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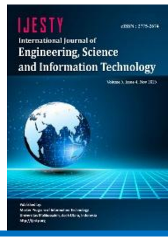

Investigating the Energy Cost for a Wireless Sensor Network using IoT by Implementing RMP Algorithm

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Abstract

Internet of Things (IoT) sensor networks frequently see energy savings since the nodes in the network are powered by their own finite batteries. While data processing uses a lot less energy than data transmission in IoT sensor nodes is expensive & energy intensive. Over the last few years, wireless sensor systems based on IoT has witnessed an evolutionary breakthrough across several industries various sectors. The Internet of Things, or IoT, is a network that allows physical items, machinery, sensors, and other devices to communicate with one another without the need for human intervention. The WSN (Wireless Sensor Network) is a central component of the IoT, which has proliferated into several different applications in real-time. Nowadays, the critical and non-critical applications of IoT and WSNs affect nearly every part of our daily life. WSN nodes are usually small, battery-powered machines. Therefore, Energy-efficient data aggregation techniques that prolong the network's lifespan are crucial. Reducing data transmission is the primary goal of many energy-saving techniques and concepts. As a result, significant energy savings can be achieved in IoT sensor networks by reducing data transfers. The proliferation of IoT-based Wireless Sensor Network has triggered a paradigm shift in the business, necessitating the use of dependable and efficient routing techniques. A compression-based data reduction (CBDR) method that operates at the level of IoT sensor nodes was proposed in this study. To recover the data at the sink or BS end, we suggest using a Randomised Matching Pursuit algorithm. Additionally, beneficial is the use of CLH and relay routing.

Keywords: *Internet of Things, Energy Saving, Compression Based Data Reduction, Randomized Matched Pursuit, Cluster Head.*

1. Introduction

The Internet is currently transitioning from a system for connecting people to one for connecting things, or the modern Internet of Things (IoT). By integrating items or things into the Web, the contemporary idea creates new businesses and applications. These items, which range from external environmental sensors to wearables inside buildings, create new sources of information, generate data for the Internet, and collectively increase the online entities' awareness of their surroundings [1]. Wireless sensor networks (WSN) are one of the key components of the IOT. WSN is a network of many distributed, wirelessly connected sensors used for physical and environmental surveillance. WSNs are an IoT branch that are widely employed in many smart technologies & services, including smart cities, smart homes, smart buildings, smart transportation, & smart healthcare [2]. Generally speaking, sensing devices have limited battery power, processing and storage capacity, radio communication range, dependability, etc. Nevertheless, they should be deployed over a large terrain. Energy conservation is crucial in WSN-based IoT because sensor nodes are powered by limited batteries. If a large number of sensors are dispersed over a large area like the deep sea or the area around volcanoes, it may be uncomfortable or extremely difficult to replace or recharge them when the batteries run out. Energy is used by IOT sensor nodes in a variety of ways, including sensing, data processing, receiving and transmitting, and more. Of these, data transmission is the most energy-intensive in terms of power usage, but data processing is thought to require far less [3]. A single bit of data transfer nearly uses as much energy as processing a 1000 processes in a typical sensor node. Because of this, figuring out how to reduce the IOT sensor nodes' power exhaustion has become crucial to extending the network's lifespan and meeting application demands.
There are too many methods and ideas focused on preserving energy, particularly on reducing data transfer [4]. When data that are identical to those received before the compression operation can be recovered after the decompression process is finished, it is referred to as "lossless compression" [5].

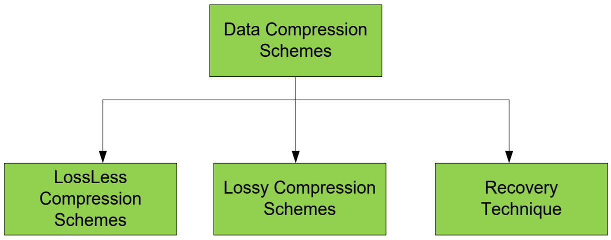

Fig 1. Classification of Data Compression technique

The main contribution of this work is to reduce transmission costs without sacrificing forecast and data processing (DP) accuracy [6]. The authors of the study [7] provide a revolutionary architecture that integrates data recovery, compression, and prediction in a way that has never been done before. In this study, we will examine five main categories of WSN data compression methods, as shown in Figure 1.

1. String-based compression techniques compress sensor data by using text data compression techniques.
2. Image-based compression techniques adapt the concept from image compression techniques and first hierarchically organise WSNs to handle sensing data.
3. The Slepian-Wolf theorem is extended by distributed source coding techniques, allowing several correlated data streams to be independently encoded and decoded at sensor nodes
4. Compressed sensing techniques compress data by using a minimum amount of randomised, non-adaptive linear projection samples.

The application of Randomized Matching Pursuit (RMP) to enhance energy efficiency in IoT and WSN addresses a significant and ongoing challenge in these fields—extending network lifetime while minimizing energy consumption. Although numerous approaches have been proposed, including hierarchical network structures, clustering, data aggregation, and energy-efficient routing protocols, the integration of RMP-based local data compression with cluster head rotation and relay routing offers a novel perspective. While the individual components of data compression, cluster head rotation, and efficient routing are well-established, their combined use through the RMP algorithm is relatively unexplored. This approach differentiates itself by practically merging existing energy-saving techniques with a modern compression algorithm, which can significantly reduce redundant data transmissions and communication overhead. The resulting layered strategy has the potential to improve network sustainability more effectively, making a meaningful and distinctive contribution to the ongoing research on energy-efficient solutions in IoT and WSNs.
The rest of the paper is organized as follows: Section.2 explains about the literature survey of the existing methods. The proposed WSN design has been explained in section.3. Section.4 gives the simulation results of the proposed work. Section.5 concludes the proposed work.

2. Literature Review

An rising number of novel jobs requiring vision, surveillance, object detection, tracking, and geolocation are being done with wireless sensors [8]. While sensor nodes are frequently battery-powered, the main purpose of WSN applications is long-term environmental monitoring. This means that in order to pro- long the life of the sensors, batteries must be preserved [9]. In sensor nodes, transmission accounts for the bulk of energy use. Compressing data is one method of reducing gearbox power use. Data compression method research is becoming essential for many applications, especially multimedia.
In present days the most important factor for improving the larger WSNs with useful applications is figuring out how to make the improve the network function for a dead time without consuming the large amount of power that can be stored in or obtained by individual wireless sensor nodes. Since the network is heavily dependent on sensor node data transmission, strategies to reduce the amount of data transferred between nodes are highly sought. As a result of this study, less network data transfer occurs because data is now compressed locally before being shared.
Although the field of data compression has been around for a while, most existing methodologies cannot be directly applied to wireless sensor nodes due to limited hardware resources, specifically data memory and programmed memory. On existing wireless sensor nodes, compression techniques may be applied, but doing so would leave limited room for other operations like sensing and transmission.

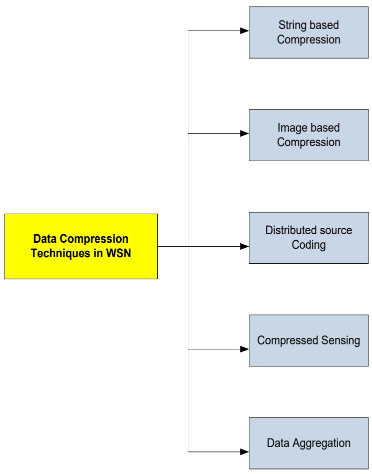

Fig 2. Data Compression method in WSN

These nodes wouldn't be able to experience the deep sleep states that would have allowed them to realise the energy savings that had motivated them to select a compression method. In recent years, WSNs have witnessed a profusion of novel data compression algorithms. Many of these techniques may correlate data gathered by sensor nodes and achieve high compression ratios with little computational cost [10].

A few of the data types that sensors can record are text, pictures, video, and audio [11]. Different types of telemetry data may need the use of different compression algorithms. The author of [12] compressed text using the LZW & Flate algorithms with DFTs. Compressing telemetry data from hyperspectral sensors installed on satellites can be done in two essentially lossless ways [13].

A distributed compression architecture was created by [14] using combined source and channel coding. This approach minimises the amount of inter-node communication needed for compression by utilising both quantised and correlated side information. A gossip communication system is used in [14] to take a similar approach. Even though universality is asserted, there are trade-offs between power, distortion, and latency issues.

A 2:1 compression ratio is achieved by compressing launch vehicle data using a modified compression technique. Various data compression techniques can be combined to produce a high compression ratio. For improved compression efficiency [15] proposed a modularised method to strike a compromise between hard- ware costs and a practical compression ratio. [16] predicted higher rates of decompression and compression using a two-stage hardware architecture.

In [17], the author explained the energy efficient WSN routing technique for IOT application by adding new nodes with existing cluster strength. Also in this paper they explained multi hub centers and sensor network forming for these nodes.

But the majority of the time, the purpose of putting a WSN into place is to keep an eye on a particular, interesting event. This paper proposes an algorithmic strategy that combines basic Huffman encoding with Run Length Encoding (RLE) to achieve compression ratios that surpass state-of-the-art methods currently in use [18-20]. Limiting the amount of data transmitted between nodes is very important because it is a significant energy drain on the network from sensor node data transfer. In order to reduce network traffic, the main objective of this study is to compress data locally before sending it and is shown in Figure 2.

3. Methods

The two steps of our suggested protocol are:

1. Setup
2. Data compression and transmission

We choose the cluster and construct the path between the source and sink nodes during the setup phase. In the second stage, we use our chosen CH and relay nodes route to compress the data from member nodes to BS and send it to the sink. We apply the fitness function-based Dingo Optimiser method to determine the optimal CLH. Figure 3 depicts N sensor nodes that are in the field, and the following assumptions were made:

1. Every sensor node and SINK node is a static node with the same significance and capabilities.
2. Every sensor node can manage any kind of traffic.
3. All sensor nodes have an equal starting energy allocation, and the network is homogeneous.
4. The transmission power of each sensor node was set, but it could be changed based on the under-radius recipient's distance.
5. All the sensors have symmetric links between nodes, and they can all determine distance using received signal strength (RSSI).
6. Every sensor node could function in both forwarding and sensing modes.
7. There is a correlation between the nearby nodes detected. Because of this, the cluster head is able to compile the information gathered from its neighbouring cluster into fixed-length packets.
8. There won't be a sink node death.

3.1. Phase of data compression and transmission

There are four steps in this phase:

1. Data collecting and compression between cluster members and CH as well as between cluster members and RLY and BS
2. Reconstruction;
3. Dynamic CH rotation and random seed re-generation
4. Utilise the CLH and RLY node updating algorithm with Dingo optimiser at the conclusion of this step

3.2. Compression and collection of data both intra- (from cluster member to CH) and inter- (from RLY to BS)

By using the member list that we established during the Intra-cluster set-up step (from cluster member to CH), memberlist=[M0,M1,..M(last-1),M(last)]. In each intra-cluster, our suggested effort begins with data collecting and compression as follows: Using the global seed W that it obtained from the BS, the last node M(last) in the memberlist generates M(last).

The measurement YM(last) is sent by the M(last) node to its previous neighbour node M(last-1) in the memberlist after it computes its compress vector (measurement) N(last) = $\eta M_{last} H M_{last}$, where HM_{last} is the reading of sensor M(last). Using the same global seed W, node M(last-1) then constructs $\eta M_{(last-1)}$. It then computes its measurement, YM(last-1)=$\eta M_{(last-1)} H M_{(last-1)}$, and transmits the summation vector, YM(last)+YM(last-1) to the node that came before it, YM(last-2). The summation value is sent to the previous node in the memberlist, and so on, until it reaches $CLHLH_i$. First, M(last-2) computes its value. Then, it adds YM(last-2) to YM(last)+YM(last-1). The compressed vector Y_i = [Y (M_0), Y M_1, ..., Y M_{last}] has already been delivered to each CLH CLH_i by the relevant cluster members. The compressed data is then sent by each CLH to the nearest RLY.

3.3. Reconstruction Step

After receiving the compress vector N= [N_1, N_2, N_3, ..., N_i], where i = [1,2,.....,nCLH] given by the Relay node, the BS generates the measurement matrix based on the predetermined random seed W. The starting data (X0) for each cluster is then recreated by the BS. The RMP algorithm, also known as the Randomised Matching Pursuit algorithm, is utilised in our suggested study and is explained in result analysis.

3.4. Random seed regeneration that is dynamic

The main idea behind this step is that instead of using the same compressed sensing matrix generated during the Setup phase in every round, the proposed work allows the compressed sensing matrix to be changed dynamically based on the state of the network and the number of nodes that are still alive. In this manner, it is possible to successfully lower the total power consumption. By sending a HELLO message to each CLH, each CLH may determine the number of dead nodes in its cluster in each round. This allows the BS to obtain the number of dead nodes in each cluster from RLY through the CLHs.

3.5. CLH rotation

Depending on the remaining energy in each cluster, CLHs decide whether to continue as CLHs or hand over their responsibilities to any other node. They then identify the remaining energy of the piggybacked cluster members to identify these nodes as the new CLHs. By balancing energy use, this technique prevents premature WSN death.

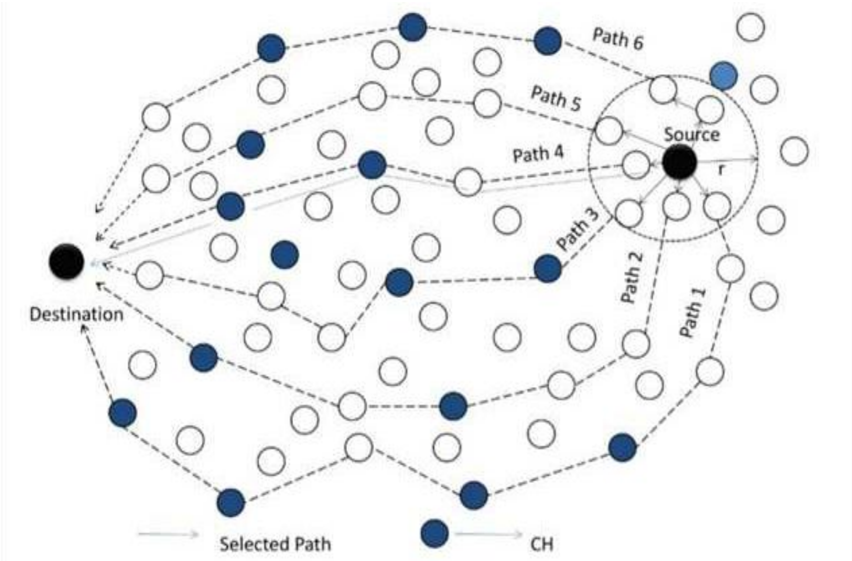

Fig 3. Proposed WSN design

Algorithm: RMP algorithm

1. INPUT: Φ: MXN → Compressive sensing matrix, y → compressed vector & S → signal sparsity
2. Result:Reassembled Signal E_k
3. Initial design:
4. T=φ; r^0 = y; k=0; F=φ; E_o=0
   do while K=k+1
5. Step forward: F= $\varphi^{+} * r^{k-1}$
   R=rand(F,q)
   H=supp(F,s) U=H ∪ R

   T=U ∪ supp($E_k - 1$)

   step:
   $W|T=\varphi_T + y^1 0$

   Update the step
   $r^k = resid(y, E_k)$
   $if\|r^k\|2 \leq \gamma ork = E_max$ then Stop

4. Results and Discussion

Performance Assessment: This section first discusses the suggested method's considerations for simulation setup before analysing the simulation's output. The simulations are performed using the NS-2 R2015a program.

4.1. Configuration for Simulation

We examined the scenario that reflects the case of variable sparsity and the same transform domain to assess the effectiveness of our approach. For modelling purposes, real-world sensor data from Intel Lab [15] is used and extrapolated to 250 node data.

$Pa = Pre < 0.1$ ……………………………………………………………………………………………..(1)

$Ps = E(Pa)$ ……………………………………………………………………………………………..(2)

where Pa= the likelihood that the error vector's values will be less than 0.1 Ps= average probability of a full recovery.

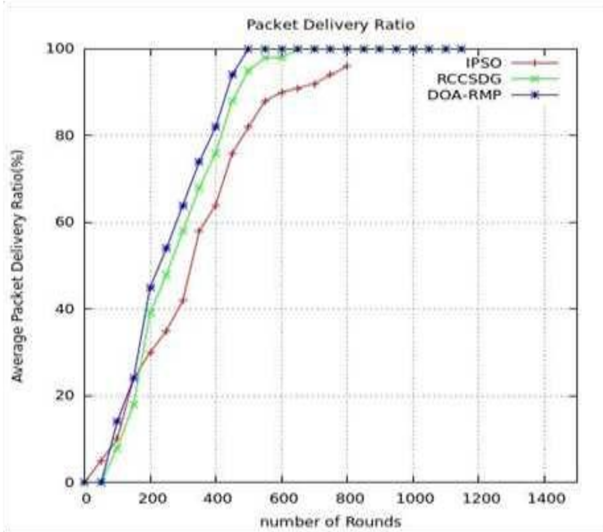

Fig 4. Number of Packet for the sensor node

To perform a transmission cost research, we employed an arbitrarily deployed network with n = 250 nodes in a 200 unit field, where each node is interfaced with r = 3 different sensors as mentioned earlier. For comparison analysis, dense random projections created with the CS method [3] serve as a baseline. Assume that every sensor node is stationary and is shown in Figure 4.

Table 1. Data Compressor Parameter

Parameter	Explanation
Din	Sensor input
Info ()	Information of node
Rcode	RLE of repeat count
Loc	Pointer location
Final stream	stream packet output
Unique	Unique data in the stream
Pk	Size of Packet
NYT	Not Yet Transmitted
Length	Stream length

1. The research makes the assumption that a single BS will receive the data collected from source IoT nodes.
2. Homogeneous SNs are those with comparable communication and processing capacities. It also considers the fact that the initial energy of every SN is the same.
3. SNs that are randomly released always have x and y coordinates that fall inside the topological
4. When utilising Euclidean distance, the distance between two nearby super- novae.

As the research indicates, it is further investigated in a number of situations with different network areas, grid/cluster counts, and node counts overall. Depending on the network area, there might be anywhere from 8 to 100 grids and a total of 100 to 1250 nodes. Table.1 offers more details on each of these possible results. Various situations are based on the hybrid routing protocol, its parameter settings, and the network layout, as documented in [12]. Figure 5 shows the energy consumption and Figure 6 gives the noise control of the proposed design.

Table 2. Compression Ratio

	Compression ratio			
Input data(bits)	Ref[16]	Ref[17]	Ref[18]	Proposed design
250	0	2.5	4	6
400	1	2.5	7	8
600	1	3	8	10
800	1	3	11	12
1000	1	3	11	14

1200	1	3	12	17
1400	1	3	14	18
1600	1	3	18	24

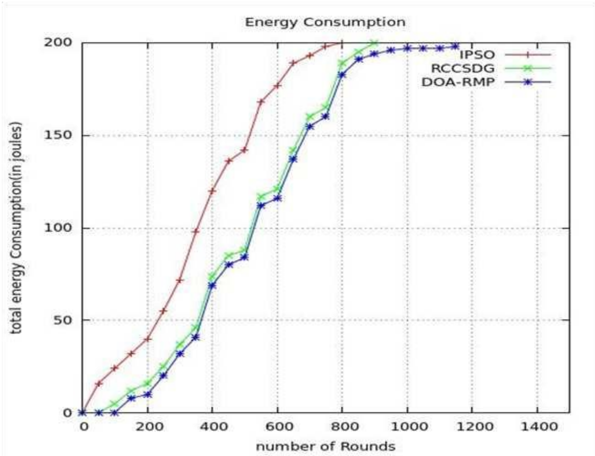

Fig 5. Energy Consumption

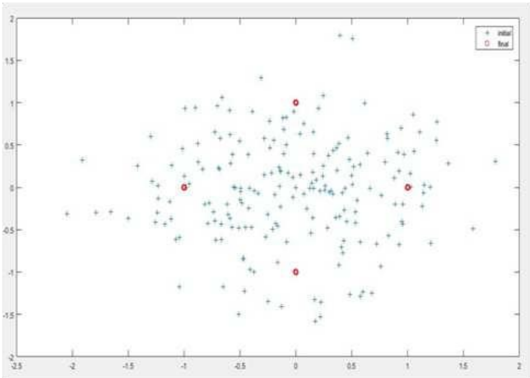

Fig 6. Noise reduction

Table 2 gives the compression ratio of different existing designs and proposed design and the output graph is shown in Figure 7.

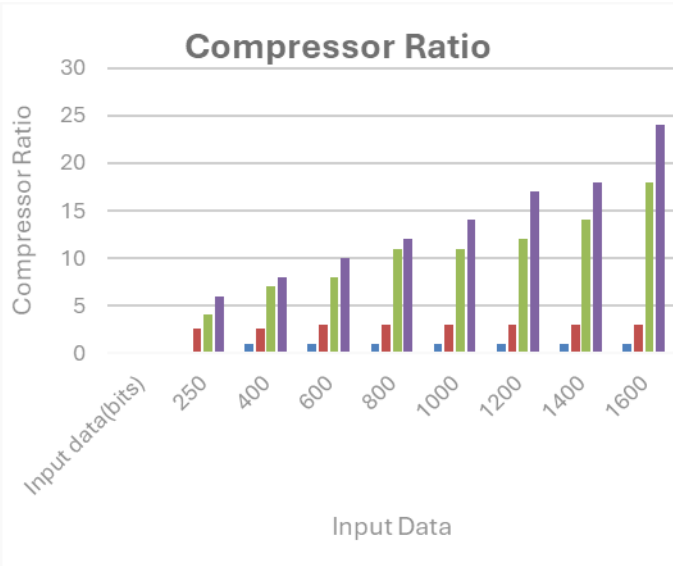

Fig 7. Compression ratio

5. Conclusion

Apart from data transmission efficiency, it is crucial to safeguard these Internet of Things (IoT)-based sensor applications against malevolent actors. Data encryption is incorporated into the study and its effects on energy consumption and network life-time are assessed. This holds significance for real-world WSNs, since the sensed data must be encrypted prior to being com-pressed and sent. RMP is examined in terms of simulation & security findings demonstrate that it adds no appreciable overheads that could lengthen the network's lifespan. In the future, data aggregation may be the focus of efforts to further improve the effectiveness of the network.

Data aggregation is the process of combining data packets utilising various bio- inspired routing techniques. This is achieved by adjusting the data sets that are collected from sensor nodes and sent to the sink, hence adjusting the minimum, maximum, and/or mean. Applications of routing algorithms and data compression techniques are necessary for efficient data aggregation.

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