electronics

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Impact Analysis of Emerging Semantic Communication Systems on Network Performance

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Abstract: With the paradigm shift from Shannon's legacy, semantic communication (SC) is emerging as one of the promising next-generation communication technologies. The new paradigm in communication technology allows the meaning of transmitted messages to be successfully delivered to a receiver. Hence, the semantic communication focuses on the successful delivery of transmitted messages such as human language communication. In order to realize such new communication, both transmitter and receiver should share the same background knowledge with each other. Recently, several researchers have developed task-specific SC systems by exploiting astonishing achievements in deep learning, which can allow the same knowledge to be shared between them. However, since such SC systems are specialized to handle specific applications, not all users can be serviced by the SC systems. Therefore, a network will face a coexistence of an SC system and a traditional communication (TC) system. In this paper, we investigate how introducing emerging SC systems affects the performance of the TC system from a network perspective. For analysis, we consider the signal-to-noise ratio (SNR) differently for the user served by an SC system and the user served by a TC system. Then, by using two different SNR equations, we formulate a max-min fairness problem in the coexistence of SC and TC systems. Via extensive numerical results, we compare the network performance of TC and SC users with and without SC systems, and then confirm that SC systems are indeed a promising next-generation communication alternative.

Keywords: performance analysis; semantic communication; coexistence

Citation: Lee, H.; Ahn, H.; Park, Y.D. Impact Analysis of Emerging Semantic Communication Systems on Network Performance. *Electronics* **2022**, *11*, 1567. https://doi.org/10.3390/electronics11101567

Academic Editor: Christos J. Bouras

Received: 2 April 2022
Accepted: 10 May 2022
Published: 13 May 2022

1. Introduction

In order to address the conflicting challenge of the ever-increasing demand for mobile traffic and the scarcity of frequency resources, semantic communication (SC) is emerging as a new paradigm of next generation communication, which is expected to move beyond Shannon [1–4]. Recently, the fifth generation (5G) of wireless communication systems has been successfully deployed to enhance the communication capacity, and the research on the sixth generation (6G) has also started for future networks. However, the approaches of 5G and 6G are still not completely free from the problem of resource scarcity. Although this problem can be alleviated by using additional high-frequency bands such as THz, the inherent problems of high-frequency signals inevitably lead to some additional issues such as blocking, power amplifier efficiency drop, and atmospheric absorption [5].

Unlike the approaches of conventional communication systems, the new paradigm of the semantic communication pursues the meaning behind bits and the brain-like cognition. In this paradigm shift, the main goal is to successfully convey the meaning of transmitted messages to a receiver rather than symbol-level error-free communication. To better understand the transfer of meaning, we discuss human communication. As we all have experienced, people can communicate well even in noisy environments. The reason of such well communication is because people share the background knowledge and experience about communication in noise environments. With the help of shared knowledge, people can obtain meaningful information even in voices that are slightly distorted by noise. In addition to the background knowledge, the success is possible because the voice signals still contain usable meaning. Therefore, for the new semantic communication, a transmitter and a receiver should be able to encode exploitable meaning, and share the background knowledge for a given task.

In order to realize the new paradigm of communication, some researchers have utilized deep learning that recently achieves remarkable progress in the field of computer vision. During the training, deep-learning based encoder and decoder networks naturally share the same background knowledge needed for given tasks. Therefore, by implementing an encoder network and a decoder network in a transmitter and a receiver, several SC systems have been developed for several fields: language transmission [6–9], speech transmission [10], and image transmission for recognition [11–13]. Especially, recent research presents a notable common result that SC systems using deep networks achieve improved performance in low SNR regime compared to traditional communication (TC) systems (a TC system refers to a communication system that utilizes traditional source coding and channel coding approaches such as Turbo coding).

Since the training optimizes deep neural networks to work well for the specific tasks, the existing SC systems also specialize in the communication of applications that handle tasks using deep networks. However, due to the task-specific development approach, SC systems cannot be used for users not using applications that can adopt the SC systems. In this case, a TC system still should be used to provide applications that are not capable of deep learning. Therefore, SC and TC systems inevitably coexist, and thus a base station (BS) should provide services to SC and TC users simultaneously. Unlike traditional network scenarios consisting of only the same TC system, the coexistence can change the network performance of TC users.

Although recent works have successfully realized semantic communication that was a conceptual idea and presented performance improvement compared to TC systems, it is still questionable how SC systems affect TC systems in a scenario where TC and SC systems coexist. In order to convince that implementing SC systems is indeed a promising solution as a next-generation communication, it is necessary to show that SC systems can coexist well with TC systems in terms of network performance, such as sum-rate improvement and SNR improvement. In other words, it is necessary to show that an SC system can be implemented without compromising the performance of a TC system. SC and TC systems Specifically, we investigate the change in the performance of TC users as some users begin to be served by SC systems. According to the common result of existing SC systems, the signal-to-noise ratio (SNR) of users served by SC systems is modeled differently from that of TC users. With the consideration of the SNR of SC and TC users, a max-min fairness problem for power control is formulated and analyzed. Extensive numerical simulations present that with the introduction of SC systems, users served by an SC system can experience better performance than when receiving services through the TC system. Moreover, a BS can allocate more transmit power to a TC system by exploiting the performance improvement by SC systems in low SNR regimes. In addition to improving the performance of users serviced by an SC system, the change in transmit power allocation also improves the sum-rate of users serviced by the TC system. As a result, this work confirms that such an SC system is a promising next-generation communication that can improve network performance without acquiring additional frequency resources.

The contributions of this work are summarized as follows:

- In this paper, we first introduce the possibility of the coexistence of SC systems and TC systems that can occur with the advent of SC systems. However, existing works only focus on the realization of semantic communication without the consideration of the coexistence of SC systems and TC systems. Therefore, we investigate the impact of the introduction of SC systems on the performance of TC systems. Specifically, we analyze the coexistence of them in terms of fairness, and thus formulate a max-min fairness problem of the performance of SC systems and TC systems;

- To formulate the coexistence problem, we introduce the signal-to-noise ratio (SNR) of an SC user by reflecting the performance difference between SC and TC systems. The modeled SNR of SC users allows modeling the coexistence of systems with different SNR characteristics;
- Via numerical results, we show that the introduction of SC systems leads to an increase in the sum-rate of a TC system, and the improvement can be up to 110%. For SC systems, it is important to ensure that SC systems can be utilized without compromising the performance of the surrounding TC system. Then, in this work, it is confirmed that such an SC system is indeed a promising next-generation communication that can improve network performance without securing additional frequency resources. We show that SC systems can coexist fairly with TC systems.

Note that the development of SC systems can be more meaningful when there is a guarantee that the SC system should be usable without degrading the performance of the TC system. This work shows the performance improvement of TC systems according to the introduction of SC systems, and thus can guarantee the significance of the SC systems.

The rest of the paper is organized as follows. The coexistence model is explained in Section 3. In Section 4, we analyze the SNR of a user served by an SC system and a user served by a TC system. By using the SNR of each system, we formulate a max-min fairness problem in the coexistence of an SC system and a TC system in Section 5. In order to show the effect of introducing an SC system, the numerical results are presented in Section 6. Finally, Section 8 concludes the paper.

2. Related Works

As deep learning has made outstanding achievements in the field of computer vision, it is confirmed that deep learning can be a promising solution to deal with difficult yet unresolved problems. The literature [14,15] argued that deep learning specializes in extracting complex but meaningful features that cannot be recognized and analyzed using conventional schemes. The advantage of deep learning has taken technologies of natural language processing [16] and audio signal processing [17] to the next level as well as computer vision [18].

To improve the performance of existing wireless technologies, several researchers have tried to apply deep-learning networks to physical (PHY) layer [19], channel estimation [20], modulation classification [21,22], resource allocation [23], beamforming [24], power control [25], and spectrum sensing [26–31]. The work [19] designed a communication system as an end-to-end reconstruction task that jointly optimizes the components of a transmitter and receiver. In [21,22], the authors improved the performance of modulation classification in MIMO through deep learning by canceling multi-user interference. In [20], they proposed a deep learning framework to improve channel estimation and DOA estimation. The works [23,25] utilized deep learning to improve existing resource management technologies such as frequency resource allocation and power allocation, and the authors of [24] proposed a deep learning framework that designs beamforming vectors for a MISO system. For spectrum sensing, the works [26–30] proposed supervised learning-based schemes to decide whether a channel is occupied by a primary user, while the authors of [31] developed an unsupervised deep learning based spectrum sensing method.

Although the existing works have introduced deep learning to the field of wireless communication, they have focused on enhancing existing wireless technologies. On the other hand, semantic communication has been proposed to open the new paradigm of communication. Astonishing progress in deep learning can make semantic communication feasible in some fields of language transmission [6–9], image transmission for recognition [11–13], and speech transmission [10]. In [9], the authors proposed a deep-learning based joint source-channel coding framework that aims to recover the meaning of a source at a receiver. That is, even if there are some errors in the received symbols, the proposed framework can successfully decode the original meaning of the transmitted symbols. Using deep neural networks, the works [6–8] developed SC systems that extract and send the semantic information of text data. To realize such SC systems, they constructed encoders using a transformer network that achieves great performance in natural language processing. In [11–13], some deep learning based encoders and decoders were proposed to extract meaningful semantic information from images. The work [13] proposed a joint transmission–recognition framework that efficiently sends image data to a server for recognition task. For an SC system of speech transmission, in [10], they adopted an SE-ResNet module that specializes in detecting meaningful information among meaningless information in feature maps.

Moreover, deep learning has been adopted to applied science such as the field of UAV/drone detection schemes [32,33]. The authors of [32] combined a deep learning network and millimeter wave (mmWave) to classify the types of drones. In [33], they utilized deep learning to detect malicious drones among valid drones.

3. Coexistence of SC System and TC System

In this section, we introduce the possibility of coexistence of SC systems and TC systems, which is the motivation of this work. Then, we describe the considered coexistence model for the problem formulation.

3.1. Possibility of Coexistence of SC System and TC System

The encoder and decoder of an SC system were developed using a deep learning network that is task-specific. If a user is processing a task that has not yet been applied to deep learning, the user still has to use TC systems. Therefore, the coexistence of SC and TC systems is inevitable.

Figure 1 shows an example of the coexistence of TC and SC systems. In this case, a BS is associated with an SC user and a TC user, and the SC user and the TC user are served by an SC system and a TC system, respectively. For the SC system, the data at the sender is encoded by an SC encoder based on deep learning networks, which extracts a symbol stream containing the exploitable meaning of the data. Then, the SC encoded symbol stream is transmitted via a BS to an SC user. The symbol stream received at the receiver is processed through an SC decoder using deep learning. In the case of the TC system, the data of a web server are encoded by a TC encoder at the BS, and the TC encoded symbol stream is also transmitted through the BS. Therefore, the BS transmits both SC and TC encoded symbol streams to each receiver via orthogonal frequency division multiple access (OFDMA). Since the BS using OFDMA allocates a dedicated frequency bandwidth to the SC system and the TC system, the SC and TC encoded symbol streams are transmitted separately via the dedicated bandwidth allocated to each system. For optimal operation, the BS should control the transmit power allocated to the subcarriers of each dedicated bandwidth by considering the performance difference between the SC and TC systems.

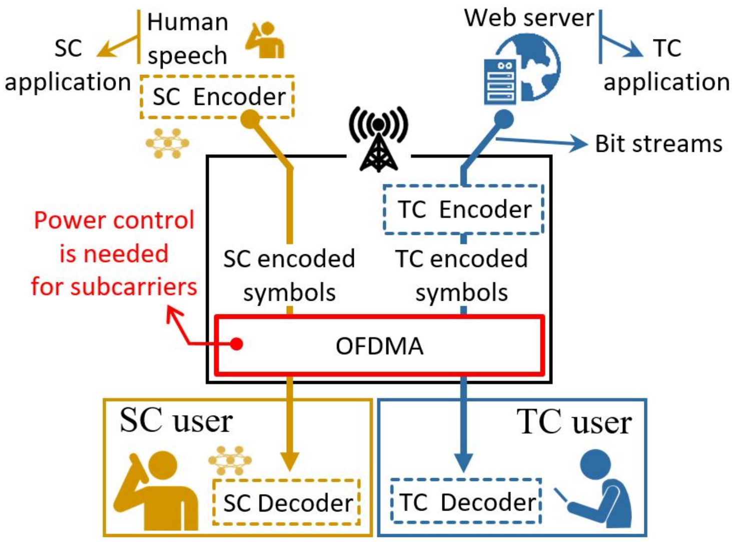


Figure 1. Conceptual coexistence scenario of SC and TC systems.

3.2. Coexistence Model

In the considered coexistence model, there are two types of applications: SC application and TC application. The SC application can be serviced by an SC system, whereas the TC application is only serviced by a TC system. Note that the SC application can actually be serviced by a TC system. Then, users who use SC applications and users who use TC applications are referred to as SC users and TC users, respectively. Therefore, SC users can be served by either an SC system or a TC system, while TC users can only receive services from a TC system. In order to analyze the effect of the introduction of an SC system, the performance change of TC users and SC users is investigated as the system providing services to SC users is changed from the TC system to the SC system.

Via a B-Hz network bandwidth, a BS provides downlink services to U_S SC users and U_T TC users, all equipped with a single antenna. The maximum transmit power is denoted by P, and the channel coefficients between each user and the BS are assumed to be the frequency-flat power spectral density (PSD) level in [34,35]. The channel coefficients for SC user i and TC user j are indicated by $h_{\mathrm{S},i}$ and $h_{\mathrm{T},j}$, respectively. The channel vector including all the channel coefficients is denoted as: $\mathbf{h} = [h_{\mathrm{S},1}, \ldots, h_{\mathrm{S},U_\mathrm{S}}, h_{\mathrm{T},1}, \ldots, h_{\mathrm{T},U_\mathrm{T}}]^\mathrm{T}$, and $\mathbf{h}(l)$ is the l-th element of $\mathbf{h}$. The bandwidth coefficients allocated to the SC user i and TC user j are represented as $\beta_{\mathrm{S},i}$ and $\beta_{\mathrm{T},j}$, respectively. The resource vector that includes all bandwidth coefficients is $\boldsymbol{\beta} = [\beta_{\mathrm{S},1}, \ldots, \beta_{\mathrm{S},U_\mathrm{S}}, \beta_{\mathrm{T},1}, \ldots, \beta_{\mathrm{T},U_\mathrm{T}}]^\mathrm{T}$, and the l-th element is $\boldsymbol{\beta}(l)$. The transmit power for SC user i and TC user j is defined as $p_{\mathrm{S},i}$ and $p_{\mathrm{T},i}$, respectively. The power vector is denoted as $\mathbf{p} = [p_{\mathrm{S},1}, \ldots, p_{\mathrm{S},U_\mathrm{S}}, p_{\mathrm{T},1}, \ldots, p_{\mathrm{T},U_\mathrm{T}}]^\mathrm{T}$, and $\mathbf{p}(l)$ is the l-th element of $\mathbf{p}$. Finally, the channel noise follows the additive white Gaussian noise.

4. Signal-to-Noise Ratio of an SC User

According to [6,8,10–13], for the same SNR value within a low SNR regime, an SC system can provide a higher performance to SC users compared to a TC system. In other words, if both the SC system and the TC system start transmission with the same transmit power, the SC system can provide a higher performance to SC users compared to the TC system. Therefore, in order to examine the effect of introducing an SC system, it is necessary to reflect the performance difference between SC and TC systems according to the SNR value. In this work, the performance difference between both systems is considered by modeling the SNR of SC users served by an SC system and the SNR of SC users served by a TC system differently.

For a TC system, the SNR of users is defined by dividing the strength of a received signal by noise, which is referred to as physical SNR. Therefore, the SNR of TC user j and SC user i served by a TC system is represented, respectively, as:

$$\gamma_{\mathrm{T},j} = \frac{|h_{\mathrm{T},j}|^2 p_{\mathrm{T},j}}{\sigma^2} \quad \text{and} \quad \gamma_{\mathrm{S},i} = \frac{|h_{\mathrm{S},i}|^2 p_{\mathrm{S},i}}{\sigma^2}, \tag{1}$$

where σ^2 is the noise PSD level.

For the same transmit power, an SC system can provide a better performance than a TC system. In general, performance improves with increasing SNR. Hence, the symbol transmitted through an SC system can be considered to be received effectively at a higher SNR than that transmitted through a TC system, which in this work is referred to as an effective SNR for the SC system. According to [6,8,10–13], for an SC system, the difference between effective SNR and physical SNR increases as physical SNR decreases. On the other hand, the SNR gain obtained by an SC system becomes smaller and zero as the physical SNR increases. For a TC system, effective SNR is naturally the same as physical SNR.

For problem formulation, the SNR of an SC user served by an SC system is defined by the effective SNR. The effective SNR is modeled by reflecting the correspondence between the performance of an SC system and the performance of a TC system. For better understanding, we discuss Figure 2, which shows an example of the performance of an SC system and a TC system with varying physical SNR, drawn based on the results of existing SC system studies [6,8,10–13]. In order to achieve the same performance (a), an SC system and a TC system require the physical SNR indicated by (a_p) and (a_e), respectively. From the perspective of the TC system, the physical SNR of the SC system is effectively (a_e), and thus the effective SNR for the SC system is (a_e). The difference between effective SNR and physical SNR decreases exponentially as the physical SNR increases. Since the effective SNR is the sum of physical SNR and exponentially decreasing difference, we model the SNR of SC user i served by an SC system by adding an exponential function and a linear function as:

$$\widehat{\gamma}_{\mathrm{S},i} = \underbrace{\frac{|h_{\mathrm{S},i}|^2 p_{\mathrm{S},i}}{\sigma^2}}_{\text{Physical SNR}} + \underbrace{\alpha \cdot \exp\left(-\frac{1}{\zeta}\frac{|h_{\mathrm{S},i}|^2 p_{\mathrm{S},i}}{\sigma^2}\right)}_{\text{Gain of an SC system}}, \tag{2}$$

where α and ζ are SC system parameters, and σ^2 is a noise PSD level. The SC system parameter α corresponds to the degree of performance improvement by an SC system. The higher the α value, the greater the performance improvement by an SC system in a low SNR region. Another SC system parameter ζ is necessary for $\widehat{\gamma}_{\mathrm{S},i}$ to be a monotonically increasing function because SNR physically should continue to increase with increasing transmit power. Hence, $\zeta > \alpha$ should be satisfied with $\partial\widehat{\gamma}_{\mathrm{S},i}/\partial p_{\mathrm{S},i} > 0, \forall t$.

Equation (2) consists of physical SNR and gain of an SC system. The gain exponentially decreases as transmit power increases, which well reflects the characteristic of performance improvement within a low SNR regime of an SC system. Note that (2) can be considered as a generalized form of the SNR of SC users served by SC systems, since it can represent various SC systems by varying α and ζ. Although (2) might not accurately model the performance difference between a TC system and SC systems for the previous studies, it still reflects the tendency of the performance difference between an SC system and a TC system. Moreover, the performance difference between an SC system and a TC system is not the same for all the previous studies. Therefore, with (2), we can sufficiently analyze the impact of the introduction of an SC system from a general point of view.

Finally, depending on the system providing an SC service to SC user i, the SNR of SC user i is expressed differently as:

$$\widetilde{\gamma}_{\mathrm{S},i} = \begin{cases} \gamma_{\mathrm{S},i}, & \text{if a TC system serves SC user } i, \\ \widehat{\gamma}_{\mathrm{S},i}, & \text{if an SC system serves SC user } i. \end{cases} \tag{3}$$

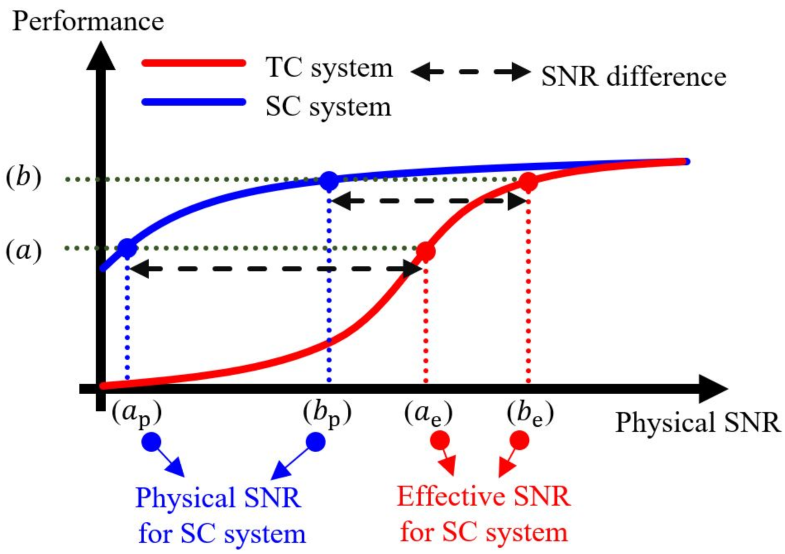


Figure 2. An illustration of correspondence of the performance of an SC system and a TC system to explain the physical SNR and the effective SNR for an SC system.

5. Impact Analysis of Introducing an SC System

In order to examine the effect of an SC system, we consider a max-min fairness problem in the coexistence of an SC system and a TC system. For problem formulation, the spectral efficiency for SC user i and TC user j is used, which is represented as $R_{\mathrm{S},i} = \log(1 + \tilde{\gamma}_{\mathrm{S},i})$ and $R_{\mathrm{T},j} = \log(1 + \gamma_{\mathrm{T},j})$, respectively. (By using the same spectral efficiency as a performance metric for both the SC system and the TC system, this work focuses on how the coexistence of systems with different SNR equations affects the performance of users). This paper considers the optimal way to fairly allocate transmit power to two different systems from a performance fairness point of view. Therefore, a max-min fairness problem for power control is written as:

$$\max_{\mathbf{p}\succeq 0} \min_{l\in[1,U_{\mathrm{S}}+U_{\mathrm{T}}]} \boldsymbol{\beta}(l)\mathbf{R}(l) \tag{4a}$$

$$\text{s.t.} \sum_{l=1}^{U_{\mathrm{S}}+U_{\mathrm{T}}} \boldsymbol{\beta}(l) \times \mathbf{p}(l) \leq P, \tag{4b}$$

$$\sum_{l=1}^{U_{\mathrm{S}}+U_{\mathrm{T}}} \boldsymbol{\beta}(l) \leq B, \tag{4c}$$

where the spectral efficiency vector is denoted as $\mathbf{R} = [R_{\mathrm{S},1}, \ldots, R_{\mathrm{S},U_{\mathrm{S}}}, R_{\mathrm{T},1}, \ldots, R_{\mathrm{T},U_{\mathrm{T}}}]^{\mathrm{T}}$, the l-th element of which is $\mathbf{R}(l)$. The objective (4a) ensures that all SC and TC users can be guaranteed the same spectral efficiency. The conditions (4b) and (4c) are the maximum power constraint and the maximum resource constraint. The constraint $\mathbf{p} \succeq 0$ is the nonnegative power condition.

For given k, (4a–4c) is solved when $\boldsymbol{\beta}(l)\mathbf{R}(l) = k, \forall l$ is satisfied. Then, by maximizing k, the optimal $\mathbf{p}^*$ is obtained. To find the optimal k, a bisection method will be used, and thus we need to find the minimum initial k and the maximum initial k, denoted as $k_{\min}$ and $k_{\max}$, respectively.

5.1. Maximum and Minimum Initial Values to Solve the Max-Min Fairness Problem

In order to obtain $k_{\min}$ and $k_{\max}$, we need to consider a set $\mathcal{K}$ including all feasible values of k. The set $\mathcal{K}$ is determined by a set that includes all feasible vectors $\boldsymbol{\beta} \circ \mathbf{R}$ for the vector space of $\mathbf{p}$, where the operator $\circ$ is element-wise multiplication. The values of $k_{\min}$

and $k_{\max}$ are the minimum and maximum elements in $\mathcal{K}$, respectively. Then, the variable $k_{\min}$ can be obtained as follows:

$$k_{\min} = \min_{\mathbf{p}\succeq 0} \max \boldsymbol{\beta} \circ \mathbf{R}. \tag{5}$$

For (5), the minimum of $(\max \boldsymbol{\beta} \circ \mathbf{R})$ can be obtained with $\mathbf{p}(l) = 0, \forall l$. Then, with $\mathbf{p}(l) = 0, \forall l$, the solution of $(\max \boldsymbol{\beta} \circ \mathbf{R})$ is calculated as:

$$k_{\min} = \max_{l} \begin{cases} \boldsymbol{\beta}(l)\log(1+\alpha)\,, l \in [1, U_{\mathrm{S}}], \\ 0\,, l \in [U_{\mathrm{S}}+1, U_{\mathrm{S}}+U_{\mathrm{T}}]. \end{cases}$$

Hence, $k_{\min} = \boldsymbol{\beta}(l)\log(1+\alpha)$. Furthermore, the variable $k_{\max}$ can be calculated as:

$$k_{\max} = \max_{\mathbf{p}\succeq 0} \min \boldsymbol{\beta} \circ \mathbf{R}. \tag{6}$$

For (6), the maximum of $(\min \boldsymbol{\beta} \circ \mathbf{R})$ can be calculated with $P/\boldsymbol{\beta}(l)$. Note that $P/\boldsymbol{\beta}(l)$ is the largest value that can be allocated to an SC system or a TC system. Therefore, with $\mathbf{p}(l) = P/\boldsymbol{\beta}(l), \forall l$, the solution of $(\min \boldsymbol{\beta} \circ \mathbf{R})$ can be obtained as:

$$k_{\max} = \min_{l} \begin{cases} \boldsymbol{\beta}(l)\log\big(1+\frac{|\mathbf{h}(l)|^2 P}{\sigma^2 \boldsymbol{\beta}(l)} + \alpha\exp(-\frac{|\mathbf{h}(l)|^2 P}{\zeta\sigma^2 \boldsymbol{\beta}(l)})\big), l \in [1, U_{\mathrm{S}}], \\ \boldsymbol{\beta}(l)\log\big(1+\frac{|\mathbf{h}(l)|^2 P}{\sigma^2 \boldsymbol{\beta}(l)}\big)\,, l \in [U_{\mathrm{S}}+1, U_{\mathrm{S}}+U_{\mathrm{T}}]. \end{cases}$$

5.2. Solution $\mathbf{p}$ for $\boldsymbol{\beta}(l)$ $\mathbf{R}(l) = k, \forall l$, with Given k

For TC user l and $l \in [U_{\mathrm{S}}+1, U_{\mathrm{S}}+U_{\mathrm{T}}]$, we have $\boldsymbol{\beta}(l)\log(1+|\mathbf{h}(l)|^2\mathbf{p}(l)/\sigma^2) = k$, and thus the explicit analytic solution $\mathbf{p}(l)$ is as:

$$\mathbf{p}^{(t)}(l) = \frac{\sigma^2\big(10^{\frac{k}{\boldsymbol{\beta}(l)}} - 1\big)}{|\mathbf{h}(l)|^2}. \tag{7}$$

For $l \in [1, U_{\mathrm{S}}]$, if SC users are served by an TC system, the optimal solution $\mathbf{p}(l)$ with a given k is obtained using the same equation as (7), which is as:

$$\widetilde{\mathbf{p}}(l) = \frac{\sigma^2\big(10^{\frac{k}{\boldsymbol{\beta}(l)}} - 1\big)}{|\mathbf{h}(l)|^2}. \tag{8}$$

If SC users are served by an SC system, $\boldsymbol{\beta}(l)\log(1+\widehat{\gamma}_{\mathrm{S},l}) = k$ can be written as:

$$\underbrace{-\frac{|\mathbf{h}(l)|^2\mathbf{p}(l)}{\sigma^2} + 10^{\frac{k}{\boldsymbol{\beta}(l)}} - 1}_{f_1} = \underbrace{\alpha\exp\big(-\frac{|\mathbf{h}(l)|^2\mathbf{p}(l)}{\zeta\sigma^2}\big)}_{f_2}. \tag{9}$$

Although an explicit analytical solution cannot be derived, we can obtain the solution for (9) by selecting the largest value of $\mathbf{p}(l)$ that satisfies $f_2 - f_1 \leq 0$ or the smallest value of $\mathbf{p}(l)$ that satisfies $f_2 - f_1 \geq 0$.

In Figure 3a, the red point at the intersection of f_1 and f_2 satisfies (9), and can be obtained by taking the maximum value within the red box (c) that satisfies $f_2 - f_1 \leq 0$. Hence, mathematically, it can be written as:

$$\widehat{\mathbf{p}}(l) = \sup\Big\{\mathbf{p}(l) | f_2 - f_1 \leq 0\Big\}. \tag{10}$$

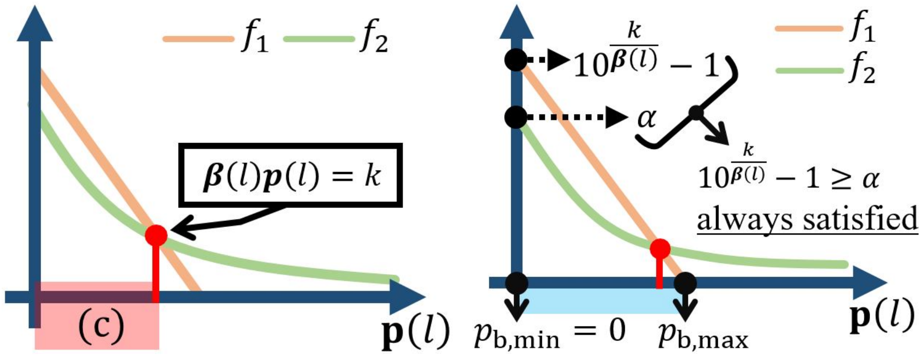
In order to find $\widehat{\mathbf{p}}(l)$, the bisection method can be performed on (10). For the bisection method, we need to obtain the minimum and maximum initial values, $p_{\mathrm{b,min}}$ and $p_{\mathrm{b,max}}$. As in Figure 3b, $p_{\mathrm{b,max}}$ is the point for $f_1 = 0$, and thus can be obtained as:

$$p_{\mathrm{b,max}} = \frac{(10^{\frac{k}{\beta(l)}} - 1)\sigma^2}{|\mathbf{h}(l)|^2}. \tag{11}$$

Since $k \geq \boldsymbol{\beta}(l)\log(1+\alpha)$ for $l \in [1, U_{\mathrm{S}}]$, in Figure 3b, the intersection of f_1 and the y-axis is always larger than that of f_2 and the y-axis. That is, there is always a single intersection of f_2 and f_1, and thus we simply set $p_{\mathrm{b,\,min}}$ to zero.

For $l \in [1, U_{\mathrm{S}}]$, the transmit power for SC user l is obtained as:

$$\mathbf{p}^{(t)}(l) = \begin{cases} \widetilde{\mathbf{p}}(l), \text{if SC user } l \text{ is served by a TC system,} \\ \widehat{\mathbf{p}}(l), \text{if SC user } l \text{ is served by an SC system.} \end{cases} \tag{12}$$



(**a**) (**b**)

Figure 3. Examples for $\boldsymbol{\beta}(l)\mathbf{p}(l) = k$. (**a**) example of the intersection of f_1 and f_2 (**b**) the maximum and minimum initial values of the bisection method for $\mathbf{p}(l)$.

5.3. Overall Algorithm

Finally, $\mathbf{p}^*$ can be obtained iteratively, which is summarized in Algorithm 1. In this work, the same frequency bandwidth is allocated to all users, $\beta = B/(U_{\mathrm{S}} + U_{\mathrm{T}}), \forall l$.

Algorithm 1: Power Control Algorithm.

Result: $\mathbf{p}^* = \mathbf{p}^{(t)}$
Initialize $t = 0$, $k = k_{\mathrm{prev}} = 0$, a small $\epsilon > 0$, $\boldsymbol{\beta}(l) = \beta, \forall l$, and any feasible $\mathbf{p}^{(0)}(l)$;
repeat
  $t \leftarrow t + 1$;
  $k_{\mathrm{prev}} \leftarrow k$;
  $k \leftarrow \frac{k_{\mathrm{min}} + k_{\mathrm{max}}}{2}$;
  For $l \in [U_{\mathrm{S}} + 1, U_{\mathrm{S}} + U_{\mathrm{T}}]$, obtain $\mathbf{p}^{(t)}(l)$ with (7);
  For $l \in [1, U_{\mathrm{S}}]$, obtain $\mathbf{p}^{(t)}(l)$ with (12);
  If $\left(\sum_{l=1}^{U_{\mathrm{S}}+U_{\mathrm{T}}} \boldsymbol{\beta}(l)\mathbf{p}^{(t)}(l) \leq P\right)$
    $k_{\mathrm{min}} = k$
  else
    $k_{\mathrm{max}} = k$
  end;
until $|k - k_{prev}| \leq \epsilon_k$;

5.4. Complexity Analysis

In Algorithm 1, the parameters k_{min}, k_{max}, $p_{\text{b, min}}$, $p_{\text{b, max}}$, and $\mathbf{p}(l), l \in [U_{\text{S}}+1, U_{\text{S}}+U_{\text{T}}]$ are closed form solutions. The bisection methods for k and $\mathbf{p}(l), l \in [1, U_{\text{S}}]$ contribute to the complexity of the power control algorithm. The complexity is as:

$$\mathcal{O}\Big(\log\Big(U_{\text{S}} \times \frac{p_{\text{b,max}} - p_{\text{b,min}}}{\epsilon_{\text{p}}} \times \frac{k_{\text{max}} - k_{\text{min}}}{\epsilon_{\text{k}}}\Big)\Big), \tag{13}$$

where ϵ_{p} and ϵ_{k} are the tolerances of $\mathbf{p}(l)$ and k, respectively. Therefore, we can control the process of Algorithm 1 using ϵ_{p} and ϵ_{k}. Both parameters are empirically determined as $\epsilon_{\text{p}} = 10^{-7}$ and $\epsilon_{\text{k}} = 10^{-7}$, respectively. With $\epsilon_{\text{k}} = 10^{-7}$ and $\epsilon_{\text{p}} = 10^{-7}$, the parameters k and $\mathbf{p}(l)$ are usually determined near $\sim 10^5$ and $\sim 10^{-4}$, and thus the settings are appropriate. Furthermore, the number of iterations required to complete Algorithm 1 is less than 1800 with probability 0.99. Since the bisection methods include simple arithmetic operations, the completion time is less than 2.6 msec with Intel(R) Core(TM) i7-9700.

6. Numerical Results

With a total of 10 users, the simulations are performed with $U_{\text{S}} \in \{1,3,5,7,9\}$, $U_{\text{T}} = 10 - U_{\text{S}}$, $\alpha \in [1,8]$, and $P = 23$ dBm [36]. To focus on performance changes due to the introduction of an SC system, all users are placed at the same distance from a BS, where the distance from a BS is $D \in [50, 198]$ meters.

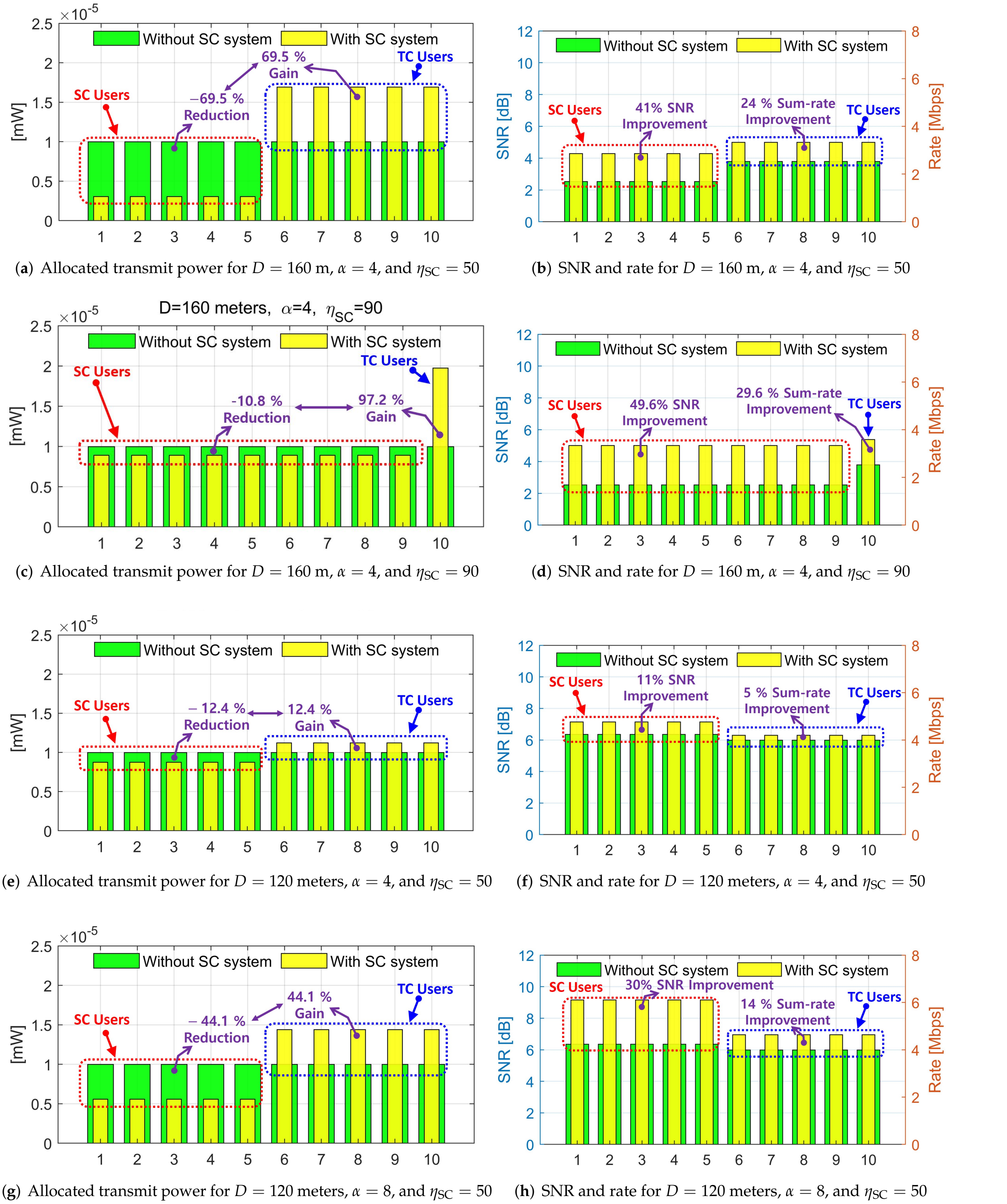
In this evaluation, we present changes in allocated transmit powers, rates of TC users, and the SNR of SC users, as the system providing services to SC users is changed from the TC system to the SC system. In the resulting figures, η_{SC} is the ratio of the number of SC users to the total number of users, and thus is obtained as $100 \times U_{\text{S}}/(U_{\text{S}} + U_{\text{T}})$. In addition, I_{TC} and I_{SC} are the sum-rate improvement of TC users and the average SNR improvement for each SC user, both of which are calculated as:

$$I_{\text{TC}} = \frac{100(T_{\text{w,S}} - T_{\text{wo,S}})}{T_{\text{wo,S}}} \quad \text{and} \quad I_{\text{SC}} = \frac{100}{U_{\text{S}}} \sum_{i=1}^{U_{\text{S}}} \frac{G_{\text{w,S}}^{(i)} - G_{\text{wo,S}}^{(i)}}{G_{\text{wo,S}}^{(i)}},$$

where $T_{\text{w,S}}$ and $T_{\text{wo,S}}$ are the sum-rate of TC users when SC users are served by an SC system and when SC users are served by a TC system, respectively. The parameters $G_{\text{w,S}}^{(i)}$ and $G_{\text{wo,S}}^{(i)}$ are the SNR of SC user i when SC user i is served by an SC system and when SC user i is served by a TC system, respectively. The reason for showing the improvement in the SNR of SC users is that the performance metrics of existing SC systems depend on SNR according to [6,8,10–13] since these increase with increasing SNR.

For $D \in \{120, 160\}$ meters, $\alpha \in \{4, 8\}$, and $\eta_{\text{SC}} = \{50, 90\}$, Figure 4 shows the allocated transmit power, the SNR values of SC users, and the rates of TC users. These results present how those values change with varying the distance D between a BS and users, the performance degree α of an SC system, and the number of SC users served by an SC system.

In the figures, the green bars are the results of the scenario with only the TC system. In Figure 4a,c,e,g, the yellow bars inside the red dotted rectangle and the blue dotted rectangle mean the allocated transmit power of SC users and TC users, respectively, when SC users are served by an SC system. In addition, in Figure 4b,d,f,h, the yellow bars inside the red dotted rectangle and the blue dotted rectangle indicate the SNR values of SC users served by an SC system and the rates of TC users, respectively.



(**a**) Allocated transmit power for $D = 160$ m, $\alpha = 4$, and $\eta_{SC} = 50$

(**b**) SNR and rate for $D = 160$ m, $\alpha = 4$, and $\eta_{SC} = 50$

(**c**) Allocated transmit power for $D = 160$ m, $\alpha = 4$, and $\eta_{SC} = 90$

(**d**) SNR and rate for $D = 160$ m, $\alpha = 4$, and $\eta_{SC} = 90$

(**e**) Allocated transmit power for $D = 120$ meters, $\alpha = 4$, and $\eta_{SC} = 50$

(**f**) SNR and rate for $D = 120$ meters, $\alpha = 4$, and $\eta_{SC} = 50$

(**g**) Allocated transmit power for $D = 120$ meters, $\alpha = 8$, and $\eta_{SC} = 50$

(**h**) SNR and rate for $D = 120$ meters, $\alpha = 8$, and $\eta_{SC} = 50$

Figure 4. Comparison of the transmit power of all users, the SNR of SC users, and the rate of TC users with and without an SC system for $D \in \{120, 160\}$ meters, $\alpha \in \{4, 8\}$, and $\eta_{SC} = \{50, 90\}$.

As in Figure 4a,c,e,g, by changing from the TC system to the SC system for SC users, additional power can be allocated to TC users while the power allocated to SC users is reduced. This is because at a low SNR, an SC system can serve SC users with the performance that the TC system can achieve at high SNR. In Figure 4b,d,f,h, the change in power allocation improves the rates of TC users, and the SC system has the effect of increasing the SNR of SC users even with lower transmit power.

In Figure 4a,c, as the number of SC users served by an SC system increases, the reduction in the allocated transmit power decreases. Then, all the reduced transmit power of SC users is allocated to the TC system. Hence, the performance of both SC users and TC users can be improved by increasing the number of SC users served by an SC system. Figure 4b,d shows that the SNR improvement of an SC user and the rate improvement of a TC user increase by 8.6 % and 5.6 %, respectively.

Figure 4a,e shows that, as the distance D decreases, the reduction in transmit power of the SC users decreases and therefore the increase in the transmit power of TC users also decreases. In the same vein, as in Figure 4b,f, the SNR improvement and the rate improvement also decrease. In other words, as the distance D increases, the performance gain due to the introduction of an SC system increases.

Finally, as in Figure 4e,g, as the performance degree α increases, the allocated transmit power to SC users decreases, and thus those to a TC system increases. That is, the higher the value of α, the greater the SNR improvement and the rate improvement as in Figure 4f,h.

To examine the overall effect of an SC system, Figures 5 and 6 present the sum-rate improvement of TC users and the average SNR improvement of SC users with varying D, η_{SC}, and α. Figures 5a and 6a show that with fixed $\alpha = 4$, I_{TC} and I_{SC} increase as the distance and η_{SC} increase. For fixed $D = 120$ meters, Figures 5b and 6b show that as both α and η_{SC} increase, I_{TC} and I_{SC} also increase. Finally, for $\eta_{\mathrm{SC}} = 50$, Figures 5c and 6c confirm that the increase in D and α leads to the increase of I_{TC} and I_{SC}.

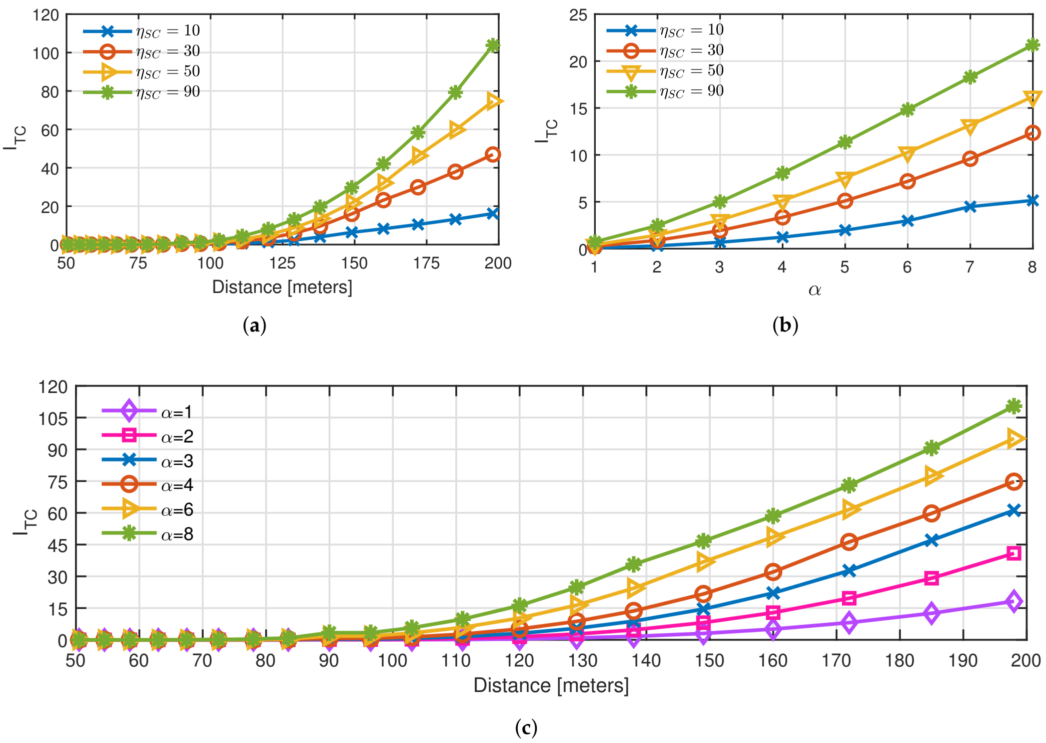


Figure 5. Sum-rate improvement of TC users for various D, α, and η_{SC}. (**a**) For $\alpha = 4$ (**b**) For $D = 120$ m (**c**) For $\eta_{\mathrm{SC}} = 50$.

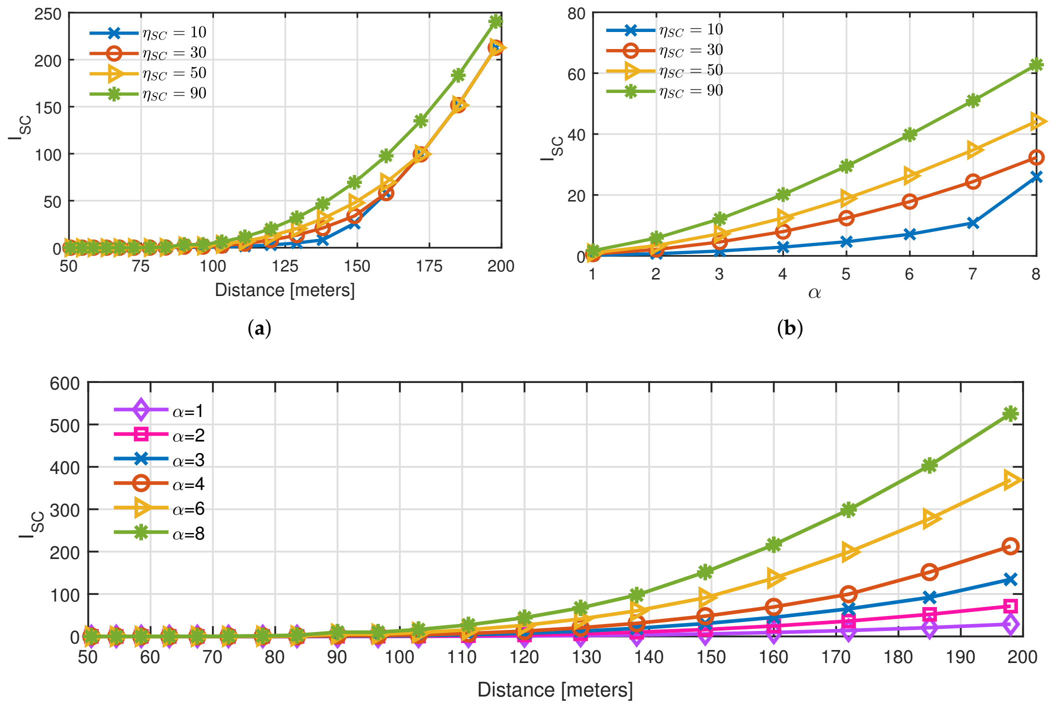


Figure 6. SNR improvement of SC users for various D, α, and η_{SC}. (**a**) For $\alpha = 4$ (**b**) For $D = 120$ m (**c**) For $\eta_{SC} = 50$.

Note that the increase in D means that users physically experience a lower SNR. That is, if TC and SC users suffer from bad channels, using an SC system for SC users can improve the performance of both TC users and SC users. As the number of users served by an SC system increases, both sum-rate improvement and SNR improvement increase. Furthermore, the results confirm that the use of existing spectral efficiency for an SC system can effectively lead to performance improvement for both SC and TC systems.

7. Discussion

Overhead of SC systems: In this section, we discuss the overhead of using SC systems. The overhead comes from the difference between an SC system and a TC system. The main difference between them is how symbols for communication between a transmitter and a receiver are generated from data. In semantic communication, the communication symbols are created using deep neural networks. That is, the processing time of the neural networks used is a dominant overhead in semantic communication and varies depending on applications. For investigating the overhead, we analyzed the public code of a recent work [6], which utilizes the popular transformer in natural language processing. The processing time of data with a batch size of 128 is only 52 milliseconds with AMD Ryzen9 5950X 16-Core processor. Like in the work [8], researchers in SC systems also consider developing lightweight deep learning-based encoders and decoders. Furthermore, the work [12] considered the wireless edge scenario and thus developed a lightweight deep learning framework. As a result, the overhead due to the processing time of neural networks can be expected to be negligible.

Privacy and security of data: Since existing works focusing on the development of SC systems did not consider the privacy and security of data, how to handle the data privacy and security could be a new research work in semantic communication. In response to data privacy issues, organizations such as the European Union have passed restrictive laws and regulations such as the General Data Protection Regulations (GDPR) [37]. Therefore, the development of a data privacy management model for semantic communication could be one of the important new studies [38].

Architecture for coexistence of SC and TC systems: Although we focus on the analysis of a coexistence of SC and TC systems in this work, we additionally discuss an architecture for the coexistence. In general, a mapping function layer is needed to integrate different systems [39]. However, the difference between the SC system and the TC system is how to create OFDM symbols from data. As shown in Figure 1, in the case of a TC system, an encoder generates OFDM symbols directly from a bit stream of data. In an SC system, OFDM symbols are generated using a deep learning-based encoder that extracts the meaning of data from a bit stream. Once OFDM symbols are created, the symbols can be simply transmitted via OFDMA. At this point, an architecture for distinguishing the bit stream of the TC system from the SC-encoded symbols is required, because the bit stream of the TC system is encoded into OFDM symbols in a BS. Such architecture for a BS could be developed using technologies such as network virtualization. Since our analysis results provide that the coexistence of SC and TC systems increases the network performance, the development of an architecture would be one of the important works in semantic communication.

8. Conclusions and Future Works

In this paper, we investigated how SC systems actually affect network performance. By considering the tendency of performance improvement by SC systems, we model the SNR of SC users served by an SC system and then formulate a max-min fairness problem. The numerical results show that changing from a TC system to an SC system for SC users increases the sum-rate performance of TC users by allocating more power to TC users, while also improving the SNR of SC users. If users suffer from low SNR and the number of SC users served by SC systems increases, an SC system can achieve a significant performance improvement. This work is meaningful in that it shows how the network performance changes when two systems with different SNR tendencies for the same transmit power coexist. It confirms that the SC system is indeed a promising next-generation alternative and improves network performance without securing additional frequency resources. Furthermore, this work guarantees that the development of SC systems is really meaningful, and then is expected to facilitate future research on the utilization of SC systems in various applications.

Finally, we believe that this paper will lead to some research on multiple input multiple output (MIMO), user management, and load balancing in the coexistence of TC and SC systems. Based on the coexistence analysis of this work, in the future, further from the coexistence analysis, we would like to develop a framework that jointly designs an SC system and a TC system to maximize the benefit of SC systems, consistent with integrated access and backhaul, another new paradigm of wireless communication [40,41]. To comprehensively evaluate the future work, we will utilize various metrics such as system performance and overheads. Additionally, semantic communication can be used for efficient data transmission. Therefore, in addition to such conventional research fields, we will study how to apply semantic communication to mobile device-based applications that require efficient transmission [42–45].

Author Contributions: Conceptualization, H.L.; methodology, H.L.; software, H.L. and H.A.; validation, H.A.; formal analysis, H.L.; resources, Y.D.P.; writing—original draft preparation, H.L.; writing—review and editing, H.A. and Y.D.P.; supervision, Y.D.P.; funding acquisition, Y.D.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the 2021 Yeungnam University Research Grant and was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. 2021R1G1A1095238, No. 2022R1G1A1005366, No. 2022R1G1A1007058).

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

5G	Fifth Generation
6G	Sixth Generation
SC	Semantic Communication
TC	Traditional Communication
SNR	Signal-to-Noise Ratio
PHY	Physical
DOA	Direction-of-Arrival
BS	Base Station
OFDMA	Orthogonal Frequency Division Multiple Access
PSD	Power Spectral Density
MISO	Multiple Input Single Output

The following mathematical symbols are frequently used in this manuscript:

$\mathcal{U}_{\mathrm{S}}$	The number of SC users
$\mathcal{U}_{\mathrm{T}}$	The number of TC users
$h_{\mathrm{S},i}$	The channel coefficient for SC user i
$h_{\mathrm{T},j}$	The channel coefficient for TC user j
$\mathbf{h}$	The channel vector including all the channel coefficients of SC and TC users
$\beta_{\mathrm{S},i}$	The frequency resource allocated to SC user i
$\beta_{\mathrm{T},j}$	The frequency resource allocated to TC user j
$\boldsymbol{\beta}$	The resource vector including all the frequency resources allocated to SC and TC users
pS, i	The transmit power allocated to SC user i
$p_{\mathrm{T},j}$	The transmit power allocated to TC user j
$\mathbf{p}$	The transmit power vector including all the transmit power allocated to SC and TC users
$\gamma_{\mathrm{S},i}$	The SNR of SC user i served by a TC system
$\widehat{\gamma}_{\mathrm{S},i}$	The SNR of SC user i served by an SC system
$\widetilde{\gamma}_{\mathrm{S},i}$	The SNR of SC user i
$\gamma_{\mathrm{T},j}$	The SNR of TC user j served by a TC system
$R_{\mathrm{S},i}$	The spectral efficiency of SC user j
$R_{\mathrm{T},j}$	The spectral efficiency of TC user j

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