Eagle International Journal of Science, Technology and Innovation

An International Peer Reviewed, Open-Access and Multidisciplinary Journal
Volume 1 | Issue 2 | October 2026 |
Website: https://eijrihs.com/index.php/eijsti/index

AI-DRIVEN SEMANTIC COMMUNICATION AND ADAPTIVE DATA COMPRESSION FOR ULTRA-LOW-LATENCY AND ENERGY-EFFICIENT WIRELESS DATA TRANSMISSION

Omeche, A. A.[1], Ekwemuka, J. U.[2], Obieze, O. E.[3]

1 Department of Electrical and Electronic Engineering, Madonna University, Nigeria.
2 Department of Computer Engineering, Southern Delta University, Ozoro, Delta State
3 Digital Dynamics Systems Inc., Enugu Nigeria.

Corresponding Email; engrobieze30@gmail.com

ABSTRACT

The growing need for quick and power-saving wireless data transmission shows that old bit-by-bit ways have limits especially when only a little bandwidth is available for the Internet of Things, factories and new 6G communication. This study suggests a system that uses artificial intelligence to send messages by meaning and to shrink data adaptively. The design has a part that pulls out meaning, a part that compresses using attention a part that checks the channel state, a controller that decides how to send and a part that rebuilds the meaning at the other end. An artificial neural network looks for the bits and sets the right compression level depending on how good the channel is, how much traffic there is and how well we need to rebuild the meaning. The whole system is set up as a problem that balances four goals: how well the meaning is rebuilt, how fast the message travels how much bandwidth is used and how much power is spent. To test it we ran a simulation where the signal-to-noise ratio ranged from 0 to 25 dB and compared the new method with old ways fixed-rate compression and non-adaptive semantic communication. The results show that we can cut the delay from 28 ms to 16 ms, a 42.86 percent drop and cut energy use from 0.85 J to 0.52 J, a 38.82 percent drop. The new method also uses bandwidth better and keeps meaning clearer even when the channel changes. This work builds a map for smart app-aware wireless data transmission, in places where resources are tight.

Keywords: Semantic communication; artificial intelligence; adaptive data compression; wireless data transmission; artificial neural network; ultra-low latency; 6G communication.

1. INTRODUCTION

Wireless communication, the Internet of Things (IoT) industrial automation, autonomous systems and smart connected devices are growing fast. This growth has made the need for efficient data transmission much larger. New communication apps now need fast data flow, little delay, dependable delivery of information and lower energy use. These needs are especially critical when building 5G and 6G wireless systems because old designs are being pushed by traffic, scarce spectrum and strict quality-of-service rules for each app (Strinati & Barbarossa 2021; Saad et al., 2020). Old wireless systems are built to send and rebuild every single bit exactly. Even though this method has helped digital communication grow it does not always separate the data that is truly needed by an app from data that adds value to its goal. As a result, sending whole data streams without looking at what they mean can add needless traffic use more bandwidth and slow things down especially when wireless networks are crowded (Shannon, 1948;. Thomas, 2006). Semantic communication has come up as a way, where the main goal is to send useful meaning instead of copying every bit exactly. By pulling out the features that matter for the task and dropping the data semantic communication can lower the amount of data sent while keeping the information that the receiver really needs. Deep learning-based semantic systems have shown that this idea works for text, images and other smart communication needs (Xie et al., 2021; Qin et al., 2021). Adding intelligence to semantic communication gives more chances to adjust the sending process when the channel changes. In wireless settings channel quality changes with how far you are, interference, movement, fading and network traffic. So a set compression level is often not good enough when conditions change. High compression cuts overhead. Can erase key information while low compression keeps quality but uses more bandwidth and energy.

Adaptive semantic transmission helps balance these opposing needs (Weng & Qin 2021; Lu et al. 2021). New studies have pushed communication into goal-driven sending smart resource use and task-focused data picking. Still key problems stay: how to tune relevance, compression, delay and energy all together. Specifically systems need ways to decide how data to send which features get priority and how compression should change when the channel shifts (Mostaani et al., 2022; Jiang et al. 2024). This study proposes a semantic communication and adaptive compression framework to make wireless data transfer super-fast and energy-friendly. The framework mixes ANN-based feature picking, adaptive compression and channel-aware sending control. The main contribution is an optimization plan that looks at semantic quality, compression level, delay and energy all together not separately. The study builds a semantic communication design, for wireless data adding ANN-based feature extraction and adaptive compression. It also creates a channel-aware compression controller that reacts to changing conditions and builds a multi-goal optimization model to cut delay and energy while keeping semantic quality. The proposed framework is compared to normal data sending fixed-rate compression and non-adaptive semantic methods to show its performance and efficiency.

2. LITERATURE REVIEW

2.1 Conventional Wireless Communication and Information Transmission

The foundation of digital communication is strongly connected with Shannon's information theory, which shows how information moves how much can be sent and how noise affects it. Shannon in 1948 showed that it is possible to have communication if the speed of sending is lower than what the channel can handle. However regular ways of sending bits focus on getting the symbols and bits right instead of making sure the information is useful for a specific job. Cover and Thomas in 2006 wrote a book on information theory covering things like entropy how to send data efficiently how to send it without errors and how to balance quality and data size. These ideas are the basis for making data smaller and using communication resources better.. Traditional ways of doing this usually look at how well the data is rebuilt, not if that data is good enough for a certain smart task.

2.2 Deep learning-based semantic communication

The growth of learning has opened up new chances for understanding meaning finding features and sending smart information over wireless. Xie and others in 2021 created DeepSC, a system that uses networks to get meaning out of text when sending it over wireless. Their method showed that sending meaning can work better in some situations than ways. Qin and others in 2021 looked at sending meaning for images using learning to combine sending and checking for errors. Their work showed that neural networks can keep image details when sending over wireless. These steps helped move communication past old ways of sending bits. Weng and Qin in 2021 looked at sending meaning for images showing how getting meaning and rebuilding it can make sending. But how well the meaning is rebuilt and how much is sent is still a choice to make.

2.3 Compression and task-oriented communication

Recent work has focused more on sending only what is needed for a specific job instead of sending all the data. Mostaani and others in 2022 looked at sending data that fits the job when there is not space to send. Their research showed that using space in the right way is important. Jiang and others in 2024 looked at how to change the way meaning is sent and how to use the space in the way for the job. Their way looked at how much data's sent and how much space is used showing that changing how meaning is sent can cut down the data sent while still getting the job done. This gives a start for making systems where the way data is sent depends on what the job needs.

2.5 Emerging semantic communication architectures

As semantic communication becomes more important for 6G networks people are looking at network setups getting meaning out of data and sending only what is needed. Recent reviews say that semantic communication is a way to make sending better in future smart networks ((Strinati & Barbarossa, 2021; Jiang et al., 2025)). Samarathunga and others in 2024 looked at a system that uses an auto encoder to send meaning for machines. Their study showed that sending meaning can help machines communicate better. Yang and others in 2025 looked at how to change the way meaning is sent for sensors showing that sending meaning that fits the job and what can be sent is important. Recently work has looked at using attention. How much to compress to deal with changing sending conditions and image content.

2.5 Research Justification

The work we looked at shows that semantic communication, deep learning and changing how much data is sent're good ways to make sending better. But there are still chances to do more: The study looks at making sure the meaning is right how much data is sent how it is sent and how much energy is used by changing how things are done depending on the sending conditions and what the job needs. It directly deals with the balance between how good the meaning's how much is sent by making a single way to handle changes in signal strength how much is needed and how good the meaning needs to be. The new way is tested with ways of measuring and, with how well the meaning works for the job. The study does this with a system that uses a network to handle meaning in communication. Unlike ways that do compression before sending the new system makes compression part of the sending process and changes based on what's needed.

3. METHODOLOGY

3.1 Research Design

The study adopted a model-based design and simulation to build and test an AI-driven semantic communication system. The architecture contains a transmitting unit, a communication channel and a receiving unit. The transmitting unit collects data, pulls out features and compresses the data adaptively. The wireless channel adds noise causes fading and may create transmission errors. The receiving unit rebuilds the representation that was sent and checks how useful it is for the target application. The system is built to work under channel conditions letting the compression method change how much information is sent based on the quality of the channel and, on the needs of semantic reconstruction. The method has five steps: data gathering and cleaning extracting semantic features with AI,

adaptive compression of semantic data, channel-aware wireless transmission and finally rebuilding the semantics and evaluating performance.

3.2 Proposed system architecture

The architecture integrates the semantic encoder, ANN-based feature selection, adaptive compression controller, wireless channel, and semantic decoder.

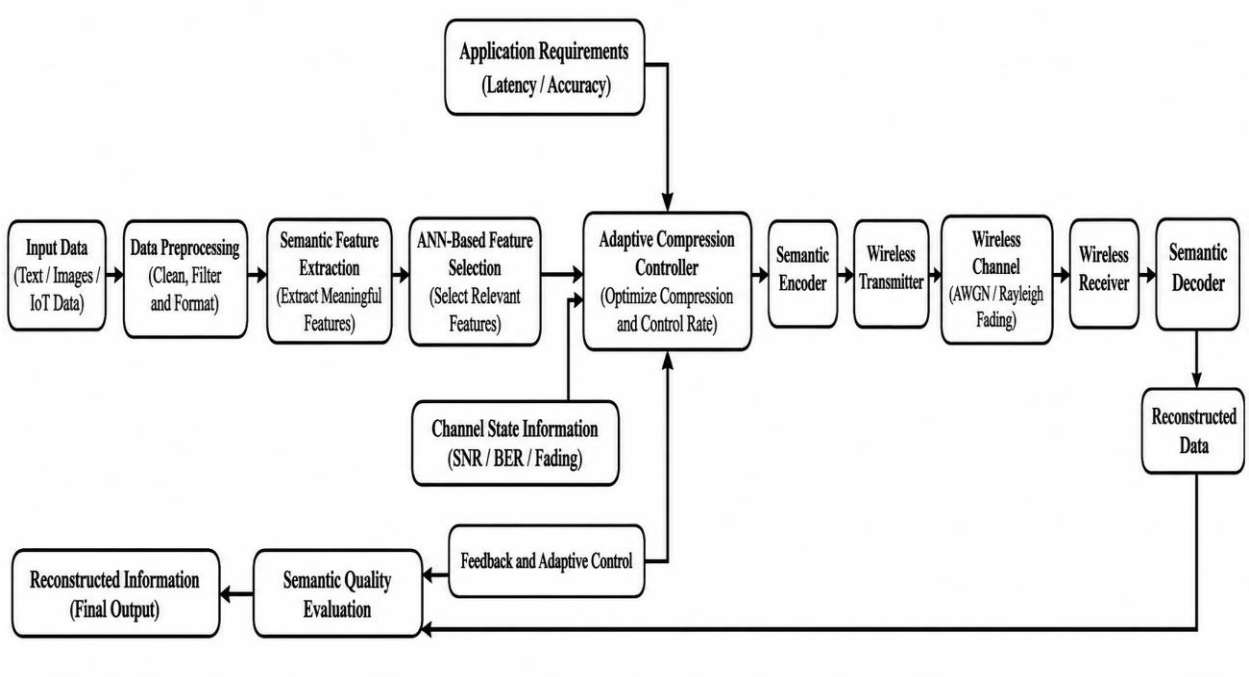

Figure 1: Proposed AI-Driven Semantic Communication Architecture

The architecture integrates a feedback mechanism through which the receiving system estimates reconstruction quality and provides information for subsequent compression adjustments. The system is distinguished by the interaction between the semantic feature-selection process and the adaptive compression controller. Rather than using a predetermined compression ratio, the controller selects the compression level according to channel conditions and application requirements.

3.3 Mathematical modelling of the proposed system

3.3.1 Input data representation

Let the input data be represented as:

$X = [x_1, x_2, \ldots, x_N]$

(1)

where X represents the original data stream and N is the number of input samples or feature elements.

The data were normalized before semantic processing. Thus,

$x_i' = \frac{xi - \mu x}{б x}$

(2)

where:

x_i' represents the normalized input.

μx is the mean of the input dataset.

$б x$ is its standard deviation.

This preprocessing operation ensures that differences in the numerical scale of input variables do not dominate the learning process.

3.3.2 AI-based semantic feature extraction

The semantic extraction module identifies the most relevant information required by the receiving application. The extracted semantic representation is expressed as:

$Z = f\theta(X)$

where:

Z is the semantic feature vector.

$f\theta$ is the trained neural network.

$\boldsymbol{\theta}$ represents the network parameters.

An attention-based feature-selection mechanism assigns importance weights to individual features thus,

$a_i = \frac{\exp(ei)}{\sum_{j=1}^{N} \exp(ej)}$

(3)

where e_i is the learned importance score associated with feature i.

The resulting semantic representation becomes:

$Z_s = \sum_{i=1}^{N} ai\ zi$

(4)

Features with higher attention weights are assigned greater transmission priority.

3.3.3 Adaptive data compression

The compression controller determines the proportion of semantic information to be transmitted.
The compression ratio is defined as:

$$CR = \frac{So - Sc}{So} \times 100\% \quad (5)$$

where:
S_o is the original data size.
S_c is the compressed data size.
The adaptive compression ratio is modelled as:

$$CR_t = g\phi(SNR_t, Q_t, L_t, E_t) \quad (6)$$

where:
SNRt is the instantaneous signal-to-noise ratio.
Qt is the required semantic reconstruction quality.
Lt is the latency requirement.
Et represents the available energy budget.
$g\phi$ is the learned compression-control function.
The compression level is constrained within an allowable range:

$$CR_{min} \leq CR_t \leq CR_{max} \quad (7)$$

The compressed semantic representation is therefore:

$$Z_c = C(Z_s, CR_t) \quad (8)$$

where (C(.) represents the adaptive compression operation.
An important implementation detail is that compression ratio in Equation (5) denotes percentage size reduction, while the retained-feature fraction is:

$$\rho_t = 1 - \frac{CRt}{100} \quad (9)$$

This distinction prevents confusion between the amount of information removed and the amount retained.

3.3.4 Wireless channel modelling

The wireless communication channel is represented by:

$$Y = hX_c + N \quad (10)$$

where:
Y is the received signal.
h represents the wireless channel coefficient.
X_c is the transmitted compressed signal.
N represents additive noise.
For an AWGN channel:

$Y = X_c + N$

(11)

The signal-to-noise ratio is:

$SNR = 10\log_{10}(\frac{Ps}{Pn})$

(12)

where P_s and P_n represent signal and noise powers, respectively.

For fading-channel evaluation, the Rayleigh fading model can also be incorporated to represent multipath propagation.

3.3.5 Semantic reconstruction

At the receiver, the compressed information is decoded using a trained semantic decoder:

$\hat{X} = f_\psi^{-1}(Z_r)$

(13)

where

$\hat{X}$ is the reconstructed information.

Z_r is the received semantic representation.

f_ψ^{-1} represents the decoder.

Semantic reconstruction quality is evaluated through:

$Q_s = \frac{Nc}{Nt} \times 100\%$

(14)

where N_c is the number of correctly recovered task-relevant features and N_t is the total number of required task-relevant features.

For image transmission, additional measures such as PSNR and structural similarity (SSIM) should be included. For text transmission, semantic similarity can be evaluated using an appropriate embedding-based metric.

3.3.6 End-to-end latency

The total communication latency is expressed as:

$T_{total} = T_p + T_e + T_c + T_{tx} + T_{rx} + T_d$

(15)

where:

T_p is preprocessing time.

T_e is semantic encoding time.

T_c is compression processing time.

T_{tx} is transmission time.

T_{rx} is reception and processing time.

T_d is decoding time.

Transmission time is calculated as:

$T_{tx} = \frac{Sc}{Rb}$

(16)

where R_b represents the effective transmission bit rate, with S_c expressed in bits.

This model validates how adaptive compression can reduce transmission time, although excessive compression may increase encoding and decoding overhead.

3.3.7 Energy consumption

The total energy consumption is modelled as:

$$E_{total} = E_{enc} + E_{comp} + E_{tx} + E_{dec} \quad (17)$$

where the terms represent energy consumed during encoding, compression, transmission, and decoding.

The transmission energy component is:

$$E_{tx} = P_{tx} T_{tx} \quad (18)$$

Where P_{tx} is the transmitter power.

This formulation is important because reducing transmitted data does not automatically guarantee reduced total energy consumption. The additional computational energy associated with semantic encoding and decoding must also be considered.

3.3.8 Multi-objective optimization

The proposed adaptive communication system seeks to minimize latency, energy consumption, and transmission overhead but the same time maintain acceptable semantic reconstruction quality.

The optimization objective is:

$$\min_{\theta,\phi} J = \lambda_1 \frac{Ttotal}{Tref} + \lambda_2 \frac{Etotal}{Eref} + \lambda_3 \frac{Sc}{So} + \lambda_4 (1 - Q_s) \quad (19)$$

subject to the following conditions: $Q_s \geq Q_{min}$, $T_{total} \leq T_{max}$, $E_{total} \leq E_{max}$, $CR_{min} \leq CR_t \leq CR_{max}$;

where λ_1, λ_2, λ_3, λ_4 are non-negative weighting coefficients whose sum is unity.

The reference values T_{ref} and E_{ref} normalize the objective terms. Q_s is expressed on a zero-to-one scale in Equation 19.

The optimization problem ensures that compression is not pursued at the expense of unacceptable semantic information loss.

3.5 Simulation parameters and experimental configuration

For the preliminary evaluation, four communication configurations were considered:

i. Conventional bit-oriented wireless transmission.
ii. Fixed-rate data compression.
iii. Non-adaptive semantic communication.
iv. Proposed AI-driven adaptive semantic communication.

The comparison was designed to establish whether the proposed architecture offers improvements over conventional and existing-style semantic transmission configurations.

Table 1: Simulation Parameters

Parameter	Value
Carrier frequency	2.4 GHz
Channel bandwidth	20 MHz
SNR range	0–25 dB
SNR interval	5 dB
Transmission power	23 dBm
Modulation	QPSK
Channel models	AWGN and Rayleigh
Input data types	Text, images and IoT
Compression range	10–80%
Minimum semantic quality	90%
Evaluation methods	Four configurations
Simulation environment	MATLAB/Simulink

These are proposed experimental settings, not measured network parameters. The 90% semantic-quality requirement is a design constraint to be verified during implementation.

3.6 Performance Evaluation Criteria

The performance of the proposed system is evaluated using the following metrics described in table 2.

Table 2: Performance Evaluation Criteria

Metric	Evaluation purpose
End-to-end latency	Measures total processing and transmission delay
Energy consumption	Measures total energy expenditure
Compression ratio	Determines data-size reduction
Semantic reconstruction quality	Measures preservation of task-relevant information
Throughput	Measures effective data delivery rate
BER	Measures bit-level transmission reliability
Bandwidth utilization	Measures spectrum resource consumption
RMSE	Measures numerical reconstruction error

The comparative improvement was calculated as:

$I_T = \frac{Tb - Tp}{Tb}$\frac x 100%

(20)

$I_E = \frac{Eb - Ep}{Eb}$ x 100%

(21)

where T_b, E_b represent baseline latency and energy, while T_p, E_p represent proposed-system latency and energy.

For bandwidth reduction:

$$I_{BW} = \frac{BWb - BWp}{BWb} \times 100\%$$

(22)

For reconstruction quality, improvement is reported in percentage points or through a clearly defined normalized comparison rather than applying the same reduction formula.

4. RESULTS AND DISCUSSION

4.1 Consolidated performance results

The results of the simulation carried out using the parameters in table 1, shown as consolidated performance results are presented as tabulated in table 3.

Table 3: Simulation Results of Comparative Performance Evaluation

Performance metric	Conventional	Fixed compression	Non-adaptive semantic	Proposed AI
Latency (ms)	28.0	23.5	19.8	16.0
Energy (J)	0.85	0.72	0.61	0.52
Bandwidth consumption (%)	100	78	64	52
Semantic utility (%)	100	96	94	96
Quality at 0 dB SNR (%)	62	70	74	78
Quality at 25 dB SNR (%)	93	95	96	98

The values in the proposed comparative result were simulated and not practical verified experimental observations. The table shows that the proposed approach gives the latency, the lowest energy consumption and the lowest bandwidth requirement among the four configurations and it keeps a high semantic utility index. An important observation is that the proposed system does not always maximize each quality measure. Rather the proposed system seeks an operating point where communication efficiency is improved and the application receives enough information to carry out successful task execution.

Overview of evaluation

The proposed system was evaluated against three alternative transmission configurations. The results in this section form a numerical scenario that shows the expected analysis and presentation of the research. Four configurations were compared namely, end-to-end latency, energy consumption, bandwidth utilization and semantic reconstruction quality.

4.2 Comparative latency performance

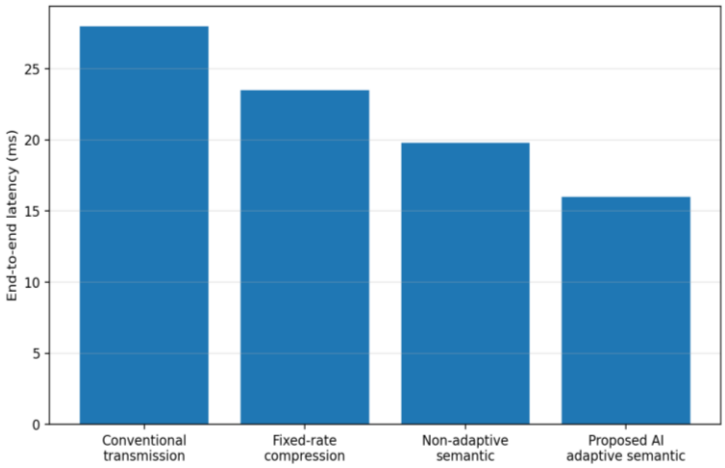

Figure 2. End-to-end Latency Comparison.

The illustrative results indicate that conventional transmission produces a latency of 28 ms, while fixed-rate compression and non-adaptive semantic communication produce 23.5 ms and 19.8 ms, respectively. The proposed adaptive semantic communication framework produces 16 ms.

The reduction in latency relative to conventional transmission is:

$I_T = \frac{28 - 16}{28}$ x 100

I_T = 42.86%.

The improvement is attributed to the reduction in transmitted data volume through semantic feature selection and adaptive compression. The results also suggest that fixed-rate compression provides a smaller latency improvement because its compression level does not respond dynamically to channel conditions.

4.3 Energy consumption performance

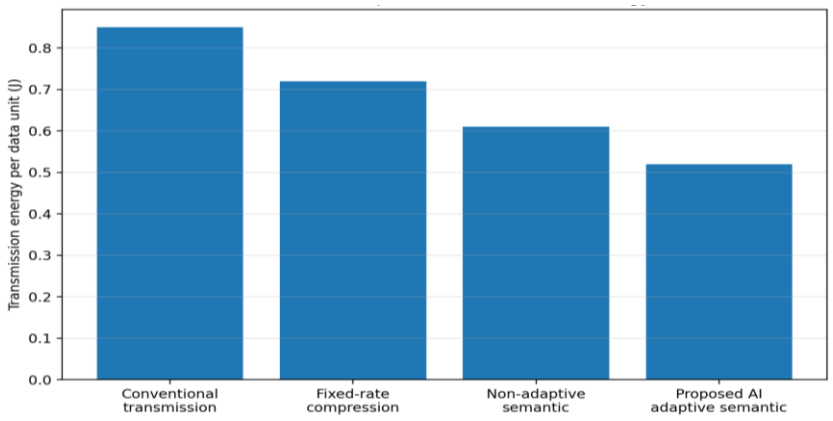

Figure 3: Transmission Energy Comparison.

The energy consumption values are 0.85 J, 0.72 J, 0.61 J, and 0.52 J for conventional transmission, fixed-rate compression, non-adaptive semantic communication, and the proposed system, respectively.

The percentage energy improvement is:

$$I_E = \frac{0.85 - 0.52}{0.85} \times 100$$

$I_E = 38.82\%$.

The result suggests that adaptive semantic compression can reduce energy expenditure by limiting unnecessary transmission of redundant information. However, the final experimental evaluation must include the energy consumed by the ANN, encoder, compressor, and decoder to ensure that the reported improvement represents total system energy rather than transmitter energy alone.

4.4 Bandwidth utilization and semantic quality

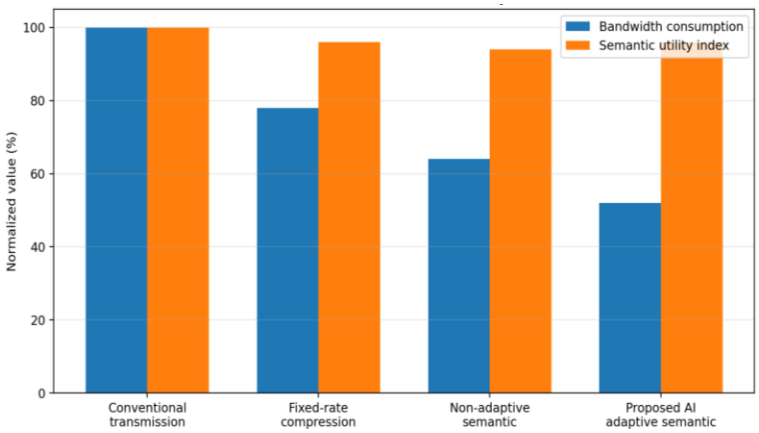

Figure 4: Bandwidth Consumption and Semantic Utility Comparison.

The conventional transmission system is normalized to 100% bandwidth consumption. Fixed-rate compression reduces this value to 78%, while non-adaptive semantic communication reduces it to 64%.

The proposed adaptive system achieves an illustrative bandwidth consumption of 52%.

The resulting bandwidth reduction is:

$$I_{BW} = \frac{100 - 52}{100} \times 100$$

$I_{BW} = 48\%$.

The proposed system also maintains a semantic utility index of 96%, suggesting that substantial data reduction can be achieved without a corresponding loss of task-relevant information. The distinction between semantic utility and exact reconstruction fidelity is important. The proposed system is intended to preserve information necessary for the intended task, not necessarily reproduce every original input element.

4.5 Effect of SNR on semantic reconstruction quality

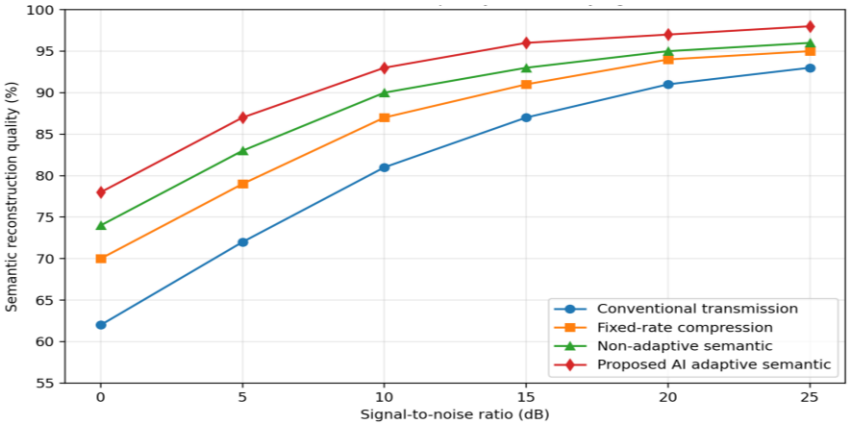

Figure 5: Semantic Reconstruction Performance under Varying SNR.

The results demonstrate that semantic reconstruction quality improves as SNR increases across all four transmission configurations. At 0 dB, the conventional system achieves 62% semantic quality, compared with 70% for fixed-rate compression, 74% for non-adaptive semantic communication, and 78% for the proposed system. At 25 dB, the corresponding values increase to 93%, 95%, 96%, and 98%. This indicates that the proposed system maintains an advantage under both poor and favourable channel conditions in the illustrative scenario. The improvement at lower SNR is particularly relevant to wireless networks experiencing interference, fading, and limited transmission power. Nevertheless, actual performance under Rayleigh fading must be established independently, as the plotted values are not measured fading-channel results.

4.7 Discussion of findings

The shown results support the reason behind adding feature extraction and adaptive compression within a standard wireless communication system. First, the latency results show the importance of sending data over the wireless channel. Conventional communication systems transmit data in bit format whereas semantic communication can prioritize information according to application requirements. This approach matches the task-focused communication idea discussed by Gündüz et al. (2023). Second, the energy results highlight the benefits of reducing extra communication. Nevertheless semantic compression needs computing power. Therefore a setup that lowers transmission energy while ignoring computing energy can lead to conclusions. Measuring all energy is essential for showing the efficiency of the wireless communication architecture. Third, the bandwidth results show the possibility of feature selection to improve spectrum use. The shown 48 percent reduction suggests that the proposed mechanism can lower transmitted data compared with the conventional baseline. Fourth the SNR results show that adaptive semantic transmission can improve reconstruction quality when channel conditions

change. The advantage comes from the controllers' ability to change compression based on channel quality of using a fixed compression ratio. Finally the results suggest that the wireless communication architecture could be useful in IoT, wireless sensor networks, intelligent transportation systems and other applications that need quick delivery of task-relevant information.

5. CONCLUSION

This study has presented a semantic communication and adaptive compression framework for improving wireless data transmission efficiency. The wireless communication architecture integrates ANN-based feature extraction, attention-based feature selection, adaptive compression, channel-state estimation and semantic reconstruction into a single communication framework. The proposed method addressed limits of bit-oriented transmission by prioritizing task-relevant information and dynamically adjusting the amount of transmitted data based on channel conditions and application requirements. The shown comparative results indicate that the wireless communication architecture can reduce end-to-end latency by 42.86 percent energy consumption by 38.82 percent and consumption by 48 percent compared with conventional transmission. The shown SNR evaluation also indicates semantic reconstruction quality when channel conditions vary. The main contribution of the research is the integration of feature selection and channel-aware adaptive compression within a multi-objective optimization framework. This provides a basis for developing wireless communication systems that balance information quality, transmission delay bandwidth use and energy efficiency. The wireless communication architecture has applications, in industrial IoT, wireless sensor networks, intelligent transportation, remote monitoring and emerging 6G communication systems. Future work should focus on implementing the wireless communication architecture in MATLAB/Simulink training the ANN with datasets evaluating the system under AWGN and Rayleigh fading conditions and validating the results through statistical comparison and ultimately experimental implementation.

REFERENCES

Bourtsoulatze, E., Kurka, D. B., & Gündüz, D. (2019). Deep joint source-channel coding for wireless image transmission. IEEE Transactions on Cognitive Communications and Networking, 5(3), 567–579. https://doi.org/10.1109/TCCN.2018.2871075

over, T. M., & Thomas, J. A. (2006). Elements of information theory (2nd ed.). Wiley.

Getu, T. M., Kaddoum, G., & Bennis, M. (2024). A survey on goal-oriented semantic communication: Techniques, challenges, and future directions. IEEE Access, 12, 51223–51274. https://doi.org/10.1109/ACCESS.2024.3381967

Gündüz, D., Qin, Z., Aguerri, I. E., Dhillon, H. S., Yang, Z., Yener, A., Wong, K. K., & Chae, C.-B. (2023). Beyond transmitting bits: Context, semantics, and task-oriented communications. IEEE Journal on Selected Areas in Communications, 41(1), 5–41. https://doi.org/10.1109/JSAC.2022.3223408

Letaief, K. B., Chen, W., Shi, Y., Zhang, J., & Zhang, Y. J. A. (2019). The roadmap to 6G: AI empowered wireless networks. IEEE Communications Magazine, 57(8), 84–90. https://doi.org/10.1109/MCOM.2019.1900271

Liu, C., Guo, C., Yang, Y., & Jiang, N. (2024). Adaptable semantic compression and resource allocation for task-oriented communications. IEEE Transactions on Cognitive Communications and Networking, 10(3), 769–782. https://doi.org/10.1109/TCCN.2023.3346481

Mostaani, A., Vu, T. X., Chatzinotas, S., & Ottersten, B. (2022). Task-oriented data compression for multi-agent communications over bit-budgeted channels. IEEE Open Journal of the Communications Society. https://doi.org/10.1109/OJCOMS.2022.3213213

Peng, X., Qin, Z., Tao, X., Lu, J., & Hanzo, L. (2024). A robust semantic text communication system. IEEE Transactions on Wireless Communications, 23(9), 11372–11385. https://doi.org/10.1109/TWC.2024.3381950

Qin, Z., Tao, X., Lu, J., Tong, W., & Li, G. Y. (2021). Semantic communications: Principles and challenges. arXiv. https://arxiv.org/abs/2201.01389

Saad, W., Bennis, M., & Chen, M. (2020). A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. IEEE Network, 34(3), 134–142. https://doi.org/10.1109/MNET.001.1900287

Samarathunga, P., Rezaei, H., Lokumarambage, M., Sivalingam, T., Rajatheva, N., & Fernando, A. (2024). An autoencoder-based task-oriented semantic communication system for M2M communication. Algorithms, 17(11), 492. https://doi.org/10.3390/a17110492

Shannon, C. E. (1948). A mathematical theory of communication. The Bell System Technical Journal, 27(3), 379–423; 27(4), 623–656. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Strinati, E. C., & Barbarossa, S. (2021). 6G networks: Beyond Shannon towards semantic and goal-oriented communications. Computer Networks, 190, 107930. https://doi.org/10.1016/j.comnet.2021.107930

Wang, Y., Han, H., Feng, Y., Zheng, J., & Zhang, B. (2025). Semantic communication empowered 6G networks: Techniques, applications, and challenges. IEEE Access, 13, 28293–28314. https://doi.org/10.1109/ACCESS.2025.3532797

Wu, J., Wu, C., Lin, Y., Yoshinaga, T., Zhong, L., Chen, X., & Ji, Y. (2024). Semantic segmentation-based semantic communication system for image transmission. Digital Communications and Networks, 10(3), 519–527. https://doi.org/10.1016/j.dcan.2023.02.006

Xin, G., Fan, P., & Letaief, K. B. (2024). Semantic communication: A survey of its theoretical development. Entropy, 26(2), 102. https://doi.org/10.3390/e26020102

Yang, H., Zhu, X., Yang, J., Li, J., Qing, L., He, X., & Wang, P. (2025). Scalable semantic adaptive communication for task requirements in WSNs. Sensors, 25(9), 2823. https://doi.org/10.3390/s25092823

Yang, W., Du, H., Liew, Z. Q., Lim, W. Y. B., Xiong, Z., Niyato, D., Chi, X., Shen, X. S., & Miao, C. (2023). Semantic communications for future internet: Fundamentals, applications, and challenges. IEEE Communications Surveys & Tutorials, 25(1), 213–250. https://doi.org/10.1109/COMST.2022.3223224