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Green Sensing and Communication: A Step Towards Sustainable IoT Systems

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Abstract With the advent of Internet of Things (IoT) devices, their reconfigurability, networking, task automation, and control ability have been a boost to the evolution of traditional industries such as health-care, agriculture, power, education, and transport. However, the quantum of data produced by the IoT devices pose serious challenges on its storage, communication, computation, security, scalability, and system's energy sustainability. To address these challenges, the concept of green sensing and communication has gained importance. This article surveys the existing green sensing and communication approaches to realize sustainable IoT systems for various applications. Further, a few case studies are presented that aim to generate sensed traffic data intelligently as well as prune it efficiently without sacrificing the required service quality. Challenges associated with these green techniques, various open issues, and future research directions for improving the energy efficiency of the IoT systems are also discussed.

Keywords Internet of Things (IoT) · Green sensing · Green communication · Wireless sensor network · Smart grid · Smart meter · Energy efficiency

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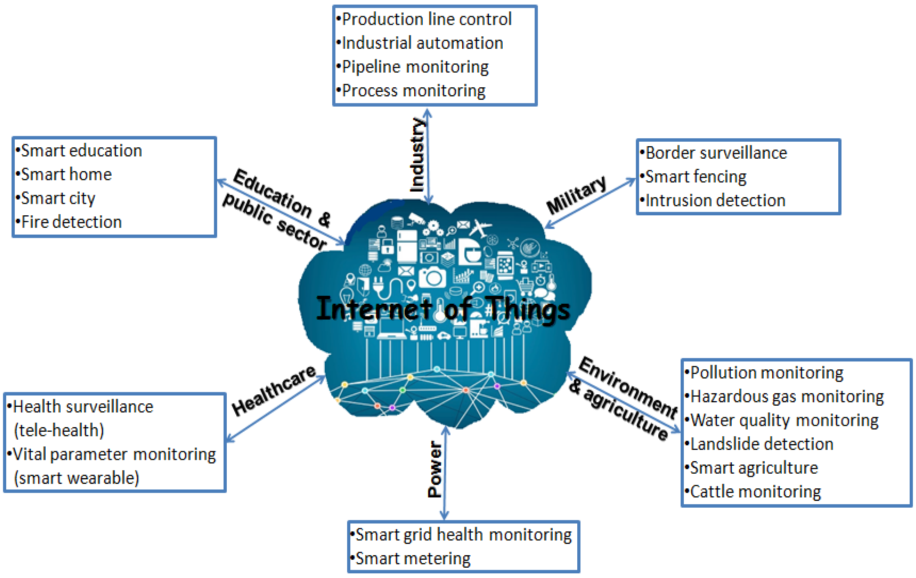

Fig. 1 IoT applications.

1 Introduction

The Internet of Things (IoT) is vital for realization of a multitude of applications across various industries, such as smart homes [56], smart city [32], smart health-care [1], environment sensing [53], smart agriculture [47], and border surveillance [34], as illustrated in Fig. 1. IoT devices (namely sensors, wearables, smart meters) used in these applications produce high-volume of data that is difficult to store, process, and communicate in real time. It is estimated that 20 to 40 billion IoT devices will be connected to the internet by the year 2020 [20]. An alarming challenge associated with the realization of these applications is the energy sustainability of the IoT systems. It encompasses the energy spent in data sensing/acquisition, communication, storage, and computation. In addition, scalability, reliability, and latency also play a significant role in the design of such systems.

To address these challenges, intelligence is imparted in the IoT devices and systems to acquire and communicate data in an energy-efficient manner [10, 11, 23, 63]. Centralized as well as decentralized implementation of the IoT systems [28], design of low-latency reliable communication systems [39], and energy-harvesting IoT systems [24] have gained significant research interest. Cloud computing, fog computing, and edge computing are looked upon to address the scalability and latency issues. In this context, a new approach, known as Multi-access edge computing (MEC) [2,5], has gained popularity due to its shorter response time, reduced energy consumption, network bandwidth saving, and data privacy. Recently, the problem of green communication is addressed from wireless channel variations perspective in works [43, 44]. In these papers, energy-efficient link-layer re-transmission strategies suitable for the IoT devices are developed using temporal characteristics of the wireless channel.

The primary focus of this article is to provide insights on energy-efficient IoT data acquisition and communication schemes.

The paper is organized as follows: Section 2 gives an overview of green sensing and communication techniques along with their applications and challenges. Section 3 presents the application of our proposed techniques to the case studies of lab environment monitoring, smart metering, and smart grid monitoring using real data-sets. A few open issues and future directions are discussed in Section 4, followed by conclusion in Section 5.

2 Green Techniques: Literature, Challenges, and Applications

This section outlines a variety of techniques developed to save energy not only at data generation points (i.e., IoT devices) but also during communication of the generated data.

2.1 Green Sensing Techniques

Wireless sensor networks (WSNs) are envisaged as a key technology enabling various monitoring applications of the IoT such as environment monitoring, remote health-care surveillance, border surveillance, etc. The devices/sensors used in these applications generate volumes of data which is often redundant and mutually correlated. A large volume of energy is consumed in these continuous sensing operations. Further, this streaming data requires reporting to a central entity for actionable decisions. This communication too consumes energy. The efficient energy utilization aspect is of utmost importance for these IoT applications. To cope with the ever-increasing energy demand, a shift from conventional periodic sensing to intelligent/smart sensing is seen in recent works. The quantum of data generated at source (i.e., sensors) is reduced intelligently by exploiting characteristics of the to-be-monitored processes. Further, the energy demand is targeted to be met primarily by the ambient resources, such as solar, wind, radio frequency energy resources. This approach is coined as **green sensing**. Although energy is saved in these green sensing techniques, it should not be at the cost of compromising sensing quality (quality of service (QoS) measure). Different green sensing techniques are discussed in the below sub-sections.

Green sensing: Intelligently reducing volume of data generated at source to increase energy efficiency of the WSN.

2.1.1 Duty Cycling

To extend the lifetimes of the energy-constrained sensors and WSNs, one of the early and widely used techniques is duty cycling [9]. The key idea is to turn on and off the mote's radio to save its energy. This alters the duty cycle (on time/(off+on time)) of the node's sensing activity. It could be implemented randomly or based on a schedule. However, random duty-cycling requires dense WSNs to guarantee enough active nodes at any point of time to provide the required quality of sensing. Random asynchronous wakeup (RAW) protocol developed in the work [46] is one such example. Recently, a machine learning-based duty cycling scheme for air pollution sensing is proposed in the work [14]. It exploits temporal correlation inherent in the pollutant to decrease the on-period (or duty cycle) of the node and predicts missing pollutant data during off-period using support vector regression technique.

In general, the duty cycling approach, especially the scheduled one, is a trade-off between energy efficiency and latency (i.e. delay in data delivery to the target node/central entity) [38].

2.1.2 Wake-up Radio

Wake-up radio: On demand activation of the radio using an active wake-up signal.

Wake-up radio (WuR) is a promising approach to reduce both energy consumption of the node and delay [38] in data delivery to the target node. The latter one is crucial for delay-sensitive IoT applications. The objective is to use a low power radio that is active all the time to listen to a wake-up signal and activate the main radio on demand. This prevents unnecessary periodic wake-up of the main radio to listen to the channel (i.e., idle listening). The WuR is categorized as active/passive based on the energy source used for receiving the wake-up signal. In the active WuR, the energy is drawn from the node's battery, while in the passive WuR, it is drawn from the radio frequency (RF) signal (wake-up signal) itself. Wireless Identification and Sensing Platform (WISP) mote, proposed in [6], is an example of passive WuR. Likewise, the authors in [36] proposed a low-cost RF energy harvester-based WuR that performs both the wake-up and energy harvesting functions.

The WuR has potential applicability in industrial wireless networks especially for time-critical applications such as fault identification, gas pipeline leakage detection, etc.

2.1.3 Sensor Scheduling

Another well-researched and popular direction to achieve green sensing is sensor selection/scheduling. A subset of sensors/wireless nodes is activated to perform sensing based on some intelligence, while the remaining sensors/nodes sleep to save energy. The essence behind this parsimonious sensor selection is the spatio-temporal correlation inherent in sensor measurements. Sparsity induced in the measurements due to this allows monitoring of the corresponding underlying process using under-sampled sensor measurements.

In this context, early works [40,70] randomly chose a fixed number of nodes for activation. However, these works do not guarantee sensing quality and energy efficiency. Thereafter, research interest shifted to propose schemes that guarantee energy efficiency and/or sensing quality. For the former one, the work [12] proposed a greedy approach of selecting sensors with maximum energy efficiency index (i.e., the difference between residual energy and transmission energy of the node). This approach failed to provide good sensing quality. Subsequently, several works focused on providing certain sensing quality. One such pioneering work [33] proposed to select linear measurements of k out of total m sensors by formulating and subsequently solving a convex optimization problem based on the D-optimality criterion of experimental design. Further, for the non-linear measurement model, a selection scheme is formulated in work [13] by employing Cramér-Rao lower bound (CRB) as a sensing performance measure. This measure characterizes mean squared error (MSE) in the estimation of the field signal sensed using a few sensors [65]. Subsequently, the authors in work [72] developed a field reconstruction algorithm based on spatial linear unbiased estimator (S-BLUE). Using the estimates, a cross-entropy method-based sensor selection method is proposed for heterogeneous sensor networks. Such collaboration between the WSNs is extremely beneficial in the context of realizing the IoT applications. The work [27] advocated a signal's correlation to design deterministic node selection strategies and developed a covariogram-based estimation of signal's covariance structure. Although, the schemes in the works [13, 27, 33, 72] save energy, they cannot guarantee the energy efficiency as they may repeatedly select nodes with low remaining energy which can create network coverage holes. Thus, to overcome this limitation, schemes developed in works [10, 11] that ensure both the sensing quality and energy efficiency of the WSN while selecting a fixed number of sensors. The measurements of these selected sensors are then utilized to estimate entire WSN field using the well-known compressed sensing (CS) [18] and Bayesian learning [67] schemes as outlined in works [10, 11, 27, 72].

The works discussed so far deal with centralized sensor selection strategies often possess high energy and communication overheads. Poor connectivity between the central entity (fusion center (FC)) and nodes leads to questions on the reliability of the centralized architecture. Additionally, these schemes may not be suitable for delay-constrained scenarios. To surmount these shortcomings, decentralized sensor selection strategies have been developed in recent studies. Nodes locally exchange information to decide their own or respective fellow nodes' activation/sleep state. In this regard, a Bayesian approach is used to develop iterative centralized and decentralized sensor selection strategies for heterogeneous sensing applications in the work [28]. Subsequently, the works [30, 31] used consensus and double-consensus averaging to solve the sensor selection problem in a decentralized/distributed manner. These works suggested the dual sub-gradient method to solve the distributed sensing problem. Further, the authors in [68] formulated a distributed collaborative sensor selection approach by combining both the sensor correlation and sensor-target distance to achieve required sensing accuracy, energy balance among sensors, and extend the network lifetime.

Besides sensing quality and energy efficiency, coverage is another important, often ignored, QoS measure of the WSNs. In a recent work [42], a distributed solution for coverage control is proposed by the application of game theory in the active sensor selection problem. The work too aimed to extend both coverage and network lifetime.

Sensor selection based green techniques has utility in a variety of IoT applications such as water quality monitoring, intrusion detection, border surveillance, health monitoring, agriculture/soil monitoring, avalanche detection, pollution monitoring, target tracking, etc.

Major drawbacks associated with the above-mentioned centralized and distributed sensor selection schemes are:

1. A spatio-temporally varying signal is sensed by fixing one of the two performance measures, namely, sensing quality and number of active nodes.
2. Unequal remaining energy associated with different nodes is ignored, which may result in network coverage outage.
3. Iterative local information exchange in distributed settings consume a lot of energy and increases the delay. However, none of the proposed distributed approaches considered energy consumption.

2.1.4 Adaptive Sampling

Adaptive sampling: Adapt the number of nodes to be activated as per the dynamics of the observed process.

A more practical approach to green sensing is **adaptive sampling** wherein the sampling rate (i.e., the number of active nodes/total number of nodes) is adapted as per the dynamics of the monitored process. Intuitively, a low (high) sampling rate suffices for sensing a slowly (rapidly) varying process. In this regard, a principal component analysis and CS-based sensing, compression, and recovery (SCoRe) framework is proposed for WSNs in the work [49]. Adaptation occurs by exponentially increasing (linearly decreasing) the sampling rate when process variations increases (decreases). Another approach [25] built a hash table capturing the sampling rate corresponding to different variations of the process and used it as a lookup during the sensing process. Recently, an adaptive sensing framework was proposed in work [23] that adapts sensing as per the process dynamics. A multi-objective optimization problem is proposed therein that jointly optimizes the sensing quality and energy efficiency of the WSN. The authors in the work [26] proposed three adaptive data acquisition approaches for industrial process monitoring applications. In that work, energy management is primarily considered along with sampling rate adaptation of the sensors. Likewise, a correlation-based adaptive measurement technique is developed in work [54] that collects data from a subset of dynamically chosen nodes and use them for inference of measurements across remaining sleeping nodes.

Most of the IoT applications require multi-sensing, i.e. sensing multiple signals/parameters simultaneously, which is a relatively new and less explored approach to sensing. In this context, multi-sensing platforms have been designed in works [4, 8]. The authors in the work [50] developed a threshold-based energy-efficient multi-sensing protocol for landslide monitoring applications. Subsequently, adaptive and hierarchical context-aware multi-sensing schemes are proposed in the work [48]. Recently, an adaptive and optimized multi-sensing approach is developed for smart environment application in the work [24]. It collectively considers the sensing quality, energy efficiency, and multiple signals' dynamics in the sensor selection process.

2.1.5 Comparison of the above mentioned green-sensing technique

The duty cycling technique is energy-efficient compared to the conventional exhaustive sensing technique which do not have off period. However, it consumes energy in idle listening and comes at the price of high latency. These shortcomings are overcome by wake-up radio (WuR). The WuR has potential applicability in industrial wireless networks. The duty cycling and WuR techniques do not depend on the type of data/signals being sensed. Exploiting characteristics of the signals being monitored (such as temporal and spatial correlation, its variations) can also play a significant role in saving energy spent in sensing. For instance, the redundancy due to the correlation(s) in the signal can be intelligently minimized by data-driven techniques such as sensor scheduling and adaptive sampling. Adaptive sampling is more energy-efficient compared to non-adaptive sensor selection (such as fixed rate sampling). These data-driven techniques can be used for applications such as environment monitoring, avalanche monitoring, health monitoring, wildlife habitat surveillance, etc. Among these applications, some are time-critical and some are not. If the adaptive sampling frameworks [23], [24] comprise a mobile data collector/robot that collects sensed data from the active nodes and sends it to the FC, then these are suitable for non real-time applications. For time-critical applications, these frameworks require the active nodes to send the sensed data directly to the FC.

2.2 Green Communication Techniques

In addition to green sensing, green communication is another key enabler for energy efficiency and sustainability in IoT. Particularly, in the sensor networks where sampling rate is pre-defined and sensing energy is not of much concern, green communication is of interest to optimize the resource utilization (especially bandwidth) for transmission and archival of IoT big data. Here, two green communication scenarios pertaining to the emerging smart grid IoT networks, namely, advanced metering and wide area monitoring and control, are presented. In this context, the smart meters and phasor measurement units (PMUs) behave as sensors and generate volumes of fine grained data from electricity distribution networks. Though acquisition and analysis of this massive data imparts intelligence to the conventional analytical framework to adapt to the dynamics of real world systems, its efficient communication and storage is a challenge.

The proposed green initiative in these applications is to intelligently prune the amount of generated data at the edge node itself, such that first level data reduction is achieved well before millions of IoT devices try to access the wireless network for transmission. It may be noted here that, prior to pruning, it is essential to study the characteristics of the data so as to preserve the useful information in the process of data compression and reconstruction. Two kinds of approaches are typically seen in the research literature for data pruning in IoT networks. These are compression based and prediction based, for delay tolerant and delay sensitive scenarios, respectively.

2.2.1 Data Pruning by Compression

For delay tolerant applications such as advanced metering, data can be pruned by applying compression algorithms on the appliance level as well as household level data. This data can have a high or a low data resolution. In state-of-the-art, it is observed that the data compression algorithms operating at the aggregation points generally work on low resolution data which is on the order of 1 sample per several minutes. These studies are based on signal processing algorithms such as singular value decomposition [55], load features based compression [61], dictionary learning and sparse encoding [66], and entropy coding [3] that exploit the temporal and spatial attributes of the data streams collected from different sensors. However, a limitation of data pruning at the collection points is that they do not address the issue of data reduction at the sensor nodes, and thus are less useful for reduction in amount of data transmitted in near-real time applications.

Since modern day smart meters can capture average power consumption data at a rate as high as 1 sample per second, compression of high granularity data at the meter level is of current research interest. In such cases, due to high sampling frequency of the smart meter data, the variations observed in load patterns are not significant. Thus, the redundancy in the data provides an opportunity to compress it before transmission. The algorithms proposed in literature for the pruning of high resolution smart meter data are based on exploitation of correlation in consecutive data samples. For instance, a lossy compression method [19] controls the amount of generated smart meter data by using piece-wise approximation of original sample pattern. Besides, loss-less compression algorithms using Huffman coding, Markov chain variants [51], and differential coding [64] are also proposed for compression of household level as well as appliance level data. It is seen that the performance of these algorithms is sensitive to sampling frequency, decimal precision of the meter reading as well as noise in the communication channel. More robust frameworks for effective characterization and reduction of high frequency smart meter data using adaptive compressive sampling are proposed in [63] and [52], respectively for single-variate and multivariate data samples, based on adaptive sparsity selection over optimum batch size before data transmission. It may be noted that since smart meters are connected to continuous power supply, extra energy overhead in implementing the data pruning algorithms is of not much interest. From green communications perspective, in this case, only the optimization of bandwidth requirement and storage space for transmission and archival of big data from smart meter to the data collection points is discussed.

2.2.2 Data Pruning by Prediction

Unlike data pruning by compression, data pruning by prediction is more suited to delay sensitive data in order to avert the requirement of buffering time for data compression. A pertinent IoT application in this context is of wide area monitoring and control in smart grids. In the research literature offline dimensionality reduction of PMU data is proposed using linear principal component analysis [69], wavelet packet decomposition [21,37], and lossless encoding [60]. These algorithms are proposed to operate at the receiver for archiving the data using minimal storage while preserving the data characteristics.

A few studies based on least square curve fitting [22], and compressive sampling [17] are also proposed for real-time reduction of PMU data. The standard reporting rate from PMU to the control center is currently fixed at 25 samples/s. However, this fixed-rate data transmission may not be very useful in terms of resource utilization since transient occurrences in the power grid are sporadic and much of the sampled PMU data is redundant. Also, non-stationarity of the data has been largely ignored during data reduction approaches proposed so far leading to inefficient compression. To address this, a novel learning-based framework based on $\epsilon-$ support vector regression [62] is proposed to dynamically prune the PMU data before transmission. Parameters of the learning algorithm are recomputed as necessary to take care of non-stationarity and maintain the accuracy and robustness of the predictions.

2.3 Energy-Harvesting Techniques

The finite battery capacity of the nodes serves as a major bottleneck of the WSNs. Available solutions such as battery replacement, using large batteries and low power hardware, etc. do not guarantee perpetual operation of these nodes. Green sensing and communication techniques alone cannot eliminate energy outage problem completely. In this regard, energy harvesting is envisioned as a potential solution and its applicability is widely researched nowadays. The energy can be harnessed from ambient sources as well as from dedicated sources. To do so, the wireless nodes are equipped with a harvester module and a rechargeable battery or a super-capacitor to store the harvested energy.

Recently, solar energy harvesting capability of the nodes [35, 57] is integrated with a multi-sensing framework for a heterogeneous WSN [24]. The authors in [29] suggested an idea of employing a few nodes for data aggregation and the remaining nodes for harvesting energy from the sensed electric signal. Further, an optimal sampling policy is designed in work [71] that minimizes the sensing error under stochastic energy constraints which arise due to random energy arrivals.

Continuous network operation still cannot be guaranteed by harvesting energy from ambient sources due to their uncertain nature. An approach for dedicated (on-demand) wireless energy transfer from a radio frequency (RF) source, known as RFET, is proposed in [41] to provide sustainable network operations. In this regard, the work in [36] investigated the possibility of building a WuR using an RF energy harvester available at the WSN node. Likewise, the works in [58, 59] presented a framework for an unmanned aerial vehicle (UAV)-based wireless charging of sensor nodes using RFET.

2.4 Challenges

Major challenges associated with reducing the energy consumption of the IoT applications are discussed in the below sections.

2.4.1 Sensing Quality and Energy Efficiency Trade-off

There are two conflicting design goals of the WSN-based IoT systems, namely, lifetime and sensing quality. Improving one hurts other. Thus, suitably handling trade-off between the sensing quality and energy efficiency (or network lifetime) is a big challenge that depends on the type of application being pursued and its requirement.

2.4.2 Coverage and Energy Efficiency Trade-off

It is important to provide coverage of the observing field in applications such as gas-leakage monitoring, chemical hazards detection, intrusion detection, etc. especially when only a few devices/nodes are activated to save energy. Thus, another challenge is to strike a balance between coverage and energy saving in the WSN-based applications.

2.4.3 Latency/Bandwidth (BW)/Energy versus Sensing Reliability

Time-critical applications such as tele-surgery, smart grid monitoring, etc. demand low latency (i.e. fast data delivery) which is often achieved either by sparse monitoring or data pruning before transmission. This saves communication BW and energy at the cost of sensing reliability (i.e. quality of information provided by the IoT devices).

2.4.4 Energy-Efficient Data Computation

Processing high volume IoT data at the device (node)-level in distributed architecture too consumes large amounts of energy. Thus, data processing is another challenge due to limited battery operated nodes.

3 Case Studies

This section discusses green schemes developed by us in previous works [23] [24], [62], [63] for three IoT applications, namely, lab environment monitoring, smart grid monitoring, and smart metering.

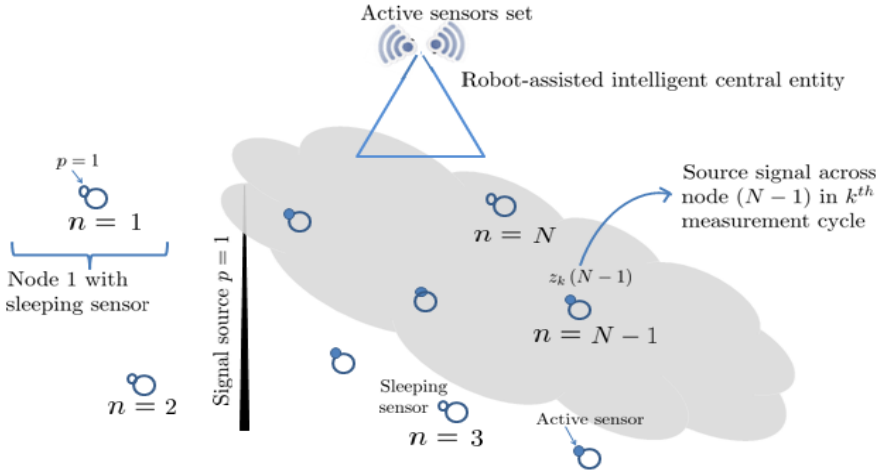

Fig. 2 Generalized monolithic-sensing scenario.

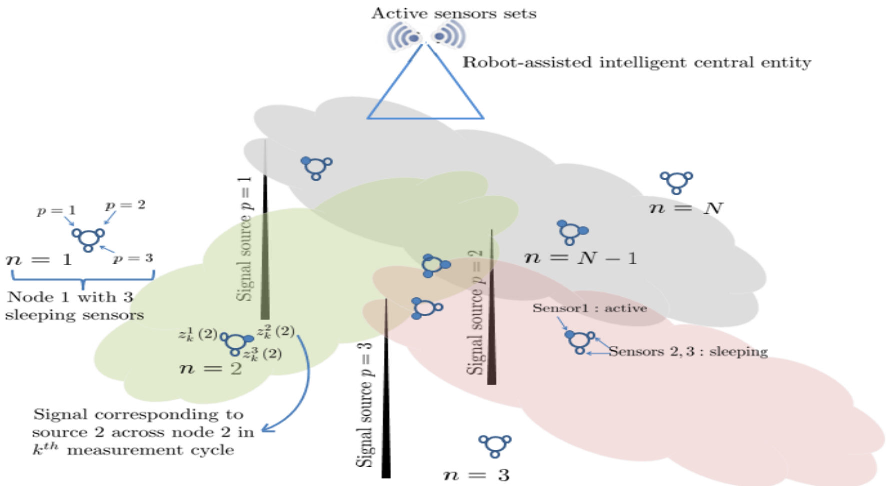

Fig. 3 Generalized multi-sensing scenario.

3.1 Lab Environment Monitoring

To reduce data volume at the generation points (i.e. IoT devices/nodes) itself, a few sensors/nodes are activated to monitor a WSN field, while the remaining ones are allowed to sleep. The spatial and temporal correlations of observed signals are used to decide the activation/sleep pattern of sensors of the WSN.

An adaptive sensor selection framework proposed in work [23] is applied on temperature data produced by a WSN deployed in Intel Berkeley lab [7] to verify its energy efficacy in performing monolithic sensing. Similarly, to simultaneously sense two parameters of the lab environment, namely, temperature and humidity, a multi-sensing framework proposed in recent work [24] is applied. This work considered the solar energy harvesting aspect as well. Additionally, detection limit constraint imposed by heterogeneous sensors is also integrated into sensor selection and signal estimation processes. Sensor selection in the monolithic [23] and multi-sensing [24] cases for a general application can be better visualized from Figs. 2 and 3 respectively.

In the adaptive monolithic [23] (multi [24])-sensing scheme, the FC solves multi-objective optimization problem(s) that find active sensor(s) set(s) by jointly optimizing the sensing quality and network energy efficiency in each measurement cycle. In the process, it is ensured that a required performance criterion (Bayesian CRB (BCRB) window $[\alpha, \beta]$) does not get violated. Further, the measured signal(s) variations are estimated and the size of the sensor(s) set(s) for next measurement cycle is appropriately adapted. Next, the FC conveys active sensor(s) schedule to the nodes. The active sensors of the nodes then sense respective monitoring parameters and nodes convey these measured signals back to the FC via a robot. The FC then iterates the same process for the next measurement cycle. Note that in multi-sensing, the FC carries out sensor selection and adaptation process for each sensor/signal type in parallel. These works assume slowly varying process(es) which enable computation of the measure BCRB using recent past signal estimates of these process(es). This knowledge is used to drive the sensor selection task in the current measurement cycle. For more details, please refer the works [23] and [24].

Figs. 4 and 5 compare performance of the adaptive optimized monolithic sensing framework proposed in work [23] with optimized subset selection scheme proposed by Chen *et al.* in [10, 11] and an adaptive sensing framework SCoRe proposed by Quer *et al.* in [49] using real data-set of temperature signal [7] as mentioned above. It can be observed that adaptive and optimized sensing of a spatio-temporally varying process increases energy efficiency of the WSN without compromising the sensing quality. Gain in energy efficiency is tabulated in Table 1. The adaptive optimized sensing scheme is respectively $\sim 67\%$ and $\sim 30\%$ more energy-efficient than the Chen's and Quer's scheme. Note that, the simulation parameters are set as proposed in work [23] (Sec. V-F) except the BCRB window $[\alpha, \beta]$, threshold δ_{th}, and node's initial energy $\eta_1(n)$ which are respectively set as $= \left[1.215 \times 10^{-5}, 0.0306\right]$ and $= \left[8.7731 \times 10^{-6}, 0.008\right]$ (for comparison with Chen's and Quer's schemes), 0.051, and 1400 units. The parameters- threshold δ_{th} and BCRB depend on the signal being observed. These are set in the current work as per the considered temperature data-set and in the work [23] as per humidity data-set considered there. The choice of the BCRB window affects the sensing quality and the threshold value is meant for capturing signal variations effectively. Likewise, a node's initial energy governs its remaining energy after execution of measurement cycle. Simulations are carried out in Matlab and optimization problems are solved using CVX [15] tool.

Likewise, performance of the multi-sensing framework proposed in work [24] and Chen's scheme [10, 11] are compared for simultaneously sensing the above-mentioned two lab parameters (temperature and humidity). It is evident

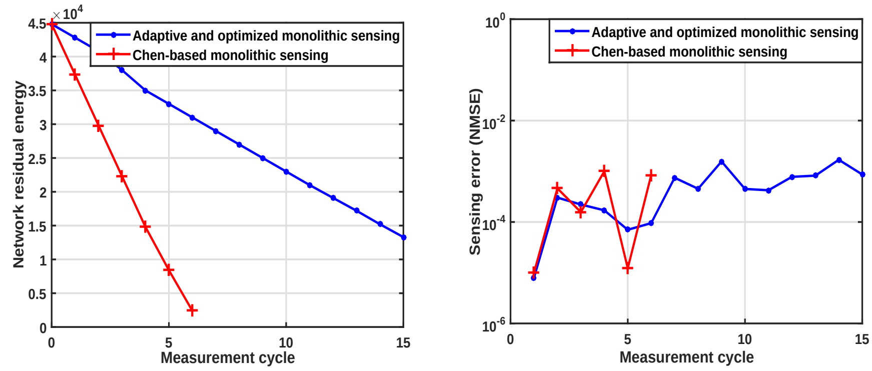

Fig. 4 Network residual energy and NMSE comparison of the adaptive and optimized monolithic sensing scheme [23] with Chen's scheme [10, 11].

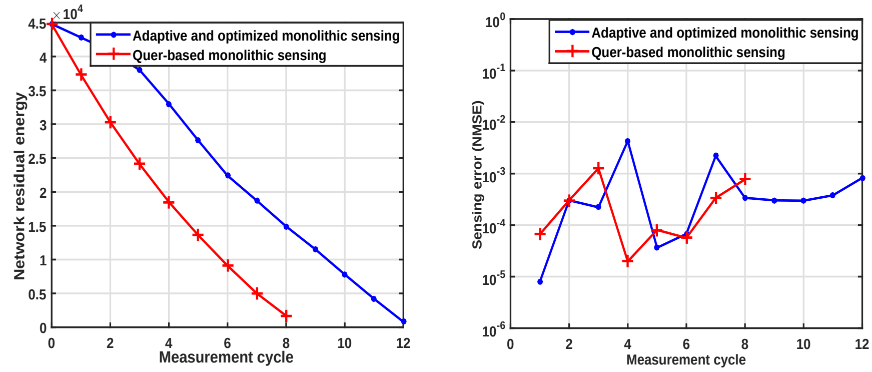

Fig. 5 Network residual energy and NMSE comparison of the adaptive and optimized monolithic sensing scheme [23] with Quer's scheme [49].

Table 1 Energy efficiency comparison for monolithic sensing case

Monolithic sensing scheme	Node energy consumption per cycle (J)	Energy efficiency gain
Chen-based [10, 11]	220.83	-
Adaptive & optimized [23]	71.875	67.45% (w.r.t. Chen)
Quer-based [49]	168.3594	-
Adaptive & optimized [23]	116.7969	30.6264% (w.r.t Quer)

from Figs. 6, 7 and Table 2 that energy-efficient smart environment sensing without sacrificing the accuracy is achievable using the adaptive multi-sensing scheme [24], with energy efficiency of $\sim 15\%$ with respect to the comparing scheme [10, 11]. In Fig. 6, increase in energy consumption is seen beyond $\sim 25^{th}$ measurement cycle. Reason being due to increase in variations of the monitored signal during these cycles, the adaptation mechanism increases the number of

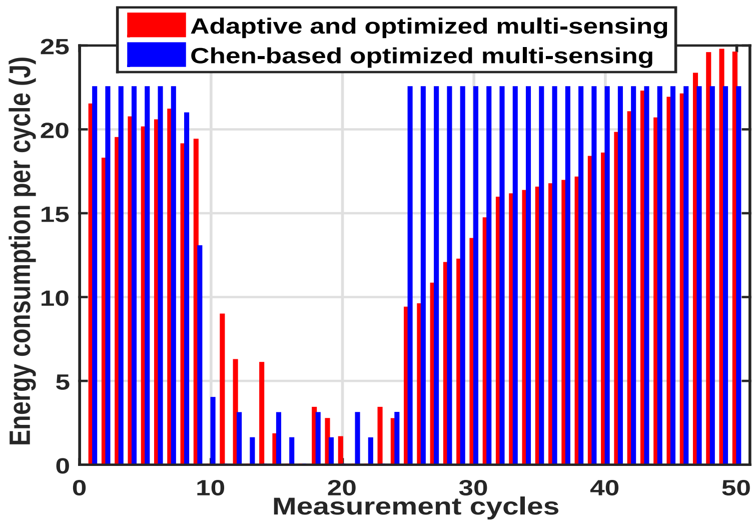

Fig. 6 Network energy consumption per cycle comparison of the adaptive and optimized multi-sensing scheme [24] with Chen's scheme [10, 11].

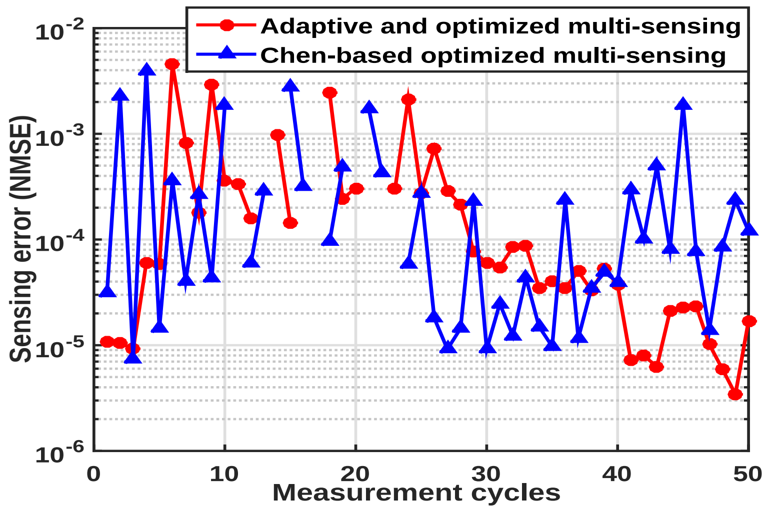

Fig. 7 Sensing quality (NMSE) comparison of the adaptive and optimized multi-sensing scheme [24] with Chen's scheme [10, 11].

active nodes (or sampling rate). This increases the energy consumption. The framework increases (decreases) the sampling rate when the variations in the signal increases (decreases). For simulations, number of nodes considered are $N = 30$, initial energy as 6 units, harvested energy as in work [24], noise variance $\sigma^2 \sim 10^{-6}$, number of parameters/signals to be observed as $P = 2$, sensing energy of temperature and humidity sensors as $\{E_s^1, E_s^2\} = \{0.2, 1.0315\}$

Table 2 Energy efficiency comparison for multi-sensing case

Multi-sensing scheme	Network energy consumption per cycle (J)	Energy efficiency gain
Chen-based [10,11]	16.04606	-
Adaptive & optimized [23]	13.52912	15.6857% (w.r.t. Chen)

units, their detection limits as $\{\rho^1, \rho^2\} = \{14.4, 38.6\}$, Bayesian CRB windows $[\alpha^1, \beta^1] = [1.1 \times 10^{-6}, 0.06]$, $[\alpha^2, \beta^2] = [3.1 \times 10^{-6}, 0.06]$, and thresholds as $\{\delta^1_{th}, \delta^2_{th}\} = \{0.05, 0.06\}$, $\{\epsilon^1_{th}, \epsilon^2_{th}\} = \{0.5, 0.5\}$. For Chen's scheme, number of temperature and humidity sensors to be activated are respectively fixed as 15 and 16.

Note that the sensing quality is determined by normalized mean squared error (NMSE) performance measure which depends on actual signal (NMSE $= \frac{\frac{1}{N}\|\text{actual signal vector - estimated signal vector}\|^2}{\frac{1}{N}\|\text{actual signal vector}\|^2}\Big)$. However, the actual signal is unknown and needs to be estimated. Thus, the above adaptive monolithic and multi-sensing frameworks uses BCRB as the measure to optimize sensing quality instead of the NMSE as done in several existing works [10,13]. The NMSE is plotted to show the achieved sensing quality by using the BCRB measure in the sensing frameworks. The NMSE values obtained are within the acceptable range as suggested in the work [23] (reference 45). Further, as the name suggests, the NMSE averages error obtained in estimates of signal across all sensors. It gauges energy in error signal against that in signal. In Figs. 4, 5, and 7, the sensing quality is an average entity. Network residual energy is not averaged because it is sum of remaining energy of all the nodes in the network.

Applications in IoT deployment may have specific needs related to the range where it is expected to deliver sensed data. In this regard, in the future work, it will be interesting to investigate the maximum distance up to which the signal can be detected by the sensors to maintain a desired QoS.

3.2 Automated Metering in Smart Cities

As discussed in Section 2.2, compression techniques are preferred for data pruning at edge devices in the IoT networks where latency is not a constraint. Here, resource savings via green communication of smart meter data is investigated by testing the performance of adaptive compressive sampling algorithm [63] on real smart meter data sampled at the rate of 1 per 30 seconds.

It is observed that though high resolution smart meter data has a rapidly fluctuating and spiky pattern indicating incoherence in time domain, it can be reasonably sparsified using discrete Fourier transform. Further, if sparsity selection is adapted to the variation of data in the compression window, optimal data reduction without much loss of information can be achieved. Also, the size of compression window is a function of temporal correlation in the consecutive data samples which is governed by the sampling frequency of the smart meter. The optimum size of compression window is evaluated based on the trade-off between bandwidth saving and reconstruction accuracy, which in turn is a function of temporal correlation in the consecutive data samples and the sampling frequency of the smart meter. In [63], it is observed that with the increase in number of samples in the compression window, bandwidth saving reduces, while the reconstruction accuracy increases. However, beyond an optimum number of samples, the nRMSE nearly saturates. This point is considered as the optimum size of the compression window. For data sampled at the rate of 1 per 30 seconds, this interval was found to be 60 seconds. Once the data is buffered to form optimally-sized compression window, sparsity for each window is decided by estimating the number of discrete Fourier coefficients containing 99.99% energy of samples in the compression window. The samples to be transmitted are then selected using a sensing matrix. At the receiver, reconstruction of compressed samples is performed using subspace pursuit [16] algorithm. Thus, substantial reduction in data volume is achieved by adaptively compressing high resolution smart meter data over successive optimally sized windows and accordingly transmitting only minimum required number of samples.

The performance of adaptive compressive sampling algorithm is measured in terms of bandwidth saving, normalized root mean square error (nRMSE), and Hellinger's distance. If n and m, respectively, be the number of samples in the data window before and after compression, then $(n - m)/n$ is used as a measure of bandwidth saving. nRMSE quantifies the accuracy of prediction, while Hellinger's distance validates the acceptability of nRMSE value for the required quality of service. For discrete probability distributions $P = \{p_1, p_2, \cdots, p_n\}$ and $Q = \{q_1, q_2, \cdots, q_n\}$, Hellinger's distance between them is defined as $H(P, Q) = \frac{1}{\sqrt{2}}\sqrt{\sum_{i=1}^{n}(\sqrt{p}_i - \sqrt{q}_i)^2}$. For this application, Hellinger's distance ≤ 0.05 is considered tolerable [45]. In Fig. 8, reconstruction performance of adaptive compressive sampling algorithm at the receiver using subspace pursuit algorithm is presented. The reconstructed data is observed to to be closely following the actual data, and the estimated nRMSE is 4.4×10^{-4}. Further the performance of adaptive compressive sampling algorithm is tested on data-sets from smart meters at 4 different locations in our university campus having sufficient pattern diversity. In Table 3, the respective performance indices at each of these locations are presented. It is observed that Hellinger's distance corresponding to nRMSE at each of the locations is well below the acceptable threshold. Thus, a mean reduction of around 37% is achieved in the bandwidth requirement for transmission of high resolution smart meter data with minimum loss of information.

A comparison of adaptive compressive sampling algorithm with the closest competitive technique based on resumable data compression [64] is presented in [63]. From the simulations, it is found that with respect to resumable data compression, bandwidth saving in the proposed adaptive compressive sam-

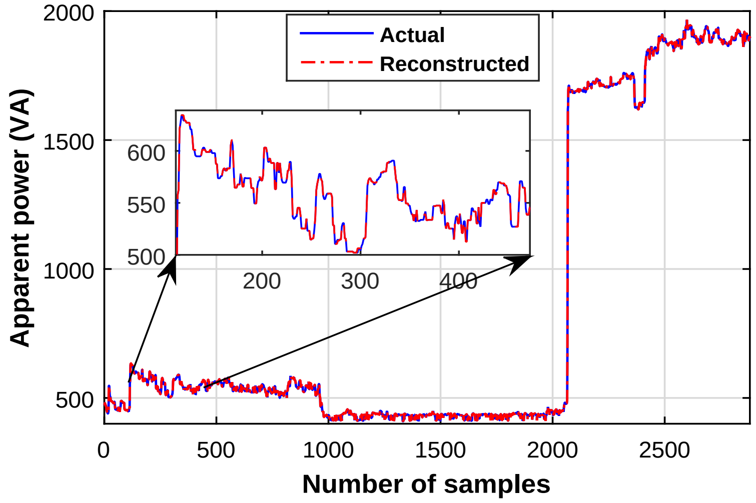

Fig. 8 Reconstruction performance of adaptive compressive sampling algorithm.

Table 3 Performance of adaptive compressive sampling algorithm at 4 different locations

Dataset	Bandwidth saving (%)	nRMSE	Hellinger's distance
Location #1	38.59	4.42×10^{-4}	0.0195
Location #2	34.91	3.38×10^{-4}	0.0153
Location #3	43.19	3.37×10^{-4}	0.0319
Location #4	33.38	3.07×10^{-4}	0.0237

pling technique is 12.8% and 7.4% higher, respectively, for data granularity of 1 s and 30 s at a comparable reconstruction accuracy. Additionally, it is also observed that the noise robustness of the proposed adaptive compressive sampling algorithm is significantly higher.

3.3 Smart Grid Health Monitoring

In this section, performance of dynamic prediction algorithm [62] is tested on different variables measured by the PMU during a real tripping event in the power grid. Each variable considered in this study has a different temporal correlation coefficient governed by the underlying process dynamics.

To handle huge data volume generated during the health monitoring in smart grid IoT network, the dynamic prediction algorithm judiciously eliminates redundant data before transmission using ϵ-support vector regression model. Flow of the algorithm comprises of training a prediction model through configuring hyperparameters and making successive one-step ahead prediction of variable samples using the prediction model. It may be noted that due to non-stationarity of PMU data, retraining of the regression model is required

Table 4 Performance of dynamic prediction algorithm for different variables measured by the PMU

Variable	Correlation	BWS (%)	RC	DI	RMSE
Frequency	0.9993	85.2	0.04	1	0.0087
Angle Separation	0.9987	80.5	0.04	1	0.008
Voltage Phase A	0.9658	81.9	0.08	0.99	0.0473
Voltage Phase B	0.9504	82.2	0.1	0.98	0.0490
Voltage Phase C	0.9421	82.4	0.09	0.99	0.0483
Rate of Change of Frequency	0.8230	85.08	0.15	1	0.0048

once the predicted sample deviates from actual value by a margin greater than predefined threshold ϵ. Hyperparameters of the learning algorithm are estimated using cross-validation optimization error. The algorithm is proposed to operate simultaneously at the PMU (i.e the edge node) and the control center. At the PMU, the learning-based model identifies and eliminates the superfluous samples, while at the control center, its counterpart estimates the omitted samples within a given error threshold.

Accuracy of sample predictions and runtime complexity of the algorithm are governed by the choice of error threshold ϵ, and length of the training set. It is observed that a larger training length does not necessarily guarantee precise predictions, thus value of optimum training length is also considered a hyperparameter and is parsimoniously selected based on the variations in the dataset. Likewise error threshold ϵ is application domain specific. Its value depends on the sensitivity of different variables measured by the PMU. Performance of the algorithm is measured in terms of bandwidth saving (BWS), retraining count(RC), disturbance identification index (DI), and root mean square error (RMSE), which signify the reduction in amount of resource requirements, runtime complexity, satisfaction of QoS, and accuracy of predictions, respectively. Bandwidth saving is the percentage of PMU data samples that are not transmitted. These are essentially the samples which are successfully predicted within the error bound ϵ at the PDC. If l is the length of powerline frequency sequence measured by PMU over a sufficiently large time interval Δ, then, $BWS = \lim_{l\to\infty}(\text{Successful predictions by PMU}/l) \times 100$. DI is a measure of goodness of the model in identifying a fault scenario. Over a large interval Δ, let l_{dist} and $\hat{l}_{dist}$ be respectively the actual and the estimated number of frequency samples designated to be in disturbed states. Then, $DI = \lim_{\Delta\to\infty}(\hat{l}_{dist}/l_{dist})$ [62]. The indices RC and DI are upper bounded by value 1, and their higher values indicate high runtime complexity and better QoS satisfaction, respectively. A comparison of performance of dynamic prediction algorithm for different variables measured by the PMU is presented in Table 4. It is observed that around 80% saving in bandwidth requirement is attained for various parameters without any degradation in QoS satisfaction, though runtime complexity for the variables having lower temporal correlation is slightly higher.

4 Avenues for Future Research

The case studies presented in the previous section clearly indicate that by the application of green techniques, substantial resource savings can be achieved in terms of energy efficiency, bandwidth, and storage space optimization in transmission and archival of massive IoT data. In this section, a few pertinent research issues and directions open for future investigation and realization of the green sensing and communication techniques are discussed.

- With large scale deployment of IoT nodes, a primary challenge has been in powering these nodes, and to externalize their lifetime. Though conventional literature suggests battery-powered operations, battery replacement can be arduous and expensive, especially when the nodes are deployed in inaccessible terrains. To this end, energy harvesting techniques from ambient sources for sustainable operation of IoT nodes such as use of solar energy, radio-frequency, and unmanned aerial vehicles assisted sensor node charging has emerged as a new research direction.
- The design of strategies that jointly optimize/handle various trade-offs discussed in Section 2.4 is the need of the hour. Multi-objective optimization and multi-interval hybrid approaches are looked upon as prospective solutions. In multi-interval hybrid approach, different optimization frameworks are employed at different energy/performance intervals which are often governed by nature of application.
- Scalability is an important practical issue in most of the IoT applications due to the involvement of multiple devices and networks. In this context, the design of distributed and hybrid schemes for sensing/monitoring is another interesting research direction. Further, existing distributed sensor selection strategies are non-adaptive to the dynamic signals being monitored. Design of adaptive distributed monolithic and multi-sensing strategies and their contribution to energy saving is another dimension to work upon.
- Integration of various system-level constraints, imposed by exhausted energy of nodes, detection limits of different sensors in heterogeneous sensing environment, is often overlooked in the green sensing techniques. To bridge the gap between theoretical and practical implementation of the IoT systems, it is vital to consider these constraints.
- Another research direction pertaining to green communication of massive IoT data is effective characterization of wireless channel for its energy-efficient usage, and design of wireless channel adaptive communication strategies to meet the QoS requirements of the respective IoT applications. A few existing schemes exploit temporal variations of the channel for enhancing its utilization as well as energy efficiency, however their applicability to IoT networks where edge devices have limited computational resources needs to be well investigated. In this context, development of simple yet efficient wireless channel prediction frameworks and protocols to facilitate reliable transmission of IoT data holds a significant research potential.

– Further, energy consumption at different layers (MAC, network, and physical layers) is handled separately in the existing literature. A cross-layer solution that jointly exploits techniques used at individual layers to save energy such as sensor management/selection, cluster formation, and power control, etc., is required to be developed to ameliorate energy efficiency of frameworks designed for the IoT applications.
– To prevent networks and sensitive information against various security attacks and eavesdropping, it is important to impart security and privacy in a network. However, relevant operations such as data encryption/decryption, attack detection, etc. consume significant amount of computation energy, while transmission of secured data incurs communication overhead. Thus, reducing energy cost while ensuring certain quality of protection (QoP) is another challenging research direction.

5 Conclusion

In this paper, a comprehensive overview of current green techniques for the IoT systems along-with their merits and demerits has been presented. Twofold benefits of the green techniques are extending the system's lifetime and achieving environmental sustainability. Various challenges and critical trade-offs associated with simultaneously balancing the system's performance and energy efficiency have been identified. Performance of data-driven green sensing and communication schemes for realizing three pertinent IoT applications, namely, lab environment monitoring, smart grid health monitoring, and smart metering, have been analyzed. It can be concluded that exploiting machine learning, multi-objective optimization, Bayesian learning, compressed sensing, etc. in data-driven green schemes significantly aid in incorporating necessary intelligence at sensing, communication, and computation levels. Around 15% more energy efficiency is achieved in adaptive and optimized multi-sensing based lab monitoring application, and 80% and 37% bandwidth saving is achieved in smart grid monitoring and smart metering applications, respectively, without degrading the required quality of service. Several open issues vital for improving energy efficiency and practical realization of the IoT applications have been identified for future research.

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