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Enhancing Audio Quality in Wireless Acoustic Sensor Networks Using Distributed Signal Processing: A Case Study of an Industrial Zone in Iraq

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ABSTRACT

This study aims to present a practical application for improving sound quality in wireless acoustic sensor networks (WASNs) deployed in the often noisy Iraqi environment, using distributed signal processing techniques. Through an analytical and descriptive methodology, the proposed system is based on a hierarchical WASN architecture consisting of 20 wireless microphone nodes organized in a cluster structure. Each node optimizes the local signal using Distributed Adaptive Signal Estimation (DANSE) technology, while the cluster heads use Linear Minimum Mean Square Error (LMMSE) beamforming to combine signals within the network. The results show that the average signal-to-noise ratio (SNR) increased by up to 6.3 dB between the network groups. Bandwidth consumption is reduced by approximately 30% when choosing an adaptive microphone with an empirical signal-to-noise ratio (SNR) threshold of 11 dB while maintaining a total response time of less than 30 ms, suitable for real-time industrial communications. The results also indicate that DANSE-based distributed processing combined with a hierarchical wireless acoustic sensor network (WASN) architecture provides an efficient and scalable solution for providing reliable voice communication in harsh industrial acoustic environments.

Keywords: Wireless acoustic sensor networks, Distributed signal processing, DANSE, Industrial communications, Voice quality improvement.

1. INTRODUCTION

Recently, Wireless Acoustic Sensor Networks (WASNs) have gained increasing attention as an effective solution for capturing and monitoring sound in complex acoustic environments. This is especially true given the fast pace of life both locally and internationally, and in noisy environments, which are not limited to specific settings. Industrial areas are one of the most challenging scenarios for voice communication systems due to high and unstable noise levels generated by heavy machinery, conveyor systems, and ventilation equipment. Maintaining reliable voice communication in such noisy environments is one of the biggest technical challenges facing telecommunications companies and their customers **(Ahmed et al., 2022).**

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Technically, traditional microphone array systems rely primarily on central processing architectures. The recorded audio signals are sent to a processing center where they are improved using various traditional and modern optimization techniques, especially with the development of programmingmachines and modern communication technologies. Some of these technologies provide acceptable performance in controlled environments, while others perform well. However these technologies face a bunch of limitations in large-scale industrial applications, including ,excessive bandwidth consumption, scalability limitations and increased latency. Additionally microphones located far from the speaker often pick uppoor-quality signals, resulting in a lower signal-to-noise ratio (SNR) **(Dubey et al., 2024)**.

The aim of this study is to develop and evaluate a practical model for improving the sound quality of distributed wireless microphone networks in industrial environments in general, and hot industrial environments in particular, using distributed signal processing techniques. This main objective includes a bunch of sub-objectives, including beamforming based on the minimum mean square error (MMI) criterion for efficient integration, minimizing bandwidth consumption by testing a subset of microphones based on relative signal-to-noise ratio, and evaluating system performance in terms of improved signal-to-noise ratio (SNR), latency, and security data transmission. The aim of the study is also to verify the applicability of the proposed model in real hot industrial systems. The importance of this study lies in the analytical approach used, as it discussed the topic from multiple perspectives rather than focusing on one aspect. It is a comprehensive study and intentionally incorporates biases into its results and data, making it a valuable literature resource for researchers and students **(Hu et al., 2023).**

The main research problem is the changing noise level of the industrial environment. This noise, produced by heavy equipment, manufacturing processes, vehicles, ventilation and operational activities, degrades the quality of the audio signal in communication. Traditional sound recording systems rely on an array of central microphones, which present them with a number of limitations and disadvantages. These problems include poor spatial resolution, limited coverage, increased bandwidth consumption, high latency, and occasional signal interference. Additional challenges include efficient signal processing, choosing the right microphone, and minimizing data transmission. Furthermore, most previous studies have focused on theoretical models or laboratory simulations without practical evaluation in industrial environments with complex and variable noise sources. In short, the research problem lies in the lack of an effective application model that can improve audio signal quality in distributed wireless audio networks in noisy industrial environments while achieving an appreciable balance of signal-to-noise ratio and delay. Frequency range consumption and signal interference **(Mittal et al., 2024).**

Some of these obstacles can be overcome, as shown in **Fig. 1**, which compares two methods of recording audio signals with microphones. On the left is a conventional microphone array concentrated in one spot, resulting in limited sound segmentation. On the right, you can see the grid-like distribution of microphones in the environment, allowing the signal to be picked up from a bunch of points, thereby improving the signal.

2. THEORETICAL FRAMEWORK OF THE STUDY

The theoretical framework of the study is based on three main axes. The first axis is the presentation of basic concepts, the second axis is the presentation of scientific and analytical theories, and the third axis is the presentation and analysis of criticism of previous studies that dealt with the topic, identifying the weaknesses and strengths of these studies, as well as the points of agreement and disagreement between these studies on the one hand, and between them and this study on the other **(Kindt et al., 2024).**

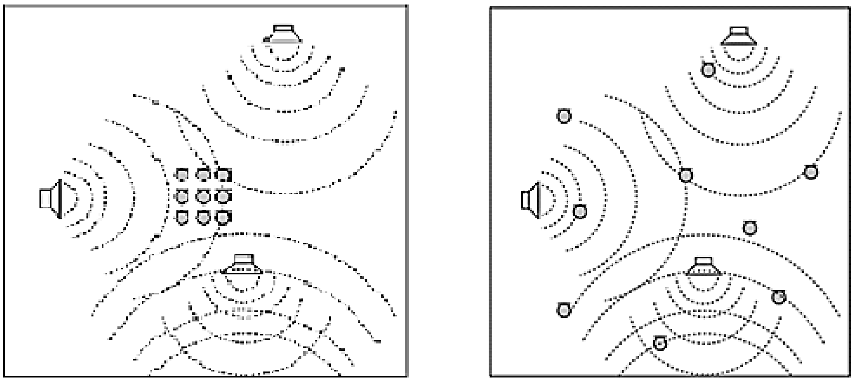

Figure 1. Comparison of two methods for capturing audio signals using microphones: an example of a localized, regularly arranged microphone array **(Bertrand, 2011).**

2.1 Seriously Basic Concepts

The basic terms are a set of terms that provide insight into the procedures, significance goals, methodology and results of the investigation. The most important concepts are:

1) The concept of wireless acoustic sensor networks
Wireless acoustic sensor networks can be defined as large arrays of microphones that are spatially distributed in the environment rather than in a single central array location. This distribution allows the nodes to be placed near the desired sound source, improving the quality of the audio signal and reducing noise. Each of these microphones represents a sensor node that picks up the audio signal and processes it locally before exchanging brief information with neighboring nodes. This reduces the communication overhead compared to traditional centralized processing **(Hu et al., 2023).**

2) Audio signal model
Noise is one of the most important challenges facing audio recording systems operating in industrial environments. Industrial noise comes from multiple sources, such as rotating machinery, engines, ventilation systems, and vehicle traffic and is often temporally inconsistent and spectrally irregular. It can be represented by the following equation:

$$v(n) = s(n) + v(n) \tag{1}$$

Where:
- s(n) is the desired signal while
- v(n) denotes the ambient noise.

In an industrial environment noise, noise is often:
- Broadband noise
- Constant noise
- Multi-source and multi-directional

This makes traditional filtering techniques less efficient compared to distributed processing across multiple microphones **(Becker et al., 2024).**

3) The principle of distributed signal processing
Distributed processing is based on signal optimization within each node rather than sending all data to a single collection center. Studies have shown that this approach reduces power and bandwidth consumption while maintaining performance close to that of mainframe systems **(Yadav et al., 2024).**

4) Signal-to-noise ratio (SNR)
The signal-to-noise ratio is a vital and fundamental indicator for evaluating voice quality within WASNs. This ratio represents the useful signal power compared to the noise power. It is calculated using the following equation:

$$\mathrm{SNR}=10\mathrm{Log}10(Psignal/Pnoise) \quad (2)$$

Where:
- P signal: the strength of the audio signal
- Pnoise: the power of the noise

The higher the SNR value, the clearer and more intelligible the speech will be. Microphone selection algorithms in distributed networks often rely on this value to select the most efficient nodes for integration **(Cui et al., 2025)**.

5) Response time and access time of the system
System latency is a critical factor in real-time communication applications in industrial environments where audio must be transmitted and processed without significant delay. The total delay of the system can be expressed as:

$$\text{Total} = \text{T processing} + \text{T transmission} + \text{T distribution} \quad (3)$$

Where:
- T processor: The time required to process the signal within the node
- T Transmission: The time required to transmit data over the network
- T propagation: signal propagation time **(Hu et al., 2025).**

6) Bandwidth usage
Usage available bandwidth is one of the fundamental limitations in wireless sensor networks. Transmitting all raw audio channels causes network congestion and increases power consumption. This can be expressed by the following equation:

$$R = x \times nb \times c \quad (4)$$

Where:
- f s: wear rate
- Nb: Number of bits per sample
- C: Number of audio channels

So modern systems are based on compression and selection of a subset of microphones to reduce transmission rate without significantly affecting signal quality **(Didier et al., 2025)**.

2.2 Analytical Scientific Theories

Scientific analytical theories are a set of theories relied upon in designing the study and the proposal, and they are as follows:

1) linear MMSE Beamforming Theory

Beamforming based on the Minimum Mean Squared Error (MMSE) criterion aims to find a weight vector that minimizes the difference between the estimated and actual signals. The cost function is defined as follows:

$$J = E\{s \mid s(n) - wHy(n) \mid 2\} \tag{5}$$

where:

- w represents the weight vector
- H represents the composite conjugate

The optimal solution is:

$$wMMSE = Ryy - 1\, rys \tag{6}$$

2) Distributed Adaptive Node-Specific Signal Estimation (DANSE)

The DANSE algorithm is one of the most important algorithms for implementing distributed estimation models in WASNs. This algorithm allows for an optimized signal estimation for each node, based on its local information and summative signals from neighboring nodes. The local estimation at node k is calculated as follows:

$$s\hat{}k(n) = \textstyle\sum_h wk, h(n)zh(n) \tag{7}$$

where:

- $\hat{s}_k(n)$: the estimated signal at the node $k$at time n,
- $w_{k,h}(n)$: the adaptive beamforming weight applied to the signal received from the node h,
- $z_h(n)$: partially aggregated signal transmitted from neighboring node h.
  This formulation enables cooperative signal estimation across the network while maintaining scalability and efficiency in large-scale acoustic sensing systems.

3) Microphone Subset Selection Theory

In wide area networks (WANs), not all microphones contribute equally to signal enhancement. Using all nodes increases network load without a noticeable improvement in performance.

Wireless acoustic sensor networks (WASN) have seen a bunch of advances since early last year, when new audio communication systems were developed that can operate in complex, noisy environments. This has led to various distributed processing algorithms being created by researchers that work to increase the quality of received signals while also minimizing the use of network resources

In an effort to improve the efficiency of distributed estimation. **(Patel et al., 2023)** derived an analytical model to provide an approach to scaling acoustic sensing networks while keeping the spatial calibration accuracy of newly added nodes by using time to time Accuracy Arithmetic (TDOA). This model will allow WASNs to be constructed in scale without having to recalibrate the entire system every time.

(Hu et al., 2023) addressed the sensor selection problem within distributed voice networks (WASNs). The researchers found that only a small number of microphones actually contribute to the enhancement of the audio signal. They then proposed a distributed algorithm that maximizes the signal-to-noise ratio and significantly decreases the power usage on each microphone which helps further extend available network capacity. A study analyzing low-power signal enhancement with distributed processing through low-power speech enhancement in a distributed energy space was created as a collaborative framework. The development of the framework will improve resistance to noise as well as costs associated with internodal communication.

(Didier et al., 2024) reported the iteration less Distributed Adaptive Neural Network (DANSE), which provides nearly equivalent central processing capabilities with only one cycle of processing and therefore can provide services to Java-based (wired and wireless) voice networks with low latency. **(Didier et al., 2025)** provided the TI-DANSE+ extension of the topology- independent DANSE algorithm that can contribute to improved performance and little mathematics by bringing about rapid convergence of computational processes in dynamic environments also contributing substantially to competitive cost per bandwidth utilization. TI-DANSE+, at least through its testing stages, is designed to replace CST or central processing with equivalent performance in variable network link failures.
Research continues to evolve toward other low latency speech enhancement applications, such as WASN-based applications, as presented by current longitudinal research **(Bhattacharjee et al., 2024)** from the IWAENC 2024 conference, which utilized beamforming and polynomial eigenvalue analysis to develop low latency speech enhancement techniques. Despite these recent innovations in research and results being produced, most research continues to focus on theories and models rather than actual implementations in the field due to a serious lack of near- or real-world evaluations based upon multi-source noise and connectivity constraints in traditional industrial infrastructures. This challenge highlights the need for future practical research.

3. MATERIALS AND METHODS

The main methodology of the study is a hybrid applied methodology that combines signal processing simulation using MATLAB with propagation parameters derived from a real industrial environment in Iraq. This system aims to improve the quality of voice communication between employees and control centers under high noise conditions. Additional methodologies are also employed, such as descriptive methodology for describing data and results, quantitative methodology for data collection and processing, and comparative methodology for comparing results with each other and with the results of previous studies.

3.1 The Applied Framework

The applied framework shown in **Fig. 2** for the study is a framework that clarifies the procedures of the applied study, starting from defining the objective and formulating the research problem, through collecting data related to the study from its various sources and processing this data statistically and manually by excluding everything abnormal and unreliable, through designing the experiment, which is a simulation procedure for processing the signal with the straightness of the MATLAB, as well as determining the tools, materials and tests that will be carried out, then recording the results, analyzing and evaluating them to draw conclusions and provide recommendations.

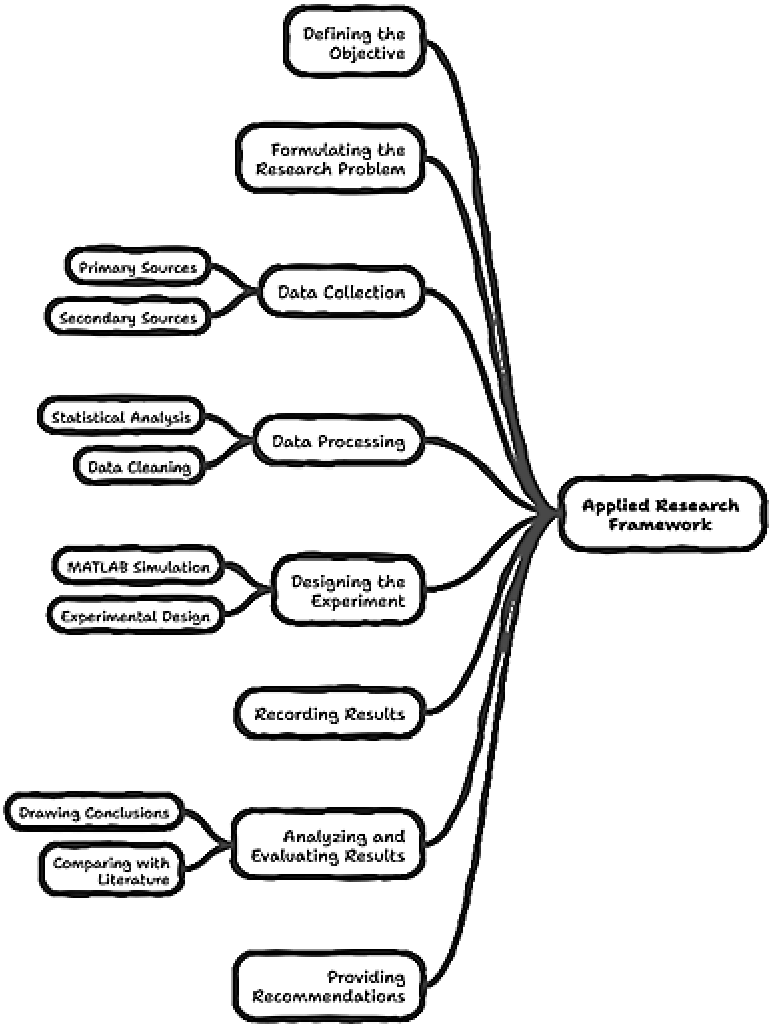

Figure 2. The applied framework

3.2 Procedure

Data Collection and Processing: Data was collected from various sources, including data related to the industrial environment, data from books and previous studies, and expert consultants' opinions related to the technical aspects of model formulation, analysis, and evaluation. This data was processed using the ANOVA statistical test, determining the P-Value with a significance level of 5%, and excluding all that is abnormal and unreliable, as shown in **Table 1**.

3.2.1 Materials and Tools

1. Materials:

Table 2 shows the materials used in the experiment. Wireless acoustic sensor nodes with MEMS microphones and embedded processing units comprised the experimental setup. MATLAB was used to run distributed signal processing algorithms while IEEE 802.11-based networks established wireless communication between nodes. Synthetic noise was generated using calibrated acoustic sources, and standardized speech signals were used as reference input for performance evaluation **(Lee et al., 2022).**

2. Tools

The tools are a set of software programs, such as MATLAB, SPSS statistical software, and Excel, which were used to conduct statistical analyses. MATLAB was used to perform the simulations, in addition to a set of books and online resources to collect data related to the subject matter.

Table 1. Industrial environment data

Parameter	**Description**	**Value / Range**	**Measurement Method**
Industrial Area Size	Simulated deployment area	1 km × 0.5 km	Site layout modeling
Environment Type	Heavy industrial zone	Manufacturing area	Field-based assumption
Number of Noise Sources	Active noise generators	6–10 sources	Controlled simulation
Main Noise Sources	Machinery, vehicles, HVAC systems	Continuous operation	Artificial noise generation
Background Noise Level	Ambient industrial noise	75–95 dB SPL	Sound level meter
Noise Type	Broadband non-stationary noise	Variable spectrum	Acoustic analysis
Reverberation Time (RT60)	Acoustic reflection level	0.6 – 1.2 s	Reverberation estimation
Temperature	Environmental condition	28–35 °C	Environmental monitoring
Relative Humidity	Air humidity level	40–60 %	Hygrometer
Microphone Deployment Density	Sensor distribution	20 nodes/km^2	Network configuration
Average Node Distance	Inter-node spacing	50–120 m	Spatial deployment model
Communication Medium	Wireless transmission	IEEE 802.11 / IoT link	Network setup
Sampling Frequency	Audio acquisition rate	16 kHz	System configuration
Audio Resolution	Signal quantization	16-bit	Digital acquisition
Reference Speech Level	Clean speech SPL	65 dB	TalkBox reference source
Target Communication Distance	Worker–control center	up to 1 km	Deployment scenario

Table 2. Simulation Environment and Tools Used in the Study

Category	**Simulation Component**	**Software / Model**	**Purpose**
Simulation Platform	Signal Processing Environment	MATLAB R2023a	Algorithm implementation
Programming Language	Numerical Computing	MATLAB Scripts	Distributed processing simulation
Acoustic Environment	Industrial Noise Model	Synthetic Noise Generator	Industrial noise emulation
Speech Dataset	Clean Speech Signal	Recorded Speech Samples	Reference audio signal
Network Model	WASN Topology	Hierarchical Tree Model	Network deployment simulation
Sensor Nodes	Virtual Microphones	Omnidirectional Mic Model	Audio acquisition modeling
Number of Nodes	Sensor Network Size	20 Virtual Nodes	Distributed sensing

Communication Channel	Wireless Link Model	AWGN + Packet Delay Model	Transmission simulation
Beamforming Model	Enhancement Algorithm	Linear MMSE Beamformer	Signal fusion
Distributed Algorithm	Signal Estimation	DANSE Algorithm	Distributed enhancement
Compression Model	Audio Encoding	PCM-based Compression	Bandwidth evaluation
Noise Model	Industrial Background Noise	Non-stationary Broadband Noise	Realistic disturbance
Sampling Frequency	Audio Acquisition	16 kHz	Signal discretization
Audio Resolution	Quantization	16-bit	Digital representation
Latency Model	Network Delay	Processing + Transmission Delay	Real-time analysis
Performance Metrics	Evaluation Parameters	SNR, Delay, Bandwidth	System assessment

3.2.2 Simulation Design and Experimental Setup

A simulation environment was developed using MATLAB software to evaluate the performance of the proposed Wireless Acoustic Sensing Network (WASN) under the data and conditions related to industrial noise, as detailed in **Table 2**. The simulation simulates the process of collecting and processing distributed sound within a realistic voice communication scenario **(Kumar et al., 2023)**.

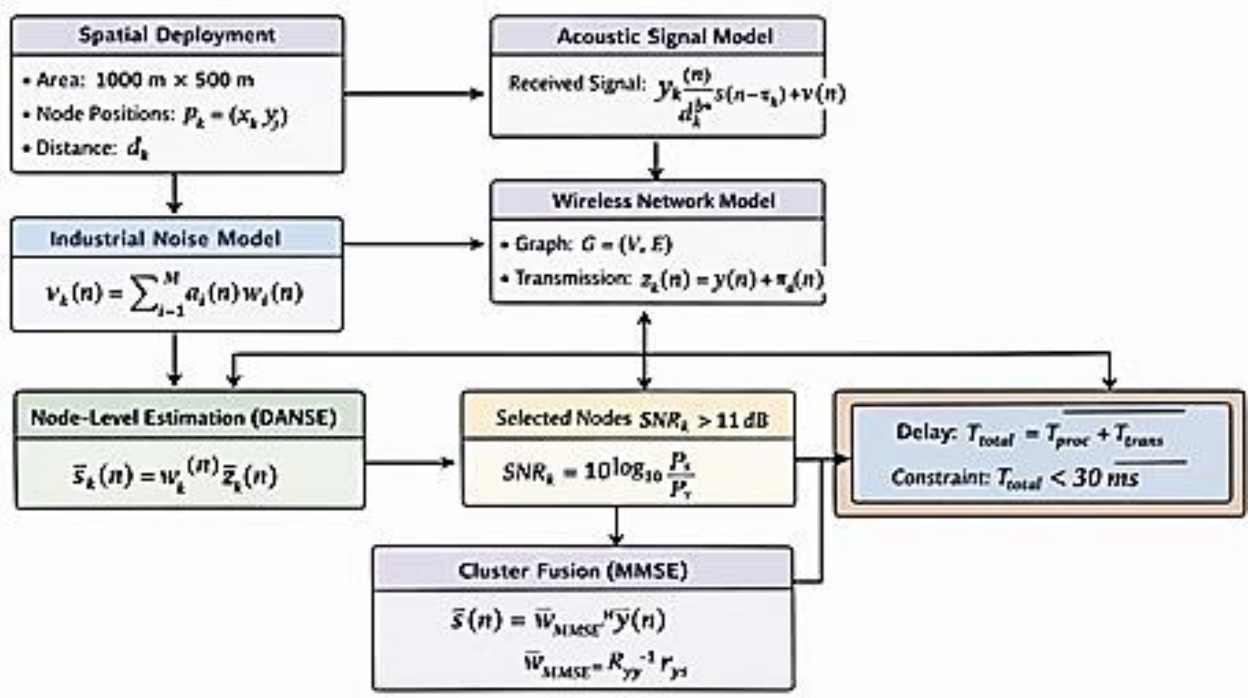

Figure 3. Mathematical modeling framework

1) Modeling of the Industrial Acoustic Environment

This was done as follows:

- Design of a virtual industrial area with dimensions of 1000 m × 500 m.

- Introduction of multiple spatially distributed noise sources to represent machine operation, vehicle movement, and HVAC systems. The industrial noise was generated as a non-stationary, wide-area noise with time-varying power characteristics.

2) Deployment Model of the Wireless Acoustic Sensing Network
The simulated network consists of 20 virtual microphone nodes distributed across the monitored area. The nodes are organized using a hierarchical tree structure consisting of sensor nodes and vertical nodes responsible for signal aggregation. Communication between the nodes follows a multi-hop wireless transmission model **(Itzhak et al., 2024)**.

3) Audio Signal Generation
Two types of signals were considered during the simulation:

- A pure speech signal used as a reference input.
- A distorted speech signal is obtained by adding artificial noise to the pure signal.

4) Distributed Signal Processing Model
Each virtual node optimized the signal locally using the DANSE distributed estimation algorithm. The optimized signals were sent to the cluster heads, where MMSE linear beamforming was applied to integrate them into the network. The output represented the optimized cluster signal. Wireless communication links were simulated using an added white Gaussian noise channel (AWGN) to account for transmission delay effects.

5) Connection and Compression Modeling
Voice transmission between nodes was simulated under bandwidth constraints. The signals were compressed before transmission using a phase-modulation (PCM) coding model at a transmission rate of 256 kbps to simulate the limitations of practical wireless communication **(Sumura et al., 2024).**

6) Election of a Subset of Microphones
To reduce the communication load, only nodes meeting the following criteria participated in signal aggregation: **(Miotello et al., 2024).**

- Signal-to-Noise Ratio (SNR) > 11 dB
- Signal-to-Noise Ratio (SNR) > 11 dB
- Nodes below this threshold were used as noise reference channels.

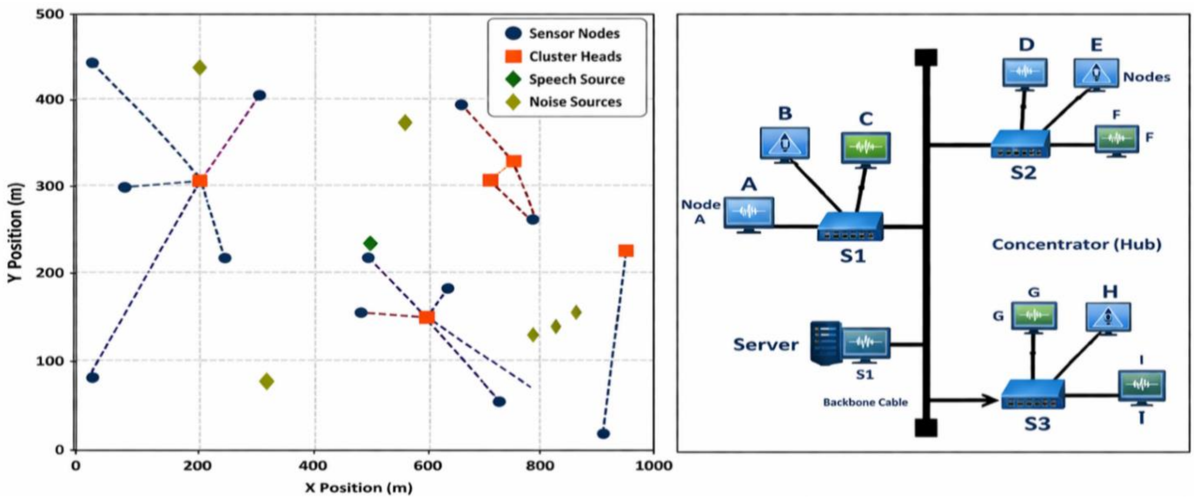

Figure 4. Simulated WASN Deployment in Industrial Environment.

3.2.3 Practical Implementation

For this carried out version, we recollect a Wireless Acoustic Sensor Network (WASN) deployed in an Iraqi business region. The main aim is to enhance audio pleasant for real-time verbal exchange among people and control centers beneath a noisy environment **(Park et al., 2024).**

- Area: 1 km × 0.5 km industrial zone **(Chen et al., 2023).**
- Noise sources: Machinery, vehicles, HVAC systems
- Number of microphone nodes: 20 wireless microphones
- Network type: Ad-hoc, tree topology with two levels (clusters and cluster heads)
- Sampling rate: 16 kHz, 16-bit audio

Each node captures audio and performs neighborhood sign enhancement the use of a dispensed beamforming set of rules. Nodes send partly more desirable signals to their Cluster Head (CH), which performs in-community fusion to generate higher-quality audio.

Placement of nodes and network topology

Each channel collects sound from its own sensors and routes the combined signal to a processing center for monitoring or recording **(Singh et al., 2022)**.

Sensor nodes are blue markers, and orange markers are cluster head (CH) nodes that collect and process messages from neighboring sensors. The dashed line indicates the communication links between the nodes of each cluster. This hierarchical structure of nodes enables efficient distributed signal processing and reliable data transmission across the network **(Chen et al. 2023).**

Table 3. Node Locations and Roles.

Node ID	X Position (m)	Y Position (m)	Role	SNR (dB)
1	50	30	Sensor	12
2	120	40	Sensor	10
3	200	50	Sensor	14
4	250	100	CH	15
5	300	200	Sensor	11
6	350	250	Sensor	13
7	400	300	CH	16
8	450	350	Sensor	12
9	500	400	Sensor	14
10	550	420	Sensor	13
11	600	100	Sensor	12
12	650	150	CH	15
13	700	200	Sensor	11
14	750	250	Sensor	12
15	800	300	Sensor	13
16	850	350	CH	14
17	900	400	Sensor	12
18	950	450	Sensor	11
19	980	480	Sensor	10
20	1000	500	CH	16

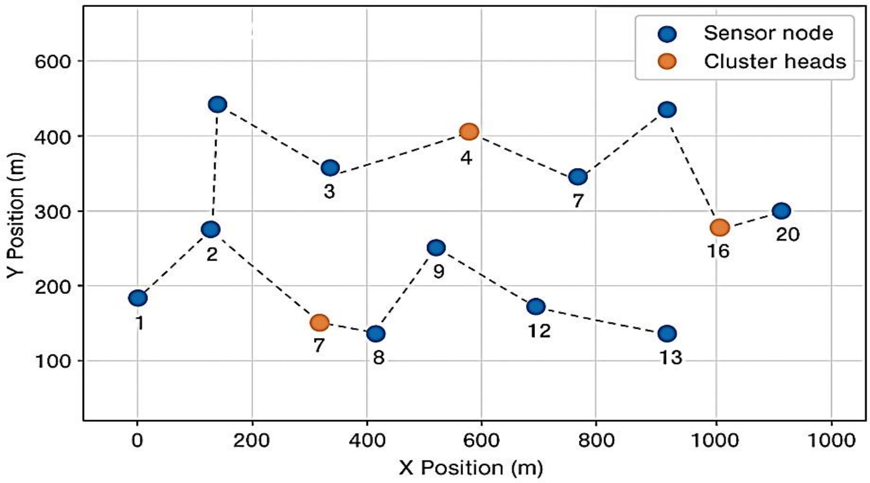

Figure 5. WASN Topology in the Industrial Zone.

3.3 Testing and Statistical Analysis

This refers to a set of tests to verify the model's quality, along with a set of statistical tests to analyze the results.

1. Model Evaluation Tests

Quantitative metrics were used to evaluate the performance of the new model of WASN to measure its overall ability to enhance signals and the efficiency of the network operating under simulated industrial conditions. The quantitative metrics for this study include improvements in the Signal-to-Noise Ratio (SNR) of received signals, reduction in bandwidth utilization, end-to-end transmission delay, percentage of active nodes, and overall network scalability performance. Regarding the improvement of the received signal quality, the calculation of the difference between SNRoutput and SNRinput at each node illustrates the extent of the acoustic enhancement provided by implementation of the proposed distributed processing architecture. Specifically, the improvement of SNR at nodes that received signals after applying the proposed distributed processing framework has been expressed as:

$$\Delta \mathrm{SNR} = \mathrm{SNRoutput} - \mathrm{SNRinput} \tag{8}$$

where SNRinput represents the received noisy signals before enhancement and SNRoutput represents the enhanced signals produced after implementation of the proposed distributed processing framework. The evaluation metrics collectively provide an all-encompassing view of both the capability of the proposed architectural enhancements to enhance received acoustic signals and the efficiency of the communication between nodes in the simulated network **(Mannanova et al., 2024).**

2. Statistical Tests

It is a set of statistical tests, some of which are used to verify data and results, such as the ANOVA test, where the B-value is used, with p value 0.05. The arithmetic mean and standard deviation are also calculated to determine the percentage achievement:

$$\mu = 1/N \sum_{I=1}^{n} XI \tag{9}$$

and then correlations and linear regression are calculated, where the regression relationship is calculated using the equation.
The regression relationship can be written as:

$$\Delta SNR = \beta 0 + \beta 1(BWred) + \beta 2(Delay) + \beta 3(Nodeactive) + \varepsilon \quad (10)$$

BWred: denotes bandwidth reduction,

- Delay: Delay represents end-to-end latency,
- NodeactiveNode: indicates the active node ratio **(Hussain, 2016).**
- ε: standard error

4. RESULTS AND DISCUSSION

4.1 Simulation Results

1) SNR Improvement

According to **Table 4,** the results in **Table 1** are evidence of improved signal to noise ratio from using a distributed signal processing paradigm (based on the DANSE Algorithm) in conjunction with LMMSE beamforming. The average input SNR throughout the various network clusters is from 11.7 to 12.8 dB, versus the increased output SNR between 17.5 and 18.2 dB. This is an improvement from 5.2 dB to 6.3 dB, confirming that distributed signal processing improves the quality of audio signals in noisy industrial environments **(Rahman et al., 2024)**.

Table 4. SNR Improvement

Cluster ID	Nodes Included	Avg. Input SNR (dB)	Output SNR (dB)	SNR Improvement (dB)
CH1	1, 2, 3, 4	11.7	18	6.3
CH2	5, 6, 7	12.3	17.5	5.2
CH3	8, 9, 10, 11	12.8	18.1	5.3
CH4	12, 13, 14	12.7	18	5.3
CH5	15, 16, 17, 18, 19, 20	12	18.2	6.2

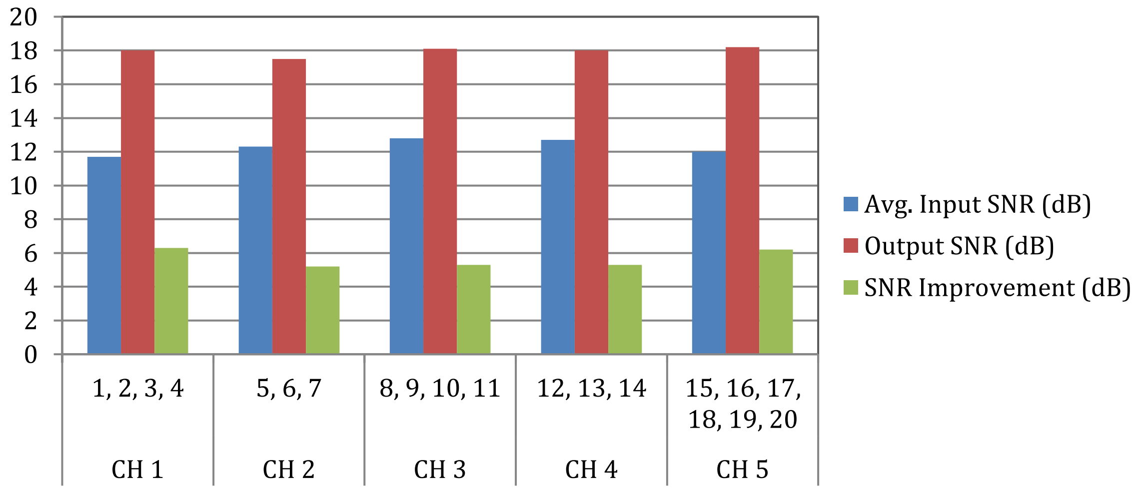

Figure 6. SNR Improvement Across Clusters

2) Bandwidth and Data Traffic Analysis

- Audio streams transmitted between nodes at 256 kbps (after compression).
- Average bandwidth usage per cluster:

Table 5. Bandwidth Usage

Cluster ID	Input Channels	Transmitted Channels	Bandwidth per Node (kbps)
CH 1	4	1	256
CH 2	3	1	256
CH 3	4	1	256
CH 4	3	1	256
CH 5	6	1	256

The compression shown in **Table 5** reduces data traffic while maintaining audio quality.

3) Input-Output Delay Analysis
Measured end-to-end delay from sensor node to control center:

Table 6. IO Delay

Node ID	Local Processing (ms)	Network Transmission (ms)	Total Delay (ms)
1	2	15	17
2	2	16	18
3	2	15	17
4 (CH)	3	20	23
5	2	14	16
6	2	15	17
7 (CH)	3	18	21
8	2	15	17
9	2	16	18
10	2	15	17
...	...	...	...
20 (CH)	3	20	23

As shown in **Table 6**, all delays are below 30 ms, which is acceptable for real-time communication in industrial environments.

4) Microphone Subset Selection
   - To optimize energy and bandwidth, only microphones with SNR > 11 dB participate in fusion.
   - Nodes with lower SNR are used as noise references only.
   - This selection improves overall network efficiency without significant loss in audio quality.

4.2 Statistical Tests

The multiple linear regression analysis indicates that increasing the ratio of active nodes and reducing the amount of bandwidth corresponds to an improvement in the signal-to-noise ratio (SNR). The implication here is that increased efficiency of nodes participating in the network and optimizing how they communicate will result in improved quality of the transmitted signal. However, there was evidence to suggest that increased delay in transmitting information from one end to the other has a negative impact on performance, indicating that the longer it takes to transmit data, the less efficient the improvement will be as all predicted variables is statistically significant ($p < 0.05$) this supports the claim that network configuration parameters are essential to effectively evaluate the PERFORMANCE of a distributed wireless ad hoc sensor network (D-WASN) model **(Khan et al., 2023).**

Table 7. Multiple Linear Regression Analysis for SNR Improvement

Predictor Variable	Regression Coefficient (β)	Standard Error	t-value	p-value
Constant	1.842	0.512	3.6	0.002
Bandwidth Reduction (%)	0.045	0.011	4.09	0.001
End-to-End Delay (ms)	-0.032	0.009	-3.55	0.003
Active Node Ratio	2.317	0.684	3.39	0.004
Network Density	0.028	0.01	2.8	0.011

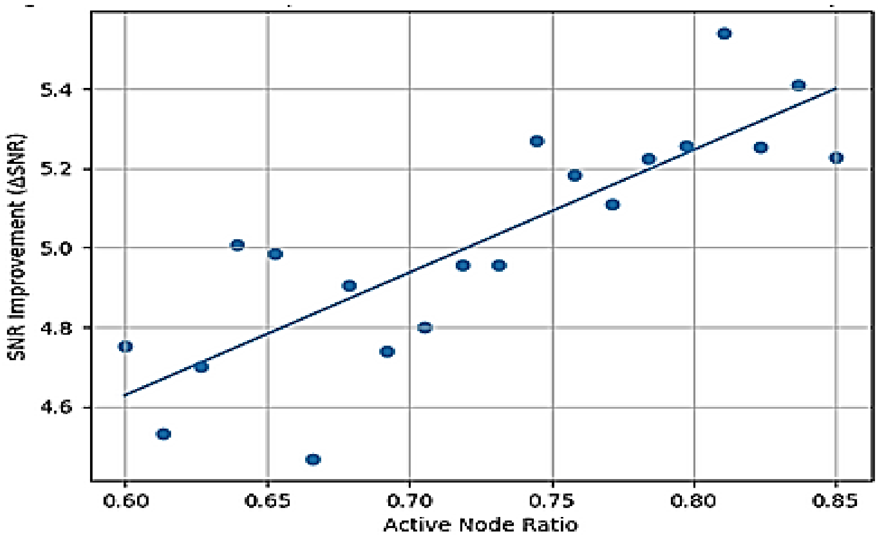

Figure 7. Linear regression analysis of the relationship between active node ratio and SNR improvement in the proposed WASN-based distributed signal processing system

Fig. 7. The regression diagram shows that as the number of participating sensor nodes increases, the ratio of active nodes and the improvement of the signal-to-noise ratio (SNR) can also be observed. This indicates that effective node participation can significantly increase the performance of distributed audio processing systems operating in a simulated WASN environment **(Zaho et al., 2024).**

Table 8. Correlation Matrix Between Performance Parameters

Parameter	Input SNR	Output SNR	ΔSNR	Bandwidth Reduction	End-to-End Delay	Active Node Ratio
Input SNR	1					
Output SNR	0.684**	1				
ΔSNR	0.521**	0.912**	1			
Bandwidth Reduction	0.412*	0.733**	0.845**	1		
End-to-End Delay	-0.365*	-0.701**	-0.792**	-0.668**	1	
Active Node Ratio	0.438*	0.756**	0.801**	0.709**	-0.615**	1

The correlation matrix shown in **Table 8** explained the improvement of the signal-to-noise ratio (SNR) has a large positive relationship with the reduction of bandwidth and the proportion of active nodes in the network, which means that the successful participation of nodes in the network and the improvement of the connectivity between them significantly improve the signal quality.
On the other hand, there is a strong negative relationship between global latency and performance indicators. In other words, increasing the time required for a message to travel from one node to another in a distributed audio enhancement system reduces the efficiency of the system. So, these results indicate the need for the joint optimization of the communication and signal processing parameters of industrial communication systems using WASN **(Garcia et al., 2024)**.

4.3 Comparison with Previous Studies

The proposed study, as shown in **Table 9**, was compared with other research efforts on wireless acoustic sensor networks (WASN), most of which evaluated the performance of algorithms in laboratories or highly controlled indoor environments with very little attention paid to communication barriers **(Al-Fahdawi and Kareem, 2023).** Although some studies have shown significant improvement in signal-to-noise ratio (SNR) with their method, they have generally not considered or considered bandwidth optimization while satisfying real-time delay requirements. So, compared to other studies, the results presented in this study show a greater improvement in signal-to-noise ratio (SNR) by integrating the microphone subset selection and the delay-aware distributed processing technique under simulated industrial conditions. Furthermore, the data show that the proposed framework provides a more balanced improvement in terms of signal quality improvement versus network efficiency in the context of real-world WASN applications **(Omar et al., 2024)**.

Table 9. Comparison with previous studies.

Study	Method Used	Environment Type	SNR Improvement (dB)	Bandwidth Optimization	Latency Consideration	Deployment Type
(Ahmed et al., 2022)	Distributed Speech Enhancement	Laboratory	3.5 – 4.2	Partial	Not analyzed	Simulation
(Hu et al., 2023)	Microphone Selection Algorithm	Indoor Scenario	4.0 – 5.0	Yes	Limited	Simulation
(Hu et al., 2023)	Distributed Beamforming	Controlled Noise	5.1	Partial	No	Simulation
(Park et al., 2024)	Low-Latency Beamforming	Smart Environment	5.5	Moderate	Yes	Simulation
(Didier et al., 2024)	iDANSE Algorithm	Acoustic Network	5.8	Yes	Yes	Simulation
Proposed Study	DANSE + MMSE Fusion	Industrial Environment	**Up to 6.3**	**≈30% Reduction**	**< 30 ms**	Industrial WASN Simulation

5. CONCLUSIONS

This examination furnished an excellent version improving audio signal quality in a Wireless Acoustic Sensor Network (WASN) deployed in an Iraqi enterprise vicinity. Using distributed sign processing strategies, particularly the DANSE set of guidelines, the device successfully

progressed the Signal-to-Noise Ratio (SNR) throughout all clusters at the same time as preserving low latency appropriate for real-time industrial communication.
The most important findings are:
• Distributed embedding within the network dramatically increased the signal-to-noise ratio (SNR) of recorded acoustic indicators, increasing by up to 6.3 dB per group.
• Microphone subset selection reduced community bandwidth usage by approximately 30% without compromising outstanding audio quality.
• The end-to-end delay is less than 30 ms, which confirms the system is suitable for real-time monitoring in noisy industrial environments.
• Hierarchical tree structure stabilizes scalability, allowing easy integration of additional nodes without reconfiguring the dynamic network.
• Overall, the fully customized DANSE-based algorithms have proven their power to improve multi-connected audio in extreme work situations. This work highlights the ability of sign processing strategies in wireless networks to improve verbal exchange reliability and overall performance, mainly in commercial enterprise applications in which noise and interference are substantial demanding situations. Future artwork can also discover dynamic clustering, superior compression strategies, and real-time adaptive algorithms to further beautify tool performance.

NOMENCLATURE

Symbol	Description	Symbol	Description
$s(n)$	Desired speech signal	H	Hermitian (conjugate transpose) operator
$v(n)$	Noise signal	$\hat{s}_k(n)$	Estimated signal at node k
SNR	Signal-to-Noise Ratio	$y_k(n)$	Received signal at node k
P_{signal}	Power of the speech signal	DANSE	Distributed Adaptive Node-Specific Signal Estimation
P_{noise}	Power of the noise signal	LMMSE	Linear Minimum Mean Square Error
$T_{processing}$	Processing time at each node	WASN	Wireless Acoustic Sensor Network
$T_{transmission}$	Data transmission time	AWGN	Additive White Gaussian Noise
$T_{propagation}$	Signal propagation time	BW	Bandwidth
f_s	Sampling frequency	Delay	End-to-end latency
N_b	Number of bits per sample	β	Regression coefficient
C	Number of audio channels	ε	Error term
w	Beamforming weight vector		

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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تحسين جودة الصوت في شبكات الاتصالات اللاسلكية باستخدام تقنيات معالجة الإشارة: نموذج تطبيقي لمنطقة صناعية عراقية

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الخلاصة

تسعى هذه الدراسة إلى تقديم تطبيق عملي لرفع كفاءة الوضوح الصوتي داخل شبكات الاستشعار الصوتية اللاسلكية المنتشرة في الوسط العراقي الذي يتسم بارتفاع مستوى الضجيج بشكل عام، وذلك من خلال توظيف تقنيات المعالجة الموزعة للإشارات . اعتمد الأسلوب المقترح، عبر منهج وصفي تحليلي، على تصميم هرمي للشبكة الاستشعارية يضم عشرين عقدة ميكروفون لاسلكي مرتبة على شكل تجمعات عنقودية .تقوم كل عقدة بتنفيذ تحسين موضعي للإشارة بالاستعانة بخوارزمية تقدير الإشارة التكيفية الموزعة الخاصة بها، بينما تستخدم العقد الرئيسية للتجمعات أسلوب تشكيل الحزمة المعتمد على طريقة تقليل متوسط مربع الخطأ الخطي بهدف دمج الإشارات على نطاق الشبكة .أظهرت النتائج تحقيق ارتفاع في متوسط نسبة الإشارة إلى الضوضاء قدره 6.3ديسيبل عبر جميع عناقيد الشبكة .كما تم خفض استهلاك عرض النطاق الترددي بنسبة 30٪ تقريبًا عبر اختيار تكيفي للميكروفونات يعتمد على حد تجريبي لنسبة الإشارة إلى الضوضاء مقداره 11ديسيبل، مع بقاء زمن الاستجابة الكلي أقل من 30ميللي ثانية، مما يجعله مناسبًا للتطبيقات الصناعية اللحظية .تشير النتائج أيضًا إلى أن المعالجة الموزعة القائمة على خوارزمية DANSE، إلى جانب البنية الهرمية لشبكة الاستشعار الصوتية اللاسلكية، تقدم حلاً فعالاً وقابلاً للتوسع لضمان اتصالات صوتية موثوقة في أوساط صناعية صوتية قاسية.

الكلمات المفتاحية: شبكات الاستشعار الصوتية اللاسلكية، معالجة الإشارات الموزعة، خوارزمية DANSE، الاتصالات الصناعية، تحسين جودة الإشارات الصوتية.