Beyond Connectivity: Semantic Communication Unlocks the Hyper-connected City with 6G

Woongsoo Na, Donghyun Lee, Nhu-Ngoc Dao, Trong-Minh Hoang, and Sungrae Cho

***Abstract*—The dawn of 6G technology presents a transformative opportunity to realize the hyper-connected city, characterized by seamless information exchange and intelligent infrastructure. However, achieving this vision requires more than simply increasing bandwidth and connectivity; it demands a shift towards semantic communication, a paradigm that prioritizes the meaning of information. This paper argues that semantic communication, powered by Artificial Intelligence (AI), is an indispensable cornerstone for building truly intelligent and responsive hyper-connected cities. We explore the core framework of semantic communication, examine the specific AI technologies that enable its implementation, and analyze experimental results demonstrating significant improvements in bandwidth efficiency, data recovery, and reduced latency compared to legacy methods. These results, derived from a testbed implementation of a semantic adaptive context lighting system, highlight the potential of AI-powered semantic communication to optimize resource allocation, enhance system resilience, and pave the way for a future where technology seamlessly enhances urban living. Although limited, our testbed results offer a compelling case for semantic communication's future relevance and potential as an enabler for hyper-connected city of the 6G era. Key areas for future research, including scalable AI models, security and privacy protocols, standardized interoperability, and robust real-world deployment and evaluation, are also discussed.**

***Index Terms*—Hyper-connected city, 6G, semantic communication, and AI.**

I. Introduction

THE dawn of 6G technology promises to unlock the full potential of intelligent, interconnected environments, leading to the vision of a hyper-connected city—a dynamic ecosystem where seamless information exchange and intelligent infrastructure create a smart, responsive urban landscape [1]. The true potential of 6G goes beyond ultra-high data rates and ultra-low latency; it lies in enabling more intelligent forms of communication. We suggest that semantic communication is the key to unlocking the full capabilities of 6G and realizing the hyper-connected city. Semantic communication transcends the limitations of traditional data transmission, focusing instead on conveying meaning, understanding context, and facilitating intelligent interactions between devices, systems, and individuals.

W. Na is with the Department of Software, Kongju National University, Cheonan, Republic of Korea. (Email: wsna@kongju.ac.kr)

D. Lee and S. Cho are with the School of Computer Science and Engineering, Chung-Ang University, Seoul 06974, South Korea (e-mail: dhlee@uclab.re.kr; srcho@cau.ac.kr

N.-N. Dao is with the Department of Computer Science and Engineering, Sejong University, Seoul, South Korea, email: nndao@sejong.ac.kr

T.-M. Hoang is with Posts and Telecommunications Institute of Technology, Hanoi 100000, Viet Nam (email: hoangtrongminh@ptit.edu.vn

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In this article, we argue that semantic communication is not just a desirable feature, but an indispensable cornerstone for building truly intelligent and responsive hyper-connected city. As we move beyond the limitations of simple data pipelines, semantic communication will enable us to make better use of the increasing amounts of data, derive actionable insights, and deliver services that are both efficient and meaningful [2]. To understand why semantic communication is so vital, we should consider how current communication paradigms fall short in meeting the complex and diverse needs of a smart urban environment. The limitations of simply transmitting data – without regard for its meaning or relevance – hinder the ability to effectively manage resources, optimize processes, and provide personalized services that are truly responsive to the needs of citizens.

The hyper-connected city of the future demands a new approach: a system where every interaction is imbued with meaning, where devices understand the context of their environment, and where decisions are made based on a shared understanding of information. This is the promise of semantic communication, and it is this vision that will be explored further in the chapters that follow. We will delve into the concept of semantic communication, examine its underlying principles (see Section II), explore the technologies that enable its implementation, and address the technical challenges that must be overcome to realize its full potential in the context of 6G-based hyper-connected city (see Section III). In addition, by exploring case studies of applying semantic communication based on simple time-series data utilized in real-world, we forecast the potential of semantic-based hyper-connected city in the future (see Section IV).

Unlike previous semantic communication studies that have primarily remained at the conceptual or simulation stage, this paper introduces a real-world testbed integrated into a smart lighting system, thereby demonstrating the feasibility of semantic communication within an operational hyper-connected city environment.

II. Semantic Communication: Concept and Framework

In an era defined by exponential data growth, the true challenge does not lie in simply transmitting information, but in discerning its meaning and leveraging it to drive intelligent action. Traditional communication paradigms, focused on efficient data transfer, often fall short in delivering the nuanced understanding necessary for seamless interaction in complex environments like the hyper-connected city.

A. Concept of semantic communication

Semantic communication transcends the conventional focus on bit-perfect transmission. It is a paradigm shift that prioritizes the accurate conveyance of meaning from source

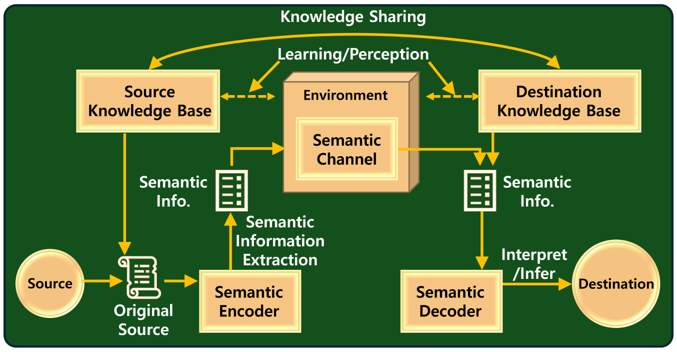

Fig. 1. The semantic communication framework.

to destination. Unlike traditional communication, which treats data as mere bits and bytes, semantic communication recognizes the inherent value of information and strives to ensure that the intended message is accurately understood by the receiver, regardless of channel noise or data loss. This involves encoding the data with contextual information, allowing the receiver to not only decode the data but also interpret its meaning within a specific context [2].

B. The core framework of semantic communication

At its heart, the semantic communication framework comprises several key components that work together to achieve intelligent information exchange as shown in Fig. 1.

- **Semantic Encoder**: The semantic encoder is the crucial first step in the semantic communication process. Its primary role is to transform raw data into a compact and meaningful semantic representation. This involves a sophisticated understanding of the data's context, relationships, and intended purpose. The encoder should go beyond simply compressing the data; it should extract the essence of the information being conveyed.
- **Semantic Channel**: The semantic channel is distinct from the physical channel. While the physical channel refers to the medium that carries encoded signals (e.g., radio spectrum, optical fiber), the semantic channel denotes the effective path over which task-relevant semantic representations are conveyed, reconstructed, and interpreted. In other words, the semantic channel abstracts the end-to-end transformation from transmitted meaning units to their recovered interpretation at the receiver
- **Semantic Decoder**: The decoder receives the semantic representation and reconstructs the original information along with its associated meaning. Using its own knowledge base and reasoning capabilities, it can interpret the encoded message and derive actionable insights.
- **Knowledge Base**: The knowledge base is a centralized repository of information that is shared by both the semantic encoder and the semantic decoder. It provides a common understanding of concepts, relationships, and context, which is essential for accurate communication and interpretation of meaning. The knowledge base can be structured in various ways, such as knowledge graphs, ontologies, or relational databases.

Although the semantic encoder, decoder, and knowledge base are positioned at the application layer, their influence extends across the protocol stack. By determining which semantic units are transmitted, the application layer directly shapes traffic patterns and data priority, which in turn affect transport-layer congestion control and network-layer routing. Furthermore, reducing redundant or non-task-relevant data lowers the required bandwidth at the physical layer and enables more efficient scheduling at the MAC layer. In this sense, semantic communication constitutes an application-layer functionality with cross-layer design implications, bridging meaning-aware processing with conventional bit-level transmission.

C. Unlocking the potential of the hyper-connected city: semantic communication

Semantic communication offers key benefits for a 6G-enabled hyper-connected city. By transmitting only task-relevant semantic information, it improves *efficiency*, reducing bandwidth use and energy consumption. It also enhances *robustness*, since meaning-oriented features allow receivers to infer missing content using generative models or knowledge bases, providing resilience beyond conventional error correction. For example, a generative model can reconstruct plausible missing content based on partial semantic labels, while knowledge-graph reasoning can fill gaps using prior associations. *Contextual awareness* further enables adaptive resource allocation and personalized services, while *interoperability* ensures seamless interaction among heterogeneous devices through shared semantics. Finally, the model is inherently *scalable*, as distributed knowledge bases support the growing number of connected devices, with consistency maintained through periodic synchronization, version control, and federated update mechanisms.

In short, semantic communication prioritizes meaning over symbols, unlocking efficiency, robustness, and intelligence that are essential for future hyper-connected cities. The following sections detail the enabling technologies and remaining challenges.

III. AI-Powered Semantic Communication for the Hyper-Connected City

Building on this conceptual foundation, we next examine how semantic communication, empowered by Artificial Intelligent (AI), can enable the hyper-connected city. To realize the full potential of semantic communication—where meaning, rather than raw data, is the primary unit of exchange—AI-driven technologies are essential. Unlike conventional communication paradigms that focus on bit-level accuracy, semantic communication requires intelligent mechanisms capable of understanding, encoding, and reasoning about the content and context of information. In this regard, we propose the AI-powered semantic communication framework depicted in Fig. 2 as a blueprint for enabling next-generation hyper-connected city under 6G networks.

A. The 6G-enabled hyper-connected city: a symphony of seamless intelligence

Earlier studies on semantic communication [2] have outlined conceptual models, but these works lack real-world integration with hyper-connected city platforms, which this paper addresses. The vision of the hyper-connected city transcends the simple notion of interconnected devices; it envisions a dynamic urban ecosystem where technology seamlessly integrates with daily life, empowering citizens, fostering sustainable growth, and enabling unparalleled levels of efficiency and responsiveness. This ambitious vision is inextricably linked to the capabilities of 6G, the next-generation of wireless

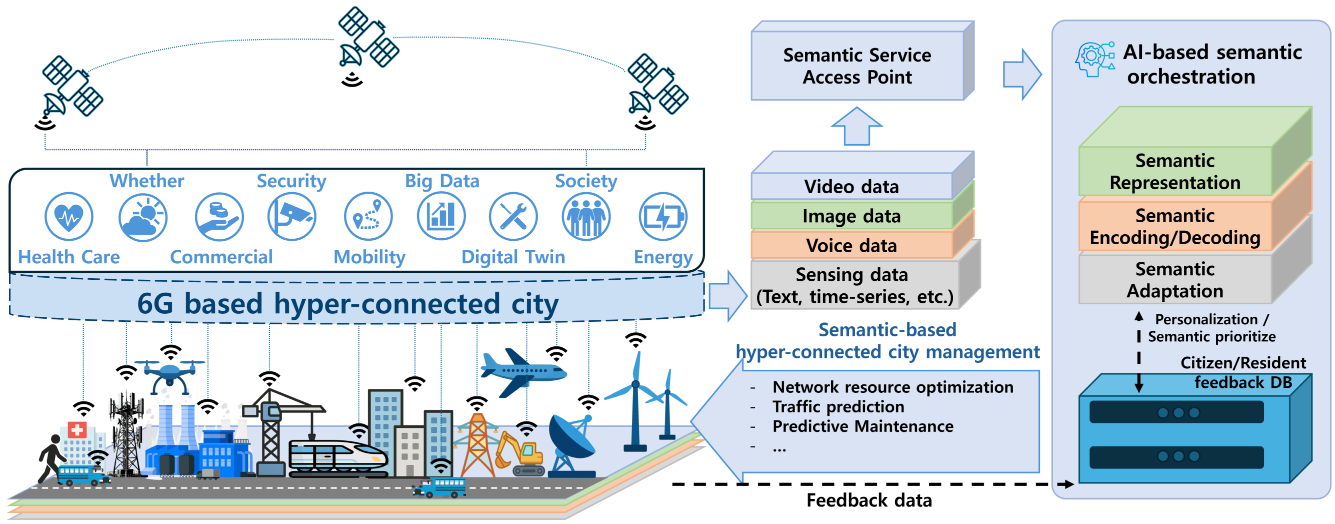

Fig. 2. AI-Powered semantic communication framework for a 6G-based hyper-connected city, with roles standardized as representation, encoding/decoding, and adaptation.

communication. 6G promises to deliver a paradigm shift in wireless connectivity, characterized by *ultra-high bandwidth*: supporting massive data throughput for bandwidth-intensive applications, *ultra-low latency*: enabling near-instantaneous communication for time-critical services, *massive connectivity*: connecting an unprecedented number of devices and sensors, *high reliability*: ensuring robust and dependable communication in challenging environments, *enhanced security*: protecting sensitive data and preventing unauthorized access, and *AI-native integration*: designing communication systems from the ground up to leverage AI capabilities. These stringent requirements directly translate into a diverse range of transformative applications within the hyper-connected city:

- **Autonomous Transportation**: Self-driving vehicles require ultra-low latency and high reliability to ensure safe real-time coordination with infrastructure and pedestrians.
- **Smart Healthcare**: Remote monitoring and telemedicine rely on high bandwidth and massive connectivity to transmit medical images and physiological data in real time.
- **Intelligent Infrastructure**: Smart grids, buildings, and factories depend on reliable, large-scale connectivity for real-time monitoring and control, enhancing efficiency and resilience.
- **Immersive Experiences**: AR/VR applications demand ultra-high bandwidth and ultra-low latency to provide seamless and interactive experiences.

B. Framework of semantic communication in a 6G hyper-connected city

Fig. 2 illustrates a vibrant 6G-enabled urban ecosystem that seamlessly interconnects various domains such as healthcare, mobility, energy, commerce, and public safety. These sectors continuously generate a vast array of heterogeneous data—including video feeds, images, voice commands, and sensor readings—collected through smart infrastructure and satellite communication.

These multimodal data streams are directed to a Semantic Service Access Point (SSAP), which functions as an intelligent gateway that aggregates heterogeneous inputs and interfaces them with the AI-based semantic orchestration module. The actual semantic processes—including representation, encoding/decoding, and adaptation— take place within the orchestration block, while the SSAP ensures structured delivery of data streams for consistent downstream processing.

The data flows into the AI-based semantic orchestration module, where three core semantic processes take place, and where feedback from citizens and service users can be incorporated to refine semantic priorities and enhance personalization:

- **Semantic Representation**: Interprets and models the underlying meaning of data.
- **Semantic Encoding/Decoding**: Compresses and reconstructs data based on its semantic content.
- **Semantic Adaptation**: Tailors the communication process to match application-specific requirements and dynamic network conditions.

The proposed framework addresses core network challenges. Semantic encoding reduces bandwidth and latency by emphasizing task-relevant information. Semantic adaptation ensures interoperability across heterogeneous networks, while feedback integration improves scalability, personalization, and Quality of Experience (QoE). Together, these mechanisms support resource efficiency, reliability, and cross-layer coordination.

This architecture not only enhances communication efficiency but also empowers real-time city orchestration. Semantic-based hyper-connected city orchestration enables key functionalities such as network resource optimization, real-time traffic prediction, and predictive maintenance of critical infrastructure. By integrating AI with semantic-aware communication, the proposed framework marks a fundamental shift toward intelligent, meaning-centric connectivity—paving the way for sustainable, responsive, and scalable hyper-connected city solutions in the 6G era.

Although Fig. 2 depicts a semantic-oriented vision for hyper-connected cities, its components align with 5G concepts. The AI-based semantic orchestration module parallels service orchestration and management in the 5G service-based architecture (SBA), while semantic encoding/decoding extends application-layer functions. Semantic adaptation also interacts with network management and orchestration (MANO) for cross-layer optimization. Thus, semantic communication

TABLE I: AI technologies and their roles for semantic communication in 6G hyper-connected city (Roles are categorized into Representation (Rep), Encoding/Decoding (Enc/Dec), and Adaptation (Adapt).)

AI technology	Role in semantic communication	Key 6G hyper-connected city applications
Bayesian Networks (BN)	**Rep** encodes causal priors for semantic variables, which leads to robust inference under loss [3], [4]	Traffic risk estimation, which results in prioritization of safety-critical messages
Support Vector Machines (SVM)	**Rep** performs lightweight classification at the edge, which reduces redundancy and highlights relevant tokens [5]	Energy anomaly detection, which enables faults to be identified without raw data overload
Reinforcement Learning (RL)	**Adapt** learns scheduling/policy for rate versus utility, which ensures efficiency under constraints [6], [7]	Urban sensing, which minimizes retransmissions while preserving urgent alerts
Deep Reinforcement Learning (DRL)	**Adapt** jointly allocates bandwidth and parity, which maintains end-to-end semantic fidelity [8], [9]	Drone video feeds, which preserve critical navigation cues
Generative Adversarial Networks (GAN)	**Enc/Dec** hallucinate missing semantic features, which conceals errors and restores plausibility [10], [11]	Channel loss recovery, which reconstructs missing structure in visual data
Federated Learning (FL)	**Enc/Dec** support distributed training, which preserves privacy and improves interoperability across domains [12], [13]	Telemedicine, which allows hospitals to share encoders without raw data exchange
Auto-encoder	**Enc/Dec** compress into bottleneck semantic code, which enables efficient transmission with bounded distortion [14]	Adaptive lighting, which allows compact spectral codes to support fine-grained control
Transformers	**Rep** captures long-range context, which reduces update frequency while maintaining coherence [15]	Forecasting, which delivers context-aware tokens for timely and concise updates

augments rather than replaces current architectures, offering an evolutionary path from 5G to 6G.

C. AI as the core enabler of semantic communication

The hyper-connected city, powered by 6G and driven by the promise of a truly intelligent and responsive urban environment, hinges on the ability to not just connect devices, but to understand the very meaning of the information they exchange. Semantic communication, with its focus on conveying intent and context, is the vital ingredient for making this vision a reality. But how do we enable machines to understand and act upon the nuances of semantic data at the scale required for a bustling metropolis? The answer lies in AI.

AI provides the cognitive horsepower needed to extract meaning from raw data, resolve ambiguities, and make informed decisions in real time, acting as the catalyst that transforms a network of connected devices into an intelligent and adaptive urban ecosystem. From enabling self-driving cars to interpret pedestrian intentions to empowering smart grids to anticipate energy demands, AI-driven semantic communication enables urban innovation.

Each AI technique plays a distinct role in semantic representation, encoding/decoding, or adaptation. For example, Bayesian Networks (BNs) support causal inference for semantic importance weighting, Support Vector Machines (SVMs) classify task-relevant semantics for compression, and Reinforcement Learning (RL) adapts redundancy and rate under channel dynamics. Table I showcases some of the core AI technologies that are essential for realizing the vision of a semantic hyper-connected city. These are not just isolated tools, but rather integral components of a holistic system that enables machines to communicate, understand, and act upon information in a way that mirrors human intelligence. They provide the crucial capabilities needed to:

- **Understand Context**: Parse complex data streams and extract the relevant context surrounding each piece of information.
- **Resolve Ambiguity**: Identify and resolve uncertainties in semantic data, ensuring accurate interpretation.
- **Infer Intent**: Determine the purpose behind the data being transmitted, allowing systems to anticipate needs and respond proactively.
- **Optimize Resources**: Allocate resources efficiently based on the semantic understanding of real-time conditions.
- **Personalize Services**: Deliver tailored experiences and services based on the unique needs and preferences of each citizen.

By examining these technologies, we can begin to appreciate the profound impact that AI will have on the future of urban living. As we delve deeper into these techniques, it becomes clear that AI is not just a supporting player in the hyper-connected city, but the very foundation upon which its intelligent systems are built. For instance, Auto-encoders and GANs jointly enable efficient semantic compression and error recovery (see Section IV), while Transformers capture context in multimodal time-series for adaptive urban services. This clarifies the concrete mechanism-level roles of AI beyond generic classification or prediction.

This is why investing in research and development of AI-powered semantic communication is so critical to unlocking the full potential of the urban landscape of tomorrow.

IV. Case Study: Adaptive Context Lighting with Semantic Communication

Hyper-connected city strives to create more human-centric environments, adaptive context lighting systems are emerging as a compelling example of how technology can seamlessly blend with our daily lives. These systems aim to replicate the benefits of natural daylight within indoor spaces, dynamically adjusting lighting to match the time of day, weather conditions, and even individual user preferences. But the challenge lies in efficiently capturing, transmitting, and recreating the complex nuances of natural light, all while adhering to the stringent requirements of 6G networks.

In this case study, we explore a novel approach that leverages the power of AI-driven semantic communication to create an adaptive and user-tailored lighting experience. This system tackles the challenges of bandwidth limitations and latency sensitivity, key concerns in 6G networks, by intelligently extracting and transmitting only the essential semantic information needed to recreate realistic lighting conditions.

The core of this approach lies in two key AI techniques:

- **Auto-encoders for semantic feature extraction**: Real-world lighting data, captured by sophisticated sensors,

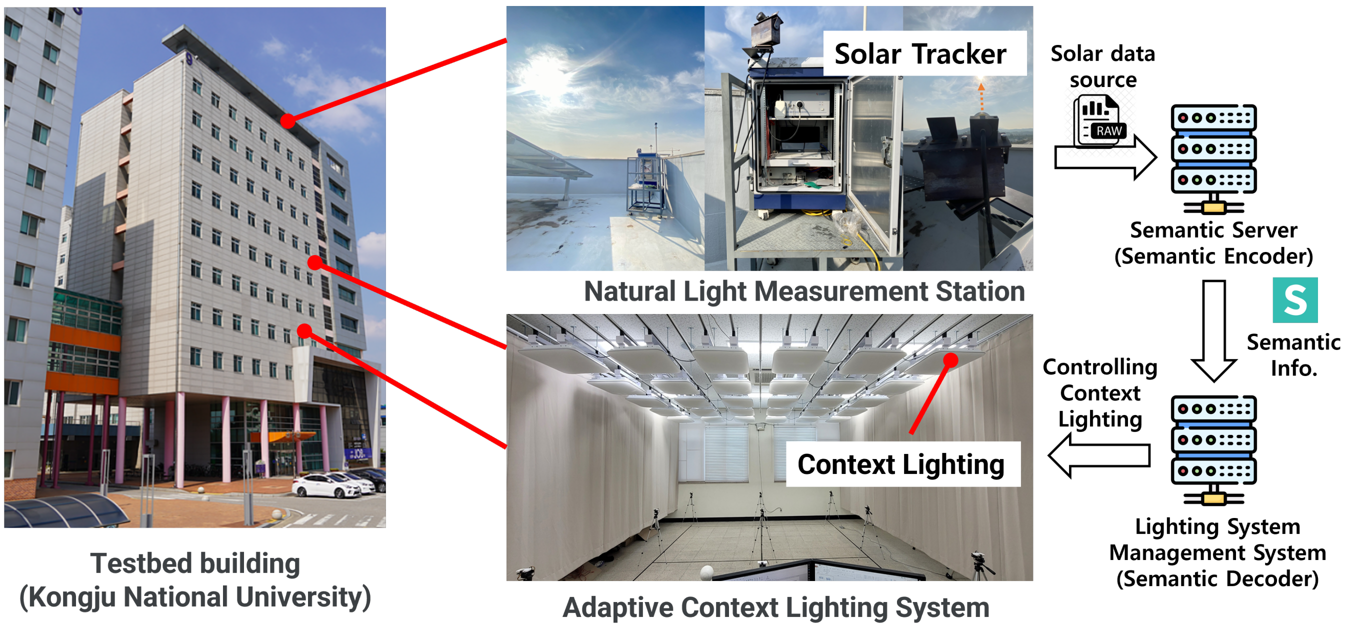

Fig. 3. Adaptive context lighting system testbed at Kongju National University, college of engineering building 8, South Korea.

is first processed by an auto-encoder. This neural network effectively learns to compress the high-dimensional lighting data into a lower-dimensional semantic representation. This compressed representation captures the key features of the lighting environment, discarding irrelevant details and significantly reducing the amount of data that needs to be transmitted. By transmitting only the semantic essence of the lighting data, we minimize bandwidth consumption, a critical requirement for scaling such systems across the hyper-connected city.

- **GANs for high-fidelity reconstruction**: On the receiving end, a GAN takes the compressed semantic representation and reconstructs a realistic lighting environment. The GAN is pre-trained on a vast dataset of natural lighting conditions, enabling it to fill in the gaps and recreate the missing details with remarkable accuracy. This GAN-based reconstruction ensures that the final lighting experience closely mirrors the nuances of natural daylight, even with limited transmitted data[1].

A. Testbed: Adaptive context lighting system

To validate the potential of semantic communication for enabling adaptive and intelligent lighting in future urban environments, we have constructed a dedicated testbed at the college of engineering building 8, Kongju National University, South Korea. This real-world testbed allows us to rigorously evaluate our approach under realistic conditions, measuring key performance metrics.

The system is designed to emulate the interaction of components within a 6G-enabled hyper-connected city, capturing and recreating natural lighting conditions within an indoor space. On the rooftop of engineering building 8, bathed in the natural light of the Korean sky, resides our natural light measurement station. This station acts as the “eye” of the system, diligently capturing the dynamic nuances of daylight.

[1]This practical testbed demonstrates how the general roles in Table I—representation via Auto-encoders, recovery via GANs, and adaptation via RL—are instantiated in a real-system.

A precision solar tracker continuously adjusts the orientation of our high-resolution light sensors, ensuring they are perfectly aligned to receive the full spectrum of sunlight throughout the day, regardless of the season or weather conditions. The sensors measure various properties of light, including color temperature—expressed in Kelvin (K) and indicating the spectral balance between warm and cool tones—intensity, and spectral distribution, providing a comprehensive profile of the ambient lighting.

All of this data is fed into a dedicated data acquisition and processing unit, which prepares the data for transmission to the core of our semantic communication system. Within an indoor space in engineering building 8, we’ve installed the adaptive context lighting system itself. This system serves as the “output” of our lighting adaptation process, using an array of controllable lighting fixtures to recreate the captured natural light conditions. The heart of this system is the matrix of context lighting, consisting of individually adjustable LED panels. Each panel can precisely reproduce a wide array of colors and intensities, allowing us to accurately simulate the subtleties of natural light. The control unit maps received semantic features to LED control parameters to reproduce the target illumination state, optionally adjusted by user feedback. The semantic communication layer performs semantic feature extraction (auto-encoder) and generative reconstruction (GAN) using the local knowledge base. This layer, along with supporting computing infrastructure, are represented as semantic encoder/decoder in Fig. 3. Semantic encoder and decoder were trained using a dataset of 10,000 spectral lighting samples and contextual metadata (e.g., occupancy patterns). Training was performed offline using PyTorch on an NVIDIA RTX 3080 GPU and then deployed onto the edge nodes. Also these devices implemented on a Raspberry Pi 4 (1.5 GHz, 4 GB RAM) and were interconnected via a 5G small-cell network with an average downlink/uplink throughput of 200/50 Mbps to light sensors and LED panels.

The 6G characteristics are then carefully emulated using a Software Defined Networking (SDN) to control bandwidth

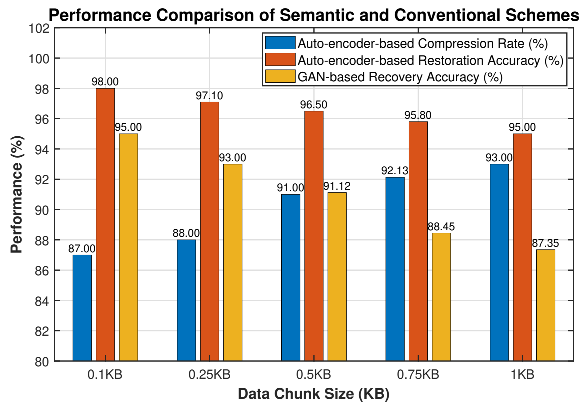

Fig. 4. Comparison of Auto-encoder and GAN-based semantic compression in terms of compression, restoration, and recovery accuracy. Both techniques demonstrate that they can sufficiently recover desired data from insufficient information.

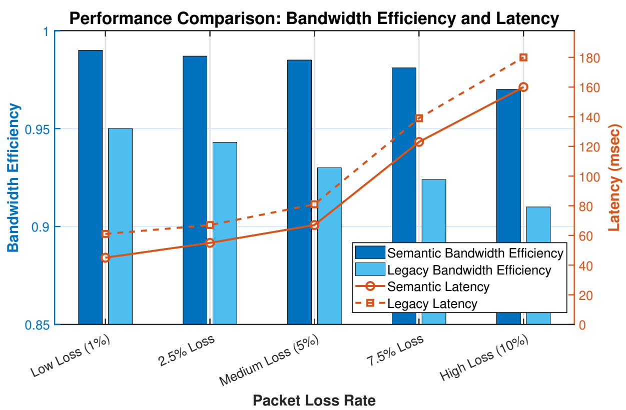

Fig. 5. Bandwidth efficiency and latency comparison between conventional and semantic communication. Semantic communication achieves higher efficiency with significantly lower delay.

limitations, latency, and packet loss to give us an accurate simulation of the 6G environment.

B. Analysis of experimental results: Semantic communication enhances bandwidth efficiency and resilience

To validate the benefits of semantic communication in a 6G-enabled hyper-connected city, we conducted a series of experiments evaluating the performance of AI-powered semantic communication techniques against traditional (legacy) communication methods. The results, summarized in Fig. 4 and 5 demonstrate a significant improvement in bandwidth efficiency, data recovery, and overall system resilience. Here, bandwidth efficiency is defined as the ratio between task-relevant information successfully reconstructed at the receiver and the total number of transmitted bits.

Fig. 4 showcases the performance of two key AI techniques – Auto-encoders and GANs – in the context of semantic communication. The x-axis represents varying data chunk sizes (0.1KB to 1KB), simulating different message lengths. The results highlight the impressive performance of Auto-encoders in both compressing and restoring data. The blue bars reveal that the Auto-encoder consistently achieves high compression rates (87-93%), even at smaller data chunk sizes. This underscores its ability to efficiently extract the most crucial information, shrinking the data footprint regardless of message length, leading to crucial bandwidth savings. Complementing this, the red bars illustrate the Auto-encoder's ability to faithfully restore the original data after compression and transmission, boasting accuracy rates ranging from 95-98%. Even after significant compression, the Auto-encoder preserves the core meaning, reliably reconstructing the original information. Furthermore, the GANs yellow bar data shows a good ability to create lost packets through its learning. Together, the Auto-encoder and GAN show that semantic communication can accurately create lost packets even in high wireless channel failure.

The data demonstrates the advantages of semantic communication over traditional methods, particularly in challenging network conditions as shown in Fig. 5. Compared with a non-semantic baseline, our framework achieved 8% lower latency (20 ms) and 50% higher bandwidth efficiency. The blue bars reveal that Semantic Communication consistently outperforms legacy methods in bandwidth efficiency, especially as packet loss increases.

This advantage stems from semantic communication's core principle: transmitting only the essential meaning, rather than redundant data. In our smart lighting testbed, for example, instead of transmitting the full sensors data set, only object-level semantic labels (*time-of-day context, illumination category, application-oriented states, etc.*) are transmitted. At the receiver, the GAN leverages not only the received features but also the locally available knowledge base (indoor lighting rules and contextual models) to reconstruct decision-level signals for control. By focusing on semantic content, we reduce the need for retransmissions in the face of packet loss. Furthermore, the latency data displays how semantic communication has a lower latency compared to legacy. This is because it can recover packets quickly. Ultimately, the benefits of semantic communication increase exponentially with the presence of higher packet loss.

V. Conclusion

This concluding section synthesizes our findings, outlines remaining challenges, and highlights concrete directions for future research. While initial results from our simplified testbed are encouraging, they offer only a limited view of semantic communication's true potential within a complex hyper-connected city. The testbed, by necessity, involved controlled environments and a limited number of simulated devices. Despite the testbed's limitations, the demonstrated improvements in bandwidth efficiency, data recovery, and reduced latency offer a tantalizing glimpse into the future of intelligent urban systems.

Key challenges remain in translating these promising results to the noisy, dynamic, and massively scaled reality of a modern metropolis. Privacy and security remain pressing issues, as semantic models inevitably handle sensitive contextual data. Interoperability across heterogeneous devices and regulatory compliance (e.g., spectrum policy, data governance) are equally vital, requiring standardized frameworks and cross-domain agreements. Potential solutions include federated learning for privacy preservation, open semantic standards for interoperability, and regulatory sandboxes for evaluating ethical and legal implications. Looking ahead, future research should move beyond small-scale testbeds toward city-wide experimental deployments that capture noisy, large-scale dynamics. Interdisciplinary collaboration with urban planners, policymakers, and ethicists will be crucial to design governance frameworks that align with both technological innovation and public trust. In addition, developing scalable semantic models that adapt across domains (e.g., healthcare, mobility, and energy) and creating benchmarking platforms for evaluating semantic accuracy and latency under real-conditions are promising directions for subsequent studies. Moving from lab to city requires innovation and collaboration, with immense potential rewards.

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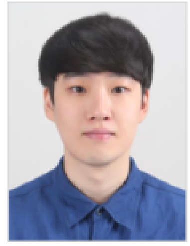
Woongsoo Na received B.S., M.S., and Ph.D. degrees in Computer Science and Engineering from Chung-Ang University, Seoul, South Korea, in 2010, 2012, and 2017, respectively. He is currently an Associate Professor with the Department of Software, Kongju National University, Cheonan, South Korea. He was an Adjunct Professor at the School of Information Technology, Sungshin Womens University, Seoul, South Korea, from 2017 to 2018, and a Senior Researcher at the Electronics and Telecommunications Research Institute, Daejeon, South Korea, from 2018 to 2019. His current research interests include mobile edge computing, flying ad hoc networks, wireless mobile networks, and beyond 5G.



Donghyun Lee received his B.S. degree in Computer Science and Engineering from Dongguk University, South Korea, in 2020. He received M.S. degrees in computer science from Chung-Ang University, Seoul, South Korea, in 2022. He is currently pursuing an Ph.D. degree in Computer Science and Engineering at Chung-Ang University, South Korea. His research interests include wireless networks, energy-efficient networks, multimedia communications, and the Internet of Things.

Nhu-Ngoc Dao received the B.S. degree in electronics and telecommunications from the Posts and Telecommunications Institute of Technology, Hanoi, Vietnam, in 2009, and the M.S. and Ph.D. degrees in computer science from the School of Computer Science and Engineering, Chung-Ang University, Seoul, South Korea, in 2016 and 2019, respectively. He is currently an Assistant Professor with the Department of Computer Science and Engineering, Sejong University, Seoul, South Korea. Prior to joining Sejong University, Seoul, he was a Visiting Researcher with the University of Newcastle, Callaghan, NSW, Australia, in 2019 and a Postdoc Researcher with the Institute of Computer Science, University of Bern, Bern, Switzerland, from 2019 to 2020. His research interests include network softwarization, mobile cloudization, intelligent systems, and the Intelligence of Things. He is currently the Editor of Scientific Reports.

Trong-Minh Hoang received the bachelor's degree in physic engineering (1994) and electronic and telecommunication engineering (1999) from Hanoi University of Science and Technology, the master's degree in electronic and telecommunication engineering (2003), and the Ph.D.'s degree in telecommunication engineering (2014) from Posts and Telecommunications Institute of Technology. He is currently a lecturer in the Telecommunication Faculty of Posts and Telecommunications Institute of Technology. He is the head of the telecommunication network department.

Sungrae Cho received his B.S. and M.S. degrees in electronics engineering from Korea University, Seoul, South Korea, in 1992 and 1994, respectively, and his Ph.D. degree in Electrical and Computer Engineering from the Georgia Institute of Technology, Atlanta, GA, USA, in 2002. He is a Professor at the School of Computer Science and Engineering, Chung-Ang University (CAU), Seoul, South Korea. Prior to joining CAU, he was an Assistant Professor with the Department of Computer Sciences, Georgia Southern University, Statesboro, GA, USA, from 2003 to 2006, and a Senior Member of the Technical Staff at the Samsung Advanced Institute of Technology (SAIT), Kiheung, South Korea, in 2003. From 1994 to 1996, he was a Research Staff Member at the Electronics and Telecommunications Research Institute (ETRI), Daejeon, South Korea. From 2012 to 2013.