

## Article

# Economic Energy Consumption Strategy Considering Multimodal Energy Under the Base Station Cluster of Multi-Device Communication Private Networks

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## Abstract

The large-scale deployment of electric power wireless private networks (EPWPNs) has significantly increased the number of base stations in substations, transmission corridors, and distribution terminals, leading to rapidly rising electricity expenditure for continuous wireless coverage and power-grid monitoring services. However, the increasing number of base stations deployed across substations and distribution networks has led to rising electricity expenditure, making cost-effective energy supply a critical challenge. To reduce the operating costs of base station clusters and enhance the economic efficiency of power supply, this paper proposes a multimodal power consumption optimization method that coordinates wind energy, solar energy, and energy storage based on user interaction behavior. First, considering user interaction characteristics and the complementarity of multiple energy sources, a dual-layer cellular network architecture consisting of macro- and micro-base stations is constructed. This architecture incorporates grid power purchases, wind power generation, and photovoltaic energy. An optimization model is then developed, which includes both equipment operation constraints and energy interaction constraints. Second, the key factors influencing energy consumption are analyzed using operational research methods. The existence of an optimal solution for the energy consumption function is demonstrated based on the Weierstrass optimization theorem. An energy-saving strategy for base stations under user group access is then derived using Karush–Kuhn–Tucker (KKT) conditions. Through spatio-temporal (ST) dynamic analysis, the coupling relationships among wind power, solar energy, energy storage, and grid electricity purchases are quantified. Based on this analysis, a multimodal cost optimization scheme utilizing dynamic bandwidth allocation is proposed. Simulation results demonstrate that, compared with traditional single-source power supply models and representative existing optimization schemes, the proposed multimodal energy scheduling framework can significantly reduce the operating cost of base station clusters while maintaining communication performance.



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## 1. Introduction

The rapid growth in mobile device usage and communication services has led to a continuous surge in network traffic demand [1]. Wireless communication is a high-energy-consuming industry, with 50 to 80 percent of its energy consumption on the base station side [2].

According to statistics, the existing operating micro-base stations consume an average of about 65 kilowatt-hours per day. At an average electricity price of 1 yuan per kilowatt-hour, the estimated annual electricity expenditure for base stations in China amounts to approximately 76.3 billion yuan. As of October 2023, the total number of base stations in China reached 3.215 million [3,4], accounting for 28.1 percent of the total number of communication base stations in the country. According to China Tower data, the typical energy consumption of base stations is around 3500 watts, and reducing the energy consumption of base stations has become an urgent problem for operators [5]. Operating in high-energy consumption mode leads to increased equipment temperature and electrical stress, thereby accelerating the aging process of base station components. Network data show that operating at room temperature can save more than 35 percent of electricity and reduce equipment failure rate by more than 30 percent compared to operating at high energy consumption and high temperature. The cost reduction will not only increase the funds for operation and maintenance such as energy storage, and improve the reliability of the base stations, but will also shorten the payback period, promote the full coverage of the base station network, increase the market penetration rate and facilitate digital transformation.

The current main methods of reducing energy consumption for base stations include technological upgrades, sleep management, and hardware upgrades. But the potential problems of these methods are also obvious, including the possibility of reducing or delaying the response speed of communication services, affecting the user experience, and the uncertain burden of requiring a large amount of funds for research and development, installation, commissioning and maintenance in the case of large-scale deployment of base stations. These issues can largely be mitigated through energy consumption modeling and optimization techniques. Therefore, this paper studies the optimization of communication energy consumption cost in LTE (Long-Term Evolution) base station groups with high data transmission requirements and large-scale Internet of Things access scenarios: under the condition of ensuring normal communication among users in the base station group, considering D2D communication among users to construct the energy consumption structure model of the LTE base station group, and seeking the existence of the minimum value and the main influencing factors of energy consumption cost. At the same time, multiple energy supply methods are considered to reduce the energy cost of the base station group. The main contributions of this paper are summarized as follows.

Different from existing studies that focus either on energy-aware base station operation or on communication-side resource allocation, this work establishes a unified optimization framework that jointly considers user association, dynamic bandwidth allocation, and multimodal energy supply. First, a joint communication–energy optimization model is formulated for private network base station clusters, explicitly coupling user interaction behavior with renewable energy utilization and grid power procurement. Second, under practical communication assumptions, the proposed model is rigorously transformed into a convex optimization problem, and the existence and uniqueness of the global optimum are formally proven using convex analysis and KKT conditions, providing a solid theoretical foundation that is often missing in related works. Third, by integrating user-interaction-driven dynamic bandwidth allocation into the energy scheduling process, the proposed framework reveals how communication-side control variables directly influence energy consumption and operating cost.

Simulation results based on realistic time-of-use electricity pricing and renewable energy profiles further demonstrate the economic advantages of the proposed approach over conventional single-source and existing optimization schemes. The main content of this paper is structured as follows. Section 1 provides a brief summary of the relevant work. Section 2 establishes and introduces the energy consumption cost model of LTE

base station groups in scenarios with high data transmission requirements and large-scale Internet of Things access. Section 3 converts the formula of the model. Section 4 presents the proof of the extreme values of the constraint function and the solution process. Section 5 presents the performance simulation and analysis. Section 6 presents the conclusion of this paper. To achieve power supply optimization for base stations in multi-energy scenarios, we reduce the amount of electricity purchased from the grid and thereby lower electricity charges. This can also play a role in peak shaving and valley filling, and can flexibly adjust energy supply based on real-time electricity prices, load demand, and the output of renewable energy to further improve energy utilization efficiency. The overall logic is shown in Figure 1.

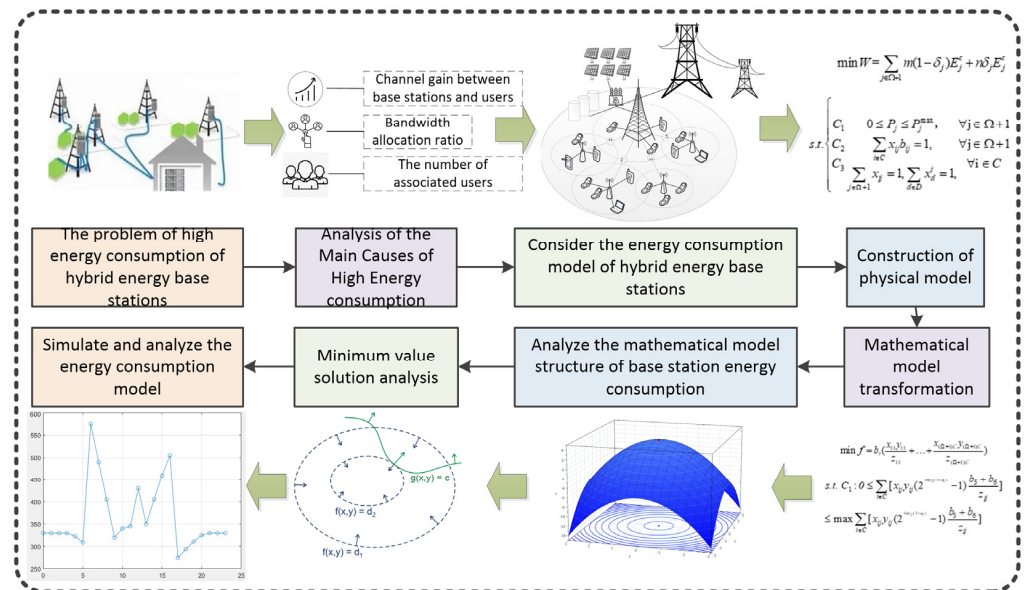


Figure 1. Overall logic.

## 2. Related Work

### 2.1. Research on Energy Consumption Reduction Strategies for Base Station Communications

Compared to previous generations of mobile communication technologies, 5G base stations—which support high data rates and large-scale deployment—exhibit significant application potential across emerging industries. One problem brought about by this is that the energy consumption required for transmitting a large amount of communication data will also increase several times, leading to a significant increase in the operating costs. An important research challenge lies in how to reduce total base station energy consumption through efficient resource allocation without compromising users' network experience. On the basis of considering the uncertainties of energy reduction and ensuring user correlation, optimizing the sum of the total transmission power of each base station to minimize the total energy cost of system base stations [6,7] can effectively control the energy allocation strategy of base stations and reduce energy consumption. Another approach is to model it as a coalition game with the aim of maximizing system throughput and ensuring the minimum threshold rate for users [8]. In response to this issue, Reference [9] focused on analyzing the energy consumption of large-scale, high-transmission-demand base stations, studied the sources of energy consumption of communication base stations, and proposed effective energy consumption control strategies. Reference [10], considering that the high-speed, large-bandwidth, and low-latency transmission characteristics of large-scale, high-transmission-demand base stations must be supported by sufficient energy, proposed the use of “smart operation” to achieve “energy conservation and emission

reduction”, reducing electricity cost expenditure. At the same time, Reference [11] designed an energy-saving power supply system for base stations and, from the perspective of control, proposed an automatic switching control strategy based on DC bus voltage information. Reference [12] conducted a comprehensive analysis and test analysis of the energy-saving effects of the three methods of energy conservation and emission reduction, conducted a data comparison study of detailed parameters, and reached a complete set of data conclusions with practical operational value. In response to the problem that many base stations are idle during periods of low communication load, Reference [13] studied the issue of multiple operators sharing base stations to achieve energy conservation and proposed a new game theory method for macro-base stations.

## *2.2. Research on the Constraint Problem of Base Station Energy Consumption*

Establishing mathematical constraint functions through actual physical models and using extremum optimization to optimize physical models has become one of the mainstream methods in current optimization research. Reference [14] proposed a capacity optimization configuration constraint model for base station photovoltaic energy storage systems to address the current problems of high energy consumption and high cost for communication operators of large-scale, high-transmission-based base stations, considering the impact of different time-of-use electricity prices and energy storage costs on the economic benefits of base station photovoltaic energy storage systems. Some of the situations in wireless sensor networks are the same as those in base stations; with the goal of minimizing communication overhead, the communication overhead model and the mathematical method for solving the optimal threshold are also feasible [15]. Reference [16] developed a mathematical model based on minimum communication overhead for the problem of additional communication overhead generated by the dynamic load balancing process. Another study proposes a network benefit maximization resource allocation problem that takes into account cache cost, benefit, and communication energy efficiency on the basis of fog wireless access networks. There are also several studies on energy consumption balance that have transformed the constraint function and solved the extremum [17]. Reference [18] constructed a multi-dimensional utility function to alleviate the energy consumption of base stations due to the increasing base station load, taking into account three factors: the accepted signal-to-noise ratio of users, the utilization of renewable energy, and the base station load. The study transformed the problem of minimizing the operating cost of multi-base station systems into a problem of maximizing the utility value of the multi-dimensional utility function. In other studies, there are also methods for balancing network energy consumption based on measurement reports (MRs) [19]. A study of time slot reallocation schemes based on centralized clustering and distributed clustering was proposed.

In summary, in the above studies, strategies such as optimizing transmission power, controlling base station energy allocation, and adopting smart operation were proposed to minimize energy cost, and multiple optimization models were proposed, such as resource allocation based on capacity optimization of photovoltaic storage systems, minimum communication overhead, and maximizing network benefits. Despite the extensive research on energy-efficient base station operation and renewable energy integration, most existing studies focus either on energy-side optimization (e.g., photovoltaic sizing, energy storage scheduling) or communication-side resource allocation independently. Moreover, many works rely on heuristic or simulation-based approaches without providing formal convexity analysis or theoretical guarantees of optimality. In contrast, this paper establishes a unified convex optimization framework that jointly considers user association, dynamic bandwidth allocation, and multimodal energy supply, and rigorously proves the existence and uniqueness of the global optimum. The main influencing factors of base station energy

consumption are identified by establishing constraint problems, and the impact of multi-energy power supply on the energy consumption of LTE base station groups is studied. The energy consumption of LTE base station groups is optimized by combining the above two methods. The model construction and solution approach is shown in Figure 2.

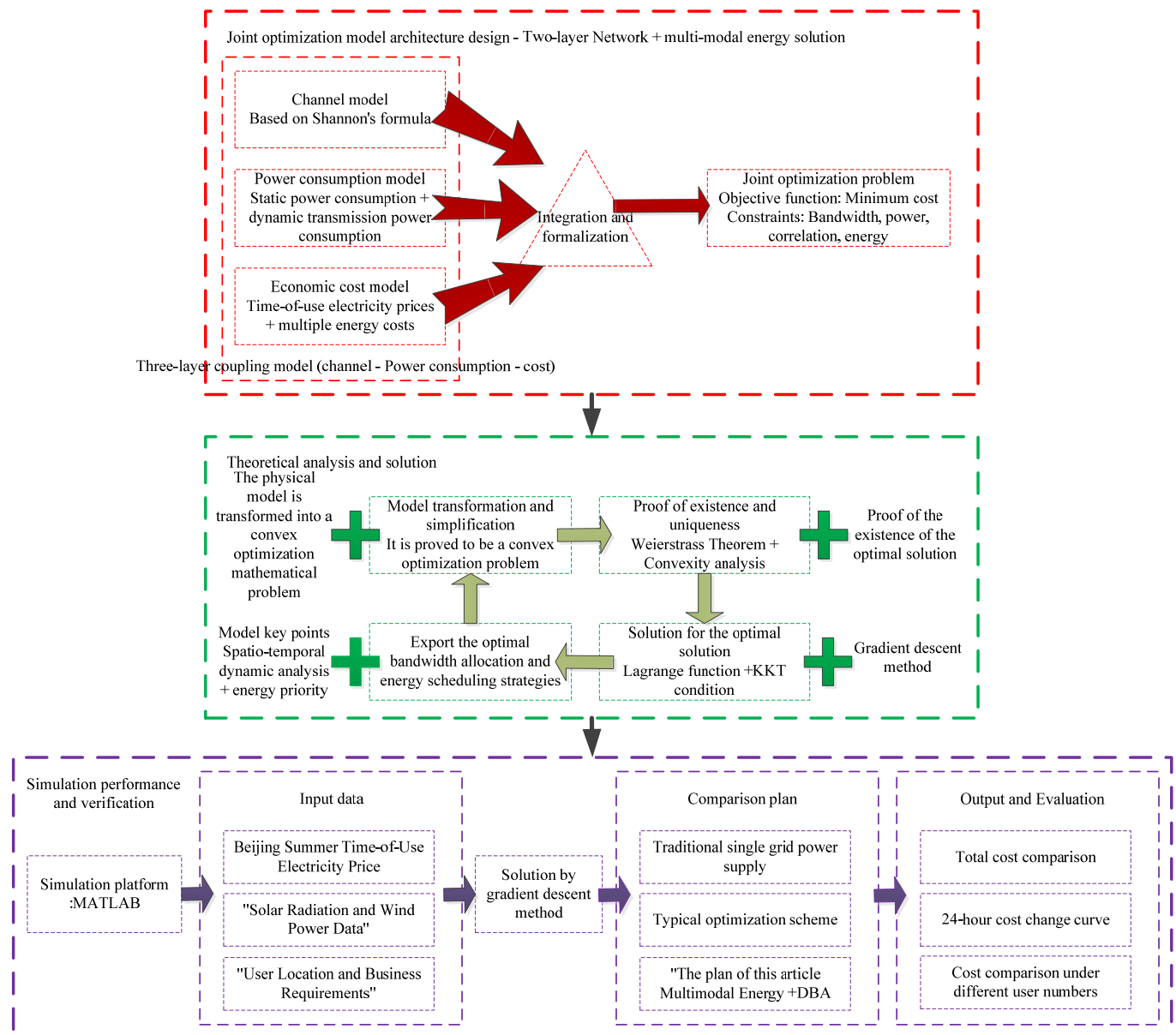


**Figure 2.** Model construction and solution ideas.

### 3. Base Station Energy Consumption Modeling

Base station types include macro-base stations, micro-base stations, pico-base stations, and flying base stations. Considering the energy consumption model and social attributes in Reference [6], and considering the multi-energy power supply scenarios of wind power generation, photovoltaic power generation, and grid power supply, a multi-energy power supply base station model based on user interaction is constructed. There is a group of multi-energy power supply double-layer honeycomb network base stations located at the center in the system [20]. These include macro-base stations (MaBSs) and micro-base stations (MiBSs). Within the coverage area of the macro-base stations, there are  $L(L \in \Omega)$  honeycomb-shaped distributed micro-base stations and  $I$  randomly distributed

users. Macro-base stations and micro-base stations are powered by multiple energy sources to ensure continuous communication within the coverage area. The base station cluster is equipped with a standard number of photovoltaic panels for self-supply of power to the base station. Eight 550 Wp photovoltaic modules are installed on the roof of the base station [21], and it can also receive power from wind turbines at the same time. We only consider the association relationship and resource allocation within  $\tau$  time interval of a. Suppose that within each time interval  $\tau$ , each communication user can only be associated with one base station, and any base station can only be powered by one type of energy within that time interval  $\tau$ . The multi-power base station model based on user interaction is shown in Figure 3.

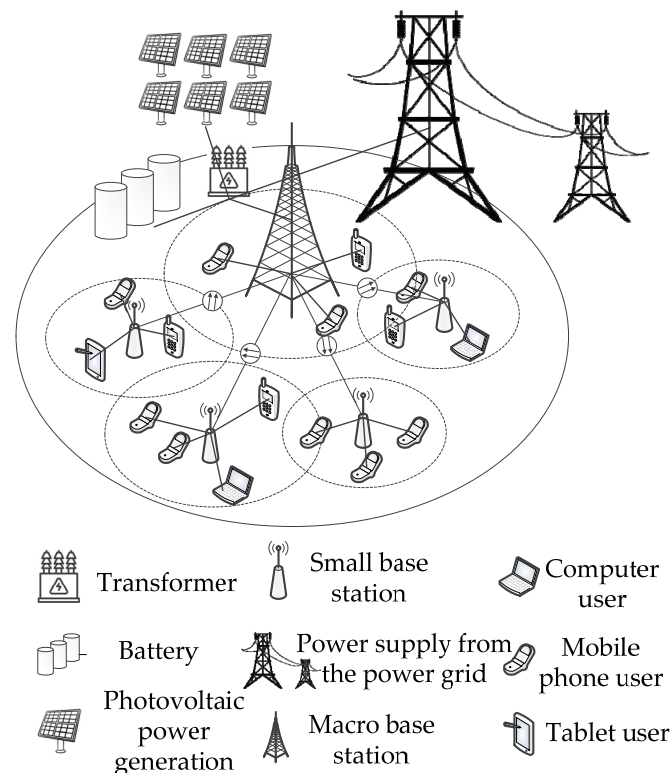


**Figure 3.** Multi-power base station model based on user interaction.

The three sub-models presented in this section—namely the channel model, energy consumption model, and cost model—are tightly integrated in a causal chain. The channel model determines the required transmission power based on user bandwidth allocation and channel quality. This transmission power, combined with static energy consumption, is then used to calculate the total energy consumption of the base station in the power model. Finally, the cost model monetizes this energy consumption under different energy source constraints and dynamic electricity pricing schemes. This layered structure ensures that the final optimization problem reflects both the physical realities of wireless transmission and the economic considerations of energy procurement.

### 3.1. Channel Model Construction

According to Shannon's formula, the actual data transmission rate of cellular users  $R_i$  should be calculated as follows:

$$Bb_{ij} \log_2 \left( 1 + \frac{p_{ij}g_{ij}}{\sigma^2 + I_{ij}} \right) = R_i \quad (1)$$

Formula (1) mainly describes the channel transmission capability between the user and the base station. The parameters in the formula determine the minimum transmission power required by the base station to meet the user's rate requirements, providing the basic input for the energy consumption model. In the formula,  $s_{ij}$  (variable) represents the percentage of bandwidth allocated by the base station to the user (0–1),  $B$  is the total bandwidth (quantitative),  $p_{ij}$  and  $g_{ij}$  are, respectively, the power and channel gain of communication between the user and the base station,  $I_{ij}$  is the comprehensive interference received by the user from the base station and other users, and  $\sigma^2$  is a constant.  $A$  represents the maximum information transmission rate in the channel with Gaussian white noise interference. The Ministry of Industry and Information Technology's second-quarter telecommunications service quality bulletin shows that the current downlink data transmission rate is approximately 131 Mbps. Considering that the usage of some users is either too high or too low, for the convenience of calculation, this value is taken as the average (quantitative). Although the SINR (signal to interference plus noise ratio) cannot be calculated as a fixed value within a certain communication area, the SINR can be stabilized within a certain small range through dynamic/closed-loop power control, AMC (Adaptive Modulation and Coding), frequency multiplexing, and network optimization techniques. This means that under the simulation background of this paper, the user group and environmental interference of the base station are relatively stable. Therefore, the average value SINR (quantitative) is taken here as the calculation parameter. These assumptions are adopted to ensure analytical tractability and to enable convex reformulation of the optimization problem. In practical systems, mechanisms such as adaptive modulation and coding (AMC), closed-loop power control, and scheduling can stabilize SINR within a limited range over short time intervals, making the use of average SINR values reasonable for long-term energy optimization.

Suppose that when users are associated with the base station and the base station allocates resources for the associated users, the channel remains stable. To simplify the noise calculation, it is assumed that the noise of cellular users connected to the micro-base station is the maximum noise and is a constant [19]. We represent the association relationship within the time interval with the binary variable  $x_{ij}$ :

$$x_{ij} = \begin{cases} 1 \\ 0 \end{cases} \quad (2)$$

After relaxation  $x_{ij} \in [0, 1]$ . In the formula, we take 1 when the user is associated with the base station; otherwise, we take 0. To make the optimization problem tractable and amenable to convex optimization techniques, the binary user–base station association variables are relaxed to continuous variables within the interval  $[0, 1]$ . This relaxation can be interpreted as time-sharing or traffic-splitting among base stations, which is a common practice in energy-efficient communication optimization. Under this relaxation, the original mixed-integer problem is transformed into a continuous optimization problem. These assumptions allow the derivation of a closed-form convex optimization model and facilitate theoretical analysis. Relaxing them would lead to a stochastic or mixed-integer formulation, which is beyond the scope of this paper and will be investigated in future work.

### 3.2. Energy Consumption Model Construction

The energy consumption model of the base station consists of static energy consumption and dynamic energy consumption. The channel gain can be obtained through the user rate requirements, then the corresponding transmission power can be obtained, and finally the dynamic energy consumption can be obtained. In the proposed model, the transmission power for each user is derived from the channel model, which is then used to compute the

corresponding energy consumption. This value is subsequently fed into the cost model for pricing analysis.

On the basis that the user has a fixed data transmission rate, the total transmission power of the full bandwidth of the base station  $P_{ij}$  can be obtained as follows:

$$P_{ij} = \left( 2^{\frac{R_i}{B_{sij}}} - 1 \right) \frac{\sigma^2 + I_{ij}}{g_{ij}} \quad (3)$$

Based on the user association, let the actual total transmission power of the base station  $P_j$  be calculated as follows:

$$P_j = \sum_{i \in C} x_{ij} P_{ij} s_{ij} \quad (4)$$

According to the user association strategy, the total power consumed by the base station  $P_j^{all}$  can be obtained as follows:

$$P_j^{all} = \mu_j P_j + P_j^s \quad (5)$$

In the formula,  $\mu_j$  is the power factor consumed by the base station for data transmission,  $P_j^s$  is the power consumed by the static circuit, and  $C$  is the user set.

### 3.3. Cost Model Construction

This section mainly relies on the energy consumption values of each base station obtained from the energy consumption model to match energy consumption with time and electricity price, thereby achieving economic cost modeling. The cost is considered the product of energy consumption and unit price, and the prices of photovoltaic, wind power, energy storage, and grid power supply are introduced. To ensure the operability and convexity of the model, it is assumed that in each time interval, the base station is solely powered by a single main energy source. In the actual system, although there may be multiple energy sources physically within a single time period, due to inverter limitations, control simplicity, and energy management strategies, within shorter scheduling intervals, the effective power supply is typically dominated by a single source, which is used as the basic strategy to build the simulation model. The proposed framework can be extended to the case of simultaneous multi-source operation by introducing continuous energy mixture variables, which will lead to a more complex but conceptually similar optimization problem.

The cost model of the base station group is constructed based on the channel model and energy consumption model, and only the correlation and resource allocation within one time interval are considered. During this time interval, the base station can only be powered by one type of energy. The energy consumption of the base station  $E_j^c$  is expressed as follows:

$$E_j^c = P_j^{all} \tau + P_D \quad (6)$$

In the formula,  $P_D$  represents the static energy consumption of the base station [14] and is taken as the average value of the static energy consumption per unit time within a day. The renewable energy  $G_j$  stored in the base station during the period is calculated as follows:

$$G_j = \eta_{dis} \left[ \min \left\{ G + G_j^H - E_j^c, E_{\max} \right\} \right] - \theta_j \quad (7)$$

In the formula,  $G_j^H$  represents the supply/capture volume of renewable energy (including wind power and photovoltaic power) in the previous period. When the photovoltaic power generation of the base station is insufficient, wind power supply or grid supply

is selected.  $G$  represents the renewable energy stored by the base station in the previous period.  $\theta_j$  indicates the low energy threshold,  $E_{\max}$  is the upper limit of the maximum energy storage of the battery, and  $\eta_{dis}$  is the discharge efficiency of the energy storage. When it is lower than this point, data transmission cannot work. The battery has a rated energy capacity of 50 kWh, with upper and lower state-of-charge (SOC) limits to prevent overcharging and deep discharging. Charging and discharging efficiencies are incorporated into the energy balance. The charging/discharging power is limited to a fixed maximum value, and the SOC is updated at each time interval according to the net energy flow.

The indicator function for setting the energy consumption type of the micro-base station  $\delta_j$  is as follows:

$$\delta_j = \begin{cases} 1, & G_j \geq E_j^c \\ 0, & G_j < E_j^c \end{cases} \quad (8)$$

In the formula, when 0 is taken, grid energy is used; when 1 is taken, renewable energy is consumed. We define  $m$  as the unit price of grid energy and  $n$  as the unit price of renewable energy [22,23], and  $m > n > 0$ .

Based on the channel model and energy consumption model, combined with the multi-energy power supply setting, while considering that the energy consumption of base stations is related to the user connection relationship and resource allocation strategy, and taking the energy consumption and the unit price of energy as the main variables, the total energy cost price  $A$  of all base stations can be obtained. We transform this energy cost savings problem into a condition optimization problem and express it as follows:

$$\begin{aligned} \min W = & \sum_{j \in \Omega+1} m(1 - \delta_j)E_j^c + n\delta_j E_j^c \\ \text{s.t.} \left\{ \begin{array}{ll} C_1 & 0 \leq P_j \leq P_j^{\max}, \quad \forall j \in \Omega + 1 \\ C_2 & \sum_{i \in C} x_{ij}s_{ij} = 1, \quad \forall j \in \Omega + 1 \\ C_3 & \sum_{j \in \Omega+1} x_{ij} = 1, \sum_{d \in D} x_d^i = 1, \quad \forall i \in C \end{array} \right. \quad (9) \end{aligned}$$

In the formula,  $A$  represents the transmission power constraint of the base station, i.e., the maximum transmission power limit;  $A$  indicates that the total proportion of bandwidth resources allocated by the base station to users is guaranteed to be 1;  $A$  indicates that a user can only be connected to one base station within a certain period of time and the downlink resources between users are multiplexed one-to-one.  $C$  is the set of the number of communication users.

#### 4. Base Station Energy Consumption Overhead Model Transformation

To facilitate optimization and analysis, it is necessary to convert the physically grounded but structurally complex model presented in Section 2 into a mathematically tractable form. The original model integrates diverse physical factors, including user–base station association, bandwidth allocation, power supply mode, and dynamic pricing, which are difficult to solve directly due to the interdependencies and nonlinearity. In this section, by identifying key decision variables and restructuring the cost function and constraints into a standard convex optimization form, the model is simplified without losing its ability to represent the real-world system. This transformation enables the use of mathematical optimization techniques—such as convexity analysis, Lagrangian duality, and KKT conditions—to identify the globally optimal energy consumption strategy. Therefore, the reformulation not only preserves the essential characteristics of the multimodal energy

supply base station system, but also lays a solid foundation for theoretical proof and algorithmic implementation in the subsequent sections.

To make the problem tractable and enable convex optimization techniques, the binary user–base station association variables are relaxed to continuous variables in the interval  $[0, 1]$ . Discrete energy selection indicators are replaced by continuous allocation ratios. This relaxation can be interpreted as time-sharing or traffic-splitting among base stations, which is widely adopted in related works. Under this relaxation, the original mixed-integer optimization problem is transformed into a continuous optimization problem, enabling the application of convex analysis and KKT conditions. This ensures differentiability and validity of the KKT-based solution.

The problem of minimizing the energy consumption of LTE base station groups in scenarios with high data transmission requirements and large-scale Internet of Things access is transformed into the corresponding mathematical model and simplified to study the existence of the minimum value. The key focus is on minimizing the energy consumption cost of base station equipment, while ensuring normal communication between users and the continuous power supply of base stations. We formalize and simplify the physical model as follows (9):

$$\begin{aligned} G_j &= x_{1\alpha}, E_j^c = x_{4\alpha}, E_j^s = x_{6\alpha}, P_j^{all} = x_{7\alpha}, \theta_j = a_2, G = a_3, \\ E_{\max} &= a_4, n = b_1, \tau = b_2, P_j^s = b_3, \mu_j = b_4, \sigma^2 = b_5, I_{ij} = b_6, \\ m &= b_7, G_j^H = \mu, s_{ij} = y_{ij}, p_{ij} = \eta_{ij}, g_{ij} = z_{ij}, j \in \Omega + 1, i \in C \end{aligned}$$

On this basis, the constraint condition  $C_1$  is simplified as follows:

$$x_{1\alpha} = \min\{a_3 + \mu - x_{4\alpha}, a_4\} - a_2 < x_{6\alpha} = x_{7\alpha} b_2 \quad (10)$$

At this point, the objective function  $f$  is calculated as follows:

$$\begin{aligned} \min f &= \sum_{j \in \Omega+1} b_7 x_{7j} b_2 \\ &= b_7 b_2 c b_3 + b_7 b_2 b_4 (b_5 + b_6) (2^{\log_2(1+a_1)} - 1) \left[ \frac{x_{11} y_{11}}{z_{11}} + \dots + \frac{x_{(\Omega+1)C} y_{(\Omega+1)C}}{z_{(\Omega+1)C}} \right] \end{aligned} \quad (11)$$

Therefore, the objective function is as follows:

$$\min f = \begin{cases} b_1 \left( \frac{x_{11} y_{11}}{z_{11}} + \dots + \frac{x_{(\Omega+1)C} y_{(\Omega+1)C}}{z_{(\Omega+1)C}} \right), x_{1\alpha} \\ = \min \left\{ a_3 + \mu - b_2 \left\{ [b_4 x_{ij} y_{ij} (2^{\log_2(1+a_1)} - 1) \frac{b_5+b_6}{z_{ij}}] + b_3 \right\}, a_4 \right\} - a_2 \\ \geq b_2 \left\{ [b_4 x_{ij} y_{ij} (2^{\log_2(1+a_1)} - 1) \frac{b_5+b_6}{z_{ij}}] + b_3 \right\} \\ b_7 \left( \frac{x_{11} y_{11}}{z_{11}} + \dots + \frac{x_{(\Omega+1)C} y_{(\Omega+1)C}}{z_{(\Omega+1)C}} \right), x_{1\alpha} \\ = \min \left\{ a_3 + \mu - b_2 \left\{ [b_4 x_{ij} y_{ij} (2^{\log_2(1+a_1)} - 1) \frac{b_5+b_6}{z_{ij}}] + b_3 \right\}, a_4 \right\} - a_2 \\ < b_2 \left\{ [b_4 x_{ij} y_{ij} (2^{\log_2(1+a_1)} - 1) \frac{b_5+b_6}{z_{ij}}] + b_3 \right\} \end{cases} \quad (12)$$

Obviously, Formula (12) is in polynomial form. Considering that the original objective function  $f$  is a piecewise function, except for the two constants  $b_1$  and  $b_7$ , all other parts are the same, and the remaining constant parts do not contain negative values. Therefore, the constant part does not affect the value point of the minimum value of the function  $f$ . The

final simplified mathematical model constraint function  $f$  for the communication overhead of LTE base station groups is as follows:

$$\begin{aligned}
 \min f &= b_7 \left( \frac{x_{11}y_{11}}{z_{11}} + \dots + \frac{x_{(\Omega+1)C}y_{(\Omega+1)C}}{z_{(\Omega+1)C}} \right) \\
 \text{s.t. } C_1 : 0 &\leq \sum_{i \in C} [x_{ij}y_{ij}(2^{\log_2(1+a_1)} - 1) \frac{b_5 + b_6}{z_{ij}}] \\
 &\leq \max \sum_{i \in C} [x_{ij}y_{ij}(2^{\log_2(1+a_1)} - 1) \frac{b_5 + b_6}{z_{ij}}] \\
 C_2 : \sum_{i \in C} x_{ij}y_{ij} &= 1 \\
 C_3 : \sum_{j \in \Omega+1} x_{ij} &= 1 \\
 C_4 : \sum_{j \in \Omega+1} x_{ij} &= 1 \\
 C_5 : y_{ij} &> 0 \\
 C_6 : (d >)z_{ij} &> 0
 \end{aligned} \tag{13}$$

Among them,  $x_{ij}, y_{ij}, z_{ij}$  are all variables greater than 0, and  $a, b$  is a constant. Since in practical applications  $b_7 > b_1 > 0$ , when condition (15) is satisfied, the local optimum of  $f$  is guaranteed to be the global optimum due to the convexity of the objective function:

$$\begin{aligned}
 \min \left\{ a_3 + \mu - b_2 \left\{ [b_4 x_{ij}y_{ij}(2^{\log_2(1+a_1)} - 1) \frac{b_5 + b_6}{z_{ij}}] + b_3 \right\}, a_4 \right\} - a_2 \\
 \geq b_2 \left\{ [b_4 x_{ij}y_{ij}(2^{\log_2(1+a_1)} - 1) \frac{b_5 + b_6}{z_{ij}}] + b_3 \right\}
 \end{aligned} \tag{14}$$

## 5. Optimization Analysis

According to the simplified mathematical model analysis in Section 3, under certain conditions such as electricity investment, operating and maintenance costs, signal-to-noise ratio, channel gain, and noise power, without considering the power supply mode, the energy consumption of the base station is mainly related to the number of associated users, the bandwidth allocation ratio, and the channel gain between the base station and users. The number of associated users is a variable that cannot be controlled. The bandwidth allocation ratio is controllable, and the utilization of resources and the overall efficiency and performance of the network can be improved through DBA (Dynamic Bandwidth Assignment). According to the analysis, the quality of the channel gain is mainly determined by the hardware. When the channel gain is good, the signal transmission quality is often better, which may reduce the transmission power required by the base station to maintain signal strength, thereby reducing energy consumption to a certain extent.

Under the relaxed continuous formulation and differentiable constraints, the optimization problem becomes convex and satisfies Slater's condition. After variable relaxation, the feasible set becomes convex and continuous. Under these conditions, the optimization problem satisfies Slater's condition, and thus the Karush–Kuhn–Tucker (KKT) conditions are both necessary and sufficient for optimality. In this section, the existence of the minimum value of the mathematical model in Section 3 is proven based on convexity analysis and the Weierstrass theorem, and optimality, uniqueness, and the solution process are analyzed.

### 5.1. Analysis of the Model's Energy Consumption Optimality

This section analyzes and presents the existence of the minimum value of the communication energy consumption cost model of LTE base station groups in scenarios with high data transmission requirements and large-scale Internet of Things access from theoretical and mathematical derivation perspectives. Thus, the corresponding certain conditions for

the existence of the minimum value can be found through mathematical derivation. In practical applications, by constraining the corresponding conditions, the energy consumption cost of the base station group can be minimized to the greatest extent on the premise of ensuring the normal operation of the base station and the normal communication of users.

Based on the simplified model of the objective function obtained in the previous section, we perform polynomial splitting of the objective function. According to the convexity theory of fractional functions and by proving the convexity of a single fractional term, it can be proven that the mathematical model of the objective function is a strictly convex function. By analyzing the continuity of the objective function under constraints and combining this with the Weierstrass extreme value theorem, it can be ascertained that the minimum value of the solution exists.

Considering the constraints and properties of the obtained objective function, in order to verify the existence and solvable nature of the optimal solution of the objective function, we use the Lagrange multiplier method. At a high level, the idea behind the Lagrange multiplier method is to turn a constrained optimization problem into an unconstrained one by adding a penalty term for violating the constraints. This penalty is controlled by the Lagrange multipliers, which act as “weights” for each constraint. Think of it as adding a “tension” or “cost” to the objective function for each constraint that is violated. By adjusting these penalties, we can find the point where the total energy consumption is minimized while still respecting the physical and resource constraints of the system. The KKT conditions are a set of four critical criteria that help us verify the optimality of the solution. Essentially, the KKT conditions ensure that we have found the best possible solution while respecting all the constraints. These conditions can be interpreted as a set of “rules” that any solution must satisfy to be considered the optimal solution.

**Theorem 1.** *Under specific constraints, the energy consumption cost model for LTE base station groups deployed in high-throughput and large-scale IoT environments exhibits a convex structure. Assuming that the user output transmission rate is constant, the static energy consumption of the base station is constant, the transmission consumption of the base station is constant, and the noise constant is constant, then the structure of the communication energy consumption overhead function model of the double-layer cellular LTE base station is a convex function, and there exists a minimum value.*

The document text continues in Appendix A.

Based on the KKT conditions, Lagrange multipliers are introduced and Lagrange functions are defined to obtain the gradient conditions, original feasibility conditions, dual feasibility conditions, and complementary relaxation conditions that need to be verified. According to the Slater condition, through example  $x_{ij}^0, y_{ij}^0, z_{ij}^0$  and verification, it can be known that if the minimum value exists, then this value is the optimal solution.

It should be noted that the convexity result holds under the assumption that the interference level and noise power are treated as fixed parameters within each optimization interval. Under this assumption, the data rate function is concave with respect to the bandwidth allocation variable, and the corresponding energy consumption function preserves convexity.

**Theorem 2.** *Existence of the minimum optimal solution of the constraint function: The unique minimum value obtained by solving based on the model of Theorem 1 is also the optimal solution of the objective function.*

The document text continues in Appendix B.

Analysis shows that, on the premise of ensuring the quality of user services, during the communication process of multi-energy power supply base stations with dense deployment

of micro-base stations, there exists a minimum energy consumption, and this minimum value is the optimal minimum value. In the process of energy consumption in base station communication, there exists a scheme that can minimize the overall energy consumption of the base station while ensuring that the communication quality is not affected. According to (11) and the power supply price, it can be known that when choosing energy sources and considering photovoltaic power supply > wind power supply > grid power supply, the overall energy consumption of the base station can be minimized.

To sum up, it can be proven that under the given base station energy consumption model and constraints, there exists an optimal solution, and the minimum energy consumption point is unique. The predictability of the system is of great significance. Under the base station energy consumption model shown in Figure 2, it is proven in Section 5.1 that the energy consumption surface is convex; i.e., the energy minimization problem can be effectively solved through the convex optimization method, and the possibility of finding the global optimal solution is relatively large.

### 5.2. Minimum Energy Consumption of the Model

To address the constrained optimization of base station energy consumption, the Lagrangian function (Equation (15)) is formulated by incorporating both the original cost objective and the system constraints via appropriate Lagrange multipliers. The solution process followed when solving the minimum value of the base station energy consumption constraint optimization problem, considering that this model is a convex optimization model, is shown in Figure 3. When transforming the problem into the form of a Lagrange function, the constraint conditions are paired with the set of Lagrange multipliers to construct the Lagrange equation:

$$L(x, \lambda, \mu) = f(x) + \sum_i \lambda_i g_i(x) + \sum_j \mu_j h_j(x) \quad (15)$$

In the formula,  $i$  represents the number of inequality constraints,  $j$  represents the number of equality constraints, and  $\lambda_i$  and  $\mu_j$  are the Lagrange multipliers of the corresponding constraints, respectively. The first term represents the total energy cost, while the remaining terms incorporate the penalty imposed by violating the bandwidth, power, and association constraints.

The KKT conditions include the following:

1. Original feasibility:

$$g_i(x^*) \leq 0, h_j(x^*) = 0 \quad (16)$$

Primal feasibility—this ensures that the original variables satisfy all physical and resource constraints of the system (e.g., bandwidth allocation must sum to 1, each user must associate with only one base station).

2. Duality feasibility:

$$\lambda_i \geq 0 \quad (17)$$

Dual feasibility—this requires that the Lagrange multipliers (interpreted as the marginal cost or “shadow price” of constraint violation) must be non-negative.

3. Complementary relaxation conditions:

$$\lambda_i g_i(x^*) = 0 \quad (18)$$

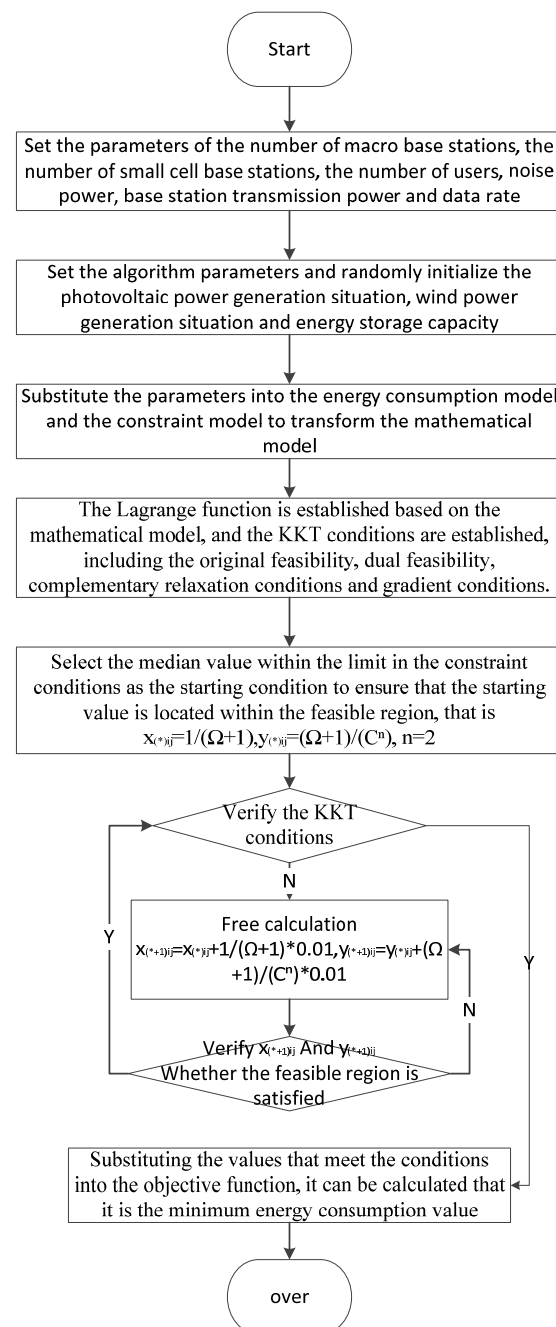
Complementary slackness—this links the constraints and their multipliers.

#### 4. Gradient conditions:

$$\nabla_x L(x^*, \lambda^*, \mu^*) = 0 \quad (19)$$

Stationarity (gradient condition)—this sets the gradient of the Lagrangian function with respect to all primal variables to zero, ensuring that we are at an extremum of the Lagrangian function with respect to all variables involved.

The interior point method is used to approximate the minimum. Once a candidate solution satisfies the KKT conditions, it is substituted into the original objective function to compute the corresponding minimum energy consumption of the base station. The extremum approximation process is shown in Figure 4.



(Among them, the variables marked with "\*" represent the preliminary optimal values.)

**Figure 4.** Extremum approximation process.

From an engineering perspective, the KKT-based solution provides an explicit guideline for bandwidth allocation adjustment under given user association and energy supply conditions. Rather than being solved centrally in real time, the derived optimality conditions can be used to pre-compute lookup tables or serve as the basis for heuristic or learning-based online algorithms in practical base station controllers.

## 6. Simulation

This section presents MATLAB R2018a-based simulations to verify the convergence of the proposed solution and to evaluate the performance of the multi-energy LTE base station energy consumption model. In order to be practical, based on summer solar irradiance and time-of-use electricity pricing in Beijing, the communication energy cost of conventional LTE base station groups is compared with that of multi-energy-powered base stations under high data transmission and large-scale IoT access scenarios. According to Section 4, it is clear that this model has a minimum value under the three key cost influencing factors presented in Section 3, and the key cost influencing factors are analyzed in combination with multiple base station energy consumption optimization methods.

### 6.1. The Solution of the Model's Minimum Energy Consumption

To evaluate the effectiveness of the proposed method, two baseline schemes are considered for comparison. The first baseline is a traditional single-source power supply scheme, in which the base station is fully powered by the utility grid without renewable energy integration or energy storage support. The second baseline represents a typical existing optimization scheme, where energy scheduling is performed based on instantaneous load and generation information without utilizing predictive models or rolling horizon optimization. All schemes are implemented under the same system parameters, load profiles, renewable generation data, and time-of-use electricity pricing to ensure a fair comparison. Suppose that the macro-base station in the system is located at the central position with a coverage radius of 500 m, and around it are seven evenly distributed micro-base stations with a coverage radius of 300 m powered by multiple energy sources. We set the total number of users to 700 and consider a random flow distribution of users. The expression for the total base station link loss is as follows:

$$L(d) = 128.1 + 37.6 \log d \quad (20)$$

The path loss expression of the micro-base station link is as follows:

$$L(d) = 140.7 + 36.7 \log d \quad (21)$$

The expression for the link loss between users is as follows:

$$L(d) = 148 + 40 \log d \quad (22)$$

The fixed data rate for users is 1 Mb/s, and each base station is allocated a bandwidth of 10 MHz. The number of system users is 20 to 100, the physical distance between users is 25 m to 75 m, and the noise power is  $-174$  dBm/Hz. Based on the known objective function and constraint conditions, the convergence process is simulated and analyzed.

Model convergence is verified using multiple optimization algorithms. As shown in Table 1, the model can converge to the minimum value within a relatively short period of time. The interior point method ultimately fails to converge to the target value, while the convergence speed of the gradient descent method is obviously better than that of the Newton method. Although the interior point method can rapidly narrow the search

range by gradually approaching the constraint boundary, resulting in a fast convergence speed, considering the influence of the obstacle parameters in the early stage of iteration, the deviation is relatively large. However, the Newton method is slower than the gradient descent method because the Hessian matrix takes time to calculate in high dimensions. The gradient descent method performs better in this model when the step size is set appropriately. Therefore, the gradient descent method is selected when calculating the minimum value of the model.

**Table 1.** Convergence simulation.

| Method                  | Time/s | Result Value/kWh |
|-------------------------|--------|------------------|
| Interior point method   | 0.0097 | 0.0090886        |
| Newton's method         | 0.0109 | 1072.832137      |
| Gradient descent method | 0.0043 | 1072.832137      |

The objective function value is measured by the minimum total daily energy consumption. The interior point method fails to converge to a feasible solution under the given constraints, and the reported value corresponds to an intermediate infeasible point. Therefore, its result is not used for performance comparison.

## 6.2. Simulation Analysis

Regarding the base station and user data in the simulation, based on the parameter settings in Section 5.1, the fixed data rate for users is set to 1 Mb/s, and each base station is allocated a bandwidth of 10 MHz. The number of system users is 20 to 100, the physical distance between users is 25 m to 75 m, and the noise power is  $-174 \sigma / (\text{dBm}/\text{Hz})$ . Suppose that the base station has the conditions for photovoltaic power generation and wind energy supply.

In the photovoltaic power generation data simulation of multi-energy power supply base stations, approximately 50 square meters of photovoltaic power generation panels are required for setting up seven base stations. The photoelectric conversion efficiency is set at 0.2 for power generation simulation. To replicate real-life situations, the solar irradiation within one day in summer in Beijing is selected. Obviously, the peak power generation mainly occurs between 9 a.m. and 3 p.m., and the operation time is from 4 a.m. to 8 p.m. Even at night, base stations still need to purchase electricity from the power grid when they are in operation. The power generation simulation of photovoltaic panels within the base station cluster within one day is shown in Figure 5.

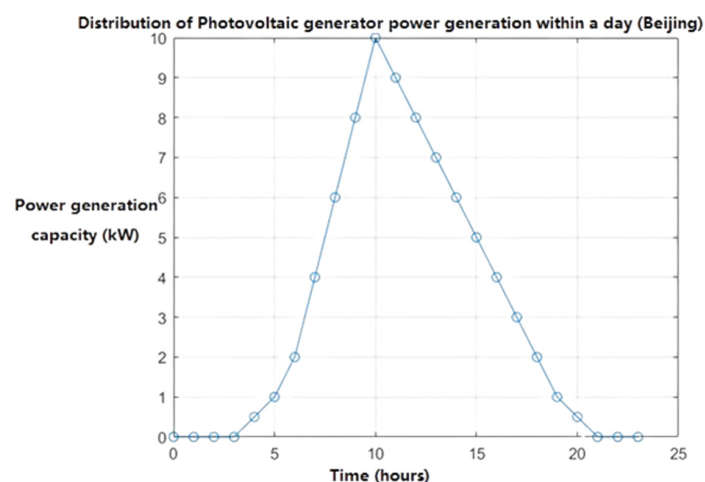


**Figure 5.** Distribution of photovoltaic power generation.

In order to make the simulation results closer to the communication energy consumption cost of the LTE base station group within one day in scenarios of high data transmission requirements and large-scale Internet of Things access, the power purchase price of the base station when choosing the grid power supply refers to the power purchase price in Beijing. The energy consumption of the operator's base station belongs to the single or two-part time-of-use energy consumption for industrial and commercial use. Considering that the power supply of the base station is at the voltage level of 1 to 10 kilovolts, the single power supply mode is selected. The specific prices are shown in Table 2. As can be seen from the table, the lowest electricity price period is from 11 p.m. to 7 a.m. the next day, which is a relatively small period for the operation of wind and solar power generation.

**Table 2.** Time-of-use electricity prices for unitary industrial and commercial users (Beijing).

| Time Division | Electricity Usage Period/hour      | Electricity Price/(CYN/KWh) |
|---------------|------------------------------------|-----------------------------|
| Peak          | 10:00–13:00∪17:00–22:00            | 1.188465                    |
| Flat section  | 7:00–10:00∪13:00–17:00∪22:00–23:00 | 0.869435                    |
| Low point     | 23:00–The next day 7:00            | 0.590284                    |

Although the simulation study is conducted using time-of-use electricity prices and renewable energy profiles from Beijing, the proposed optimization framework is not limited to a specific geographical location. The model structure depends only on generic inputs such as renewable generation profiles, electricity pricing schemes, and base station load characteristics, all of which can be readily replaced by region-specific data. Therefore, the proposed framework can be directly extended to other urban or rural deployment scenarios by adjusting the corresponding energy and pricing parameters, without modifying the core optimization formulation.

Based on the time-of-use electricity price for power purchase in the power grid, if the average energy consumption of the base station per hour per day is 3.8 kilowatt-hours, then the average daily power purchase cost is CYN 80.4526. If wind power is purchased, considering that Inner Mongolia and Xinjiang are Class I resource areas and the on-grid electricity price is 0.51 CYN/(kWh), the line loss cost in the on-grid link is calculated by the on-grid electricity price  $\times$  the verified line loss rate  $\div$  (1 – verified line loss rate), and the line loss cost is 0.0157 CYN/(kWh). Then, the comprehensive electricity price is approximately 0.6757 CYN/(kWh). The average daily electricity purchase expense is approximately CYN 59.5. Suppose that the maximum allowable installation capacity of photovoltaic power is 25 kW, the construction cost of photovoltaic power generation is 3735 CYN/(kWh), the maximum power generation capacity of a single photovoltaic module is 400 W, the payback period is 15 years, the maintenance cost per unit output power is 0.21 CYN/(kWh), and the maximum allowable installation capacity of energy storage is 15 kWh. The installation investment cost per unit capacity is 1000 CYN/(kWh), the annual operation and maintenance cost per unit capacity is 100 CYN/(kWh), and the average daily attenuation rate is taken as 0.04%. Then, the photovoltaic construction cost is approximately CYN 93,375, the annual operation and maintenance cost is approximately CYN 5.25, the energy storage construction cost is approximately CYN 25,000, and the operation and maintenance cost is approximately CYN 2500. The cost comparison of the three power supply schemes over five years is shown in Figure 6:

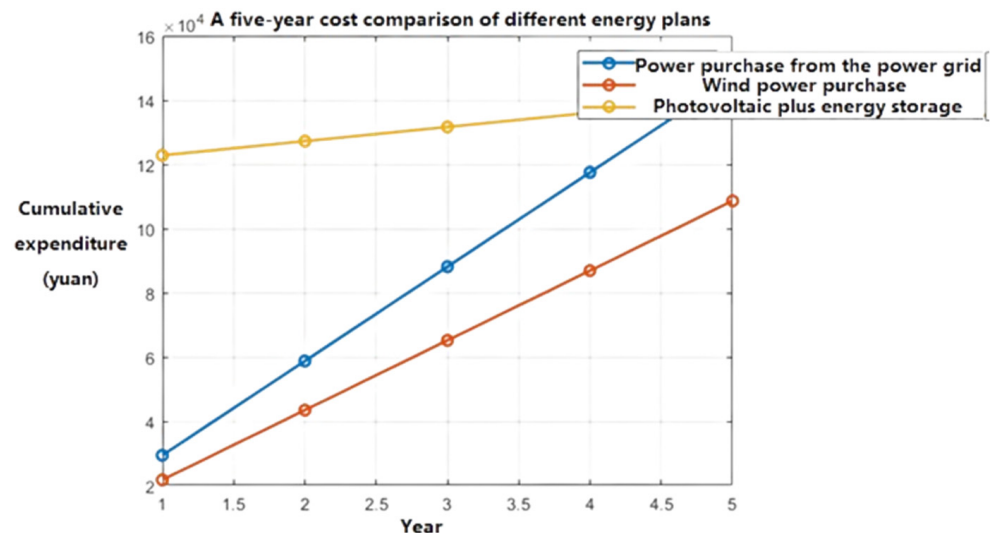


**Figure 6.** Comparison of annual operating costs under grid-only, photovoltaic-assisted, and multi-modal energy supply schemes for a single base station.

Based on the time-of-use electricity price for industrial and commercial use in Beijing, when only the power supply from the power grid is used as the energy supply for the base station, referring to the load per hour of the base station within a day in reference [14], and taking into account the user activity level, the electricity consumption cost of the base station group within a day is simulated as shown in Figure 7.

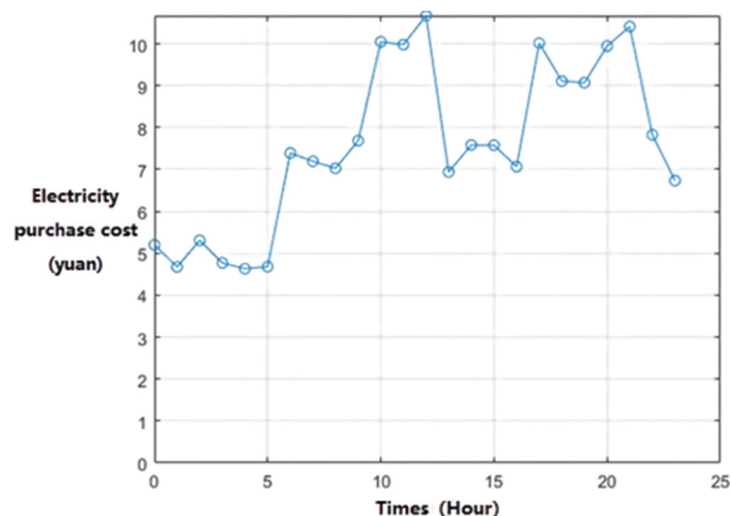


**Figure 7.** The power supply overhead of the grid used by the 24 h base station group.

As can be seen from Figure 7, the daily communication energy consumption and power purchase cost of the base station group is approximately CYN 181.95. The main time periods for power purchase cost are concentrated in the morning and evening. It can be analyzed that it is related to the user activity level.

Based on the time-of-use electricity prices, according to the construction of the minimum energy consumption model for multi-energy base station groups, the multi-energy power supply base station groups of wind and solar power are considered. Photovoltaic power generation is the supply for the base stations themselves. When the power supply is insufficient, wind power generation is selected. Secondly, the power supply from the power grid is considered. The simulated energy consumption of the base station group within 24 h is shown in Figure 8. Meanwhile, consider obtaining

the optimal bandwidth allocation percentage based on the user association situation in the minimum energy consumption model. It can be seen from Figure 6 that when considering the optimal bandwidth allocation simultaneously under this multi-energy power supply model, the total daily communication overhead of the base station group is CYN 125.40. Obviously, when considering multi-energy power supply from wind power, at midday and in the morning when sunlight is better, the amount of electricity that base stations need to purchase from the power grid is significantly reduced, and the cost of purchasing electricity within a day is reduced by approximately 31.08%. It can be seen from Figure 9 that when considering the optimal bandwidth allocation situation, the total daily power purchase cost of the base station is approximately CYN 116.56, which is further reduced by 7.05% on the basis of Figure 10.

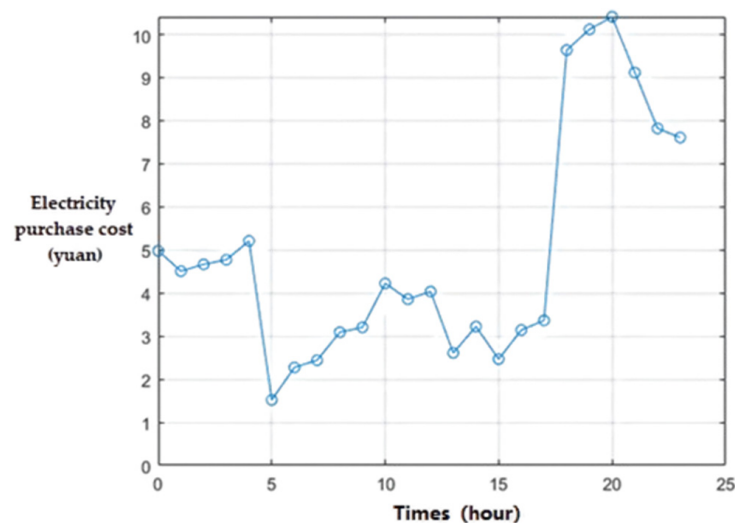


**Figure 8.** The multi-energy power supply overhead used by the 24 h base station group.

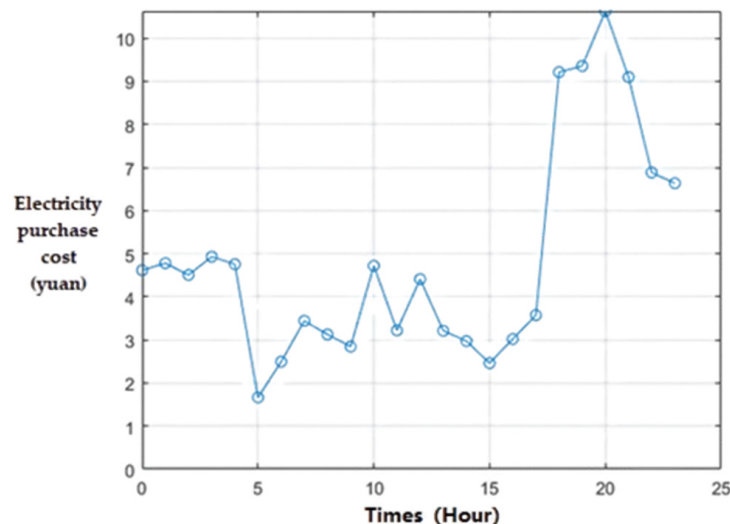


**Figure 9.** The multi-energy power supply overhead of the 24 h base station cluster (considering the allocation ratio).

To verify the impact of the main influencing factors of the communication overhead of LTE base station groups analyzed in Section 4 on the actual communication energy consumption overhead of base station groups in scenarios with high data transmission requirements and large-scale Internet of Things access, the key factors of the adaptive sensing user–base station association algorithm Co-social-D2D EAAUA in Reference [6], the maximum reference signal receiving power max-RSRP (Reference Signal Received

Power) algorithm in Reference [24], and the base station preference bias factor algorithm BSRP algorithm in Reference [25] are optimized. We compare these with the overhead situation of the original algorithm when the number of users increases. The simulation results are shown in Figure 8. These three algorithms are the connection scheme algorithms between base stations and users. The algorithms are optimized by adjusting the percentage of user bandwidth based on the user connection scheme. It can be seen from Figure 10 that the algorithm optimized for key factors has a slightly better overhead situation than the original algorithm when the number of users served by the base station increases. From a computational perspective, the proposed optimization problem is convex after variable relaxation, and its complexity scales polynomially with the number of users and base stations. Specifically, the number of decision variables increases linearly with the number of users and base stations, while the constraint structure remains sparse. Therefore, the proposed method is computationally tractable for dense deployments and can be efficiently solved using standard convex optimization solvers or gradient-based methods, as demonstrated by the convergence behavior in Figure 10. It should be noted that the simulations are conducted under a deterministic scheduling framework using fixed load and renewable generation profiles. Therefore, the reported results correspond to representative operating scenarios rather than statistical averages over random realizations. While stochastic variations are not explicitly considered in this study, the deterministic comparison effectively highlights the structural performance differences among different energy management strategies.

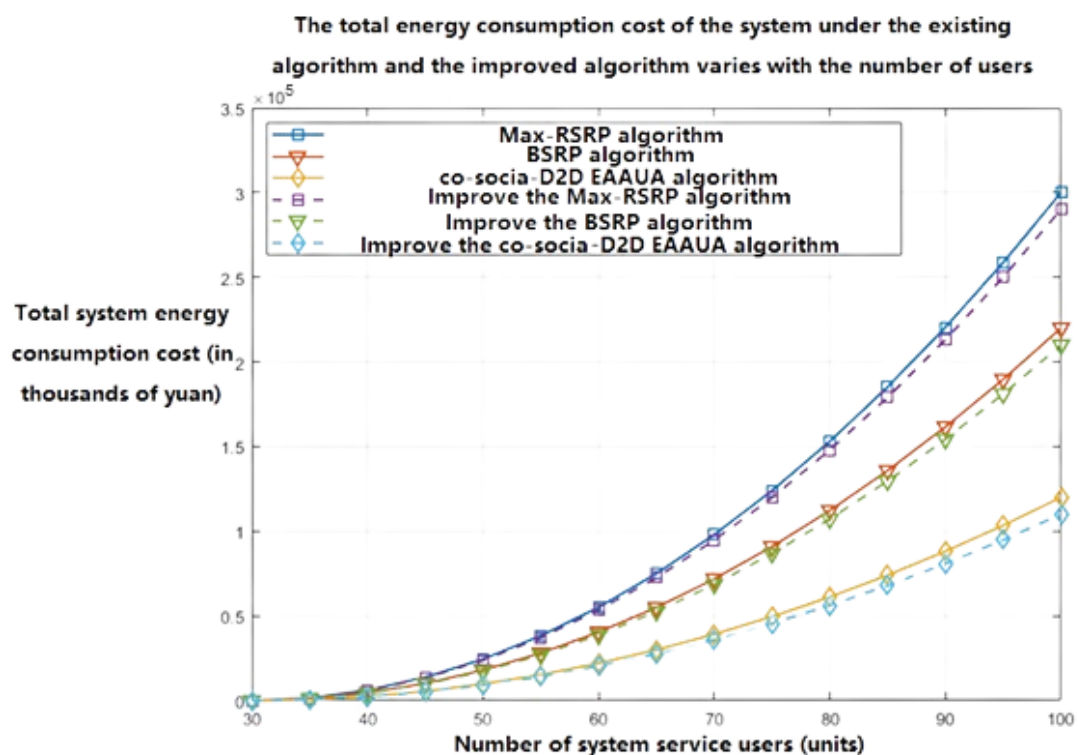


**Figure 10.** The variation in the total energy consumption of the system with an increase in the number of users.

When only grid power supply and photovoltaic power generation are considered, the energy consumption strategy of base stations is shown in Table 3 as follows:

**Table 3.** Electricity consumption strategy simulation (only considering photovoltaic and grid power supply).

| Time        | Energy Consumption of Base Stations (kWh) | Photovoltaic Energy Supply (kWh) | Energy Storage Charging/Discharging (kWh) | Energy Storage (kWh)     | Energy Purchased from Power Grid (kWh) |
|-------------|-------------------------------------------|----------------------------------|-------------------------------------------|--------------------------|----------------------------------------|
| 00:00–07:00 | 20                                        | 0                                | +27.78 (Charging)                         | 25 → 50                  | 20 + 27.78                             |
| 07:00–10:00 | 15                                        | 15                               | −0 (Do not act)                           | 50 → 50                  | 0                                      |
| 10:00–13:00 | 25                                        | 40                               | −5.56 (Discharge)                         | 50 → 44.44               | 0                                      |
| 13:00–17:00 | 20                                        | 50                               | +0 (Do not act)                           | 44.44 → 44.44            | 0                                      |
| 17:00–22:00 | 15                                        | 0                                | −16.67 (Discharge)                        | 44.44 → 27.77            | 0                                      |
| 22:00–23:00 | 5                                         | 0                                | +0 (Do not act)                           | 27.77 → 27.77            | 5                                      |
| 23:00–24:00 | 0                                         | 0                                | +22.23 (Charging)                         | 27.77 → 50               | 24.7                                   |
| Total       | 100                                       | 90                               | Charging +50,<br>Discharge −22.23         | End battery<br>power: 50 | 47.48                                  |

The charging and discharging values of the energy storage system are calculated based on an hourly energy balance with a fixed time resolution. The battery has a rated energy capacity of 50 kWh, and the charging/discharging power is limited to a constant maximum value. Therefore, the energy variation in each time interval is obtained by multiplying the power limit by the duration of the corresponding time period. The state of charge (SOC) of the energy storage system is updated according to the energy balance in each time interval. Specifically, the SOC variation is determined by the charging or discharging energy within the corresponding period, subject to the rated capacity and power constraints of the battery, also considering the loss of charging and discharging efficiency.

By comparing the results, it can be seen that the proposed model has better energy consumption performance and to some extent meets the demand for reducing the energy consumption of base station communication. According to the derivation process, in this context, when the base station group uses renewable energy as much as possible, the energy consumption of this base station group is the lowest, the best economic rationality and the highest rate of return can be achieved within the multi-energy supply base station, and the minimum energy consumption point can always be found according to the energy consumption curve of the base station.

It should be noted that the proposed multimodal energy optimization scheme achieves its maximum benefit under sufficient renewable energy availability. In extreme cases with limited renewable generation, the system performance degenerates to that of grid-powered operation, without introducing additional cost penalties.

## 7. Conclusions

A study was conducted on minimizing the energy consumption of multi-power supply base stations based on user communication. Under the premise of ensuring normal user communication, direct connection communication was carried out while considering the multi-energy power supply scenarios of wind power generation, photovoltaic power generation, and grid power supply. Based on this, a physical model of base station energy consumption was established. According to the mathematical model, it was found that the optimal energy consumption is related to the user association and the percentage of bandwidth allocation. The Weierstrass theorem and Karush–Kuhn–Tucker (KKT) conditions were used to prove the existence and uniqueness of the minimum energy consumption value in the model. The resulting optimality and convergence speed of the algorithm were analyzed, and it was confirmed that the surface of the base station energy consumption problem is convex. The physical conditions required for the base station to reach the minimum energy consumption were mapped. Through analysis, we found that the energy

consumption of the base station was mainly related to the number of associated users, the bandwidth allocation ratio, and the channel gain between the base station and users. The simulation results show that the established model can be analyzed by combining the spatio-temporal diversity of renewable energy. Experiments show that, compared with the traditional power supply strategy for base station operation, this model can reduce the economic cost of communication energy consumption by approximately 35.94% by considering the multi-energy power supply of the base station and the dynamic bandwidth allocation of related users. Through the multi-energy power supply of wind and solar energy, the proposed method achieves an average operating cost reduction of approximately 31.08%, with a maximum reduction of up to 35.94% under optimal parameter settings. Optimizing power supply for base stations in multi-energy scenarios can reduce the amount of electricity purchased from the grid, thereby lowering electricity charges. On the other hand, it has the function of peak shaving and valley filling. It can also flexibly adjust energy supply based on real-time electricity prices, load demand, and the output of renewable energy, further improving energy utilization efficiency. Considering that the energy consumption adjusted for key control variables of base station communication is significantly lower than that of conventional communication, the proposed optimization method has better energy efficiency performance, and the given model has better performance in reducing the energy consumption of LTE base station groups in scenarios with high data transmission requirements and large-scale Internet of Things access. These improvements can, to a certain extent, enhance funding for energy storage infrastructure, improve base station reliability, shorten payback periods, support full network coverage, boost market penetration, and accelerate digital transformation.

Compared with existing studies, the key innovation of this work lies in integrating the dynamic bandwidth allocation based on user interaction perception with a rigorously verified convex multi-modal energy optimization framework, establishing a unified convex optimization framework that simultaneously considers user correlation, dynamic bandwidth allocation, and multi-modal energy supply. It strictly proves the existence and uniqueness of the global optimal solution, provides a minimum energy consumption strategy for multi-modal energy supply combined with user interaction, and offers theoretical guarantees and practical insights for the energy-saving operation of base stations.

However, the proposed model still has some limitations. In practical deployment, this optimization assumes that the user distribution and the output of renewable energy are relatively stable, but this assumption may not hold true in a dynamic urban environment. Secondly, when deployed in a large base station cluster with highly heterogeneous energy configurations, scalability may become a problem. Additionally, during actual use, all the following aspects need to be taken into consideration: how to accurately predict short-term load and renewable energy generation, integrate it with the existing base station energy management system, and perform real-time optimization in a dense network. Future work should address the complexity and real-time issues that arise when algorithms operate under fluctuations in user traffic and changes in renewable energy sources. It should consider random load fluctuations and the uncertainty in renewable energy generation, and extend the proposed framework to random scenarios, thereby enabling statistical performance evaluation under different operating conditions.

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**Data Availability Statement:** The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

**Conflicts of Interest:** Author Chenguang Wu is employed by the State Grid Henan Electric Power Company. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

|      |                              |
|------|------------------------------|
| MR   | Measurement Report           |
| MiBS | Micro-Base Station           |
| MaBS | Macro-Base Station           |
| DBA  | Dynamic Bandwidth Assignment |

## Appendix A

*Appendix A.1. The Model of Energy Consumption Cost of LTE Base Station Groups in Scenarios with High Data Transmission Requirements and Large-Scale Internet of Things Access Has a Convex Structure of the Constraint Function Under the Given Constraints*

In this work, the optimization variables include the bandwidth allocation ratio and the relaxed user–base station association variables, while channel gain, interference, and noise power are treated as fixed parameters within each time interval. Therefore, the convexity analysis is performed with respect to these optimization variables only.

The convexity analysis is performed with respect to the relaxed continuous variables, while channel gain, interference, and noise power are treated as fixed parameters within each optimization interval. According to standard convex composition rules for fractional programming, the objective function is convex over the feasible domain.

It is obvious that the objective function  $f$  is the sum of multiple fractions. According to the convexity theory of fraction functions, if the objective function  $f$  is the sum of multiple fractions and each fraction is convex, then the objective function is also convex. Therefore, it is only necessary to prove that each fraction  $\frac{x_{ij}y_{ij}}{z_{ij}}$  is strictly convex in the positive number field to prove that the objective function is convex.

According to the convexity theory of fractional functions, if  $\frac{x_{ij}y_{ij}}{z_{ij}}$  and the single fractional term function  $f(x_{ij}, y_{ij}, z_{ij})$  satisfies the following conditions, then function  $f(x_{ij}, y_{ij}, z_{ij})$  is a convex function:

1.  $x_{ij}, y_{ij}$  is an affine function, i.e., a polynomial function with a maximum degree of 1.
2.  $z_{ij}$  is a positive affine function, i.e., a polynomial function with a positive value of the highest degree of 1.

Constraint conditions  $C_1$  and  $C_2$  are affine constraint conditions, and constraint condition  $C_3$  is a linear constraint condition. According to the definition of convex programming, it can be ascertained that the constraint set defined by constraint conditions  $C_1$ ,  $C_2$ , and  $C_3$  is a convex set. Combining the constraint conditions  $C_1$ ,  $C_2$ ,  $C_3$ ,  $C_4$ ,  $C_5$ , and  $C_6$ , the variables  $x_{ij}$ ,  $y_{ij}$ , and  $z_{ij}$  are restricted within a bounded closed range, so it can be ascertained that the constraint set is compact; i.e., the objective function is convex. The convexity of the objective function is established based on standard convex composition rules. Specifically, the data rate function is concave with respect to the transmit power under fixed interference, and the reciprocal energy consumption function is convex on the positive domain. According to the properties of convex fractional functions and the fact that the feasible domain is convex after

variable relaxation, the overall objective function is convex. Similar convexity arguments have been widely adopted in energy-efficient communication optimization problems.

According to the Weierstrass theorem, if the objective function is continuous and the set of constraints is compact, the function must have a minimum or minimum value on the set of constraints.

Since  $x_{ij}$ ,  $y_{ij}$ , and  $z_{ij}$  are all positive, according to the constraint conditions, the denominator is not zero. Therefore, each term of  $\frac{x_{ij}y_{ij}}{z_{ij}}$  is continuous, and thus the objective function  $\min f$  is also continuous. According to the constraints  $C_2$ , and  $C_3$ , it can be known that the variable  $A$  is all limited within the bounded range, and according to the constraints, it can be known that  $x_{ij}$ ,  $y_{ij}$  is a finite positive value. Moreover, the constraint set is closed and bounded in a finite-dimensional space.

According to the above two conditions, it can be known that, based on the “Weierstrass extremum theorem” [20], the objective function has a minimum value on the constraint set.

According to the aforementioned analysis process of the convexity of the objective function, it can be ascertained that since each fraction term  $\min f$  of the objective function  $\frac{x_{ij}y_{ij}}{z_{ij}}$  is strictly convex, according to the convex function determination theorem, the objective function is also strictly convex; i.e., the objective function satisfies that for any  $u \neq v$ , there is the following:

$$f(\lambda u + (1-\lambda)v) < \lambda f(u) + (1-\lambda)f(v) \quad (A1)$$

In other words, the minimum value is unique.

## Appendix B

### Appendix B.1. Existence of Minimum Optimal Solutions for Constrained Functions

Based on the objective function and constraint conditions, the Lagrange multiplier  $\lambda, \mu, v, k$  is introduced, and the Lagrange function is defined as follows:

$$L(x_{ij}, y_{ij}, z_{ij}, \lambda, \mu) = \sum_{i \in C, j \in \Omega+1} \frac{x_{ij}y_{ij}}{z_{ij}} + \lambda \left( \sum_{i \in C} x_{ij}y_{ij} - 1 \right) + \mu \left( \sum_{j \in \Omega+1} x_{ij} - 1 \right) + v \left( \sum_{i \in C} [x_{ij}y_{ij}(2^{\log_2(1+a)} - 1) - 1] \right) + k \left( \max \sum_{i \in C} [x_{ij}y_{ij}(2^{\log_2(1+a)} - 1) - 1] \right) \quad (A2)$$

From the above formula, we take the partial derivatives of  $x_{ij}$ ,  $y_{ij}$ , and  $z_{ij}$  and set them to 0 to obtain the gradient conditions:

$$\frac{\partial L}{\partial x_{ij}} = \sum_{i \in C, j \in \Omega+1} \frac{y_{ij}}{z_{ij}} + \lambda \sum_{i \in C} y_{ij} + \mu(\Omega + 1) + v \left( \sum_{i \in C} y_{ij}(2^{\log_2(1+a)} - 1) \right) = 0 \quad (A3)$$

$$\frac{\partial L}{\partial y_{ij}} = \sum_{i \in C, j \in \Omega+1} \frac{x_{ij}}{z_{ij}} + \lambda \sum_{i \in C} x_{ij} + v \left( \sum_{i \in C} x_{ij}(2^{\log_2(1+a)} - 1) \right) = 0 \quad (A4)$$

$$\frac{\partial L}{\partial z_{ij}} = - \sum_{i \in C, j \in \Omega+1} \frac{x_{ij}y_{ij}}{z_{ij}^2} = 0 \quad (A5)$$

The original feasibility conditions to be verified are as follows:

$$0 \leq \sum_{i \in C} [x_{ij}y_{ij}(2^{\log_2(1+a_1)} - 1) \frac{b_5 + b_6}{z_{ij}}] \leq \max \sum_{i \in C} [x_{ij}y_{ij}(2^{\log_2(1+a_1)} - 1) \frac{b_5 + b_6}{z_{ij}}] \quad (A6)$$

$$\sum_{i \in C} x_{ij}y_{ij} = 1$$

$$\sum_{j \in \Omega+1} x_{ij} = 1$$

The dual feasibility condition is verified to ensure that the Lagrange multiplier is non-negative under the maximum and minimum values:

$$\lambda \geq 0, \mu \geq 0, v \geq 0, k \geq 0 \quad (\text{A7})$$

The complementary relaxation condition is verified as it is necessary to ensure that the Lagrange multiplier multiplied by the corresponding constraint function is zero under the maximum and minimum values:

$$\lambda \left( \sum_{i \in C} x_{ij} y_{ij} - 1 \right) = 0 \quad (\text{A8})$$

$$\mu \left( \sum_{j \in \Omega+1} x_{ij} - 1 \right) = 0 \quad (\text{A9})$$

$$v \left( \sum_{i \in C} [x_{ij} y_{ij} (2^{\log_2(1+a)} - 1) - 1] \right) = 0 \quad (\text{A10})$$

$$k \left( \max \sum_{i \in C} [x_{ij} y_{ij} (2^{\log_2(1+a)} - 1) - 1] \right) = 0 \quad (\text{A11})$$

According to the Slater condition [26], in convex optimization problems, if there exists a strictly feasible point (i.e., the point where all inequality constraints strictly hold), then the solution under the KKT condition exists.

Suppose that there exists points  $x_{ij}$ ,  $y_{ij}$ , and  $z_{ij}$  as strictly feasible points, which satisfies all the constraints under the KKT condition and the inequality constraints hold. The location is as follows:  $x_{ij}^0 = \frac{1}{|C|(\Omega+1)}$ ,  $y_{ij}^0 = |C|(\Omega+1)$ , and  $z_{ij}^0 = 1$ .

Substituting the constraint conditions and verifying the calculation, we obtain the following:

$$\sum_{i \in C} x_{ij}^0 y_{ij}^0 = \sum_{i \in C} \frac{1}{|C|(\Omega+1)} \cdot |C|(\Omega+1) = \sum_{i \in C} 1 = |C| \quad (\text{A12})$$

$$\sum_{j \in \Omega+1} x_{ij}^0 = \sum_{j \in \Omega+1} \frac{1}{|C|(\Omega+1)} = (\Omega+1) \cdot \frac{1}{|C|(\Omega+1)} = \frac{(\Omega+1)}{|C|(\Omega+1)} = \frac{1}{|C|} \quad (\text{A13})$$

$$\begin{aligned} \sum_{i \in C} [x_{ij}^0 y_{ij}^0 (2^{\log_2(1+a)} - 1) - 1] &= \sum_{i \in C} \left[ \frac{1}{|C|(\Omega+1)} \cdot |C|(\Omega+1) (2^{\log_2(1+a)} - 1) - 1 \right] \\ &= \sum_{i \in C} [(2^{\log_2(1+a)} - 1) - 1] = \sum_{i \in C} [(1+a-1) - 1] = \sum_{i \in C} [a-1] = |C|(a-1) \end{aligned} \quad (\text{A14})$$

According to  $a > 0$ , it can be ascertained that  $a-1 < a$ . We assign the value  $a$  such that  $a$  satisfies  $0 \leq |C|(a-1)$ , i.e.,  $a > 1$  (which can be other positive values) or  $C \neq 0$  can satisfy the original feasibility condition.

1. For  $\lambda \left( \sum_{i \in C} x_{ij} y_{ij} - 1 \right) = 0$ , since  $\sum_{i \in C} x_{ij}^0 y_{ij}^0 = |C|$ , it is obvious that  $\lambda = 0$  conforms.
2. For  $\mu \left( \sum_{j \in \Omega+1} x_{ij} - 1 \right) = 0$ , since  $\sum_{j \in \Omega+1} x_{ij}^0 = \frac{1}{|C|}$ , it is obvious that  $\mu = 0$  conforms.
3. For  $v \left( \sum_{i \in C} [x_{ij} y_{ij} (2^{\log_2(1+a)} - 1) - 1] \right) = 0$ , since  $\sum_{i \in C} [x_{ij}^0 y_{ij}^0 (2^{\log_2(1+a)} - 1) - 1] = |C|(a-1)$ , it is obvious that  $v = 0$  conforms.
4. For  $k \left( \max \sum_{i \in C} [x_{ij} y_{ij} (2^{\log_2(1+a)} - 1) - 1] \right) = 0$ , since  $\sum_{i \in C} [x_{ij}^0 y_{ij}^0 (2^{\log_2(1+a)} - 1) - 1] = |C|(a-1)$ , where  $a > 1$  (can take other positive values) or  $C \neq 0$ , it is obvious that  $k = 0$  satisfies.

From the above derivation, it can be ascertained that based on this objective function and constraint conditions, there exists a minimum value that satisfies the conditions, and this minimum value is the optimal solution.

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