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Energy-Saving Measurement in LoRaWAN-Based Wireless Sensor Networks by Using Compressed Sensing

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ABSTRACT In modern monitoring systems, it is essential to deploy sensor nodes and deliver related data to the information center. Wireless sensor networks (WSNs) usually work in harsh environments with vibration, temperature variations, noise, humidity, and so on. The batteries of sensor nodes are always not replaceable because of difficult access. Most of existing literature tries to prolong network lifetime by improving sleep scheduling strategies and deployment methods, independently or jointly. However, the congenital defects of mesh network can't be avoided completely. To overcome the technology challenges, this paper develops a LoRaWAN-based WSN and investigates its energy efficient scheduling method. Firstly, the basics and the limits of LoRaWAN are introduced and the feasibility and the considerations of LoRaWAN-based star wireless sensor network are discussed. Secondly, an improved compressed sensing algorithm named ISL0 (improved SL0) is proposed for network data reconstruction and compressed sensing algorithm can reduce the number of LoRa nodes transmitting data packets to avoid collision and latency. Thirdly, a sleep schedule method is proposed to reliably monitor environment data and device operating status. By using the proposed method, not only the abnormal information can be detected on time, but also the overall network data can be recorded termly. Simulation and measurement results verify all nodes have same power level at different times, and the network lifetime is maximized.

INDEX TERMS WSNs, LoRa, LoRaWAN, energy efficient scheduling, compressed sensing.

I. INTRODUCTION

Wireless sensor networks (WSNs) play crucial role for production process control and safety monitoring, and they have been widely used in many domains such as toxic gas leak detection [1], condition monitoring and fault diagnosis [2] and industrial process automation [3], etc. Different from WSNs, traditional solution is to apply wired systems to monitor environment and production process. Due to harsh environments with vibration, temperature variations, noise, humidity and the like, wired systems have many disadvantages, e.g., high cost, difficult to deploy, and being not scalable [4]. With the development of wireless communication technology and ultra-low power sensor, wireless sensor networks (WSNs) which consist of many tiny and inexpensive sensor nodes have been deemed an impactful tool to replace the wired systems. WSNs have plenty of advantages, for example, the use of wireless sensor nodes can avoid the cost of a large number of cable, sensor nodes dense deployment can improve system reliability, and fast and efficient deployment can enhance the system scalability.

Compared with traditional wired systems, a nature shortage of WSNs is that the batteries of sensor nodes are always not recharged because of difficult access. Therefore, energy-saving measurement is the focus for researchers in recent years. RFID (radio frequency identification) and Zigbee, as low-power wireless communication technologies, have become the current research hotspots. The maximum communication distant of RFID sensor tag is a few tens of meters, and it communicates with a central base station (BS)

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by using single-hop type, so RFID-based WSN can't meet the demand of long-distance monitoring [6]. Communication between Zigbee-based node and its neighbors is single-hop, and multi-hop relay communication is used by a node to send information to the sink node. In a multi-hop WSN, the amount of data transmitted by different nodes and the amount of processing at different monitoring points has different contribution for the overall energy consumption of the network. In order to prolong the lifetime of WSN, paper [7] tried to apply the two-phase geographic greedy forwarding (TPGF) geographic routing algorithm in CKN (connected K-neighborhood)-based duty-cycled industrial wireless sensor networks. A distributed clustering strategy is used in paper [8] to improve the communication network topology, the network is fully distributed and data transmission does relay on the sink node. Paper [9] paid attention to the applicability and limitations of four connected target coverage (CTC) algorithms in WSNs. In paper [10], the received signal strength indication (RSSI) is used to estimate the distance between the transmitter and the receiver before transmitting the sensor data, and then, the energy-aware sensor node can calculate the lowest transmission power. In paper [11], a compressive sensing based clustering joint annular routing data gathering scheme is proposed to improve the lifetime of the mesh network, which can reduce the amount of data of the nodes in the near-sink region. However, these researches can only improve the performance of mesh network, can't avoid the defects of multi-hop network fundamentally. The nodes nearer the sink node carry heavier traffic loads, which would deplete their energy faster, leading to energy hole problem. Different from the mash network, the nodes of the star network transmit the data packets to the sink directly, the energy hole problem can be avoided. LoRa technology can form a large-scale, low-power, reliable, and flexible star network, since LoRa has the advantages of long communication distance, large network capacity and strong anti-interference ability [12]. In LoRaWAN (LoRa wide area network)-based WSNs, sensor nodes communicate with the gateway directly and the network server configures the optimal gateway for each LoRa sensor node. The communication range of LoRa node is around 5 *km* in urban areas and more than 10 *km* in suburban areas, and a gateway can control hundreds or thousands of LoRa nodes. But taking into account the impact of collision and latency, the distance between the gateway and the LoRa nodes must be close enough and the number of LoRa nodes should be limited in real-time cases [13].

The LoRaWAN-based wireless sensor network is a star network, all LoRa nodes transmit sensor data to LoRa getway at the set time. However, the sensing data of adjacent nodes are similar, if the whole network data is treated as a matrix, the matrix is sparse. So the compressed sensing reconstruction algorithm can accurately reconstruct the data of WSN with much fewer sampling points. To improve the lifetime of the star network, the probability of each node being selected to transmit data is same, which can ensure that the power consumption of each node is same.

The main contributions are as follows.

1) An improved compressed sensing reconstruction algorithm named ISL0 is proposed for wireless sensor network data reconstruction. In ISL0 algorithm, the complex trigonometric function is used to replace the Gaussian function to get better approximation effect. The component-wise approximated gradient direction is used to increase convergence speed.
2) An energy scheduling mechanism is proposed to maximize the lifetime of the star network. By using the proposed energy scheduling mechanism, the nodes have same load and all nodes have same power level at same time.

The combine of ISL0 algorithm and energy scheduling mechanism improve the network lifetime greatly while not affecting the network monitoring effect. This paper is organized as follows. The related works has been introduced in Section 2. The LoRa basics and the network architecture are briefly introduced in Section 3. Section 4 discusses the improved SL0 (ISL0) algorithm. In section 5, a sleep schedule method is proposed. We discuss the simulation and measurement results in Section 6. Finally, the conclusions are presented in Section 7.

II. RELATED WORKS

As a burgeoning theory, compressed sensing can efficiently sample and accurately reconstruct the data of WSN with much fewer sampling points than Nyquist theory, the development of compressed sensing opens up new ideas for the energy efficient scheduling of WSN, which means that part of non-essential nodes do not need to work. In order to obtain the complete data of wireless sensor network, the compressed sensing reconstruction needs to be used in data center.

In wireless sensor network, the sensing data of adjacent nodes are similar, if the whole network data is treated as a matrix, the matrix is sparse, so compressed sensing algorithm can be applied to reconstruct overall network data from few sampling points. Various methods have been proposed to deal with this problem, they can divided into two categories: minimizing the l^1 norm by using LP (linear programming) technology and minimizing the l^0 norm directly. BP (basis pursuit) algorithm [15] is the most popular method based on minimizing the l^1 norm. By using LP technology, large-scale problems with lots of mixtures can be handled easily. However, the calculating speed is very slow. Another approach named MP (matching pursuit) [16] and its improvement named OMP (orthogonal matching pursuit) [17] are based on direct minimization of the l^0 norm, which are very fast. As greedy algorithms, their estimated errors are big. To overcome the instability of minimizing the l^0 norm, an approach based on in paper [18], called SL0. This method performs faster than those methods based on minimum l^1 norm, even with same or better accuracy. SL0 convert l^0 norm to an approximate continuous function by using the family of Gaussian function, and the steepest descent method is used to solve the minimization of approximate continuous function.

TABLE 1. Performance Comparison of LoRa, ZigBee and RFID. ASK (Amplitude Shift Keying), Q-QPSK (Offset Quad-Phase Shift Keying), FSC (Frame Checksequence), CRC (Cyclic Redundancy Check).

Wireless communication technology	Maximum transmit power	Maximum receiving sensitivity	Modulation mode	Network topology model	Anti-interference technology
LoRa (Semtech SX1276 chip)	20dBm	-148dBm	LoRa	Star network	FEC and FHSS
ZigBee (TI CC2530 chip)	10dBm	-92dBm	O-QPSK	Star network/ mesh network	FSC
RFID (FUJITSU MB97R804B)	18dBm	-6dBm	ASK	Star network	CRC

However, the Gaussian function is not ideal smooth continuous function to approximate l^0 norm and the search path of the steepest descent method is actually jagged, these problems limit the accuracy and convergence speed of SL0 algorithm. We propose an improved SL0 (ISL0) algorithm, in which a complex trigonometric function is used to replace the Gaussian function to approximate l^0 norm and a novel modified Newton's direction method is used to replace the steepest descent method to enhance the convergence rate. Simulation results show that ISL0 has better performance than previous approaches. The compressed sensing algorithm also provides a new idea for LoRaWAN to break through its limits, because the compressed sensing algorithm can greatly reduce the number of LoRa nodes that transmit data simultaneously and then reduce receive delay of the gateway.

III. LoRaWAN BASED WIRELESS SENSOR NETWORK

A. LoRaWAN BASICS

LoRaWAN is a Low Power Wide Area Network (LPWAN) promoted by LoRa Alliance, which determines the communication protocol and network architecture and uses LoRa modulation and demodulation proposed by Semtech as the physical layer. Essentially, LoRa modulation is chirp spread spectrum modulation technology [19]. Different from many existing wireless sensor networks adopt a mesh network architecture, LoRaWAN network utilizes long range star architecture as shown in Figure 1. LoRaWAN consists of getaways retransmitting messages between LoRa sensor nodes and a network server. Gateways connect to network server via standard IP link while LoRa sensor nodes communicate to one or many gateways by using single-hop type. The network server filters redundant received packages, configures the optimal gateway for each LoRa sensor node, and perform adaptive spreading factor $SF \in \{7, 8, \ldots, 12\}$, etc [20]. The performance comparison of LoRa, ZigBee and RFID is listed in Table 1. Compare to traditional wireless communication technology, LoRa has the following advantages [21]:

- Long-range communication: Without regard to the specific environment, the communication distance depends on the link budget (typically given in decibels). LoRaWAN has a greater link budget than any other wireless communication technology, because LoRa demodulation technology can improve the receiving sensitivity to a great extent. As shown in Fig.2, LoRa signal can be received successfully even if the signal power is 25dB lower than the average noise power. In other words, the LoRa device can receive the LoRa signal submerged in the noise.
- Long battery lifetime: The LoRa nodes are asynchronous and send sensor data whether event-driven or scheduled. LoRaWAN can save battery energy compared to synchronous networks, because the synchronous communication will consumes significant energy of sensor node. On the other hand, LoRa

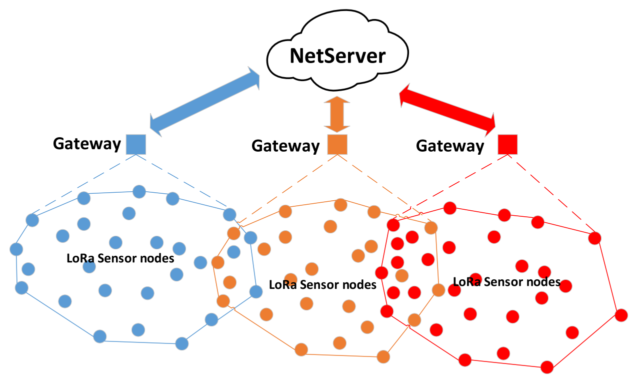

FIGURE 1. Star architecture of LoRaWAN.

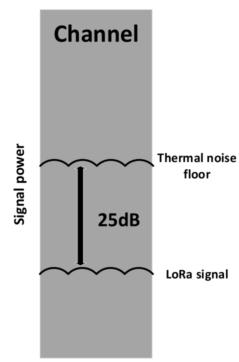

FIGURE 2. Energy comparison between LoRa signal and noise.

sensor nodes communicate with gateway directly without relay nodes, this way can also increase battery lifetime.

- Large network capacity: LoRaWAN can achieve a high network capacity by using a multichannel multi-modem transceiver in the gateway. And the LoRa signals are actually orthogonal with each other when diverse spreading factors are applied, so it is possible that data messages sent by different LoRa nodes are received by a same gateway simultaneously.
- Strong anti-interference ability: In order to improve the anti-interference ability, the forward error correcting (FEC) codes and frequency hopping spread spectrum (FHSS) are employed in LoRaWAN protocol.

B. LIMITS OF LoRaWAN

The limits of LoRaWAN mainly exists in two aspects. The first limiting factor is the duty cycle regulation in the ISM (industrial, scientific and medical) bands [22]. The greater SF allows longer communication distance and needs longer time on air (TOA), which means longer off-period [23]. The second limiting factor is the collision. Although a multichannel multi-modem transceiver and the pseudo-random channel hopping method are natively used in LoRaWAN to reduce the collision probability. However, when multiple nodes which have same distance from the gateway choose the same SF and channel to transmit data simultaneously, a collision will be caused [13]. Taking into account the impact of collision and latency, the distance between the gateway and the farthest LoRa node must be close enough and the number of LoRa nodes should be limited in real-time cases.

C. SYSTEM DESCRIPTION

For the attractive advantages of LoRaWAN mentioned above, as the rising star of IoT, it can be designed to form a large, low-power, reliable, and flexible wireless sensor network. We consider a large-scale LoRaWAN-based WSN with N gateways. For each subnet $G_i(i = 1, 2, \cdots N)$, a gateway locates at the center of the deployment region and corresponding LoRa sensor nodes are distributed randomly in a circular area. At early stage, LoRa sensor nodes in the overlapping area send their data packages to multiple gateways, and the packages are forwarded by gateways to network server. The benefit of doing so is that network server can select an optimal gateway for every LoRa sensor node. To simplify network deployment, the same number of LoRa sensor nodes (M) is deployed in each sub-network, so the total number of LoRa sensor nodes is $N \times M$.

In order to monitor multiple status information of manufacturing equipment and production environment, the number of sensors deployed in WSN is huge. However, the subnet has same network structure, and a single gateway can theoretically cover hundreds of square kilometers. To simplify network model, we suppose that only one gateway is deployed in the center of coverage area, and a total of M corresponding LoRa sensor nodes uniformly distributed in a circular area. Each LoRa sensor node is powered by an energy-constrained battery, and has three working state: active, semi-sleep and sleep modes. The working state of LoRa sensor node is controlled by the network server, and control commands are sent to the nodes through the gateway. Active nodes read the sensor data and send them through the gateway to the network server in every cycle. Semi-sleep nodes read the sensor data in every cycle time. When the reading is bigger than the preset threshold, sensor data will be sent to the network server. In the same amount of time, semi-active mode is more energy efficient than active mode. Sleeping nodes enter an interrupt and wait to be wake up by the network server, so the sleeping node consumes no power.

The purpose of energy efficient scheduling is to prolong network lifetime. Suppose that the initial battery energy of each LoRa node is same and the power consumption of three working state is different, so it is challenging to ensure that each node has a same power level after some cycles. On the other hand, the timeliness is critical to production safety, that is, the sensor should recognize the abnormal data in time and LoRa node should send the abnormal data to the network server timely. The problem that needs to be studied in this paper is to deploy M LoRa nodes (denoted by $n_{i1}, n_{i2}, \cdots, n_{iM}$) within a subnet G_i, and then to find work schedules at different cycles so that the network lifetime is maximized, while the production risk is minimized.

IV. IMPROVED SL0 ALGORITHM

It is significant for safety production to monitor necessary environmental information, the equipment running status and product quality with dense deployment of sensors. Wireless sensor networks, especially, the energy-saving sensing strategies with energy-constrained sensor nodes have got unprecedented concern in recent years [24], [25]. Compressed sensing (CS) can be used to optimize the measurement process of energy-limited system [14].

Suppose that m sensor nodes are sampled in a set of n sensor nodes by CS-based algorithm, it can be expressed as $\boldsymbol{y}(t) = \boldsymbol{Ax}(t)$ in which $\boldsymbol{y}(t)$ is the m $\times$ 1 vector of measuring signals, $\boldsymbol{x}(t)$ is the n $\times$ 1 vector of source signals and A is the $m \times n$ measurement matrix. The purpose of compressed sensing is to reconstruct $\boldsymbol{x}(t)$ by handling $\boldsymbol{y}(t)$. In order to reconstruct the source signals from the measurement signals successfully, the sources must be sparse in a domain. Obviously, the data of WSN meet the above condition.

Mohimani *et al.* [18] propose a method based on direct minimum l^0 norm (the solution of $\boldsymbol{y} = \boldsymbol{Ax}$ for which $\|x\|_0$ is minimized) called SL0, this method performs faster than those methods based on minimum l^1 norm, even with same or better accuracy. The l^0 norm is a discontinuous function, SL0 converts it to an approximate continuous function by using the family of Gaussian function:

$$f_\sigma(x_i) = \exp\left(\frac{-x_i^2}{\sigma^2}\right) \tag{1}$$

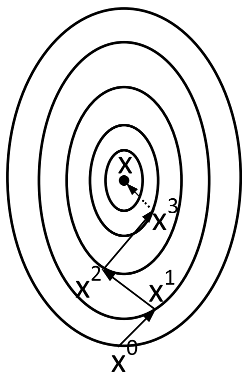

FIGURE 3. **Jagged search path of the steepest descent method.**

where σ is a parameter which decides the quality of the approximation. The optimization problem of the discrete function is transformed into the optimization problem of the continuous function. In the iterative process of solving, the steepest descent method is used to approximate the optimal solution. However, SL0 has two aspects that can be improved:

- Selecting the appropriate smooth continuous function to approximate l^0 norm is the key issue of SL0. To get better approximation effect, more excellent function should be used to replace the Gaussian function.
- To solve the optimization problem, Line search directions are an important method. The search direction of the steepest descent method is the negative gradient direction, the adjacent search directions are orthogonal, and the search path is actually jagged (as shown in Figure 3). Jagged search path greatly reduces the convergence rate, so more desirable search direction should be adopted.

A. COMPLEX TRIGONOMETRIC FUNCTION

In this paper, we propose an improved SL0 (ISL0) algorithm, in which a complex trigonometric function is used to replace the Gaussian function, it is mathematically expressed as:

$$f_\sigma(x_i) = 1 - \sin\left(\arctan\left(\frac{x_i^2}{\sigma^2}\right)\right) \tag{2}$$

where σ is a parameter which decides the steepness of the complex trigonometric function. The performance comparison between complex trigonometric function and Gaussian function is shown in Figure 4. The parameter σ is set to 0.5, 0.1 and 0.05. From Figure 4, we can know the complex trigonometric function is steeper than the Gaussian function with same σ, so the approximation of the complex trigonometric function to l^0 norm is better than that of the Gaussian function, and the proposed complex trigonometric function is the unit impulse function when the value of σ tends to zero:

$$\lim_{\sigma\to 0} f_\sigma(x_i) = \begin{cases} 1, & x_i = 0 \\ 0, & x_i \neq 0 \end{cases} \tag{3}$$

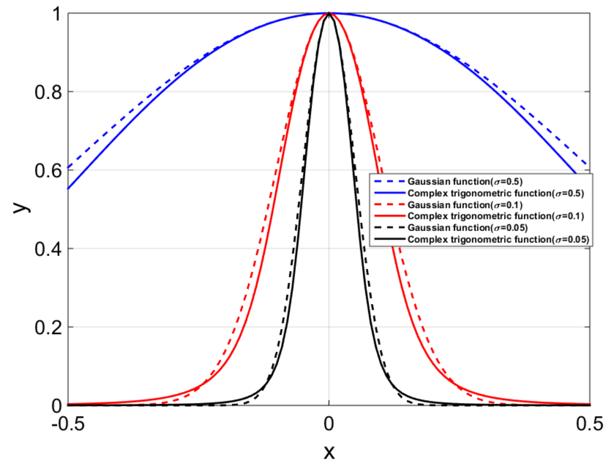

FIGURE 4. **Performance comparison between complex trigonometric function and Gaussian function.**

The solution of the minimum l^0 norm ($\min \|\boldsymbol{x}\|_0$) can be find by minimizing $F_\sigma(\boldsymbol{x}) = n - \sum_{i=1}^{n} f_\sigma(x_i)$ with a very small value of σ [18], So the reconstruction of the source signals can be converted to an optimization problem, which can be expressed as:

$$\begin{aligned} &\min F_\sigma(\boldsymbol{x}) \\ &\textit{subject to} \quad \boldsymbol{y}(t) = \boldsymbol{A}\boldsymbol{x}(t) \end{aligned} \tag{4}$$

When $\sigma = 0$, $F_\sigma(\boldsymbol{x}) = \|\boldsymbol{x}\|_0$, but in fact, the sparseness of $\boldsymbol{x}$ is not ideal, so $F_\sigma(\boldsymbol{x})$ is not smooth when $\sigma \to 0$, and there will be many local minimum. In order to ensure convergence to the global minimum, a descending sequence $\sigma_1, \sigma_2, \sigma_3, \cdots$ is selected, and search the minimum for each objective function with each σ_i until the value of σ is small enough.

B. CAG (COMPONENTWISE APPROXIMATED GRADIENT) DIRECTION

The steepest descent method is also called gradient method, it is one of the most classic methods to find the optimal solution of the optimization problem [26]. However, the search direction of the steepest descent method is the negative gradient direction, the adjacent search directions are orthogonal, and the search path is actually jagged and the search step size is uncertain. The direction of the steepest descent is only the fastest descent in the direction of local, in the overall situation, the descent is relatively slow. Especially when the isosurface of the objective function is very flat oval, ellipsoid or similar graphics, the convergence rate is slower. The negative gradient direction is not good choice to solve the optimization problem in the overall situation. Compared to the steepest descent method, the Netwon method is more popular in solving optimization problem for its fast rate of convergence [27]. In this paper the Netwon method [28]–[30] can be described as follows:

The implementation process of line search methods are defined as an iterative formula, and in k-th iteration:

$$\boldsymbol{x}^{k+1} = \boldsymbol{x}^k + t_k \boldsymbol{d}_k, \quad k = 0, 1, 2, \cdots \tag{5}$$

where d_k is the search direction and t_k is the step length. Let $g(\boldsymbol{x}) = \nabla F(\boldsymbol{x})$ is the gradient of $F(\boldsymbol{x})$ and $H(\boldsymbol{x}) = \nabla^2 F(\boldsymbol{x})$ is the Hessian matrix. In pure Netwon method, $t_k = 1$ and the search direction in k-th iteration is constructed as follows:

$$d_k = -H^{-1}(\boldsymbol{x}^k) g(\boldsymbol{x}^k) \tag{6}$$

For pure Netwon method, the search direction d_k may not be a descent one when the Hessian matrix is not positive, which can't satisfy the function value is monotonically decreasing. If the initial points is away from the minimum, the significant computational work is needed to search the minimum. So it is crucial for the effectiveness of method to modify the definition of Newton direction or modify the Hessian matrix. However, excessive pursuit of monotonicity will lead to slow convergence to a certain degree. To solve above problem, componentwise approximated gradient (CAG) method [28] is introduced in this paper. In CAG method, the gradient direction is replaced by some gradient components which are selected via a filter mechanism and the procedure will be obligated to move away the area of current point in the event of the starting point is not good.

An approximation $q(x^k)$ of gradient $g(x^k)$ is used, it is the sum of components $\left[q_1(x^k), q_2(x^k), \cdots, q_i(x^k), \cdots, q_n(x^k)\right]$, and each component of $q(x^k)$ is defined by the corresponding gradient component of $[g_1(x^k), g_2(x^k), \cdots, g_i(x^k), \cdots, g_n(x^k)]$. In order to obtain a diminishing direction, each component of $q(x^k)$ must take the minimum value, and the approximation $q_i(x^k)$ of the gradient component $g_i(x^k)$ are constructed by selecting an auxiliary point from the zero contour of $g_i(x^k)$ which are named pivot point [31], [32]. A gradient component $g_i(x^k)$ corresponds to the pivot point x_i^k of $g_i(x)$. If $g_i(x^k)$ is less than or equal to $g_i(x^{k-1})$, the *i-th* approximation component in *k-th* iteration $q_i(x^k)$ can be replaced by the *i-th* gradient component in *k-th* iteration $g_i(x^k)$. On the contrary, the *i-th* approximation component in k-th iteration $q_i(x^k)$ is equal to the function as follows:

$$q_i(x^k) = \partial_n g_i(x^k)(x_n^k - x_n^{k,i}) \tag{7}$$

where $\partial_n g_i(x^k)$ represents the *n-th* order derivative of $g_i(x^k)$, x_n^k represents the pivot point of the *n-th* gradient component in *k-th* iteration $g_n(x^k)$, and the value of $x_n^{k,i}$ can be calculated by the one-dimensional equation:

$$g_i(x_1^k, \cdots, x_{n-1}^k, \cdot) = 0 \tag{8}$$

keeping the first $n-1$ components $x_1^k, \cdots, x_{n-1}^k$ is fixed. In *k-th* iteration, the approximation $q(x^k)$ can be calculated by the function as follows:

$$q(x^k) = q_1(x^k) + q_2(x^k) + \cdots + q_n(x^k) \tag{9}$$

So we can obtain the iterative formula for the solution of equation (4):

$$\boldsymbol{x}^{k+1} = \boldsymbol{x}^k - H^{-1}(\boldsymbol{x}^k) q(\boldsymbol{x}^k) \tag{10}$$

And the CAG direction

$$\hat{d}_k = -H^{-1}(\boldsymbol{x}^k) q(x^k) \tag{11}$$

The specific steps of CAG method is described as follows.
Step 1: Initialize the initial point x^0, the maximum number of iterations $k = J$ and the maximum number of gradient components $i = n$.
Step 2: Let $k = 1$ and $x^1 \leftarrow x^0 - H^{-1}(x^0)g(x^0)$, where H is the Hessian matrix and $g(x^0)$ is the gradient in x^0.
Step 3: Let $k = k + 1$.
Step 4: Judging weather k is equal to J+1. If so, execute step 14, else execute step 5.
Step 5: Let $i = 1$.
Step 6: Judging weather $g_i(x^k)$ is less than or equal to $g_i(x^{k-1})$. If so then execute step 7, else execute step 8.
Step 7: Set $q_i(x^k) \leftarrow g_i(x^k)$.
Step 8: Set $q_i(x^k) \leftarrow \partial_n g_i(x^k)(x_n^k - x_n^{k,i})$.
Step 9: Let $i = i + 1$.
Step 10: Judging weather i is equal to $n + 1$. If so, execute step 11, else execute step 6.
Step 11: Calculate $q(x^k) \leftarrow \sum_{i=1}^{n} q_i(x^k)$.
Step 12: Calculate $x^{k+1} \leftarrow x^k - H^{-1}(x^k)q(x^k)$.
Step 13: Jump to step 3.
Step 14: Set $x \leftarrow x^J$.
Step 15: End.

C. ALGORITHM STEPS OF ISL0

In the actual implementation of ISL0, In order to ensure convergence to the global minimum, a descending sequence $\sigma_1, \sigma_2, \sigma_3, \cdots$ is selected, and the minimum for each objective function with each σ_i should be find until the value of σ is small enough. For some σ, the reconstructed signal $\boldsymbol{x}$ in the last few iterations, fixing the maximum number of iterations J will cause a waste of computing resources. The deviation between $\boldsymbol{y}$ and $\boldsymbol{Ax}$ can be used to decide whether to end the iteration process. In *k-th* iteration, the deviation $\boldsymbol{r}$ can be calculated as follows:

$$\boldsymbol{r}^k = \boldsymbol{y} - A\boldsymbol{x}^k \tag{12}$$

If the equation (13) is satisfied, the iteration process can end in current σ_i.

$$\left| \boldsymbol{r}^k - \boldsymbol{r}^{k-1} \right| \le e \tag{13}$$

where e is a small enough positive number. The proposed ISL0 algorithm is summarized as table 2.

V. PROPOSED SCHEDULING METHOD

Taking into account the cost and harsh deployment environment, the battery of network node is always not updatable. Paper [33] proposes a packet aggregation routing scheme to reduce the amount of redundant and transmission delay and thus reduce the energy consumption of the multi-hop network. In this work, the LoRaWAN-based WSN is a star network, and not all of the nodes work at the same time. To maximize the network lifetime, a scheduling method is

TABLE 2. Implementation process of the proposed ISL0 algorithm.

Initialization: Set the initial value of $\boldsymbol{x}$, the initial σ =1, the initial deviation $\boldsymbol{r}$ =0, $\beta = 0.8$ and the value of e.
for $\sigma = 1$ to 0.01 do
  In k-th iteration
    Calculate the CAG direction $\hat{d}_k$
      $\boldsymbol{x}^k \leftarrow \boldsymbol{x}^{k-1} + \hat{d}_k$
      $\boldsymbol{r}^k \leftarrow \boldsymbol{y} - A\boldsymbol{x}^k$
      if $\left|\boldsymbol{r}^k - \boldsymbol{r}^{k-1}\right| > e$
        $k \leftarrow k+1$
      else
        $\boldsymbol{x} \leftarrow \boldsymbol{x}^k$
      end if
  end iteration
  if $\sigma > 0.01$
    $\sigma \leftarrow \sigma \times \beta$
  else
    $\hat{\boldsymbol{x}} \leftarrow \boldsymbol{x}$
  end if
end for
Return $\hat{\boldsymbol{x}}$

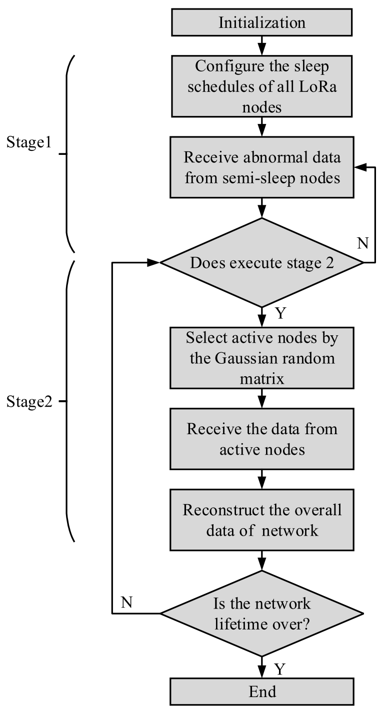

FIGURE 5. Flowchart of the network server.

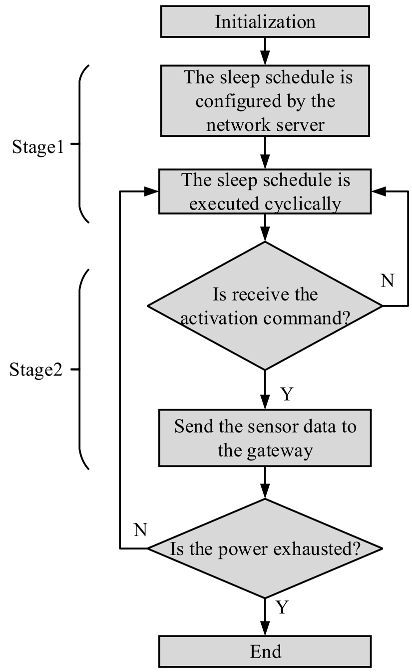

FIGURE 6. Flowchart of each LoRa node.

proposed to reasonably arrange the working state of all LoRa nodes at different times, allow some LoRa nodes to be in semi-sleep mode or sleep mode. The node in semi-sleep mode switches off its sensing device, and the sleeping node switches off its sensing and communication device simultaneously. The suggested scheduling method is shown in Figure 5 and Figure 6, which is explained as follows. Two stages are included in the proposed method. In stage 1, the sleep schedule of each LoRa node should be configured. Let l denote the length of sleep schedule, and the sleep schedule of i-th LoRa node can be expressed as $[T_{i1}, T_{i2}, \cdots T_{il}]$. Only sleep and semi-sleep state are arranged in the sleep schedule, and m semi-sleep nodes are selected randomly in a cycle. The number of m is decided by sensor coverage and LoRa node deployment density. Suppose that all sensors have the same coverage, the greater the deployment density, the greater the number of m. After the sleep schedules of all node are configured, they will be executed cyclically until the gateway send control commands to all nodes to execute the stage 2. Stage 2 is like an interrupt operation for each LoRa node, the network server determines which nodes are activated, and the number of active nodes is decided by the compression rate (the ratio of the number of active nodes to the total number of nodes). According the data of active nodes, the data of whole network can be reconstructed in the network server by using the proposed ISL0 algorithm. In ISL0, the measurement matrix is the Gaussian random matrix. When stage 2 is finished, all LoRa nodes continue to work according to the sleep schedule.

The energy consumption of semi-sleep node and sleep node is lower than that of active node, and only part of LoRa nodes are active in stage 2, so the network lifetime is prolonged to a great extent.

VI. RESULT ANALYSIS AND DISCUSSION

Firstly, a standardized 256 × 256 Lena gray image is used to test performance of compressed sensing algorithms. Secondly, a test system of LoRaWAN is set up as shown Figure 7.

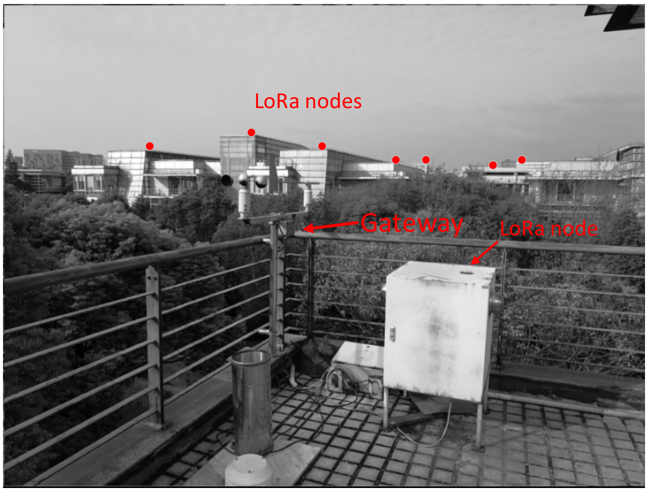

FIGURE 7. Test system of LoRaWAN.

The number of LoRa sensor nodes M is 200 and the number of gateway is 1. In order to estimate the lifetime of proposed scheduling method, the sampling rate α (the ratio of the number of semi-sleep nodes to the total number of nodes) is 0.3, 0.5, 0.7 or 1 in stage 1; the compression rate cr (the ratio of the number of active nodes to the total number of nodes) in stage 2 is 0.5, 0.7 or 1; the length of the sampling period in stage 2 is 20 times that of stage 1; the average power consumption of sleep node, semi-sleep node and active sleep node in per sampling cycle is 0, 1 and $2W$; and initial battery power of each node is $1800J$.

A. SIMULATION RESULTS OF ISL0

Firstly, a standardized 256 × 256 Lena gray image is used to test performance of compressed sensing algorithms. Secondly, a test Figure 8 shows the peak signal to noise ratio (PSNR) of different compressed sensing algorithms with different compression ratios. PSNR represents the ratio of the maximum possible power of the signal to the destructive noise power that affects its accuracy. The larger the PSNR, the better the reconstruction accuracy. From figure 8 and table 3, we can know that the reconstruction accuracies of SL0, ISL0 and BP are better than that of OMP, and the reconstruction accuracy of ISL0 is the highest when the compression ratio is greater than 0.33. The total operate time of different compressed sensing reconstruction algorithms with a different compression ratio is shown Figure 9. It is clear that SL0 and ISL0 are highly faster than OMP and BP, and ISL0 runs the fastest in the four algorithms. ISL0 not only overcomes the problem of heavy computational load of minimizing l^1 norm, but also overcomes the problem of high sensitivity of minimizing l^0 norm to noise.

B. PERFORMANCE TESTING OF LoRaWAN

For a deep understanding of collision and latency in LoRaWAN, we perform two sets of experiments in our test system. Firstly, one LoRa node sends different size data packages to the gateway with different SFs. TOAs in different

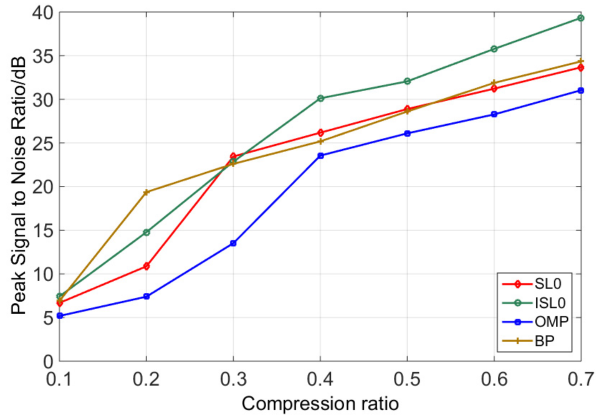

FIGURE 8. PSNR of different compressed sensing algorithms with different compression ratios.

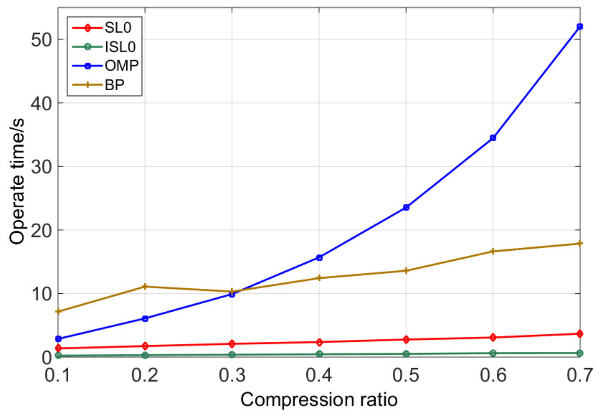

FIGURE 9. Operate time of different compressed sensing algorithm with different compression ratios.

TABLE 3. Relationship of the throughput and the number of LoRa nodes.

Number of nodes	50	100	150	200	250
Throughput (%)	86	69	52	33	27

situations are shown in figure 10. Large SFs mean long communication and big TOA. In order to reduce data transfer delay in real-time scenarios (the transmission time of the signal from the node to the gateway is less than 1 second), we should decrease the distance between LoRa nodes and gateway. Secondly, the LoRa nodes send data packages to the gateway regularly. The relationship of the throughput (the ratio of the number of received packages to the total number of packages) and the number of LoRa nodes is shown in table 3. The LoRa nodes locate in a circular area and a gateway locates at the center of the deployment region. The radius of the circular area is limited as 2 km. The throughput decreases as the number of LoRa nodes increase.

C. MEASUREMENT RESULTS OF ISL0 IN TEST SYSTEM

In order to reduce data latency, the radius of the circular area is limited as 2 km, which means the smaller SFs will be used to decrease TOA of data packages. The LoRa nodes are randomly distributed in the circular area to reduce the

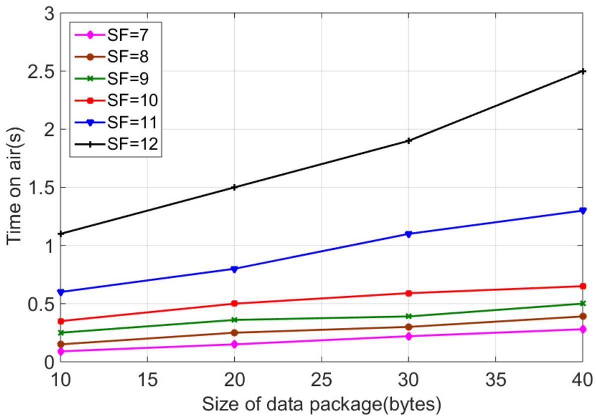

FIGURE 10. Time on air of LoRaWan in different situations.

TABLE 4. Ratio between REMS and the average value of different compressed sensing algorithms with different compression rate.

Algorithms \ cr	0.1	0.3	0.5	0.7	0.9
OMP	0.2132	0.0746	0.0985	0.1096	0.1087
BP	0.1785	0.0434	0.0955	0.0979	0.0968
SL0	0.1544	0.0423	0.0951	0.0946	0.0936
ISL0	0.1323	0.0420	0.0813	0.0892	0.0887

probability that the nodes have the same distance from the gateway. Table 4 shows the ratio between root-mean-square error (RMSE) and the node average value of the different compressed sensing algorithms in our test system with different compression rates. The ratio between RMSE and the average value represents the performance of proposed method. The Lower compression rate means fewer LoRa nodes transmit data packages and lower probability of collision. However, when the compression rate is low, the ratio between RMSE and the average value is high, the reconstruction accuracy of WSN is indeed poor. When the compression rate is 0.5, 0.7 and 0.9, the ratio between RMSE and the average value is higher than that of 0.3. The main reason is that the bigger cr brings higher probability of collision.

D. LIFETIME OF PROPOSED SCHEDULING METHOD

The key of the proposed scheduling method is to make sure each node has the same average power consumption in per sampling cycle. To achieve this purpose, the semi-sleep nodes are selected randomly in each cycle of stage 1 and the Gaussian random matrix is used as the measurement matrix in ISL0 to make sure each node is selected with the same probability in stage 2. The total lifetime of LoRaWAN-based WSN is defined as the number of sampling cycle that each node can work. Figure 11 shows that the total lifetime of LoRaWAN-based WSN with different α and cr. When the value of α is same, the greater cr, the longer the network lifetime. So the use of ISL0 can greatly prolong the network lifetime. Since the network lifetime is only related to the values of α and cr, the number of nodes does not affect the network lifetime. In practical application process, we can set

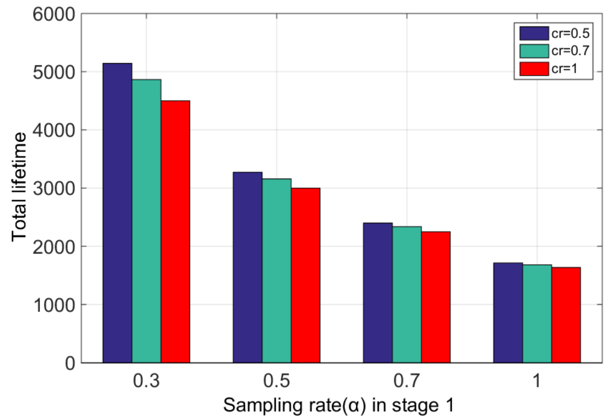

FIGURE 11. Total lifetime of LoRaWAN-based WSN with different α and cr.

neatly the values of α and cr depend on the node deployment density and the reconstruction accuracy requirements.

VII. CONCLUSION

In this paper, LoRaWAN based star wireless sensor network is introduced to monitor environment data and device operating status. Since the subnet has same network structure in LoRaWAN based WSN, the energy efficient scheduling scheme in signal gateway network can be popularized in multi-gateway network. Firstly, the basics and the limits of LoRaWAN are introduced. In order to avoid the limits of LoRaWAN in real-time applications, the considerations of LoRaWAN-based star wireless sensor network are discussed. Then, to prolong the network lifetime, a sleep scheduling scheme based compressed sensing is proposed. The proposed scheme is divided into two stages. In stage 1, the sleep schedule is configured by the network server and each node executes its sleep schedule cyclically. The sleep schedule contains sleep mode and semi-sleep mode, and the semi-sleep nodes is select randomly in each cycle. In stage 2, an improved SL0 algorithm named ISL0 is used to reconstruct the overall network data from part of node data. Simulation and measurement results show that ISL0 has better performance than the previous compressed sensing algorithms. The lifetime of star WSN with the proposed sleep scheduling scheme is only related to the values of α and cr, and the total number of nodes does not affect the network lifetime. All nodes have same power level at different times, and maximization of battery energy utilization is achieved. The compressed sensing algorithm can greatly reduce the number of LoRa nodes that transmit data simultaneously and then reduce receive delay of the gateway, and it provides a new idea for LoRaWAN to break through the limits.

In our future research, we can improve our work from the following aspects:

1) More effective compressed sensing reconstruction algorithm will be studied to obtain more accurate data of wireless sensor network.
2) Better LoRaWAN-based WSN energy scheduling mechanism will be studied to extend the lifetime of wireless sensor network.

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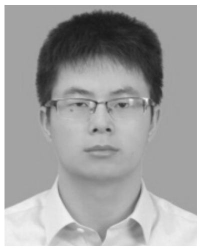

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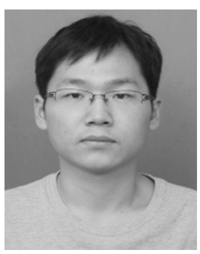

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