Measurement and Analysis for Power Quality Using Compressed Sensing

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Abstract

Advanced metering system (AMI) is a new advanced metering system for the two-way measurement and interaction operation in Smart Grid, single-phase power quality parameters measurement has become one of the most attractive research topics in recent years. A CS approach based on two-dimensional image compression for power quality analysis is proposed. Since the sampling information of power quality (PQ) has outstanding frequency-domain sparse characteristics; it can be applied into the analysis of theoretical model with two-dimensional image compression algorithm using compressed sensing (CS). According to the single-phase power quality measurement using compressed sensing, a two-dimensional sparse measurement model on voltage, current and power signals is established. Only a few amount of points of electrical state power signal is sampled. Using these samples, power signal is recovered in order to effectively detect the operating status of the power quality parameters involving harmonic, instantaneous power disturbance, etc. The performance of the proposed approach and other different schemes are compared through numerical experiments and analysis of compression sampling ratio (CSR), signal to noise ratio (SNR), mean squared error (MSE), energy recovery percentage (ERP). Numerical results have shown that CS based power quality analysis approach behaves extremely well in practice.

Key Words: Compressed Sensing (CS), Power Quality (PQ), Two-Dimensional Sampling, Sparse Measurement

1. Introduction

In recent years, power quality (PQ) analysis [1–3] in single-phase grid has been has become one of the most attractive research topics. The attraction is mainly due to the follow reasons (1) Single-phase power load characteristic becomes more sophisticated and diversified. For saving energy and reducing environmental pollution, the nonlinear, harmonic-rich load becomes a major source of power quality problems. (2) The user requirements on the reliability of power supply become higher and higher. The precision electronic and power electronic devices controlled by computer and microprocessor have sensitive increasingly demands on power quality. Once some PQ problem is happened, it will cause serious equipment failures, and evenly lead to the entire system collapse with huge economic losses and burden [4]. (3) For discrete power generators of smart grid, large and complex transmission and distribution equipments consist in large and complex power system [5]. While more and more solar, wind, geothermal and other small-scale power generators access to smart grid, it will cause some problems, such as bias voltage, flickering fluctuations, harmonics pollution, increasing reactive power factor and other issues [6]. Based on the above description, monitoring functions of PQ in smart meter test-bed has great potential.
Traditional processing method of PQ information (current, voltage, power and etc.) is adopted as Nyquist theorem; compressing operation must wait after PQ data is sampled. We must firstly obtain a complete signal sample, and then project it onto a particular basement, and finally encode and transmit the most important component and its location in the projection vector. However, this signal separated method for PQ (such as acquisition, compression, positioning detection and identification) is not optimal one (1) According to Nyquist theory, whole of the original signal is required in the PQ sampling process. In resident areas and urban communities with highly intensive smart meters, the original sampling signal has a huge amount of data information. It requires high hardware processing speed and storage capacity. (2) It will make big waste of commutating data by deserting most of the components after the complete projection of the original signal vector is obtained. Because all of the location information about important perturbations needs to be recorded, redundant data will result to waste limited storage space in hardware system. With the development of wireless communication technology and the scale expansion of the smart meters in smart grid, the available frequency band resource will be reduced and limited. How to achieve effective and timely collection of large-scale power in the wireless networks, how to reduce network information storage burden and the processing and transmission cost of heterogeneous data, all become the focuses of issues to be resolved presently.

2. Related Works

2.1 PQ Measurement and Analysis

PQ is the electrical properties of measuring public power services in smart grid. A number of research works [7–9] had been proposed about sampling strategy, data compression, and detection location, evaluation of disturbances parameters. There are many distributions research of time-frequency domain applied with advanced measurements by sampling PQ signal of Nyquist theorem such as classic FFT, and S transform [10]. Hilbert-Huang Transform (HHT) [11] presently, etc. According to Nyquist theorem, it requires sampling instantaneous PQ signal with high frequency. As a result, those traditional methods need expensive hardware devices, and have to store mass PQ sampling data. In practical PQ measurement test-bed, it needs complicated devices to carry out distributed long-term monitoring on transient signal measurement and real-time analysis. Thus the high cost of devices and massive data transmission prevent the traditional methods from satisfying the wireless network and intelligent trend of smart meter.

Currently, compression methods of sampling information are mainly classified into three types of ways: lossless compression, lossy compression, and hybrid compression. Lossless compression algorithms include Huffman coding, arithmetic coding, and dictionary coding; lossy compression algorithms include compression algorithms based on FFT, DCT, DWT, and intelligent DWT [12–14]. On one hand, those lossless compression algorithms never consider reconstruction tolerance ranges in practical engineering computing application. Now days, most studies have only focused on applying loss compression on power supply system, some of their research have widely been applied practically in power data compression. On the other hand, PQ measurements based on conventional image compression method require professional hardware and software with extremely high sampling rate for the recovery of the high frequency PQ signal [15]. If the system gets massive sample data to analyze, it will burden the data storage and will decrease network performances by large-scale data transmission to remote monitoring terminal.

2.2 Introduction of Compressed Sensing

In 2006, David L. Donoho et al. proposed CS (compressed sensing) theory, that sparse signal with suitable reconstruction algorithm can be recovered from a very small set of measurements that far fewer than conventional measurement limited by Nyquist theorem. According to CS [16], it can sample and compress PQ information synchronously without any prior knowledge. Generally, CS theory basically consists of three steps: (1) finding the sparsest decomposition of a signal, (2) designing applicable compression representing matrix, which well approximates the original N length signal for the least M coefficients, (3) designing corresponding reconstruction algorithm, which can reconstruct original signal length in N from observed M coefficients which are gained from step 2.
We firstly introduced the definitions of sparse, compressible, and K-sparse

2.2.1 Definition of Sparse
Signal vector $x \in \mathbb{R}^n$ is transformed in orthogonal basis $\Psi$ to vector $S = \Psi^T x$.

$$\|S\|_p = \left(\sum_{i} |S_i|^p\right)^{1/p} \leq R \quad (1)$$

For any $0 < p < 2$ and $R > 2$, formula (1) satisfies. Then vector $S$ is sparse in orthogonal basis $\Psi$ [17].

2.2.2 Definition of K-sparse
If signal $x$ of length $N$ can be transformed in sparse transform matrix $\Psi$ to $K$ orthogonal vectors, in other word, $x$ can be transformed into $S$ which only have $K$ none-zero coefficients, and $K << N$. $x$ denotes in those formula:

$$x = \sum_{i=1}^{K} S_i \Psi_i \quad \text{or} \quad x = \Psi S \quad (2)$$

$$x = \sum_{i=1}^{K} S_i \Psi_i \quad \text{or} \quad x = \Psi S \quad (3)$$

$x$ is K-sparse when $x$ satisfies (3), where $S_i$ ($i = 1, 2, 3, \ldots, K$) are none-zero element of $S$ ($n = 1, 2, 3, \ldots, N$).

2.2.3 Definition of Compressible
Signal vector $x \in \mathbb{R}^n$ can be transformed to vector $y$ which consisted of exponentially decaying coefficients in orthogonal basis $\Psi$. In formula (2), vector $S$ is consisted of several big elements and many small elements. Hence, it is possible to approximate sparse signal $x$ only with the big coefficients of $S$. From the above definition, if $x$ is compressible, then its compressive sampling process can be formulated as follow:

$$y = \Phi x = \Phi \Psi S = \Theta S \quad (4)$$

where orthogonal basis matrix $\Psi \in \mathbb{R}^{N \times N}$ is transformed by matrix $\Theta = \Phi \Psi \in \mathbb{R}^{M \times N}$. The recovery process of compressed sensing is to reconstruct N-dimensional signal vector $x$ from measured M-dimensional vector $y = \Theta S$: firstly, this process solves the inverse problem of formula (4), and obtains sparse coefficients $S$. Secondly, it reconstructs K-sparse signal $x$ by bringing $S$ into formula (2). Finally, it solves the optimizing problem:

$$\min \|\Psi^T \tilde{x}\|_0, \ s.t. y = \Phi \Psi S \quad (5)$$

where $\|\cdot\|_0$ is the $l_0$-norm (the number of none-zero coefficients). In 2007, Candes, Donoho et al. proposed the famous RIP theory (restricted isometry property) [18, 19], which specialized a sufficient condition that promises signal can be recovered from compressible measured matrixes, and demonstrated that 0-norm solution is equivalent to 1-norm solution in compressed sensing problem. Hence, signal recovery problem can be regarded as $l_1$-norm optimizing solution [20], and formula (5) is equivalent to following:

$$\min \|\Psi^T \tilde{x}\|_1, \ s.t. y = \Phi \Psi S \quad (6)$$

Finally, we will define several performance indexes: CSR (compression sampling ratio), SNR (signal to noise ratio), MSE (mean squared error), and ERP (energy recovery percentage) to objectively appraise the reconstructed results of PQ signals.

$$\text{CSR} = \frac{N_c}{N} \times 100\% \quad (7)$$

$$\text{SNR} = 10 \log \frac{\sum_{i=1}^{N} |f(i)|^2}{\sum_{i=1}^{N} |f(i) - \hat{f}(i)|^2} \quad (8)$$

$$\text{MSE} = \frac{\sum_{i=1}^{N} |f(i) - \hat{f}(i)|^2}{\sum_{i=1}^{N} |f(i)|^2} \times 100\% \quad (9)$$

$$\text{ERP} = \frac{\sum_{i=1}^{N} |\hat{f}(i)|^2}{\sum_{i=1}^{N} |f(i)|^2} \quad (10)$$

where $N$ is total sampling number of original signals, $N_c$ is the reserved sample number of signals after sparse sampling, and $\hat{f}(i)$ is the reconstructed signal.
3. Power Quality Measure Algorithm Base on Compressed Sensing

3.1 Power Quality Signals Present in Two-Dimensional Sparse Matrixes

There is not a common power quality standard worldwide. Power quality standards definition from the International Electrotechnical Commission (IEC) is taken as the standards in this paper. The IEC’s power quality standard: equipment must tolerate voltage dips on the AC mains. Both standards specify the same depths and durations of voltage dips, and explain how to apply these dips to single-phase and three-phase equipment.

3.1.1 Sparse Representation of Current and Voltage Signals

In stable condition of linear load, voltage and current signals are both sine waveforms in 50 Hz theoretically. But in unstable condition of nonlinear load, they are affected distorted by some inductances, capacitances, or other nonlinear factors. PQ Harmonics have N*50 Hz frequency affected signals [21]. It is shown in formula (11), voltage and current signals mainly consist of periodic or quasiperiodic signals in practical condition, and it exists a lot of information redundancy in periods or between periods.

\[
 f(t) = \sin(2\pi * S / t) + \sin(2\pi * 2S / t) + \sin(2\pi * 3S / t) + \ldots 
\]

(11)

Generally signal-phase load condition seldom changes greatly, so voltage and current signals can be regarded as periodic signals in short time period and sparse in frequency domain. To increase the sparsity of voltage and current signals, we transform those single-dimension signals to two-dimension matrixes. The transform strategy is that: for sampled voltage and current signals of KHz, which consist of \( N = 0.02 \times K \) sampled data in one period, is taken every adjacent \( N \times N \) data to constitute matrixes. The matrixes’ row are constructed from adjacent data in same period and stringed by data of same time in adjacent period. In those matrixes, each line contains information of harmonics and each column is almost stable. The current and voltage signal matrixes are transformed into sparse matrixes with FFT, whose elements are exponential decaying and elements of big value are mainly located in the central area.

Because voltage and current signals are related to each other, they have very similar distributions in frequency domain. Handling them separately would result in a waste of computing and storage resources. In this paper, they are combined into one complex matrixes, whose real part comes from voltage signal and imaginary part comes from current signal. The matrixes are realized CS processing in single process, and are reconstructed to separate signals after all iterations. By this way, hardware system will have much less burden of computing and storage. However, in practical signal-phrase power system, their value amplitudes would be quite different. If the CS process combines voltage and current signals into new matrixes directly, problem would happen in later steps. Hence the signal of larger amplitude would have more big elements and leave more elements after CS process. According to the CS theory, it recovers signals mainly base on the minority big elements. If the difference of amplitude is large enough, the signal of smaller amplitude would not be recovered successfully for the lack of elements. For this problem, here we note the multiple number \( A \) for their amplitudes, and balance the signals to the same amplitude before matrix combination operation. And then we reconstruct separately their signals with \( A \). With this method, detail characteristics of both voltage and current signals are maintained greatly.

As shown in Figure 1, the FFT of voltage and current combined signal matrix can be obtained by the following steps: 1. Voltage (real part) and current (imaginary part) values are set up a new single combined matrix \( S \). 2. FFT is introduced into the complex matrix \( S \) for sparse solution. 3, FFT matrix from step 2 is transformed into the
absolute value matrix for showing large numbers distribution in Figure 1. 4 Grayscale processing in the absolute matrix can obtain the first result of Figure 1 (white means the maximum value of absolute value matrix, black means the minimum value of it). The second result of Figure 1 is obtained using radial sample matrix [22] which can be obtained by the following steps: 1. A radial sample matrix of radial number 35 is introduced for sampling first result of Figure 1. 2. Grayscale processing in radial sample matrix for the second result of Figure 2 (white part means “1”, black part means “0”). From the two results of Figure 1, voltage and current combined matrix’s FFT is exponential decayed and its large value elements locate in central lines. Here use radial sample matrix to sample the combined matrix’s FFT. This sample method would reserve all large value information and enough small values so as to meet RIP, finally original signals can be reconstructed from its sampled matrix.

3.1.2 Power Signals Present in Sparse Matrixes

Power signals are directly related to voltage and current signals, so that they have the same distribution in frequency domain. Here use the same CS method to deal with power signals, but differently every kind of power signals does FFT separately and compressed sensing alone.

Because high-frequency PQ components exist in widely ranges in practical conditions, there are difficulties in deciding best radial sample number. Under stable linear load condition, active power, reactive power and apparent power are almost keeping in constant. Under condition of motors, switch power supply and other non-linear loads, there would be vast high-frequency components and they are changing all the time. According to the feature of power signals, here advance adaptive radial sample algorithm to balance efficiency and quality of compressed sampling: try the least radial sample number, and add radical sample number accord adaptive algorithm until the sampled matrix meet RIP. With the help of the adaptive algorithm, the process dealing with power signal reaches the proximately best solution with only a few iterations, saves sources and stabilizes services quality in different conditions.

3.2 Power Quality Signal Reconstruction Algorithm

3.2.1 Current and Voltage Signal Reconstruction Algorithm

In [23–26], there are many researches focused on fast, reliable and low-consumed reconstruction algorithm. In [23], an adopted TV (total variation) method is introduced to achieve compressed sampling on images. As most of natural picture are sparse in variation, Candès et al. advanced TV reconstruction algorithm for two-dimension picture according to its directed singularity feature [24]. For voltage and current signals, the FFT of combined matrix are directed singular in some directs and contain of variational structures. Based on those features, here specializes an optimized TV method for voltage and current signals.

Power signal $S$ in formula (4) under sparse based on $\Psi_0$, can be reconstructed by solving follow optimization problem:

$$\min \frac{3}{3} H(S) \equiv L(S) + \lambda TV(S)$$  (12)

where $L(S)$ is the difference between reconstructed signal’s 2-norm and original signal’s 2-norm.

$$L(f) = \frac{1}{2} \| \Theta_0 S - y \|^2$$  (13)

According to features of practical sample voltage, current signal and related compressed sensing algorithm for two-dimension picture [25], and the FFT of com-
bined voltage and current signal matrix’s last element of each line is adjacent to first element of next line, here adopts following method to calculate $D_j^S$ and $D_k^S$:

$$
D_j^S = \begin{cases} 
S_{j,k} - S_{j+1,k} & 1 \leq j < N \\
0 & j = M 
\end{cases} \quad (14)
$$

$$
D_k^S = \begin{cases} 
S_{j,k} - S_{j,k+1} & 1 \leq k < N \\
S_{j,k} - S_{j+1,k} & k = N \cap 1 \leq j < N \\
0 & k = N \cap j = N 
\end{cases} \quad (15)
$$

Do iteration under following formula, obtain optimal solution.

$$
S_j^{t+1} = S_j^t + u\nabla_j H(S^t) \quad (16)
$$

$$
u = \alpha^{-1} \quad (17)
$$

$$
\nabla_j H(S) = \nabla_j (L(S)) + \nabla_j (TV(S)) \quad (18)
$$

$$
\nabla_j (TV(S)) = \left( \frac{D_j^S}{\| \nabla_j S \|} + \frac{D_k^S}{\| \nabla_k S \|} \right) \frac{D_j^S}{\| \nabla_j S \|} + \frac{D_k^S}{\| \nabla_k S \|} \quad (19)
$$

$$
|\nabla_j f| = \sqrt{(D_j^S f)^2 + (D_k^S f)^2 + \varepsilon} \quad (20)
$$

where $\alpha$ is constant attenuation coefficient.

### 3.2.2 Power Signal Reconstruction Algorithm

The power signal reconstruction algorithm is the same as reconstruction of voltage or current signals, except an adaptive step added after sparse transform as shown in Figure 3. $S_0$ is FFT of power signal two-dimension matrix $s_0$. $R_c$ is radial sampling matrix with radial number $c$, $c_0$ is initial value for $c$, and $d_0$ is initial step length. To promise enough data for reconstructing, matrix $y$ which obtains from radial sample must meet following conditions:

$$
\| y \| > (1 - A) \| S_0 \| \quad (21)
$$

$$
y = R_c \times S_0 \quad (22)
$$

where $A$ is the constant max maximum information loss ratio.

Power signal matrix $S_p$ transforms to sparse matrix $F_p$ under sparse basis matrix $\psi_0$. Sparsity of $F_p$ varies with load condition in wide range. To promise an effective and qualitative compressed sensing algorithm on power signal, here advances a self-adaptive algorithm.

To make a fast judgment on whether original $S_p$ can be proximately reconstructed from the reserved information in radial sampled matrix $y_n$, here calculates $y_n$ 1-norm to $S_p$ 1-norm ratio.

$$
y_n = C_n \ast S_p \quad (23)
$$

$$
\| y_n \| \geq (1 - A) \| S_p \| \quad (24)
$$

where $n$ is radial number of radial sample matrix, $A$ is the constant maximum information loss ratio.

For the optimal $n$ for effective and qualitative, $n$ is the smaller the better when satisfying formula (24).

$n$ is obtained by solve the following optimization problem:

$$
\min_n(C_n \ast S_p) \geq (1 - A) \| S_p \| \quad (25)
$$

Formula (25) is the constraint condition. The problem solves by following steps.

Step 1. $n = n_0$, obtain radial matrix $C_{n_0}$, and calculate $y_{n_0}$. If $y_{n_0}$ satisfy formula (24)? Yes, end; No, next step.

Figure 3. Flow chart of power signal compressed sensing.
Step 2. \( n_1 = n_0 + d_0 \), obtain radial matrix \( C_{n_1} \), calculate \( y_{n_1} \). If \( y_{n_1} \) satisfy formula (24)? Yes, \( n = n_1 \), end; No, next step.

Step 3. \( d_k = \alpha d_{k-1} \left( \frac{1}{\|y_n\|_2} - \frac{1}{\|y_{n-1}\|_2} \right) \), where \( \alpha \) is constant attenuation coefficient. If \( d_k < d_{\text{min}} \)? Yes, \( d_k = d_{\text{min}} \); No, \( d_k = \lfloor d_{\downarrow} \rfloor \). Where \( d_{\text{min}} \) is minimum step length.

Step 4. \( n_{k+1} = n_k + d_k \), obtain radial matrix \( C_{n_{k+1}} \), calculate \( y_{n_{k+1}} \). If \( y_{n_{k+1}} \) satisfy formula (24)? Yes, \( n = n_{k+1} \), end; No, back to step 3.

With the optimal \( n \), we sample \( S_p \) with radial sample matrix of radial number \( n \), then do the same process as reconstructing voltage and current signal to reconstruct power signal.

### 4. Experiment and Performance Analysis

#### 4.1 Recovery and Processing Sampling Data about Voltage and Current

Based on theoretical research purposes mentioned described, we have establish a set of smart meter test-bed with CS measurement. In Figure 4, this test-bed platform consists of three wireless nodes as smart meters, ZigBee wireless gateway, Ethernet router and terminal data server PC. For a single meter node, energy metering chip ADE7878 measures all information of single-phase load with internal hardware signal circuit and obtains voltage/current value, active power, reactive power, apparent power and etc. It transmits sampling data to STM32 system with SPI interface. STM32 system realizes PQ data storage with multi-tasking operating system (uC-OS). In ZigBee wireless network, the measuring node transmits all of PQ information to PC server. And we can configure node’s charging settings online with infrared remote controller. Its LCD display shows PQ parameters real-time dynamically.

In different load conditions, original sampling data in single-phase grid is send to PC terminal, and is regarded as raw data for CS recovery analysis with MATLAB. To show recovery effects under various load conditions, chip ADE7878 in smart meter is used to fixed sampling rate at 4 KHz with two different loads. Load 1: 1 K linear resistor; Load 2: 5 W nonlinear switching power load. By several empirical estimations and optimal experimental analysis, recovery model parameters of voltage/current are set as follows: the recovery upper limit of iteration number is 150; the gradient convergence criterion is 1e-3. The Load 1 waveforms of CSR, SNR, WSE and PER in different sampling rate are shown in Figure 5.

In order to reduce the recovery distortion, sampling ratio threshold of signal compressing is set at 95%, gradient convergent factor of full gradient algorithm \( \alpha \) is 0.6. According to CS experimental data of voltage and current signals, when the radial orbit sampling number is 95%, it can recover 95.46% original data and CS sparse sampling rate is 41.06%. In the case of Load 1, SNR is 47.1368 dB, MSE is 0.52%, ERP is 100% and radial sampling number (RSN) is 35 in following contrasted experiments.

Figure 4. Smart meter test-bed with CS measurement.

Figure 5. CS performance waveforms of voltage/current signals.
In Figures 6–13, the result comparisons are shown on original/recovered waveforms of voltage/current signals with the load 1 and load 2 conditions. In Table 1, the result comparisons can be shown about statistical recovery parameters of compressing voltage/current data. From the contrast experiments above, it shows that we can recover voltage/current signals very well in Load 1 and signal absolute error is below to 3%. In Load 2, it can also recover sampling signals of voltage/current, and its absolute error is below to 7%. The FFT waveforms of original/recovered waveforms of voltage/current signals are shown in the second results in the Figures 6 and 7.

Table 1. Statistical recovery parameters of compressing voltage/current data

<table>
<thead>
<tr>
<th>Load</th>
<th>SNR (dB)</th>
<th>MSE (%)</th>
<th>ERP (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage of load 1</td>
<td>47.1368</td>
<td>0.52</td>
<td>100</td>
</tr>
<tr>
<td>Current of load 1</td>
<td>44.1162</td>
<td>0.69</td>
<td>100</td>
</tr>
<tr>
<td>Voltage of load 2</td>
<td>29.4472</td>
<td>4.06</td>
<td>99.86</td>
</tr>
<tr>
<td>Current of load 2</td>
<td>15.2204</td>
<td>10.57</td>
<td>96.90</td>
</tr>
</tbody>
</table>

From these results, it can be shown that harmonic parts of the original signals in different frequency are still maximizing preserved in recovery voltage/current signals.

In Table 1, it can be shown that voltage/current signals are regarded as one combined signal for CS processing, so that their correlation will be decayed in Load 2. The recovery performance of current signal is not good as ones of voltage signal; it will be our research objective in the next step.

4.2 Recovery and Processing Sampling Data about Power

In contrast experiments of power recovery signals, two different scenarios are selected to show the CS algorithm performance with the same power load. In the same 220 V AC environment, Scenario 1 is the recovery experiment of nonlinear load in stable state; Scenario 2 is recovery experiment of the same nonlinear load in on-off state. According to adaptive recovery algorithm of power signals mentioned above, Scenario 1 and Scenario 2
have the same experimental parameters: initial sampling number $c_0$ is 25; convergence parameter $\mu$ is 0.8; termination error rate $\epsilon$ is 0.08. In Scenario 1, RSN for apparent power is 25; RSN for active power is 90; RSN for reactive power is 25. The recovery waveform of power signals is shown in Figure 9.

In Scenario 2, RSN for apparent power is 25; RSN for active power is 84; RSN for reactive power is 25. The recovery waveform of power signals is shown in Figure 10.

In Table 2 and Figure 11, it can be shown that MSE and ERP of power recovery signals in Scenario 1 and Scenario 2 are low, but their SNR to increase. We will improve CS algorithm to increase power SNR and recovery accuracy.

From the comparisons of recovery accuracy, radial orbit number adopted in adaptive algorithm gains experiment result with non-sparse and unstable characteristics of power sampling data. It can recover dynamic retails of apparent power and active power signals efficiently. For active power signal, CS recovery data causes individual big errors randomly due to some sample data are irregular and aperiodic, CS algorithm would work well at those moments. But we can try to reduce this error by digital analysis and processing method later. Overall, the reactive power and apparent power of the sampling signal have small error of recovery experimental results.

4.3 Comparison to Related Approaches

As shown in [27], power disturbance signals of ty-
pical transient and short duration are set up in typical theoretical model. It samples voltage signals sparsely with CS, and advances a kind of CS method about single ideal disturbance conditions. The proposed algorithm obtains 27% sampling rate of the Nyquist’s, has more than 35dB SNR for single signal reconstruction and more than 22 dB SNR for multiple signals reconstruction.

In previous work, we tested CS algorithm using random sample matrix shown as Figure 8 to sample the voltage and current signal combined matrix’s FFT. Using this matrix can recovery power signal in condition 1, but its recovered signal shown in Figure 12 is inferior to Figure 6. What’s more, as recovery signal shown in Figure 13, CS method with random sample matrix cannot recovery original matrix properly in condition 2. The percent difference between original and recovered signals in Figure 7 is obviously smaller than that in Figure 13.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>SNR (dB)</th>
<th>MSE (%)</th>
<th>ERP (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Active power of scenario 1</td>
<td>54.4266</td>
<td>0.74</td>
<td>99.98</td>
</tr>
<tr>
<td>Reactive power of scenario 1</td>
<td>52.3280</td>
<td>0.39</td>
<td>100</td>
</tr>
<tr>
<td>Apparent power of scenario 1</td>
<td>74.5060</td>
<td>0.09</td>
<td>100</td>
</tr>
<tr>
<td>Active power of scenario 2</td>
<td>47.4444</td>
<td>1.50</td>
<td>99.97</td>
</tr>
<tr>
<td>Reactive power of scenario 2</td>
<td>50.8442</td>
<td>0.45</td>
<td>100</td>
</tr>
<tr>
<td>Apparent power of scenario 2</td>
<td>94.1266</td>
<td>0.04</td>
<td>100</td>
</tr>
</tbody>
</table>

Figure 9. Sampling and recovery waveforms of power signals in Scenario 1.

Figure 10. Sampling and recovery waveforms of power signals in Scenario 2.

Table 2. Statistical recovery parameters of compressing power data
soradial sample method gets the similar results. And in both condition random sample matrix do 10% more calculation. In sharp contrast, signal sampled by radial sample matrix as in Figure 7 are much better. In theory, random sample matrix performs better then radial sample matrix, for its random sample might preserve more detail of different frequencies. However, in practical power signal FFT is mainly depend on some frequencies, and radial sample matrix collect most important information.

5. Conclusion and Future Work

This paper has presented an improved CS method using the complex matrix consisted of voltage and current signals to analyze power signal. With the smart testbed, real data is sampled and reconstructed through the
proposed CS algorithm. The sampling rate of voltage and current signals is Nyquist’s frequency by 41.06%. The reconstruction SNR of linear load is more than 44 dB, while that of nonlinear load is increased more than 15 dB. Because actual sampling rate of smart meter test-bed is lower than that of the idealistic one in [27], actual reconstruction matrix is smaller than that of the idealistic one, and we can adopt lower sample rate at the sampling number of the same radial orbit. If smart meter hardware is set with faster sample rate, it will further improve sampling rate of CS algorithm.

Based on two-dimensional image compression algorithm principle, single-phase power quality parameters (voltage, current, power, etc.) was obtained better experiment results and improved performance with different scenarios and load conditions. Under the basic guarantee premise of the transmission quality of wireless signals, power quality signals are taken down-sampling and data compression by the signal sparsity in the frequency domain. When the data compression ratio is below 50%, it still gets satisfying recoverd signal and reduces the data amount of wireless networks effectively. This method can reduce the pressure of the network data and improve the quality of the received signal. Due to the different time and geographical restrictions of smart gird, nonlinear load of single-phase grid users changes greatly. It increases the measurement and recovery difficulties of power quality signals. In the wireless network environment of smart meter test-bed, how to dynamically real-time change the radial sampling number of voltage, current and power signal for the minimum signal distortion rate, and how to recover the maximum extent of sampling data with the minimum amount of information based on adaptive sampling recovery algorithm in smart meter test-bed will be our next research directions and focuses in the future.

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