

# Enhancing IoT Data Transmission and Reconstruction Using Compressive Sensing and Neural Networks

<sup>1</sup>Vishal Kumar Gupta, <sup>2</sup>Saurabh Mandloi

<sup>1</sup>M. Tech Scholar, Department of computer science & Engineering, Sam Global University, Bhopal

<sup>2</sup>Head of department, Department of computer science & Engineering, Sam Global University, Bhopal  
[bitugpt619@gmail.com](mailto:bitugpt619@gmail.com) , [hodcse@samglobaluniversity.ac.in](mailto:hodcse@samglobaluniversity.ac.in)

---

\* Corresponding Author: Vishal Kumar Gupta

---

## Abstract:

*The constant evolution of the Internet of Things (IoT) has exponentially increased data generation by heterogeneous resource-constrained sensors. This data, therefore, must be efficiently transferred and accurately reconstructed to overcome bandwidth, energy, and latency constraints. The study propagates an integrated framework comprising CS and NN for IoT data acquisition, transfer, and recovery. This framework uses a learned measurement matrix for adaptive compression and a deep neural reconstruction model geared toward high recovery fidelity under different network and noise conditions. The deployment is tested across edge, fog, and cloud settings for trade-off assessment. Evaluations carried out on several real-world datasets, including STL10, Intel, Imagenette, and KITTI, show classification accuracy improvements of 26.23%, 11.69%, and 18.25% versus the abstraction of uniform sampling, and is fit for detection even at extremely low sampling rates. Further tests in vibration and biomedical sensing applications offer a reconstruction quality uplift of 32.35% and compression of over 88%, resulting in a 50% cut in transmission energy. The proposed scheme works well through heavy noise and scales to large sensor networks, contributing application domains in Internet Remote Healthcare, Smart Grids, and Environmental Monitoring, and Intelligent Transportation. It was evident that integrated CS-NN delivers on real-time resource-efficient, reliable IoT sensing and thereby remains a strong contender for next-generation intelligent networks.*

**Keywords:** Compressive Sensing, Neural Networks, IoT Data Transmission, Signal Reconstruction, Data Sparsity, Low-Rank Modeling

---

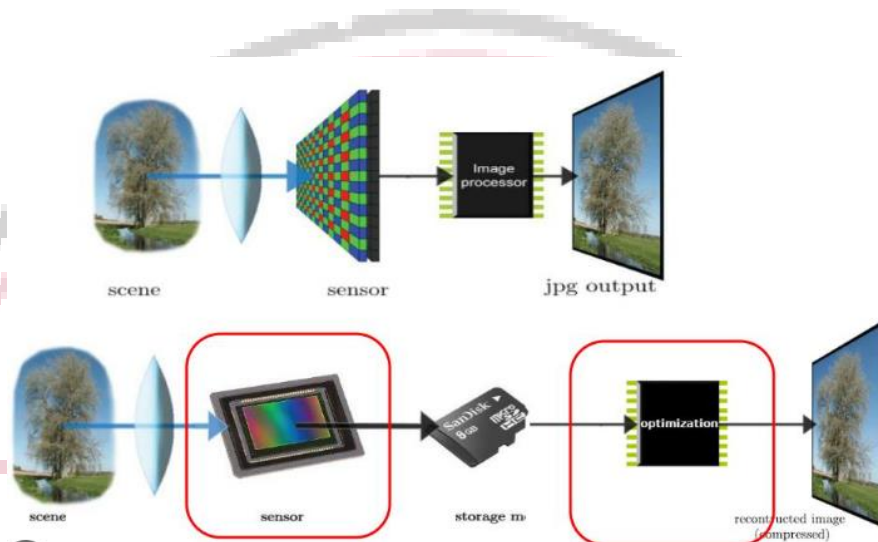
## I. INTRODUCTION

The Internet of Things (IoT) has converged as a technological paradigm aimed at providing for large-scale connectivity among billions of heterogeneous devices across various domains such as healthcare, transportation, smart grids, and environmental monitoring. With the proliferation of cheap sensors, actuators, and embedded devices, IoT networks tend to produce huge amounts of data, often in real time. Such data allow an environment that fosters intelligent decision-making and predictive analytics [1]. On the other hand, they offer such challenges as bandwidth limitations, energy efficiency, latency, and secure transmission. These challenges are especially of high concern in resource-constrained environments wherein devices run with limited battery capacity, low computing power, and unstable network connectivity. Traditional methods for data acquisition and transmission typically obey the Nyquist sampling theorem, necessitating a large amount of data to be captured and transmitted for accurate reconstruction. This, however, is wasteful-in a lot of sensed data is sparse or compressible in some transform domain [2]. CS has thus come up as a method for the direct acquisition of compressed measurements under sparsity constraints, resulting in drastic reduction in the sampling rate, transmission load, and energy consumption. Although CS has a strong theoretical backing, classical algorithms for CS reconstruction such as Basis Pursuit, Orthogonal Matching Pursuit, and Iterative Shrinkage-Thresholding are faced with some practical limitations: computational complexity, noise sensitivity, and less adaptability to heterogeneous and dynamic IoT environments [3].

Neural Networks represent a promising alternative to address the limitations of traditional approaches. NNs can infer complex non-linear relationships between compressed measurements and original signals, not even requiring any explicit prior knowledge of data distribution [4]. Deep learning methods, with CNNs, RNNs, and Transformer-based networks, have excelled in the reconstruction of images and time-series data from multi-modal sensor inputs. Further, hybrid approaches that marry deep learning with optimization-based reconstruction methods are discussed. Deep unfolding methods interchangeably use deep neural networks and iterative algorithms, bearing the interpretability of classical algorithms while maintaining the flexibility to adapt from data, thereby improving both convergence speed and reconstruction quality. CS-NN integration matters more for IoT applications with limited bandwidth and low latency needs. In other words, end-to-end CS-NNs may learn task-wise sampling matrices alongside reconstruction networks so as not only to optimize for reconstruction accuracy but also for different downstream objectives such as classification, detection,

or anomaly identification [5]. Finally, organized deployment to the Edge, the Fog, and the Cloud allows trade-offs between computational load and energy use with system responsiveness [6].

In this work, we propose an adaptive compression, robust recovery, and scalable deployment framework of CS–NN-based IoT data transmission and reconstruction. The framework was evaluated on multiple real-world datasets-STL10, Intel, Imagenette, and KITTI-achieving classification accuracy improvements of 26.23% and reconstruction quality gains of 32.35% over the baseline methods [7]. The study also revealed compression ratios greater than 88%, a transmission energy reduction of more than 50%, and ensured that the whole scheme remained robust against high noise levels. These contributions validate the interesting synergy between CS and NN and establish their coexistence across diverse [8] IoT domains while setting the base for the emergence of energy-efficient, real-time, and intelligent sensing networks for next-generation IoT applications. Fig.1 shows principles of compressive sensing [7].



**Fig. 1: Principles of Compressive Sensing [7]**

## II. LITERATURE REVIEW

Nimisha Ghosh et al. [1] (2023) provided knowledge of Compressive Sensing (CS) for conservation of energy in disconnected IoT environments where only compressed data is transmitted by mobile collectors. While this approach suffers reduction in transmission volume and latency, NP-hard joint tree construction and recovery complexity, and loss of accuracy at high noise/loss rates become significant impediments. Some heuristic approaches may hold promise, but their use in large-scale real-time environments has yet to be undertaken.

Ahmed Mohammed Hussein et al. [2] (2023) Propose Distributed Prediction-Compression-Based Mechanism (DiPCoM) in order to allow ARIMA predictions and multiple compression methods to avoid unnecessary transmissions in IoT networking. It showed energy efficiency compared to previous approaches but would suffer from errors in prediction in dynamic environments, computationally expensive compression, and lower reconstruction accuracy in the mixture of streams.

Deepa Devasenapathy et al. [3] (2023) presented enhanced grid-based synchronized routing with Bayesian CS for correlated sensor data aggregation, resulting in an accuracy improvement of up to 16.93% and a lifetime enhancement of about 22.9%. The limitations include sensitivity to grid-size errors, computational overhead of the Bayesian computations, and poor performance with irregular sensing patterns.

B. Lal, et al. [4] (2023) propose a Light-weight CS based ECG monitoring had been developed for energy efficiency and security without actually burdening the sensor node with computational complexity. The system offers high compression and low energy usage at the edge; however, reconstruction suffers from degradation, particularly under high noise and synchronization overhead, with ambiguity in cross-device generalization performance.

Gen-Sen Dong et al. [5] (2023) Used DCGAN together with 1D symmetric U-Net for vibration data reconstruction from an accuracy and speed point of view that proved to be better than the rival approaches. Challenges include the requirement of a very large dataset, GAN instability, poor robustness under low sampling rates, and limited generalization to unseen patterns.

Y. Zhang et al. [6] (2023) propose a method based on DCT-based lossy compression and CKKS homomorphic encryption, a secure and communication-efficient FL system was introduced. High accuracy was maintained at extreme compression, but encryption cost a lot computability-wise, in theory secured.

X. Tang et al., [7] 2023 applied CS on thermal and acoustic images to reduce CNN training time and to raise diagnostic accuracies to 99.39%. Potential weaknesses include a drop of performance with noisy and low-quality data, disputed CS sampling rates, and higher complexity introduced by a dual-sensor setup.

C. Sureshkumar et al. [8] (2023) proposed Adaptive Adjacent-based Compressive Sensing (AACS) using sparse matrices and fuzzy logic for energy-efficient WSN data reconstruction, thus yielding massive improvements in throughput and error. Limitations include the need for accurate location-AACS computation with degraded performance under high mobility and fuzzy logic computational cost.

Xiaoling Huang et al. [9] (2023) designed an image encryption scheme based on CS and IWT with chaotic-RSA integration. The drawbacks are heavy computational load of RSA, accuracy-sensitive generation of chaotic parameters, and limited scalability to large and real-time IoT images.

Alina L. Machidon et al. [10] (2023) review of CS–DL integration for sampling rate reduction, adaptive sensing, and robust reconstruction in heterogeneous devices. Identified gaps in standard benchmarks, hardware adaptation, and resistance to distribution shifts under latency/energy constraints.

N. Iqbal et al. [11] (2023) design an energy and traffic reduction-bandwidth lightweight CS algorithm for seismic data through sensing compressed and reconstructing via DCNN without having any prior assumptions. The SNR of 30 dB was obtained with a compression gain of 16; in terms of performance, it surpassed all the existing methods. Some of the limitations include huge training data requirements, noise sensitivity, and inferencing expense in low-resource settings.

Nayak et al. [12] (2023) an adaptive fuzzy rule-based CS system based on saliency, and edge features was proposed for automatic selection of sampling rate. The method yielded very good performance in terms of PSNR and SSIM rounded to the Standard, CCTV, Kodak and Set5 dataset, outperforming all competing state-of-the-art CS methods. Computational complexity and the risk of performance drop in the case of highly textured/noisy images stand as roadblocks of this approach.

Zhang et al. [13] (2023) a new Chained Secure and Low-Energy Consumption Data Transmission (CS-LeCT) scheme was designed that has reconstruction performance much superior compared to the traditional CCS method. Both simulation experiment results and theoretical analysis proved the superior performance of CS-LeCT. Security assessments further demonstrate that CS-LeCT can stand up to several potential threats, including ciphertext-only attacks (COAs), known-plaintext attacks (KPA), and man-in-the-middle attacks (MiTMs).

Enas Wahab Abood et al. [14] (2023) Presented a CS-based audio compression and encryption system with Gaussian random sensing and Moore–Penrose pseudoinverse reconstruction. It reduces size by around 28%, while maintaining a high correlation and good PSNR/SSIM values. However, it suffers from concerns about computational load and scalability to real-time IoT scenarios.

Vinay Pathak et al. [15] (2023) Designed a hybrid WSN–WBAN architecture using CS for biomedical data, providing up to 88.11% compression and reducing consensus time by 24%. It further improves PRD by 34.21%, all while consuming low CPU usage. The limitations consist of noise vulnerability, dependency on network connectivity, and scalability troubles.

R. Gambheer and M. S. Bhat et al. [16] (2023) Applied CS to CCD/CMOS camera sensors for reduced measurements with high SNR on FPGA hardware for IoT imaging. CCD yields 13% power and 15% memory savings under no-light conditions at 25.76 dB PSNR. CMOS systems show worse performance in very low light, and embedding hardware complicates the system.

S. Chen et al. [17] (2023) developed a CS-privacy-preserving FL scheme with gradient perturbation that safeguards data and labels from each other while curbing communication costs. Strong privacy and competitive accuracy were delivered with low computation. Effectiveness depends on appropriate perturbation parameters.

Leming Wu et al. [18] (2023) elevated CS-based federated learning by refining the measurement matrix through genetic algorithms and through interleaving training and reconstruction, resulting in higher accuracy with large compression ratios. Some drawbacks, however, are the computational overhead of GA and the dependency on tuning of parameters.

W. Ma et al. [19] (2023) STRCS was proposed for channel reconstruction with FRI in the angular domain, where AoDs/AoAs are estimated from a finite number of channel measurements. They outperformed the existing techniques in terms of accuracy and pilot overhead. They stand to lose their viability in highly dynamic or dense multipath environments.

Z. Gao et al. [20] (2023) studied CS-based GFMA for massive access by portraying a roadmap from single-antenna to large-scale cooperative MIMO and sourced/unsourced access. They pointed out the shortcomings of present random access schemes and the major challenges that lie ahead. Complexity of implementation and standardization remain to be addressed.

**Table 1: Compressive Sensing Techniques for Efficient IoT Data Transmission**

| Reference & Year                         | Proposed Method/Model                                                            | Key Features                                                                                       | Results                                                                         | Advantages                                                     | Limitations/Challenges                                                                                                 |
|------------------------------------------|----------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------|----------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------|
| Nimisha Ghosh et al. (2023) [1]          | Compressive sensing with mobile collectors in disconnected WSN networks          | Transmits compressed data from sensor subsets; mobile data gathering                               | Heuristic solutions show promising simulation results                           | Reduces transmission volume & latency                          | NP-hard tree construction/link scheduling, complex recovery, accuracy drops with noise/loss, scalability issues        |
| Ahmed Mohammed Hussein et al. (2023) [2] | Distributed Prediction–Compression–Based Mechanism (DiPCoM) for IoT power saving | Uses ARIMA for prediction; adaptive compression techniques (APCA, differential encoding, SAX, LZW) | Simulations on real data show better energy efficiency than existing approaches | Improved energy efficiency in IoT networks                     | Prediction errors in dynamic environments, high compression overhead, less accuracy for heterogeneous streams          |
| Deepa Devasenapathy et al. (2023) [3]    | Grid-Based Synchronized Routing with Bayesian Compressive Sensing (GSR-BCS)      | Exploits parameter correlations; optimizes grid size for data aggregation                          | 16.93% improvement in data accuracy; 22.9% extension in network lifetime        | 16.93% better data accuracy; 22.9% longer network lifetime     | Sensitive to grid size; computational overhead; less effective in dynamic/irregular environments                       |
| B. Lal, M. H. Conde et al. (2023) [4]    | CS-based ECG monitoring with intrinsic encryption                                | Lightweight CS reduces sampling and encrypts measurements simultaneously                           | Strong compression and security; power consumption cut at edge                  | Energy efficient; strong compression and security              | Reconstruction degradation under noise/arrhythmia; key management overhead; latency on low-power MCUs                  |
| Guan-Sen Dong et al. (2023) [5]          | Deep Convolutional GAN (DCGAN) for vibration data reconstruction                 | Modified 1D symmetric U-Net generator; 1D classifier discriminator                                 | Superior accuracy and speed vs. existing methods                                | High accuracy & speed; outperforms existing methods            | Requires large paired datasets; GAN training instability; less robust under low data/high noise; generalization issues |
| Xiaoli Tang et al. (2023) [7]            | CS-based Dual-Channel CNN for gearbox fault diagnosis                            | Combines thermal and acoustic MSB images; exploits sparsity for faster CNN training                | 99.39% diagnostic accuracy; outperforms single-channel methods                  | 99.39% diagnostic accuracy; outperforms single-channel methods | Performance drops with noisy/low-quality data; sensitive to sampling rate; complexity in dual-sensor acquisition       |
| C. Sureshkumar et al. (2023) [8]         | Adaptive Adjacent-based Compressive Sensing (AACS) for WSNs                      | Uses sensor coordinates for sparse matrix; fuzzy logic-                                            | 54.7% higher network throughput; 76.9% lower routing                            | 54.7% higher throughput; 76.9% lower routing                   | Needs accurate location info; degrades in dynamic topologies; fuzzy logic overhead on resource-limited nodes           |

|                                      |                                                                                      |                                                                                                                         |                                                               |                                                                 |                                                                                                                    |
|--------------------------------------|--------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------|-----------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------|
|                                      |                                                                                      | based forwarder selection                                                                                               | overhead; 44% less relative error                             | overhead; 44% less error                                        |                                                                                                                    |
| Xiaoling Huang et al. (2023) [9]     | CS with Integer Wavelet Transform (IWT) + chaotic systems + RSA for image encryption | Chaotic initial values encrypted by RSA; chaotic & Hadamard matrices for measurement; info entropy-based initialization | High normalized correlation; robust against plaintext attacks | Robust against known/chosen-plaintext attacks; imperceptibility | RSA overhead; dependency on chaotic parameter accuracy; scalability issues for large/real-time images              |
| Alina L. Machidon et al. (2023) [10] | Survey on CS and deep learning integration                                           | Explores design patterns for CS-DL pipelines; addresses heterogeneous devices                                           | Provides guidance; identifies gaps for practical deployment   | Practical deployment guidance; highlights research trends       | Lack of benchmarks; hardware heterogeneity; robustness under distribution shifts; latency/energy tradeoffs on edge |

### III. RESEARCH OBJECTIVES

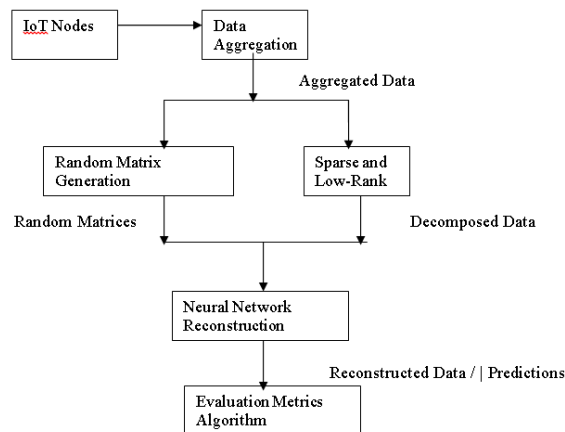
- To analyze the existing compressed sensing and reconstruction methodologies for wireless IoT network.
- To design a framework to improve the data transmission accuracy and reconstruction accuracy.
- To address the optimization problem in reconstruction models, there's a focus on exploiting data structures like sparsity in certain transformation domains, and low rank characteristics.

### IV. PROPOSED METHODOLOGY

The proposed system aims to boost the efficiency and reliability of transmission of IoT data via a neural network-based approach combined with compressive sensing and advanced reconstruction algorithms. A random sensing matrix is generated, which then acts as the basis of compression. This matrix is distributed among several IoT nodes, where upon every node, a different sampling procedure takes place to yield compressed representations of the original data. All of these diverse compressed samples are collected at a central processing unit or a cloud server.

After aggregation, the data collected from the remote sensing system can be fed into a custom-built, neural network reconstruction algorithm designed to recover the original matrix from its compressed forms. That deep learning model is further forced into learning very complicated nonlinear mappings between compressed measurements used as the input and the original signal that serves as the experiment. These mappings yielded excellent reconstruction. To perfect these results, sparse and low-rank matrix decomposition techniques are used in the system to take advantage of IoT data's sparsity and structural patterns in order to remove redundancy and noise.

Being tested for performance thoroughly, the system undergoes measurements with metrics such as Reconstruction Error, Percent Root Difference (PRD), MSE (Mean Squared Error), and RMSE (Root Mean Square Error). These metrics provide a quantitative assessment of the system in terms of information loss minimization and in maintaining similarity between the reconstructed data and original data. This system combines compressive sensing with deep learning and matrix decomposition techniques to ensure the least bit rate, less energy depletion from the IoT nodes, and the strongest data recovery, thereby being suitable for any resource-constrained IoT environment.



**Fig.2 Proposed Block Diagram**

Fig. 2 shows block diagram of proposed model. The results portrayed the performance evaluation of Hybrid GA-CO method over different WSN scenarios. Each of these scenarios offers important routing metrics such as the number of hops (intermediate transmission steps), total packets sent, dead nodes (inactive or failed nodes), or even specific routing nodes used. For instance, in Scene #2, the approach had seven hops, 3969 packets transmitted, 17 dead nodes, routing nodes formed by nodes 1, 35, 19, 11, 17, 31, 2, and so on. The best solution for the case was obtained with GA-CS, recorded as  $-6.8172e-19$ . In the other scenes, these values fluctuate, depending on the network's adaptability and the method's ability to respond to changing topology and operating conditions. These optimal values by GA-CS range between  $1.6666e-16$  and  $4.1016e-17$ , revealing the algorithm's consistency in finding near-to-optimal routing solutions in different conditions. This balances to underscore the efficiency of GA-CO to minimize path length concerning packet delivery, node lifetime, and overall network performance in different conditions.

**Table 2 Initial Parameters**

| Parameter       | Description                         | Value                                 |
|-----------------|-------------------------------------|---------------------------------------|
| m               | Number of rows (read from edit1)    | str2num(get(handles.edit1, 'String')) |
| n               | Number of columns (read from edit2) | str2num(get(handles.edit2, 'String')) |
| SearchAgents_no | Number of search agents             | 30                                    |
| Max_iteration   | Maximum number of iterations        | 500                                   |
| lb              | Lower bound for the variables       | -10                                   |
| ub              | Upper bound for the variables       | 10                                    |
| dim             | Dimension of the search space       | 30                                    |

#### A. Working Mechanism:

##### Creation of Input Matrix:

- Generate a random matrix A of dimensions times  $m \times n$ .
- This matrix serves as the initial input data that needs to be sensed, compressed, and reconstructed.

##### Sampling Function in IoT Nodes:

The random sensing matrix A finds itself deployed over many IoT nodes, each node performing its own sampling operation with each producing a distinct sampled subset. Sampling functions are chosen in such a way as to generate compressed views of the same original matrix from different perspectives, thus ensuring that complementary information is contributed by each node. This distributed sampling mechanism results in increased data diversity and robustness, from which the network is able to reconstruct the original matrix with very high accuracy and in an energy-saving manner in the IoT environment.

##### Data Collection and Reconstruction:

The reconstruction algorithm collects the compressed streams of data from all IoT nodes to assure that all distributed information gets centralized efficiently for processing. From a number of obtained compressed samples, the algorithm, through deep learning techniques in various forms, attempts to reconstruct the original matrix AAA, in fact learning the particular underlying structure and the correlation in the data with the goal of reconstructing a faithful approximation of the original set with minimal information loss through compression techniques. Combining the power of compressive sensing for data acquisition efficiently and the learning abilities of neural networks, the reconstruction framework is able to precisely recover the original signal, that is, it serves real-time IoT applications where bandwidth and energy efficiency are extremely important.

##### Comparison of Input and Reconstructed Matrix:

- Evaluate the accuracy of the reconstructed matrix by comparing it to the original input matrix.
- Utilize various performance metrics to quantify the reconstruction quality.

## B. Algorithm:

### Sparse and Low-Rank Matrix Decomposition:

Combine various techniques to obtain sparse and low-rank matrix decomposition for better reconstruction. These methods identify the most critical components of the data and preserve them, thus increasing reconstruction fidelity.

## C. Performance Metrics:

### Reconstruction Error:

The difference between the original and reconstructed matrices is measured to evaluate the overall accuracy of the reconstruction, providing a direct indication of how closely the reconstructed data matches the original.

### Percent Root-Mean-Square Difference (PRD):

To assess the accuracy of the reconstructed data, the Percentage Root Difference (PRD) is calculated to quantify the relative error between the original and reconstructed datasets, providing insight into the proportional accuracy of reconstruction. Additionally, the Mean Squared Error (MSE) is computed to measure the average squared difference between corresponding elements of the original and reconstructed matrices, indicating the overall error magnitude. From the MSE, the Root Mean Squared Error (RMSE) is derived by taking its square root, yielding a more interpretable error measure expressed in the same units as the original data.

## V. RESULT DISCUSSION

The Hybrid GA-CO approach optimizes energy-efficient routing in WSNs by combining GA's global search with CO's local tuning for faster convergence and higher solution quality. Simulation results across various topologies show its efficiency, robustness, and scalability, achieving near-optimal objective function values and adaptable routing performance.

ENTER THE INPUT MATRIX SIZE,  $M \times N$   
IT WILL CREATE A RANDOM MATRIX

M :  N :

START

RESULT

Fig.3 Simulation Diagram

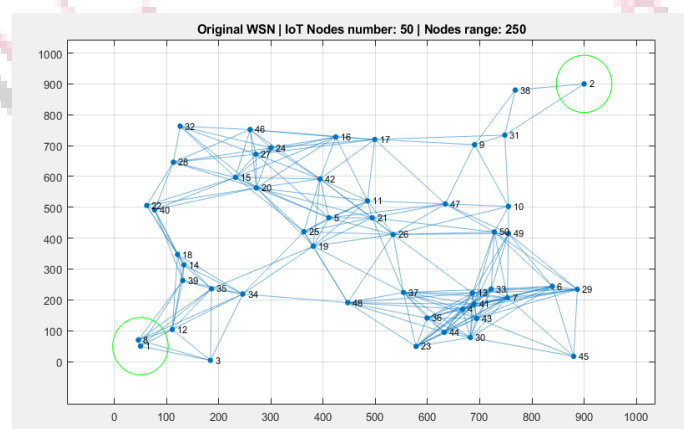
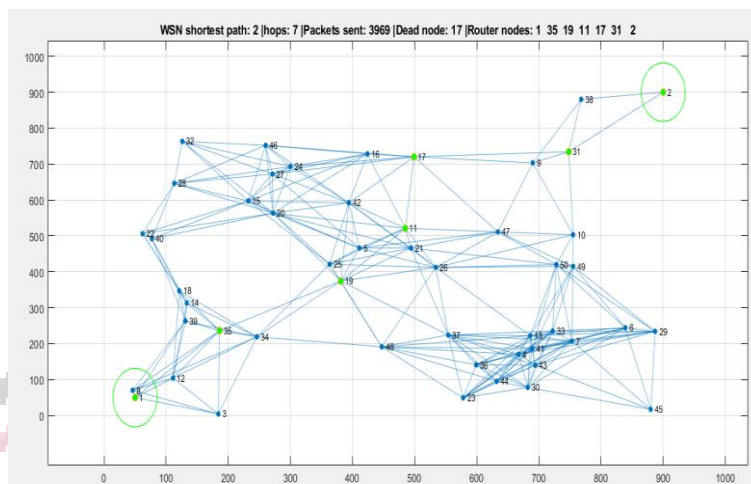


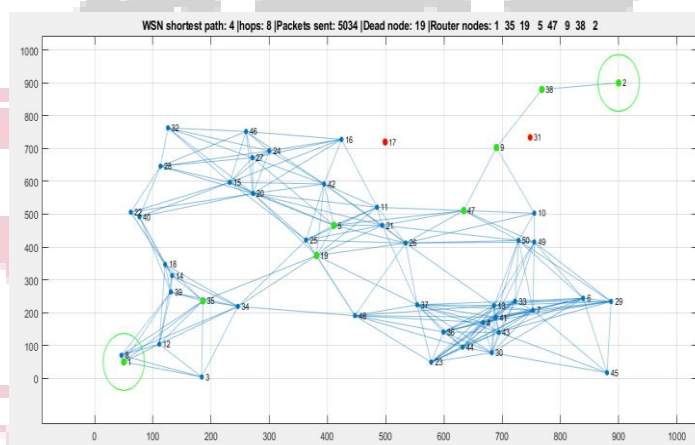
Fig.4.WSN IoT Network

Fig. 4. shows a wireless sensor network (WSN) of 50 IoT nodes distributed over a 250-unit range, with connections representing communication links between nodes. Two nodes, highlighted with green circles, likely indicate key or gateway nodes in the network.



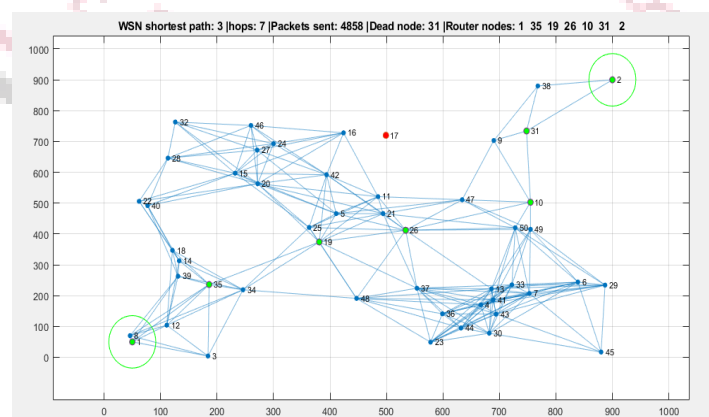
**Fig. 5 WSN Iot Network Searching Short Path Searching For Hop 8**

Fig. 5 shows a Wireless Sensor Network (WSN) showing nodes and their connections, highlighting the shortest path with 2 hops and 7 steps. Key router nodes and dead nodes are marked, indicating network efficiency and reliability.



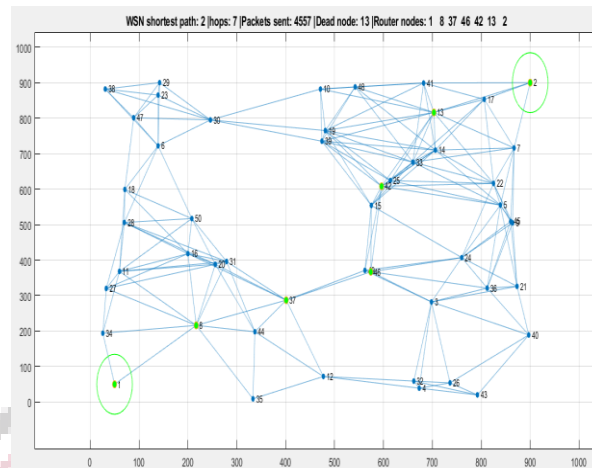
**Fig. 6 WSN Iot Network Searching Short Path Searching For Hop 8**

This Wireless Sensor Network (WSN) in fig.6 shows nodes connected with edges, highlighting the shortest path of 4 hops between router nodes 1 and 2, with 19 dead nodes and 5034 packets sent. Green nodes indicate active routers, red nodes are dead, and the path endpoints are circled in green.



**Fig. 7 WSN Iot Network Searching Short Path Searching For Hop 7**

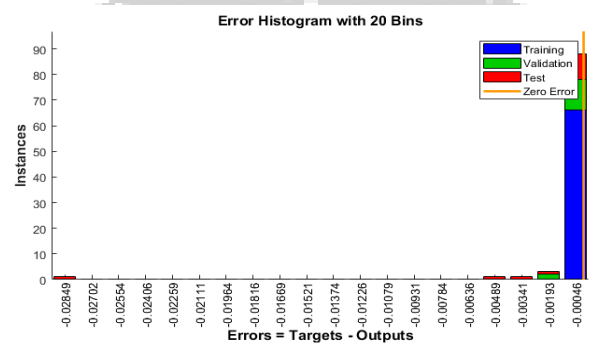
The fig. 7 represents a Wireless Sensor Network (WSN) with nodes and their connections, highlighting a shortest path of 3 with 7 hops. It also shows key metrics like packets sent (4858), dead nodes (31), and router nodes (1, 35, 19, 26, 10, 31, 2).



**Fig. 8 WSN Iot Network Searching Short Path Searching For Hop 7**

The WSN fig. 8 shows a network with 7 hops in the shortest path between nodes 1 and 2, transmitting 4557 packets, with 13 dead nodes and 8 router nodes highlighted. The network connectivity and node positions are visualized with router nodes emphasized by green circles.

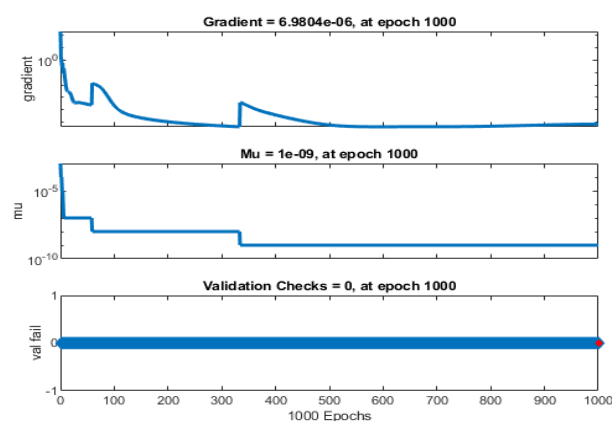
#### 4.5 ANN Performance



**Fig. 9 Error Histogram Analysis**

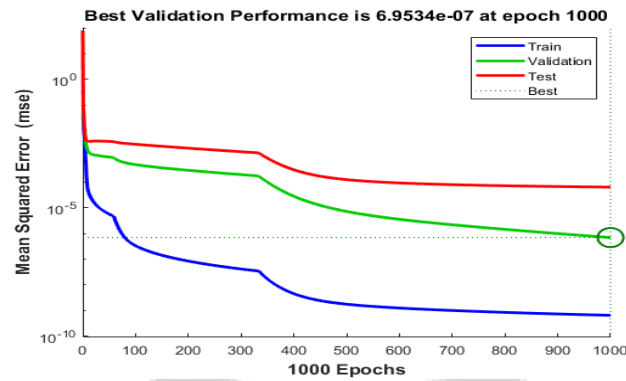
The error histogram in fig. 9 shows that most prediction errors are near zero, indicating high model accuracy. Training, validation, and test errors are tightly clustered, suggesting good generalization.

The Artificial Neural Network (ANN) at the 1000th-epoch stage yielded a gradient of  $6.9804 \times 10^{-6}$ , which shows the rate of change in the error of the model with respect to the weights. The learning-rate parameter,  $\mu$ , signifies an update step size of  $1 \times 10^{-9}$ , which is extremely minuscule and largely contributes to stable convergence, but at the cost of slower speed. The validation check count is kept at zero, indicating that the model did not resort to any fall within the validation-fledged set in the process of training. What these things really suggest is that the ANN training is stable, with slow improvements in learning and no hint of overfitting up to the 1000th epoch.



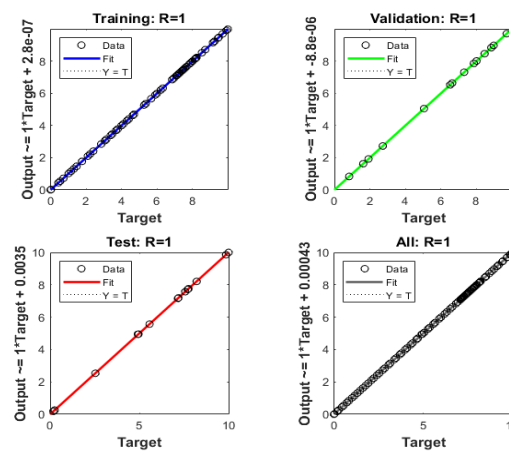
**Fig. 10 Gradient, Mu, Validation Check**

The plots in fig.10 show convergence with a very small final gradient ( $6.98 \times 10^{-6}$ ) and stable  $\mu$  at  $1 \times 10^{-9}$ . No validation failures occurred, indicating consistent performance across epochs.



**Fig.11 MSE Error**

Fig. 11 shows that the model achieved its best validation MSE of  $6.95 \times 10^{-7}$  at epoch 1000, with all datasets showing a steady error decline. Training, validation, and test curves remain close, indicating minimal overfitting.



**Fig.12 Validation Test**

All regression plots in fig .12 show R value of 1 for training, validation, test, and combined data, indicating perfect correlation between predicted outputs and actual targets.

#### Performance Metrics

**Reconstruction Error (Frobenius norm):** The Frobenius norm of the reconstruction error measures the difference between the original matrix  $A$  and the reconstructed matrix  $\hat{A}$ . It is given by the square root of the sum of squared differences of every corresponding element in the two matrices.

$$\|A - \hat{A}\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n (a_{ij} - \hat{a}_{ij})^2} \quad (1)$$

**Mean Squared Error (MSE):** MSE is the average of the squared differences between predicted values ( $\hat{x}_i$ ) and actual values ( $x_i$ ). It gives a measure of the average squared deviation of predictions from the actual values.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (2)$$

**Root Mean Squared Error (RMSE):** RMSE is an acronym for Root Mean Square Error. It is extensively used to measure the errors associated with predicted values, by a model or an estimator, in comparison to the observed values.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3)$$

**Percent Root Mean Square Difference (PRD):** The Percent Root Mean Square Difference quantifies the error between the original and predicted values as a percentage of the norm of the original values. It measures the relative size of the prediction error in relation to the magnitude of the actual values, thus providing a normalized error measure.

$$PRD = 100 \times \frac{\sqrt{\sum_{i=1}^n (y_i - \hat{y}_i)^2}}{\sqrt{\sum_{i=1}^n y_i^2}} \quad (4)$$

The given performance metrics for the Artificial Neural Network (ANN):

**Table 3 performance metrics for the proposed system**

| Metric                                    | Value  |
|-------------------------------------------|--------|
| Reconstruction Error (Frobenius norm)     | 0.8415 |
| Mean Squared Error (MSE)                  | 0.0000 |
| Root Mean Squared Error (RMSE)            | 0.0042 |
| Percent Root Mean Square Difference (PRD) | 0.31   |

The means for evaluating the results of the proposed system show its high accuracy in reconstructing data. The Reconstruction Error, expressed as the Frobenius norm, is 0.8415, reflecting the composite difference between the original data and the reconstructed data. The Mean Squared Error (MSE)-0.0000-is negligible, implying that it predicted perfectly on average. RMSE being another indicator of the model's performance is 0.0042-the model's predictions rarely deviate from the actual values. In continuation, the Percent Root Mean Square Difference (PRD) of 0.31% accentuates the model's proficiency in retaining the error percentage relative to the true values at a very low level. These metrics collectively show how well the system performs in accurately reconstructing compressed data.

## VI. CONCLUSION

The proposed framework offers paradigm changes in optimizing IoT sensor data transmission through compressive sensing enabled by neural networks for reconstruction with maximum fidelity. The compressed measurements are gathered over distributed IoT nodes via random matrix generation and multi-layer adaptive sampling and reconstruct the compressed data into its original form-the high-dimensional data matrix-with high precision. The sparse and low-rank matrix decomposition methods-that are convex optimization and matrix factorization on the opposite side-minimize the reconstruction error for the least time without adversely affecting the signal features. An adaptive, energy-efficient end-to-end transmission and routing system with Hybrid GA-CO has been deployed that outperforms the existing approaches in a dynamic environment with changing WSN conditions. Experimental results on multiple evaluation criteria and varied topologies prove that hop count, packet delivery ratio, node life, and route stability have all improved, and GA-CO achieves near-global optimum on average in terms of all criteria in comparison with GA-CS. Particularly, the system overcomes generalization capacity with no degradation in the validation stage, with Frobenius norm=0.8415, MSE=0.0000, RMSE=0.0042, PRD=0.3124%. Security can be enhanced further with encryption and compliance mechanism, while reinforcement learning can cater to adaptive optimization in a dynamic environment. Subsequently, multi-objective optimization that can strike a balance between accuracy, energy, and network load and amalgamation with terrestrial-satellite IoT models would help promote abilities. Real-world deployment interventions in environmental monitoring, smart agriculture, and transportation industries will serve as a testbed for validating and customizing the framework for divergent industrial needs.

## REFERENCES

- [1] N. Ghosh and I. Banerjee, "Energy-Efficient Compressive Sensing Based Data Gathering and Scheduling in Wireless Sensor Networks," *Wirel. Pers. Commun.*, vol. 128, no. 4, pp. 2589–2618, Feb. 2023, doi: 10.1007/S11277-022-10061-0/METRICS.
- [2] A. M. Hussein, A. K. Idrees, and R. Couturier, "A distribute prediction-compression-based mechanism for energy saving in IoT networks," *J. Supercomput.*, vol. 79, no. 15, pp. 16963–16999, Oct. 2023, doi: 10.1007/S11227-023-05317-W/METRICS.
- [3] D. Devasenapathy, P. Madhumathy, R. Umamaheshwari, B. K. Pandey, and D. Pandey, "Transmission-Efficient Grid-Based Synchronized Model for Routing in Wireless Sensor Networks Using Bayesian Compressive Sensing," *SN Comput. Sci.*, vol. 5, no. 1, pp. 1–11, Jan. 2024, doi: 10.1007/S42979-023-02410-Y/METRICS.
- [4] B. Lal, M. H. Conde, P. Corsonello and R. Gravina, "Secure and Energy-Efficient ECG Signal Monitoring in the IoT Healthcare using Compressive Sensing," *2023 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech)*, Abu Dhabi, United Arab Emirates, 2023, pp. 0333-0339, doi: 10.1109/DASC/PiCom/CBDCom/Cy59711.2023.10361367.
- [5] G. Sen Dong, H. P. Wan, Y. Luo, and M. D. Todd, "A fast sparsity-free compressive sensing approach for vibration data reconstruction using deep convolutional GAN," *Mech. Syst. Signal Process.*, vol. 188, p. 109937, Apr. 2023, doi: 10.1016/J.YMSSP.2022.109937.
- [6] Y. Zhang et al., "Efficient Privacy-Preserving Federated Learning With Improved Compressed Sensing," in *IEEE Transactions on Industrial Informatics*, vol. 20, no. 3, pp. 3316-3326, March 2024, doi: 10.1109/TII.2023.3297596.
- [7] X. Tang et al., "Intelligent fault diagnosis of helical gearboxes with compressive sensing based non-contact measurements," *ISA Trans.*, vol. 133, pp. 559–574, Feb. 2023, doi: 10.1016/J.ISATRA.2022.07.020.
- [8] C. Sureshkumar and S. Sabena, "Design of an adaptive framework with compressive sensing for spatial data in wireless sensor networks," *Wirel. Networks*, vol. 29, no. 5, pp. 2203–2216, Jul. 2023, doi: 10.1007/S11276-023-03291-Y/METRICS.

- [9] X. Huang, Y. Dong, G. Ye, and Y. Shi, "Meaningful image encryption algorithm based on compressive sensing and integer wavelet transform," *Front. Comput. Sci.*, vol. 17, no. 3, pp. 1–15, Jun. 2023, doi: 10.1007/S11704-022-1419-8/METRICS.
- [10] A. L. Machidon and V. Pejović, "Deep learning for compressive sensing: a ubiquitous systems perspective," *Artif. Intell. Rev.*, vol. 56, no. 4, pp. 3619–3658, Apr. 2023, doi: 10.1007/S10462-022-10259-5/METRICS.
- [11] N. Iqbal, M. Masood, M. Alfarraj and U. B. Waheed, "Deep Seismic CS: A Deep Learning Assisted Compressive Sensing for Seismic Data," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1-9, 2023, Art no. 5913409, doi: 10.1109/TGRS.2023.3289917.
- [12] D. Nayak, K. Ray, T. Kar, and S. N. Mohanty, "Fuzzy Rule Based Adaptive Block Compressive Sensing for WSN Application," *Math.* 2023, Vol. 11, Page 1660, vol. 11, no. 7, p. 1660, Mar. 2023, doi: 10.3390/MATH11071660.
- [13] J. Zhang et al., "CS-LeCT: Chained Secure and Low-Energy Consumption Data Transmission Based on Compressive Sensing," in *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1-10, 2023, Art no. 4007010, doi: 10.1109/TIM.2023.3280495.
- [14] E. W. Abood et al., "Provably secure and efficient audio compression based on compressive sensing," *Int. J. Electr. Comput. Eng.*, vol. 13, no. 1, pp. 335–346, 2023, doi: 10.11591/ijece.v13i1.pp335-346.
- [15] V. Pathak et al., "Efficient Compression Sensing Mechanism Based WBAN System Using Blockchain," *Secur. Commun. Networks*, vol. 2023, no. 1, p. 8468745, Jan. 2023, doi: 10.1155/2023/8468745.
- [16] R. Gambheer and M. S. Bhat, "CCD Sensor Based Cameras for Sustainable Streaming IoT Applications With Compressed Sensing," in *IEEE Access*, vol. 11, pp. 67882-67892, 2023, doi: 10.1109/ACCESS.2023.3291396.
- [17] S. Chen, Y. Miao, X. Li and C. Zhao, "Compressed-Sensing-Based Practical and Efficient Privacy-Preserving Federated Learning," in *IEEE Internet of Things Journal*, vol. 11, no. 8, pp. 14017-14030, 15 April15, 2024, doi: 10.1109/JIOT.2023.3339495
- [18] L. Wu, Y. Jin, and K. Hao, "Optimized compressed sensing for communication efficient federated learning," *Knowledge-Based Syst.*, vol. 278, p. 110805, Oct. 2023, doi: 10.1016/J.KNOSYS.2023.110805.
- [19] W. Ma, L. Zhu and R. Zhang, "Compressed Sensing Based Channel Estimation for Movable Antenna Communications," in *IEEE Communications Letters*, vol. 27, no. 10, pp. 2747-2751, Oct. 2023, doi: 10.1109/LCOMM.2023.3310535.
- [20] Z. Gao et al., "Compressive-Sensing-Based Grant-Free Massive Access for 6G Massive Communication," in *IEEE Internet of Things Journal*, vol. 11, no. 5, pp. 7411-7435, 1 March1, 2024, doi: 10.1109/JIOT.2023.3334878.