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Two-Tier Configuration Model for the Optimization of Enterprise Costs and User Satisfaction for Rural Microgrids

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Abstract: The construction costs and operational challenges of rural microgrids have garnered widespread attention. This study focuses on grid-connected rural microgrids incorporating wind, solar, hydro, and storage systems, and proposes a two-tier optimization configuration model that considers both enterprise costs and user satisfaction. The upper-tier model aims to minimize enterprise costs, covering construction, operation and maintenance, as well as penalties for a curtailment of wind, solar, and hydro power. The lower-tier model evaluates power reliability and cost-effectiveness to maximize user satisfaction. Using the particle swarm optimization algorithm, this study analyzes a case in Yudaokou, Hebei Province, and proposes three optimization schemes: minimizing enterprise costs, maximizing user satisfaction, and a compromise between the two. The optimal scheme, which employs 17 photovoltaic panels, 12 wind turbines, and 15 energy storage units, achieved a user satisfaction score of 0.90. This two-tier planning model provides practical insights for the rational configuration of rural microgrids and reveals the nonlinear relationship between costs and user experience.

Keywords: rural microgrid; two-tier planning; particle swarm optimization

MSC: 90C31

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1. Introduction

China's rural landscapes are replete with copious wind, solar, and hydro resources, culminating in substantial renewable energy production. Following recent advancements in rural electrification, the use of renewable energy sources in these areas has increased significantly [1,2]. As of the first half of 2023, the cumulative installed capacity for renewable energy in China ascended to 1.322 billion kilowatts, representing 48.8% of the nation's total installed capacity [3]. Nevertheless, the deployment of renewable energy sources in rural locales as substitutes for conventional power generation accentuates their vulnerability to environmental contingencies like weather, engendering a pronounced variability in energy output. Such a variability may precipitate short-term power surpluses or deficits, markedly influencing load operations within rural settings and precipitating user dissatisfaction [4–6]. Enhancing the stability of the power supply typically results in higher overall costs for companies [7,8]. Consequently, the optimization of rural microgrid allocation, taking into account both the comprehensive costs to enterprises and user satisfaction, has emerged as a pivotal aspect of contemporary research.

The optimal configuration of a microgrid entails the strategic development of schemes for micro-source integration within the grid to augment energy efficiency whilst guaranteeing system stability [9]. Research on microgrid configurations primarily focuses on the economic and environmental benefits, as well as stability. In the context of microgrids' economic benefits, the primary objectives include minimizing the operational costs [10], maximizing grid enterprise profitability [11], and reducing the aggregate net present value of construction and operational expenses [12]. These objectives are mainly achieved through methodologies such as game model and deep reinforcement learning [13,14], which help reduce operational costs and enhance economic efficiency. Evaluating the environmental merits of microgrids underscores the imperative to optimize renewable energy source utilization [15], diminish greenhouse gas emissions [16], and amplify the ecological rewards [17]. The attainment of these objectives is facilitated through the deployment of intelligent algorithms that orchestrate a power generation strategy and consumption blueprint [18], thus elevating the microgrid's environmental sustainability. In an evaluation of microgrid stability, the complexities of managing distributed power generation and mitigating output uncertainty are adeptly navigated by integrating conditional value-at-risk models [19], robust stochastic models [20], or opportunistic stochastic constraints [21], thereby fortifying operational stability. Nevertheless, in the context of escalating competition within the power market, enterprises are compelled to prioritize the augmentation of user experiences as a strategic measure to secure a larger market share. Contemporary research on rural microgrids infrequently incorporates user satisfaction with electricity services into the overarching goals, necessitating a dual focus not only on corporate profitability but also on maximizing customer contentment within these grids.

In the domain of a rural microgrid construction cost analysis, deep reinforcement learning [13] effectively addresses the complex multivariate decision-making challenges. However, it struggles with ensuring stability and convergence, posing difficulties in identifying the global optimal solution. Genetic algorithms [15], while demonstrating significant efficiency and reliability, depend on stochastic processes that can yield varying outcomes across different runs, resulting in instability. Moreover, approaches like game theory [14] and stochastic constraints [11,19] address equipment allocation in microgrids. The game-theoretical models demand precise participant data and system parameters, whereas stochastic constraints manage renewable energy's uncertainty but falter in highly deterministic scenarios. The particle swarm algorithm employed in this research achieves an optimal balance between global and local searches by strategically adjusting inertia weights and learning factors. Furthermore, the particle swarm algorithm preserves the memory of the most promising particles throughout the iterations, offering a significant advantage in addressing the complex two-tier planning problem in rural microgrids. In the two-tier programming problem presented in this study, the objective functions are two conflicting aspects, which can be balanced by PSO by retaining the global and local optimal solutions. The memory function ensures that the algorithm does not lose those potentially high-quality solutions found in the previous iterations while searching globally, effectively improving the quality of understanding. Consequently, the particle swarm algorithm is particularly advantageous for solving the two-tier model developed in this study.

Prior research on rural microgrids has focused on construction costs, and although different studies and model-solving methods have been adopted, they have mainly focused on the economic benefits of rural microgrid construction, often neglecting the assessment of user satisfaction, especially the studies that comprehensively reconcile enterprise costs and user satisfaction which are fewer in number. In addition, most of the existing research on microgrids focuses on cities, with fewer studies on rural microgrid planning. To fill these gaps, this study employs a two-tier planning model that aims to reconcile the discrepancy between firms' construction costs and consumers' experiences with electricity services. The main contribution of this study is the development of a rural microgrid construction strategy that achieves the dual goals of minimizing firms' costs and enhancing rural consumers' electricity experiences. Moreover, this research substantiates the viability of a two-tier, grid-connected microgrid optimization framework, offering crucial insights for the logical planning and appropriate equipment configuration of rural microgrids, thereby supporting their continued expansion and development.

The remainder is structured as explained below. Section 2 constructs the structure of rural microgrids and conducts a feature analysis. Section 3 constructs a two-tier programming model. Section 4 proposes a solution plan and uses the actual case data later employed for a solving and sensitivity analysis in Section 5. Finally, Section 6 provides the conclusion and proposals for future work. The symbols and explanations used in this study are as follows (Table 1).

Table 1. Glossary of Terms and Units.

Symbol	Explanation	Unit
C_{CONST}	Construction cost	USD
C_{OMT}	Operational, maintenance, and testing cost	USD
C_{waste}	Penalty cost	USD
C_{PV}, C_{WT}, C_{HS}, C_{ES}	Individual investment expenditures for Photovoltaic power plants, wind turbines, hydropower stations, and energy storage facilities	USD
C_{GCI}	The aggregated investment cost for all grid-tied inverters	USD
N_{PV}, N_{WT}, N_{HS}, N_{ES}	Quantity of photovoltaics, wind turbines, hydro Generators, and energy storage	Unit
i	Discount rate	-
n	Projected lifespan	Year
C_{PV}^{OMT}, C_{WT}^{OMT}, C_{HS}^{OMT}, C_{ES}^{OMT}	The unitary average costs associated with the operation, maintenance, and testing (OMT) of individual photovoltaic power stations, wind turbines, hydropower stations, and energy storage facilities	USD
C_{GCI}^{OMT}	Annual average expenditure for the OMT Activities of all grid-tied inverters	USD
C_{PV}^{waste}, C_{WT}^{waste}, C_{HS}^{waste}	Penalization factors for the abandonment of solar, wind, and hydroelectric power	USD
P_{max}^{PV}, P_{max}^{WT}, P_{max}^{HS}	The maximal power outputs achievable by photovoltaic systems, wind turbines, and hydro stations	kW
$P_{s.t.}^{PV}$, $P_{s.t.}^{WT}$, $P_{s.t.}^{HS}$	The actual power outputs from photovoltaic systems, wind turbines, and hydroelectric stations	kW
T	The maximal quantity of hours per day during which electrical power is wasted	Hour
C_{MG}	The comprehensive economic cost	USD
N_{PV}^{max}, N_{WT}^{max}, N_{HS}^{max}	The upper limits on the number of photovoltaic, wind turbine, and hydroelectric devices	Unit
P_{DG}	The aggregate output power generated by distributed power sources	kW
P_{load}	Power consumption	kW
μ	The power generation margin within the microgrid	-
P_{PV}, P_{WT}, P_{HS}	The output powers of an individual photovoltaic unit, wind turbine, and hydropower unit	kW
U_R	Reliability	-
U_E	Cost-effectiveness	-
α	The importance of electricity reliability	-
β	The importance of electricity cost-effectiveness	-
T_{PO}	The annual duration of power outages experienced within the rural microgrid	Day
T_{year}	The period constituting one calendar year	Day
P_m	The electricity tariff charged to residents prior to the establishment of the rural microgrid	USD
P_g	The rate post-establishment	USD
$U_{R,min}$	Minimum reliability	-

2. Characteristics and Structure of Rural Microgrids

2.1. The Characteristics of Rural Power Distribution Networks

The rural microgrid serves as a pivotal foundation for the establishment of innovative power systems, facilitating the advancement and utilization of distributed energy resources within rural locales. Analyzing the structure and features of rural microgrids can greatly improve the reliability of an energy supply and its consumption efficiency. This plays a critical role in advancing the amalgamation and utilization of renewable energy resources, as well as in the sustainable progression of rural socio-economic frameworks. Distinguished by four salient features, rural microgrids cater to the unique demands and conditions prevalent in rural settings, in contrast to conventional microgrids:

(1) Weak grid structure. Most rural microgrids have a simple, single-line power supply configuration due to a weak grid architecture. This straightforward structure connects to the main power grid and includes connection points, distributed power generators, and energy storage systems. While the single-line power supply framework offers cost efficiencies, it harbors the potential for power supply instability [22]. Rural microgrids typically possess the capability to seamlessly integrate with or disconnect from the main grid, allowing for adjustments between grid-tied and wholly independent operations based on demand [23]. This confers a significant level of flexibility and self-reliance.

(2) Abundant forms of energy. Rural regions often have facilitated access to diverse renewable energy sources, laying a robust foundation for rural microgrid development. This observation is made with objectivity, devoid of subjective assessments. Among the renewable energy sources prevalently harnessed in rural microgrids, there are wind, hydro, photovoltaic, and biomass energy sources [24–26]. The plethora of energy varieties offers an economically sustainable and ecologically benign solution for rural locales. Furthermore, this diversification diminishes reliance on external energy sources, bolstering energy security and fostering sustainable advancement in rural regions.

(3) Poor quality of electricity. The employment of renewable energy sources within rural microgrids often leads to an intermittent and unpredictable power supply, adversely impacting the stability and reliability of the electrical energy provided [27]. Moreover, constraints in energy storage and management systems, arising from technological limitations and investment restrictions, can impede efforts to mitigate supply instability [28]. This confluence of factors can precipitate power quality concerns, including voltage instability and frequency variations, adversely affecting rural microgrid consumers. Such complications can detrimentally influence daily living and economic operations.

(4) Low user satisfaction. Power quality instability within rural microgrids directly influences the electricity experience of users, potentially detracting from their overall satisfaction. Recurrent power interruptions and voltage fluctuations can gravely impact residents' quality of life and disrupt the routine operations of businesses [29]. Moreover, rural microgrids frequently face challenges in delivering dependable services and swift responses in the face of extreme weather events or equipment malfunctions, owing to the technical and financial limitations.

2.2. The Structure of Rural Microgrids

The architecture of a microgrid underpins its operational safety and ensures the energy system's flexibility and resilience. These qualities are vital during the construction, operation, and maintenance phases of the microgrid. Microgrids are currently categorized into three types based on their characteristics: DC, AC, and AC/DC hybrid microgrids [30]. The prevalent structure in rural microgrids is the AC/DC hybrid microgrid [31], encompassing both AC and DC buses. This configuration forms AC and DC sub-microgrids, facilitating bidirectional power flow via bidirectional converters. It melds the benefits of both the AC and DC microgrids; the AC/DC hybrid microgrid is capable of simultaneously powering AC and DC loads, thereby minimizing the power conversion losses. Its ability to operate independently or integrate seamlessly with larger power grids enhances its reliability. Consequently, the AC/DC hybrid microgrid presents extensive development potential [32]. The architecture of the AC/DC hybrid microgrid is illustrated in Figure 1.

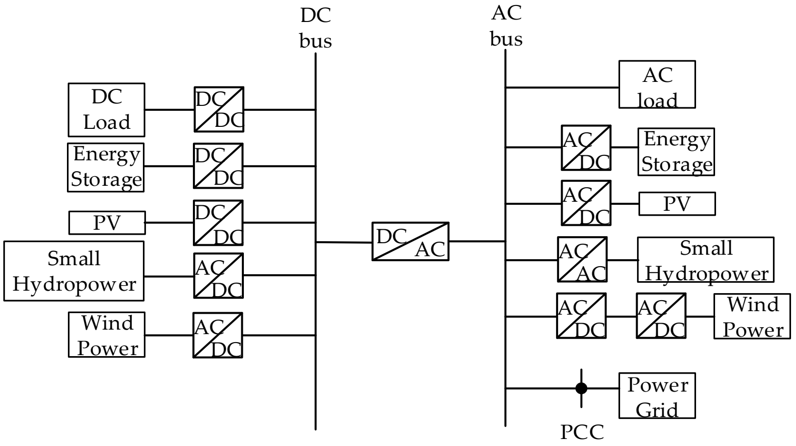


Figure 1. Structure of AC/DC hybrid microgrid.

The unique structure and characteristics of rural microgrids engender the distinct objectives among participating stakeholders. From an enterprise perspective, the aim is to build and manage microgrids with the least possible investment, concurrently enhancing the subpar power quality in rural microgrids for sustainable development. For users, the primary goal is to attain an improved power experience. Pursuing enhanced user satisfaction typically necessitates increased investment from the enterprise. The conflict between the user and the enterprise is prevalent [33]. Consequently, identifying an optimal microgrid construction plan that meets the varied needs of both businesses and consumers is paramount.

3. Interconnected Rural Microgrid Two-Tier Planning Model

The inherent ability of microgrids to generate and consume electrical energy locally bestows upon them significant flexibility, rendering them a pivotal element in the evolution of future smart grids. Nevertheless, the variability, randomness, and intermittency inherent in distributed energy sources may precipitate power outages and voltage instability within microgrids, adversely affecting consumers' electricity usage experiences. To augment consumers' electricity usage experiences, power companies are compelled to bolster their investment in microgrids, aiming to enhance stability. Achieving a balance between the economic returns for power companies and the satisfaction levels of consumers has emerged as a critical consideration in the construction and operational strategies of microgrids. Consequently, this research proposes a two-tier planning model aimed at devising an optimized configuration for rural microgrids.

In actual microgrid construction scenarios, there are often many uncertainties involved. To reduce unnecessary details and better focus on the core issues, this article makes the following assumptions in the modeling process: (1) The equipment performance is fixed and will not decrease with external environmental factors or aging. (2) Ignore the uncertain factors and assume that the uncertainty of the external environment will not affect the model parameters. (3) Constant cost, believe that both the construction and operation costs are constant and not affected by the market or inflation.

3.1. Minimum Cost Model for Microgrid Construction and Operation

The overarching objective of the upper-tier planning model, addressing the two-tier planning dilemma of rural microgrids, is to minimize the aggregate economic cost. This comprehensive cost framework includes the following: the discounted construction costs of the microgrids (C_{CONST}) [17], the ongoing operation and maintenance expenses (C_{OMT}) [31], and the penalty costs associated with wind and hydro variability (C_{waste}) [21]. Thereby providing a metric for assessing the financial efficacy of the utility's development and operational endeavors.

(1) Construction Cost C_{CONST} of the rural microgrid:

$$C_{CONST} = C'_{CONST} \frac{i(1+i)^n}{(1+i)^n - 1} \tag{1}$$

$$C'_{CONST} = C_{PV}N_{PV} + C_{WT}N_{WT} + C_{HS}N_{HS} + C_{ES}N_{ES} + C_{GCI} \tag{2}$$

C_{PV}, C_{WT}, C_{HS}, and C_{ES} denote the respective individual investment expenditures for photovoltaic power plants, wind turbines, hydropower stations, and energy storage facilities. These expenditures encompass the cumulative costs associated with equipment acquisition, transportation, and the construction activities prior to an operational deployment. C_{GCI} encapsulates the aggregated investment cost for all the grid-tied inverters. Furthermore, N_{PV}, N_{WT}, N_{HS}, and N_{ES} signify the quantities of units established for each type of renewable energy installation, serving as pivotal decision variables within this analytical framework. C'_{CONST} is defined as the comprehensive cost arising from the microgrid's construction, whereas i specifies the discount rate, and n delineates the projected lifespan, in years, throughout the microgrid's entire lifecycle.

(2) Operational, Maintenance, and Testing Cost C_{OMT} of the rural microgrid:

$$C_{OMT} = C'_{OMT} \frac{i(1+i)^n}{(1+i)^n - 1} \tag{3}$$

$$C'_{OMT} = C^{OMT}_{PV}N_{PV} + C^{OMT}_{WT}N_{WT} + C^{OMT}_{HS}N_{HS} + C^{OMT}_{ES}N_{ES} + C^{OMT}_{GCI} \tag{4}$$

C^{OMT}_{PV}, C^{OMT}_{WT}, C^{OMT}_{HS}, and C^{OMT}_{ES} delineate the unitary average costs associated with the operation, maintenance, and testing (OMT) of the individual photovoltaic power stations, wind turbines, hydropower stations, and energy storage facilities, respectively. C'_{OMT} is defined as the construction, operation, and maintenance cost of the microgrid. Concurrently, C^{OMT}_{GCI} specifies the annual average expenditure for the OMT activities of all the grid-tied inverters.

(3) Penalty Cost C_{waste} for Wasted Wind, Light, and Water in the rural microgrid:

$$C_{waste} = C'_{waste} \frac{i(1+i)^n}{(1+i)^n - 1} \tag{5}$$

$$C'_{waste} = \sum_{s=1}^{S} DP(s) \sum_{t=1}^{T} \left[C^{waste}_{PV}\left(P^{PV}_{max} - P^{PV}_{s.t.}\right) + C^{waste}_{WT}\left(P^{WT}_{max} - P^{WT}_{s.t.}\right) + C^{waste}_{HS}\left(P^{HS}_{max} - P^{HS}_{s.t.}\right) \right] \tag{6}$$

The term 'Abandoned wind, light, and water' describes a situation where the power grid produces more electricity than is needed. The unutilized potential generating capacity of renewable energy sources that could theoretically produce more energy but due to natural conditions or technological constraints produce less than their maximum potential can also be considered 'waste'. As a result, the excess electricity generated by these sources is not effectively utilized. In response to this challenge, numerous countries and regions have instituted penalty charges for the abandonment of wind, solar, and hydroelectric energy [34]. Such a policy aims to incentivize power generation entities to refine their renewable energy forecasting and planning practices, thereby diminishing the propensity for energy abandonment, and concurrently bolstering the power grid's reliability and economic efficiency.

In Equation (6), C'_{waste} is defined as the penalty cost of the microgrid. The variable D denotes the annual total number of days. S represents the peak number of days characterized by the occurrence of events leading to the abandonment of solar, wind, and hydroelectric resources. The function $P(s)$ quantifies the likelihood of such abandonment on the s-th day for wind, solar, and hydroelectric sources. Furthermore, the coefficients C^{waste}_{PV}, C^{waste}_{WT}, and C^{waste}_{HS} serve as penalization factors for the abandonment of solar, wind, and hydroelectric power, respectively. The terms P_{max}^{PV}, P_{max}^{WT}, and P_{max}^{HS} denote the maximal power outputs achievable by photovoltaic systems, wind turbines, and hydro stations, respectively. The actual power outputs from photovoltaic systems, wind turbines, and hydroelectric stations at a given time t are represented by $P_{s.t.}^{PV}$, $P_{s.t.}^{WT}$, and $P_{s.t.}^{HS}$, respectively. Lastly, T signifies the maximal quantity of hours per day during which electrical power is wasted.

The total cost of construction and operation of rural microgrids, taking into account the three types of costs of rural microgrid construction, is as follows:

$$\begin{aligned} MinC_{MG} &= C_{CONST} + C_{OMT} + C_{waste} \\ &= (C_{PV}N_{PV} + C_{WT}N_{WT} + C_{HS}N_{HS} + C_{ES}N_{ES} + C_{GCI})\frac{i(1+i)^n}{(1+i)^n - 1} \\ &+ \left(C_{PV}^{OMT}N_{PV} + C_{WT}^{OMT}N_{WT} + C_{HS}^{OMT}N_{HS} + C_{ES}^{OMT}N_{ES} + C_{GCI}^{OMT}\right)\frac{i(1+i)^n}{(1+i)^n - 1} \\ &+ \left\{\sum_{s=1}^{S} DP(s) \sum_{t=1}^{T} \begin{bmatrix} C_{PV}^{waste}\left(P_{max}^{PV} - P_{s.t.}^{PV}\right) \\ +C_{WT}^{waste}\left(P_{max}^{WT} - P_{s.t.}^{WT}\right) \\ +C_{HS}^{waste}\left(P_{max}^{HS} - P_{s.t.}^{HS}\right) \end{bmatrix}\right\}\frac{i(1+i)^n}{(1+i)^n - 1} \end{aligned} \tag{7}$$

C_{MG} represents the comprehensive economic cost.

Microgrid systems must follow specific constraint conditions during operation. These constraints are established based on practical demands and scenarios, defining the acceptable range for setting decision variables as follows.

Constraints on the number of distributed power source installations:

$$0 \le N_{PV} \le N_{PV}^{max} \tag{8}$$

$$0 \le N_{WT} \le N_{WT}^{max} \tag{9}$$

$$1 \le N_{HS} \le N_{HS}^{max} \tag{10}$$

The variables N_{PV}^{max}, N_{WT}^{max}, and N_{HS}^{max} denote the upper limits on the number of photovoltaic, wind turbine, and hydroelectric devices, respectively, that can be installed, taking into account site-specific and miscellaneous constraints. These variables are integers, representing the count of units. In light of the plentiful water resources available in the Yudaokou region, the power grid company has formulated plans to erect a hydropower station, aiming to harness the full potential of hydropower generation. Consequently, the construction of at least one hydropower station is mandated.

The power constraints are as follows:

$$P_{DG} \ge P_{load}(1 + \mu) \tag{11}$$

$$P_{DG} = P_{PV}N_{PV} + P_{WT}N_{WT} + P_{HS}N_{HS} \tag{12}$$

The symbol P_{DG} denotes the aggregate output power generated by the distributed power sources. P_{load} presents power consumption. The generation margin μ within the microgrid is introduced due to the need to ensure that the microgrid system can operate stably and cope with possible load fluctuations or emergencies. Furthermore, the variables P_{PV}, P_{WT}, and P_{HS} correspond to the output powers of an individual photovoltaic unit, a wind turbine, and a hydropower unit, respectively.

3.2. Maximum User Satisfaction Model

Rural consumers prioritize electrical stability and affordability, acknowledging that rural microgrids often suffer from inferior power quality compared to their urban counterparts. Consistent with the prevailing research on customer satisfaction, this study proposes the assessment of satisfaction through the dimensions of reliability U_R and the cost-effectiveness U_E of electricity consumption [35]. Consequently, the objective function to quantify customer satisfaction is delineated as follows:

$$MaxU = \alpha U_R + \beta U_E \tag{13}$$

$$\alpha + \beta = 1 \tag{14}$$

The parameters α and β are assigned to quantify the importance of electricity reliability and cost-effectiveness, respectively. In recognition of the escalating demand for an uninterrupted and stable electricity supply in rural regions crucial for residential and agricultural development, α is apportioned a value of 0.6, whereas β is allocated a value of 0.4.

(1) Reliability in the context of microgrid systems signifies the system's ability to provide a stable and uninterrupted power supply. This aspect is particularly pivotal in rural locales, where the consistency of electricity directly influences the community's quality of life and operational normalcy. A dependable power supply underpins the smooth operation of essential infrastructure, thereby enhancing the living conditions of residents, especially in education and healthcare. The measure of reliability is typically gauged by the duration of power outages [36], given that the extent of these disruptions bears a significant impact on the daily lives and productivity of the rural populace. Extended power interruptions can severely hamper community life, impacting vital sectors like agriculture and healthcare. The formula to quantify reliability is detailed as follows:

$$U_R = \left(1 - \frac{T_{PO}}{T_{year}}\right) \times 100\% \tag{15}$$

The variable T_{PO} represents the annual duration of power outages experienced within the rural microgrid, a metric intrinsically linked to the quantity of distributed power sources integrated during the microgrid's construction. Concurrently, T_{year} denotes the period constituting one calendar year.

(2) Cost-effectiveness encapsulates the optimal utilization of electrical resources to satisfy residents' electricity needs in an economical manner. Given the prevalent concern about electricity pricing in rural settings, the ability to deliver cost-efficient electrical services is paramount to enhancing the satisfaction levels for residential electricity consumption. The cost-effectiveness metric is quantifiable through the ratio of the diminished electricity bill post-microgrid implementation to the preceding electricity bill [37]. The formula for calculating this indicator is specified as follows:

$$U_E = \frac{P_m - P_g}{P_m} \times 100\% \tag{16}$$

The variable P_m denotes the electricity tariff charged to residents prior to the establishment of the rural microgrid, whereas P_g represents the rate post-establishment; both metrics are expressed in USD per kilowatt-hour.

Current standards mandate that the reliability of a power supply in rural areas should not dip below the national benchmark, identified as $U_{R,min}$. As a result, customer satisfaction concerning rural microgrids is subject to the specified constraint.

$$U_R \geq U_{R,min} \tag{17}$$

The two-tier planning model described in this investigation includes a crucial data exchange process between its hierarchical levels. The upper-tier enterprises formulate and disseminate the construction, operational, and maintenance blueprints for the rural microgrid. These actions invariably influence critical parameters, including electricity reliability for sub-tier users. As a result, there are consequential impacts on customer satisfaction. After receiving feedback on customer satisfaction, these enterprises will recalibrate the microgrid's optimization scheme based on the input from the sub-tier users, with the objective of realizing a global optimum.

4. Solution of a Two-Tier Planning Model for Rural Microgrid

The development of a comprehensive two-tier planning model for grid-connected rural microgrids is presented in this study. Initially, the planning problem, inherently two-tiered, is reformulated into a single-tier problem utilizing the KKT conditions. Subsequently, the particle swarm optimization algorithm is employed to effectively solve the reformulated model.

4.1. Decoupling of Two-Tier Planning Models

A two-tier model addressing both enterprise costs and user satisfaction is developed. Initially, the user satisfaction objectives and constraints are transformed into a system of equations and inequalities through the construction of a Lagrangian function for the sub-tier problem. Subsequently, the derived Karush–Kuhn–Tucker (KKT) conditions are incorporated as additional constraints within the overarching enterprise cost framework, thereby converting the two-tier problem into a unified single-tier optimization challenge that integrates both the upper-tier directives and the sub-tier KKT conditions.

The KKT conditions embed the sub-tier optimization problem as a constraint of the upper-tier problem, so that the whole optimization problem can be treated uniformly at one level, thus transforming the two-tier optimization problem into a single-tier optimization problem. Subsequently, the sub-tier of this study is modeled as a KKT condition that includes a single inequality constraint, expressed in the following general form:

$$\min f(X) \tag{18}$$

$$s.t. g(X) \le 0 \tag{19}$$

Then, define the Lagrangian function as follows:

$$L(X,\lambda) = f(X) + \lambda g(X) \tag{20}$$

The KKT condition containing only one inequality constraint is as follows:

$$\nabla_X L = 0 \tag{21}$$

$$\lambda g(X) = 0 \tag{22}$$

$$\lambda \ge 0 \tag{23}$$

$$g(X) \le 0 \tag{24}$$

The sub-tier model of this study can be summarized as equations (13) and (17). Upon establishing definite values for the variables N_{PV}, N_{WT}, N_{HS} within the upper-tier model, the corresponding Lagrangian function for the sub-tier model can be articulated as follows:

$$L(N,\lambda) = -\alpha U_R - \beta U_E + \lambda U \tag{25}$$

$$U = U_{R,\ min} - U_R \tag{26}$$

In Formula (25), λ is the Lagrangian operators with inequality constraints.

Based on the KKT conditions of the sub-tier model, the following is deduced:

$$\alpha + \lambda = 0 \tag{27}$$

$$\lambda(U_{R,\ min} - U_R) = 0 \tag{28}$$

$$\lambda \ge 0 \tag{29}$$

The transformation of the two-tier programming model into a unified single-tier programming framework is achieved by applying the KKT conditions. This reconstructed single-tier planning model has Equation (7) as the objective, and (8) to (12) in the original upper constraints and (27) to (29) in the original lower constraints are made into the constraints of the single-tier planning model.

4.2. Solution Algorithm

This study uses the particle swarm optimization (PSO) algorithm to solve the planning problem, which is recognized as the most effective algorithm to date [38,39]. The algorithm has high applicability and is often applied to solve problems such as the optimal scheduling of microgrids. Initially, the number of particle swarms is set to 50 and the maximum number of iterations is 100, with each particle having different position and velocity attributes. It then evaluates the fitness of each particle against the objective function, with the aim of minimizing the comprehensive cost to the enterprise. Following this, both the individual and group optimal solutions are updated, with subsequent adjustments made to the velocity and position of each particle in alignment with these solutions. The pursuit of the group optimal solution is conducted through relentless iteration and meticulous convergence checks. Adjustments to the velocity and position of the particles are continuously made in response to the evolving individual and group optimal solutions, culminating in the attainment of the group optimal solution via persistent iteration and convergence verification.

Upon converting the two-tier planning problem into a single-tier model, this study employs the particle swarm optimization algorithm to address the solution. The algorithm enhances its capability to escape local optima through adjustments in the inertia weight, achieving a balance between global and local searches [38]. Furthermore, its capacity to memorize optimal solutions notably improves its performance in addressing the two-tier planning challenges [39]. Initially, the algorithm randomly initializes a population of particles, each characterized by distinct spatial coordinates x_i and velocity attributes v_i. x_i represents the decision variable, specifically the number of devices deployed in a rural microgrid, whereas v_i denotes the velocity of each particle within the decision space. Subsequently, the particle swarm optimization algorithm computes the fitness value $f(x_i)$ for each particle based on the objective function, which aims to minimize the total enterprise cost $f(x)$, and the respective positions x_i of each particle. The algorithm then updates both the individual and collective optimal solutions, refining the personal best position $pbest_i$ and the global best position $gbest_i$ based on the fitness values $f(x_i)$ of the particles. Further adjustments to each particle's velocity and position are governed by the inertia weight ω, along with the individual and social learning coefficients c_1 and c_2, as detailed in Equations (30) and (31). r_1 and r_2 are random numbers with values between zero and one, ensuring the randomness of the speed updates and helping to avoid getting stuck in local optima. The updated particle velocity and position are v_i^{t+1} and x_i^{t+1}, respectively.

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 \left(pbest_i - x_i^t\right) + c_2 r_2 \left(gbest_i - x_i^t\right) \tag{30}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{31}$$

Larger values for C1 enhance the local search but may cause the algorithm to get stuck in local optima. Increasing C2 strengthens the global search, helping to avoid local optima, but it might lead to an excessively fast convergence. The parameter w controls the global search capability and adjusts the search precision. To achieve better search accuracy, the learning coefficients c1 and c2 were set to 2 and the inertia weight was set to 0.8 [1]. If the maximum number of iterations is reached or the global optimal solution stabilizes, exhibiting negligible changes, the algorithm terminates and outputs the results. Otherwise, the algorithm persists in computing the fitness values $f(x_i)$ for each particle, continuing iterations until it can output both the optimal design solution for the microgrid, represented by $gbest$, and the minimal total enterprise cost, denoted by

$f(gbest)$. The flowchart depicting the particle swarm optimization algorithm is illustrated in Figure 2 below.

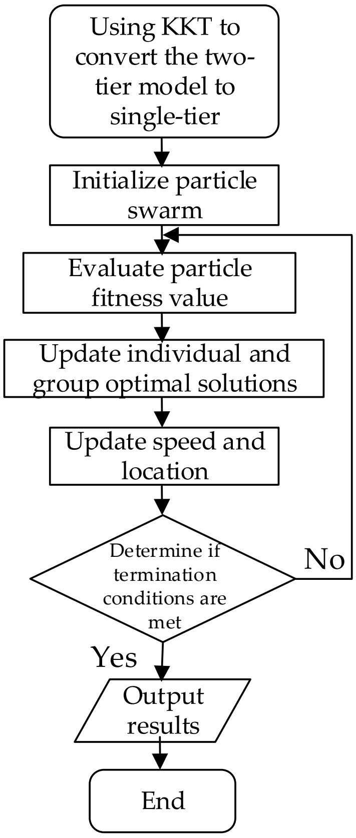


Figure 2. Solution flowchart.

Optimal solutions in particle swarm optimization algorithms are achieved through rigorous computation and meticulous convergence verification. When compared to the existing ant colony algorithm, the particle swarm algorithm exhibits superior computational efficiency [40]; relative to the simulated annealing algorithm, the particle swarm algorithm demonstrates faster convergence rates [41]; in comparison to mixed integer programming, the particle swarm algorithm is more adaptable to handling nonlinear and nonconvex challenges [42]. Consequently, the exceptional performance of PSO on the continuous optimization challenges affords it significant advantages in addressing the microgrid planning issues.

5. Case Study

5.1. Input Data

Yudaokou epitomizes the plateau countryside, situated at the confluence of the northern Hebei mountains and the Mongolian plateau. It is endowed with an abundance of renewable energy resources, including wind and solar energy. Despite its wealth of resources, the area contends with a frail distribution network, an extensive power supply radius, and the challenges inherent to rural microgrids, including a substandard voltage and three-phase imbalance. These issues make it an exemplary case study. The geographical location of Yudaokou is shown in Figure 3. In this study, wind and solar resource data, along with load data from Yudaokou, serve as the inputs for a comprehensive simulation and analysis, with the resultant data map depicted in Figure 4. The average daily local load is 3670 kW and the variance is 138,094.3. Detailed information for each distributed power device within the system is catalogued in Table 2, while the penalty costs associated with the rural microgrid are uniformly set at 0.0828 USDs/kW·h.

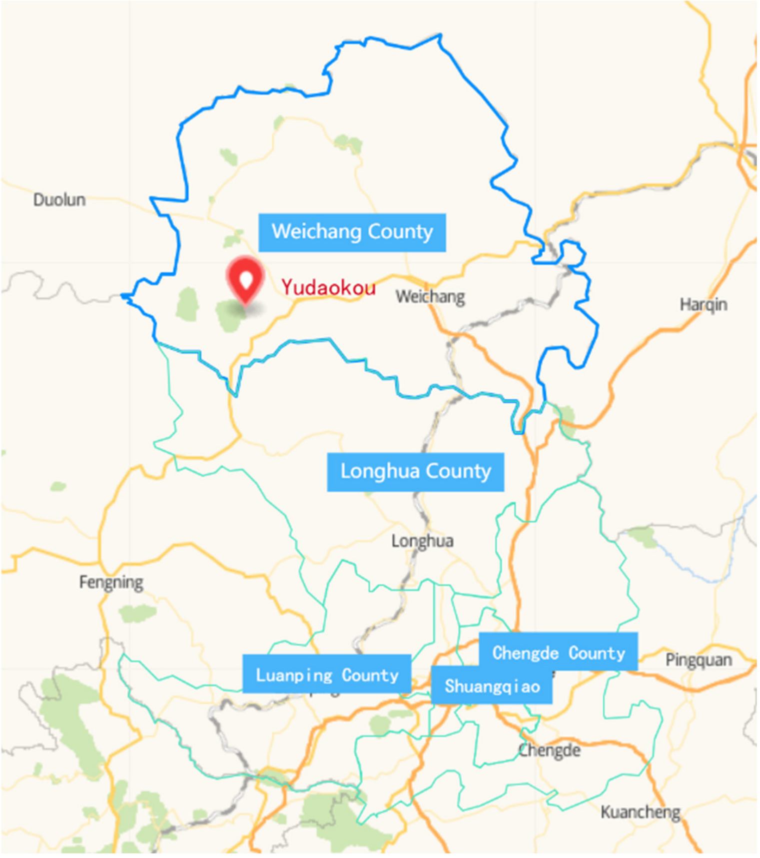
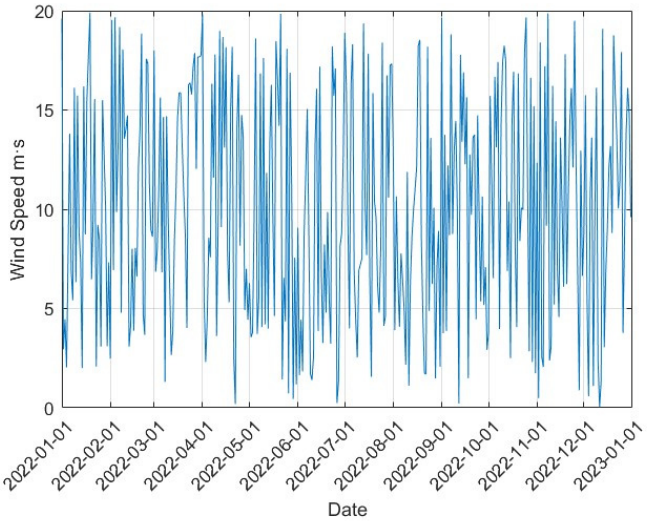
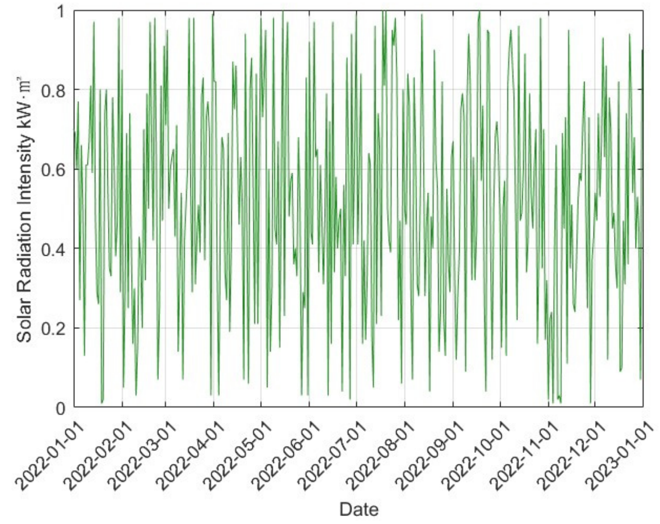


Figure 3. Geographical location of Yudaokou.

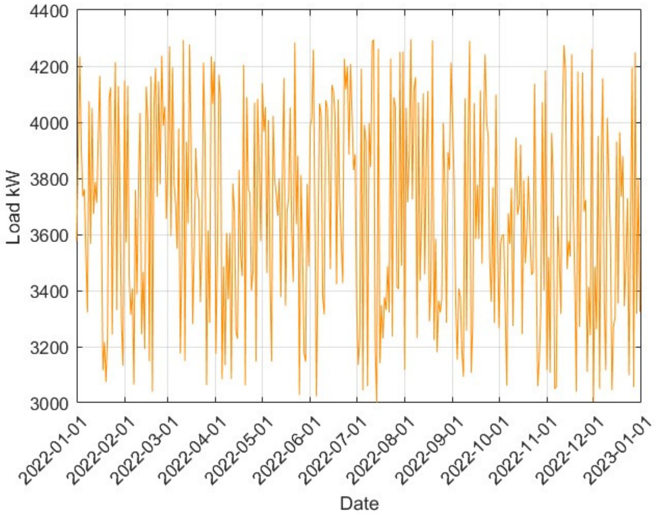


(**a**) Wind speed curve

Figure 4. *Cont.*



(**b**) Solar radiation intensity curve



(**c**) Load curve

Figure 4. Wind speed, solar radiation intensity, and load data curves.

Table 2. Distributed power supply equipment information.

Equipment	Construction Costs (USD/Group)	Operation and Maintenance Costs (USD/kw·h)
Photovoltaic	27,600	1.4×10^{-3}
Fan	41,400	4.1×10^{-3}
Small hydropower	414,000	3.59×10^{-2}
Energy storage	13,800	1.4×10^{-3}
Grid connected inverter	13,800	0

The reference to 'USD/group' in the table refers to the construction cost of each complete unit of equipment, rather than the cost of the individual components or parts of the equipment.

5.2. Optimization Results

Different objectives are considered in this study by constructing three scenarios including the cost-only [12] and user satisfaction-only [15] schemes commonly seen in current research.

Scheme 1: This cost-only scheme takes enterprise profits as the main starting point, and takes the lowest comprehensive cost of construction, operation, and maintenance of the rural microgrid enterprises as the planning objective, and reduces the construction and operation cost of the microgrids by reducing the number of equipment units, so as to control enterprise expenditures. At the same time, this scheme will also incorporate user satisfaction into the constraints to ensure that it can meet the most basic power requirements of users.

Scheme 2: This user satisfaction-only scheme takes the user as the main part, and takes maximizing user satisfaction as the main goal of rural microgrid construction. By increasing the amount of equipment to improve the reliability of the user's power consumption, it improves the user's satisfaction. At the same time, this scheme incorporates the construction, operation, and maintenance costs of the microgrid enterprises into the constraints to ensure that they are not beyond the affordability of the enterprises.

Scheme 3: This scheme considers the cost of enterprise construction, operation, and maintenance of the microgrids, as well as user satisfaction, ensuring that neither the construction and operation costs are too high nor that user satisfaction with electricity services is too low. This is achieved through the planning of rural microgrids using the two-tier planning model proposed in this paper.

The data from Yudaokou and the specified equipment parameters yield varied configuration outcomes, as delineated in Table 3. Observation reveals that Scheme 1 uses 15 sets of photovoltaic panels and 12 sets of wind turbines, marking it as the configuration with the fewest devices. While this scheme stands out for its cost-effectiveness, securing the lowest construction, operation, and maintenance costs, it unfortunately leads to diminished customer satisfaction. Such shortcomings could adversely affect rural activities, including livestock farming and electric heating, thereby hampering the cultivation of positive relations between companies and their users. The underlying cause of the diminished customer satisfaction likely stems from an insufficient number of photovoltaic panels and wind turbines to meet the peak demands during operation, thereby detracting from the users' electricity consumption experience.

Table 3. Optimization results of rural microgrids under different schemes.

Scheme	Photovoltaics/Group	Fan/Group	Small Hydropower/Group	Energy Storage/Group	Construction Cost (USD)	Operation Cost (USD)	Total Cost (USD)	User Satisfaction
1	15	12	1	11	5,187,822	4,236,198	9,424,020	0.83
2	19	18	1	15	6,343,729	4,741,811	11,085,540	0.99
3	17	12	1	15	5,793,297	4,306,923	10,100,220	0.90

Scheme 2 is characterized by the deployment of 19 PV sets and 18 wind turbines. The augmentation in the number of photovoltaic panels and wind turbines enhances the system's power supply capacity and reliability, thereby significantly elevating customer satisfaction. Although high customer satisfaction is assured, the utilization of additional and more expensive equipment incurs elevated construction, operation, and maintenance costs for the microgrid, potentially imposing a financial burden on the company. Consequently, opting for this solution presents a significant challenge for companies.

The rural microgrid construction plan delineated in this study, Scheme 3, thoughtfully balances business costs and customer satisfaction by using 17 PV sets and 12 wind turbines. Since the increase in customer satisfaction is smaller when the basic needs of the customer are met by additional equipment, a higher increase in customer satisfaction can be obtained by increasing the amount of equipment by a smaller number of units only. This design endeavors to achieve a harmonious equilibrium between cost efficiency and customer satisfaction, positioning it as a strategic compromise between Scheme 1 and Scheme 2. Most rural microgrids, in practice, are developed using schemes that prioritize minimizing the total cost to the enterprise [10,11]. However, the method proposed in this study considers both the enterprise costs and user satisfaction. Compared to the cost minimization strategy, two sets of photovoltaic and four sets of energy storage devices were added, the costs of construction increased by USD 605,475, resulting in an 8.4% increase in user satisfaction. The total cost increased from USD 9,424,020 to USD 10,100,220, an increase of 7.1%. On average, an increase of USD 96,600 can increase user satisfaction with electricity services by 0.01. Additionally, the utility value, defined as the ratio of user satisfaction to total cost, is significantly higher in the proposed scheme. This analysis suggests that, compared to the conventional rural microgrid construction schemes commonly implemented, the proposed model offers considerable improvements in balancing cost efficiencies and user satisfaction, potentially revolutionizing rural electrification strategies. While Scheme 3 may not reach the pinnacle of optimization in either domain, it offers a viable compromise that ensures a considerable degree of customer satisfaction. Despite not attaining optimal results in either aspect, Scheme 3 introduces a pragmatic compromise, facilitating enhanced customer satisfaction at a reduced investment cost for the enterprise. This approach bears significant implications for fostering positive enterprise–user relations and proves more apt for practical implementation. The convergence curve of the particle swarm algorithm is shown in Figure 5, and the calculated optimal value of the firm's cost is USD 10,100,220.

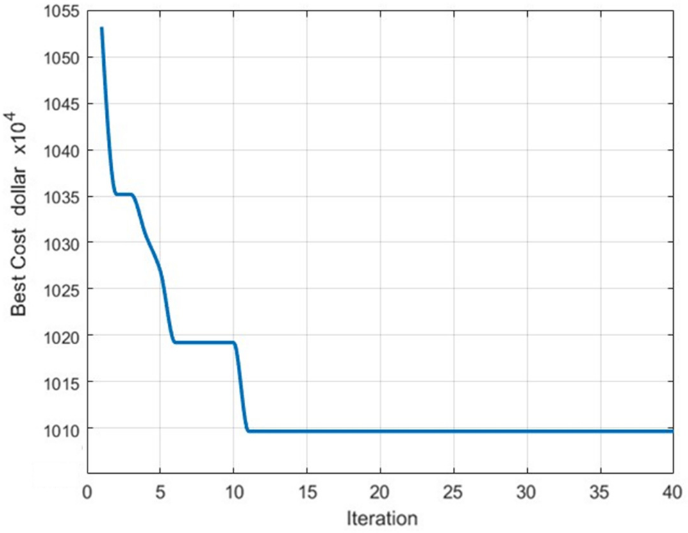


Figure 5. Iterative convergence curves for particle swarm optimization algorithms.

5.3. Parametric Analysis

(1) Anticipated construction costs

Projected construction expenses constitute a crucial component of the overall costs associated with rural microgrids, exerting a direct influence on both the feasibility and the detailed implementation strategies of such construction endeavors. The anticipated construction costs significantly dictate the volume of the equipment procured, and the scale of the microgrid, among other factors. Operating within a constrained budget may necessitate adjustments in the system's size or performance capabilities, thereby influencing the microgrid's actual efficacy. An accurately projected construction cost can optimize economic returns for the business while concurrently enhancing customer satisfaction with electricity consumption. Should the anticipated construction cost undergo alterations, the corresponding adjustments in microgrid construction schemes are illustrated in Table 4. An analysis of the three construction scenarios presented in Table 4 reveals that an increase in the anticipated construction costs correlates with simultaneous rises in both the total costs of rural microgrids and customer satisfaction. However, an analysis of the data in Table 4 indicates that the expected construction costs, total construction costs, and user satisfaction do not escalate in equal proportions, nor do they follow a linear progression. Further scrutiny of the construction scenarios in Scenario 2 and Scenario 3 reveals that even minor modifications to the expected construction costs can result in significant enhancements in user satisfaction. This implies that companies may avoid increasing the initial investment, which could adversely affect the financial sustainability of the project, without necessarily enhancing the customer's experience.

Table 4. Optimization configuration results under different anticipated construction costs.

Scheme	Anticipated Construction Cost (USD)	Photovoltaics/ Group	Fan/ Group	Small Hydropower/ Group	Energy Storage/ Group	Operation Cost (USD)	Total Cost (USD	User Satisfaction
1	4,444,738	12	14	1	11	4,178,882	8,623,620	0.80
2	5,614,406	16	15	1	13	4,150,474	9,764,880	0.89
3	5,187,822	15	12	1	11	4,236,198	9,424,020	0.83

The configuration of microgrids exhibits pronounced disparities across varying levels of the anticipated construction costs. Within the constrained budget scenarios, companies might gravitate towards more cost-effective yet lower-performing equipment. Such decisions could lead to a failure to meet user demands during peak periods, consequently affecting customer satisfaction adversely. Conversely, a more generous budget facilitates the incorporation of more efficient albeit costlier devices, thereby enhancing the system's overall efficiency and customer satisfaction, albeit at the expense of a higher total cost. Furthermore, these findings suggest that the relationship between customer satisfaction and escalating costs is not invariably linear. Beyond a specific cost threshold, further financial inputs may yield only marginal enhancements in satisfaction. This intimates the presence of an optimal cost nexus, beyond which the returns on investment progressively diminish.

(2) Customer satisfaction

The construction process for rural microgrids must also prioritize user satisfaction, given its significant impact on the requisite quantity of microgrid equipment. A paramount objective of rural microgrids is the provision of stable and dependable electrical power. Elevating investment in equipment can bolster the power supply's reliability through enhanced system redundancy and adaptability, among other strategies, culminating in heightened user satisfaction. Table 5 delineates the construction scenarios for the microgrids across different levels of user satisfaction. It is manifest that both the total construction costs and the quantity of equipment units within the rural microgrids escalate in correlation with increasing user satisfaction. However, an examination of the data in Table 5 on user satisfaction and total construction costs reveals that higher construction costs yield diminishing returns in terms of increased satisfaction with electricity services. This observation corroborates the existence of a rural microgrid construction strategy that can deliver a more satisfactory electrical service experience at a moderate total construction cost.

Table 5. Optimization configuration results of rural microgrids under different user satisfaction levels.

Scheme	User Satisfaction	Photovoltaics/ Group	Fan/ Group	Small Hydropower/ Group	Energy Storage /Group	Construction Cost (USD)	Operation Cost (USD)	Total Cost (USD)
1	0.70	10	12	1	11	3,811,742	4,059,778	7,871,520
2	0.90	17	12	1	15	6,343,729	4,741,811	10,100,220
3	0.80	12	14	1	11	4,444,738	4,178,882	8,623,620

The configuration schemes for equipment within rural microgrids demonstrate notable variations across differing anticipated levels of user satisfaction. Diminished user satisfaction precipitates a reduction in both the number of equipment units and the overall enterprise cost. However, this trade-off, balancing lower user satisfaction against reduced enterprise costs, may aggravate tensions between users and enterprises, undermining efforts to forge and nurture positive cooperative relationships.

A combination table is included in Table 6 to facilitate a comparative analysis and more intuitively observe variations in microgrid construction schemes under different parameter settings. From this analysis, it can be observed that the anticipated construction costs represent a pivotal factor for enterprises engaged in the development of rural microgrids. This cost directly influences the quantity of equipment to be deployed. The optimal configuration scheme endeavors to maximize customer satisfaction while remaining within the enterprise's financial constraints. Enterprises have the capability to enhance the electricity experiences of users by tailoring the rural microgrids' configuration scheme to the anticipated levels of user satisfaction. Consequently, variables, including the anticipated construction costs and customer satisfaction, significantly impact the rural microgrids' optimal configuration, necessitating enterprises to weigh both cost-effectiveness and user experience in their planning and decision-making processes to ascertain the most appropriate configuration under specific conditions.

Table 6. Optimization configuration results of rural microgrids under different objectives.

	Scheme	User Satisfaction	Photovoltaics/ Group	Fan/ Group	Small Hydropower/ Unit	Energy Storage /Group	Total Cost (USD)
Construction solutions in different schemes	1	0.70	10	12	1	11	7,871,520
	2	0.90	17	12	1	15	10,100,220
	3	0.80	12	14	1	11	8,623,620
Construction solutions under different anticipated construction costs	1	0.80	12	14	1	11	8,623,620
	2	0.89	16	15	1	13	9,764,880
	3	0.83	15	12	1	11	9,424,020
Construction solutions under different user satisfaction	1	0.70	10	12	1	11	7,871,520
	2	0.90	17	12	1	15	10,100,220
	3	0.80	12	14	1	11	8,623,620

6. Conclusions

A two-tier planning model is proposed to address the insufficient consideration of users' electricity experiences in rural microgrid construction. This model focuses on both comprehensive costs and user satisfaction. The proposed scheme minimizes enterprise costs while maximizing user satisfaction, effectively resolving the conflict between these two factors in microgrid construction. The model takes the minimum enterprise comprehensive cost as the upper objective function, considers the microgrid construction, operation, maintenance, and power abandonment costs, and reasonably plans the microgrid scale, equipment configuration, and operation and maintenance strategies; using the user's satisfaction with electricity services as the lower objective function, considers reliability and the economy, improves the user's quality of life and electricity experience, and puts forward the configuration scheme of the rural microgrid through the case study. The findings indicate that enhancements in construction costs frequently correlate with improvements in customer satisfaction with electricity services, consistent with prior scholarly work. However, these variables do not change proportionately or follow a linear relationship. In contrast to the cost-only and user satisfaction-only schemes, the scheme proposed in this study, which balances the costs and satisfaction, increased both the construction and operation costs by adding two photovoltaic groups and four energy storage groups compared to the original scheme, which increased the total cost by 7.1%, but customer satisfaction with electricity services increased by 8.4%. The final construction cost was USD 5,793,297 and the operation cost was USD 4,306,923 for a total cost of USD 10,100,220, demonstrating its high utility value. This approach effectively resolves the tension between enterprise costs and customer satisfaction, achieving a better balance of the objectives for both enterprises and users. Furthermore, this study examines the impacts of expected construction costs and user satisfaction on the optimal allocation outcomes of rural microgrids, offering crucial insights for future microgrid developments. Currently, this study used the case of Yudaokou for a simulation analysis. Although the area has typical wind and solar resources, it cannot represent all rural microgrids. The differences in resources and electricity demands in different geographical regions may lead to a decrease in the applicability of these results. Therefore, the promotion and application of these research results in other regions or countries may be limited, and this research focuses solely on general rural microgrid construction scenarios. Future efforts will aim to design and implement rural microgrids tailored to the unique requirements of AC/DC hybrid systems.

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