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Abdelaal, Mohamed; Theel, Oliver; Kuka, Christian; u. a.

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Research Article

Improving Energy Efficiency in QoS-Constrained Wireless Sensor Networks

Mohamed Abdelaal,¹ Oliver Theel,¹ Christian Kuka,¹ Peilin Zhang,¹ Yang Gao,¹
Vasilisa Bashlovkina,² Daniela Nicklas,³ and Martin Fränzle¹

¹Carl von Ossietzky University of Oldenburg, 26129 Oldenburg, Germany

²Grinnell College, Grinnell, IA 50112, USA

³University of Bamberg, 96047 Bamberg, Germany

Correspondence should be addressed to Mohamed Abdelaal; mohamed.abdelaal@informatik.uni-oldenburg.de

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Energy saving is often achieved via “squeezing” other application-sensitive Quality of Service (QoS) parameters such as delay and throughput. Accordingly, energy-saving methods must consider those QoS parameters. In this paper, we survey the most recent work on energy efficiency in WSNs and we discuss the impacts of these methods on the QoS provided. Moreover, we propose a novel divide-and-conquer procedure to deal with the trade-off between energy consumption and other QoS parameters. The idea is to tackle a certain source of energy consumption to minimize the drawn energy. Subsequently, this energy-saving method is refined to consider other service qualities. To support the correctness of our claim, three energy-saving methods, taking the QoS issues into consideration, are given as examples. The first method exploits a so-called Fuzzy transform for shrinking the wireless traffic with highly precise lossy data compression. In the second method, the sensing module is targeted by employing reliable virtual sensors. Such sensors compensate the unavailability of main energy-hungry sensors during sleep periods. The third method exploits a self-adaptive mechanism to improve the QoS parameters via deliberately reducing the lifetime below the maximum time and exploiting design-time knowledge.

1. Introduction

In general, Wireless Sensor Networks (WSNs) consist of spatially distributed autonomous sensor nodes (SNs) over a sensing field to monitor physical or environmental conditions, such as temperature, sound, and pressure. As it can be seen in Figure 1, the SNs readings are conveyed in a cooperative manner to a base station. Some deployed nodes may have additional resources (super SNs) or may have additional tasks (routing nodes). Such networks have some features that differentiate them from other wireless networks including (1) deployment in harsh environments and (2) strong restrictions on hardware and software capabilities in terms of processing speed, memory storage, and energy supply. Such sensors usually carry limited, irreplaceable energy resources. Therefore, lifetime adequacy is a significant restriction of almost all WSNs.

Being one of the conflicting constraints with energy consumption in WSNs, adequate QoS provision has been addressed in the recent research. For example, Rao et al. [1] consider the trade-off between network performance optimization and lifetime maximization in real-time WSNs as a joint nonlinear optimization problem. Based on the solution of such a mathematical optimization problem, they developed an online distributed algorithm to achieve the appropriate trade-off. Even though these efforts have been exerted to balance the network performance and lifetime, the practical applications might require an expected lifetime and a high QoS level. Under this circumstance, always balancing the trade-off is not sufficient per se.

Chen et al. [2] design an adaptive fault-tolerant QoS control algorithm to satisfy the application QoS requirements in query-based WSNs. They developed a mathematical model where the lifetime of the system is considered as a system

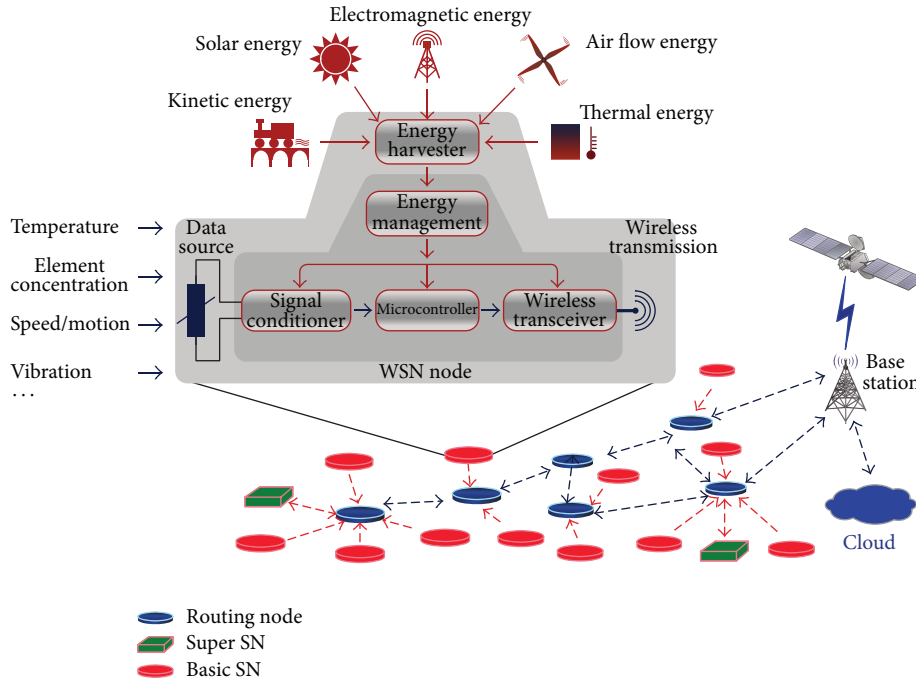


FIGURE 1: A general architecture of Wireless Sensor Networks.

parameter, to determine the optimal redundancy level that could satisfy QoS requirements while prolonging the lifetime. However, Chen et al. aimed at maximizing the lifetime while maintaining QoS parameters such as the fault tolerance. The network dynamics in their application have not been fully considered. Jemal et al. [3] adopt a self-adaptation strategy to optimize the energy consumption. They developed a probabilistic approach that estimates part of the QoS, namely, the residual energy, to conserve the transmission energy, thus extending the sensor node's lifetime. Their approach is based on a *hidden Markov chain* and the *Fuzzy logic*, consisting of learning and predicting steps. However, they did not pay enough attention to the QoS provision in WSNs. In addition, the relationships between the residual energy (considered as a QoS metric by the authors) and the QoS metrics on the network scale are still missing.

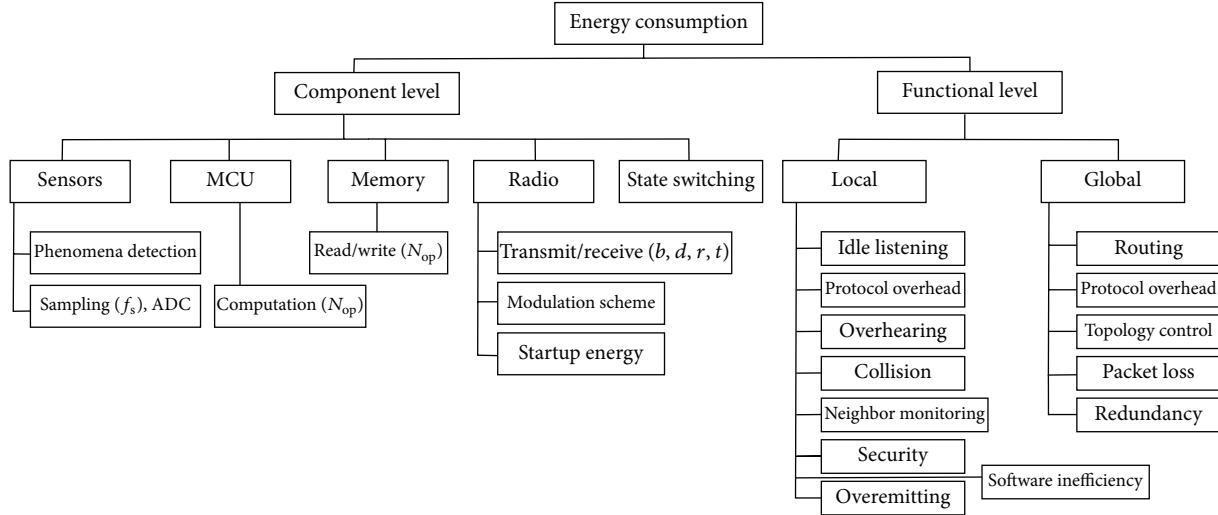
In this paper, we target breaking the “downward spiral” between reducing a certain QoS measure and extending the network's lifetime. Actually, the application-relevant QoS parameters cannot be ignored. In lieu of solving complex optimization problems to manipulate the natural trade-off between energy efficiency and other QoS parameters, we propose to divide and conquer the procedure. The strategy is to develop ideas mainly for energy efficiency and then refine such ideas to improve the QoS parameters. Three detailed examples are given in order to support the proposed strategy [7–9].

First, we focus on reducing the radio energy consumption via data encoding. The literature reports on lossy compressors such as wavelet transform and model-based methods. In this context, we propose to exploit a recently developed Fuzzy transform for sensor data compression. Actually, the

Fuzzy compressor shows a comparable precision performance with the aforementioned methods. However, we seek to further improve the recovery precision through adapting the transformation. Accordingly, a modified transformation, referred to as FuzzyCAT, is proposed. FuzzyCAT has high compression ratios and high precision as well by detecting the input signal curvature and dynamically modifying the transform's approximating function.

Second, virtual sensing is exploited being a novel technique for reducing energy consumed by energy-hungry sensors (GPS, gas sensors, etc.) and simultaneously reducing the event-miss probability. Generally, virtual sensors are orchestrations of HW/SW components that are able to sense a phenomenon which can be directly sensed by an “energy-hungry” sensor. The method is evaluated through two case studies including object tracking and gas leak detection. In both studies, lifetime of the main sensors is significantly extended. Moreover, virtual sensing reliability is improved through adopting ontology-based generated rules for sensor selection where sensing quality and environmental conditions are the selection criteria.

Third, we develop a new concept for the interplay between energy efficiency and QoS requirements. Instead of maximizing the lifetime, we restrict ourselves to only meet the application expected lifetime, but improving the QoS provided. A self-adaptive framework is proposed to respond to the environmental dynamics. Moreover, a hierarchical MAPE (monitor-analyze-plan-execute) architecture forms the global control loop. The obtained results show improvements on the provided quality while confining the lifetime within the expected time frame. As a proof of concept, the three aforementioned methods are examined



f_s = sampling frequency
 N_{op} = number of clock operations
 b = number of bits to be transmitted
 d = distance between sender and receiver
 r = data rate
 t = transmit power

FIGURE 2: Taxonomy of energy consumption sources in WSNs.

using different tools including the Cooja simulator of Contiki OS, probabilistic model checking, and real experiments with TelosB sensor nodes.

For the paper to be self-contained, the WSN technical literature is surveyed to identify the heavy energy consumers in different application scenarios. Based on this survey, a new taxonomy of energy efficiency methods in WSNs is constructed with classifying these methods into *data-oriented* methods, *network-oriented* methods, and *node-oriented* methods. Existing taxonomies are mostly either outdated or incomplete [5, 10–13]. This motivates us to write a brief survey including all recent endeavors in this arena. Moreover, we briefly provide comments on the impact of such energy efficiency methods on other service qualities. To summarize, the main contributions of this paper are as follows:

- (i) We sidestep complex optimization problems via proposing to divide and conquer the procedure by which the energy-QoS trade-off is manipulated.
- (ii) We give three detailed examples in order to support the proposed strategy.
- (iii) We survey the recent endeavors for energy efficiency and QoS control in WSNs.
- (iv) We classify these methods into *data-oriented* methods, *network-oriented* methods, and *node-oriented* methods.

The paper is structured into two main parts. The first part elaborates on three examples of refined energy efficiency methods, including FuzzyCAT data encoding, reliable virtual sensing, and lifetime planning. In Section 2, the problem of saving energy while considering other application-relevant QoS parameters is formulated. Furthermore, it discusses the

main energy consumers in WSNs. The Fuzzy transform-based data compression technique is explained in Section 3. Moreover, ideas for improving the recovery precision and the detection latency are discussed. Section 4 introduces the concept of virtual sensing for energy efficiency and demonstrates how the system reliability can be significantly improved. The third example of planning the entire lifetime with self-adaptive mechanisms is demonstrated in Section 5. Section 6 comprises the second part of this paper. It introduces a novel taxonomy of energy efficiency methods. Moreover, it discusses the negative impacts of such methods on other QoS parameters. Finally, a conclusion together with an outlook is addressed in Section 7.

2. Preliminaries

2.1. Problem Definition. Energy efficiency in WSNs is generally a fertile research area. The WSN literature has been submerged with many energy conservation and harvesting techniques. Symbolically, the energy consumption problem can be denoted as shown in (1). Under the assumption As_m of allocating an amount of energy for each SN, a sensing system Sys (operating in the environment Env) has to satisfy the user's specifications $Spec$. These demands could be formally translated as given in (2a)–(2c). Equation (2a) expresses the objective function, denoted by \bar{E}_{tot} , which is the total consumed energy by a WSN consisting of n sensor nodes $\{S_1, \dots, S_n\}$. The term V constitutes the set of energy consumers including the *component level* and the *functional level*, as shown in Figure 2. From our perspective, this objective function should be governed by two paramount criteria:

- (i) As denoted in (2b), the actual lifetime \bar{L} of each sensor node s has to be confined between the time

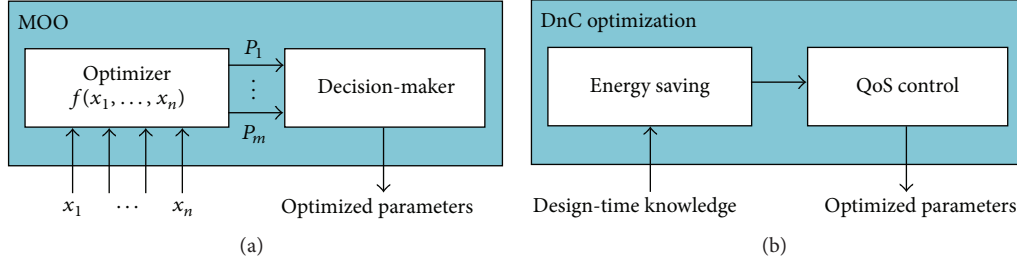


FIGURE 3: Difference between the proposed divide-and-conquer (DnC) technique and the general MOO method.

L_{task} required to complete the assigned task and the maximum lifetime L_{max} which is obtained at the expense of degrading other QoS parameters.

- (ii) The quality set \bar{Q} , defined in terms of m quality measures $\{q_1, \dots, q_m\}$, should satisfy the minimal application requirements ψ . Hence, a small space could tolerate the trade-offs as defined in (2c):

$$\text{Asm} \vdash (\text{Env} \parallel \text{Sys}) \text{ sat Spec}, \quad (1)$$

$$\min_V \tilde{E}_{\text{total}}(V), \quad (2a)$$

$$L_{\text{task}} \leq \tilde{L}(s) < L_{\text{max}} \quad \forall s \in \{s_1, s_2, \dots, s_n\}, \quad (2b)$$

$$100\% \geq \bar{Q}(s) = \{q_1, q_2, \dots, q_m\} \geq \psi. \quad (2c)$$

At first glance, the above problem looks contradicting. However, we show through the given three examples that providing the best-effort service quality while offering an extended lifetime beyond the task lifetime is feasible. Figure 2 depicts a comprehensive taxonomy of the various energy consumption sources in WSNs. We divided them into two levels including the “component” and “functional” levels. The former comprises the local sources of energy dissipation at each node s , required to accomplish the assigned task. The latter is a category in which energy is wasted due to inefficient medium access, routing, or topology control.

The contribution of each of these consumers in overall energy consumption depends on the application scenario. From a data-centric prospective, WSN applications could be distinguished according to the aggregation manner into *periodic sampling*, *event-driven*, or *hybrid* scenarios. In the first category, the measured data has to be sent periodically to the gateway for further processing. Thus, the data traffic will be extremely dense, especially with short acquisition periods. Moreover, the probability of collisions, idle listening, and inefficient routing is raised therefore.

In the category of event-driven applications, data transmission is highly less frequent compared to the previous category. However, other sources may dominate the energy consumption. For instance, Kim et al. [14] list the sources of energy consumption of the H-mote with a Hybus sensor board which contains five sets of air quality monitoring sensors. Power consumption of both, the NO_2 and VOC sensors, is over 30 mW; thus, about 66% of the total energy consumption of the node is drawn by the sensing module. As

a consequence, more attention should be given to decrease such overconsumption in data acquisition.

Finally, the third category of WSNs applications considers heterogeneous WSN in which the measured data is frequently transmitted. Simultaneously, the network continuously samples the environment for detecting predefined events. The office monitoring scenario [15] belongs to this category. In this application, individuals should be localized in an event-driven manner. Furthermore, environmental conditions have to be also repeatedly collected for controlling the heat and light systems.

2.2. Divide-and-Conquer Technique. In this paper, we propose the *divide-and-conquer* (DnC) optimization technique performed potentially at both the design-time and/or the run-time. The idea is to achieve the required task with minimal energy consumption. Subsequently, the relevant QoS parameters are gradually improved. The literature reports on *multiobjective optimization* (MOO) methods. Figure 3 depicts a conceptual comparison between the proposed DnC technique and MOO methods. As it can be seen in Figure 3(a), the optimizer is stimulated by a set of input parameters $\{x_1, \dots, x_n\}$, such as transmit power, reporting frequency, and sensing range. The MOO methods mostly utilize complex frameworks to produce multiple optimal plans $\{P_1, \dots, P_m\}$, and the decision-maker has to choose the best among them, depending on the priorities of the objectives to be achieved.

Kellner and Högrefe [16] propose multiobjective ant colony optimization (MOACO) algorithms that are capable of considering multiple objectives at the same time. The MOACO algorithms provide a compromise between security and efficient routing. Ferentinos and Tsiligiridis [17] utilize *Genetic Algorithms* (GA) to optimize the self-organizing network and energy management, taking into consideration communication constraints and energy conservation characteristics. Similarly, Martins et al. [18] introduce a hybrid MOO algorithm to solve the coverage and connectivity problem. Moreover, their algorithm enhances the network performance in terms of network lifetime, by joining a multiobjective on-demand algorithm employing GA and a local online algorithm.

Aside from the profits cultivated from employing these MOO algorithms, their computational overhead is questionable. The impact of such additional burden is highly notable, especially with resources-taxed sensor nodes. Alternatively, we propose the DnC technique to simplify these

optimizations. As depicted in Figure 3(b), the DnC technique considers energy efficiency as the first objective that has to be accomplished. Afterwards, QoS can easily be improved via refining the energy-conservation method in light of the design-time knowledge. To prove the applicability of our proposed DnC technique, we provide three examples of energy-conservation methods that consider QoS improvement. Each of these examples covers one of the aforementioned categories of WSNs application scenarios.

For time-driven scenarios, we propose a novel compression technique exploiting the recently developed Fuzzy transform (F -transform) [7]. Despite the existence of much research work in this field, our method differentiates itself via adapting the algorithm parameters according to characteristics of the signal of interest. For the event-driven applications, we propose another novel approach based on the concept of virtual sensing to mitigate the burden of such consumers. Moreover, our method is refined to improve the system reliability and minimize the event-miss probability. Finally, we propose a novel self-adaptive framework for improving the service quality in the hybrid applications category. In the next section, we indicate the proposed DnC technique via explaining the first given example of data compression exploiting the F -transform and the curvature detection algorithm.

3. Fuzzy-Based Data Compression

Data compression methods have basically been classified into *lossless* and *lossy* approaches. The former has zero recovery error while offering relatively small compression ratios. Since numerous applications tolerate limited precision reduction, lossy compressors provide an excellent solution, delivering high compression ratios with very low information loss. The lossy compression methods can be further classified into

- (1) *transform-based techniques* such as the discrete cosine transform (DCT) or the discrete wavelet transform (DWT) [19];
- (2) *model-based techniques* like the derivative-based prediction (DBP) [20] or the lightweight temporal compression (LTC) [21], and so forth;
- (3) *compressive sampling (CS)* [4].

The first category is typically linear transformations that map data on a space where computation is simpler. Given the temporal correlation of sensed data, most resulting coefficients approach zero and are discarded, so the mapped space can be easily entropy-coded. In the second category, the signal's temporal correlation is exploited to approximate it by a sequence of line segments. The information loss is controlled by a user-set error margin: whenever the approximating line deviates from the next data point by more than the error margin, the current line parameters are sent and a new approximation is started. We note that the authors of [20] utilize the same idea in designing derivative-based prediction (DBP) modelling, a greedy algorithm that linearly approximates the signal, although their work is not data compression per se. The key difference between LTC

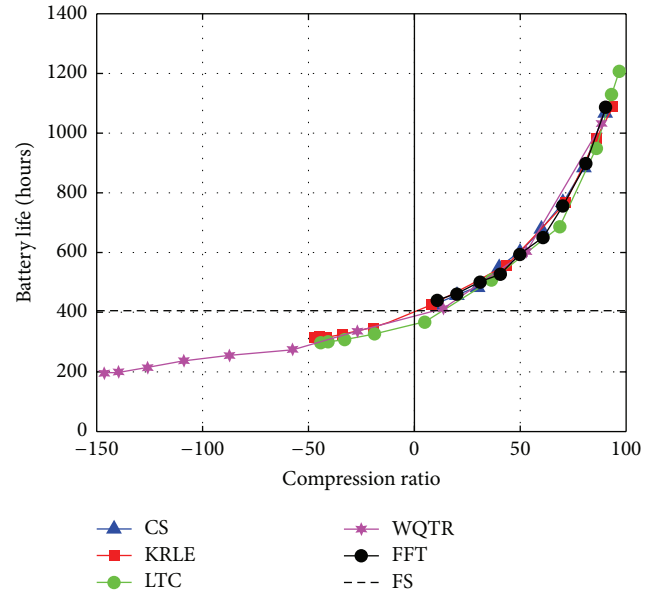


FIGURE 4: The SN lifetime running various compression algorithms where FS shows the classification accuracy for the full (uncompressed) signal [4].

and DBP is that LTC transmits the parameters of a line once it has exhausted its approximating potential, whereas DBP sends out the line parameters (the model) immediately after the learning phase and waits until the model adheres to the “incorrectness” definition to compute a new one. Admittedly, both algorithms proved to be successful by finding application in real WSNs.

Compressive sensing is a novel method which displaces the traditional mantra of “sample then compress” with “compress while sampling.” Its core idea is to sample below the Nyquist rate and then use numerical optimization methods to recover full-length signals from a small number of randomly collected samples [4]. For the CS method, the computational burden is customarily transferred to the sink; however, the recovery process is relatively complex. Figure 4 depicts a realistic comparison between various compression algorithms including the K-run-length encoding (KRLE), the LTC method, the DWT method, the run-length encoding (WQTR), and the low-pass filtered fast Fourier transform (FFT) [4]. As it can be seen, the different methods result in approximately the same battery lifetime. However, both CS and FFT have an advantage of avoiding negative values which result when the compression process increases length of the original data.

The aforementioned comparative analysis, among existent data compressors, motivates us to adopt the DnC strategy when compressing sensor data. To this end, a Fuzzy transform-based compression (FTC) method is devised. Subsequently, we introduce an adaptive version, referred to as Fuzzy Compression Adaptive Transform (FuzzyCAT). FuzzyCAT considers better accuracy while preserving periodicity and resilience to lost packets. The next discussion highlights

the idea behind both F -transform and the FuzzyCAT compression method.

3.1. FTC Compression. The *Fuzzy transform* is defined as a Fuzzy set mapper of a continuous/discrete function into an n -dimensional vector [22]. Assume time series is confined into an interval $\phi = [a, b]$ as a universe. This domain is Fuzzy-partitioned by Fuzzy sets $A_1, \dots, A_k, \dots, A_n$, given by their basic function A_k . On the one hand, the *direct F -transform* converts an original signal into an n -dimensional vector, where n corresponds to the number of Fuzzy sets applied. The *inverse F -transform*, on the other hand, approximates the original signal utilizing the Fuzzy vector. Definition 1 formulates the direct F -transform in terms of the uniform basic function. Each Fuzzy vector element F_k represents the weighted average of the data points $f(x_j) \in [x_{k-1}, x_{k+1}]$. The transformed data can be retrieved by means of the inverse operation.

Definition 1. Assume a discrete function $f: \phi \rightarrow R$ known at points x_1, \dots, x_l has been applied to F -transformer such that, for each $k = 1, \dots, n$, there exists $j = 1, \dots, l: A_k(x_j) > 0$. Then, the n -tuple of real numbers $[F_1, \dots, F_n]$ is given by

$$F_k = \frac{\sum_{j=1}^l f(x_j) A_k(x_j)}{\sum_{j=1}^l A_k(x_j)}, \quad (3)$$

$$f_{F,n}(x) = \sum_{k=1}^n F_k A_k(x). \quad (4)$$

In [7], we perform a comparative analysis between Fuzzy transform-based compression (FTC) and the LTC method. The comparison metrics include recovery accuracy, that is, root mean square error (RMSE) between an original signal and a recovered signal, and compression ratio (CR). Simulation results show similar performance, where CR delivered by FTC is 10, whereas LTC compresses the input data by a ratio of 9.17. RMSE is 3.67% for FTC and 3.89% for LTC. However, in case of FTC, we notice that peak values of the RMSE metric occur at curvature areas of the original signal.

One way to ensure smoothness, thus minimizing the reconstruction error of FTC on interesting intervals of the signal, is to implement data preconditioning such as sorting. It is known that many lossy compressors act as low-pass filters, only preserving signals of low frequency or low curvature. Therefore, the idea of sorting the discrete signal is not specific to FTC. It can rather be adapted to other lossy algorithms. In our case, applying quick sorting to the data before compression indeed reduces the RMSE dramatically, since all high fluctuations are removed. However, this comes at a high cost to the overall performance: since the sorted and compressed signal requires “back-sorting” at the sink node on top of performing the decompression. The vector of resorted indices of each data point has to be sent along with the Fuzzy vector. As a consequence of this naïve approach, the compression ratio plummets.

Figure 5 depicts the normalized RMSE as a function of the CR where FTC has been applied to different window sizes

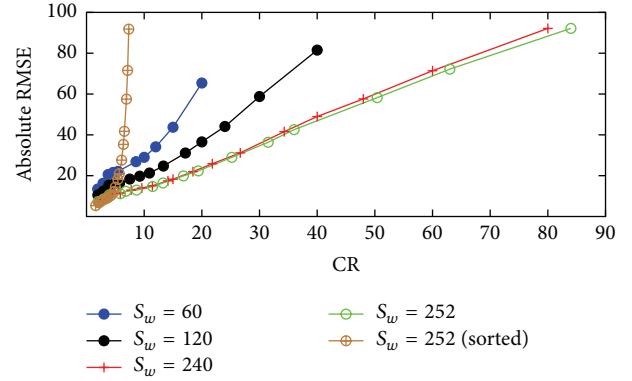


FIGURE 5: Reconstruction error of regular and sorted data for different window sizes.

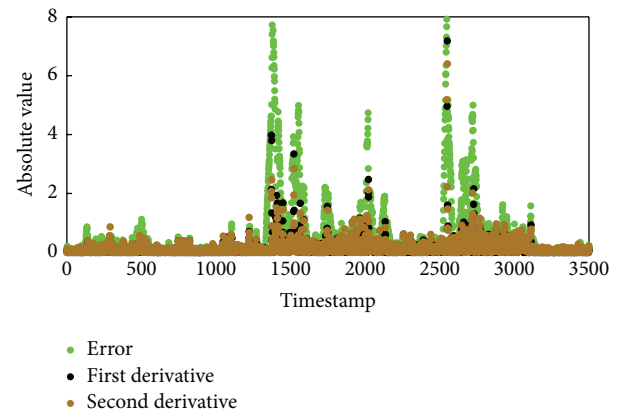


FIGURE 6: The first and the second derivatives as measures of smoothness.

(S_w). Note that the purple data points, corresponding to the performance of the transform with sorting, exhibit a strong upward trend already at very low compression ratios. It seems as if the resulting curve has an asymptote at $CR = 10$, which makes it highly undesirable compared to regular FTC. The uncompressed vector of indices transmitted together with the FTC vector completely undermines the compression. With that being said, we maintain that sorting combined with compressing can be a viable technique, especially for less smooth signals. An idea for future work is to implement an injective function between permutations and long integers in which sending the uncompressed vector of indices will be replaced by transmitting a single long integer denoting a unique permutation.

3.2. FuzzyCAT Compression. The core idea behind FuzzyCAT is to increase resolution of the F -transform during high fluctuation areas of the original signal. Specifically, narrower Fuzzy sets are dynamically added whenever the signal exhibits high curvature. To this end, FuzzyCAT monitors the second derivative of the signal, which is an indicator of signal curvature. Figure 6 graphs the absolute error of the reconstructed signal along with the first derivative $D_x f$ and the second derivative $D_{x^2} f$ of the original signal $f(x)$ as

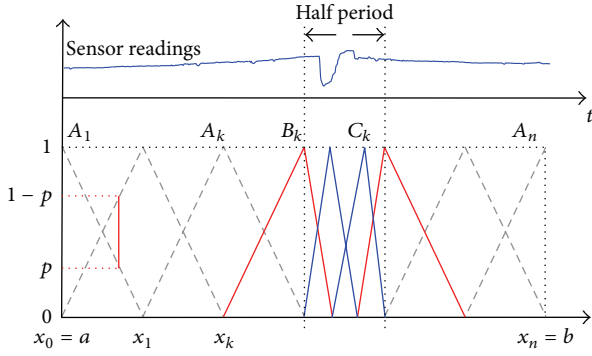


FIGURE 7: Structure of the adaptive basic function.

functions of time. As it can be seen in the figure, there exists a certain correlation between the absolute error and both of the first and the second derivative. Figure 7 depicts an explanatory view of the adaptive basic function. The original signal is delineated at the top, and the Fuzzy sets constructed by FuzzyCAT for that signal are displayed at the bottom. The regular Fuzzy sets are applied whenever the signal is smooth. In the half period where fluctuations were detected, narrower Fuzzy sets are applied (in blue). Note that, to fulfill the unity requirement, that is, $\sum_{k=1}^n A_k(x) = 1$, the triangular Fuzzy sets adjacent to the high-resolution half period (in red) are asymmetric. To reduce the computation burden of FuzzyCAT, the three basic functions, that is, A_k , B_k , and C_k , are only computed once in a node's lifetime and stored away. The program iterates over half periods of the window size.

Comparing the performance of LTC, FTC, and FuzzyCAT involved compressing and recovering a 1000-point segment of the temperature dataset while varying the parameters of each algorithm: error margin for LTC, number of coefficients for FTC, and the number of additional Fuzzy sets per half period for FuzzyCAT. The two remaining parameters of FuzzyCAT, $T_{\text{deriv}\%}$ and $T_{\text{percent}\%}$, were optimized such that the maximum quality factor (QF) is achieved (see Figure 8) [19]. Figures 8(a) and 8(b) depict QF values for different CR and RMSE. The values of CR and RMSE that achieve the highest QF are used to determine the parameters $T_{\text{deriv}\%}$ and $T_{\text{percent}\%}$ as shown in Figure 8(c). Hence,

$$\text{QF} := \frac{\text{CR}^2}{\text{RMSE}}. \quad (5)$$

The algorithm's parameters such as $T_{\text{deriv}\%}$ and $T_{\text{percent}\%}$ were optimized as shown in Figure 8(c). The selected values of these parameters represent pairs of thresholds that yield the maximum QF factor, defined in (5). Figure 9 shows the results of the comparison. Note that, depending on the error margin, LTC can yield different reconstruction errors with the same compression ratio. Obviously, LTC has a slightly smaller error than FuzzyCAT for compression ratios below 50. Beyond this threshold, the LTC error curve sharply increases, giving an advantage to FuzzyCAT. For FuzzyCAT, adding extra Fuzzy sets cut the RMSE by more than half, a 52% decrease relative to the regular FTC method, while the resulting compression ratio was only 25% percent lower than the original one.

Aside from the accuracy metric, FuzzyCAT and LTC were also evaluated in terms of the consumed energy. We ran a series of experiments using TelosB sensor nodes (CM5000 MSP) with the Contiki OS. A WSN was deployed to collect temperature, humidity, and light intensity readings. To create fluctuations in the measured signal, the indoor light level has been frequently changed during the experiment. The setup involved a network under the ContikiMAC radio duty cycling protocol in the Rime stack. For the fairness of the experiment, the parameters of each algorithm were set such that both resulted in the same normalized RMSE. Figure 10(a) delineates the power consumed via broadcasting the LTC and the FuzzyCAT vectors. In fact, FuzzyCAT consumes 96.07% less energy than LTC for fixed throughput. This significant gain comes along with another decrease in the processing power consumption as shown in Figure 10(b). Although these results apply only to our settings, they give a "good" insight into FuzzyCAT superiority over the model-based compressors.

3.3. Limitations of FuzzyCAT. Intuitively, the proposed FuzzyCAT method has some drawbacks that should be here identified. However, we provide solutions which could highly mitigate the incurred burden of such drawbacks:

- (i) The most obvious disadvantage of FuzzyCAT hides in the fact that the computation of the transform requires iterating through the whole window of data points, before sending the compressed vector, which increases the *latency* of measurements. Contrary to DBP where a new model is sent as soon as the signal deviates from the previously established model, FuzzyCAT cannot be used in systems where immediate feedback is required. At each round, the latency is limited to a certain value and then reset to zero on the next scheduled transmission.
- (ii) Since FuzzyCAT records information about the curvature of each half period of the time series window before applying the transform, it needs to store the whole vector of uncompressed measurements in the mote's memory. This is problematic, given that most motes have very *limited storage* left after an operating system is installed. During our experiments with CM5000 MSP motes, we found that we cannot compress more than 1000 data points at a time without running out of memory. However, this problem would not occur if motes with extended memory are used.
- (iii) Spreading the overhead by sending vectors of values comes at a price of having to respect the *maximum packet size*. Rime, the networking protocol we used, set that limit to 127 bytes, which accounting for the header allowed us to send no more than 28 floats at a time. This issue can be easily addressed by splitting the vector of compressed values into smaller vectors in case it exceeds the maximum packet size. This feature is automatically implemented in some other network protocols.

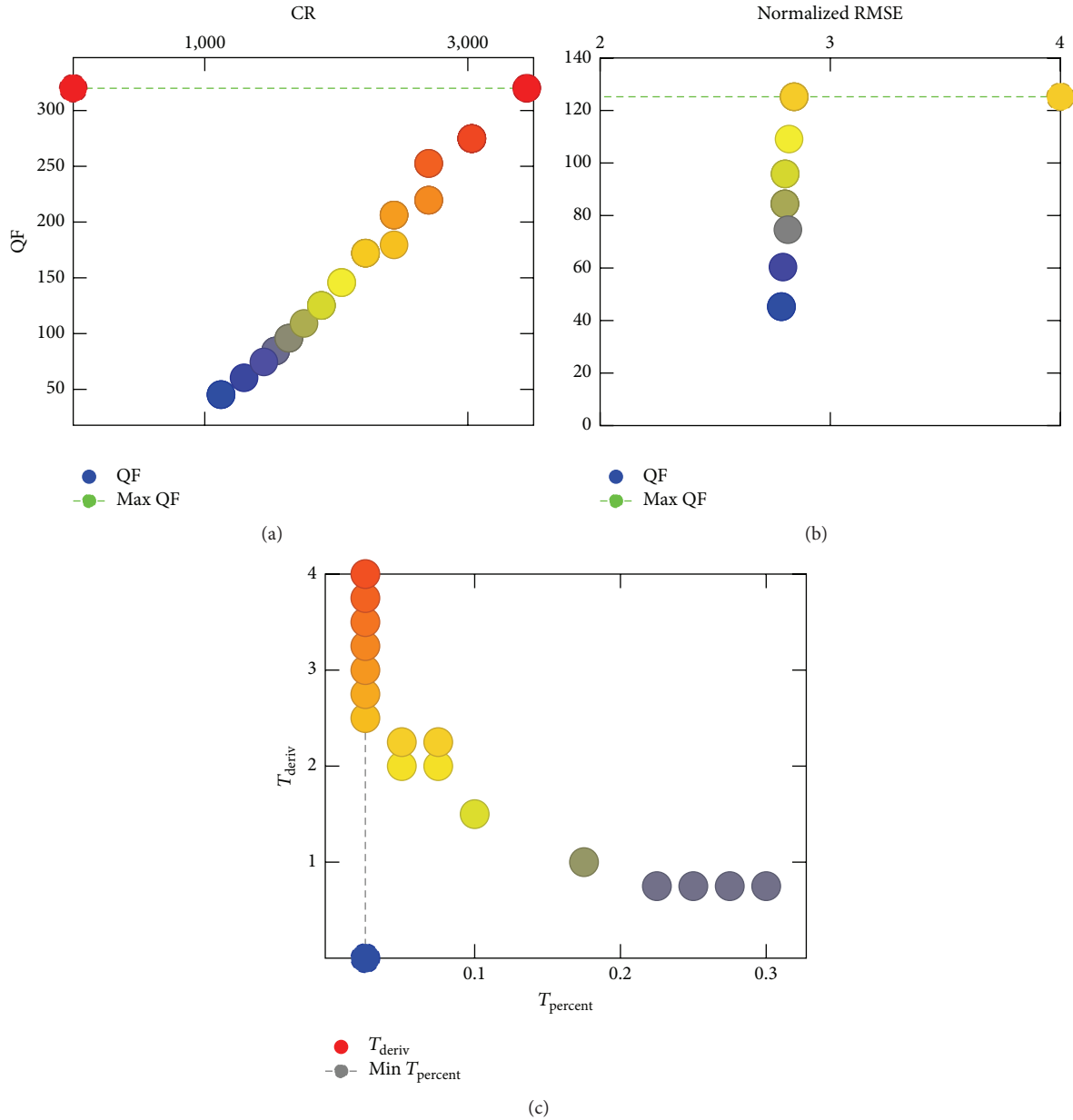


FIGURE 8: Determining the optimum thresholds for Berkeley lab data.

- (iv) Another potential difficulty is that the *parameters* of FuzzyCAT, of which there are five, must be carefully chosen to suit the application. For instance, the window size ω , the number n of Fuzzy sets, and the number e of extra narrower Fuzzy sets added per half period must satisfy the preconditions; otherwise, integer division results in incorrect compression and higher reconstruction errors. The thresholds T_{deriv} and $T_{percent}$ must also be adapted to the type of signal expected by the application. Fortunately, this fine-tuning needs to occur only before the deployment of the WSN and no further adjustment is required.
- (v) Finally, as we mentioned previously, the measurements that include both positive and negative values

must be *offset* by a constant for the decompressor to correctly compute the inverse transform.

As one can see, the disadvantages of FuzzyCAT are certainly workable and by no means undermine the overall value of the method, especially in consideration with its beneficial characteristics such as stellar energy efficiency, low complexity, and periodicity. Next, we explain our proposed method for shortening the reporting delay.

3.4. Cooperative Prediction Scheme. In this section, we set up an efficient prediction method at the aggregating node for reducing the delay incurred through compression. The main idea is to enable aggregating nodes to forecast the vector F_{x,t_2}

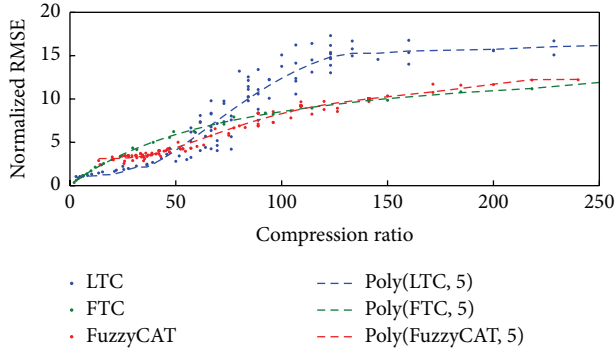


FIGURE 9: Normalized error versus compression ratio of LTC, FTC, and FuzzyCAT.

exploiting the readings at $t = [t_1, t_1 + \delta, t_1 + \Delta t]$, as expressed in (6). Hence,

$$\hat{F}_{x,t_2,t_3} = \sum_{t_1}^{\Psi} f(F_{x,t_1}) + \sum_{\Psi}^{\beta} f(F_{y,t_1}) + \sum_{\beta}^{\Delta t} f(F_{z,t_1}) \quad (6)$$

$$\text{subject to } \frac{\rho_{x,y}}{(\beta - \Psi)} < H > \frac{\rho_{x,z}}{(\Delta - t_1)}, \quad (7)$$

where $f(F_{x,t_1})$, $f(F_{y,t_1})$, and $f(F_{z,t_1})$ are the predictions stimulated from sensor nodes x , y , and z , respectively. Equation (7) denotes that the cross-correlation functions $\rho_{x,y}$ and $\rho_{x,z}$ should be within a certain boundary H . Otherwise, the nodes y and z cannot be utilized for determining the prediction \hat{F}_{x,t_2,t_3} . The advantages of this approach are that (1) it does not require additional communications, (2) it is independent of the prediction model, and (3) the computation overhead is done at the sink nodes, where energy is assumed to be affordable. The applicability of such a method is tested with the real readings extracted from Intel lab. These sensor nodes are close enough to each other in order to generate highly correlated data. A combination from the three nodes stimulates four predictors, as denoted in (6) where $t_1 = 0$, $\Psi = 40$, and $\beta = 70$.

For evaluating this study, we exploit the predictive analysis of the collected time series. Initially, prediction can be classified into (1) *classification*, that is, forecasting the outcome from a set of finite possible values; (2) *regression*, that is, forecasting a numerical value; (3) *clustering*, that is, summarizing data and identifying groups of similar data points; (4) *association analysis*, that is, extrapolating relationships between attributes; and (5) *deviation analysis*, that is, estimation of exceptions in major trends or structures [23]. In fact, our criteria to select the prediction model were the simplicity to reduce any computational overhead and the ability to precisely predict times series such as temperature, humidity, and light intensity. Particularly, we evaluated three different predictors:

(i) *Single exponential smoothing* (ESP) [24]: it assigns exponentially decreasing weights as the observations get older.

(ii) *Linear regression model* (LR) [25]: it estimates the forecast by finding the best-fitting straight line through the time series points.

(iii) *Holt-Winters smoothing* (HW) [24]: it takes into account seasonal changes as well as trends of the time series. Seasonality can be characterized as the tendency of time series data to exhibit behavior that repeats itself every fixed period.

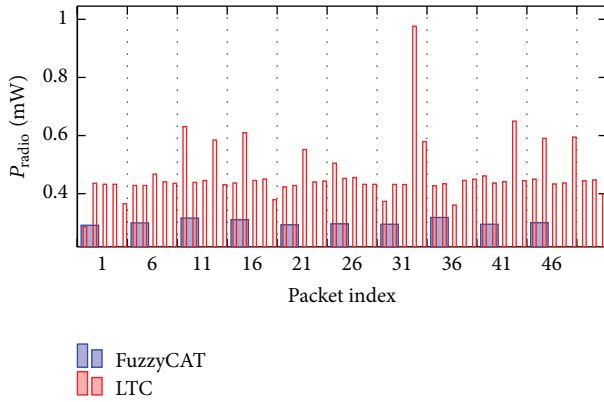
As depicted in Figure 11, the original temperature values $f(x)$, extracted from sensor nodes 3, 4, and 6 (SN_3, SN_4, and SN_6), and various time series predictions are delineated. Obviously, both of the linear regression and the Holt-Winters smoothing (damping factor = 0.7) predictors approximately follow the envelope of the original data. Although the single exponential smoothing method is examined with two different weights ($\alpha = 0.1$ and $\alpha = 0.8$), it did not exhibit high precision. This could be explained in light of the fact that such predictors typically do not consider the trend and the seasonality components of the time series. In fact, these predictors were given here to only examine the proposed cooperative prediction method. Nevertheless, other predictors have to be examined in terms of their accuracy and their ability to shorten the compression delay. Finally, we can conclude that the proposed cooperative prediction method is feasible for mitigating the burden of any incurred delay.

In the next section, the second DnC example of reliable virtual sensors is discussed in detail. The goal of such virtual sensors is to reduce the energy burden of the energy-hungry sensors while offering a low event-miss probability.

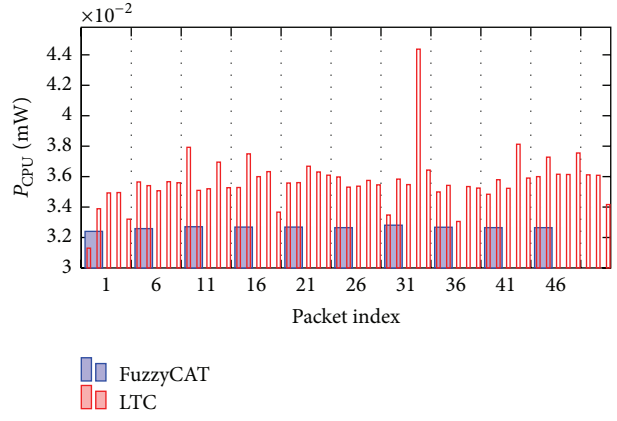
4. Reliable Virtual Sensing

Recent ideas for reducing the energy consumption of sensing modules circle around *adaptive sampling*, *model-based active sampling*, and *hierarchical sampling* [11]. The former dynamically adapts sampling rates by exploiting some characteristics of the collected data streams, such as the spatio/temporal correlation. Yang et al. [26] introduce a framework which adapts sampling rates based on battery level, energy harvesting level, and characteristics of the gathered data. Alternatively, a model of the sensed phenomenon is constructed in the model-based active sampling. Thus, future values can be predicted with certain accuracy and the acquisition rate can be minimized. Jain and Chang [27] develop a distributed algorithm based on the Kalman-filter estimation error to dynamically adjust the sampling rate within a predefined range.

The aforementioned methods often do not consider the event-miss probabilities. In real-time scenarios, unavailability of the sensors due to adaptive acquisition plans may lead to missing interesting events. Hierarchical sampling, on the other hand, has been employed with multimodal SNs which comprise different sensors for measuring certain phenomena [11]. Each of those sensors is characterized by specific performance features, that is, resolution and energy consumption. Hence, hierarchical sampling adapts the acquisition rate based on a trade-off between accuracy and energy consumption. In this paper, we contribute to



(a)



(b)

FIGURE 10: Power consumption of TelosB sensor nodes running LTC and FuzzyCAT.

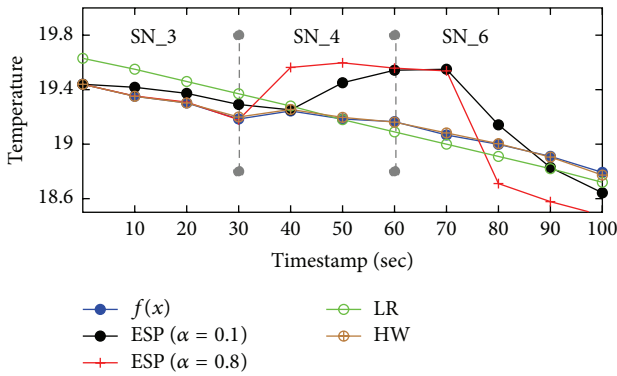


FIGURE 11: Cooperative multisource prediction of temperature readings.

this category through a novel approach, referred to as the *virtual sensing* (VS), to decrease the energy dissipated by those sensing modules while offering very low event-miss probabilities. Figure 12 illustrates a flowchart of the sensing module with employing virtual sensors. After deploying the sensor nodes, the main sensors are activated once to monitor the environment. If nothing is interesting, the virtual sensor is activated in lieu of the main sensor. The virtual sensors are continuously polled until an interesting event is detected. Then, the main sensor is again invoked. For the sake of illustration, below we introduce an example of virtual gas leak detection using a set of energy-cheap sensors.

4.1. Example: Virtual Gas Leak Sensor. Gas sensors typically consume approximately between 500 and 800 mW on each sample. Somov et al. [28] develop a WSN for detecting the combustible gases inside a building. They utilized a pulse heating profile to reduce the sensor energy consumption. However, the gas sensor is still energy-hungry due to the continuous data acquisition. Hence, invoking the DnC strategy is beneficial to drastically reduce the energy consumption and the event-miss probability. Inspired by the work done in

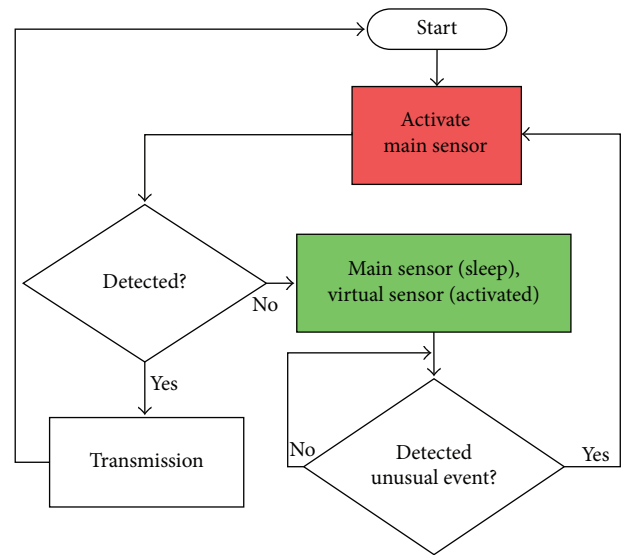


FIGURE 12: Virtual sensing flowchart.

[29], a gas sensor could be replaced by a light sensor which stands in front of a chemical film whose color is altered with the existence of gases. Accordingly, the light sensor indirectly detects the gas presence whenever the film's color is changed.

Probabilistic model checking has been customized to evaluate the proposed VS method in terms of energy consumption and detection latency. Figure 13(a) demonstrates lifetime of the μ -radar sensor versus different probabilities of gas leak. The lifetime gradually decreases as the gas leak probability increases. In fact, the resultant lifetime presented in [28] is a deterministic value where it was empirically computed, assuming the occurrence of no gas leaks. We compare the lifetime obtained in [28] with our result determined at $P_{gl} = 0$. At small values of P_{gl} , the proposed mixed approach, of VS together with the PWM technique, highly increases the lifetime relative to the pure PWM method. Aside from the lifetime extension, we also examine the system performance

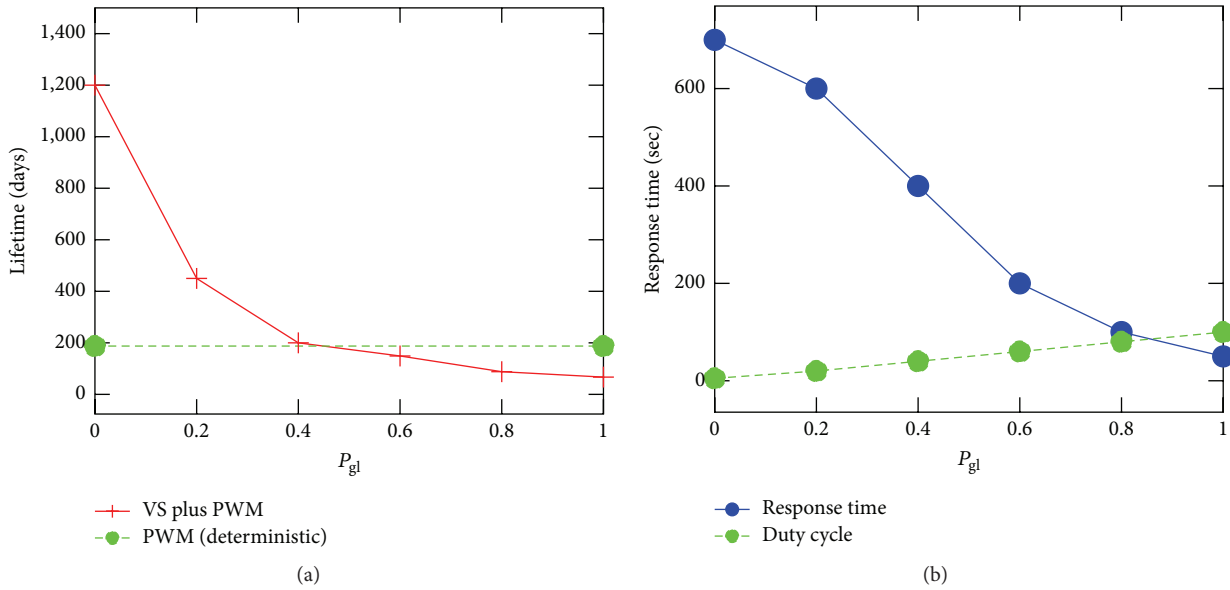


FIGURE 13: Comparison between virtual sensing together with the PWM method and the pure PWM technique.

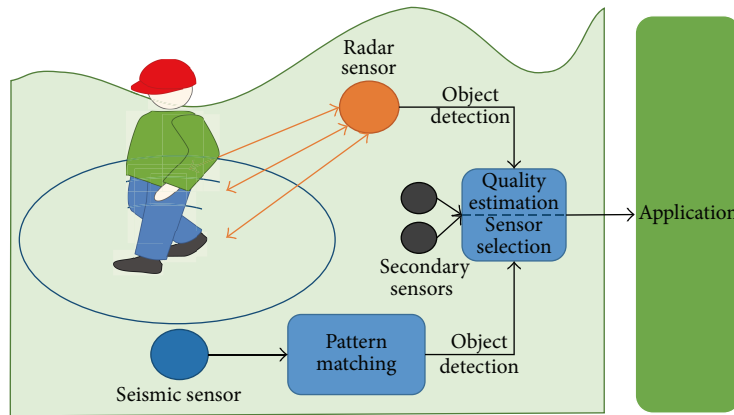


FIGURE 14: System structure with real and virtual sensors.

in terms of the incurred delay. As shown in Figure 13(b), response time of the virtual sensors is significantly shortened by increasing their duty cycle.

Replacing real sensors with an orchestration of heterogeneous sensors imposes sensing reliability risks. To select the appropriate sensor to answer a sensing query, quality conditions of each sensor have to be estimated by looking up the relationship between the sensors and their readings. Using ontology, it is possible to generate rules for switching among sensors depending on observable properties in the feature of interest. To transform this information into processing instructions, we have to concatenate the required sensing devices to have the observed property values at hand. The run-time evaluation of the sensor selection rules could result in a highly dynamic selection of the most reliable sensor. A more detailed overview of the ontology-based decision-making algorithm is given in [8]. In the sequel, an

object tracking mechanism is discussed as well as how virtual sensing can be beneficial in this field.

4.2. Case Study: Reliable Virtual Object Tracking. An object tracking system consisting of real and virtual sensors is delineated in Figure 14. The key idea underlying the virtual object tracking sensor V is to stretch (or compress) seismic traces until it best matches one of the reference traces in the codebook (B_1, \dots, B_z) . The quality estimation mechanism utilizes secondary sensors to monitor the quality of sensors. Based on this quality, the rules, generated by the ontology, determine the well-suited sensor.

Dynamic time-warping (DTW) has been used to match the seismic patterns. The DTW precision has been examined prior to being incorporated into the virtual sensor. Figure 15 depicts samples of precision results obtained from contrasting the codebook to some targeted and nontargeted

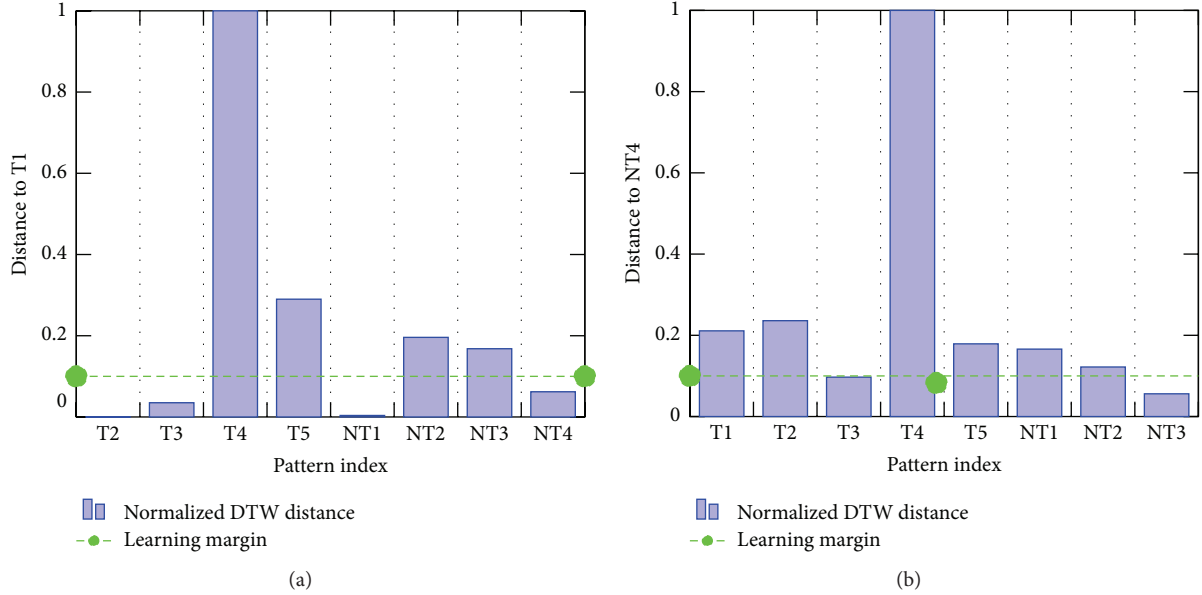


FIGURE 15: Examples of DTW matching for the recorded vibration patterns.

patterns. The vertical line denotes the normalized DTW distance between the measured pattern $T1$ and the codebook patterns. Knowing that $DTW(A, A) = 0$, pattern A_{indoor} is matched with A_{outdoor} to clarify the process of selecting the best match. Figure 15(b) depicts a similar comparison between the NT4 and all other vibration patterns. Obviously, the DTW algorithm has successfully matched the indoor and outdoor pairs through adopting the minimum DTW interdistance.

Real experiments over TelosB sensor nodes have confirmed the virtual sensors advantages: they save circa 99.93% of the energy needed for tracking a mobile object. Furthermore, a benchmark for the reliability parameters versus the lifetime and the event-miss probability has been constructed via large-scale simulation. Table 1 lists the impact of the quality thresholds on the μ -radar lifetime and the overall event-miss probability. For large values of accuracy and selectivity margins, the virtual sensor V frequently triggers the sensor S leading to lifetime reduction. Nevertheless, invoking the main sensor typically avoids any event-misses. For low thresholds, fewer calls are provoked increasing the lifetime. However, the event-miss probability may only increase if the seismic sensor functions outside its operating environmental properties.

In the next section, we elaborate on our third proposed idea of lifetime planning for extending the operational lifetime and simultaneously improve the provided service quality.

5. Lifetime Planning

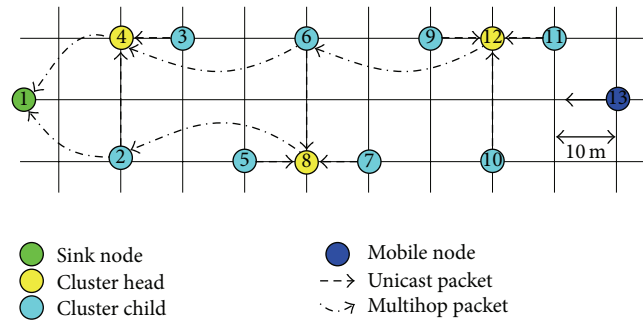
The third given example of the DnC strategy is WSN lifetime planning in light of environmental and application-related dynamics. Often, sensor nodes, in these cases, consume an amount of energy to continue functioning even after the

TABLE 1: Impact of varying the selectivity and accuracy margins of the virtual sensors on the event-miss probability and the lifetime.

Accuracy	Selectivity	Lifetime (days)	Event-miss probability
0.1	0.1	993.069	0.838
0.2	0.2	989.889	0.754
0.3	0.3	989.02	0.679
0.4	0.4	983.032	0.499
0.5	0.5	824.488	0.451
0.6	0.6	783.057	0.368
0.7	0.7	498.785	0.227
0.8	0.8	443.325	0.208
0.9	0.9	412.277	0.135
1.0	1.0	380.536	0.019

task lifetime. The WSNs literature explored possible trade-offs between the energy efficiency and other QoS parameters [71, 72]. In such articles, the design-time knowledge is completely discarded. As a result, we propose a novel approach, referred to as the *lifetime planning*, for affording a higher level of QoS by investing the wasted remaining energy beyond the lifetime L_{task} .

The self-adaptation mechanism relies on the autonomic *monitor-analyze-plan-execute* (MAPE) reference model [73]. According to the MAPE framework, the collected context information has to be processed to discover interesting events. In addition, reactions have to be generated in light of these detected events. A priori knowledge of the application scenario leads to the definition of a set of possible events. Hence, reactions can be earmarked even before deployment [74]. Nevertheless, environmental dynamics typically result in unexpected events which could also be exploited. Consequently, a “good” reasoning engine should be employed to

FIGURE 16: Office monitoring testbed implemented in *Cooja* simulator.

make use of nearly any interesting event. In this work, we choose to make the self-adaptation mission rely on ECA rules due to being hardware-friendly especially with the “taxed” resources in WSNs.

As a proof of concept, the next section discusses our implementation of an office monitoring scenario. This case study is investigated to examine the network performance with and without integrating the lifetime planning strategy.

5.1. Case Study: Office Monitoring Scenario. In real office monitoring applications, several interesting events emerge due to the environmental dynamics. The occurrence of such events is exploited to reconfigure the network in light of the lifetime planning strategy. For instance, detecting of whether the person is “stationary” or “walking” triggers a set of reconfigurations. During the “walking” activity, the connectivity is continuously altered based on the distance between the *static sensor nodes* (SSNs) and the *mobile sensor nodes* (MSNs). Hence, the transceiver duty cycle f and the sampling rate r_s have to be quickly modulated. Moreover, the interference is waving when walking. Thus, transmission power T_{tx} should be also modified to overcome the imposed interference. The daily pattern of day and night is also of interest to our self-adapting mechanism. The hallway has mostly low traffic at night. Accordingly, less data has to be reported to the sink node. Hence, service quality could be customized to save energy.

The design-time knowledge is a valuable resource for drastically decreasing the computational burden on the reasoning engine. Such knowledge is exploited to engineer the QoS lower and upper boundaries. At run-time, the QoS metrics are continuously monitored. A set of secondary sensors, such as temperature and light sensors, forward their readings to the reasoning engine. If these readings exhibit an interesting event, then the quality metrics are accordingly adjusted. In the next section, we elaborate on the reasoning engine and how it reacts to unexpected events.

5.2. Performance Evaluations. An experimental study of the office monitoring scenario has been performed to evaluate the proposed lifetime planning strategy. As earlier explained,

the goal of our strategy is to improve the WSNs service qualities while providing adequate network lifetime. Hence, a proactive adaptation mechanism based on the MAPE framework has been adopted. To fulfill this goal, we have to determine whether lifetime planning improves the provided QoS relative to static heuristics and blind adaptation methods. Furthermore, we have to check whether the resultant network lifetime is beyond or below the user/application requirements. Finally, we have to check the proposed method’s ability to keep the provided QoS between two predefined boundaries.

As mentioned previously, a scenario of office monitoring is engineered for evaluation purposes. The inherent dynamics, in such a scenario, are to be exploited to show the consequences of planning the service quality levels throughout the entire lifetime. Figure 16 shows the structure of the proposed office monitoring scenario. A network of *TelosB* sensor nodes has been simulated in the *Cooja* simulator of the *Contiki* OS. The simulator runs on a virtual machine with 2.5 GHz processor and 8 GB RAM with the Ubuntu OS. Specifically, the testbed consists of eleven static sensor nodes (SSNs), which monitor the observed area, measure environmental parameters, and forward detection packets to the sink. The network is divided into three clusters to avoid flooding the network with excessive control packets. Another set of mobile sensors nodes (MSNs) represents the indoor traffic. These MSNs broadcast identification packets to the nearby SSNs. To localize the mobile nodes, the sink node processes the received signal strength (RSS) values for communication links between the MSNs and the nearby SSNs.

For a comparative analysis, we contrast the lifetime planning strategy to three different methods including (1) *lifetime maximization* (Max), (2) *lifetime minimization* (Min), and (3) *blind adaptation* (Blind) [74]. The first column of Table 2 defines each method in terms of the actual lifetime L . The first two cases represent a fixed strategy in which the controllable parameters P are assigned minimal or maximal values, respectively. The blind method, inspired from [74], exploits the environmental dynamics in a proactive manner to optimize the system performance. Below, we discuss the implementation details of the lifetime planning and the blind adaptation methods. Specifically, four rules have been designed. Two of them monitor the environmental events

TABLE 2: Mode selection for office monitoring scenario.

Local mode (MSNs)		Walking (traffic, speed)				Stationary (speed)	
Local mode (SSNs)		Static				Static	
Scenarios		Low, low	Low, high	High, low	High, high	Low	High
Number of MSNs		1	1	4	4	1	4
Speed (m/sec)		0.5	1	0.5	1	—	—
Max: $L \geq L_{\max}$	P_{tx} (dBm)	-7	-7	-7	-7	-7	-7
	r_c (Hz)	8	8	8	8	8	8
Min: $L \leq L_{\text{task}}$	P_{tx} (dBm)	0	0	0	0	0	0
	r_c (Hz)	64	64	64	64	64	64
Blind: $L < L_{\max}$	P_{tx} (dBm)	-7	-7	-7	-3	-7	-7
	r_c (Hz)	8	16	16	64	8	16
Planning: $L_{\text{task}} < L < L_{\max}$	P_{tx} (dBm)	-7	-3	-3	0	-7	-3
	r_c (Hz)	8	32	64	64	32	32

in light of the criteria listed in Table 2. The other rules are developed to confine the service qualities into their predefined ranges.

Table 2 summarizes the operational mode (rows) and all possible scenarios (columns) for lifetime maximization, blind adaptation, and lifetime planning methods. In fact, adopting general criteria, such as the traffic size and the speed of mobile nodes, mostly covers all possible events. The settings are classified in light of the MSN's state, that is, whether being mobile or stationary. The mobility state has been further classified in accordance with the speed and number of mobile nodes. Thus, four cases emerge by considering only two linguistic variables, *low* and *high*, as expressed in the table. Each strategy has different values of the transmission power P_{tx} and the channel check rate r_c , which substitutes the duty cycle. For the blind adaptation, the values indicated in the tables have been selected to reduce the power consumption, as proposed in [74]. Alternatively, the values for the lifetime planning strategy have been derived based on the required lifetime L_{task} by means of the mapping functions. Below, we discuss the obtained results in light of the aforementioned research questions.

5.2.1. Evaluating the QoS Metrics. Figure 17 depicts the impact of applying lifetime planning, blind adaptation, and the maximization strategy on the service qualities. Figures 17(b) and 17(c) show a comparison between the four strategies in terms of the average *packet delivery ratio* (PDR), representing a realistic measure of the reliability \mathcal{R} , and the average delay \mathcal{D} in milliseconds. The PDR is defined as a ratio between the number of received packets and the number of transmitted packets. The horizontal axes comprise the ID number of cluster heads and children, according to Figure 16. In these experiments, we focus on the communication link between cluster heads and their children. Accordingly, quality values of the sink and the cluster heads (nodes 1, 4, 8, and 12) have been zeroed in the figures. Both quality metrics have been obtained via averaging the results over several runs for the various scenarios, listed in Table 2.

As expected, the lifetime planning strategy achieves highly better reliability and delay than the other approaches, as can be seen in Figures 17(b) and 17(c), respectively. Particularly, lifetime planning has approximately 9.6% and 20% higher PDR than the blind adaptation and maximization method, respectively. Similarly, lifetime planning has about 53% and 78% less delay than the other methods. This superiority is reasonable due to spending more energy in case of the lifetime planning strategy. However, we still need to check the impact of such improvements on the lifetime.

5.2.2. Evaluating the Lifetime. Figure 17(a) delineates the lifetime of cluster heads and children for each strategy. The average lifetime obtained with lifetime planning is about 41.6% and 54.5% less than the other methods. Nevertheless, the achieved network lifetime (approximately 100 days) meets the planned task lifetime, used for estimating the QoS boundaries. These results are confirmed by Figure 17(d) which shows the radio duty cycle of each node as a percentage. With lifetime planning, the nodes activate their transceivers for longer time than for blind adaptation. This additional energy cost contributes to the enhancement of the communication reliability and the detection delay.

5.2.3. Evaluating the QoS Boundaries. Finally, we need to indicate how the expected lifetime is met. Figure 18 depicts the average reliability and average delay for node 6 during several runs over the various scenarios. In both subfigures, the QoS boundaries represent horizontal thresholds colored in green. Obviously, blue and red lines, representing lifetime planning and blind adaptation, have approximately the same behavior, that is, increment and decrement. For the delivery ratio, the lifetime planning values (in blue) are confined between the two green thresholds, as shown in Figure 18(a). Alternatively, the blind adaptation (in red) is reduced without any restrictions to reduce the energy consumption. Figure 18(b) shows a similar behavior for the delay metrics.

To sum up, our proposed lifetime planning approach improves the QoS metrics by exploiting an additional amount

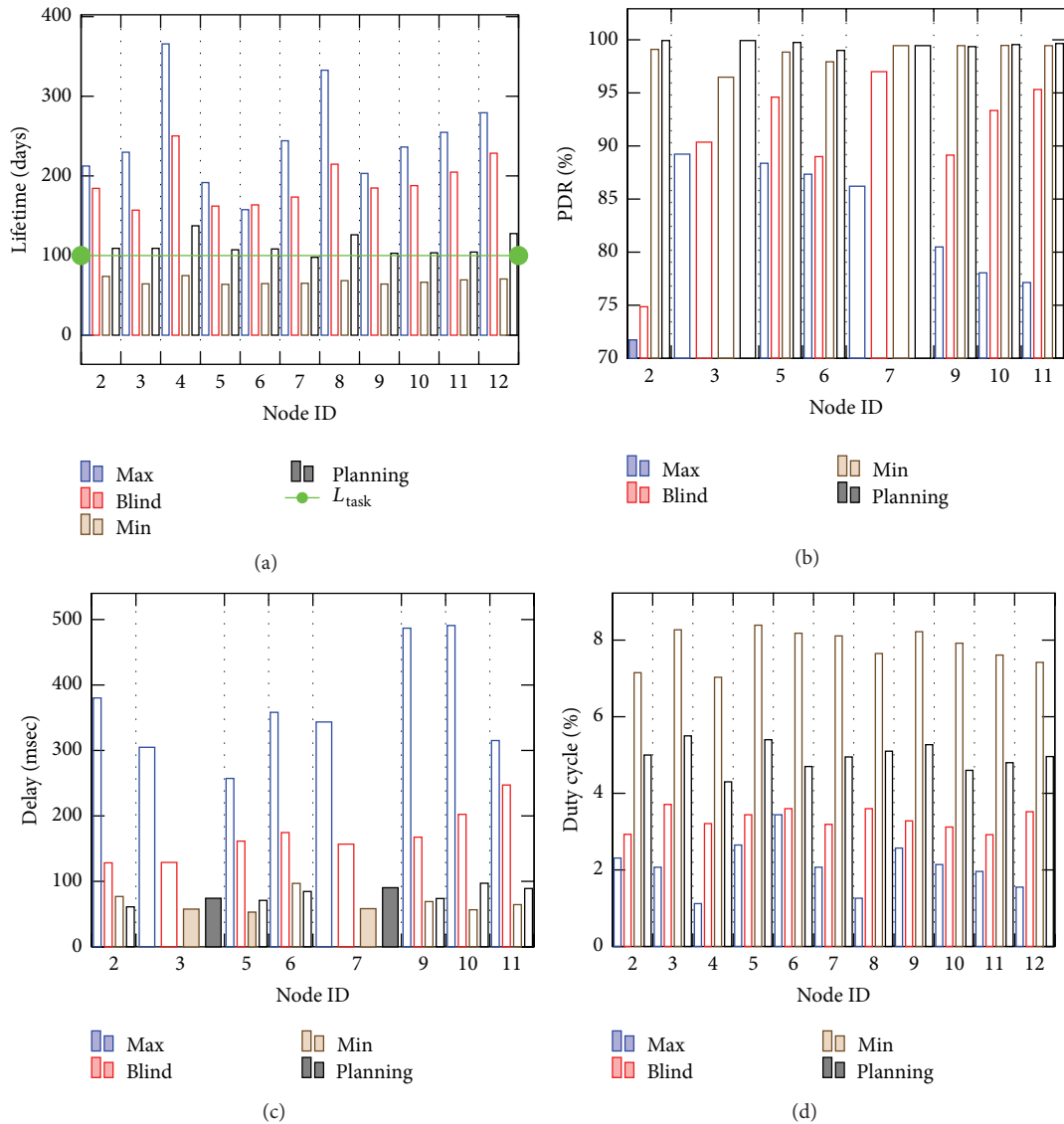


FIGURE 17: Comparison between lifetime maximization (Max), blind adaptation (Blind), lifetime minimization (Min), and lifetime planning (Planning).

of energy. Such energy is gained from limiting the lifetime to the application total task time. Simulation results show that lifetime planning highly improves the QoS metrics. This profit comes at the expense of reducing the WSN lifetime while the new lifetime is still adequate to complete the assigned task. In the next section, we provide a novel taxonomy of energy-saving methods in WSNs. We briefly discuss the advantages and disadvantages of each method along with the impact on other QoS parameters such as latency, throughput, and accuracy.

6. The State of the Art

In this section, we provide a new taxonomy of energy conservation in WSNs including the recent main endeavors. Several taxonomies of the WSNs energy conservation exist;

however, these taxonomies are outdated; that is, they do not comprise recent methods such as compressive sensing and network coding. Moreover, the impact of reducing the energy consumption on other QoS parameters is not clearly discussed [5, 10–13]. Initially, energy management in WSNs has been divided into *energy supplying* and *energy conservation*. The former denotes supplying each node with additional energy during run-time to fully (or partially) energize the sensor nodes. The energy provision is typically achieved either through scavenging the surrounding energy sources, such as kinetic energy, solar energy, electromagnetic energy, air flow energy, and thermal energy, or through wireless power transfer. Currently, external power supply sources, in many cases, exhibit a noncontinuous behavior which can cause system malfunctioning [75]. From our perspective, there should be interplay between energy harvesting and

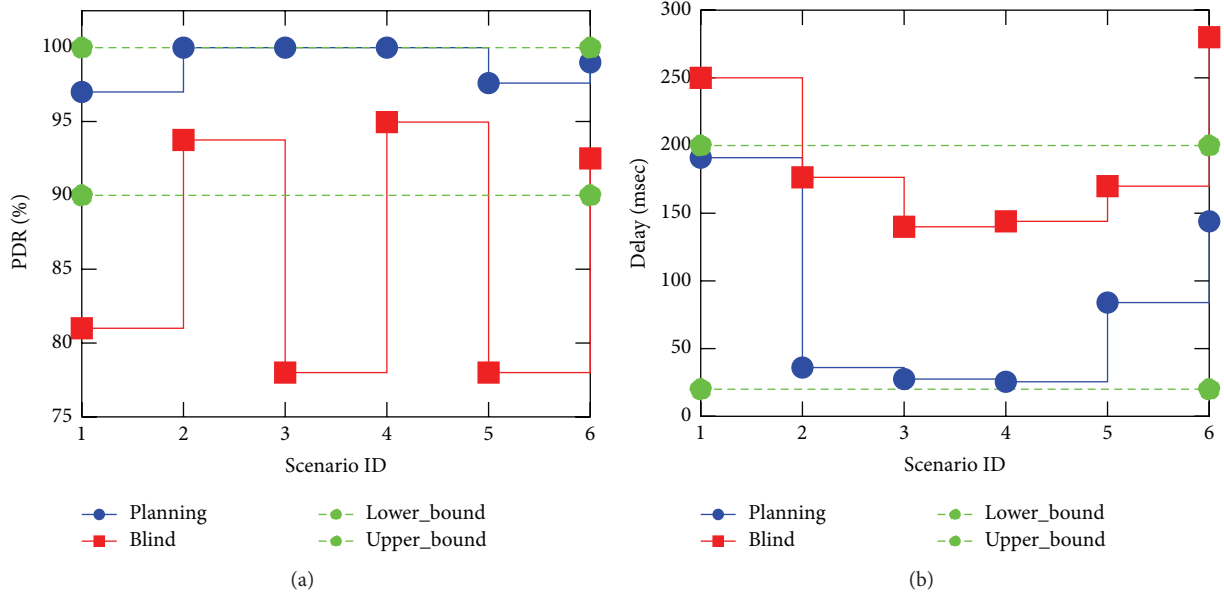


FIGURE 18: Comparison between the controlled and blind (a) delivery ratio and (b) delay.

conservation in a unified framework that avoids wasting the collected energy. In this paper, we only focus on the energy-saving methods and how they deal with other QoS parameters.

As can be seen in Figure 19, the energy-saving approaches can be classified into three categories roots as follows:

- (i) *Data-oriented methods*: this category is divided according to the WSN applications into time-driven methods and event-driven methods. As the name implies, the former subcategory is concerned with the radio communication module which dominates the energy consumption in the time-driven scenarios. Methods utilized to alleviate the burden of frequent data acquisition or energy-hungry sensors belong to the latter category.
- (ii) *Node-oriented methods*: this category encompasses local methods for modulating hardware components, software components, or both of each node. The methods introduced in this category fit well with both event- and time-driven WSN applications.
- (iii) *Network-oriented methods*: this category mainly targets the energy consumed for maintaining network functionality.

In the sequel, the various methods are explained in more detail and examples of recent work are given. Moreover, the impact on application-relevant QoS parameters is discussed.

6.1. Node-Oriented Methods. In this category, energy-saving methods, whose scope is within the individual SNs, are discussed. In fact, the methods listed here are general enough to cover the event-driven and the time-driven WSN application scenarios. These energy-saving methods are designed

to optimize the SN's performance without prior knowledge of the assigned task or application scenario. These methods are divided into *low-power hardware* and *energy-aware software*. The former branch encompasses methods for manipulating the SN's hardware components. This manipulation is achieved either by adding additional modules such as the wake-up receivers or by employing alternative technologies such as directed antenna and Ultrawideband (UWB) communication systems. The latter branch comprises examples of methods for saving energy through modifying the embedded software. The mentioned ideas range from developing energy-aware μ -operating systems to designing self-managing (i.e., self-configuration, self-healing, self-optimization, and self-protection) software components.

6.1.1. Low-Power Hardware

(a) *Directed Antenna.* The core idea is to improve the transmission range and throughput via signal transmission and reception in one direction in lieu of the omnidirectional manner. Directed antenna schemes are advantageous due to allowing multiple communications in close proximity within the same bandwidth. In other words, directed antenna schemes permit the spatial reuse of bandwidth. Directed transmission also sidesteps possible overhearing, for a given range. However, their main advantage is that they consume less energy than that drawn by an omnidirectional antenna. The main disadvantage of directed antenna schemes is their need for localization methods to determine the direction of transmission and reception [30].

(b) *Wake-Up Receivers.* In this section, ideas for engaging wake-up receivers are briefly described. In general, wake-up receivers are used to trigger the main receivers whenever an incoming signal is detected by wake-up receivers.

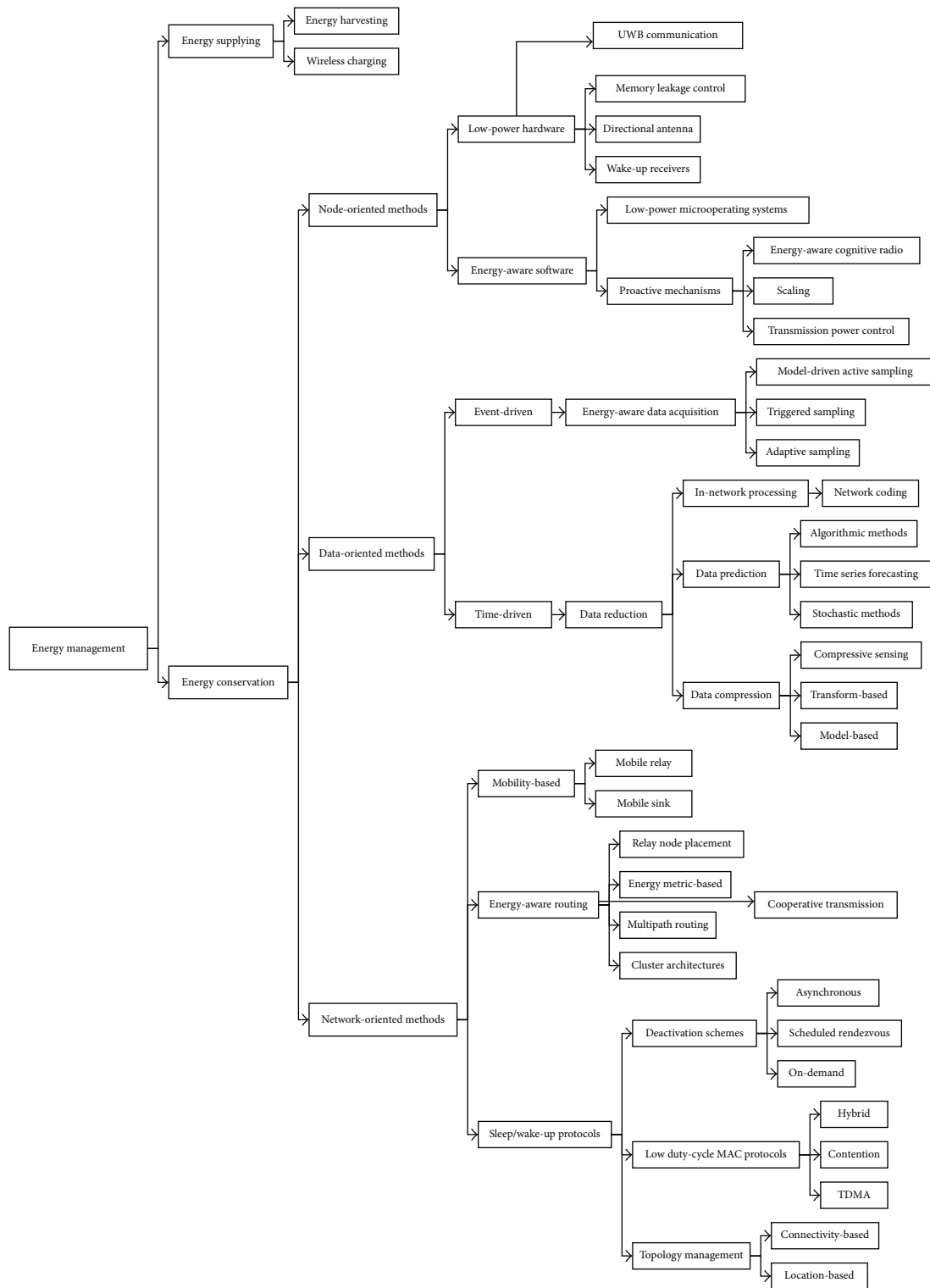


FIGURE 19: Taxonomy of energy conservation techniques in WSNs.

Accordingly, unnecessary activation of the main power-hungry receivers for idle listening is avoided, leading to significant energy saving. Based on their energy sources, wake-up receivers can be active- or passive-powered devices.

The active wake-up receivers are powered using the internal battery. However, powering the wake-up radio can highly affect their energy gain. Recent hardware developments have provided realistic approaches to power the wake-up radio

passively. In this case, wake-up radios are entirely powered by the wake-up signal and therefore do not need any additional battery supply [31].

The channel on which the wake-up signal is sent can be the same one as the main radio communication channel (i.e., shared channel), or a separate channel can be used for wake-up signaling [32]. Although a separate channel increases the cost and complexity of the SN, the energy gain of deactivating the main receiver outweighs this additional overhead. The wake-up signal can be a single wake-up tone or a bit sequence. In range-based wake-up receivers, all the SNs that receive the tone activate their main transceiver. In identity-based wake-up receivers, the wake-up signal may consist of a bit sequence to address the destination. After the reception of a wake-up signal, nodes check whether the bit sequence refers to them. If so, then the destination wakes up. Mostly, radio signals are employed as wake-up signals in radio-based wake-up receivers [32]. Alternatively, acoustic wake-up receivers are triggered by acoustic signals. When the observed level of the external sound reaches a threshold, the wake-up circuitry is turned on.

Ba et al. [33] consider the programmable RFID tags to implement a passive wake-up radio for WSNs. The wake-up radio is realized using a passive RFID tag as the wake-up signal receiver, whereas an RFID reader acts as the wake-up radio transmitter. However, the results reveal that the wake-up range is relatively limited compared to the ZigBee-compliant sensor mote communication range. Moreover, the radio wake-up transmitter requires high energy consumption that cannot be applied to all SNs. Later in [31], the authors propose an RFID range extension method through energy harvesting.

(c) *UWB Communication.* Ultrawideband (UWB) is a short-range wireless communication technology based on transmission of very short impulses emitted in periodic sequences. The advantages of UWB communication technology over WiFi and ZigBee are as follows [34]. Compared to narrow band ZigBee and WiFi, UWB offers significant advantages with respect to robustness, energy consumption, and location accuracy, as it spreads the transmit signal over a very large bandwidth (typically 500 MHz or more). However, UWB is not a viable approach for communication over longer distances. Moreover, several challenges emerge in the hardware development, dealing with MAC and multipath interference, and understanding propagation characteristics.

(d) *Memory Leakage Control.* The leakage current can be controlled to save the energy waste [35]. Different approaches are proposed in this arena such as (1) ones which make their leakage management decisions based on performance feedback, (2) techniques that manage cache leakage in an application-intensive manner (e.g., by periodically turning off cache lines), and (3) techniques that utilize feedback from the program behavior. Singh and Moez [36] examine several leakage reduction techniques applied to binary and ternary content addressable memories. Accordingly, they show that leakage can be reduced by a factor of 168 over nonoptimized designs.

6.1.2. Energy-Aware Software

(a) *Low-Power Microoperating Systems.* Microoperating systems (μ OSs) in WSNs are classified into *event-driven* μ OS and *multithreaded* μ OS. The former are efficient in terms of resources utilization. The latter μ OSs have superior event processing capabilities [37]. Recent μ OSs, such as Contiki and SOS, comprise generic abstractions to manage the power consumed by peripherals of the sensor devices. On the one hand, μ OSs can accomplish significant energy reduction by performing energy-aware task scheduling and resource management. On the other hand, compilers have been studied to generate efficient code in terms of power consumption [35]. For instance, *spill code reduction* techniques managed to save energy and improve the overall system performance. *Power-aware instruction scheduling* is also a known technique for decreasing energy consumption.

(b) *Energy-Aware Cognitive Radio.* In general, cognitive radio (CR) is a new technology by which the wireless devices can intelligently sense and exploit the portions of unused spectrum of the licensed networks. Recently, the CR concept has been exploited for resource allocation in existent network infrastructures such as the WSNs. This leads to founding a new paradigm, referred to as the cognitive radio sensor networks (CRSNs) [38]. CRSNs are WSNs which encompass intelligent wireless communication systems able to determine the most favorable operating parameters (cognition) based on the radio environment and its own capability (awareness). Accordingly, they reconfigure the radio parameters (reconfigurability). Such dynamic adaptations lead to more efficient utilization of the allocated radio resources. A CRSN permits not only modulation adjusting, coding, and radiated power control, but also learning and adjusting component characteristics to reduce the energy dissipation [39]. Another track in this field is the software-defined radio (SDR) technology. This method enables fully programmable wireless transceivers which automatically adapt their communication parameters to network demands, which improves context-awareness.

(c) *Scaling.* The core idea of scaling methods is to dynamically adapt the processor's operating voltage and frequency based on instantaneous computational load requirements. As a result, significant processing power can be saved. This method is referred to as *dynamic voltage scaling* (DVS) [40]. Additionally, *dynamic modulation scaling* (DMS) is a well-known method for reducing broadcasting energy with respect to the number of packets that need to be transmitted at that particular time interval [41]. However, DMS methods may increase the overall system latency due to the inherent complexity.

(d) *Transmission Power Control.* In this category, the radio transmission power is dynamically adjusted in accordance with the residual energy and the network load. Chu and Sethu [42] propose a game-theoretic approach to control transmission power of every SN taking into consideration the uneven energy consumption distribution. However, transmission

TABLE 3: Summarizing the various node-oriented energy-saving methods.

Method	Explanation	Influenced QoS	Reference
Directed antenna	Signal transmission and reception in one direction in lieu of the omnidirectional manner	Coverage, more complexity	[30]
Wake-up receivers	Triggering the deactivated receiver whenever an incoming packet is detected	Communication delay	[31–33]
UWB communication	Transmission of very short impulses emitted in periodic sequences	Connectivity, communication reliability	[34]
Memory leakage control	Reducing the memory leakage current	—	[35, 36]
Low-power μ -OSs	Energy-aware task scheduling and resource management	Run-time operation	[35, 37]
Energy-aware CRSNs	A self-adaptive mechanism for allocating radio resources	Latency, complexity	[38, 39]
Scaling	Adapting the operating voltage and frequency based on instantaneous computational load	Processing latency	[40, 41]
Transmission power control	Adapting the transmission power according to the residual energy and network load	Connectivity, interference, communication reliability	[42]

power decrease may have negative impacts on communication latency, interference, and connectivity. Specifically, reducing the transmission power leads to increasing the number of hops to convey data. These additional hops result in superfluous delay. Moreover, connectivity can be changed; hence, transmission power control has to be accompanied with a suitable topology control method. Although transmission power control methods are related to topology control, they cannot be tagged as a topology control technique.

6.1.3. Discussion. The aforementioned methods deal with saving energy at the node level. Several ideas have been examined either on real WSN testbeds or using simulations. Indeed, all these methods provide uneven contributions to the energy efficiency problem. However, negative impacts on other service qualities often stem from only focusing on the energy problem. Table 3 summarizes the discussed methods and their influences on other service qualities. For instance, the additional complexity of directed antenna emerges from the need for an accurate localization system; hence, the energy consumption and the processing time are increased. Moreover, the coverage of such directed antenna-equipped SNs is arguable where many hops have to be achieved in order to reliably communicate between two nodes with no line of sight.

To sum up, the node-oriented methods are extremely beneficial for reducing energy consumption. Moreover, they do not depend on the application scenario. However, the significance of each method relatively relies on the application features. For instance, wake-up receivers are ideal for high-frequency data reporting, whereas their gain is reduced by less frequent data transmission. In this paper, lifetime planning is considered a contribution to the category of energy-efficient software.

6.2. Data-Oriented Methods. In this section, several ideas of reducing the sampled and transmitted data are to be discussed. In this category, the methods are broadly divided, according to the data aggregation scheme, into *event-driven* methods and *time-driven* methods. The former method

mainly focuses on reducing the burden of data sampling and processing to prolong the event-based WSN application scenarios. The latter method circles around minimizing the radio energy burden of time-driven WSN scenarios. Much research work has been devoted to the handling of these two objectives. Below, examples of such efforts are briefly described.

6.2.1. Event-Driven Methods

(a) Model-Based Active Sampling. The core idea behind model-based active sampling is to reduce the number of data samples by using a computed model. Initially, an abstraction of the sensed phenomenon is determined through a forecasting model. This model predicts the next readings, hence avoiding the burden of sensing each data sample. In such a method, both source and sink nodes have to run the same predication model. Both of the forecasting model's accuracy and nature of the monitored phenomenon have a significant impact on the effectiveness of such model-based active sampling. Gedik et al. [43] propose ASAP, an adaptive sampling approach to energy-efficient periodic data collection in WSNs. ASAP splits the network into clusters such that SNs with close readings are assigned to the same clusters. Within each cluster, a dynamically changing subset of the SNs is selected as samplers such that the sampler nodes' readings are directly collected, whereas the values of the nonsampler nodes are predicted by probabilistic models.

(b) Adaptive Sampling. According to the Nyquist theorem, the minimum sampling frequency (F_s) needed for correct reconstruction of the original signal should be $F_s = 2 \times F_{\max}$, where F_{\max} is the maximum frequency in the power spectrum of the considered signal. Unfortunately, choosing F_{\max} is not trivial because it cannot be known a priori, thus leading to the choice of an unnecessary high sampling frequency, and the maximum frequency may vary over time. To overcome this problem, several research works propose an adaptive algorithm that dynamically estimates the current maximum frequency in accordance with the temporal/spatial

correlation among acquired data and/or the residual energy. For instance, Alippi et al. [44] propose an adaptive sampling algorithm for snow monitoring applications. The current maximum frequency of the signal is determined by using a first set of acquired samples and relies on the CUSUM test to detect changes in such a frequency. The change is detected when the current maximum frequency happens to be above or below a threshold for some consecutive samples. Alternatively, Jain and Chang [45] propose an adaptive sampling method based on the outcome of a Kalman filter. They implement the algorithm in a decentralized fashion; that is, the Kalman filter is executed on each SN. Such solutions might not be feasible in WSNs consisting of tiny devices with limited computational capabilities. It is conclusive that with adaptive sampling a compromise between sampling rate which will influence the resources usage and accuracy needs to be achieved. The degree of complexity of the model will also influence both the accuracy of the estimated model and the resource usage.

(c) *Triggered Sampling.* The core idea behind triggered sensing (sometimes referred to as *hierarchical sampling*) is to equip the SN with different sensors to measure the same phenomenon. Each of these sensors is characterized by its own accuracy and power consumption. On the one hand, simple sensors are energy-efficient while offering relatively limited precision. On the other hand, complex sensors are more accurate at the expense of higher energy consumption. In trigger sampling, low-power sensors enable coarse-grained characterization of the sensing field. The energy-hungry sensors are activated whenever needed to improve the coarser description. In this paper, reliable virtual sensing is proposed as a contribution in this arena.

6.2.2. Time-Driven Methods

(a) *Data Compression.* In general, radio power consumption strongly depends on the packet size. Therefore, removing data redundancy is essential to find a more compact representation. Compression (sometimes called *encoding*) may be *lossless* or *lossy*. The former grants the exact original data to be reconstructed from the compressed data. *Huffman coding* and *Arithmetic coding* are samples of lossless compression. In lossy compression methods, the recovered signals, at the base station, are somehow different from the original signals. This error is typically acceptable in manifold WSN applications. Examples of this class comprise the *wavelet transform* and the *Fourier transform* [76]. The point of interest of lossy methods over lossless ones is that, in some cases, a lossy method can produce much smaller compressed signals than any known lossless method, while still meeting the requirements of the application [77]. In this paper, we contribute to this category via proposing the FuzzyCAT compressor.

(b) *In-Network Processing.* The idea behind in-network processing methods is to reduce the traffic at intermediate nodes between the sources and the sink through performing data aggregation (e.g., computing average of sensor readings within a predefined time window). Several ideas exist for

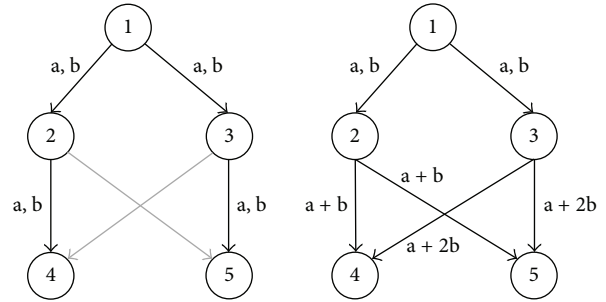


FIGURE 20: An example of a network coding method [5].

the aggregating function. However, the most appropriate in-network processing method is application-dependent. Fasolo et al. [46] provide a comprehensive survey about in-network processing techniques.

Network coding (NC) is a new in-network processing method which exploits the characteristics of the wireless medium (in particular, the broadcast communication channel). It has mainly been developed to reduce the traffic in broadcast scenarios by sending a linear combination of several packets instead of a copy of each packet. Figure 20 depicts an example of the network coding strategy [5]. In this example, a five-node topology is constructed such that node 1 has to broadcast two packets, a and b . Without the NC approach, if nodes 1, 2, and 3 store and omnidirectionally forward the data packets, this will generate six packet transmissions (2 per each node). Alternatively, nodes 2 and 3 can transmit a linear combination of data items a and b with the NC approach. Accordingly, nodes 2 and 3 have to send only a single packet. Nodes 4 and 5 can decode the packet by solving linear equations. As a result, two packets are saved in total in this example. In general, the NC approach exploits the trade-off between computation and radio communication where data transmission is more energy-hungry.

Despite the advantages of the NC strategy for saving energy and for improving the communication reliability, Voigt et al. [47] report on several drawbacks, including (1) strongly increased delay and (2) high overhead due to lack of adaptability. Accordingly, research efforts have to be exerted in this arena to overcome such limitations.

(c) *Data Prediction.* This method is similar to the model-based active sampling in which an abstraction of the sensed phenomenon is created. The model frequently predicts the sensor readings within certain error bounds. Identical predictors have to be implemented at the sensors and the sink nodes. If the prediction model is accurate enough, then queries issued by users can be evaluated at the sink without sampling real values. Otherwise, explicit data transmission between SNs and the sink is mandatory. Such approaches need to periodically validate and update their models in order to avoid rapid deterioration in the predicted values. Indeed, data prediction reduces the number of data packets sent by the various SNs and the energy needed for communication as well. The main forecasting schemes are classified into

algorithmic methods, time series forecasting, and stochastic methods.

The core idea behind the algorithmic methods is to estimate a stochastic characterization of the phenomenon to be measured [11]. This estimation can be achieved in two different ways. In the first way, data is to be mapped into a random process described in terms of a *probability density function* (PDF). Through combining the computed PDFs with the observed samples, the data prediction can easily be obtained. In the second way, a state space representation of the phenomenon is derived, so that forthcoming samples can be predicted by filtering out a nonpredictable component modeled as noise. Chu et al. [48] propose a robust approximate technique that utilizes replicated dynamic probabilistic models to minimize communication from SNs to the sink node. Although this approach is general, its computational overhead makes it ill-suited for tiny SNs with limited computational capacities.

In time series forecasting, a set of historical values is used to predict a future value in the same series. The time series method explicitly considers the internal structure of data [11]. In general, a time series can be decomposed into three components, a trend, a season, and a remainder. The trend component can be described by a monotonically increasing or decreasing function that can be approximated using common regression techniques. Once the trend is fully characterized, the resulting model can be used to predict future values in the time series. The moving average (MA), the autoregressive (AR), or the autoregressive moving average (ARMA) models are simple examples of time series predictors which are easy for implementation and provide an acceptable accuracy. Santini and Römer [49] choose Least Mean Square (LMS) over Kalman filter since it does not require a priori knowledge of the desired measurements. This implies that the sink and the sensors do not need to agree on a predefined model. Miranda et al. [78] show that a well-tuned AR estimator may be used to estimate data series in cluster-based one-hop WSNs.

The stochastic methods rely on a heuristic or a state-transition model describing the sensed phenomenon [49]. Such algorithmic approaches derive methods to construct and update the model on the basis of the chosen characterization. For instance, Han et al. [50] propose an energy-efficient data collection (EEDC) method which is well-suited in inquiry-based applications. In such scenarios, each SN relates to upper and lower bound and the difference between bounds denotes the accuracy of sensed values. In EEDC, bounds are transferred to sink and are updated later according to the request. In general, algorithmic approaches are too complex for computation and sometimes generate communication overhead.

6.2.3. Discussion. The aforementioned methods deal with saving energy through data manipulation. Table 4 summarizes the discussed methods and their influences on other service qualities. Although these methods prove to be successful in reducing the energy consumption, they often have negative impacts on other service qualities. As an example, data compression highly reduces the burden of radio communication

by removing data redundancy and shrinking the number of packets. In most cases, lossy data compressors are utilized due to their ability to achieve higher compression ratio than what can be obtained via the lossless compressors. Therefore, users have to accept a certain level of accuracy degradation in the recovered data after decompression. Moreover, data compression methods, in many cases, spend a considerable amount of time for storing the uncompressed patterns and for evaluating the compression algorithm. The resultant delay may be harmful in time-critical WSN applications such as smart grid monitoring. In Section 3, the aforementioned limitations of data compression methods are tackled through proposing a novel compression algorithm, referred to as *FuzzyCAT*. In such a compressor, accuracy is highly improved via dynamically adapting the algorithm characteristics in accordance with the original signal's curvatures. Moreover, the latency is investigated in light of a new cooperative multisource prediction scheme.

As listed in Table 4, triggered sampling is another method in which the duty cycle of energy-hungry sensors is highly reduced. However, most ideas in this arena suffer from the complexity of the new heterogeneous sensing system. In Section 4, this problem is targeted via proposing the invocation of virtual sensors as secondary sensors. Such sensors are extremely energy-efficient and can be easily designed by commercial off-the-shelf (COTS) components. In addition, reliability of such a new heterogeneous sensing system is improved. An ontology-based automatic rule generation method is developed to dynamically select between the main sensors and the virtual ones in light of the virtual sensor's accuracy and the environmental conditions.

6.3. Network-Oriented Methods. In this category, energy-saving methods, whose scope is within the entire network, are discussed. Indeed, the methods listed are general enough to cover the event-driven and the time-driven WSN application scenarios. These energy-saving methods are designed to optimize the WSN's performance without prior knowledge of the assigned task or application scenario. The taxonomy has three main classes, namely, *mobility-based methods, energy-aware routing, and sleep/wake-up protocols*. The former employs mobile sinks or mobile relay nodes in order to reduce the number of multihops. The energy-aware routing methods deal with data propagation within the network in a way that reduces the total energy consumption. Finally, sleep/wake-up protocols focus on reducing the number of active SNs to eliminate possible redundancy. Below, the philosophy behind each class is briefly explained.

6.3.1. Mobility-Based Methods. Mobility-based methods rely on employing either mobile sinks or mobile relay nodes in order to reduce the number of multihops, thereby minimizing the transmission cost [51]. These mobile nodes are often attached to mobile entities in the environment such as vehicles, animals, or dedicated robots. Specifically, mobility-based methods increase the network lifetime through reducing the burden on bottleneck nodes. In general, SNs closer to the sink have to relay more packets so that they are subject

TABLE 4: Summarizing the various data-oriented energy-saving methods.

Method	Explanation	Influenced QoS	Reference
Model-based active sampling	Reducing the number of data samples by using a computed model	Accuracy	[43]
Adaptive sampling	Dynamically estimating the sensor's sampling rate	Event-miss, complexity	[44, 45]
Triggered sampling	Equipping the SN with different sensors to measure the same phenomenon	Complexity, sensing reliability	Section 4
Data compression	Reducing the packet size by removing data redundancy	Latency, recovery accuracy	Section 3
In-network processing	Reducing the traffic at intermediate nodes through performing data aggregation	Complexity, latency	[5, 46, 47]
Data prediction	Constructing an abstraction of the sensed phenomenon	Accuracy	[11, 48–50]

to premature energy depletion, even with applying other energy efficiency techniques mentioned above. Through adding mobility, the traffic flow can be altered with mobile data collectors. Ordinary nodes wait for the passage of the mobile device and route messages towards it. Accordingly, the number of multihop radio communications is highly reduced. As a consequence, ordinary nodes can save energy thanks to reduced link errors, contention overhead, and forwarding.

Silva et al. [52] introduce a comprehensive survey of mobility models in WSNs. This survey considers the mobility feature from different perspectives, including the MAC layer and the network layer. The authors also propose the network of proxies (NoP) concept to relieve SNs from performing complex mobility tasks by moving them to the network side. Jain et al. [53] present the MULE architecture as an alternative to an ad hoc network. The MULE architecture is a three-tiered design, including sensors, mobile ubiquitous entities, and sink nodes. The key idea of MULE is to exploit the presence of mobile nodes in the environment by using them as forwarding agents. Sugihara and Gupta [54] investigate the trade-off between saving energy by employing mobile collectors and the increased data delivery latency. Generally, with controllable mobile nodes, the mobile displacement can be studied to prevent high latency, buffer overflow, and energy depletion.

6.3.2. Energy-Aware Routing Methods

(a) *Relay Node Placement.* Network partitioning and energy holes can be sidestepped by the optimal placement of SNs through even distribution or by adding a few relay nodes with enhanced capabilities. Ergen and Varaiya [55] focus on optimally locating the relay nodes to prolong the network lifetime. Alternatively, Misra et al. [56] define the location of each relay node at design-time. These locations are governed by the energy harvesting potential. The authors focus more on estimating the minimum number of relay nodes to achieve

connectivity or survivability, while ensuring that the relay nodes harvest large amounts of ambient energy.

(b) *Energy Metric-Based.* The core idea of this category is to consider the consumed energy as a criterion in the path setup phase. In other words, selecting routes can be accomplished in light of the residual energy in lieu of the shortest path strategy. For example, Liu et al. [57] propose an adaptive double cost function-based routing (DCFR) algorithm. Besides the end-to-end energy consumption, the node's remaining energy, and the achieved suboptimally balanced energy consumption, the DCFR algorithm additionally includes energy consumption rate in its cost function. Akkaya and Younis [58] present an energy-aware QoS routing mechanism which tries to balance energy consumption and throughput. The trick of this protocol is to look for a delay-constrained path with the least possible cost based on a cost function defined for each link. Alternative paths with larger costs are tried until one is identified, which meets the end-to-end delay requirement and maximizes the throughput.

(c) *Cooperative Communication.* In this direction, several single-antenna devices are used to improve the received signal's quality. Such devices cooperate to form a virtual multiple-antenna transmitter. Overhearing is typically a superfluous phenomenon in which data directed to a certain node is also received by this node's neighbors. The core idea of cooperative transmission (CT) or communication schemes is to engage the overhearing neighboring nodes in the data retransmission phase. The manifold versions of the same data are then combined at the receiving node to improve the signal-to-noise ratio (SNR) relative to the conventional non-CT communication, based on transmit diversity and array gains [59]. The CT schemes deliberately combat multipath fading and shadowing. Accordingly, the transmit power can be reduced, the data rate can be increased, and the transmission range can be extended.

In most cases, sensor nodes in the proximity of the sink node rapidly die due to relaying the packets from

the other nodes in the network. In battery-powered WSNs, this unbalanced energy consumption eventually leads to network partitioning. In other WSNs powered by energy harvesting devices, access to the sink node may be therefore constrained. The authors in [60] apply CT range extension to extend network life by exploiting the energy of less-burdened nodes. Then, data routing excludes the burdened nodes. Accordingly, duty cycling of nodes over the entire network is balanced, as normal relay sensors can be replaced by other cooperative nodes.

(d) *Multipath Routing.* In fact, multipath routing enables energy to be balanced among nodes by alternating forwarding nodes. The idea is to determine the k -shortest forwarding paths to the sink node. Afterwards, a single route is chosen so that the energy consumption is minimized. Radi et al. [61] provide a comprehensive analysis of the most recently proposed multipath routing protocols for WSNs. Ming Lu and Wong [62] exploited the path diversity provided by the multipath routing approach to prolong the network lifetime. This gain is achieved by distributing network traffic over multiple node-disjoint paths using a cost function depending on the energy levels and hop distances of the nodes. Accordingly, it allocates the traffic rate to each selected path. Alternatively, Yahya and Ben-Othman [63] presented the REER protocol, a robust and energy-efficient multipath routing protocol. The REER protocol uses the residual energy, node available buffer size, and signal-to-noise ratio to predict the next hop through the paths construction phase. To sum up, multipath routing protocols are energy-efficient relative to the single-path protocols. However, the incurred burden of handling and examining multipaths expands the computational overhead. Therefore, simplifying those methods may be considered as an open research issue.

(e) *Clustering Architectures.* These protocols are suitable in case of continuous transmission due to the presence of redundant data. Specifically, this approach is based on splitting the network into groups called *clusters*. In each cluster, one node is elected as a *cluster head* (CH) which aggregates the packets from its cluster members. The CH node is responsible for coordinating the members' activities and communicating with other CHs or the base station. This architecture limits energy consumption since (1) it reduces the communication range inside the cluster which requires less transmission power, (2) it limits the number of transmissions thanks to the fusion performed by CHs, (3) it reduces energy-intensive operations such as coordination and aggregation to the cluster head, (4) it enables powering off of some nodes inside the cluster while the CH takes forwarding responsibilities, and (5) it balances energy consumption among nodes via CHs rotation [64]. Additionally, cluster architectures also improve network scalability by maintaining a hierarchy in the network. Optimizing the collected information might be accomplished by the cluster head in order to decrease energy and traffic. Examples of hierarchical clustering include the low-energy adaptive clustering hierarchy (LEACH), the power-efficient gathering in sensor information systems

(PEGASIS), and the adaptive periodic threshold-sensitive energy-efficient sensor network protocol (APTEEN).

6.3.3. *Sleep/Wake-Up Protocols.* The sleep/wake-up protocols exploit network redundancy to extend the network longevity by switching a number of redundant SNs into sleep mode. Radio transceivers, in most cases, consume the majority of the energy available. Hence, switching the transceiver into sleep mode helps to greatly prolong the network lifetime. Specifically, active SNs can be switched off according to the workload.

(a) *Deactivation Schemes.* This section discusses the main sleep/wake-up schemes implemented as independent protocols on top of the MAC protocol (i.e., at the network or the application layer). The independent sleep/wake-up protocols can be further subdivided into three main categories, namely, *on-demand methods*, *scheduled rendezvous methods*, and *asynchronous methods*. The key idea behind the scheduled rendezvous methods is to achieve synchronous activation for a SN and its neighbors. Initially, SNs wake up according to a wake-up schedule, and they remain active until communication with their neighbors is finished. Afterwards, they are deactivated until the next rendezvous time. Time synchronization among the neighboring SNs is generally assumed. Keshavarzian et al. [65] present a multiparent scheme which provides forwarding nodes with different wake-up schedules. The active neighboring SNs have to be partially overlapping to allow SNs to communicate with their neighbors. This method takes a cross-layer approach and exploits the existence of multiple paths between the SNs to improve the energy efficiency of the wake-up process while meeting the message delay constraints.

The asynchronous protocols enable each SN to wake up whenever it wants and still be able to communicate with its neighbors. In such a scheme, no explicit information exchange is required among the neighboring SNs. Although asynchronous methods are simpler to implement, they are not as efficient as synchronous methods, and in the worst case their guaranteed delay can be very high. Paruchuri et al. [66] present a randomized approach, referred to as RAW, to address the protocol design issues of asynchronous wake-up methods. The RAW protocol enables each SN to make local decisions on whether to sleep or to be active. It allows the existence of several paths between a source and a destination and, thus, a packet can be forwarded along any of such available paths.

In the on-demand methods, SNs are deactivated and then they are only switched on when another SN wants to communicate with them. The main challenge is how to timely trigger the sleeping SNs whenever other SNs are willing to communicate. In particular, multiple radios with different energy/performance trade-offs are utilized. In other words, a low-rate and low-power radio can be dedicated for signaling, and a high-rate but more power-hungry radio can be used for data communication. Schurgers et al. [67] introduce STEM, a topology management technique that trades off power saving

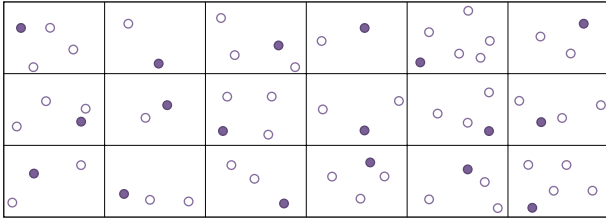


FIGURE 21: Location-based duty cycling [6].

versus path setup latency. The proposed technique consists of a separate radio operating at a lower duty cycle. Upon receiving a wake-up message, it turns on the primary radio, which takes care of the regular data transmissions.

6.3.4. Topology Management. In many cases, SNs are deployed with high level of redundancy to ensure space coverage and to cope with possible node failures occurring during or after the deployment. The idea behind topology management protocols is to deactivate some nodes while maintaining network coverage and connectivity. The decision of either activating or deactivating nodes typically depends on the application's needs. Accordingly, topology management protocols dynamically modulate the WSN topology for the sake of minimizing the number of active nodes, hence prolonging the network lifetime. Choosing the active SNs can be accomplished in two ways by a *location-based approach* or a *connectivity-based approach*. In the former approach, the sensing field is divided into cells as shown in Figure 21. In each cell, a single SN (solid node) is activated while others (hollow nodes) are switched to sleep mode [6]. Consequently, power consumption and collisions are reduced. The latter procedure determines the minimum number of nodes that still guarantee network connectivity. Redundant SNs are deactivated [68].

6.3.5. Low Duty-Cycle MAC Protocols. MAC protocols are responsible for the coordination between neighbors. Optimizing MAC protocols leads to significant reduction in power consumption. For instance, *time division multiple access* (TDMA) is a well-known MAC protocol. Data collision is avoided by dividing the time frame into slots. The time frames are divided into slots where each node is assigned two fixed time slots for transmitting and receiving packets. As a result, SNs are active during their assigned slots and inactive during other slots. Advantages of the TDMA protocol comprise eliminating data collision and conserving significant amount of energy. However, this technique requires precise synchronization among the various nodes which may be difficult in many situations [69].

Alternatively, contention-based MAC protocols allow nodes to independently access the shared wireless medium [70]. These protocols propose minimizing collisions rather than avoiding them completely. Contention-based protocols depend on a carrier sensing mechanism called *carrier sense multiple access* (CSMA). In this mechanism, transceivers are switched on only for listening to the traffic before

broadcasting in order to check the availability of free channels [11]. Finally, hybrid protocols dynamically modify the protocol behavior to the contention's level. They behave as a contention-based protocol when the level of contention is low and switch to a TDMA scheme when the level of contention is high.

6.4. Discussion. The aforementioned methods deal with saving energy at the network level. Although all these methods provide solutions to the networking overhead, negative impacts on other service qualities may emerge. Table 5 summarizes the discussed methods and their influences on other service qualities. As an example, deactivation methods strive to minimize the network duty cycle to overcome idle listening and redundancies. Nevertheless, this action increases the communication delay where each node has to wait for its neighbors to wake up and then it can start broadcasting. Even the synchronized version of these algorithms may suffer from latency due to time deviations and the additional computational overhead of the synchronization algorithm.

7. Conclusion

The paper has two main contributions. We provide an up-to-date taxonomy of the main energy-saving methods in WSNs. Analyzing the impacts of such methods on other QoS metrics motivated us to propose a novel method, referred to as divide-and-conquer (DnC) method. The core idea behind DnC method is to control the QoS parameters while providing adequate network lifetime. DnC method spends energy only to meet a predefined WSN's task time. Thus, an amount of energy is saved where it can be used to enhance other QoS metrics. As a proof of concept, three different examples, for extending the operational lifetime while improving the application-relevant QoS parameters, are given. Each of these methods targets a certain set of WSN application scenarios. First, a highly precise data compression method was verified to reduce the WSN power consumption in periodic sampling applications. The lessons learned here are as follows: (1) FuzzyCAT recovers the input data with high accuracy while offering high compression ratios, (2) model-based approaches are only recommended with delay-sensitive applications which report low-frequency data, and (3) it is feasible to considerably mitigate the delay incurred due to forming a compression window in transform-based compressors. In many cases, the delay is critical whenever the measured data is significant. In such cases, transform-based compression has to be accompanied with a decision-making algorithm. Implementing such an idea for different transform-based methods is left for further extensions. Moreover, we plan to perform an extensive comparative study among the main compression methods.

For event-driven scenarios, reliable virtual sensors can significantly reduce the power consumption and the event-miss probabilities. We prove the ability of virtual sensors to substitute the main energy-expensive sensors. Furthermore, ontology-based rules are efficiently employed to select between main and virtual sensors according to their quality. We could conclude that (1) adaptive sampling is an effective

TABLE 5: Summarizing the various network-oriented energy-saving methods.

Method	Explanation	Influenced QoS	Reference
Mobility	Employing mobile sinks or mobile relay nodes to reduce the number of multihops	Latency	[51–54]
Relay node placement	Adding few relay nodes with enhanced capabilities	Complexity	[55, 56]
Energy metric-based	Considering the consumed energy as a criterion in the path setup phase	Throughput, latency	[57, 58]
Cooperative communication	Using several single-antenna devices to improve the received signal's quality	Complexity	[59, 60]
Multipath routing	Alternating the forwarding paths for balanced energy distribution	Computational overhead	[61–63]
Clustering architectures	Splitting the network into groups for limiting the multihops	Latency	[64]
Deactivation schemes	Sleep/wake-up schemes implemented as independent protocols on top of the MAC protocol	Connectivity, coverage, latency	[11, 65–67]
Topology management	Deactivating some nodes while maintaining network coverage and connectivity	Latency	[6, 68]
Low duty-cycle MAC protocols	Reducing the sensors' duty cycle to eliminate the idle listening	Throughput, latency	[11, 69, 70]

method; however, it is not suitable for event-driven applications; (2) it is feasible to design virtual sensors for any energy-hungry sensor; and (3) the ontology can be used to solve hard problems in WSNs especially with large-scale heterogeneous networks. For future work, we plan to investigate other QoS metrics that could be affected by the insertion of virtual sensors. Moreover, we may investigate a combination of Kalman filtering with statistical hypothesis testing to provide a general, systematic way of designing virtual sensor setups.

Finally, a self-adaptive mechanism has been devised to implement lifetime planning. Through this method, lifetime is deliberately planned beyond the task time. Thus, more energy is spent for improving the service quality. To sum up, we found out that (1) blind adaptation may lead to an increase in the lifetime, but the QoS metrics will not be considered, and (2) planned adaptation mechanisms can simply improve both sides through exploiting design-time knowledge. For future work, we consider setting up a real testbed to evaluate the proposed approach in a more realistic manner. Moreover, the overhead of our hierarchical MAPE adaptation architecture will be analyzed.

Competing Interests

The authors declare that they have no competing interests.

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