

A Novel Approach: Effective Compressive Sensing in Power Network Problem

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Abstract: A sparse power matrix is a type of two-dimensional data that conveys the amount of electric power each node, connected to an electric power meter sensor. The need for sensors increases in large power networks. This is problematic due to the increase in the number of sensors resulting in increased costs, the installation is more complicated, attenuation of sensor power, and requires maintenance. In order to reduce the use of sensors and increase the effectiveness of power to the sensors, electrical power measurements can be carried out at certain nodes. This also increases performance due to an efficient communication channel bandwidth and reduces power system data storage. This paper estimates the minimum required sensors on a power grid using compressive sensing (CS). The present study proposes a novel reconstruction algorithm for CS, the effective-OMP (E-OMP), to address this power network problem. E-OMP determines the minimum number of sensors in use. The study simulations reveal that E-OMP can save power from sensor use and preserve storage space. The proposed reconstruction algorithm generates NMSE less than 0.05 and has guaranteed high reconstruction accuracy compared to other ones (OMP, IRLS, and L1 reconstruction algorithms).

Keywords: compressive sensing, effective-OMP, power network, reconstruction.

一种新颖的方法：电网问题中的有效压缩感测

摘要：稀疏功率矩阵是一种二维数据，用于传输连接到电表传感器的每个节点的电量。在大型电力网络中，对传感器的需求增加。这是有问题的，这是由于传感器数量的增加导致成本增加，安装更加复杂，传感器功率衰减并且需要维护。为了减少传感器的使用并提高传感器的电源效率，可以在某些节点上执行电功率测量。由于有效的通信信道带宽，这也提高了性能，并减少了电力系统数据的存储。本文使用压缩感测 (CS) 估计电网上所需的最少传感器。本研究提出了一种新颖的 CS 重构算法，即有效 OMP (电子邮件)，以解决该电网问题。电子邮件确定使用的最小传感器数量。研究仿真表明，电子邮件可以节省传感器使用的电能并节省存储空间。与其他算法 (OMP, 红外光谱和 L1 重建算法) 相比，提出的重建算法生成的 NMSE 小于 0.05，并保证了较高的重建精度。

关键词：压缩传感，有效 OMP，电网，重建。

1. Introduction

In the light of the global energy crisis, greater effort must be put into achieving energy efficiency to reduce the amount of energy needed; one way of doing this is to minimize the use of devices or systems in a particular industry. One motivation for increasing energy efficiency is reducing financial costs. According to the International Energy Agency, increasing energy efficiency in buildings, industrial processes, and transportation can reduce the world's energy needs by one-third by the year 2050 [1, 2]. One such in industrial power grid is electricity distribution systems which includes a sensing system for adjustment between source and electric load [3, 4]. A system built using a number of sensors is needed to apply this mechanism. Currently, the number of sensors is adjusted based on the number of consumers and penetration node, and increasing the number of these sensors will increase the demand for power. This also results in increased costs, complex installations, sensor attenuation, and additional maintenance. Metric sensors have the ability to detect, process, and forward information signals within the network, resulting in increased data exchange and increased storage space on the network [42]. Therefore, an efficient technique is needed that uses communication channel bandwidth and saves storage space. Savings can be made by reducing the number of sensors or the volume of power system data; thus, the technique must reduce the use of sensors whilst ensuring the existing control system continues to work optimally.

A recent mathematical method that can reduce the number of samples needed when gathering data was introduced by Donoho in 2006 and known as CS [33]. Before CS, a conventional method called the Nyquist–Shannon sampling theorem was used for signal sampling. Here, the sampling frequency is performed at least twice to measure the highest frequency in the signal [5]. In contrast, CS enables reconstruction of data with a smaller number of sample than the Nyquist–Shannon theorem [6]. Thus, the present study applies CS to an electrical distribution control system to reduce the number of sensors that are needed.

CS techniques have been used in a huge variety of applications and industries. They are commonly used in signal or image reconstruction applications [5, 7]. CS-based biomedical signal reconstructions have been reported for electrocardiogram (ECG) signals [8], respiratory sounds [9, 10], and electroencephalogram (EEG) signals [11]. CS simulations for images, such as MRI imaging, have also been proposed [12, 13, 14, 15, 41]. Yet another application of CS is processing radar

signals [16] to estimate the source of the signal more efficiently. In terms of communication networks, the method has been used to estimate network traffic [17, 18, 19, 20] and conduct channel estimations on wireless sensor array network [21]. CS has proven to be very good at minimizing the number of samples needed while still being able to reconstruct the data accurately. Common reconstruction methods include L1, orthogonal matching pursuit (OMP), iteratively reweighted least squares (IRLS), and Lq norms. All methods have been simulated and performed well in their respective study results; however, each method has a drawback. For example, OMP adopts a greedy algorithm that can perform a rapid reconstruction but is less accurate. Meanwhile, IRLS is an improvement on L1; it provides high accuracy but is more time-consuming [22].

This lack of a “perfect solution” has prompted the present study to further investigate CS simulation and develop a new reconstruction method for other applications. This study proposes several methods for reconstructing sensor data from power systems using the CS approach. It posits that measurements of electrical parameters can be carried out at certain nodes without having to install sensors on every node. The simulation uses an open dataset consisting of two dimensions (rows and columns) assuming that at these points, installed reader sensors record the use of electric power. The study uses singular value decomposition (SVD) as a sparsity technique. It proposes a new reconstruction method called effective-orthogonal matching pursuit (E-OMP) and compares it with general reconstruction methods such as L1, IRLS, and conventional OMP to detect any performance improvements from using the new method. The performance parameters analyzed here include NMSE, compression ratio, and time processing.

The remainder of the paper is organized as follows: Section II presents an overview of CS. Section III explains power system network and power signal representation. Section IV describes the proposed method for power signal CS and outlines the performance parameters. Section V presents the datasets and performance analysis. Finally, Section VI concludes and makes recommendations for future work.

2. Related Works

According to Teheou et al., power signal compression methods can be categorized into two groups: lossless and lossy [23]. Lossless methods include Lempel-Ziv [24] and Huffman coding [25].

Lossy methods include discrete wavelet transform (DWT) [26, 27], wavelet packet transform (WPT) [28, 29], mixed transform and parametric method [30], and parametric coding [31, 32]. Parametric coding is a compression technique used on signals that can be represented by different parameters. These parameters will be stored in a dictionary and can be returned to the original signal based on the parameters.

CS starts with parametric coding in the acquisition and reconstruction process. CS acquisition is calculated by the inner product between the sparse input signal $\mathbf{x} \in \mathbb{R}^{N \times 1}$ and the measurement matrix $\mathbf{A} \in \mathbb{R}^{M \times N}$, where $M \ll N$. The compressed measurement result is $\mathbf{y} \in \mathbb{R}^{M \times 1}$. The acquisition model is shown in equation (1) [33].

$$\mathbf{y} = \mathbf{A}\mathbf{x} \quad (1)$$

The sparse signal is obtained from an appropriate base transformation. This transformation aims to reduce the size of the input signal. The transforms use cosine and sine forms, such as the discrete Fourier transform (DFT) and the discrete cosine transform (DCT) [34, 35]. The potential transform methods for electric power signals are DWT and WPT. The relationship between the sparse signal (\mathbf{x}) and the non-sparse signal (\mathbf{s}) in the transformation domain (Ψ) is expressed in equation (2).

$$\mathbf{s} = \Psi\mathbf{x} \quad (2)$$

where $\Psi \in \mathbb{R}^{N \times N}$ and $\mathbf{s} \in \mathbb{R}^{N \times 1}$.

In [31], the authors developed a dictionary of damped sinusoids for the compression of electric signals. The parameters were obtained by the matching pursuit (MP) technique [36]. The MP algorithm approximates sequential signals iteratively using dictionary elements. The MP technique is related to the compressive sensing area and has been developed by a community of researchers. Tropp and Gilbert extended an orthogonal version, named orthogonal MP (OMP), which has become popular [37].

3. The Research Method

This paper's research method consists of several steps: (1) We have searched the previous literature

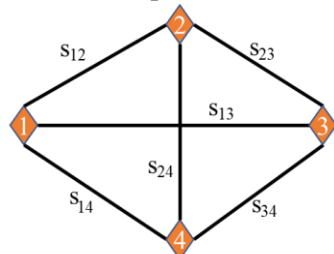


Fig. 1 The illustration of the mesh power network

describing the compression of the signal power by CS and other methods than CS. (2) We use data sources or datasets for this research from the sparse matrix collection displayed in Table 1. These data represent the electricity network, with the values of the matrix elements indicating the power passing through the network. (3) Since the datasets are sparse matrices, we apply the datasets acquisition to generate compacted data with a much smaller size. This acquisition produces a high compression ratio but does not affect much the power effectivity. The high compression ratio implies the low resource used for monitoring the power signal. Thus, we can do the resource-saving for lower costs. (4) This acquisition affects the lossy datasets when reconstructed. Thus, we design the acquisition and reconstruction by singular value decomposition and reconstruction. This design makes sure the acquired data is sparse. This design also helps the reconstructed datasets be of high quality, similar to the original datasets. (5) We use several types of CS reconstruction and compare the performance. In this paper, we also use e-OMP or OMP with minor modification to reconstruct the acquired data after singular value reconstruction, producing the best performance in reconstructed datasets quality and the time processing. This minor modification enhances the OMP performance with a faster process and better NMSE.

4. The Proposed Technique

Fig. 1 illustrates the mesh power network, which consists of mesh routers and links. In this study, the links pass the signal, which represents power. A power network with an N mesh router can be represented in a 2-dimensional matrix of size $N \times N$. If the power signal is expressed as \mathbf{s} , the power flowing in the network can be represented according to the following matrix equation:

$$\mathbf{S} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1N} \\ S_{21} & S_{22} & \cdots & S_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ S_{N1} & S_{N2} & \cdots & S_{NN} \end{bmatrix} \quad (3)$$

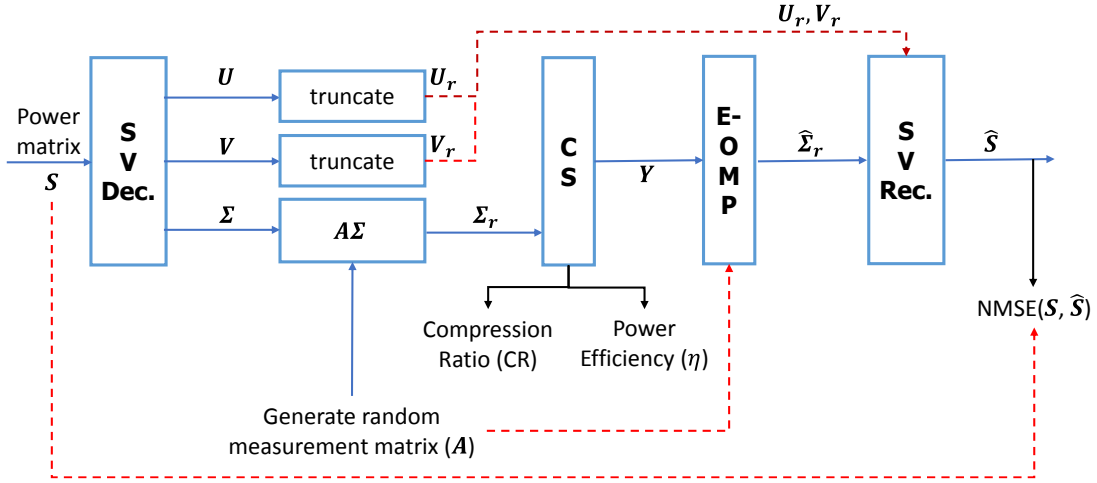


Fig. 2 The proposed block diagrams

We propose a novel approach for obtaining the sparse matrix by decomposing the input power matrix applications. The sparse matrix is sampled with a random Gaussian measurement matrix. The proposed reconstruction algorithm has the role of recovering the sampling results to a matrix that approaches the input matrix. The E-OMP novelty is to change the iteration of the previous algorithm OMP by adjusting the position of the singular value on the SVD diagonal matrix. Fig. 2 shows the block diagrams of the proposed methods with the details of each step given below:

1. Given a power matrix $S \in \mathbb{R}^{N \times N}$
2. SV decomposition is used to divide the given power matrix into 3 matrices $U \in \mathbb{R}^{N \times N}$, $\Sigma \in \mathbb{R}^{N \times N}$ and $V \in \mathbb{R}^{N \times N}$. The sparse matrix is a matrix Σ , that contains significant values from the input matrix S .

3. We use a random Gaussian measurement matrix, A , which fulfills Restricted Isometric Property (RIP) property [38], as shown in equation (4):

$$\begin{aligned} (1 - \delta_s) \cdot \|\Sigma_r\|_2 &\leq \|A \cdot \Sigma_r\|_2 \leq \\ (1 + \delta_s) \cdot \|\Sigma_r\|_2 & \end{aligned} \quad (4)$$

where $0 < \delta_s \ll 1$.

4. Compressed measurement is measured according to equation (1). It becomes a matrix equation as follows:

$$Y = A \cdot \Sigma_r \quad (5)$$

5. For reconstruction, we proposed a new reconstruction algorithm, E-OMP. It reconstructs the matrix $\hat{\Sigma}_r$ by finding the value of each of its constituent elements $\hat{\sigma}_i$. The E-OMP algorithms are shown below:

Input:

- Compressed matrix $Y \in \mathbb{R}^{m \times r}$
- Column vector from n^{th} column of Y , $y_n \in \mathbb{R}^{m \times 1}$, where $Y = [y_1 \ y_2 \dots \ y_r]$
- Orthonormal measurement matrix, $A \in \mathbb{R}^{m \times r}$ with $m \leq r$
- Column vector from n^{th} column of A , $a_n \in \mathbb{R}^{m \times 1}$, where $A = [a_1 \ a_2 \dots \ a_r]$

Output:

- Reconstructed singular value vector $\hat{\sigma}_i \in \mathbb{R}^{r \times 1}$ matrix
- Reconstructed matrix $\hat{\Sigma}_r \in \mathbb{R}^{r \times r}$ as a diagonal matrix

Procedure:

- 1) Initialization with the iteration $i = 1$
- 2) Denote $\Delta = a_i$, containing a vector with size $m \times 1$
- 3) Calculate $\hat{\sigma}_i = (\Delta^T \Delta)^{-1} \Delta^T y_i$
- 4) Repeat 2 and 3 until $i = r$
- 5) Create reconstructed matrix $\hat{\Sigma}_r$ as a diagonal matrix of $\hat{\sigma}_i$, where $\hat{\Sigma}_r = \text{diag}[\hat{\sigma}_1 \hat{\sigma}_2 \hat{\sigma}_3 \dots \hat{\sigma}_r]$

$$\text{Thus, } \hat{\Sigma}_r = \begin{bmatrix} \hat{\sigma}_1 & 0 & \dots & 0 \\ 0 & \hat{\sigma}_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \hat{\sigma}_r \end{bmatrix}$$

6. After reconstruction, the reconstructed matrix $\hat{\Sigma}_r$, U_r , and V_r are rearranged into the approximate given power matrix using SV reconstruction, as presented in equation (6):

$$\hat{S} = \sum_{i=1}^r \hat{\sigma}_i u_i v_i^T = \hat{\sigma}_1 u_1 v_1^T + \dots + \hat{\sigma}_r u_r v_r^T \quad (6)$$

The difference between OMP and E-OMP is at the index i in the above procedure. In OMP algorithm, index i at a_i is obtained by the following equation (7):

$$i = \text{argmax}_{i \in \{1, 2, \dots, r\}} A^T y_n. \quad (7)$$

E-OMP removes this equation, and replaces i with the iteration index as the row position of the singular

value in the diagonal matrix. This causes E-OMP to be more effective than the OMP procedure [40].

From Fig. 2, the complexity of SVD process is $O(N^3)$. The CS acquisition had a complexity $O(R^3)$, where R is the truncated size of the row or column from S matrix. The reconstruction also had a complexity $O(R^3)$. Due to $N > R$, the complexity of the overall system is dominated by the SVD as $O(N^3)$ [40].

The performance of the novel algorithms is compared to other reconstruction schemes. We use the compression ratio (CR), power efficiency (PE/ η), and normalized mean square error (NMSE). The compression ratio describes the level of compression that occurs due to the application of a system that is measured between the size of an uncompressed matrix and a compressed matrix. The higher the level of compression, the greater savings in storage space. The compression ratio equation is expressed as follows:

$$CR = \frac{N^2}{R^2 + 2NR} \quad (8)$$

Power efficiency describes the ratio of the input power to the output power. The power illustrates the energy that is used by the system to collect data. The equation of power efficiency (η) is shown in (9).

$$\eta = \frac{P}{P_0} \times 100\% \quad (9)$$

$$P_0 = \sum_{i=1}^N \sum_{j=1}^N |S(i,j)| \quad (10)$$

$$P = \sum_{i=1}^N \sum_{j=1}^R |\hat{U}(i,j)| + \sum_{i=1}^R \sum_{j=1}^R |\hat{Z}(i,j)| + \sum_{i=1}^N \sum_{j=1}^R |\hat{V}(i,j)| \quad (11)$$

where P_0 is the total power of the matrix S and P is the total power of matrixes \hat{U} , \hat{Z} , and \hat{V} .

The success of reconstruction is measured by the NMSE parameter, which minimizes the square of the error value. NMSE is calculated between the original power matrix, S , and the reconstructed power matrix \hat{S} . Given the two matrixes $S(i,j)$ and $\hat{S}(i,j)$, NMSE is represented as follows:

$$NMSE(S, \hat{S}) = \frac{\|S(i,j) - \hat{S}(i,j)\|_2^2}{\|S(i,j)\|_2^2} \quad (12)$$

5. Experiment Results and Discussion Dataset

This paper simulates datasets from SuiteSparse matrix collection that shown in Table 1 [7, 39]. There are three datasets, which are 2-dimensional matrixes that have rows, columns, and non-zero values. We assume that these matrices are representations of the electricity network, with the values of the elements in each matrix indicating the power passing through the network. In addition, we suppose that the network installed sensors for reading electricity meters in each node.

Table 1 SuiteSparse matrix collection [7, 39]

Id	Name	Rows	Columns	Non-zero	Kind	Date
Dataset 1	1138_bus	1138	1138	4.054	Power network problem	1985
Dataset 2	494_bus	494	494	1.666	Power network problem	1985
Dataset 3	662_bus	662	662	2.474	Power network problem	1985

6. Performance Analysis

Simulation one shows the E-OMP performance for all datasets. The results are shown in Fig. 3, which illustrates the trade-off between NMSE and PE at different numbers of sparsity (10–200). The measurement number is $0.5 \times$ sparsity number. NMSE-1 and PE-1 show the results from dataset-1; NMSE-2 and PE-2 show the results from dataset-2, and NMSE-3 and PE-3 show the results from dataset-3. The changes in the sparsity number within the three datasets do not impact the power effectivity, with PE in each dataset

reaching 50% in almost all ranks. Dataset-1 has a larger set of data than the others. For a sparsity number of less than 30, dataset-1 produces the smallest NMSE, followed by dataset-3 and dataset-2.

Fig. 4 shows the performance comparison of the reconstruction algorithms in dataset-1. The simulation results show that the E-OMP performance is as good as the L1 performance. With a sparsity number of 20, all reconstruction algorithms generate NMSE of less than 0.05.

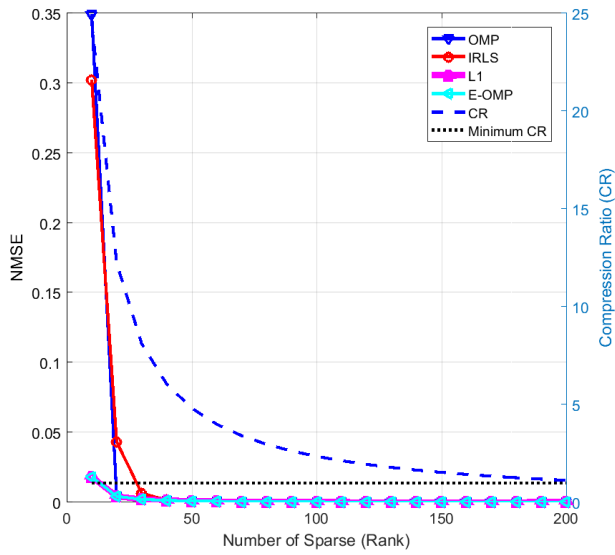


Fig. 3 Trade-off between NMSE and power effectivity (PE) at different number of sparse and dataset

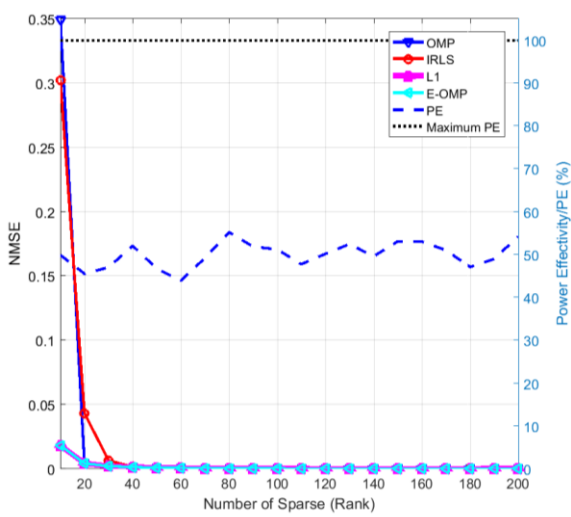


Fig. 4 Trade-off between NMSE and power effectivity (PE) at different number of sparse and reconstruction algorithms

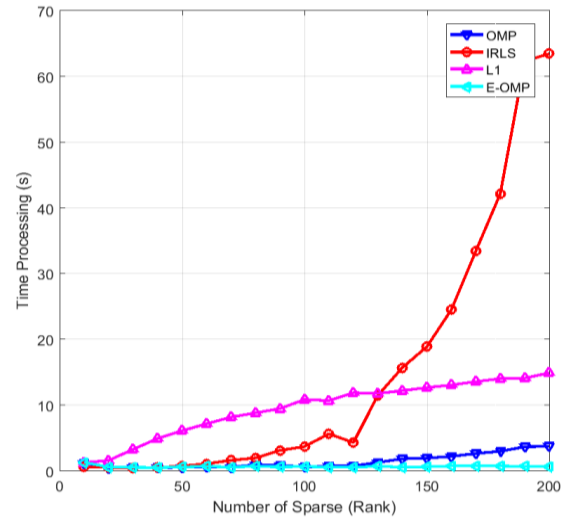


Fig. 5 Trade-off between NMSE and compression ratio (CR) at different number of sparse and reconstruction algorithms

Fig. 5 illustrates the trade-off between NMSE and CR in all reconstruction algorithms. Testing was carried out on dataset-1. The test results show that up to a sparsity number of 200, CR is produced above the minimum CR threshold.

Fig. 6 shows the processing time required by all reconstruction algorithms in dataset-1. The simulation results show that the greater the number of sparse, the longer the processing time. The E-OMP reconstruction algorithm is superior, with the fastest processing time compared to other reconstruction algorithms at the same number of sparse.

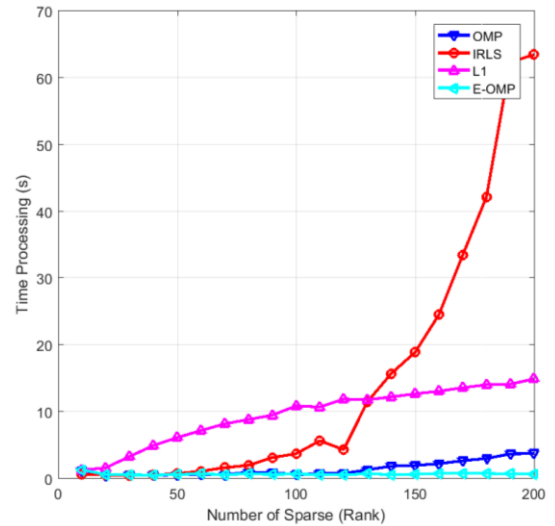


Fig. 6 Time processing at different number of sparse and reconstruction algorithms

The test results show that the proposed method can reconstruct the sensor data with an NMSE less than 0.05. E-OMP can generate a higher reconstruction

accuracy compared to other reconstruction methods. However, the sparse matrix collections in [7] and [39] have low-rank properties; in fact, the actual measurement results in the power network do not guarantee sparsity. Therefore, the model that was built has provided a sparsity method that does not work optimally. Moreover, we did not explore any other sampling techniques because, according to [18], Gaussian is the best technique for two-dimensional internet traffic data.

7. Conclusion

In this study, we proposed a novel reconstruction algorithm named E-OMP, based on the concept of compressed sensing using SVD sparsity to achieve bandwidth and power efficiency. This system is appropriate for large networks. The natural power matrix data has a compressible property, therefore supporting the CS process. E-OMP performance is analytically proven in terms of power consumption and bandwidth requirements and demonstrates substantial savings compared to previous reconstruction algorithms, such as OMP, L1, and IRLS. In addition, E-OMP is superior in speed of processing. In the future, the proposed method is expected to be applied in large power networks to improve sensor efficiency, increase transmission bandwidth efficiency, and save memory resources in the database system.

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