer programming.

Model-Based Active Sensing

This technique builds a forecasting model of the sensed phenomenon with an initial set of sampled data (Figure 6). Once the model is available, the next data can be predicted by the model verified over time instead of through continuous frequent sampling in the field, which saves the energy consumed for data sensing and transmission. Whenever the requested accuracy is not satisfied, the model is updated or reestimated to adhere to the new dynamics of the physical phenomenon under observation. 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 one out of K data will be transmitted to the sink. Once data is received, the model is updated by integrating the incoming information, and the parameters are broadcast back to the network units. The consequence is that model-based active sensing reduces the energy needed for data acquisition and transmission to the sink.

Model-based active sensing was first proposed in [18] in the framework of the *Barbie-Q* (*BBQ*) query system. The query system relies on a probabilistic model and a query planner in the sink. Starting from a given number of samples, a probability density function of a set of attributes is derived, which can be exploited to obtain spatial and temporal correlations. The planner builds a query plan including a list of sensors and the most relevant quantities to obtain. For example, when a 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 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 method is suggested in [19]; this method is called an adaptive sampling approach to data collection (ASAP). In contrast with BBQ, ASAP splits the network into clusters: a cluster formation phase elects cluster heads and assigns nodes to clusters. The similarity of sensor readings and the hop count are used to group nodes within the same cluster. 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 determines those sampler nodes that best capture the spatial and temporal correlations among the other sensor readings. Probabilistic models are built for not-used nodes. 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 given by a *Utility-Based Sensing and Communication* protocol that is presented in the context of a glacial-environment monitoring application [20]. In this case, a limited-window linear regression model is used to forecast samples. The algorithm for updating the sampling frequency runs at the network nodes: if the predicted value falls outside the confidence interval, then the sampling frequency is increased to a predefined maximum value. This improves the accuracy during the model update. If the prediction lies within the confidence interval, the sampling frequency is decreased by a given factor, unless a minimum predefined frequency is reached. In addition to the sensing model, the authors also define 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 in which data is sampled with lower frequency are preferred to routes in which nodes spend more energy for sampling.

Conclusions

We have surveyed the main research for extending the lifetime of sensor units with 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 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. Triggered sensing is particularly suitable for object/event detection systems. It uses low-power, low-resolution sensing units to activate high-resolution and more power-consuming sensors that allow more effective object/event detection. Multi-scale sensing is particularly suitable for environmental monitoring applications, since it identifies those areas that require a more accurate observation.

Techniques based on activity-based adaptive sampling are very promising as they are general and efficient. However, most of the proposed solu-

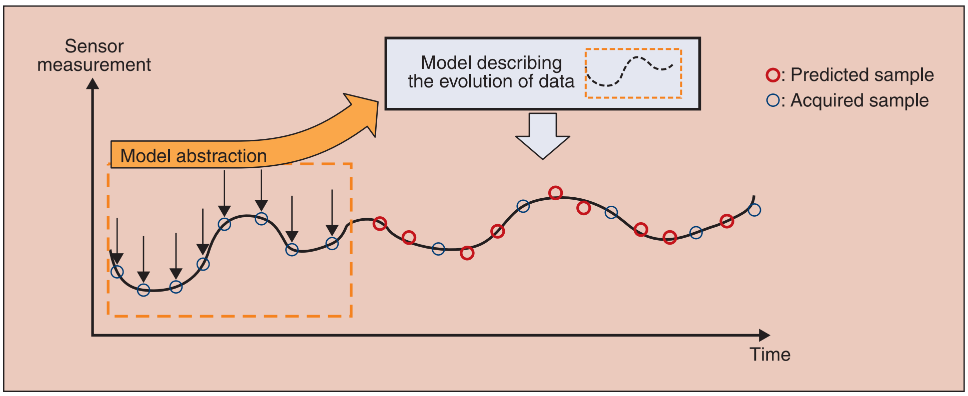

Fig. 6. Model-based active sensing creates a model of the physical phenomenon under observation and predicts incoming data verified by samples over time without the need to acquire them.

tions are limited to either temporal or spatial correlation. A more energy-efficient approach would be obtained by using a spatio-temporal correlation.

It is emphasized that reducing the amount of acquired data by using adaptive sampling techniques also reduces the energy consumed for data communication. It is important to note that when using adaptive sampling, data losses introduced by the sensor network cannot be tolerated, and 100% reliability is required in the communication from sensor nodes to the sink. 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 because they require rather huge computations. To this end, additional work should focus on reducing the complexity of these solutions so that viable distributed approaches can be afforded as well.

Harvesting-aware adaptive sampling 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 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. 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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K. Yunseop, R.G. Evans, and W.M. Iversen, "Remote sensing and control of an irrigation system using a distributed wireless sensor network," *IEEE Trans. Instr. Meas.*, vol. 57, pp. 1379–1387, Jul 2008.

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