Hindawi
Mathematical Problems in Engineering
Volume 2021, Article ID 6782664, 17 pages
https://doi.org/10.1155/2021/6782664

Research Article

Awareness Modeling and Computing for Quality-Aware Coordination

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Received 12 August 2021; Revised 18 October 2021; Accepted 3 November 2021; Published 29 November 2021

Academic Editor: Jun Li

In this paper, we address the issues of the trade-off between QoS and QoE with an analytical analysis based on mathematical modeling under a unified normalization measurement. We model through computation the awareness of QoS and QoE with a strategy of quality-aware QoE-QoS coordination. A balanced coordination is proposed using modeling correlations between user experience and service performance. The main contributions of this paper include three main parts. First, a comprehensive mapping is modeled in a close form to illustrate the analytic correlations between QoS, QoE, and data communication. Second, an analytical method to analyze and coordinate the nonlinear trade-off between QoE and QoS is proposed based on the theoretical proof with discussions on necessary-sufficient conditions. Third, an algorithmic framework is provided to perform QoE-QoS coordination based on quality-awareness computing with a test proof. An assessment model for user experience quantification is built with the mean opinion score (MOS) test. Quality-aware QoE and QoS models are built based on the subspace learning strategy. Simulations are given to prove the feasibility and effectiveness of the proposed method. The results show that the operations with the proposed solution can be obtained analytically with balanced efficiency in both user experience performance and network performance.

1. Introduction

Quality of service (QoS) supplies a solid base for a system to provide a service, reflecting the collective effect of service performance with quantitative parameters through the controllable behavior of a system [1, 2]. Quality of experience (QoE) puts more emphasis on user experience as a result, while QoS focuses more on the side of system behavior and performance [3], which reflects the value of the facility from the perspective of user experience [4]. However, due to the constraints on resource management in wireless communications [5, 6], there is a trade-off between QoS and QoE. Data communications with a high-level QoE need to consume the resources in the network, which brings containment to QoS, so it is complicated to achieve a simultaneous optimization of QoE and QoS under a network environment with limited resources.

Aiming at achieving the trade-off, a reliable data transmission control (DTC) can ensure both effective communication and information management of the network [7], and data transmission with QoE-QoS means that a balanced trade-off needs to manage many factors. Existing works, such as [8–10], discuss related solutions to the challenges in data communication and resource management but lack the considerations of QoE-QoS coordination. It is still a challenge to design a process with integration of solutions to QoE and QoS optimization.

In practice, QoE is negatively related to the disturbance of QoS [3], while a higher level of QoS does not always guarantee a better performance in QoE. As a case in point

with an example of network energy efficiency (NEE) to illustrate QoS in wireless sensor networks, QoE would be inferior during the optimization of NEE [11]. Due to the nonlinear constraints within limited resources, the coordination between QoE and QoS cannot be optimized only through a simple inverse control but requires the consideration of the nonlinear relationship between the two indicators to design an optimal data control process, especially for the optimization of multiple objects.

In this paper, we mainly focus on the coordination between QoE and QoS, as well as a solution with a corresponding DTC strategy to perform the optimal coordination of the system when QoS and/or QoE have been set as a desired optimal object. We firstly build up an analytical model to illustrate the nonlinear correlation between data communications and network performance. By the features of data communication, we propose quality-aware computing strategies with analytic feature-based computing to enable the system to be aware of the quality of both service and experience. The contribution of this work includes an analytic method to coordinate nonlinear QoE-QoS trade-off and a methodological framework to achieve QoE-QoS balance with the awareness of the quality in both service and experience. Corresponding theoretical proofs and test proofs with simulations are given to show the feasibility and effectiveness of the proposed method.

2. Scenario

As an exemplified engineering scenario, a wireless sensor media network (WSMN) is a sensing network (as shown in Figure 1), in which the IoT networks (e.g., [12, 13]) serve as a type of system that consists of a collection of wireless media sensors (e.g., camera, microphone, temperature sensor) and actuators, where each sensor has its own identity (ID) corresponding to its location and collects event data in its associated region. Similarly, each actuator has the location-related ID too.

To implement the computation in the system, an agent-based model is usually applied to abstract and design the system [14], and an agent-based model is suitable for engineering implementation of a complex system and software with embedded agents [15]. The implementation of the WSMN is performed with a set of computing devices, and the nodes with computing ability serve as agents. In this paper, the engineering trade-off between QoS and QoE is abstracted as an analytical balance under a unified normalization measurement. QoE refers to the user experience of percepting the information by humans. We model the awareness of QoS and QoE for the computation with the autonomous software agents, and the process for performing the coordination is programmed based on the following modeling.

3. Quality-Awareness Modeling

3.1. QoS Awareness Modeling. In this section, we model the QoS awareness with data communication measurements. As the performance of data communication, sender bitrate (SBR) and packet rate (PR, equivalent to frame rate in some cases) are the base of the environment. Under this environment, the performance can be quantified by the measurement packet error rate (PER), where PER can be formulated as

$$PER = 1 - (1 - \mathrm{BER})^{\mathrm{LD}}, \tag{1}$$

where BER refers to the bit error ratio and LD, which is a shortened form of load of data, refers to the quantity of data load. In most network systems, the QoS is involved in data load LD during communication. Usually, LD refers to data load. In wireless communication, BER can be formulated as a Rayleigh fading with path loss exponent β and the distance of relay d as

$$BER = (a - b\beta \log(d))^{-1}, \tag{2}$$

in which a and b represent the coefficients for formulating the channel features (e.g., $a = 79$, $b = 10$). Based on that, packet loss rate (PLR) can be further formulated as

$$PLR = 1 - (1 - \mathrm{PER})(1 - \mathrm{PCR}), \tag{3}$$

where PCR represents packet collision rate and can be obtained by

$$PCR = 1 - (1 - p_t)^{n-1}, \tag{4}$$

in which p_t refers to transmission probability in the network with n nodes.

Through (1)–(4), network level QoS can be modeled with PCR, PLR, and PER as parameters that focus on the QoS effect in data communication, while sender bitrate (SBR) and packet rate (PR) are application level parameters that focus on QoS effect in data applications. Network level parameters are related to application level parameters. For example, PER is determined by network adaption, and PR and SBR are determined by service adaption [16]. In this paper, we focus on data-communication-based QoS.

3.2. QoE Awareness Modeling. When experiencing the same data, the QoE can be mainly determined by the quality of data, and we model the data X with quality related features. We firstly use principal component analysis (PCA) to extract features. Given data $X \in R^{m\times n}$, an optimal projective transformation $P \in R^{n\times n}$ can be found as $\widehat{X} = XP$ with minimal mean squared error under a maximal variance $D(\widehat{X}) = E(\widehat{X} - E\widehat{X})^2$, in which $E(\cdot)$ refers to the operator to obtain an expected value of a random data X. With the projection, the variance $D(\widehat{X}) = E(\widehat{X})^2 = P^T E(X^T X)P = P^T \Phi P$, and it can be seen that Φ is the covariance matrix of the data X. With diagonalization projection, the variance can be transformed into $D(\widehat{X}) = \Lambda$, where Λ represents a diagonal matrix with eigenvalues $\Lambda = \mathrm{diag}\{\lambda_1, \lambda_2, \ldots, \lambda_n\}$, which quantifies the contributions of corresponding projected features.

Based on the formulation above, the relation between data and QoE can formulated as

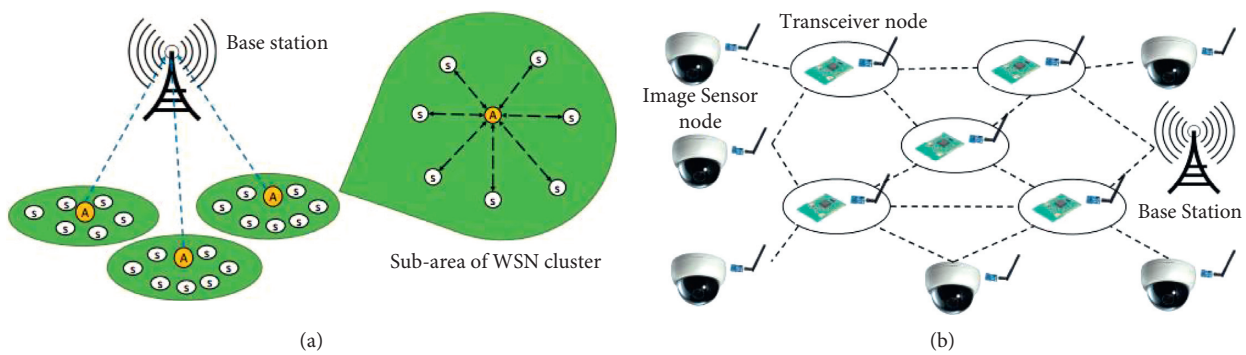

Figure 1: (a) The scenario of an agent-based wireless sensor media network (WSMN), where A represents an agent and S represents sensors in the area; (b) an example of the implementation of a subarea cluster in agent-based WSMN, where the transceivers with embedded computing components serve as agent clusters to reinforce the robustness of the network with multiagent systems.

$$\text{QoE} = \sum_{i}^{k} \beta i \lambda i = B, \overrightarrow{\Lambda}, \tag{5}$$

in which B refers to an operator of feature selection (e.g., a weighted binary vector) and k refers to the dimension of selected features. Diverse experience preferences can be represented by various combinations with B. To simplify the stochastic covariance Φ, the variance of data C_{xx} is usually applied as

$$C_{xx} = \frac{1}{n-1}\left(X^T X\right), \tag{6}$$

and $D(\widehat{X}) = P^T C_{xx} P$. Combining this with (5), we can represent the QoE awareness of data X by corresponding B and P. With the QoE and QoS awareness modeling, we can further process the quality of service and experience via the quantitative analysis as follows.

4. QoS Awareness Computing

4.1. Network Level QoS Awareness. In this section, we present network level QoS awareness computing, based on network level parameters considering NEE under PER. The NEE_{PER} can be formulated as

$$\text{NEE}_{PER+} \frac{Eu\,LD}{Eu\,(LD + \hbar + \tau) + Es + Ed}\,(1 - \text{PER}), \tag{7}$$

where $\hbar$ refers to the head of data encapsulation and τ represents the tail. The energy consumption for decoding E_d and communication E_u can be calculated by

$$Eu = \frac{\text{PTE} + \text{PO} + \text{PRE}}{\text{DR}}. \tag{8}$$

The start-up energy consumption E_S can be calculated by

$$E_S = P_{\text{TST}} T_{\text{TST}} + P_{\text{RST}} T_{\text{RST}}, \tag{9}$$

in which the power consumed in transmitter P_{TE} and receiver P_{RE} can be obtained by the design of the circuit components in transmitting and receiving systems, as well as the start-up power consumed in transmitter P_{TST} and receiver P_{RST}. The output power P_O for transmission and start-up time of transmitter and receiver (T_{TST}, T_{RST}) can be obtained by description or practical experiment of systems. Data rate (DR) is usually a known parameter.

Figure 2 shows an example of the QoS assessment under NEE based on PER. After hitting the peak, the trend of the NEE declines with the increase of data load in communication.

4.2. Coordination with QoS Awareness. QoS awareness can be represented by NEE, and influential factors include E_u, L_D, $\hbar$, τ, E_s, E_d, BER, and PER. In practice, energy consumption for decoding E_{d} and useful energy in communication E_u are relatively stable because once the system and deployment are determined, the related parameters including data load, $\hbar$, τ, power consumption PTE and PRE, output transmit power PO, start-up power PTST and PRST, and start-up time TTST and TRST can be specified. Therefore, we can simplify those parameters as a set of constants.

In wireless communication, BER is influenced by a physical channel with environmental features, but it is to model the unreliable communication environment accurately, especially when considering a large area with multiple sensors in a monitoring system. Therefore, we design a channel-coding-based QoS awareness module for the system to detect error, thus implementing a feedforward QoS estimation.

Channel coding [17–19] can be introduced to simplify the strategies considering the limited computing resource available in the wireless networks. Instead of using (2) to perform BER estimation based on wireless communication channel model, feedforward error detection (FED) computes BER directly by the data received with the error detection from support channel coding, which divides the information of the source into independent blocks and then processes and encodes them. When encoding, each m bit is assigned to independent processing, and the processed result will be transformed into a series of binary codes with a length $n\,(n > m)$. Block codes are used for fixed-size blocks (packets) or symbols of a known size. The decoding time of the block code and the length of the group have a polynomial relationship. In the processing, the information sequence of the

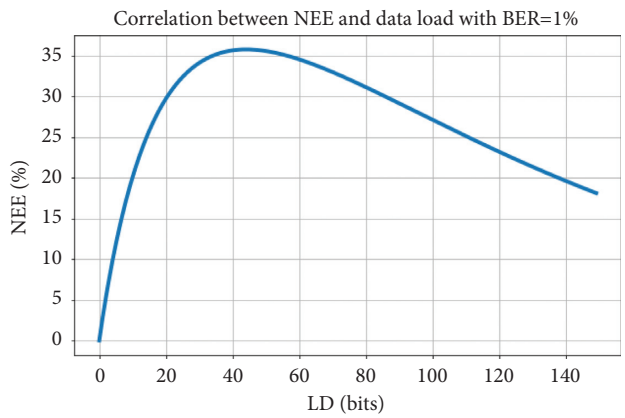

Figure 2: BER = 1%, $E_u = 2\,\mu$J/bit, $E_S = 30\,\mu$J/bit, $Ed = 0.01\,\mu$J/bit, $h = 15$ bit, $\tau = 5$ bit.

source is divided into independent blocks for processing and encoding.

To implement the FED solution, BCH (Bose–Chaudhuri–Hocquenghem) coding [20–22] is applied as the coding strategy for soft FED module to compute BER estimation BER*. Therefore, even without the knowledge of the communication environment, the system can still estimate the channel state by calculating the Hamming distance between received data and error bit detection.

Considering the multiple sensors and many different sets of data received in the network with delays, we simplify the quantitative QoS awareness as a linear BER proportional value with the mean of the BER estimation from all the received data, that is,

$$\psi = a\frac{\sum_N \mathrm{BER}_i^*}{N} + W, \tag{10}$$

where BER_i^* refers to the estimated BER with the feedforward method of ith record, N refers to the number of data sources (or the number of received records within a unit period) in the scope, a refers to the coefficient representing the sensitivity of the QoS in the network, and w refers to a correction to improve the robustness against the interference from jittering BER in the network since BER perturbation is not uncommon in wireless communication.

What is noticeable is that ψ serves as QoS awareness of intensity, which represents the pressure of the communication in the network based on the sense of BER. The ψ increase implies incidents such as channel degradation, communication interference, and congestion.

Based on this QoS awareness, a simplified calculation can be designed, which is significant for an embedded agent with small scale computing power. Instead of using (1), the QoS awareness can be used to estimate the PER too, which yields

$$\mathrm{PER}^* = 1 - (1-\psi)^L D. \tag{11}$$

Correspondingly, the NEE-based QoS adjustment can be realized by

$$\mathrm{NEE}_{\mathrm{PER}^*}\frac{Eu\,LD}{Eu(LD + \hbar + \tau) + Es + Ed}\left(1 - \mathrm{PER}^*\right). \tag{12}$$

Thus, we build up the QoS awareness with the connection of the NEE and data load, which enables us to estimate the channel and its QoS without having the a priori knowledge of the wireless environment and network layouts. Due to the lack of constraints, more adaptive strategies can be introduced to perform autonomous coordination. In the next section, we will discuss how to coordinate the network communication with the QoS awareness.

5. QoE Awareness Computing

5.1. Quality-Aware User Experience Modeling. To describe user's experience, we introduce a mean opinion score (MOS) [4] as a criterion to measure the QoE, modeling the correlation between the k and MOS. Figure 3 shows an image as a benchmark in the MOS test. The resolution of the chosen image is 530×530. We reconstruct the image with different numbers of $k, k \in [1, 530]$. The data transmission samples are divided into 10 groups as $G_i, i = 1, 2, \ldots, 9, 10$; i.e., $G_i = \{I_i, I_{i+10}, I_{i+20}, \ldots, I_{i+520}\}$, where I_k represents the image data transmission with k features, and each group G_i has 53 images. Figures 3(b)–3(d) show data transmission examples of I_k with $k = 100$, 200, 300.

As a QoE measurement, the MOS test was attended by 25 participants. Each participant was shown the original image as shown in Figure 3(a) as a ground truth MOS = 5 benchmark and then gave MOS score to the data transmission examples with different k. Figure 4 gives the statistics of MOS result given by the participants. By fitting MOS to represent QoE, based on the MOS test, the QoE can be modeled by

$$\mathrm{QoE}_{\mathrm{MOS}} = \alpha \times \mathrm{erf}\,(sk) + \gamma, \tag{13}$$

$$\mathrm{erf}\,(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{t^2}\,\mathrm{d}t, \tag{14}$$

in which α refers to a parameter of the QoE scale, is empirical offset, and sensitivity weight of user experience $s \in (0, 1]$ is obtained based on user experience. The number of features k is the subjective weight of user's experience (shown in Figure 5).

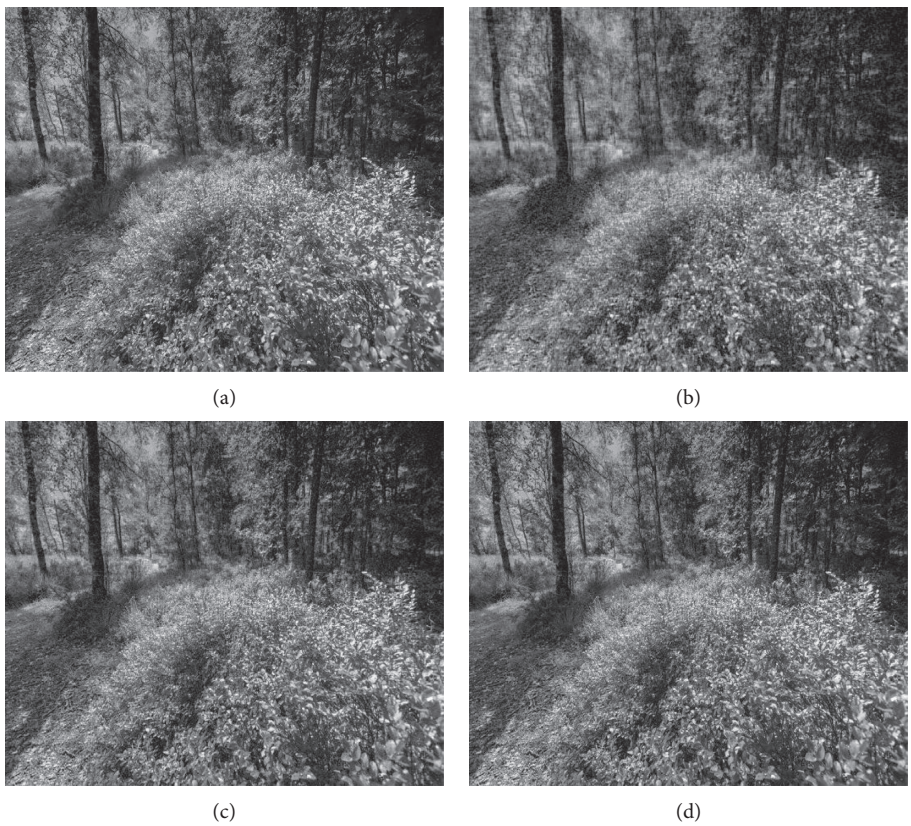

Figure 3: (a) Original image for MOS test; data transmission image with (b) $k = 100$ for MOS test, (c) $k = 200$ for MOS test, and (d) $k = 300$ for MOS test.

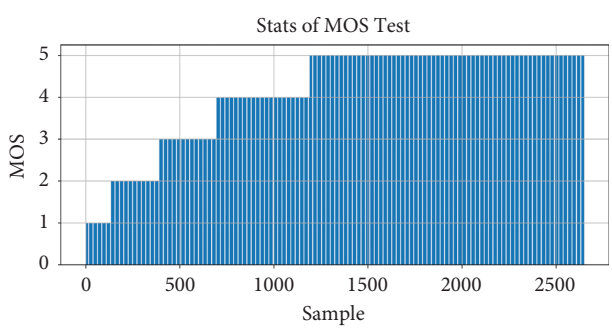

Figure 4: The statistics of MOS experiment.

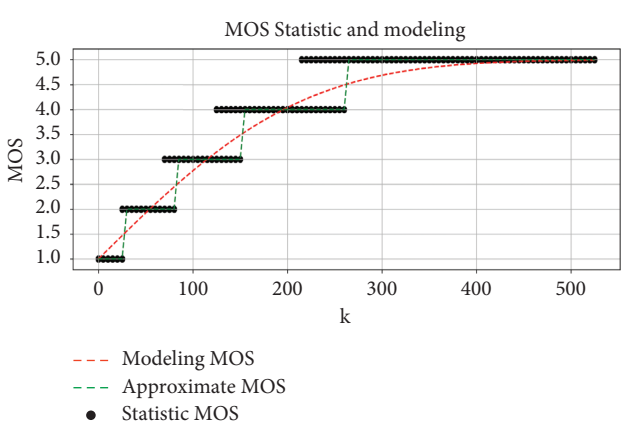

Figure 5: QoE modeling by MOS fitting.

Based on the statistics (shown in Figures 4, and 5), the data feature can be used to represent the level of user experience, which bridges the gap between QoE and data communication by (5) and (13) in terms of the features and load of the data. Thus, we quantify the QoE by using MOS and its fitting (13) to build up the relation between QoE and k features of data. With this bridge, the awareness-based coordination can be performed as follows.

5.2. Coordination with QoE Awareness. We noticed that there are some works projecting QoS to MOS with statistics (e.g., [23]); however, there exists a lack of methods for adjusting QoS by using MOS as a switcher to perform DTC directly. To represent the direct quantification of the experience, we take MOS as a trigger for feature selection, and the coordination strategy can be formulated as

$$k = \frac{1}{s}\mathrm{erf}^{-1}\left(\frac{\mathrm{MOS} - \gamma}{\alpha} - \varepsilon\right). \tag{15}$$

Therefore, the lower bound of feature selection can be obtained by setting the lower bound of the experience of MOS. Typically, $\alpha = 4$, $\gamma = 1$, $\varepsilon = 0.0006$ in a 5-level MOS system, and Figure 5 shows the modeling result of QoE based on the MOS test. Based on the awareness modeling above, QoE can be further formulated as a function of data load L_D as

$$\mathrm{QoE} = \alpha \times f(L_D) + \gamma, \tag{16}$$

where $f(\cdot)$ represents the nonlinear mapping. The number of features is positively correlated to the quantity of data load L_D. Corresponding to (13) and statistics shown in Figure 4, the correlation can be fitted as

$$f(L_D) = \mathrm{erf}(\rho L_D). \tag{17}$$

In addition, corresponding QoE can be formulated as

$$\mathrm{QoE} = \alpha \times \mathrm{erf}(\rho L_D) + \gamma, \tag{18}$$

in which ρ refers to the data-experience sensitivity. Thus, the gap between the relations of data load L_D and number of features k can be bridged by ρ and s.

In practice, the lower bound of the selected features can be more useful to perform data load control in communication under a limited-resource condition. When setting the infimum of MOS, inf (MOS), the data load for lower-bound DTC coordination can be performed by

$$\inf(L_D) = \frac{1}{\rho}\mathrm{erf}^{-1}\left(\frac{\inf(\mathrm{MOS}) - \gamma}{\alpha} - \varepsilon\right). \tag{19}$$

With the experience residual ε, the DTC strategy can be performed to fit various sensitivities.

Considering the effect of the data communication, we design a soft shifter to adjust the data load by the switcher k as agent-based computing, in which data load of content L_D is proportional to k, and k can be used as the ratio switcher of the transmission data. With encoding efficiency μ and encapsulation data size δ, a linear switcher can be formulated as

$$L_{D+} = \mu k + \delta. \tag{20}$$

Encoding efficiency varies on coding format, and encapsulation varies on the design of packet and protocol due to the head and tail block, configuration, and error controlling bits. By adjusting k, the data load can be tuned. Let data of content $\mu k = L_D$; the correlation between efficiency μ, user sensitivity weight s, and data-experience sensitivity ρ can be formulated as

$$\frac{s}{\rho} - \mu = 0, \tag{21}$$

which reveals a fact that when users are very sensitive to the experience from the data, the requirements of encoding efficiency and data-experience representation are higher, and when the performance of data-experience representation is high, the requirements of the encoding efficiency for achieving the experience at the same level can be compromised.

6. Quality-Aware Coordination

6.1. QoS Awareness-Based Coordination. Based on the analysis above, the data communication has its impacts on the performance of QoS. According to the definition of the NEE in (7), the correlation between data load and BER is nonlinear. However, the network characteristics are different under different network parameters. According to the mathematical analysis for optimization [24, 25], we first give the conditions for optimal QoS coordination in the network environment.

Theorem 1. *With given E_u, E_s, E_d, h, τ, L_D, BER under NEE–L_D correlation defined by (7) and (1), the necessary and sufficient conditions for optimal NEE-based QoS coordination can be formulated as*

$$L_D^3 + \theta L_D^2 + \vartheta L_D < \phi, \tag{22}$$

$$\begin{cases} a = 1 - \mathrm{BER} \\ b = h + \tau + \dfrac{\mathrm{Es} + \mathrm{Ed}}{\mathrm{Eu}} \\ \theta = 2b \\ \vartheta = \dfrac{b^2 + 2b}{\ln a} \\ \phi = 2b(1 - b\ln a) \end{cases}. \tag{23}$$

Proof. According to (1) and (7), the derivative result of NEE can be formulated as

$$\frac{\mathrm{dNEE}}{\mathrm{d}L_D} = \frac{aL_D \ln(a)L_D^2 + \mathrm{b}a^L DL_D \ln(a) + \mathrm{b}a^{L_D}}{(\mathrm{LD} + \mathrm{a})^2}, \tag{24}$$

$$a = 1 - \mathrm{BER}, \quad b = h + \tau + \frac{\mathrm{Es} + \mathrm{Ed}}{\mathrm{Eu}}, \tag{25}$$

$$\frac{\mathrm{d}^2\mathrm{NEE}}{\mathrm{d}L_D^2} = \frac{a^L D\Psi}{(L_D + b)^3}, \tag{26}$$

$$\Psi = L_D^3 \ln^2 a + 2bL_D^2 \ln^2 a + b^2 L_D \ln^2 a + 2bL_D \ln a + 2b^2 \ln a - 2b. \tag{27}$$

When $\Psi < 0$, NEE is convex, which yields

$$L_D^3 + 2bL_D^2 + b^2 L_D + \frac{2b}{\ln a} L_D < 2b(1 - \ln a). \tag{28}$$

Combining the terms, (28) can be rewritten as (22) and (23). When the relationship between NEE and L_D is a convex function, there exists at least one optimal solution to NEE-based QoS coordination in the given network environment, which draws the conclusion.

According to (22) and (23), define discriminant L as (29). Based on Theorem 1 when $L < 0$, there exists optimal NEE-based QoS coordination in the wireless network. Under a certain BER, L_D can be a variable parameter to adjust the discriminant

$$L = L_D^3 + \theta L_D^2 + \vartheta L_D - \phi. \tag{29}$$

Figure 6 shows a simulation to describe the correlation between L and L_D as an example of discriminant L adjustment by L_D, in which BER = 1%, Eu = 2 μJ/bit, Es = 30 μJ/bit, Ed = 0.01 μJ/bit, h = 15 bit, the corresponding parameters θ = 70.01, ϑ~−5740.59, ϕ~243912.61, the minimal L~−313743.43, and the approximate solution to $L = 0$ is LD~67.78. Within the range represented by the blue part, the necessary and sufficient conditions for optimal NEE-based QoS coordination are satisfied.

Figure 7(a) shows an example about the nonlinear correlation between BER and data load L_D. As can be seen from the figure, when the amount of data is 0, the NEE in the network is not the best. On the contrary, when the amount of data in the network gradually increases, the NEE also rises accordingly until it hits a peak, and then it shows downward trend. Although the rising and falling are nonlinear characteristics, the whole is a convex function characteristic, which matches the conclusions of Theorem 1, so there is a maximum value (L_D^*, NEE^*) as the optimal spot.

Unlike the correlation between data load L_D and NEE, the correlation between BER and NEE shows a monotonous declining trend. Figure 7(b) shows an example about the nonlinear correlation between NEE and BER. Therefore, when taking BER and L_D as variables of NEE, only L_D can be used as a parameter for coordination for hitting the optimal NEE-based QoS.

Figure 8 shows, for example, that when BER is determined, L_D can be used as a trigger to adjust the QoS through NEE. To further optimize QoS by adjusting NEE with data load L_D and the stationary point L_D^* can be obtained by the following theorem. □

Theorem 2. *Under certain $\hbar$, τ, Es, Eu, Ed, the adjustment of data load LD to the optimal QoS under NEE criterion can be obtained by*

$$L_D^* = \frac{\sqrt{\left(b_c^2 - 4b_c/\ln(1 - \mathrm{BER})\right)} - b_c}{2}, \tag{30}$$

$$b_c = \hbar + \tau + \frac{E_u}{E_s}. \tag{31}$$

Proof. Considering the $\mathrm{NEE_{PER}}$ as the QoS in (12) and (1), applying (24) and (25), and setting

$$\frac{\mathrm{dNEE_{PER}}}{\mathrm{d}L_D} = 0, \tag{32}$$

we have the solution that

$$L_D = \frac{-b \ln a \pm \sqrt{b^2 \ln^2 a - 4b \ln a}}{2 \ln a}. \tag{33}$$

Because $L_D > 0$, the result (30) can be obtained by excluding the negative solution.

In practice, b_c represents the average bit load for communication. Considering the distribution and varieties of the data sources (sensors) in the network, we simplify the network features of each source as a set of parameters including $S_i = \{\hbar, \tau, E_{si}, E_u, E_d\}_i$, where i refers to the ith data source or sensor. As for the aggregator, the estimation of the channel can be performed by calculating the mean value of the parameters of each data source i, which can be formulated as

$$\overline{S} = \sum_i^N \frac{S_i}{N} = \{\overline{\hbar}, \overline{\tau}, \overline{E}_s, \overline{E}_d, \overline{E}_u\}, \tag{34}$$

where N refers to the number of the data sources. Accordingly, we can obtain the optimal QoS adjustment by k *as* k_{NEE}^* with the following corollary. □

Corollary 1. *In a network with N data sources, with each data source i having a certain set of $\{\hbar, \tau, E_{si}, E_u, E_d\}_i$, the estimated adjustment k to the optimal QoS under NEE criterion can be obtained by*

$$k_{\mathrm{NEE}}^* = \frac{\sqrt{\left(b_c^2 - 4b_c/\ln(1 - \mathrm{BER})\right)} - b_c}{2\mu}, \tag{35}$$

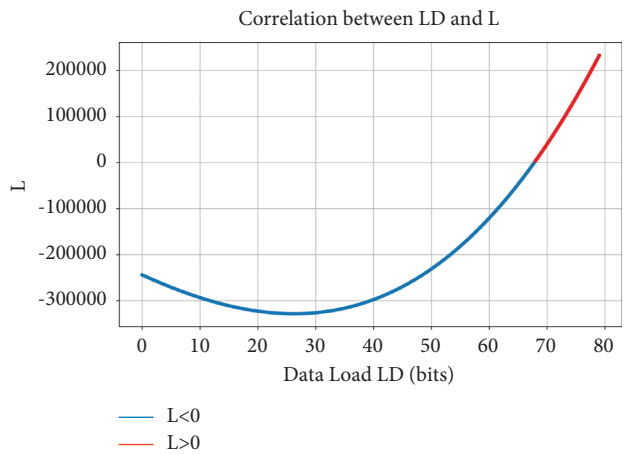

Figure 6: An example of discriminant adjustment.

where

$$b_c = \overline{h} + \overline{\tau} + \frac{\overline{E}_s + \overline{E}_d}{\overline{E}_u}, \tag{36}$$

in which $\overline{h}, \overline{\tau}, \overline{E}_s, \overline{E}_d, \overline{E}_u$ *can be obtained by (34).*

Proof. By substituting (11) and (38) into (12) and using Theorem 1, the result (38) can be obtained as optimal target k with the stationary state

$$\frac{\mathrm{dNEE_{PER}}}{\mathrm{d}k} = 0. \tag{37}$$

The conclusion can be drawn after the calculation. □

6.2. Normalized Coordination. The infimum of MOS can be obtained by (15) and (19). By using (30), (31), (2), (1), and (3), the optimal data load can be found, and k can be determined by (36) and (19) with a given MOS. Therefore, the MOS interconnections with BER, PER, and PLR can be built, as well as the interconnections between QoS and QoE. QoE can be tuned by DTC via the impacts of L_D on NEE and predicted with switcher k via the correlations between NEE and MOS. To hit the balance between QoS and QoE, we need to normalize QoE and QoS under an analytic domain with the same measurement. Thus, we formulate the balance switcher k_B under the normalization between QoE and QoS as

$$k_B = \arg\min_k \left(\frac{\mathrm{MOS}(k)}{\mathrm{MOS}^*} - \frac{\mathrm{NEE}(k)}{\mathrm{NEE}^*} \right). \tag{38}$$

MOS has its scale range from 0 to 5, and we use (18) to estimate the NEE* and (7) to predict MOS (k). With normalization, the trigger k can shift both the MOS and NEE at the same time, thus tuning the QoE and QoS coordination.

7. Simulation

In this section, we present mathematical simulations of our modeling and approach. The channel model is built using (7)–(12), and the parameters of the communication environment in the simulation are given in Table 1. We first describe the setup of our simulation for QoS and QoE-QoS coordination and then evaluate the performance of our proposed approaches for the corresponding optimal coordination.

7.1. QoS Optimal Coordination. The experiments in this section serve as the test proofs of the proposed method to optimize the QoS by NEE adjustment based on data load. As for the experiments, the first experiment is mainly to verify the impact of a single adjustment strategy using Theorem 2 on NEE-based QoS when the BER changes, and the second experiment is to consider the comprehensive adjustment results on a network with multiple different sources. The experimental network is established by 6 sensors and 1 aggregator. Figure 9 shows the scenario, in which (a) represents experiment 1 with one sensor as the data source for one agent A in data transmission applications, and (b) represents experiment 2 with 6 sensors as data sources s_i $(i = 0, 1, 2, 3, 4, 5)$ in data aggregation applications.

7.1.1. Experiment 1: QoS Optimal Coordination for Transmission. In experiment 1, the system with one agent and one sensor is taken as the scenario to evaluate how the proposed method works when facing an unstable channel with serious BER fluctuation.

As a case in point, we choose a scenario of the change bit error rate at the receiving end caused by the transmission channel noise or sudden interference in the communication system for the test. A typical change of this kind appears as the channel BER gradually recovers after a certain period of increase. Based on the Monte Carlo random method, we simulate the BER channel by randomly discarding a certain percentage of code bits and filling error bits. The change of BER is shown in Figure 10; it rises first and then decreases.

Correspondingly, by using the method proposed in this paper, the adaptively optimal data volume is shown in Figure 11. Figure 12 shows the change trend of the original NEE when the default data amount is 16 bits and the optimized NEE change trend after the adaptive data amount adjustment strategy is adopted. It can be seen from the figure

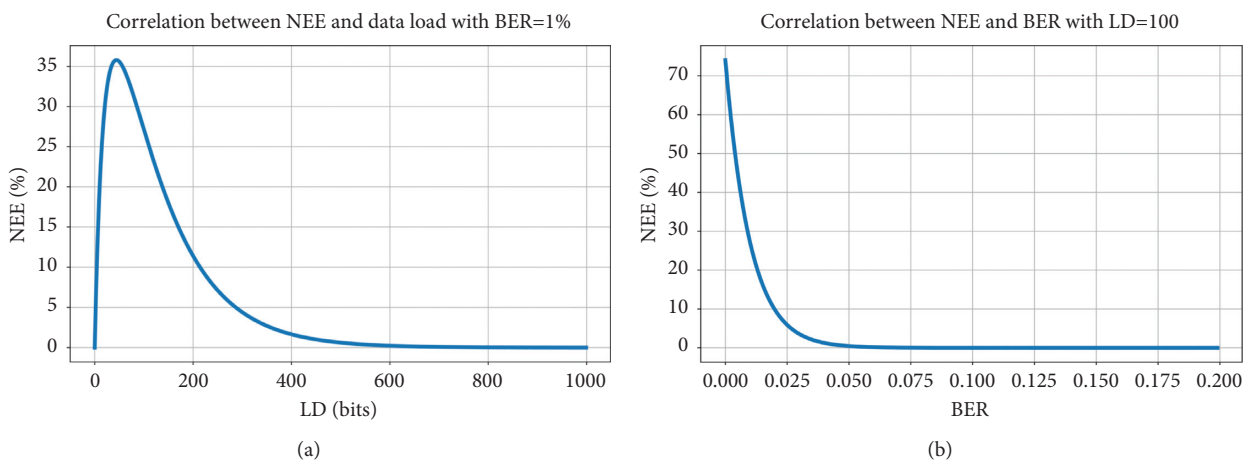

Figure 7: (a) Correlations between L_D and NEE, where BER = 1%, PER = $1-(1-\text{BER})^{\text{LD}}$, Eu = 2 μJ/bit, Es = 30 μJ/bit, Ed = 0.01 μJ/bit, $h = 15$ bit, $\tau = 5$ bit; (b) correlations between BER and NEE, where $L_D = 100$ bits, PER = $1-(1-\text{BER})^{LD}$, $E_u = 2\,\mu$J/bit, $E_s = 30\,\mu$J/bit, $E_d = 0.01\,\mu$J/bit, $h = 15$ bit, $\tau = 5$ bit.

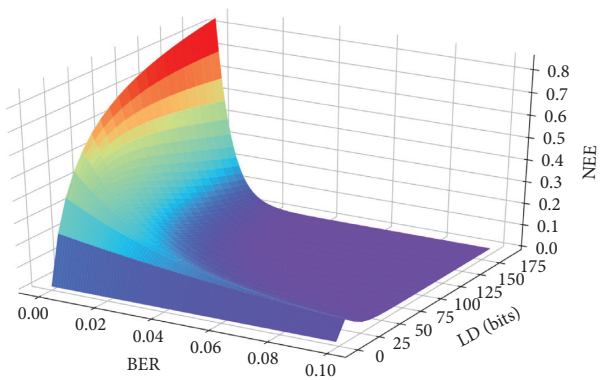

Figure 8: Correlations between BER, L_D, and NEE, where PER = $1-(1-\text{BER})^{\text{LD}}$, Eu = 2 μJ/bit, Es = 30 μJ/bit, Ed = 0.01 μJ/bit, $h = 15$ bit, $\tau = 5$ bit.

that after the proposed strategy is adopted, the downward trend of NEE is slowed down, and the decline of NEE has been relieved by lifting both the trend and the minimum of the NEE.

To evaluate the effectiveness of the optimization, we introduce optimization ratio r as the criterion to measure the result, which is formulated as

$$r = \frac{\text{NEE}^* - \text{NEE}}{\text{NEE}}, \tag{39}$$

where NEE represents the original NEE, and NEE* represents the NEE after the optimization. Figure 13 shows r with varying optimization with the changing BER as shown in Figure 10.

The result shows that by adjusting the data volume by the proposed method (as shown in Figure 11), the system can constrain the decrease of NEE (as shown in Figure 12), under the condition of channel degradation (as shown in Figure 10), thereby ensuring a certain degree of QoS performance. It can be seen from Figure 14 that through the QoS coordination strategy proposed in this paper, the optimized result has been significantly improved compared to the preoptimized result, and the improvement of efficiency in NEE will be adaptively improved with the severity of the BER degradation. Near the worst case of BER (0.11 in Figure 10), NEE increased by 50% (shown in Figure 14), which verifies the feasibility and effectiveness of the proposed method.

7.1.2. Experiment 2: QoS Optimal Coordination for Aggregation. The second experiment shows how the proposed strategy works in a wireless network with distributed data sources under a considerable BER increase. The agent will aggregate the data from different sources from s_0 to s_5 and estimate the BER by FED strategy. The BER change by using the data from different sources is shown in Figure 14 with the estimation of the overall ψ defined in (10) as the QoS awareness of the channel degradation. The overall degradation rises from about 5% to 12% averagely, which implies a significant channel incident (e.g., interference or congestion).

To deal with the degradation, the proposed method enables the agent to coordinate the network performance

Table 1: Parameters of simulations.

Parameters	Value	Meaning
β	3.5	Path loss exponent
d	10 m	Relay distance
n	10	Number of the nodes in the network
h	12 bits	Head bit size in a unit data packet
τ	6 bits	Tail bit size in a unit data packet
p_t	0.0025	Transmission probability
E_u	2 μJ/bit	Communication energy
E_s	30 μJ/bit	Energy consumed for start-up
E_d	0.01 μJ/bit	Energy consumed for decoding
BER	0.003	bit errors rate
PCR	0.0267	Data collision probability
DR	200 Kbyte/s	Data rate

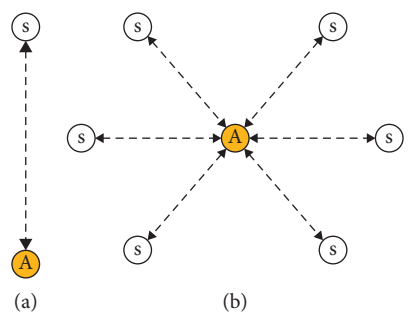

Figure 9: The scenario of experiment 1 (a) and experiment 2 (b), where s represents a sensor node and A represents an aggregation agent node.

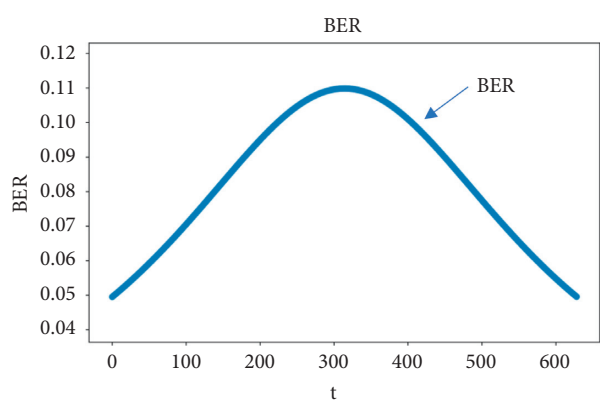

Figure 10: Simulation of BER dynamics changing in experiment 1.

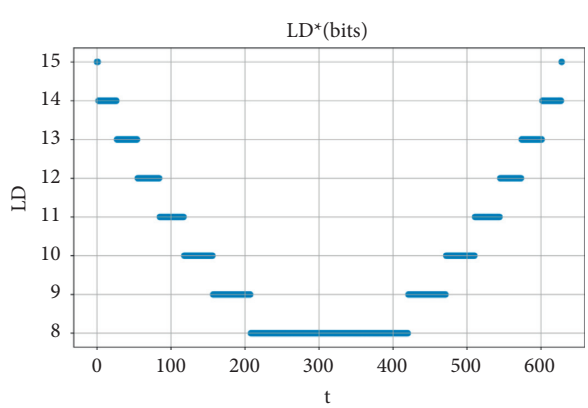

Figure 11: Optimized data load adapted to BER changing in Figure 10.

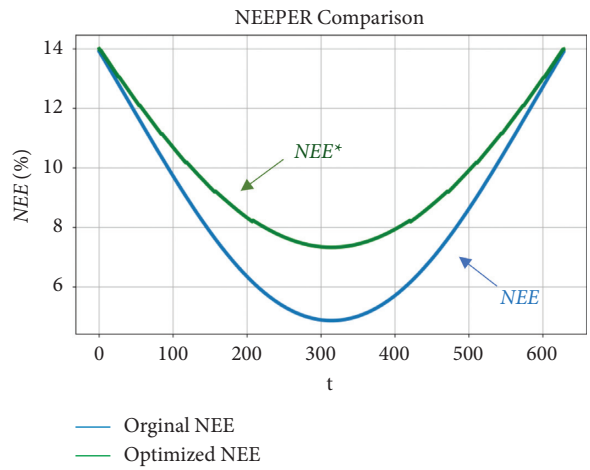

Figure 12: NEE comparison before and after optimization in experiment 1.

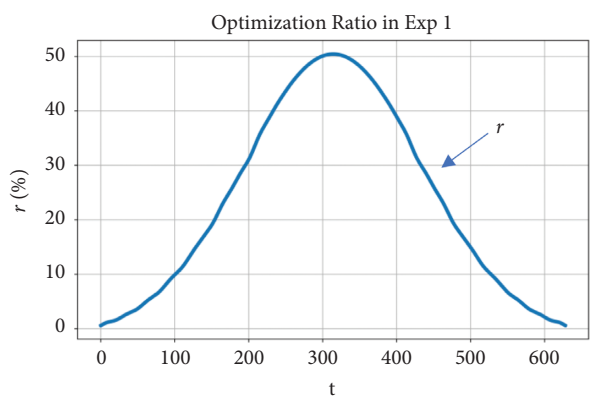

Figure 13: Optimized ratio evaluation in experiment 1.

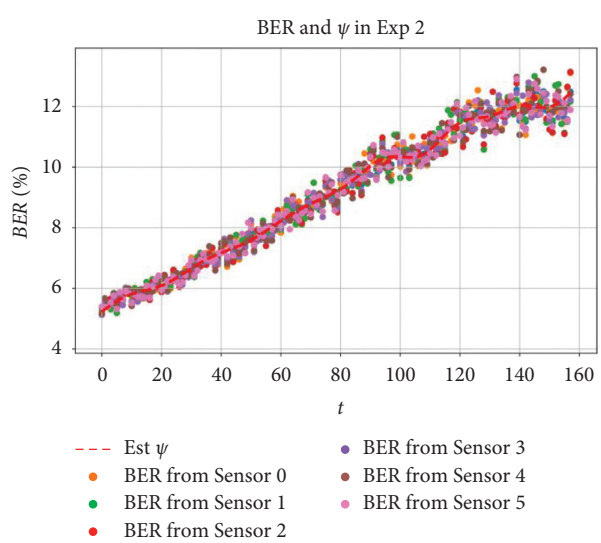

Figure 14: Degradation simulation of BER in experiment 2.

adaptively by adjusting the data load permission L_D. Figure 15 shows the optimal data volume with the variety of the QoS awareness of the intensity. The adjustment of L_D can be seen as a trigger to shift the characteristic of the communication as shown in Figure 12, which provides a bridge between BER and L_D and has a positive correlation.

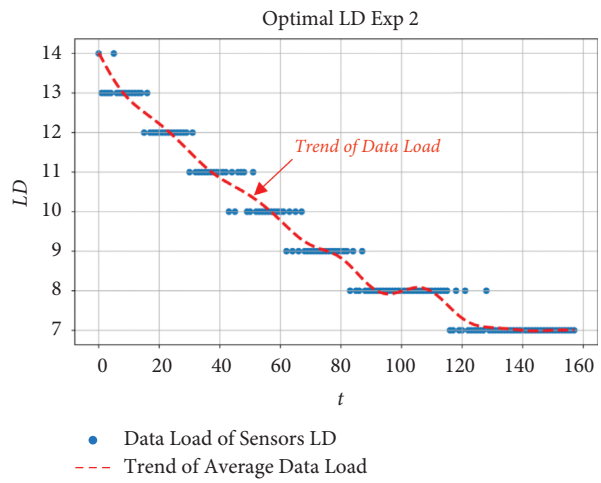

Figure 15: Optimized data load LD in experiment 2.

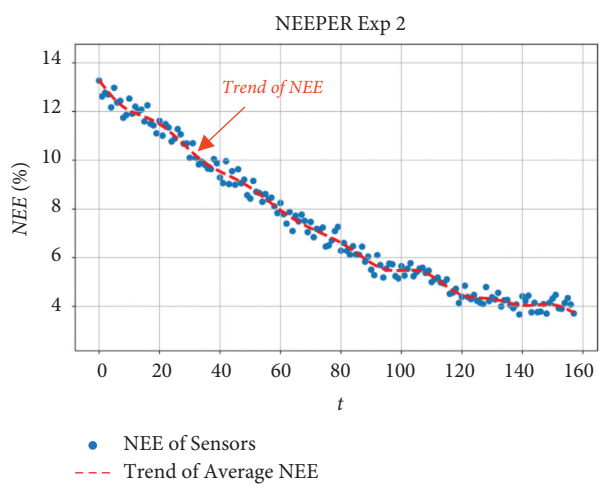

Figure 16: NEE without data load optimization in experiment 2.

Correspondingly, Figures 16 and 17 show the corresponding NEE with and without data load optimization. Figure 18 shows the change trend of the overall original NEE under $L_D = 16$ bits and the overall optimized NEE change trend. After the adaptive data amount adjustment strategy is adopted, the downward trend of NEE is slowed down, and the decline of NEE has been relieved with higher minimum of the NEE.

To evaluate the effectiveness of the optimization, Figure 19 shows r with varying optimization with the changing BER as shown in Figure 1. The statistics of some adjustment are listed in Table 2. As can be seen in Figures 18 and 19, although NEE and NEE* both show downward trends with the increase of BER, the trend of r is positively correlated with the BER, which is the reason why the proposed method can help to stabilize the QoS while BER affects the NEE negatively.

7.2. QoE-QoS Balance Coordination. In the QoE-QoS coordination experiment, the data for transmission is an image (as shown in Figure 3(a)) with the resolution of 530×530 pixels in JPEG format. The encoding coefficient μ is 0.8066, data-experience sensitivity ρ is 0.47, and sensitivity weight s is 0.38. The balance between QoE and QoS is measured by the production J_C as the coordination efficiency of the solution, defined as

$$J_C = \text{MOS} \times \text{NEE}. \tag{40}$$

Figure 20 shows the correlation between J_C, MOS, and NEE. The higher J_C is, the more balanced the management is. $J_{C\text{-PER}}$ refers to the comprehensive performance of $\text{MOS} - \text{NEE}_{\text{PER}}$ management and $J_{C\text{-PLR}}$ refers to $\text{MOS} - \text{NEE}_{\text{PLR}}$.

According to the MOS test, the solution k for the optimal QoE has been found as shown in Figure 5. We collect the lower bound of k feature switcher for good QoE (MOS = 4) as inf $(k)_{\text{MOS}=4}$, and excellent QoE MOS = 5 as k^*_{MOS}. The switcher is at about $k = 240$ for good experience and 533 for excellent experience.

As shown in Figure 21, when switcher $k = 92$ as $k_{\text{NEE}}{}^*$, the NEE reaches its peak at 55% under PCR = 0.0267.

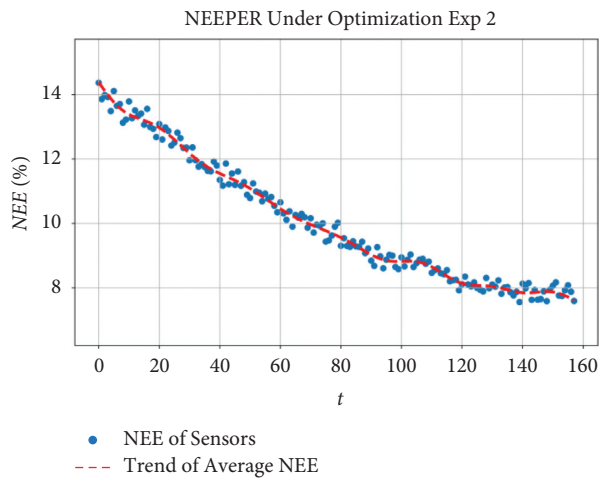

Figure 17: NEE with data load optimization in experiment 2.

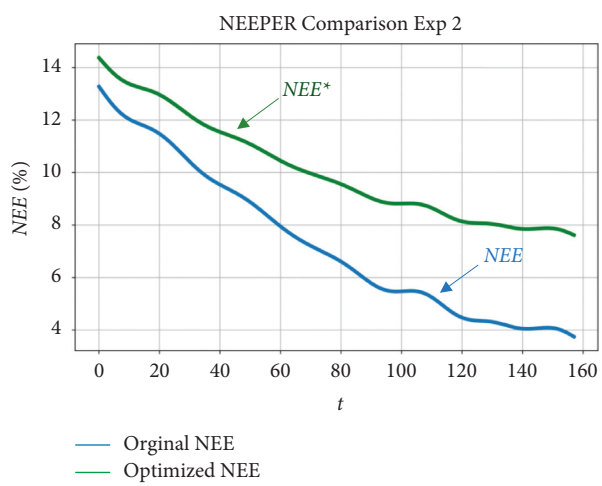

Figure 18: NEE comparison before and after optimization in experiment 2.

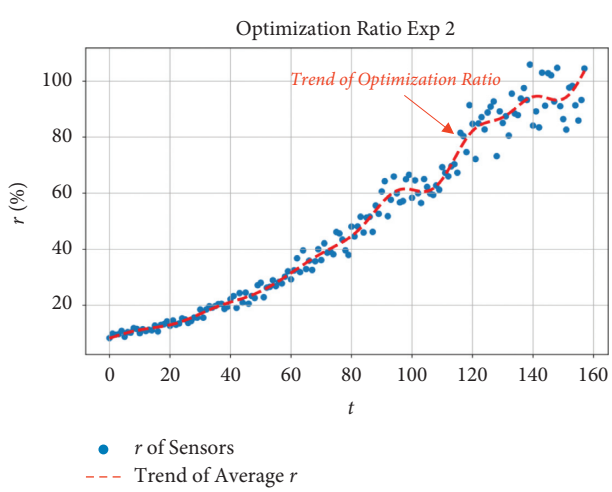

Figure 19: Optimized ratio evaluation in experiment 2.

Table 2: Statistics of some typical adjustment.

BER	LD optimized	Original NEE	Optimized NEE	Optimized ratio
5.16%	15	13.45%	14.52%	8%
5.62%	14	12.43%	13.71%	10%
6.65%	13	10.44%	12.15%	16%
7.26%	12	9.39%	11.43%	22%
8.12%	11	8.09%	10.54%	30%
9.04%	10	6.89%	9.76%	42%
10.07%	9	5.74%	9.01%	57%
12.20%	8	3.91%	7.75%	98%

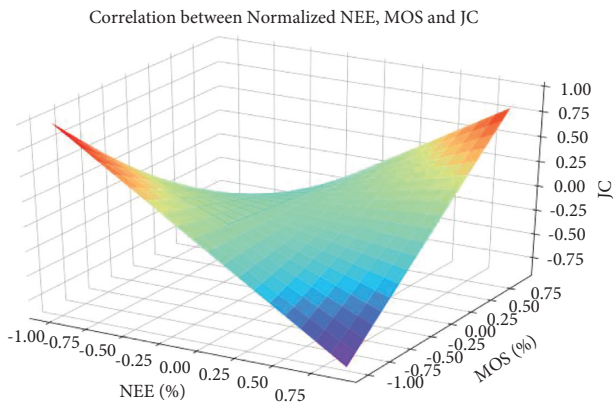

Figure 20: Optimal solution for QoS management.

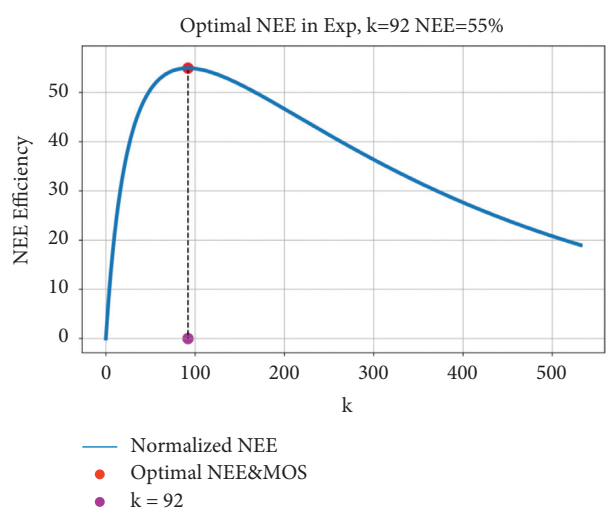

Figure 21: Optimal solution for QoS management.

Figure 22(c) shows the corresponding data representation under the switcher k^*_{NEE}. Figure 23 illustrates the simulation of balanced coordination. It can be seen from the illustration that, by applying the proposed method, the balanced solution $k_B = 234$ preserves both the normalized NEE at 78% and MOS at 79%, while the trade-off between NEE and MOS makes QoE and QoS negatively correlate before and after the balanced solution.

Figure 22 shows a comparison between the displayed results, and Table 3 shows a detailed comparison between the evaluations by different optimal strategies. The balanced k_B with highest $J_{C,}$ coordinates both the QoE and QoS simultaneously to an acceptable level for both metrics. As shown in Figures 22(b) and 22(c), inf $(k)_{\mathrm{MOS}} = 4$ and k^*_{MOS} provide a good solution to QoE, the QoS performance, which is inferior, consuming more than 1 second to transmit the data. On the other hand, k^*_{NEE} reaches an excellent QoS performance (completing the transmission within 1 s) but sacrifices user experience (with only 2 in MOS). Balanced coordination of k_{B} achieves an optimal QoE and QoS at the same time, enabling the system to complete data communication with an acceptable level in both the performance (data transmission within 1 s) and user experience (MOS = 4).

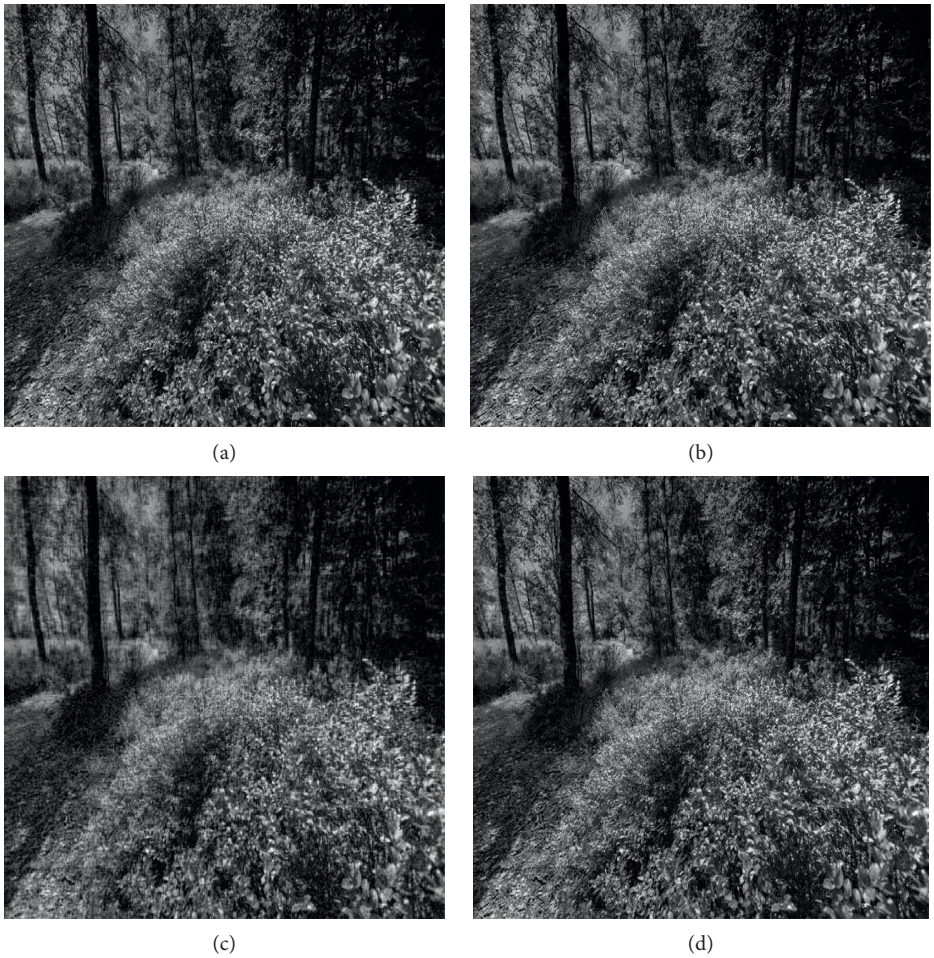

Figure 22: The displayed result by (a) inf $(k)_{\text{MOS}=4}$; (b) k^*_{MOS}; (c) k^*_{NEE}; (d) k_B.

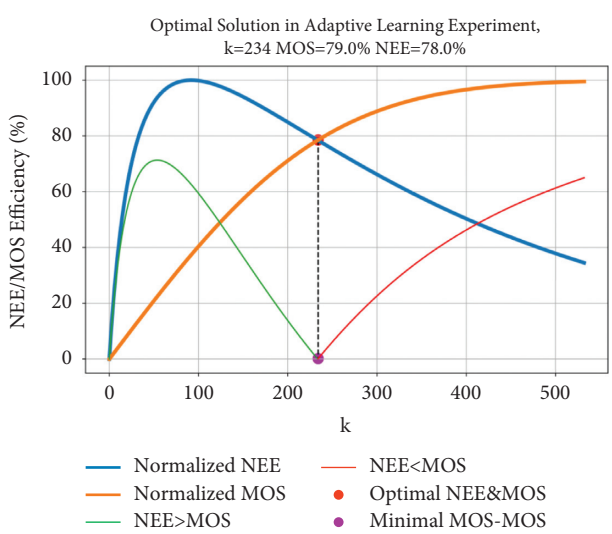

Figure 23: Optimal solution for QoE-QoS coordination.

Table 3: QoE-QoS simulation results.

Parameters	k^*_{NEE}	k^*_{MOS}	Inf $(k)_{\mathrm{MOS}=4}$	k_B
k	92	530	282	237
L_D	74 k	429 k	227 k	191 k
T_t	0.3710 s	2.1456 s	1.13731	0.9558
MOS_P	1.8213	4.9813	4	3.8313
MOS	2	5	4	4
NEE%	100	34.5332	66.6511	78.3832
PER%	24.1512	79.7812	41.6720	50.4943
J_C	0.2132	0.1911	0.2912	0.3432

8. Conclusions

This paper frames the problem of when QoS and QoE are both selected as the target of optimization and how to coordinate the data communication to reach the optimal metrics. The engineering problem of balance and coordination between QoS and QoE is addressed. A series of mathematical models of quality awareness in QoS, QoE, and QoE-QoS are established with theoretical proofs. Through an analysis based on mathematical modeling of unified normalized measurement, we normalize the domains of QoE and QoS in the same scale and perform regularization to map the measurement under the same domain with an analytical simplification. Based on QoS and QoE awareness modeling, with the correlation between user experience and service performance, a DTC-based nonlinear balance coordination strategy is proposed with test proofs, which improves the efficiency of the strategy, and can shift data traffic k to achieve single optimization or mutual balance of QoS and QoE. With the mathematical simulations, the evaluation shows that the proposed models and coordination computing are feasible to relieve the negative impacts of channel limitation and degradation and hit the QoS-QoE trade-off, providing a theoretical and algorithmic basis for the engineering practice of network agent programming.

Abbreviations

LD: Load of data
NEE: Network energy efficiency
$\mathrm{NEE}_{\mathrm{PER}}$: NEE based on PER
QoS: Quality of service
QoE: Quality of experience
PCA: Principal component analysis
PLR: Packet loss rate
PCR: Packet collision rate
PER: Packet error rate
PR: Packet rate
SBR: Sender bitrate.

Data Availability

No data was used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

This work was supported by Science Foundation of Education Department of Anhui Province (KJ2019ZD74) and Talent Project of Education Department of Anhui Province (gxgnfx2021200 and gxbjZD2021117). The research was also supported by SmartSys WorkGroup International Research of Intelligent Computing Grants (SW2019IRICG12).

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