

Real-Time Lossless Compression for Ultra-High-Density Synchrophasor and Point on Wave Data

Chang Chen, *Student Member, IEEE*, Weikang Wang*, *Student Member, IEEE*, He Yin, *Member, IEEE*, Lingwei Zhan, *Member, IEEE*, Yilu Liu, *Fellow, IEEE*

Abstract—Modern advanced Phasor Measurement Units (PMUs) are developed with ultra-high reporting rates to meet the demand for monitoring the power systems dynamics in detail. Due to the large volume of data, the communication and storage systems are seriously challenged with the presence of Ultra-High-Density (UHD) synchrophasor and Point on Wave (POW) data. Therefore, it is an urgent task to compress the UHD data for more efficient communication and data storage. This paper proposes several methods to compress the synchrophasor and POW data in a lossless manner. First, an Improved-Time-Series-Special Compression (ITSSC) method is proposed to compress the UHD frequency data. Second, a Delta-difference Huffman method is combined with the TSSC algorithm to compress the UHD phase angle data. Finally, a cyclical high-order delta modulation method is proposed to compress the UHD POW data. The proposed models are extensively tested and compared with different existing lossless compression algorithms using the field-collected synchrophasor and POW data at different reporting rates. The results indicate that the proposed algorithms are efficient in performing lossless compression for the UHD synchrophasor and POW data in real time.

Index Terms— lossless data compression, ultra-high density, synchrophasor data, point on wave data, Improved-TSSC method, Huffman encoding method

I. INTRODUCTION

With the increasing demand to analyze the complex power system dynamics, the Phasor Measurement Unit (PMU) is required to provide Ultra-High-Density (UHD) data. Recently, the advanced PMUs developed by FNET/GridEye are reported to provide synchrophasor and Point on Wave (POW) data at an extremely high reporting rate, e.g. 6000 Hz, which is much faster than other devices that have been recorded [1]-[3]. However, the UHD data will significantly challenge the underlying communication network and the server storage due to its massive data size [4]. Therefore, intelligent online

compression methods are essential for UHD data to maintain the efficiency of communication and storage.

The compression techniques generally are classified into two fields: lossy compression and lossless compression. Lossy compression approaches can have a better compression performance though sacrificing the accuracy of the data [5]. However, online compression of UHD data needs to maintain data accuracy for future analyses. Therefore, the lossless compression algorithms that can exactly reconstruct the raw data are preferred for the online compression of UHD data. Lossless compression can be categorized into dictionary-based and prediction-based algorithms. The dictionary-based method compresses the repetitive patterns into a shorter codeword. The computational time of some dictionary-based methods, such as LZ77 and LZW, is a great concern, though they can achieve a high compression ratio (CR) for archived data. On the other hand, the prediction-based methods need prior knowledge of the data characteristics, which allows the algorithm to transfer the raw data into some residuals. Then, some methods can be adopted to compress the residuals.

Some methods have been proposed to compress synchrophasor data in a lossless manner [6]-[14]. However, these methods are optimal only for archived data, and the online compression is mostly implemented by lossy compression methods [15], [16]. The Time-Series Special Compression (TSSC) method is a dedicated algorithm developed for the Streaming Telemetry Transport Protocol. It is a potential tool for the UHD frequency data compression which changes slightly due to the high sampling rate. However, this method does not consider the effect of the number of the Immediate Predecessors (IPres), N , and the size of the moving window where the Valid Bits (VBs) are recorded, M , on the Compression Ratio (CR), making it not the optimal solution for the UHD frequency data. The approaches to achieve high CR for the phase angle data generally consist of two stages, preprocessing and encoding [6]. By preprocessing, the raw data is transferred to the intermediate form with low entropy, so that it can be encoded by an entropy compression algorithm in the second stage. The Huffman method is one of the most widely used entropy method, which minimizes the average code length in bits by constructing a Huffman table for the data. However, regarding the real-time UHD phase angle compression, the Huffman table information should be reconstructed for every next frame, which introduces more information to each frame, restricting the CR.

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C. C., W. W. and H. Y. are with the University of Tennessee, Knoxville, TN 37996 USA (e-mail: cchen75@utk.edu, wwang72@utk.edu, hyin8@utk.edu).

L. Z. is with the Oak Ridge National Laboratory, Oak Ridge, TN 37831 USA (e-mail: zhanl@ornl.gov)

Y. L. is with the University of Tennessee, Knoxville, TN 37996 USA, and the Oak Ridge National Laboratory, Oak Ridge, TN 37830 USA (e-mail: liu@utk.edu).

For the UHD Point on Wave (POW) data, traditional algorithms use tools such as the Fast Fourier Transform (FFT) to obtain the signal frequency, constructing an estimated POW signal [17], [18]. Lossless compression can be achieved by combining these tools with lossless encoding algorithms such as Huffman encoding. However, the running time of the FFT is the concern for the real-time PMU compression. [19] proposes a High-order Delta Modulation (HDM) algorithm to preprocess the POW data to some residuals, and it employs the Huffman encoding method afterward. However, the HDM signal does not repeat frequently in one frame, making Huffman method hard to compress well.

This paper proposes some methods to efficiently compress the UHD synchrophasor and POW data in real time. First, an Improved-TSSC (ITSSC) method is proposed to quickly compress the UHD frequency data. This method set the N and the M as variables. In this way, the optimal algorithm for the UHD frequency data compression can be obtained at runtime. For the UHD phase angle data, the Huffman-TSSC method is proposed, where the Huffman table information is compressed in stage 3 by the TSSC method to increase the compression performance. Finally, The Cyclical High-order Delta Modulation (CHDM) method is proposed for the UHD POW data due to its cyclicity. Considering that the CHDM signal does not occur frequently but has fewer VBs in one frame, it is compressed by assigning code words based on the length of the VBs. According to field testing, the proposed methods show satisfying compression performances.

In Section II, the ITSSC method is proposed to compress UHD frequency data based on its characteristics. In Section III, the Huffman compression method is combined with the TSSC algorithm to compress the UHD phase angle data. In Section IV, the cyclical characteristics of the UHD POW data are discussed, and the CHDM-VB method is proposed. Section V tests the proposed methods with both the collected data and a PMU variation, high-speed Universal Grid Analyzer (UGA). Finally, a summary of the proposed methods is presented in Section VI.

II. IMPROVED-TSSC FREQUENCY COMPRESSION METHOD

A. UHD Frequency Data Characteristics

A PMU data frame contains a batch of GPS-synchronized measurement data. It benefits the PMU communication efficiency by including synchrophasors in a single frame to reduce the data streaming rate. Fig. 1 shows one sample frame of the UHD frequency data, where the reporting rate is 1440 Hz. In this case, the PMU streams 10 frames per second, where each frame has $n=144$ frequency measurements.

As is seen from Fig.1, although the trend of the UHD frequency data is like a random walking, the high reporting rate reduces the difference between any two consecutive measurements. Traditional compression methods, such as entropy encoding, generally require the raw data to be repetitive, which is not suitable for the UHD frequency data. The TSSC method is applicable to compress the erratic but small-variation values. However, it is not the optimal solution to compress the real-time UHD frequency data. First, this

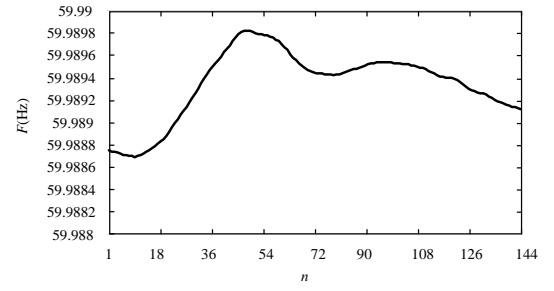


Fig.1 UHD frequency data

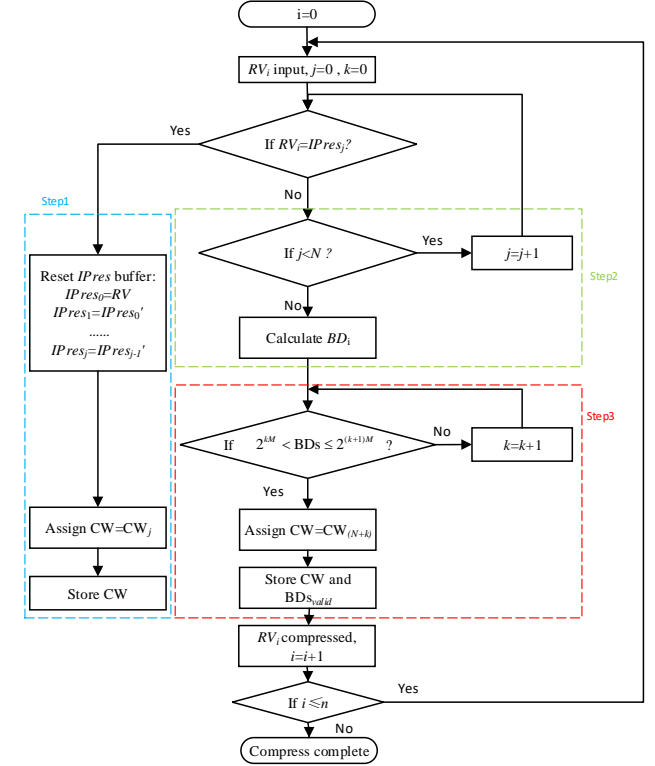


Fig. 2 ITSSC compression algorithm diagram

method sets $N=3$, while a larger N makes the processes RV more likely to match one of the $IPres$, thus a higher Compression Ratio (CR) could reach as no BD is calculated. Second, the TSSC method sets $M=4$ bits, which could lead to extraneous zero prefix, thus it decreases CR. For example, assume that the BDs is 00011101 in binary, where only the last five bits, 11101, are valid. However, the recorded BDs will be 00011101, when $M=4$, because it records the 3 prefix zeros to make up 4 digits. As opposed to it, when $M=2$, the BDs will be 011101, which reduces 2 bits. However, it is not optimal to naively use the largest N and the smallest M . This is because these parameters will increase the bit length of the CW, thus decreasing the CR as well.

To efficiently compress the UHD frequency data in real time, this paper proposes an Improve-TSSC (ITTS) method. The ITSSC sets N and M as variables, so that the optimal parameters for the UHD frequency compression can be obtained at runtime.

B. ITSSC Method for UHD Frequency Data

Fig. 2 shows the flow chart of the ITSSC method. As illustrated, this method transforms each value into a fixed-length CW and the BDs. Note that the ITSSC method

compresses Raw Values (RVs) one after another due to the dependency of the current value and its predecessors. The specific steps to compress the i -th RV, RV_i , are as follows:

a) *Step 1: Compare with immediate predecessors.*

There is a vector of N IPres ($IPres=[IPres_0, IPres_1, \dots, IPres_{N-1}]$) in the allocated buffer, where $IPres_0$ is the most recent immediate predecessor. These values are kept so that they can be compared with the current RV. If the RV equals any value in the $IPres$, a CW will be generated to directly represent RV_i . In this way, RV_i is transformed into a fixed-length CW with fewer bits.

b) *Step 2: Calculate BDs.*

If no value in the $IPres$ matches RV_i , an XOR algorithm is used to calculate the BD of the RV_i (BD_i) by

$$BD_i = RV_i \wedge IPres_0 \quad (1)$$

where \wedge is the XOR operator.

As demonstrated, the ITSSC method is an XOR bitwise compression approach and operates only in binary rather than in floating values, making the operation faster than arithmetic-based methods.

c) *Step 3: Valid bits (VBs) of BDs determination, and VB-based CW assignment.*

Per its definition, the BD indicates the variation between RV_i and $IPres_0$. For the UHD frequency data, the BDs are supposed to be small. However, BDs are, by default, 32-bit integers, which means only some lower bits can represent the difference. Discarding the meaningless prefix zeros to get the VBs of the BDs (BD_{valid}) is the next step for ITSSC to reduce redundancy.

However, discarding all the prefix zeros can create more scenarios than only discarding a fixed number of prefix zeros, which requires more CWs. Therefore, instead of discarding all the prefix zeros, BD_{valid} is determined by the criterion as follows

$$2^{kM} < BD_i \leq 2^{(k+1)M} \quad (2)$$

where $k=0,1,2,\dots, \mathcal{L}(BD_{valid})/M-1$, $\mathcal{L}(\cdot)$ is the bit length calculation function. Once the criterion (2) is satisfied, the last $(k+1)M$ bits of the BDs are BD_{valid} , and the corresponding CW will be stored accompany by the BD_{valid} .

C. Compression Performance

The CR is defined as the ratio between the original and the compressed sizes of a data frame, which can be expressed as follows for the ITSSC method

$$CR = \frac{n \times \mathcal{L}(RV) + \mathcal{L}(\text{FrameHeader})}{n \times \mathcal{L}(CW) + \mathcal{L}(\text{FrameHeader}) + \sum_{i=0}^{n-1} \mathcal{L}(BD_i)} \quad (3)$$

Theoretically, the limit of the CR for the proposed ITSSC method can be estimated by

$$\lim_{n \rightarrow \infty, BD=0} \left[\frac{n \times \mathcal{L}(RV) + \mathcal{L}(\text{FrameHeader})}{n \times \mathcal{L}(CW) + \mathcal{L}(\text{FrameHeader}) + \sum_{i=0}^{n-1} \mathcal{L}(BD_i)} \right] = \frac{\mathcal{L}(RV)}{\mathcal{L}(CW)} \quad (4)$$

As mentioned, the compression performance of the ITSSC method is affected by the N and the M . As is seen from (4), to pursue a higher CR, a minimized $\mathcal{L}(CW)$ should be determined by

$$\mathcal{L}(CW) = \left\lceil \log_2 \left(N + \frac{\mathcal{L}(RV)}{M} \right) \right\rceil \quad (5)$$

where $\lceil \cdot \rceil$ is the operator that rounds a number up to the next largest integer.

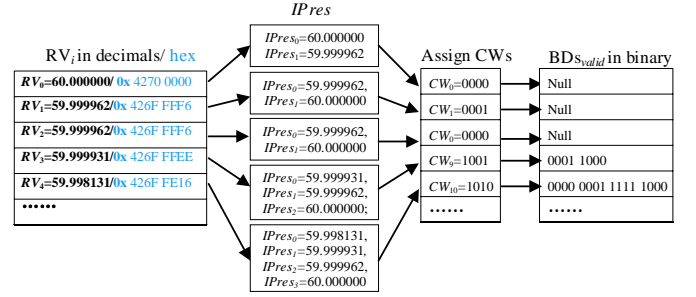


Fig. 3 ITSSC frequency compression process example ($M=8, N=9$)

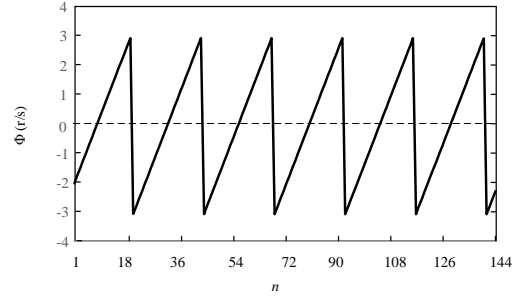


Fig. 4 UHD phase angle data sample frame

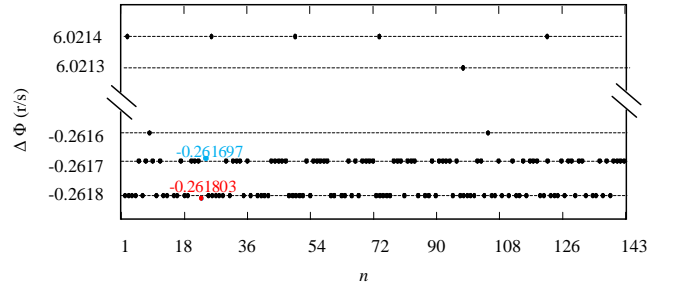


Fig. 5 $\Delta\Phi(n)$ of UHD phase angle data

D. Compression Example

Fig. 3 shows an example for the ITSSC method to compress a batch of RVs ($RV_i, i=0,1,2,3,4$), where $N=9$, $IPres_0=60.000000$, $IPres_1=59.999962$, $IPres_j=0$ ($j=2,3,\dots,8$); $M=8$; $\mathcal{L}(RV)=32$ bits, and $\mathcal{L}(CW)=4$ bits. In this example, $RV_0 \sim RV_2$ equals one of the $IPres$, so they are only assigned with CWs in order, but no BDs information is required. For RV_3 , since it does not match any of the $IPres$, the BDs are calculated. Although only the last 5 bits contain the valid information of the BDs, the last 8 bits are recorded as BD_{valid} according to the criterion (2). Then, RV_3 is added to the PVs buffer as the new $IPres_0$. RV_4 has a similar compression process as RV_3 , which has a longer BD_{valid} . The CR of this example is 3.63, which means that 72.5% of the space was saved after the compression.

III. PHASE ANGLE COMPRESSION METHOD

A. UHD Phase Angle Data Characteristics

Fig. 4 shows one sample frame of UHD phase angle data. The reporting rate of this example is 1440 Hz, where 10 frames are sent per second and each has $n=144$ measurement points. As can be seen from Fig. 4, the phase angle data has a relatively

fixed slope rate in each cycle.

Fig. 5 shows a slope distribution of UHD phase angle data, which is the difference value between two consecutive values $\Delta\phi(n)$

$$\Delta\phi(n) = \phi(n) - \phi(n-1) \quad (6)$$

As is seen from Fig. 5, UHD $\Delta\phi(n)$ data is highly repetitive. However, the repetition is intermittent.

It is mentioned in the Introduction section that the Huffman table information should be reconstructed for every next frame if the Huffman encoding method is exploited to compress the UHD phase angle data. This is because each frame has a unique Huffman table, and the loss of a single frame will lead to the decompression failure for the subsequent frames if their Huffman tables are dependent. However, including the Huffman table information introduces more information to each frame, restricting the CR. Considering that the different values in the Huffman table variate slightly due to the high sampling rate, this paper exploits the TSSC method as stage 3 to compress the Huffman table information, forming the Huffman-TSSC compression method.

B. Preprocessing algorithms

There are several methods proposed for the preprocessing, including the slack reference encoding (SRE), the swinging door (SD), the piecewise linear online trending (PLOT), and the difference encoding [8]-[12]. The SRE uses one node as a reference to predict the others, which is only applicable for a multi-nodes system but not for independent PMU data online compression. SD and PLOP are lossy methods that replace raw data with a set of parameters under given error limits; these methods cannot maintain data accuracy. Besides, [6] proposes the DEFC method to predict phase angle values by compensating a frequency-related element. As UHD $\Delta\phi(n)$ has lower entropy than raw data, Delta Encoding (DE) that transforms raw data into the differences between sequential data via (6) shows the potential of compressing UHD phase angle data[11].

C. Encoding techniques

Various algorithms have been proposed to encode the preprocessed data. These algorithms include run-length encoding (RLE), the Huffman compression method, etc.

The RLE simplifies the consecutive repeated values into a single value and the number of its repetition. This method is efficient when the same data value occurs consecutively [13]. However, it is unable to have a good performance for UHD phase angle data as the preprocessed data occurs intermittently.

The Huffman compression method is one of the most widely used techniques. It first builds the Huffman table, which consists of the different values and their occurrence frequency. Then a Huffman tree is constructed, which assigns the CWs with fewer bits to the values that occur more frequently [11]. Unlike the RLE, Huffman encoding does not require the data to be consecutively repeated. It compresses the data efficiently if it has some frequently observed values. Additionally, it is easy to be implemented and faster than dictionary encoding methods.

Technically, the limit of the CR for the Huffman-based method is

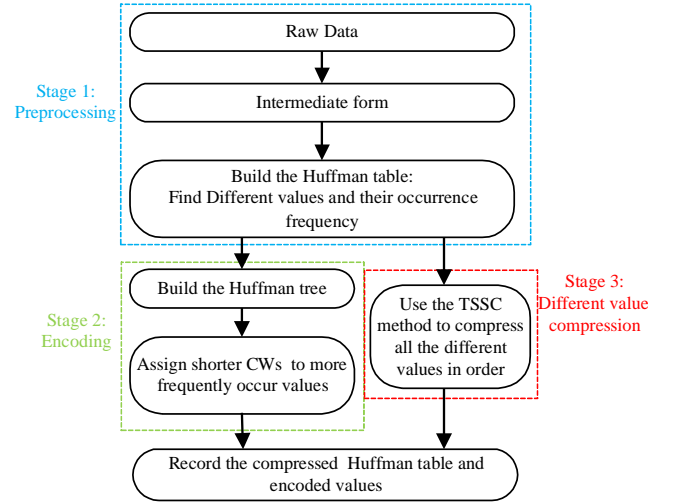


Fig. 6 Flow chart of the DE-Huffman-TSSC compression method.

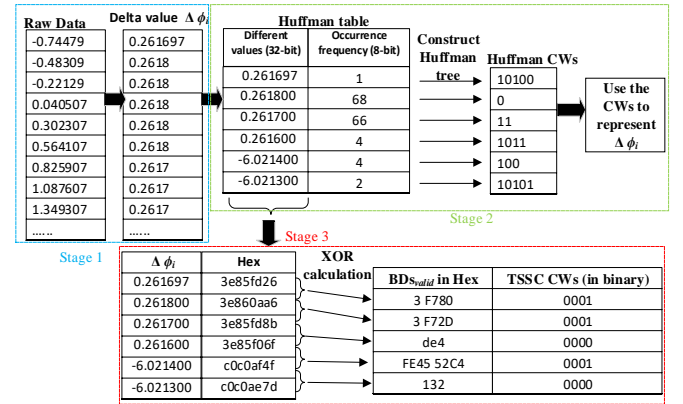


Fig. 7 The Huffman-TSSC compression example.

$$\lim_{n \rightarrow \infty} (CR) = \frac{n \times \mathcal{L}(RV) + \mathcal{L}(\text{FrameHeader})}{\sum_{i=0}^{n-1} \mathcal{L}(CW_{i_Huff}) + \mathcal{L}(\text{FrameHeader})} = \mathcal{L}(RV) \quad (7)$$

where CW_{i_Huff} is the Huffman CW.

D. Huffman-TSSC Phase Angle Compression Algorithm

Since the Huffman table introduces more information to each frame, restricting the CR, the TSSC method is exploited to compress the different values in the Huffman table. Fig. 6. shows the stages of the Huffman-TSSC method for phase angle compression. Stage 1 is to preprocess the raw data to the intermediate form $\Delta\phi(n)$ by DE, and then the Huffman table is built for $\Delta\phi(n)$. Then, in stage 2, a Huffman tree is built, which assigns shorter CWs to $\Delta\phi(n)$ that occurs more frequently, so that $\Delta\phi(n)$ can be compressed to some CWs with less bits. In stage 3, the TSSC method is used to compress the Huffman table, where $N=1$, $M=4$, and XOR are operated between any two consecutive different values of the Huffman table.

Fig.7 shows an example of the proposed Huffman-TSSC method. As is seen, the data is first preprocessed to $\Delta\phi(n)$ that could repeat. Then, a Huffman table is built for $\Delta\phi(n)$. After that, the $\Delta\phi(n)$ that occurs the most frequently are compressed to the shortest CWs based on the Huffman tree. Finally, the Huffman table is compressed to CWs and BD_{valid} via the TSSC method, so that the Huffman table can take up fewer bits. In this example, the CR is increased by 20%.

IV. POINT ON WAVE DATA COMPRESSION

A. UHD Point on Wave Data Characteristics

Fig. 8 shows a UHD Point on Wave (POW) example, where the values are expressed in 16-bit integers. As is seen, the POW signal is almost a sinusoidal wave, which can be expressed as

$$x(k) = A \sin(\omega T_s k + \varphi) \quad (8)$$

where A , ω , and φ are the amplitude, angular frequency, and the phase angle of the POW. The A , ω , and φ can change between every two points in practical. However, since the sampling rate is quite high, the changes of A and ω can be very small.

Fig. 9 shows a sample frame of the HDM signal, which contains 600 points. As mentioned in Section III, the Huffman table needs to be reconstructed for every frame if Huffman method is used. However, it can be seen from Fig.9 that the residuals do not tend to repeat frequently in one frame, making Huffman algorithm unable to compress it well.

To compress the UHD POW data in real time, this paper proposes a CHDM-VB method. The Cyclical High-order Delta Modulation (CHDM) model that takes A , ω , and φ as inconstant parameters is deducted. Based on the model, a criterion to determine the optimal differential order is established, thus the optimal high-order delta modulation signal is obtained. Differential operation is then carried out cyclically for the obtained data to further reduce the VBs. Since the data processed by the aforementioned approaches have fewer VBs, it can be better compressed via the VB-based CW assignment method. Since this algorithm simply employs arithmetic operations, its running speed is higher than the FFT-based methods.

B. CHDM-VB Compression Method

Fig.10 shows a flow chart of the algorithm, where the compression steps are as follows:

a) Step 1: CHDM

Assuming $x_0(k-1) = A_{0(k-1)} \sin[\omega_{0(k-1)}(k-1) + \varphi_{0(k-1)}]$ is the POW value at time t_{k-1} and $x_0(k) = A_{0(k)} \sin[\omega_{0(k)}k + \varphi_{0(k)}]$ is the next point of value, the difference value between these two values, $x_1(k) = x_0(k) - x_0(k-1)$, can be derived as

$$x_1(k) \approx A_{1(k)} \cos[\omega_{1(k)}k + \varphi_{1(k)}] \quad (9)$$

where $A_{1(k)} = 2 \sin[(\varphi_{0(k)} - \varphi_{0(k-1)})/2] \times A_{0(k)}$, $\omega_{1(k)} = \omega_{0(k)}$ and $\varphi_{1(k)} = (\varphi_{0(k)} + \varphi_{0(k-1)})/2$.

As is seen from (9), by calculating the difference value between any two adjacent points, the POW data is transferred to a new set of data, where the amplitude $A_{1(k)}$ is much smaller than $A_{0(k)}$. The data set $x_1(k)$ is termed as the 1st DM.

Similarly, the 2nd DM data set can be calculated by

$$x_2(k) = x_1(k) - x_1(k-1) \quad (10)$$

$x_2(k)$ can also be expressed as a sinusoidal wave $x_2(k) \approx A_{2(k)} \sin[\omega_{2(k)}k + \varphi_{2(k)}]$, where $\varphi_{2(k)} = (\varphi_{1(k)} + \varphi_{1(k-1)})/2$, $A_{2(k)} = -2 \sin[(\varphi_{0(k)} - \varphi_{0(k-2)})/4] \times A_{1(k)}$, and $\omega_{2(k)} = \omega_{0(k)}$.

Such differential operations can be repeated many times. However, it can be seen that $A_{2(k)}$ is not necessarily smaller than $A_{0(k)}$. When the differential order increases to a certain number, the amplitude could increase. In this case, the compressed data has more VBs, which requires more CWs and decreases the CR.

A criterion is set to determine the optimal differential order

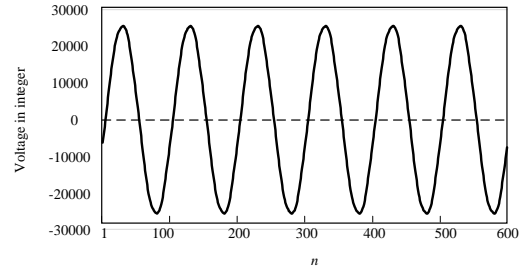


Fig. 8 UHD POW (voltage) data sample.

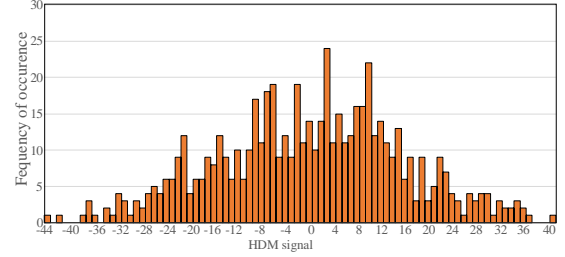


Fig.9. An example of frequency occurrence of HDM signal.

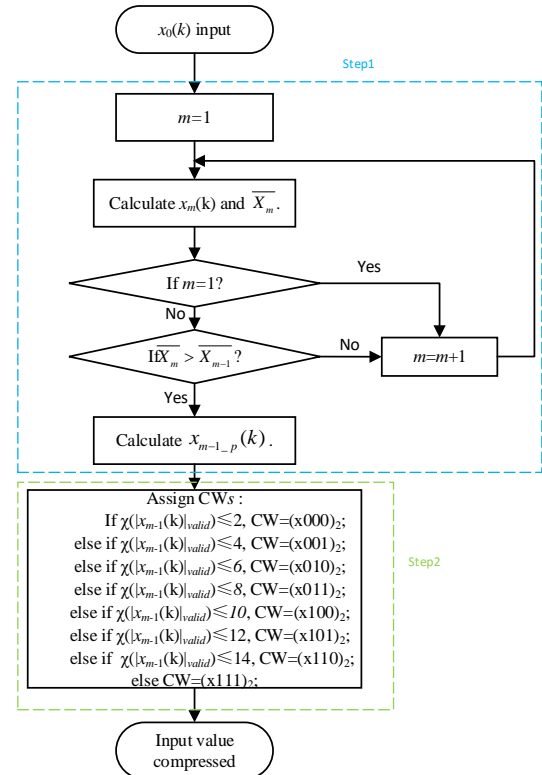


Fig. 10 CHDM-FLA algorithm flow chart

when the data set has fewer VBs, which is expressed as

$$\overline{X}_m = \frac{\sum_{k=0}^{n-m} \mathcal{L}(|x_m(k)|_{valid})}{n-m} \quad (11)$$

where $\mathcal{L}(|x_m(k)|_{valid})$ is the VBs of the absolute value of $x_m(k)$. The smaller the $|x_m(k)|$, the smaller the \overline{X}_m , the higher the CR. Therefore, if $\overline{X}_m > \overline{X}_{m-1}$, $x_{m-1}(k)$ is considered as the optimal differential data set that has fewer VBs.

$x_{m-1}(k)$ is a sinusoidal wave that has the same cycle as $x_0(k)$, so the values tend to be cyclical. Therefore, the high-order differential data set $x_{m-1}(k)$ can be processed by a periodically differential operation as follows

TABLE I
UHD FREQUENCY COMPRESSION RATIO OF COLLECTED DATA

$\begin{matrix} N \\ M \end{matrix}$	2	4	8	12	14	16	24	28	30	32
1	3.17	3.31	3.35	3.38	3.39	3.40	3.43	3.45	3.45	3.46
2	3.65	3.72	3.76	3.82	3.84	3.85	3.40	3.40	3.41	3.41
4	3.82	3.90	4.00	3.60	3.61	3.63	3.69	3.31	3.33	3.34
8	3.38	3.50	3.24	3.31	3.02	3.04	3.10	3.12	2.62	2.62
16	2.25	2.18	2.12	2.18	2.20	2.07	2.13	2.15	2.16	2.03

*The shading represents the $\mathcal{L}(\text{CW})$

2 bits	3 bits	4 bits	5 bits	6 bits
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$x_0(0)$	$x_1(0)$	$x_{m-1}(0)$	
$x_0(1)$	$x_1(1)$	$x_{m-1}(1)$	
$x_0(2)$	$x_1(2)$	
$x_0(3)$	$x_1(3)$	$x_{m-1}(1/T_{sfnom}-1)$	
$x_0(4)$	$x_1(4)$	$x_{m-1}(1/T_{sfnom})$	
$x_0(5)$	$x_1(5)$	$x_{m-1,p}(k)$
.....	$x_{m-1}(n-m)$	
.....		
$x_0(n-1)$	$x_1(n-1)$			
$x_0(n)$				

Fig. 11 The CHDM table

$$x_{m-1,p}(k) = x_{m-1}(k + \frac{1}{T_{sfnom}}) - x_{m-1}(k) \quad (12)$$

Fig.11 shows the CHDM table that indicates the CHDM compression process. As is seen, the high-order DM data sets (x_1, \dots, x_{m-1}, x_m) are calculated. Based on the criterion in (11), the optimal high-order differential data set x_{m-1} is determined. Then, the differential operation is processed periodically for the x_{m-1} . The original data is therefore transferred to the intermediate form that is colored in the blue background.

b) Step 2: VB-based CW assignment

The CHDM-preprocessed values are not highly repeated, which makes it difficult to be compressed by the entropy methods. However, they have fewer VBs compared with raw values. Therefore, they can be efficiently compressed by discarding the prefixed meaningless zeros and assigning fix-length CWs, which is similar to Step 3 of the ITSSC method. Note that the CWs for POW data consists of two parts, i.e. a sign bit that indicates if $x_{m-1}(k)$ is positive or negative and several bits that represent the VBs of $|x_{m-1}(k)|$.

V. DATA COMPRESSION TESTS

In this paper, experiments are carried out in offline and online modes, using the field-collected UHD data of the wide-area monitoring system (WAMS), FNET/GridEye and Oak Ridge National Laboratory (ORNL) [20]-[22]. In the offline tests, the frame header is not considered, i.e. $\mathcal{L}(\text{FrameHeader})=0$. In the online tests, the algorithms are implemented in IEEE C37.118.2 PMU communication protocol and $\mathcal{L}(\text{FrameHeader})=32$ bytes. Since the data frame complies with the standard protocol, there is no need to change the original circuit of the measurement device.

Note that each of the frame header has only one timestamp. This timestamp is related to the first measurement point of the data set. Since the data in each frame is consecutive in time

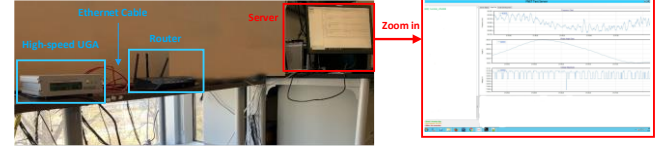


Fig. 12 Online experiment system setup

series, the rest timestamps of the data can be easily obtained when the sampling rate is known. For example, assuming that the sampling rate is 1000Hz and the reporting rate is 10Hz, each of a data frame consists of 100 measurement values. If the timestamps of the 100 values are “2020-01-01 00:00:00.000”, “2020-01-01 00:00:00.001”, “2020-01-01 00:00:00.002”, ..., “2020-01-01 00:00:00.099”, respectively, then the timestamp of the frame will be “2020-01-01 00:00:00.000”.

Fig. 12 shows the experiment system setup, where the compression methods are implemented into a PMU variation, Universal Grid Analyzer (UGA). The UGA is connected to a router via an ethernet cable, and the router is connected to the remote router that the server is connected. The remote testing server decompresses the compressed data frames and shows the data plot in real time.

The frequency and phase angle data are 32-bit values and their reporting rates are 1440Hz, where 10 frames are sent per second and each has $n=144$ measurement points.

A. UHD Frequency Compression Tests

a) The effect of different algorithm settings

To find the optimal parameters (N and M) for the ITSSC method, tests are conducted with the data collected by the high-speed UGAs. The results are shown in Tab. I, where different shading indicates different $\mathcal{L}(\text{CW})$.

As is seen from Tab. I, when M is fixed, the CR increases with N if $\mathcal{L}(\text{CW})$ does not change as more values are in the $IPres$. However, if $\mathcal{L}(\text{CW})$ becomes larger with N , the CR becomes smaller. This is because the CW, in this case, takes up more bits, which offsets the positive effects of the increase of N on the compression performance. For the M , when $\mathcal{L}(\text{CW})$ is fixed, the CR decreases with it as more meaningless prefix zeroes are recorded. When the increase of M decreases $\mathcal{L}(\text{CW})$, the CW takes up less space while more prefix values are recorded. Therefore, the CR could become either larger or smaller.

The CR is 4.0 when $M=4, N=8$, which is the highest among all the test results. Therefore, they are the optimal parameters of the ITSSC method.

b) Online compression experiments

TABLE II
REAL-TIME CR OF DIFFERENT ALGORITHMS FOR UHD FREQUENCY DATA

Method	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10	ACR
ITSSC	3.23	3.51	3.11	3.51	3.92	3.16	4.28	3.47	3.62	3.57	3.51
Huffman-based	3.05	3.20	3.15	3.45	3.68	3.05	4.31	3.47	3.56	3.07	3.34

TABLE III

REAL-TIME ACR OF DIFFERENT ALGORITHMS FOR UHD PHASE ANGLE DATA

Stage 1 Stage 2& Stage 3	DE	1 st LP	DEFC
TSSC	3.78	3.83	3.56
Huffman	8.10	5.32	2.13
Huffman-TSSC	8.90	5.71	2.23

TABLE IV

REAL-TIME CR OF THE HUFFMAN-TSSC METHOD FOR UHD PHASE ANGLE DATA

Day 1	Day 2	Day 3	Day 4	Day 5
6.68	7.02	7.28	7.36	7.15
Day 6	Day 7	Day 8	Day 9	Day 10
8.10	6.25	7.81	6.41	7.67

The proposed ITSSC method with optimal parameters is tested by implementing the code into the UGA. As a reference, the traditional Huffman compression method combined with the DE preprocessing is also tested, where the results are shown in Tab. II. As is seen, the Average CR (ACR) of the ITSSC method is 3.51, exceeding that of the Huffman-based method, 3.34. Notice that the CR of the ITSSC method shown in Tab. I is greater than that shown in Tab. II. This is mostly because the frame size is 0.

Note that the experiments are carried out under day-to-day operations, where events (generation trip, load disconnection, oscillation) and noises (mainly spikes) are constantly observed. Based on the performance evaluation, we believe the proposed methods can achieve a good CR under these scenarios.

B. UHD Phase Angle Compression Tests

a) Different algorithms comparison

Tab. III shows the compression performance of the Huffman-TSSC method compression performance. As references, the TSSC-based and the Huffman-based methods are also tested. Additionally, different preprocessing algorithms are combined. As is seen from Tab. III, DE, 1st LP, and DEFC perform similarly with the TSSC-based method for UHD phase angle data, where 1st LP has the highest CR 3.83 among them. For the Huffman-based encoding algorithms, the DE combined method has the highest CR 8.1 among all the tests. This method is 2 times of the TSSC-based method. However, when combined with DEFC, the Huffman-based method has the lowest CR 2.13, which means that the DEFC is not suitable to preprocess UHD phase angle data. When using the TSSC method to compress the Huffman table information, the ACR can be increased by 10%, where the DE-processed algorithm has the highest ACR, which is 8.9. Therefore, the proposed Huffman-TSSC method that is preprocessed by DE is optimal for UHD phase angle data compression.

b) Online compression experiments for phase angle data

The proposed Huffman-TSSC method is tested for several days in PMUs. The results are shown in Tab. IV. As is seen

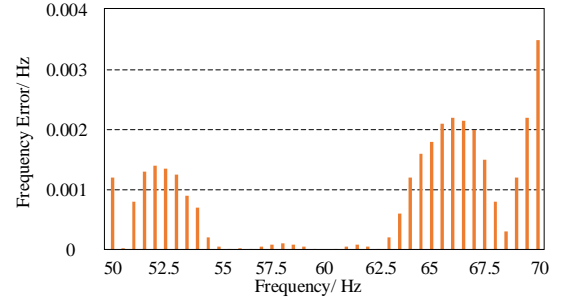


Fig. 13 Frequency error of the high-speed UGAs.

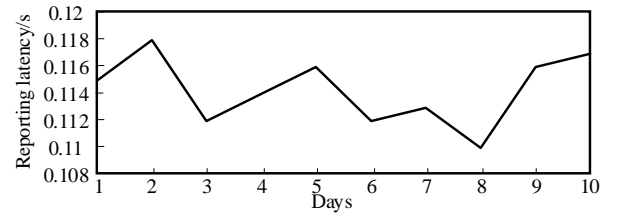


Fig. 14 Reporting latency for high-speed UGA with synchrophasor data compression methods implemented

from Tab. IV, the proposed method compresses the UHD phase angle data efficiently. The ACR of experiments is 7.2, which is less than the offline CR due to the frame header.

C. UHD Synchrophasor Data Online Compression Tests

a) Compression ratio

Since the frequency and the phase angle data are usually monitored simultaneously, they will be sent out at the same time as well. Therefore, it is more efficient for communication to compress them into one frame. To confirm the ACR for the UHD UGAs, experiments are also carried out to compress both the frequency and phase angle data.

The ITSSC method is used for the UHD frequency compression, where the parameters are $M=4$ and $N=8$. For UHD phase angle data, the proposed Huffman-TSSC method is used. Although the literature on the lossless compression of streaming data for power system monitoring is limited [23], it is reported that the ACR of the lossless compression methods that has been reported is 3 [24]. In the experiments of this paper, the ACR of the UHD synchrophasor data is 4.90, which exceeds the previously reported state-of-the-art by the time the paper was written.

b) PMU reporting latency

The high-speed UGA is designed for both measuring and protecting power systems. As shown in Fig.13, the frequency error of the high-speed UGA is less than 0.004Hz, which satisfies the IEEE C37.118.1-2014 standard for both P-class (protection) and M-class (measurement) PMUs. It is also stated in the standard that the PMU real-time output reporting latency shall below $2/F_s$ and $7/F_s$ for P-class and M-class PMUs, respectively, where F_s is the reporting rate and $F_s=10\text{Hz}$ in this

TABLE V

ACR OF DIFFERENT METHOD FOR FNET UHD POW DATA IN REAL TIME					
CHDM-VB	CHDM-H	HDM-VB	HDM-H	FFT-VB	FFT-H
3.19	1.53	1.91	1.62	1.80	1.61

TABLE VI

ACR OF DIFFERENT METHOD FOR ORNL UHD POW DATA					
CHDM-FL	CHDM-H	HDM-FL	HDM-H	FFT-FL	FFT-H
3.33	1.60	1.58	1.40	1.20	0.90

paper

This paper measures the reporting latency of the high-speed UGAs with the proposed compression method implemented. The reporting latency during different days is shown in Fig. 14. As is seen, the maximum reporting latency is 0.118s, which is lower than the IEEE standard limits 0.2s and 0.7s for the P-class and M-class PMUs, respectively.

D. UHD POW Data Compression Tests

a) FNET/GridEye data tests

The POW data is 16-bit and sampled at 6000Hz. Fig.15 shows the compression performance of the proposed CHDM-VB method, and several combined methods are also tested as references. As is seen from Fig.15, the CHDM-VB method can always compress POW data more aggressively than the others. The compression ratio of the CHDM-VB method is about 3.2, while that of the other methods are 1.2~2.

Tab. V lists the ACRs of the proposed and reference methods, where the Huffman method is abbreviated as “H”. As can be seen, the proposed cyclical difference calculation can dramatically increase the ACR from 1.8 (FFT-VB) to 3.19 (CHDM-VB). Additionally, the Huffman coding does not perform well for online UHD POW data compression compared with the VB method due to the non-repeatability of the preprocessed POW data. It is also noticed that the ACR of the proposed CHDM-VB method is higher than the ACR that has been reported, which is 3, thus further confirming the compression performance of the CHDM-VB method.

The reporting latency of the high-speed UGA with the CHDM-VB implemented is tested for the UHD POW data. The maximum reporting latency during the ten-day experiment is 0.125s, which is lower than the IEEE standards limits 0.2 s and 0.7s for the P-class and M-class PMUs.

b) ORNL data tests

Fig.16 shows a sample of the UHD POW data collected by ORNL at a sampling rate of 3840 Hz, where an event occurs at 0.06s and disappears at around 0.28s. Use CHDM-VB method to compress the POW data, and compare it with other reference methods. The compression performance is listed in Tab. VI. As is seen from Tab. VI, the CHDM-VB method also has a good compression performance for the 3840 Hz POW data, whose ACR is 3.33, while the ACRs of other methods are less than 1.6.

Fig. 17 shows the optimal HDM differential signals for the ORNL collected POW data shown in Fig. 16, which contains

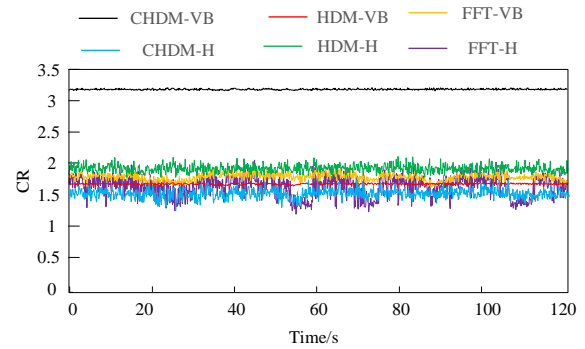


Fig. 15 CR of different algorithms for UHD POW data

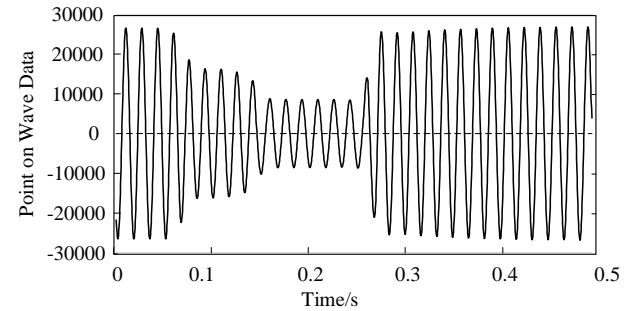


Fig. 16 ORNL POW data

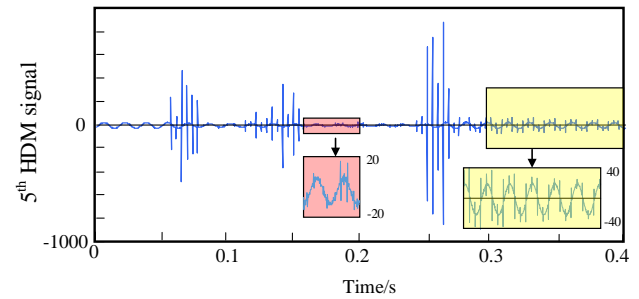


Fig. 17 HDM signals

an event and has an ACR of 3.12. As is seen, the high-order DM signal has some spikes due to the magnitude change of the raw POW data, which may affect the compression performance of the method. However, most of the points still have less VBs, making it possible to be compressed well.

VI. SUMMARY

This paper proposes several methods to compress the UHD synchrophasor and POW data in a lossless and real-time manner. The methods are designed for advanced PMUs to compress data packets efficiently and quickly before its transmission to the server. The proposed methods address the communication efficiency and memory space issues on the server side.

The proposed methods are tested with the field-collected data, and the algorithms are implemented in a high-speed PMU to compress data in real time. The results show that the proposed methods have extraordinary compression efficiency, where the average compression ratio of the synchrophasor data is 4.9, and that of the POW data is 3.3.

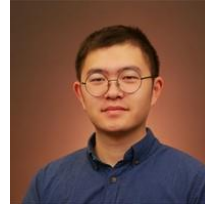
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Chang Chen (S'19) received the B.S. and Ph.D. degree in the Electrical Engineering from Sichuan University, Sichuan, China, in 2015 and 2020, respectively.

Her research interests include wide-area power system measurement, harmonic modeling and analysis, power quality, etc.



Weikang Wang (S'15) received the B.S. degree in computer science from the School of Control and Computer Engineering, North China Electric Power University in 2016.

He is currently pursuing the Ph.D. degree in computer engineering with the University of Tennessee, Knoxville. His research interests include wide-area monitoring, situation awareness, big data, and machine learning.



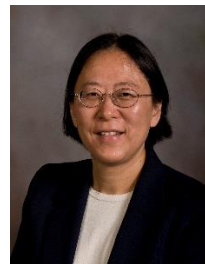
He Yin (S'13-M'16) received the B.S. and Ph.D. degree in the electrical and computer engineering from University of Michigan-Shanghai Jiao Tong University Joint Institute, Shanghai Jiao Tong University, Shanghai, China in 2012 and 2017, respectively. He is currently a postdoctoral researcher at Center for Ultra-Wide-Area Resilient Electric Energy Transmission Networks (CURENT), University of Tennessee, Knoxville, TN, USA.

His research interests include optimization and decentralized control of microgrid, and PMU design.



Lingwei Zhan (M'15) received the B.S. and M.S. degrees in electrical engineering from Tongji University in 2008 and 2011, respectively, and the Ph.D. degree from the Department of Electrical Engineering and Computer Science, University of Tennessee, Knoxville, in 2015. He is currently a Research and Development Staff with Oak Ridge National Laboratory.

His research interests include advanced grid sensors, PMU, synchrophasor measurement algorithm, wide-area power system monitoring, renewable energy sources, FACTS, and HVDC



Yilu Liu (S'88-M'89-SM'99-F'04) received her M.S. and Ph.D. degrees from the Ohio State University, Columbus, in 1986 and 1989. She received the B.S. degree from Xian Jiaotong University, China.

Dr. Liu is currently the Governor's Chair at the University of Tennessee, Knoxville and Oak Ridge National Laboratory (ORNL). Dr. Liu is elected as the member of National Academy of Engineering in 2016. She is also the Deputy Director of the DOE/NSF co-funded engineering research center

CURENT.

Her current research interests include power system wide-area monitoring and control, large interconnection-level dynamic simulations, electromagnetic transient analysis, and power transformer modeling and diagnosis.