Embracing Big Data with Compressive Sensing: A Green Approach in Industrial Wireless Networks

Linghe Kong, Daqiang Zhang, Zongjian He, Qiao Xiang, Jiafu Wan, and Meixia Tao

Abstract

New-generation industries heavily rely on big data to improve their efficiency. Such big data are commonly collected by smart nodes and transmitted to the cloud via wireless. Due to the limited size of smart node, the shortage of energy is always a critical issue, and the wireless data transmission is extremely a big power consumer. Aiming to reduce the energy consumption in wireless, this article introduces a potential breach from data redundancy. If redundant data are no longer collected, a large amount of wireless transmissions can be cancelled and their energy saved. Motivated by this breach, this article proposes a compressive-sensing-based collection framework to minimize the amount of collection while guaranteeing data quality. This framework is verified by experiments and extensive real-trace-driven simulations.

Introduction

The Industry 4.0 revolution is taking place in this big data era. Benefiting from the analysis of big data, customized services can be provided, production efficiencies are optimized, and emerging industries are gradually growing. In quite a few modern industries, big data are collected by smart nodes and transmitted via wireless. For example, in a manufacturing plant, ubiquitous sensors gather environmental data to support the fine-grained adaptation of cooling systems; smart urban crowdsensing applications [1] acquire real-time data from thousands of mobile phones to make local communities and cities more sustainable.

For the smart node, whether sensor or phone, wireless transmission is one of the biggest electricity burners. A field test [2] shows that the power consumption of WiFi in a popular smartphone is about 500 mW, while its battery is only 1200 mAh and 3.7V Li-Ion. In other words, this smartphone could support at most $1200 \times 3.7/500 = 8.88$-hour WiFi transmission even in the ideal case.

To address the dilemma between the demand of big data collection and the limited energy in smart nodes as shown in Fig. 1, it is urgent to design a novel green collection solution. Such a solution is promising to facilitate big-data-based modern industry.

Plenty of techniques have been developed for energy-efficient wireless networks, such as antenna gain [3] and placement strategy [4]. Considering the feature of big data, this article introduces a new direction: data redundancy.

Redundant data widely exist in big data, and they usually contribute little to the efficiency improvement of next-generation industries. If we do not collect these redundant data and only collect the principal data, huge amounts of power consumption will be saved. Promising as it seems, however, one challenging problem arises: How can we distinguish whether a certain datum is principal or redundant before collecting all data? No wireless transmission can be saved in traditional methods because they have to collect all data and then analyze the redundancy.

To tackle the challenge, this article proposes a novel compressive-sensing-based collection framework. Compressive sensing [5] is an advanced mathematic theory for data completion using very few sampled data. The proposed green collection framework consists of two core components. First, to reduce the number of transmissions, an online learning component predicts the minimal amount of data that needs to be collected. These data are considered as the principal data, and their amount is constrained by compressive sensing. Second, a local control component running at every node further tunes the collection strategy according to the dynamics and unexpected situations. Combining these two components, this framework reduces power consumption and guarantees data quality simultaneously. Extensive real-trace-driven simulations are conducted to demonstrate the efficacy and efficiency of the proposed framework. Open issues and future research directions on this green collection framework are also discussed.

The proposed solution is a general framework. It is easy to add customized components into this framework according to the demands of industrial applications. We believe the green collection framework has wider implications and prospects for big-data-based industry than those explored in this article.

Aiming to reduce the energy consumption in wireless, the authors introduce a potential breach from data redundancy. If redundant data are no longer collected, a large amount of wireless transmissions can be cancelled and their energy saved. Motivated by this breach, the authors propose a compressive-sensing-based collection framework to minimize the amount of collection while guaranteeing data quality.

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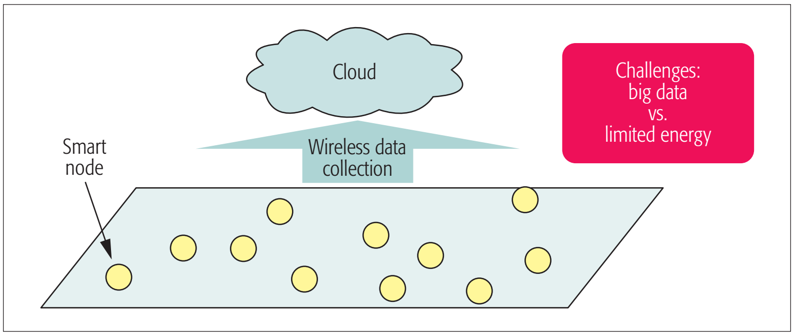

Figure 1. In wireless data collection applications, the distributed smart nodes sense and transmit data to the cloud. The dilemma is between the big data to be transmitted and the limited energy in smart nodes.

Background

The green collection framework typically works at the intersection of three research areas: big data, energy-efficient data collection, and compressive sensing.

Big Data

Both academia and industry are paying a great deal of attention to the explosive growth of data. Lynch [6] posed the open question in *Nature*: How do your data grow? This article attracted many scientists to start working in the area of big data. Baraniuk [7] reported in *Science* that the bottleneck of signal processing now is data deluge: the amount of data generated worldwide (1250 billion GB in 2010), which is dominated by sensory data, is growing by 58 percent per year. The revolution of big-data-driven industry has spread all over the world.

Energy-Efficient Data Collection

The energy constraint is a critical problem in big data collection. According to [8], battery capacity has only doubled in the past 35 years. Moreover, the hazardous sensing environment precludes manual battery replacement. The energy constraint is unlikely to be solved in the near future due to the size limitation of smart nodes.

However, collecting and transmitting big data consume a lot of power in smart nodes. For example, the transmission power of WiFi is up to 500 mW, LTE is up to 200 mW, Bluetooth is up to 100 mW, and ZigBee is up to 5 mW.

Hence, green methods are investigated from the physical layer to the application layer in wireless networks [9–12]. Although existing solutions are highly diverse, none of them take data redundancy into consideration.

Compressive Sensing

Compressive sensing [5] is a generic method to recover the whole condition with only a few sampled data. Several effective compressive sensing applications have been developed in the data completion field [13] (e.g., traffic estimation and video streaming). It has been proven that the whole environment can be near-optimally recovered even if there are more than 70 percent sensory data are missing [14], which motivates us to exploit compressive sensing to reduce the amount of data collection.

Problem Statement

In a big data collection system, smart nodes are usually distributed in the given area to sense data and transmit these data to the cloud via wireless communications. The cloud analyzes the collected data and provides customized service or production. Suppose there are a total of n nodes, and the period of monitoring time is evenly divided into t time slots. Every node collects data once per time slot at most. With the growth of the scale in industrial applications, the total collected data are very big.

The big data can be represented as a large matrix X, where every element is the data collected by one node at one time slot. A matrix with no empty elements means that all data are collected, which indicates 100 percent data quality but costs nt wireless transmissions.

On one hand, to reduce the number of transmissions, it is desired that only principal data are collected. Assume that the amount of principal data is ρ and $\rho << nt$. On the other hand, to guarantee the data quality, it is desired that the principal data are adequate to represent the whole big data, that is, the recovered matrix $\hat{X}$ is close to the complete X, where $\hat{X}$ is the matrix computed by compressive sensing using only principal data.

From the above, we state the problem as follows: The green collection problem aims to minimize the amount of principal data ρ for energy saving and is constrained by $\hat{X} \approx X$ for quality assurance.

Two main metrics are defined to measure the performance of green collection solutions:

- Energy consumption ratio α: This ratio can be approximated as ρ/nt, that is, transmitting the amount of principal data over transmitting the total big data, in which we consider the consumption is equal for every transmission.
- Data error ratio ε: The average error between recovered matrix and complete matrix, that is, $\varepsilon = ||\hat{X} - X||/||X||$.

Real Data Analysis

Before describing the design of a green collection framework, we analyze the redundancy feature in big data. We observe that most big datasets have obvious redundancy. The possible reasons include redundant smart nodes deployed for data collection, nodes in close or the same locations sensing similar data, and sensory data usually having strong correlation with time variance.

Then we introduce three real traces and validate their low-rank properties, which implies the data redundancy in common sensory data. The three datasets are gathered by real projects.

The Intel Indoor experiment was gathered by the Intel Berkeley Research lab. There are totally 54 nodes placed in a 40 m × 30 m room. Every node reports data every 30 s. From all the gathered data, we select 50 nodes' × 4000 slots' data to form a complete dataset.

The GreenOrbs project is a real-world sensor network for forest surveillance. More than 500 nodes are scattered on Tianmu Mountain, China, and gather temperature, light, and humidity data once every 5 min. We select 249 × 500 data from GreenOrbs.

The OceanSense project contributes our third dataset. This dataset contains 20 nodes deployed in the sea of Taipingjiao, China. Each node reports temperature and light every 2 min. We select 15 × 1000 data from OceanSense.

From the three selected datasets, we generate six complete matrices: Indoor-Temp, Indoor-Light, Forest-Temp, Forest-Light, Ocean-Temp, and Ocean-Light for analysis.

Redundancy Discovery

Data at different locations over different times are usually not independent, resulting in a low-rank structure (i.e., some data are redundant). In order to mine the redundancy, we analyze the selected matrices using singular value decomposition (SVD) [14], which is an effective non-parametric technique for revealing a low-rank structure. In Fig. 2, we illustrate the cumulative distribution function (CDF) of top- percent singular values in the selected matrices. The X-axis presents the normalized number of singular values. The Y-axis presents the ratio of the cumulative values of top-percent singular values. This figure implies that the sum of all singular values is always contributed by only a few top singular values in real data. For example, the top 5 percent singular values contribute 92 percent of sum singular values in Indoor-Temp. The universal existence of such trends reveals the low-rank structures in these traces. These redundancy features indicate that big data can be near-optimally recovered by compressive sensing even if only a few data are collected.

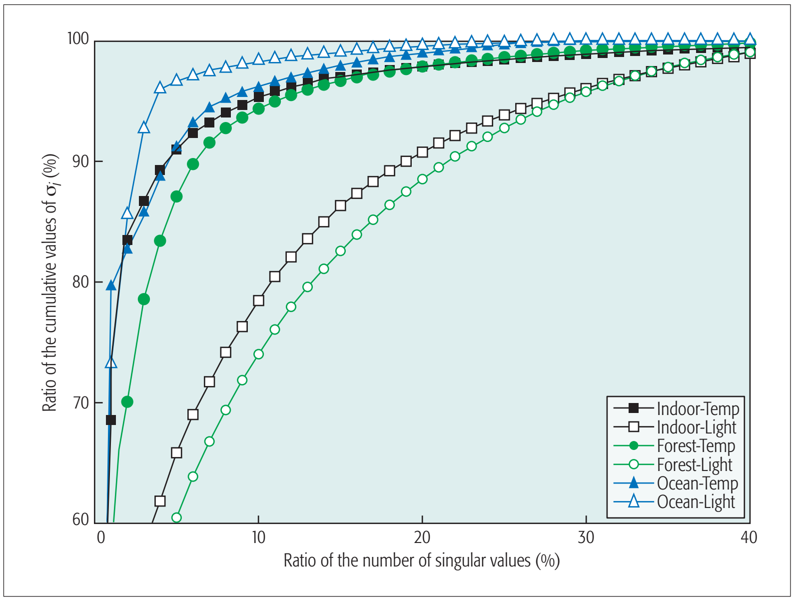

Figure 2. CDF of singular values to explore the redundancy feature in real datasets.

Green Collection Framework

Inspired by the observed feature, a novel green collection framework is designed in this section.

Design Overview

The architecture of our green collection framework is illustrated in Fig. 3, which consists of two core components.

First, the **online learning** component runs at the cloud side. Leveraging the historical data and compressive sensing, this component predicts the minimal amount of data that needs to be collected in the near future. Then this component transforms the data amount to be the collecting probability and reports the probability to every node.

Second, the **local control** component runs at every node. Since the collecting probability provided by the online learning component is an average value from the global view, it may not be suitable for an individual node. Resorting to the adaptive control theory, this component adaptively tunes one node's collecting probability according to the dynamics and unexpected situation.

The advantages of this framework include:

- This framework is easy to implement in practice.
- The high-complexity compressive sensing and prediction are computed at the centralized cloud side. The distributed computing at the node side is low-complexity local control.
- This framework tactfully takes advantage of compressive sensing to reduce the power consumption while guaranteeing the data quality by both global prediction and local adjustment.

Detailed designs of two components are introduced in the following two subsections. Moreover, we pose open problems and discuss some future research directions about this framework.

Online Learning Component

As per the analysis in the previous section, data redundancy universally exists in big data. Existing mathematical tools can analyze the redundant data at the cloud side after collecting all data. However, because a certain node has no global view, when it senses a datum, it is not easy to distinguish whether this datum is principal or redundant. Thus, it cannot locally decide whether to transmit this datum to the cloud or not.

Leveraging the advantage of compressive sensing, this problem can be simplified. Note that compressive sensing can achieve near-optimal matrix completion if a minimal amount of data (related to the rank) are collected and these data are randomly distributed in the matrix. Thus, instead of distinguishing an individual datum, our design aims to acquire the minimal amount of data and near-optimally recover all of the data by compressive sensing.

The online learning component operates as follows.

•Predicting the minimal amount of data collection for compressive sensing. First, the change of rank in historical data can be analyzed at the cloud side using SVD. Second, applying the prediction methods [15] on the historical ranks, we can estimate the rank in the next time slot. To achieve an accurate prediction, the classic ARIMA model is adopted for rank estimation, which considers both trend and periodicity. Third, the minimal amount of data K can be derived by compressive sensing theory [13].

•Adding the margin in the predicted amount. Since the environment is dynamic, a predicted K may not be adequate for near-optimal recovery. Hence, we introduce some margin into the predicted amount by $\rho = \beta K$, where β is the margin coefficient, and we define ρ as the amount of principal data in this article.

• Computing the collecting probability. The collecting probability P can be computed by $P = \rho/nt$, which indicates that the collecting probability of every node at every time slot is P. The cloud will broadcast this probability to all nodes once it has P.

Local Control Component

After receiving P from the cloud, a smart node could collect data at every time slot with probability P. However, this probability is an average result from the global view without considering the individual difference of every node. For example, in a noise detection application, indoor noise changes less frequently than outdoor noise does. Obviously, the collected data from an outdoor node are more important than those from an indoor node.

To achieve a better data quality, the local control component is designed. This component runs at every node and self-adapts the value of P_i according to P, dynamics, unexpected issues, neighbor status, residual energy, and link quality.

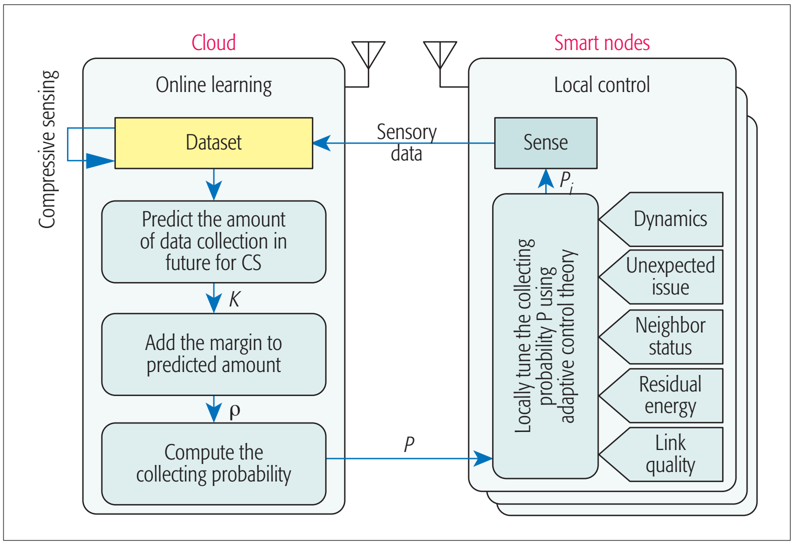

Figure 3. Architecture of the green collection framework.

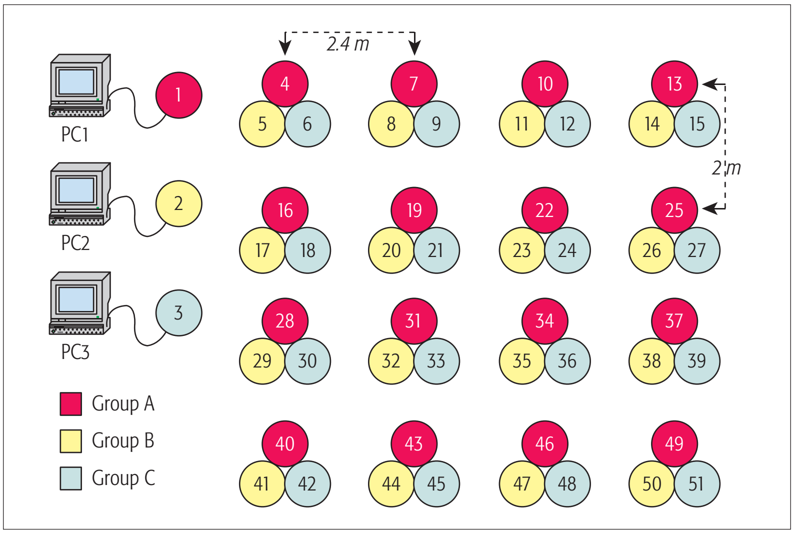

Figure 4. Experiment settings.

Dynamics: The recent sensed datum is compared to the previous sensed data. If the change of data is stable or periodic, P_i can be decreased gradually. If an aperiodic and frequent change of data happens, P_i is gradually increased.

Unexpected Issue: If any unexpected issue is detected, P_i could be increased sharply. For example, a smartphone detects a traffic crash; if there is no other smartphone nearby, this smartphone enlarges P_i immediately.

Neighbor Status: Using the same example of the traffic crash, if there are many smartphones nearby, each one could keep its P_i for data collection.

Residual Energy: When the residual energy in a node is not enough, it reduces its collecting rate P_i for energy saving and reports this condition to the cloud.

Link Quality: The transmission power depends on the link quality of the wireless channel. Generally, a poor channel caused by interference or mobility results in large transmission power and multiple retransmissions. Hence, P_i is reduced when the link quality becomes poor.

The local control component is not limited to the above aspects. More aspects can be appended to this control component as input.

Performance Evaluation

We implement a real testbed and conduct trace-driven simulations to evaluate the performance of the proposed green collection framework (GCF).

Experimental Implementation

Experimental Testbed: Our testbed includes a total of 51 TelosB sensor nodes. They are divided into three groups, A, B, and C, carrying out different data collection methods for comparison. Each group has 16 nodes to sense environmental data and 1 sink node to gather these data. In a 7.2 m × 6 m open-air area, 4 × 4 = 16 positions are selected to deploy nodes as a grid. As shown in Fig. 4, at each position, there are three sensor nodes, which belong to three respective groups. A total of 48 nodes are deployed in the area. The other three sink nodes are connected to three laptops.

Each group with 17 sensor nodes organizes its own network. These nodes transmit data using ZigBee. There are 16 ZigBee channels in the 2.4 GHz industrial, scientific, and medical (ISM) band. The three groups of WSNs work during the same period with three non-overlapping channels, so there is no interference among them.

Implementation Setting: There are some common configurations for the three groups. The duration of every time slot is set as 1 min. The collected data are stored in a database in the laptop according to our customized format including timestamp, node ID, temperature, humidity, light, voltage, and received signal strength indicator (RSSI).

The individual configuration for each group is as follows. Group A: Collection Tree Protocol (CTP). The TinyOS library provides the code of CTP. The radio is always on for data transmission. Group B: Fixed low-duty-cycle (FLDC12.5), one cycle is set to 4 h with 0.5-h active state and 3.5-hour sleep state. Thus, the duty-cycle is 12.5

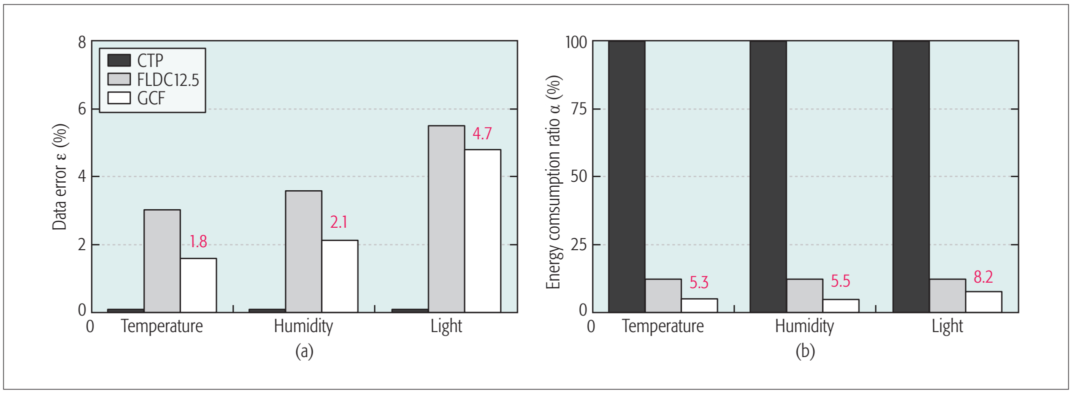

Figure 5. Experiment results: a) experimental performance: data factor; b) experimental performance: energy consumption.

GCF outperforms classic data collection methods in this experiment. Compared with CTP, GCF is much better on energy efficiency within the requirement of data quality. Compared with FLDC12.5, both methods can achieve the data quality, but GCF performs much better on power consumption.

percent. (Different duty cycles are also tested at 50, 25, and 6.25 percent. We only show FLDC12.5 here because it has the lowest power consumption subject to the error ratio ≤ 5 percent.) Group C: GCF with the requirement of error ratio ≤ 5 percent.

Experiment Results: The data quality and power consumption are compared among three groups. All three groups run 10 days for temperature, 10 days for humidity, and 10 days for light collection and recovery.

The metric of data quality is the data error ratio ε. Figure 5a plots the histogram of ε in different groups in different environments. Group A: Since CTP gathers all data, it has no error, ε = 0. Group B: FLDC12.5 loses 87.5 percent environmental data. Although the missing data are estimated by compressive sensing, error ratios are 3.1 percent in temperature, 3.6 percent in humidity, and 5.4 percent in light. Group C: GCF offers satisfactory results on data quality. Due to the accurate prediction and local feedback control, GCF displays ε = 1.8 percent in temperature, 2.1 percent in humidity, and 4.7 percent in light after compressive sensing. In summary, the comparison result indicates that the GCF can ensure the accuracy requirement.

The power consumption is measured by the energy consumption ratio α. The results of energy consumption ratio are displayed in Fig. 5b. Group A: The radio keeps turning on in CTP, so α = 100 percent. Group B: Since the duty cycle is fixed in FLDC, α =12.5 percent. Group C: The number of transmissions in GCF changes according to the dynamic environment. From Fig. 5b, we observe that α = 5.3 percent in temperature, 5.5 percent in humidity, and 8.2 percent in light. The results imply that GCF is better than FLDC12.5 and much better than CTP in energy saving in our experiment.

GCF outperforms classic data collection methods in this experiment. Compared to CTP, GCF is much better on energy efficiency within the requirement of data quality. Compared to FLDC12.5, both methods can achieve the data quality, but GCF performs much better in power consumption.

Trace-Driven Simulation

Simulation Setting: Although the experiment verifies the efficacy and efficiency of GCF, it only carries out in an experimental scenario with some limitations such as small-scale sensor networks and small area. In order to test the extensive applicability of GCF, we conduct the simulations based on the three real datasets introduced earlier. These three datasets are on diverse scales (50, 249, 15 nodes), diverse areas (40 m × 30 m, 200 m × 100 m, and 300 m × 100 m), and diverse scenarios (indoor, forest, and ocean). Every dataset is simulated by CTP, FLDC50, FLDC25, FLDC12.5, FLDC6.25, and GCF, respectively. The requirement of data error ratio is still set ≤ 5 percent.

Simulation Results: Figure 6 shows the data error and energy consumption ratios of different data collection methods among indoor, forest, and ocean datasets in our simulations.

We can find in Figs. 6a, 6b, and 6c that every ε is 0 for in CTP; for FLDC, the smaller duty cycles result in larger error ratios; and the error ratios of GCF are less than 5 percent in all three scenarios.

The energy consumption ratios of CTP, FLDC50, FLDC25, FLDC12.5, and FLDC6.25 are 100, 50, 25, 12.5, and 6.25 in Figs. 6b, 6d, and 6f. These values are fixed, and are independent of scenarios or environments. Nevertheless, such ratios of GCF are dynamic corresponding to the diverse scenarios or environments. Most energy consumption ratios α of GCF are smaller than 10 percent. For example, α in Ocean-Temp and Ocean-Light are only 6.0 percent, and in Indoor-Temp 7.5 percent.

In summary, the results in the simulation are similar to the performance in the experiment. The proposed GCF guarantees the data quality with low energy consumption. The most important property of GCF is its self-adaptation to the dynamics, making it outperform existing methods in nearly all scenarios.

Discussion

Using data redundancy and compressive sensing to reduce power consumption is a new concept in wireless big data collection. Open issues and research directions are worth investigation in the future.

There are still two open issues in the proposed framework. First, the current GCF cannot achieve a minimal amount of data collection because it adopts random collection from a global view but does not optimize the collection amount on every individual node. A more accurate collection method is desired to save more

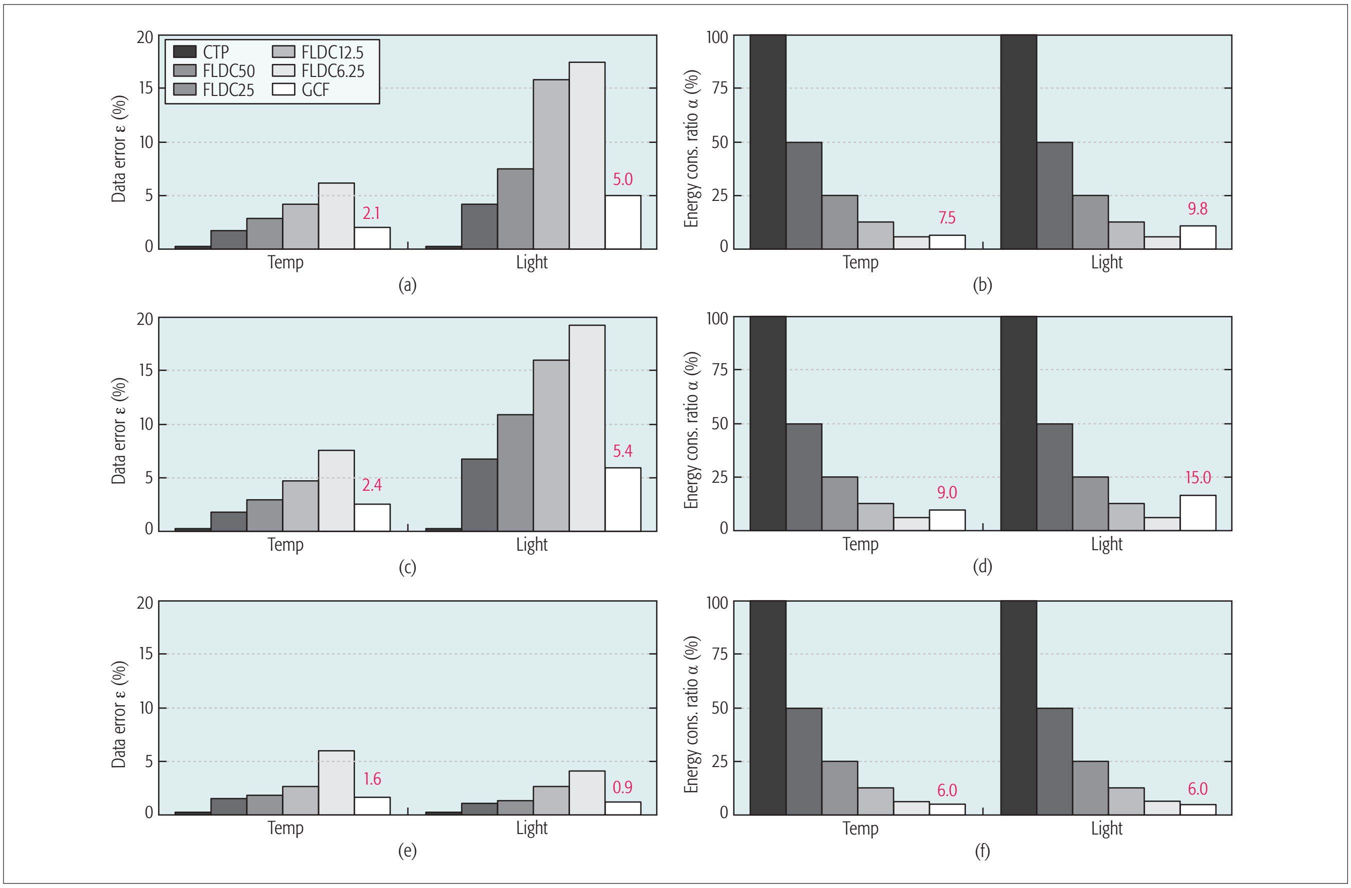

Figure 6. Simulation results: a) indoor dataset simulation: data error; b) indoor dataset simulation: energy consumption; c) forest dataset simulation: data error; d) forest dataset simulaiton: energy consumption; e) ocean dataset simulation: data error; f) ocean dataset simulation: energy consumption.

power consumption. Second, there is a trade-off between the recovery accuracy and the total collection amount. Deriving the theoretical curve to present the trade-off relationship is still an open issue.

The GCF also produces several promising research directions. One valuable direction is to study the correlation between multi-source data to further reduce the amount of data collection. For example, we can collect some light data to estimate not only the light but also the temperature distribution due to their high correlation. The second significant direction is false data detection. To maintain the data quality, false data should be detected and removed from the collected principal data. In addition, this work only considers the correlation in the time domain. If the positions or trajectories are known, space correlation could further optimize the amount of mobile data collection. Last but not least. in a multihop network, network coding and other data aggregation techniques can be taken into account to further reduce the total amount of data collection.

Conclusion

A green collection framework is proposed in this article to save energy in big-data-based smart industries. The core contribution of this framework is to reduce the number of transmissions by leveraging the compressive sensing theory. The evaluation results demonstrate that the proposed framework dramatically decreases the power consumption compared to existing approaches while the data quality is guaranteed.

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