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RESEARCH ARTICLE

A MULTIPLEXED TRANSMISSION SYSTEM FOR ENVIRONMENTAL MONITORING WITH CONVOLUTION ENCODING AND VITERBI DECODING

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Abstract

Reliable transmission of environmental sensor data over noisy wireless channels remains a critical challenge in large scale environment monito ring systems. Ensuring data integrity while maintaining low latency and bandwidth efficiency is essential for real-time applications. The proposed work presents an efficient simulation framework for multiplexed transmission of data using Convolutional Encoding and Viterbi Decoding. The proposed system combines multiple sensor streams via Time Division Multiplexing and applies a Convolutional encoder with a code rate 1/2, constraint length 7, generator polynomials (171, 133) to enhance error resilience. Transmission is modeled over an Additive White Gaussian Noise (AWGN) channel, and both hard and soft decision Viterbi decoding algorithms are evaluated. Simulation results show that at 6 dB SNR, the system achieves a zero Bit Error Rate (BER) for all four sensors using both hard and soft decision decoding. At lower SNRs (e.g., 2 dB), soft decision decoding reduces BER to as low as 0.0100, significantly outperforming hard decision decoding. The framework also maintains low latency, with average encoding time of 0.1232 seconds, hard decoding time of 0.0070 seconds, and soft decoding time of 0.0060 seconds. These results confirm the proposed work's effectiveness in achieving reliable, real-time transmission of environmental data under noisy conditions, making it suitable for scalable and efficient environmental monitoring applications.

Introduction:-

Environmental monitoring is crucial for addressing global challenges such as climate change, resource management, and urban development. Networks of spatially distributed sensors have evolved to become key technologies for real-time data acquisition on environmental variables such as temperature, humidity, air quality, and soil moisture. However, transmission of this data over wireless channels reliably remains difficult, especially as sensor deployments grow larger and communication conditions become increasingly noisy due to interference and signal fading.For efficient transmission of data received from multiple sensors over a shared communication medium, Time Division

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Multiplexing (TDM) is commonly employed, which assigns distinct time intervals to each sensor, enabling orderly and collision-free data flow. Although TDM improves bandwidth utilization and simplifies receiver design it does not provide for inherent protection against transmission errors introduced by noisy channels. Therefore, forward error correction techniques like convolutional encoding combined along with Viterbi decoding areused to enhance communication reliability. These methods introduce redundancy and use maximum likelihood decoding to detect and correct errors without requiring retransmissions, which makes them highly suitable for time-sensitive and resource-constrained environmental monitoring applications.Despite advancements in sensing and wireless technologies, there remains a pressing demand for robust and scalable transmission schemes that maintain low latency while ensuring data integrity. This work presents a MATLAB-based simulation framework integrating time division multiplexing with convolutional encoding and both hard and soft decision Viterbi decoding to address these needs. The proposed system demonstrates effective, low-delay transmission of multiplexed data over noisy channels, offering a foundation for reliable wireless monitoring systems applicable to critical domains such as disaster management, precision agriculture, and urban planning.

Literature Survey:-

GPU-based Viterbi decoder capable of achieving an extremely high throughput of 76.5 Gb/s using 4-bit quantization was presented. The study emphasizes the use of massive parallelism and memory optimization techniques to significantly reduce decoding latency. Interleaving strategies are employed to maintain data integrity during handling of large volumes of input streams. This approach demonstrates the feasibility of real-time processing for high-speed communication systems. Such hardware-accelerated decoding is highly relevant for environmental monitoring frameworks that require processing of large-scale sensor data efficiently.[1] Long-distance quasi-distributed FBG sensor system based on time-division multiplexing using heterodyne detection was developed which demonstrated and enhanced sensitivity and feasibility of multiplexed sensing over 42 km, thereby supporting efficient multi-sensor monitoring for large-scale applications [2]. High-speed convolutional encoder and Viterbi decoder was developed and optimized for FPGA deployment in software-defined radio systems, with emphasis on hardware acceleration, coding parameters, and algorithmic structures [3].CRC-assisted bit flipping algorithm was developed to enhance soft-decision Viterbi decoding. By selectively flipping unreliable bits based on CRC checks, the method improves the frame error rate by 0.6–0.8 dB compared to conventional CRC-assisted SOVA, while requiring only minimal additional CRC overhead. This technique ensures reliable sensor data transmission under harsh noise conditions, providing a practical solution for maintaining data integrity without any substantially increase in the decoding complexity or latency [4].

LoRa-based image transmission system employing time-division multiplexing was implemented to enable synchronized multi-sensor communication, highlighting TDM’s effectiveness in coordinating low-power IoT nodes for reliable multi-sensor data transfer [5]. Low-power asynchronous Viterbi decoder was developed to reduce energy consumption in digital communication systems, emphasizing efficiency in resource-constrained environments. A Forward Error Correction (FEC) system with convolutional encoding and Viterbi decoding was also done, demonstrating BER improvements in noisy channels [6]. An analysis of FPGA-based implementation of convolutional encoders was made to evaluate speed and performance. The findings underscore the trade-offs between coding efficiency and implementation complexity [7]. Indoor optical wireless communication (Is-OWC) system was implemented using convolutional encoding and Viterbi decoding to improve the error correction in optical links [8]. TDM-based vector signal synthesizer was developed using photonic time-stretch techniques to improve bandwidth efficiency, supporting the use of time-division multiplexing for handling multi-sensor data streams [9]. Performance analysis of convolutional codes with a fixed code rate of ½ was done , evaluating BER under varying SNR conditions [10]. Viterbi decoder implementation on reconfigurable FPGA platforms, comparing hard- and soft-decision architectures in terms of resource utilization and speed [11].

SOPC-based implementation of convolutional encoders and Viterbi decoders with variable constraint lengths, supporting constraint length 7 and generator polynomials (171, 133), which align with the current MATLAB simulation framework was implemented to enhance error resilience in multiplexed sensor data transmission [12]. Optimized design of convolutional encoders and Viterbi decoders was studied for efficient digital data transmission, focusing on reducing complexity yet maintaining accuracy [13]. A forward error correction system using convolutional encoding and Viterbi decoding, demonstrating BER improvements in noisy environments [14].high-speed, low-power Viterbi decoder tailored for Trellis-Coded Modulation (TCM) systems, focusing on latency optimization to support real-time sensor communication [15].

DC-free binary convolutional codes to suppress low-frequency spectral components in encoded data, enriching the theoretical understanding of coding variants and inspiring future designs for energy- or frequency-constrained transmission environments was referred [16]. May analysed the BER performance of Viterbi decoding for 64-QAM and 64-DAPSK modulated OFDM signals under AWGN and fading channels, highlighting the effectiveness of soft-decision decoding in noisy environments for improved reliability in sensor data transmission [17].The reviewed works provided key insights into the design of convolutional codes, TDM systems, and Viterbi decoders across both simulation and hardware platforms. They highlighted the importance of balancing reliability, efficiency, and latency in noisy environments. These findings provided relevant background information for the development of the proposed MATLAB framework, guiding the choice of coding parameters, decoding techniques, and multiplexing strategies for scalable and noise-resilient environmental monitoring.

Methodology:-

This section presents methodology used to simulate the proposed system in MATLAB. The framework integrates convolutional encoding, time-division multiplexing (TDM), and Viterbi decoding to support reliable data transmission in the presence of channel noise.

Convolutional Encoding:-

Convolutional encoding is employed to introduce redundancy and improve resilience against channel noise. A configuration with code rate 1/2, constraint length K=7, and generator polynomialsG1=171(oct) and G2=133(oct) is selected. This design offers strong error correction capability in noisy wireless environments and has been widely adopted in communication systems such as satellite and deep-space telemetry. In the proposed framework, convolutional encoding plays a critical role in ensuring reliable recovery of time-division multiplexed sensor data streams transmitted over resource-constrained channels. Its incorporation enables robust performance evaluation when it is combined with hard- and soft-decision Viterbi decoding, forming the basis for the comparative analysis presented in this work.

Time Division Multiplexing (TDM):-

TDM is employed to integrate the multiple sensor streams into a single transmission channel. Each sensor is assigned a unique time slot in a periodic sequence, allowing a round-robin fashion transmission of their outputs without overlap. Let M be the total number of sensors and xk(m) the m-th bit from the k-th sensor. The multiplexed output y(n)is generated by:

$y(n) = x_k(m)$, where $n=M\cdot m+k, k=0, 1\ldots, M-1$.

This structured interleaving enables the receiver to demultiplex the signal by simply tracking bit positions. In this project, four virtual sensors (temperature, humidity, soil moisture, air quality) are simulated and combined using this scheme.

Viterbi Decoding:-

The Viterbi decoder is responsible for reconstructing the original bitstream by analyzing paths through a trellis diagram defined by the convolutional code. It estimates the most likely input sequence that may have produced the received encoded signal, based on accumulated path metrics.

Two decoding strategies are tested:

- Hard decision decoding, where incoming symbols are set to either binary 0 or binary 1.
- Soft decision decoding, where received signals are quantized to reflect confidence levels in bit values.

Soft decision decoding takes advantage of additional signal information and typically yields better bit error rate (BER) performance in noisy environments.

Project Workflow:-

The flow diagram of the proposed system is shown in Figure 1.

Fig 1:Flow Diagram

The end-to-end workflow for the proposed system is summarized as follows:

1. Sensor Data Generation:
   Four streams of synthetic binary data are generated to simulate environmental sensors. These streams serve as the system's input sources.
2. TDM-Based Multiplexing:
   The individual sensor outputs are interleaved using the TDM method described earlier. This produces a single bitstream containing all sensor data in a known order.
3. Convolutional Encoding:
   The multiplexed stream is encoded using the rate-1/2 convolutional code with a constraint length of 7 and generator polynomials 171 and 133. This adds redundancy for error.
4. Modulation and Channel Transmission:
   Encoded bits are modulated using Binary Phase Shift Keying (BPSK), where:
   $s(t)=2\cdot b(t)-1, b(t)\in\{0,1\}$.
   The modulated signal is transmitted over a simulated Additive White Gaussian Noise (AWGN) channel to emulate real-world communication noise.
5. Reception and Demodulation:
   The receiver demodulates the BPSK signal and processes the result through both hard and soft decision Viterbi decoders to evaluate performance under different SNR conditions.
6. Demultiplexing:
   After decoding, the system separates the bitstream back into four individual sensor data streams by reversing the TDM process based on the known interleaving pattern.
7. Performance Analysis:

The system's accuracy is quantified using the Bit Error Rate (BER) metric:

$$\text{BER} = \frac{\text{Number of incorrect bits}}{\text{Total transmitted bits}}$$

BER values are recorded across a range of SNR levels (0 dB to 14 dB), and both decoding latency and encoding time are measured for evaluation. The simulation demonstrates that soft decision decoding consistently outperforms hard decision decoding in terms of BER, particularly at low SNRs. At 6 dB SNR and above, error-free recovery is achieved. These results confirm the robustness and reliability of the proposed framework in Wireless Sensor Network applications.

Results:-

This section presents and analyzes the implementation strategy of the proposed system, along with the results obtained from MATLAB simulations.The performance of the proposed multiplexed environmental monitoring system is evaluated through MATLAB simulations under varying SNR conditions. The results validate the convolutional encoding's effectiveness, Viterbi decoding, and adaptive demodulation in ensuring reliable data transmission.

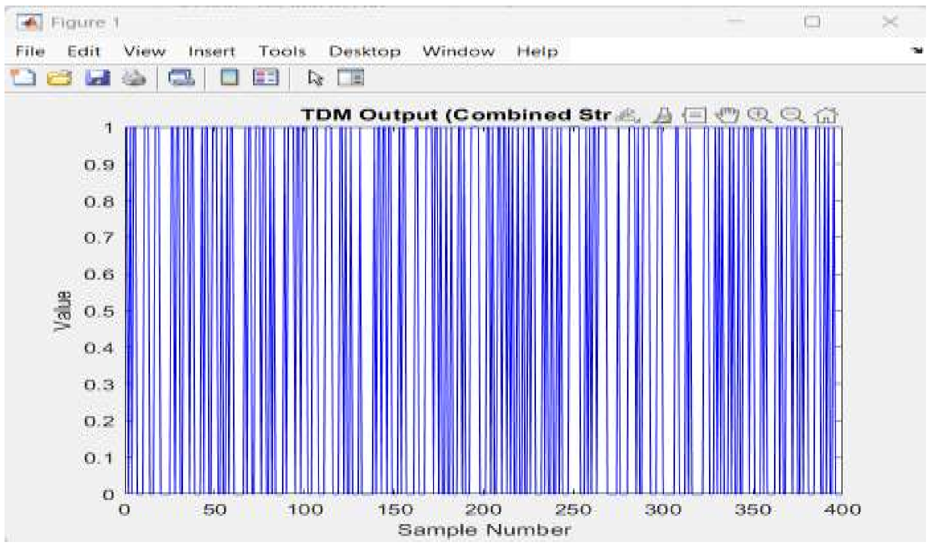

Fig. 2. TDM output showing interleaved sensor data streams for synchronized transmission.

Time Division Multiplexing (TDM) successfully combined parallel sensor data streams (temperature, humidity, soil moisture, and air quality) into a single synchronized sequence, as shown in Figure 2. Each sensor was allocated a fixed time slot of 31.25 µs, corresponding to one-fourth of the 125 µs sampling period at 8 kHz. This ensured seamless integration of the four sensor streams without overlap, maintaining strict synchronization and preserving the temporal characteristics of each channel.

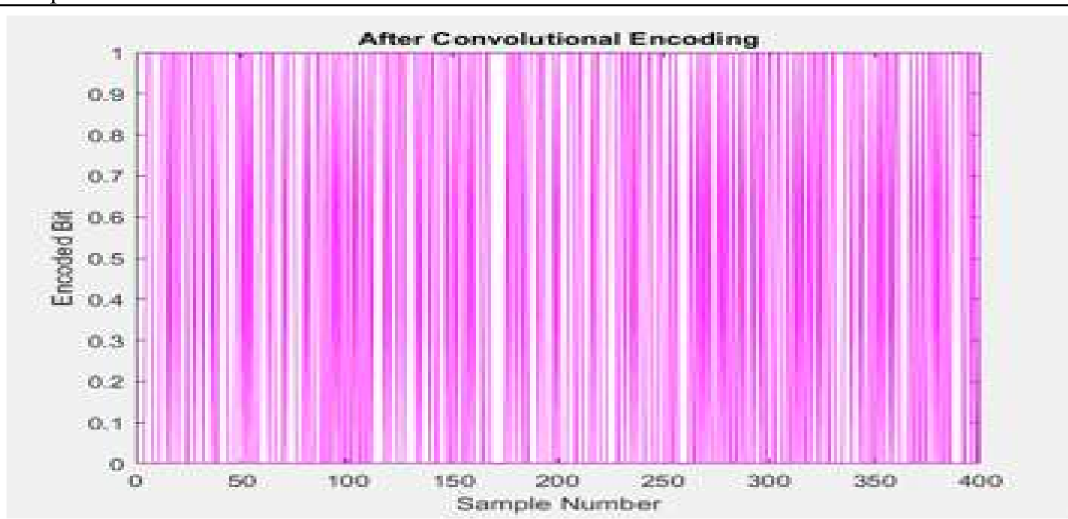

Fig. 3. Encoded output using rate-1/2 convolutional code with constraint length 7.

The rate-1/2 convolutional encoder (constraint length 7, polynomials 171 and 133) introduced redundancy by generating two output bits for each input bit as shown in Figure 3.The encoded stream displayed characteristic periodic transitions, reflecting the encoder's memory depth and polynomial tap configurations. This redundancy ensures robust error correction capabilities during transmission over noisy channels.

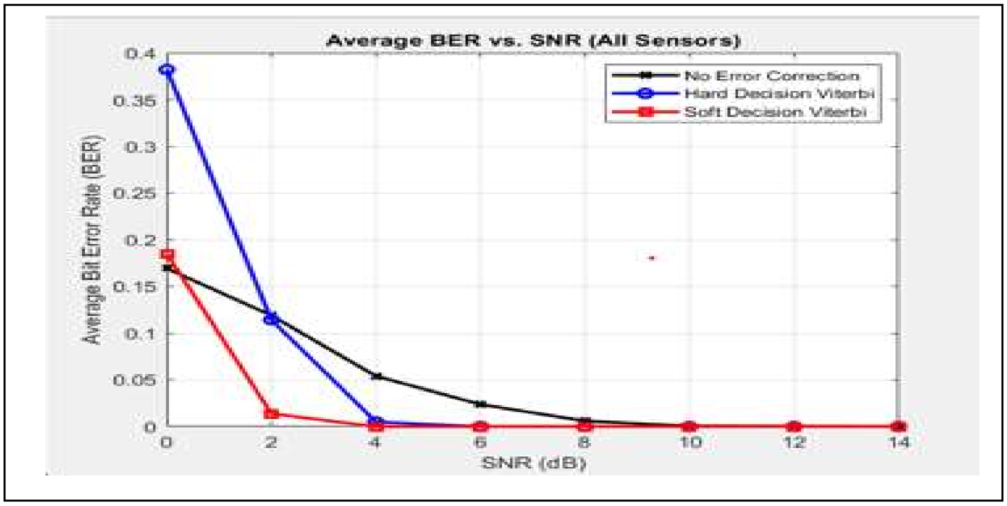

Fig. 4. Average BER vs. SNR across sensors. Soft decoding outperforms hard decoding, especially at low SNR.

The average bit error rate (BER) across all sensors decreased rapidly with increasing SNR, demonstrating the system's noise resilience as shown in Figure 4. For example, at 2 dB SNR soft-decision Viterbi decoding reduces BER by approximately an order of magnitude compared with hard-decision decoding (soft: ≈0.011–0.016 vs hard: ≈0.104–0.124 across sensors). By 4–6 dB both decoding methods achieve effectively error-free performance for the simulated sequence length (BER ≈ 0), while uncoded transmission exhibits residual errors. These results confirm that soft-decision decoding provides substantially better reliability at low SNRs and enables earlier convergence to error-free operation in our setup.

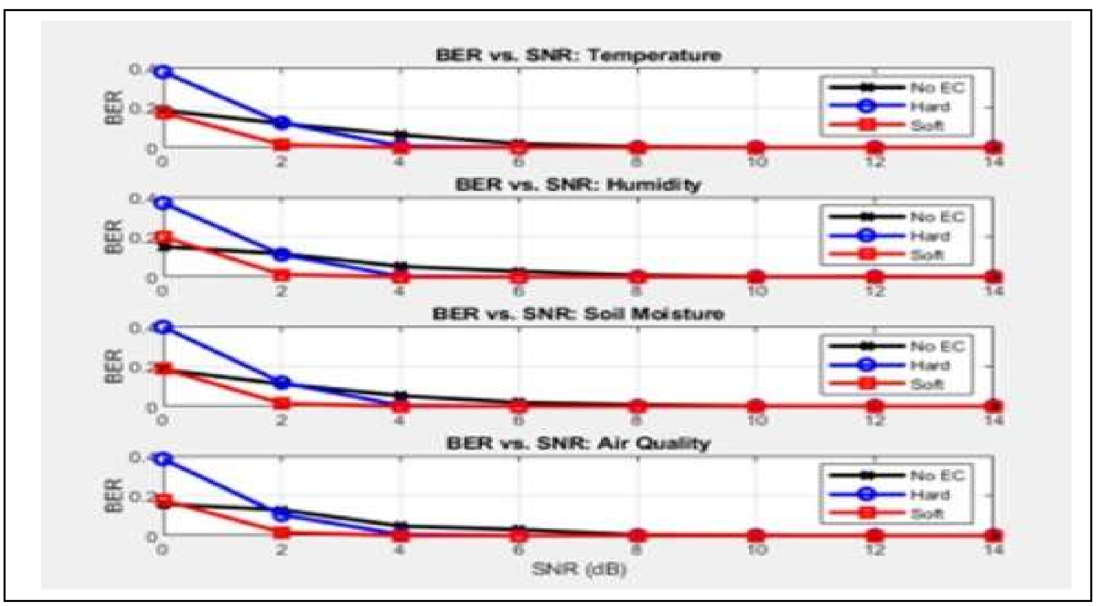

Fig. 5. Sensor-specific BER vs. SNR. Minor variations observed due to data characteristics.

Individual sensor BER curves show minor differences arising from data characteristics, as illustrated in Fig. 5. For uncoded transmission at 8 dB, the BER varies across sensors (Temperature: 3.7×10^{-3}, Humidity: 8.7×10^{-3}, Soil: 7.5×10^{-3}, Air: 3.7×10^{-3}), whereas Viterbi-decoded streams achieve effectively zero BER at and above 8–10 dB. At 10 dB, the uncoded BER for soil and air sensors is 1.2×10^{-3}, while both hard- and soft-decision decoding yield BER ≈ 0 for all sensors, confirming uniform reliability of the coded system across heterogeneous data streams.

Table I: Bit error rate performance Across sensors with0 db and 2 db

SNR (dB)	Sensor	No Error Correction	Hard Viterbi	Soft Viterbi
0	Temperature	0.1860	0.3783	0.1735
	Humidity	0.1511	0.3695	0.2010
	Soil	0.1823	0.3970	0.1873
	Air	0.1573	0.3833	0.1773
2	Temperature	0.1199	0.1236	0.0137
	Humidity	0.1611	0.1111	0.0112
	Soil	0.1111	0.1186	0.0137
	Air	0.1286	0.1036	0.0162

TABLE II :BIT ERROR RATE PERFORMANCE ACROSS SENSORS WITH4 DB, 6 DB AND 8-14 DB SNR

SNR (dB)	Sensor	No Error Correction	Hard Viterbi	Soft Viterbi
4	Temperature	0.0637	0.0075	0.0000
	Humidity	0.0524	0.0025	0.0000
	Soil	0.0524	0.0037	0.0000
	Air	0.0474	0.0062	0.0000
6	Temperature	0.0187	0.0000	0.0000
	Humidity	0.0275	0.0000	0.0000
	Soil	0.0187	0.0000	0.0000
	Air	0.0300	0.0000	0.0000
8–14	All	≤0.0087	0.0000	0.0000

Table I. and Table II. summarize the bit error rate (BER) performance of the proposed system across four environmental sensors under varying SNR conditions. At low SNR (0–2 dB), uncoded transmission exhibits high error rates, while convolutional coding with Viterbi decoding significantly improves reliability. Soft-decision decoding consistently outperforms hard-decision decoding, achieving near-zero BER as early as 4 dB. Beyond 6 dB, both decoding methods achieve error-free transmission, while uncoded data still shows residual errors. This validates the robustness of the coding scheme in noisy wireless environments.

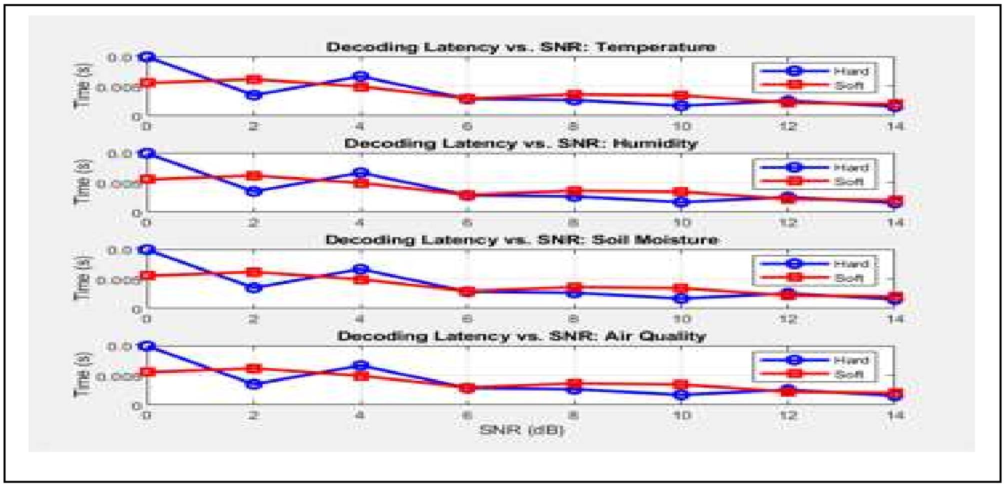

Fig. 6. Decoding latency vs. SNR for each sensor. Soft decoding incurs modest latency overhead.

Decoding latency varied between 2–8 ms across the SNR range, as shown in Figure 6. Both hard- and soft-decision Viterbi decoding exhibited a decreasing trend with higher SNR, converging to 2–3 ms at 12–14 dB. This reduction arises because fewer backtracking operations are required under low-error conditions. Interestingly, in this implementation, soft-decision decoding was marginally faster than hard-decision decoding, reflecting efficient handling of quantized reliability metrics. Overall, both approaches achieved millisecond-level latency, suitable for real-time sensor monitoring applications.

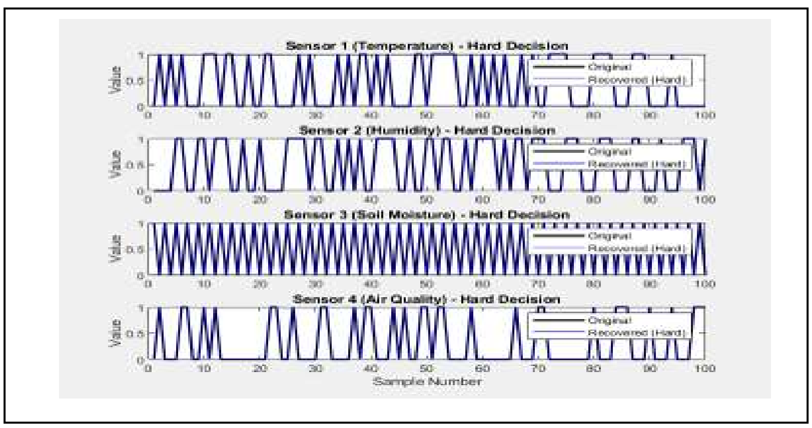

Fig. 7. Recovered vs. original sensor data using hard decision decoding at 8 dB SNR.

Hard-decision decoding demonstrated reliable error correction with moderate computational demands, as shown in Figure 7. At 8 dB SNR, the BER reached effectively zero across all sensors (Table I), with the recovered signals closely overlapping the originals. Decoding latency decreased with increasing SNR, converging to 2–3 ms at higher SNRs, which makes this approach attractive for resource-constrained or real-time applications. However, its error-correction capability remains less robust than soft-decision decoding at low SNRs.

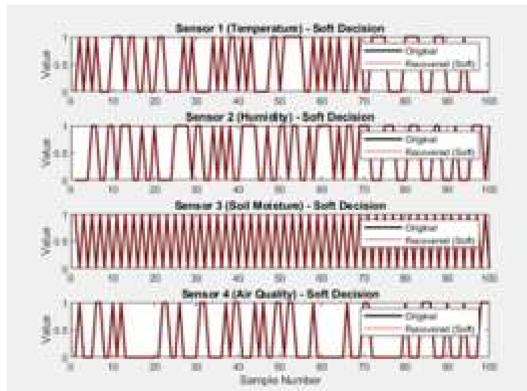

Fig. 8. Recovered vs. original sensor data using soft decision decoding. Lower BER at reduced SNR.

TABLE III :AVERAGE ENCODING AND DECODING TIMES

Process	Time (s)
Encoding	0.1232
Decoding (Hard)	0.0070
Decoding (Soft)	0.0060

Table III. presents the average encoding and decoding times measured during simulation. Encoding required approximately 0.12 s, reflecting the computational overhead of convolutional coding, while both hard- and soft-decision Viterbi decoding completed within 0.01 s. Interestingly, soft-decision decoding was slightly faster than hard-decision decoding in this implementation, indicating efficient quantized metric processing. These results confirm thatthe proposed framework can achieve robust error correction without imposing significant latency, making it suitable for real-time environmental monitoring applications.

Conclusion and Future Scope:-

In this work, an efficient multiplexed transmission framework for environmental monitoring has been developed using TDM, convolutional encoding, and Viterbi decoding. MATLAB simulations confirmed its ability to combine multiple sensor streams, apply error correction, and maintain data integrity under noisy conditions. Soft decision decoding achieved the best BER performance, albeit with slightly increased latency, offering flexibility for application-specific trade-offs. The system demonstrated high reliability and low latency across varying SNRs, validating its suitability for real-time sensor networks. These findings establish a strong foundation for future work involving hardware implementation, adaptive coding, and integration with IoT and edge computing platforms.Future work can also explore extending the study to more complex wireless channel models, such as Rayleigh and Rician fading, to evaluate robustness under realistic propagation conditions. The framework may be optimized for energy efficiency, which is critical in battery-powered sensor networks. Additionally, scalability studies with a larger number of sensors and varying data rates could be performed to assess system performance in dense IoT deployments. Integration with FPGA or SDR-based platforms will further enable real-time validation, paving the way for practical field deployment in environmental monitoring and smart city applications.

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