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Compressed Sensing-Based Multi-Layer Data Communication in Smart Grid Systems

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Received June 27, 2013; revised August 26, 2013; accepted September 3, 2013; published September 30, 2013

Abstract

Compressed sensing is a novel technology used in the field of wireless communication and sensor networks for channel estimation, signal detection, data gathering, network monitoring, and other applications. It plays a significant role in highly secure, real-time, well organized, and cost-effective data communication in smart-grid (SG) systems, which consist of multi-tier network standards that make it challenging to synchronize in power management communication. In this paper, we present a multi-layer communication model for SG systems and propose compressed-sensing based data transmission at every layer of the SG system to improve data transmission performance. Our approach is to utilize the compressed-sensing procedure at every layer in a controlled manner. Simulation results demonstrate that the proposed monitoring devices need less transmission power than conventional systems. Additionally, secure, reliable, and real-time data transmission is possible with the compressed-sensing technique.

Keywords: Compressed sensing, home area network, multi-layer data communication, smart grid, wireless sensor network, zigBee

A preliminary version of this paper appeared in IEEE, ICIEV 2012, May18-19, Dhaka, Bangladesh. This work was supported by the 2013 Research Fund of University of Ulsan.

http://dx.doi.org/10.3837/tiis.2013.09.008

1. Introduction

Smart Grid (SG) is a promising technology that includes an auto-balancing, self-monitoring power control system and taking advantage of advancements in Information Technology (IT) and telecommunications that integrates various generation concepts and technologies. It explores two-way communication technology, smart metering, updated control theory, dynamic optimization theory and machine-to-machine (M2M) communication in order to ensure the capabilities of superior network, efficient, secured distribution of energy, flexible, economical and cyber safety. The accurate control and management theory make an SG more reliable to reach in its goal. Moreover, in SG communications there are a number of devices that are exploited for the supervision and feedback information of grid, which requires a significant amount of device power. In this respect, intelligent and low cost monitoring and control systems enabled by online sensing technologies are essential for maintaining the safety, reliability, efficiency and uptime of an SG [1-3].

A home area network (HAN) is one of the most essential subsystems in an SG to manage the on-demand power requirements of end-consumers. There is an urgent need for cost-effective wireless monitoring and diagnostic systems for HAN that improve system reliability and efficiency by optimizing the management of electric power systems. Therefore, ZigBee plays an important role as a new wireless standard, which targets to a low power, low data-rate, and short-range wireless data transformation [4-7].

Fundamentally, compressed sensing (CS) offers a new method of compression and coding in order to minimize the storage and cost. This innovative method shows that sparse or compressible signals can be recovered precisely from a small number of random linear projections that contains sufficient information. As the information of power consumption does not change in all the home together as well as it does not change rapidly in the order of milliseconds, which shows the sparsity of data. Consequently, this phenomenon leads more adaptive opportunity to transfer the information in SG system through CS methodology. A number of approaches of utilization of CS technique in wireless sensor network and SG have been have been reported in the previous works [8-12]. M. Balouchestani et al. represented a survey of CS theory and showed a comparative analysis of WSN with CS and without CS [8]. Application of CS theory was described in [9]. X. Wang et al. explained CS based random routing for multi-hop WSN [10]. Moreover, P. Zhang et al. [11] did Performance and delay analysis of WSN by using CS. In addition, compressed meter reading in SG system was proposed by H. Li et al. [12]. However, the task of transmitting information of electricity consumption from a Smart Meter (SM) to the central controller is tricky due to the following major facts:

Monitoring Device Power and Lifetime

An SG system consists of a large number of devices that store, gather, and transmit accurate information about electricity consumption between the generation units and the end users. More accurate management of data transmission enables more competent supervision with lower transmission power, thereby increasing the lifetime of devices [3, 13-14].

Spectrum Scarcity

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Spectrum is a limited resource, so wireless devices need to transmit data to other devices efficiently. Traditional methods are not adequate to achieve optimal spectrum management because of inevitable change of spectrum requirements to transmit data [15-16].

Delay Sensitivity

Power load information should be updated in real time because electricity consumption changes frequently. Otherwise, any delay of data transmission in the SG system would make the whole system futile [17].

Security Requirement

An SG communication network is an aggregate of multiple networks with varying levels of communication and coordination between power providers, operators, and customers. Therefore, an assurance of high security is required for communication in the SG system because it is a likely target of sophisticated cyber attacks, which can be launched from any vulnerable component in the highly distributed system [18-20].

Considering the above challenges, in this paper, we propose a multi-layer version of the complete SG system with CS-based [21-23] data transmission offered at every layer. In the proposed design, we consider a HAN developed by ZigBee to transmit the electricity-consumption information. Moreover, at all layers in the SG system, the electricity-consumption information is transmitted in a controlled manner i.e., if there is no significant change in the information, it is treated as unchanged or zero. Therefore, CS is utilized in a controlled manner i.e., if the information of a node cannot satisfy a certain threshold value, it is treated as zero. And, compression is associated with proper routing of the nodes in the system. The simulation results illustrate that the proposed method transfers data effectively with lower power, in lesser time, and in a more secure manner than the traditional method.

The rest of this paper is structured as follows. In section 2, the system model is introduced. Next, in section 3, CS background and data transmission process is explained, and section 4 contains simulation results. Finally, conclusions are drawn in section 5.

2. System Model

The overall structure of the proposed SG model is depicted in **Fig. 1**, and the constituents of the system are described in the following subsections.

2.1 Home Appliances

Home appliances are the power-consuming devices in the SG, and they are connected to a smart meter.

2.2 Smart Meter

A smart meter is a device that is used to collect the electricity-consumption information from home appliances. A HAN can be established with home appliances and a smart meter (using ZigBee or other devices). Smart meters enable two-way communication between the meter

and the central system. Unlike home-energy monitors, smart meters can gather data for remote reporting.

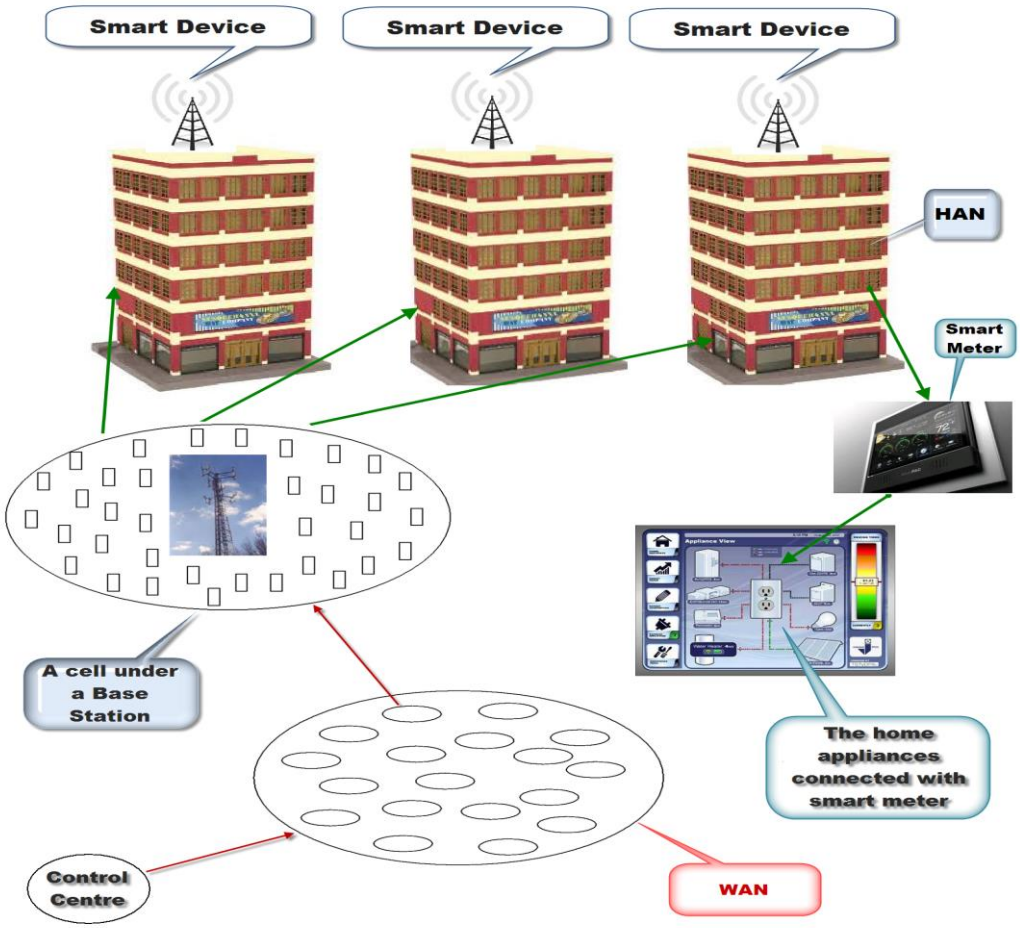

Fig. 1. Overall structure of the proposed smart-grid system.

2.3 Home Area Network

A HAN is used to collect electricity-consumption information of home appliances and supply the information to upper layer. In this paper, the HAN consists of ZigBee and smart devices. Because they are superior to other devices (Bluetooth, Wi-Fi, etc.) ZigBee devices are preferred for the HAN. A ZigBee system maintains a protocol that was developed particularly for wireless devices to ensure low power consumption and a long battery life. A ZigBee device can be a full-function device (FFD) or a reduced-function device (RFD). It allows up to 254 nodes in a network. ZigBee devices are of three types : ZigBee coordinator (ZC), ZigBee router (ZR), and ZigBee end device (ZED). ZC and ZR are FFDs. Note that the ZED (RFD) cannot relay messages or allow other nodes to connect to the network through it. Therefore, ZED consumes less battery power and has a long lifetime. ZigBee supports star, peer-to-peer, cluster tree and other network topologies. When compared with Bluetooth or Wi-Fi devices, these devices may take only milliseconds to exit their sleep state. M. Balouchestani et al.

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observed that the Bluetooth and ZigBee protocols consume lesser power (for both transmission and reception) than Wi-Fi and UWB technologies, and ZigBee is superior to Bluetooth [8]. In addition, ZigBee provides a fair communication range of 10–100 m while maintaining significantly low power (1–100 mW) and thus lowers cost. Practical examples of this scenario can be easily found in the context of ZigBee networks [4-6]. However, in the proposed HAN, home appliances are connected to smart meters. And, smart meters are connected to smart devices through ZigBee nodes where smart devices communicate with the WAN through a base station (BS).

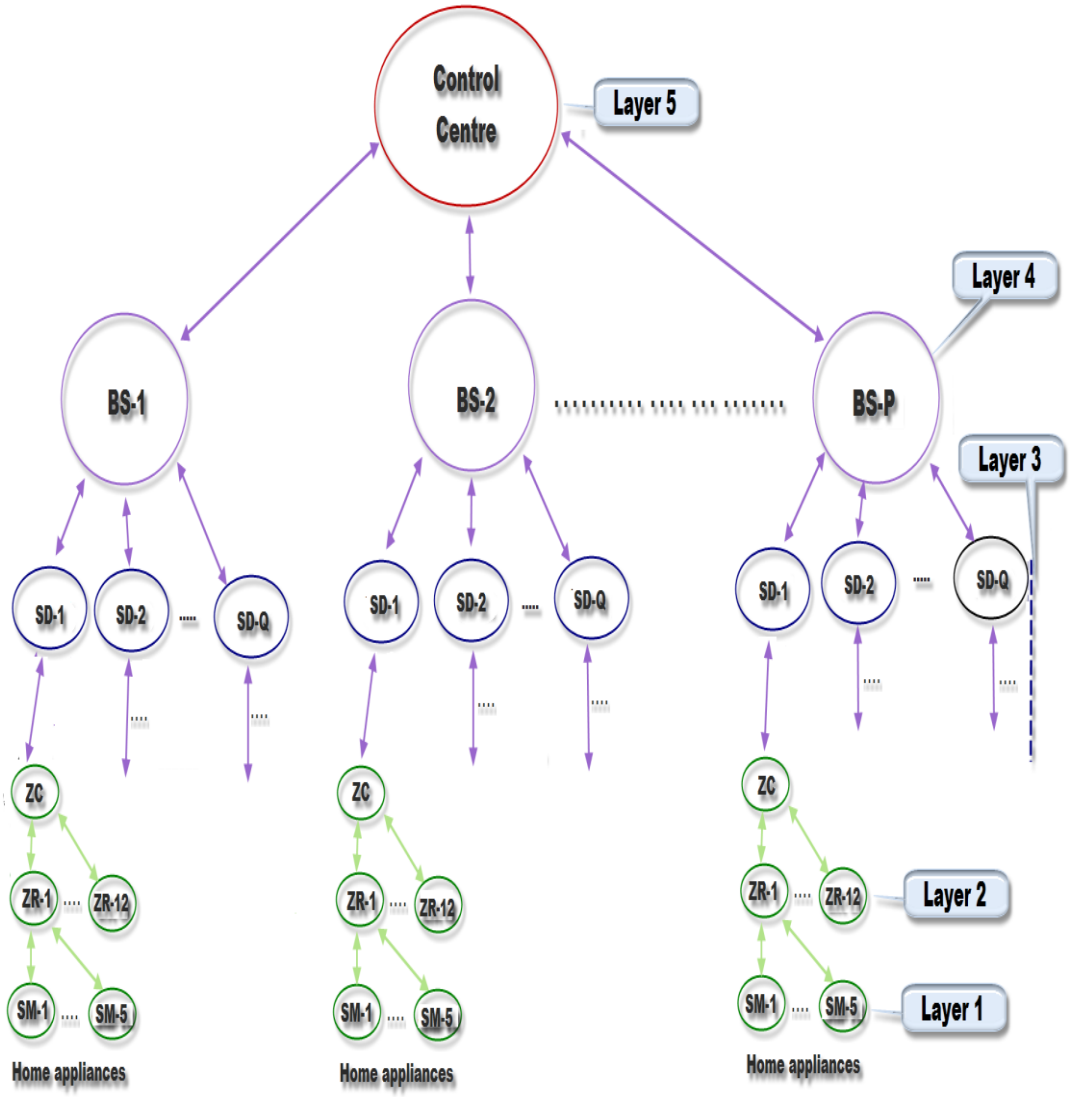

Fig. 2. The proposed layer system of the entire system model.

2.4 Smart Device

Although the definition of a smart device can vary, in our SG system, the term smart device is used to refer to a multi-functional device that acts as the following:

- An intelligent device that uses bandwidth in the TV band for its data transmission and reception associated with a BS.
- A home gateway device that continuously supplies electricity demand information to the upper layer i.e., a BS.

2.5 Wide Area Network

In the proposed system model, the WAN is divided into several clusters. In order to develop a standard for cognitive radio (CR), the IEEE 802.22 working group was formed in November 2004. The IEEE 802.22 standard defines the physical (PHY) layers for a wireless regional area network (WRAN) using white spaces within the television bands [24].

2.6 Control Centre

The control centre (CC) receives the electricity-consumption information for processing and storage. This data is used to optimize the electrical power generation and/or distribution.

3. Compressed Data Transmission Scheme

3.1 The Theory of Compressed Sensing

3.1.1 Compressible Data

For simplicity, consider a real-valued, one-dimensional, discrete-time signal x with a finite length N, which can be viewed as an $N \times 1$ column vector in $\Re^N$ with elements $x(n)$, *for* $n = 1, 2, \ldots, N$. Any signal $x \in \Re^N$ can be expanded in an orthonormal basis $\Psi = [\Psi_1, \Psi_2, \ldots \Psi_N]$ as follows [23]:

$$x = \sum_{i=1}^{N} \Psi_i \alpha_i = \Psi \alpha \tag{1}$$

where $\alpha_i = \langle x, \Psi_i \rangle = \Psi_i^T x$ and T denotes transposition, and α is the coefficient sequence of x. Clearly, x and α are equivalent representations of the signal, with x in the time or space domains and α in the ψ domain. When only K of α_i coefficients are nonzero, K << N, the signal x is compressible and has a sparse representation, called K sparse. Sparsity determines the efficiency of signal acquisition and decreases the resources needed for storage and transmission.

3.1.2 Sampling and Sensing

Consider a general linear measurement process that has $M < N$ inner products between x and a collection of vectors $\{\Phi_j\}_{j=1}^{M}$ in $y_j = \langle x, \Phi_j \rangle$. Arrange the measurements y_j in an $M \times 1$ vector y and the measurement vectors Φ_j^T as rows in an $M \times N$ matrix Φ. Then, by substituting Ψ

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from (1), y can be written as

$$y = \Phi x = \Phi \Psi \alpha = \Theta \alpha \tag{2}$$

where y is an $M \times 1$ column vector, and Θ is a fixed $M \times N$ matrix independent of the signal x. It is possible to design M measurements ($K < M << N$) with enough accuracy to reconstruct the signal [25], [26]. The measurement matrix must allow the reconstruction of the N-length signal y from $M < N$ measurements. Since $M << N$, generally, recovering x from y is an ill-posed problem. However, If y is K sparse and the K locations of the nonzero coefficients are known, it can be solved by providing $M \geq K$. A well condition for any vector v sharing the same K nonzero entries as α and some q > 0 is

$$1 - q \leq \frac{\|\Theta v\|_2}{\|v\|_2} \leq 1 + q \tag{3}$$

The matrix Θ must deserve the lengths of these particular K-sparse vectors. Satisfying a sufficient condition referred to as the restricted isometric property (RIP) is necessary for stability of the reconstruction. From the compressed-sensing theory, a K-sparse signal can be reconstructed from N measurements if M satisfies the following conditions:

$$M \geq C\mu^2(\Phi, \Psi) K \log N \tag{4}$$

$$C\mu^2(\Phi, \Psi) \log N \leq \frac{K}{M} \tag{5}$$

where C is a positive constant. Here, $\mu^2(\Phi, \Psi)$ is the coherence and is defined as

$$\mu(\Phi, \Psi) = \sqrt{N} \max_{1 \leq i, j \leq N} \left| \langle \Phi_i, \Psi_j \rangle \right| \tag{6}$$

For a smaller coherence between Φ and Ψ, fewer measurements are needed to reconstruct the signal [23]. Both the RIP and incoherence can be achieved with high probability by merely selecting Φ as a random matrix. For example, let the matrix elements $\Phi_{i,j}$ be independent and identically distributed (iid) random variables from a Gaussian probability density function with zero mean and variance $\frac{1}{M}$. Then, the measurements y are merely M different randomly weighted linear combinations of the elements of x. An $M \times N$ iid Gaussian matrix $\Theta = \Phi I = \Phi$ can be shown to have the RIP with high probability if (4) is satisfied. Therefore, K-sparse and compressible signals of length N can be recovered from only M random Gaussian measurements by solving the convex optimization problem with probability $1 - O(e^{-\lambda N})$ for some $\lambda > 0$ if (4) is satisfied. In practice, using a random measurement matrix is a convenient choice because a random basis has been shown to be largely incoherent with any fixed basis, and $M \sim 2K$ is usually sufficient to satisfy (4).

3.1.3 Data Restoration

The signal can be recovered by ℓ_1 norm minimization. The recovered signal is denoted as $\hat{x}$ and can be written as

$$\hat{x} = \arg\min_{y = \Phi x} \|x\|_{\ell_1} \tag{7}$$

It has been shown that ℓ_1 reconstruction of K-sparse signals is exact with a high probability if it satisfies (4). From (4), it is evident that, if the value of K increases, a higher number of

measurements are required to satisfy the equation. Moreover, if the value of K increases the number of measurements of M required to maintain the compression ratio ($\frac{K}{M}$) increases from (5). However, (7) is a convex optimization problem, which can exactly recover the sparse or compressible signal with a high probability [21] [22]. Many methods can be used for the reconstruction of the compressed signal. Some efficient algorithms are the least square method, basis pursuit (BP) [27], chaining pursuit (CP) [28], matching pursuit (MP) [29], and orthogonal matching pursuit (OMP) [30].

3.2 Data Sparsity Condition in the Smart Grid System

The major reasons for data sparsity in the SG system are as follows:

- In the smart grid, the power-consumption information of each house is transferred to the central controller in order of milliseconds. However, the power consumption in each house does not continuously vary in the order of milliseconds. For instance, in a house the power consumption may change few times in a period of one hour. Therefore, for most of the remaining time, the data has zero value.
- Moreover, because the power consumption in all the houses does not vary dynamically at the same time, the number of smart meters simultaneously transmitting nonzero information is very small when compared with the total number of meters in a particular SG system.
- Additonally, although electricity consumption changes occur, by considering a comprehensive scenario in this paper, we can assume that the change can be negligible when there is no significant change in information. Therefore, the smart meters that have no significant change in power load will have zero value.

Thus, in a particular network, the number of smart meters simultaneously transmitting is very small when compared with the total number of meters. Most of the smart meters have zero data i.e. most of the elements of the vector are zero. This verifies the sparsity of smart-grid communication and makes compressed sensing reasonable.

3.3 System Model Layers

From the system model (**Fig. 1**), we can observe that a WAN with a CC consists of a number of clusters with a BS in every cluster. In this work, we consider P as the number of clusters in a WAN. Because every cluster has a BS as a cluster head, the total number of base stations is P $(a = 1, 2, \ldots, P)$. Under each BS, the number of SDs is Q $(b = 1, 2, \ldots, Q)$, and each SD has *12* ZRs through a ZC. Every ZR has 5 ZEDs, and every ZED is physically inserted into an SM. Further, the ZED is considered as layer 1, the ZR as layer 2, ZC and SD as layer 3, BS as layer 4, and CC as layer 5. A tree diagram of the complete system and the layers is given in **Fig. 2**.

3.4 Compressed Data Collection and Transmission

In the proposed system model, each layer receives the compressed data (electricity-consumption information) from its lower layer (layer 2 to the CC), gathers data, and makes decisions to transmit data to its upper layer. Data reception, gathering, and transmission include the following mechanisms:

- Each parent node collects data from all of its child nodes, and instead of sending individual information of each child node, it sends the summation results to its upper

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layer.

- Data is sent to the upper layer if there is a significant change in electricity consumption. If the data of any node is below a threshold value, the information is treated as zero.
- The required information is transmitted using compressed sensing.

3.4.1 Compressed Data Transmission at Every Layer

The data of any layer is denoted by x_b *(b* = 1, 2,…, *N).* The random basis vector at each layer is denoted by $\Phi_{j,b}$ (*j* is the number of row measurements and *j* = 1, 2,…, *M)*. Every layer uses its random basis vector, computes the signals $\Phi_{j,1}x_1, \Phi_{j,2}x_2, \ldots, \Phi_{j,N}x_N$, and transmits the signals to the upper layer. Each upper layer knows the random basis vector of the layer immediately below it. We can use the following general formula to demonstrate the reception of a signal by any layer from its lower layer:

$$y_j = \sum_{b=1}^{N} \Phi_{j,b} x_b \tag{8}$$

For *N* nodes, mathematically we can transform (8) as

$$y_j = \Phi_{j,1}\ \Phi_{j,2} \ldots \Phi_{j,N} \begin{pmatrix} x_1 \\ x_2 \\ . \\ . \\ x_N \end{pmatrix} \tag{9}$$

From (8) and (9) above, we obtain

$$\begin{pmatrix} y_1 \\ y_2 \\ . \\ . \\ y_M \end{pmatrix} = \begin{pmatrix} \Phi_{1,1} & \Phi_{1,2} \ldots & \Phi_{1,N} \\ \Phi_{2,1} & \Phi_{2,2} \ldots & \Phi_{2,N} \\ . & . \ldots . & . \\ \Phi_{M,1} & \Phi_{M,2} \ldots & \Phi_{M,N} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ . \\ . \\ x_N \end{pmatrix} \tag{10}$$

The data of the second layer (ZR) is denoted by x_b (*b* = 1, 2, …, 12). The random basis vector at each ZED is denoted by $\Phi_{j,b}$ (*j* is the number of rows and *j* = 1, 2,…, *M*). The ZRs use their random basis vectors, compute the signals $\Phi_{j,1}x_1, \Phi_{j,2}x_2, \ldots, \Phi_{j,12}x_{12}$, and transmit the signals to the ZC. The ZC knows the random basis vector of every ZR. From (10), we get the following equation for 12 nodes and *M* measurements:

$$\begin{pmatrix} y_1 \\ y_2 \\ . \\ . \\ y_M \end{pmatrix} = \begin{pmatrix} \Phi_{1,1} & \Phi_{1,2} \ldots & \Phi_{1,12} \\ \Phi_{2,1} & \Phi_{2,2} \ldots & \Phi_{1,12} \\ . & . \ldots & . \\ \Phi_{M,1} & \Phi_{M,2} \ldots & \Phi_{M,12} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ . \\ . \\ x_{12} \end{pmatrix} \tag{11}$$

From (11), it is evident that all the data is transmitted by *M* measurements (M < 12) to its parent node (ZR).

3.4.2 Data Gathering and Routing Process

As the previously mentioned, the ZigBee nodes can transmit properly within a 10-m range. Therefore, in the proposed HAN, the nodes are assumed to be at an appropriate distance for communication with one another. Further, we consider a HAN with a coverage area of 30 m^2. Further, all the nodes (ZRs and ZC as shown in **Fig. 3**) are kept within a distance of 10 m (on average) vertically and horizontally, and three measurements are taken for reconstruction. For every ZR, there are five ZEDs, which are not shown for simplicity. The ZEDs cannot be used as relay nodes, so they send the information directly to the ZR, which sums up the information and checks the threshold value. If the information does not satisfy the threshold value (positive or negative), it is treated as zero.

However, during the formation of the route, every source node (ZR) gathers data of its adjacent and other nodes and transmits it to the sink node (ZC). Then, the sink node takes all the measurements and gathers the information by removing their random basis vector. The data gathering and routing from ZR to ZC are explained below.

Because the ZigBee devices are in fixed locations, it is more convenient to transmit data from them than from a conventional sensor. It is assumed that the ZC maintains total time T_t for receiving all measurements from the ZR. Further, it has time synchronization for each measurement and sends the signal to ZR after getting each measurement, after which it starts sending the next measurement. The change in electricity demand is denoted by β and is defined as

$$\beta = \Pr(T_{t+1}) - \Pr(T_t) \tag{12}$$

Further, the increase and decrease in electricity demand are denoted as β_1 and β_2 respectively. Let us assume that δ_1 and δ_2 are the threshold values for the increase and decrease in electricity demand respectively. Therefore, for the increase and reduction in electricity demand, the signal is

$$x_b = \begin{cases} 1, & if\ \beta_1 \geq \delta_1 \\ -1, & if\ \beta_2 \geq \delta_2 \\ 0, & otherwise \end{cases} \tag{13}$$

In other words, the information of any node is treated as zero if it does not satisfy the threshold value for electricity demand changes given in (13).

If every route contains only a small number of nodes, as shown in **Fig. 3**, the projections will be sparse. However, because individual nodes do not transport their data separately but combine it with the received value for the partial projection, this leads to energy savings. Note that a small number of such routes should be sufficient for good reconstruction. For this, an algorithm is recommended for three measurements of data transmission from layer 2 to layer 3. The data communication process consists of two steps: the network setup phase and the data transmission phase.

- **Network Setup Phase**

The network setup steps are executed only once before starting the data transmission process and need not be repeated every time data is transmitted. In the SG system, the nodes are in a static position in the HAN, and the system designer designs the position of the nodes in the building to achieve optimal performance. Thus, in this paper, we assume that the nodes are placed in a fixed position in the simulation area. Then, the system designer will predesign the

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routing algorithm based on the position of the nodes so that the RIP condition is satisfied for reconstruction. Here, we present a simple routing algorithm. In the routing algorithm, ZC will periodically broadcast the location information of the nodes. The adjacent nodes ensure their presence by exchanging their location information with node number. And, three source nodes are determined for data transmission. However, if any node is damaged or fails the link, the route is reestablished. The steps are explained in the next section.

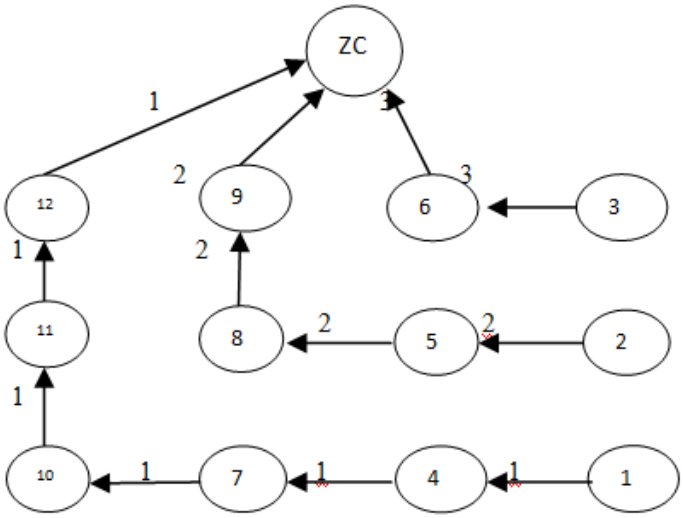

Fig. 3. A data transmission scenario for ZC with 3 measurements

- **Data Transmission Phase**

The route formation, data gathering, and taking of measurements are done according to the following algorithm:

Algorithm 1
First measurement:
1. Start from the 1st node as the sink node,
2. If it has an adjacent node on the left, choose the left node as the next-hop node,
3. Else, if it has no left node, then choose the upper node as the next-hop node, and repeat steps 1–2 until you reach the sink node.
4. Else, choose the right upper node, and repeat steps 1–3 until you reach the sink node.

Second and third measurements:
5. For the 2nd and 3rd measurements, start from the 2nd and 3rd nodes respectively and repeat steps 2–4.

A typical example is shown in **Fig. 3**. In the figure the first, second, and third measurements are denoted by 1, 2, and 3 respectively. From (11) we can write the following measurement matrix for **Fig. 3**.

$$\begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & F_{1,8} & 0 & F_{1,10} & F_{1,11} & F_{1,12} \\ 0 & & 0 & F_{2,4} & F_{2,5} & 0 & F_{2,7} & 0 & F_{2,9} & 0 & 0 & 0 \\ F_{3,1} & F_{3,2} & F_{3,3} & 0 & 0 & F_{3,6} & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_{12} \end{pmatrix} \tag{14}$$

Consequently, the transmission of data from layer 2 to the other layers follows the same procedure as mentioned above. A node in each layer knows the random basis vector of its immediate lower layer. After accepting data from its lower layer, every layer recovers the original signal and transmits the summation result of all the child nodes. Consequently, for 12 ZRs, Q number of SDs, and P number of BSs, we can derive the mathematical equation from (8), (9), and (10) by replacing the value of N. Furthermore, ZR to SD, SD to BS, and BS to CC follow the M measurement matrix for 5 ZRs and Q number of SDs respectively, where M depends on the number of nodes and their sparsity level. Also, the threshold values δ_1 and δ_2 indicate a very small amount of data, which does not affect the total electricity-consumption information for the corresponding layer, and the value is set for every layer independent of other layers.

3.4.3 Distance Measurement

Let us assume that the position of a node is $\ddot{P}(r,s)$, the position of its adjacent node is $\ddot{P}(\bar{r},\bar{s})$, and the central node (collector) position is $\ddot{P}(\tilde{r},\tilde{s})$. Then, the distance from any node to its adjacent node is defined as

$$D(r,s) = \sqrt{(r-\bar{r})^2 + (s-\bar{s})^2} \tag{15}$$

And, the distance from any node to the central node can be written as

$$\hat{D}(r,s) = \sqrt{(r-\tilde{r})^2 + (s-\tilde{s})^2} \tag{16}$$

where $D(r,s) \le \hat{D}(r,s)$, Therefore, for direct transmission (from any node to collector node), the calculated average minimum distance from any ZR to ZC is ≈ 19.7 m. For our proposed scheme, with three measurements (shown in **Fig. 3**.), the distance is ≈ 5.975 m.

4. Performance Evaluation

4.1 Device Power Monitoring and Achieving Longer Lifetime

We evaluated the performance of the proposed scheme with various measurements. The reconstruction error and required transmission power are shown (**Fig. 4, 5, 6, and 7**) for different measurements and compression ratios. In **Fig. 4(a)**, the reconstruction error versus the number of measurements with different sparsity levels for 12 nodes is shown. The reconstruction error is defined as (17):

$$E_r = \left\| x_b - \hat{x}_b \right\|^2 \tag{17}$$

where x_b is the original signal and $\hat{x}_b$ is the reconstructed signal. A hundred simulations were performed for every measurement, and the least square method (LSM) is used for signal reconstruction. There are many useful reconstruction algorithms for compressed sensing such

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as BP, CP, MP, and OMP. In this paper, however, we have chosen a basic reconstruction algorithm i.e., the LSM because the paper is mainly focusing on the application of compressed sensing in the SG system. The comparision of reconstruction errors of different reconstruction algorithms is out of scope of this paper.

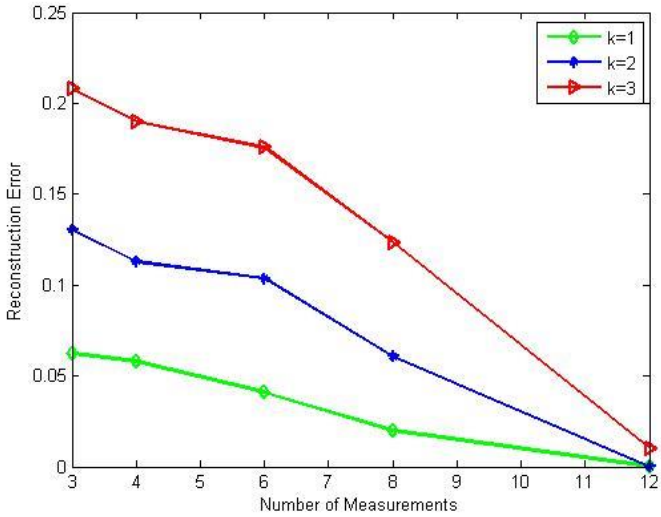

Fig. 4(a)

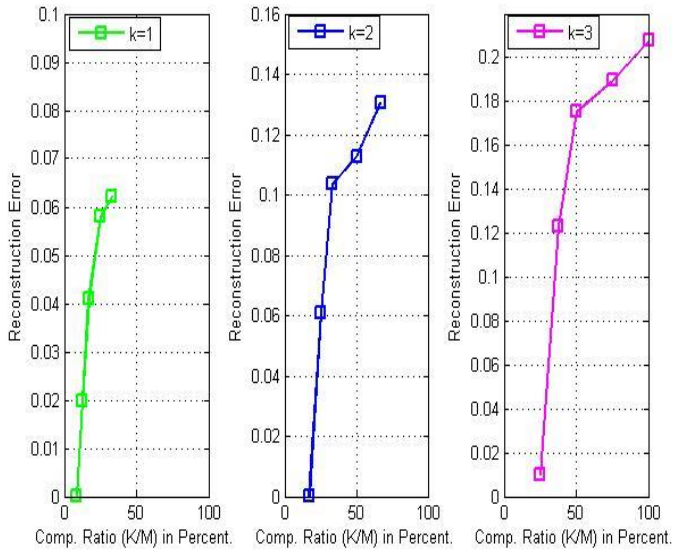

Fig. 4(b)

Fig. 4. Plots of **(a)** reconstruction error versus number of measurements and **(b)** reconstruction error versus compression ratio.

From **Fig. 4(a)**, we can observe that the reconstruction error decreases as the number of measurements increases. **Fig. 4(b)** shows the number of measurements (M) in terms of the compression ratio (K/M), expressed as percentage, associated with different sparsity levels for 12 nodes. For different values of sparsity levels: $k = 1$, $k = 2$, *and* $k = 3$, and for each sparsity

level and different number of measurements (*M =3, 4, 6, 8, 12*), the compression ratio and their reconstruction error are verified. This observation can be explained by (4) and (5).

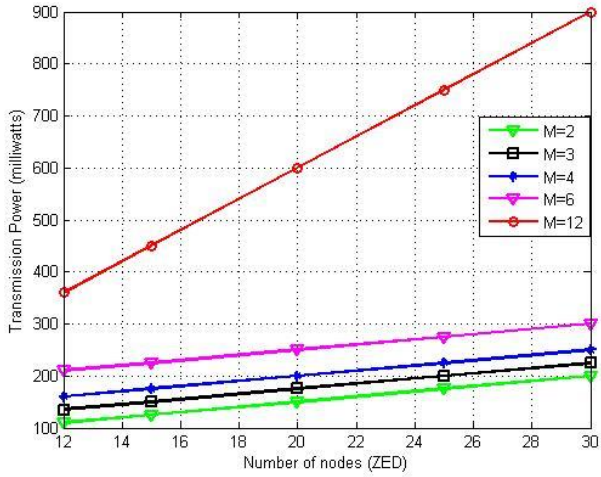

Fig. 5. Required transmission power for different numbers of nodes and measurements.

The transmission power of wireless sensor nodes depends on the transmission distance and the number of bits transmitted. The simulation parameters are given in Table 1.

Table 1. Simulation Parameters

MAC protocol	*ZigBee/ IEEE 802.15.4*
ZigBee node types (utilized)	*ZED, ZR, ZC*
ZigBee device types	*ZED-full function device* *ZR, ZC-reduced function device*
Total simulation area	30 m^2
Average distance between nodes (*ZR, ZC*)	10 *m*
Average transmission power (P_{rr})	20 *mW*
Average transmission power (P_{rc})	30 *mW*
Sparsity *(k)*	1–3
Number of measurements *(M)*	2–12

In this data gathering scheme, we assume that every node is power constrained, and that it can transmit to its adjacent node only, and the ZC receives data only from its adjacent ZRs (as shown in **Fig. 3**). The transmission power depends on the transmission distance and the number of bits being transmitted over that distance. We assume the following average transmission powers: 20 mW for transmission from ZR to its adjacent node (P_{rr}) and 30 mW for transmission from any ZR to its nearest ZC node (P_{rc}). For *M* measurements, the average power (in *mW*) is denoted by P_C and can be calculated as following:

$$P_C = (M \times P_{rc} + (N - M) \times P_{rr}) \tag{18}$$

Let us define,

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$$P_C = \begin{cases} P_{C1}, \; if \; N = M \\ P_{C2}, \; if \; N > M \end{cases} \tag{19}$$

Therefore, the power gain for any N and M can be denoted as P_g and written as

$$P_g = \frac{P_{C1}}{P_{C2}} \times 100 \tag{20}$$

where N is the total number of nodes, and M is the total number of measurements.

Further, the required transmission power and the transmission power gain are observed in **Figs. 5 and 6** for different number of nodes with five and four measurements respectively. **Fig. 5** illustrates that the transmission power is the highest for maximum number of measurements (M =12) and lowest for minimum number of measurements (M = 2). The transmission power gain is shown in **Fig. 6**. From **Fig. 6**, it is clear that for a lower number of measurements (M = 6), a higher gain is achieved with a higher cost of reconstruction error. Moreover, as the number of nodes is increased, the gain decreases intuitively because of a relatively lower measurement. Because the proposed scheme transmits compressed data instead of individual data to the ZC, the device power and lifetime are increased

To show the inverse relationship between the reconstruction error and power consumption for different values of compression ratio, the performance is shown in **Fig. 7** with a 3-D plot for 12 nodes and sparsity level K = 2. In **Fig. 7**, we can observe that the reconstruction error decreases as the compression ratio increases. However, more transmission power is required to transmit the signal. Therefore, there is a trade-off between the reconstruction error and required transmission power to design the system.

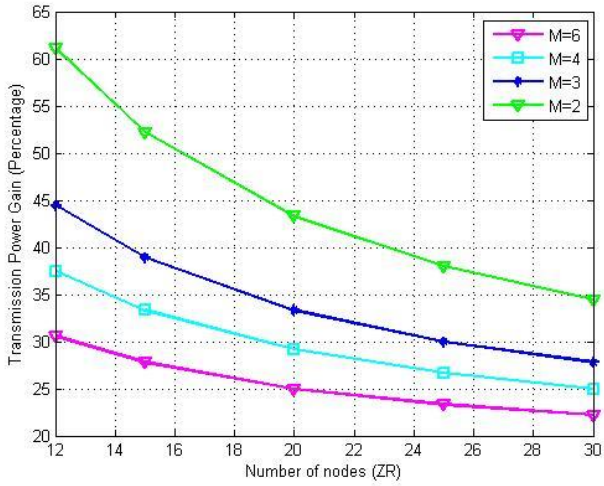

Fig. 6. Transmission power gain for different numbers of nodes and measurements.

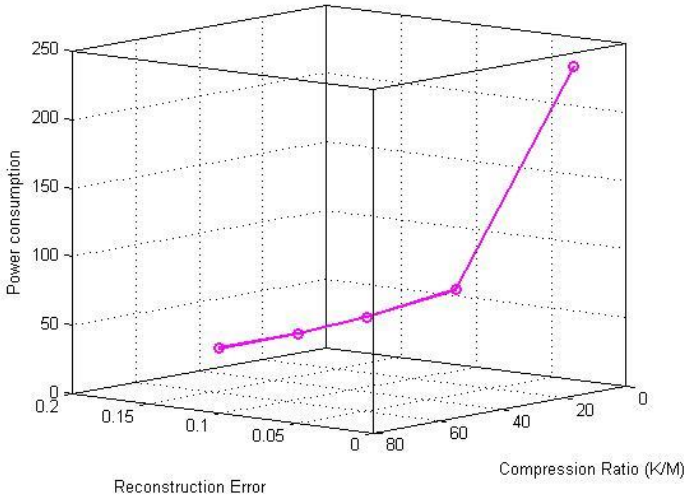

Fig. 7. 3-D plot of transmission power consumption versus reconstruction error versus compression ratio.

4.2 Delay and Spectrum Scarcity Reduction

The transmission distance in the general and compressed processes is given by (15) and (16). From the equations, we can see that, for three measurements, the necessary distance for compressed transmission is approximately one-fourth of that needed for conventional-data transmission. Moreover, the time synchronization for the conventional and compressed-data transmissions can be shown in Figs. **8(a) and 8(b)**.

Fig. 8(a). Time synchronization for the conventional system.

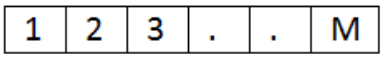

Fig. 8(b). Time synchronization for the compressed-data transmission system.

Figs. 8(a) and 8(b) illustrate the time synchronization for conventional (i.e., for data transmission of N nodes) and compressed-data (i.e., data transmission for $N > M$ measurements) transmissions repectively. Thus, the compressed-data transmission system plays a significant role in saving time for data gathering over the large SG system. Moreover, as shown in **Fig. 3**, instead of transmitting the information of individual nodes, the proposed scheme transmits compressed data. Thus, each node does not transmit to the ZC directly but transmits through neighboring nodes. To transmit individual data through the network, the system requires a large bandwidth and results in high traffic for synchronization. On the contrary, in the proposed compressed-data transmission system, every layer transmits compressed data aided by its neighbor node thus saving a significant portion of the spectrum. This is possible because in the proposed scheme, we transmit compressed data rather than individual data to the ZC. Consequently, this system is a solution for the problems of spectrum scarcity and traffic congestion during communication with upper layers.

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4.3 Secured Data Transmission

As shown in (10), the information of all the nodes is multiplied by a pseudorandom matrix and has the form: $\Phi_{j,1}x_1, \Phi_{j,2}x_2, \ldots \Phi_{j,N}x_N$, where the pseudorandom number $\Phi_{j,1}, \Phi_{j,2}, \ldots \Phi_{j,N}$ of any layer is known to its immediate upper layer. To construct the original signal from the received signal, any receiver device must have information of the pseudorandom number. Because an attacker has no information of the pseudorandom number, the information is prevented from eavesdropping and cyber attacking during data transmission in the entire SG.

5. Conclusion

We have demonstrated a model of the multi-layer communication structure for SG systems. In the proposed system, a HAN using ZigBee is considered to transfer the electricity-consumption information because it requires low power and provides better efficiency when compared with other devices. Additionally, at every layer of the SG system, the CS transmits the information of electricity consumption in a controlled manner. Finally, the simulation results of data transmission from layer 2 to layer 3 are illustrated and the efficiency and security of the proposed method over the traditional method is shown. Because the basic data-transmission method of the other layers is the same, the procedure and performance measurements are shown for only layers 2 and 3. Our work is expected to contribute toward the development of the SG system and can be the subject of future research prospects.

Acknowledgement

This work was supported by the 2013 Research Fund of University of Ulsan.

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