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Multi-Objective Interval Planning for 5G Base Station Virtual Power Plants Considering the Consumption of Photovoltaic and Communication Flexibility



Abstract: - This article proposes a multi-objective interval collaborative planning method for virtual power plants and distribution networks. On the basis of in-depth analysis of the operational characteristics and communication load transmission characteristics of the base station, a virtual power plant 5G base station participating in the cellular respiration demand response model was constructed. A multi-objective interval optimization model for collaborative planning of virtual power plants and distribution networks has been established. The calculation results have verified the effectiveness of the method.

Keywords: cellular base stations; virtual power plants; distribution networks; electric power system planning; communication flexibility; multi-objective interval optimization

1 INTRODUCTION

With the rapid rise of 5G digitization and its applications, as the core infrastructure connecting communication users and radio access networks, the construction scale of 5G base stations shows explosive growth. In order to support the large-scale grid connection of 5G base stations, related scholars have conducted a lot of research on 5G base station issues.

As an emerging load, 5G base stations belong to typical distributed resources [1], which have attracted widespread attention from scholars both domestically and internationally, and have achieved some research results. For example, reference [2] proposed a cost optimization model for base station clusters; Reference [3] comprehensively considers waste heat utilization, base station sleep, and "water/energy production and sales"; [4] A method for analyzing the energy storage potential of 5G base station scheduling considering communication load has been proposed. However, the above research on the participation of 5G base station flexibility in power grid interaction still has the following shortcomings: the above research only considers a part of base station flexibility, and does not fully consider the impact of various uncertainty factors on system decision-making. At the same time, there is no research on the changes in renewable energy consumption levels after station load is connected to VPP.

Most existing uncertainty studies use stochastic optimization or robust optimization to handle uncertainty. For example, reference [5] proposes a two-stage robust model for active distribution networks. However, stochastic optimization relies on a large amount of reliable historical data, and its applicability is low due to the difficulty in obtaining accurate data on communication users, power loads, and renewable energy output [6]. Robust optimization usually only considers the worst-case scenario of achieving system objectives, resulting in overly

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conservative results. Therefore, the above methods cannot meet the needs of collaborative decision-making between 5G base stations and distributed networks well.

Therefore, this article proposes a multi-objective interval cooperation model for virtual power plants and distribution networks that takes into account the flexibility of 5G base station communication. Firstly, an in-depth analysis was conducted on the interaction mechanism between virtual power plants and distribution networks, and a 5G base station demand response model was established. Then, considering the configuration of 5G base station equipment and the selection of access nodes during the operation phase of the virtual power plant, as well as the expansion of the distribution network capacity, the interval method is adopted to handle uncertain factors such as communication loads, achieving coordinated convergence of system economic and environmental goals.

2 5G BASE STATION MODELING IN VIRTUAL POWER PLANTS

2.1 Energy domain constraint

The energy domain constraints primarily characterize the power consumption characteristics of various devices in 5G base stations during the transmission of communication data.

$$P_{j,t}^{BS} = P_{j,t}^{out} + P_{j,t}^{fixed}, \quad \forall j \in \Omega^{BS}, t \in \Omega^T \quad (1)$$

$$P_{j,t}^{out} = I_{j,t}(P^0 + \Delta p P_{j,t}^{TR}) + (1 - I_{j,t})P^{sleep}, \quad \forall j \in \Omega^{BS}, t \in \Omega^T \quad (2)$$

$$P_{j,t}^{TR} = (1 - p^{OH}) \frac{P^{TRmax}}{b^{max}} b_{j,t}^{tr} + p^{OH} P^{TRmax} k, \quad \forall j \in \Omega^{BS}, t \in \Omega^T \quad (3)$$

In the Formula: $j(\Omega^{BS})$ —5G base station collection; $t(\Omega^T)$ —Interval set; $P_{j,t}^{BS}$ —Total power consumption of base station j , kW; $P_{j,t}^{out}$ —Dynamic power consumption, kW; $P_{j,t}^{fixed}$ —Static power consumption, kW; P^0 —No-load power consumption, kW; P^{sleep} —Sleep power consumption, kW; $P_{j,t}^{TR}$ —The transceiver transmits power, kW; P^{TRmax} —Maximum transmission power consumption, kW; Δp —The slope of the transceiver in relation to the dynamic power consumption of the load; $I_{j,t}$ —0-1 variable of the transceiver operating state; p^{OH} —The proportion of a fixed signaling signal to the transmitted power; b^{max} —Maximum bandwidth utilization of the transceiver, MHz; $b_{j,t}^{tr}$ —Transceiver bandwidth usage, MHz; k —Weighting factor^[19].

2.2 Communication domain constraint

The communication domain constraint primarily characterizes the dynamic changes in the communication operation and the connection relationship of users in 5G base stations, aiming to ensure the normal operation of the 5G base stations in the area and meet the data demands of the communication end-users.

$$\sum_{j \in \Omega^{BS}} x_{j,m,t} = 1, \forall m \in \Omega^{User}, t \in \Omega^T \quad (4)$$

$$\varphi_{j,m,t} = \frac{g_{j,m} P_{j,t}^{TR}}{\sigma^2}, \forall j \in \Omega^{BS}, m \in \Omega^{User}, t \in \Omega^T \quad (5)$$

$$g_{j,m} = \begin{cases} A(l_{j,m}/l_0)^{-\eta}, & l_{j,m} \geq l_0, \\ A, & 0 \leq l_{j,m} \leq l_0, \end{cases} \forall j \in \Omega^{BS}, m \in \Omega^{User} \quad (6)$$

$$R_{j,m,t} = B_{j,m,t} \log_2(1 + \varphi_{j,m,t}), \forall j \in \Omega^{BS}, m \in \Omega^{User}, t \in \Omega^T \quad (7)$$

$$R_{j,m,t} \geq R_{m,t}^{req} x_{j,m,t}, \forall j \in \Omega^{BS}, m \in \Omega^{User}, t \in \Omega^T \quad (8)$$

In the Formula: $m \in \Omega^{User}$ —Communication user set; $x_{j,m,t}$ —The connection between the base station and the user; $\varphi_{j,m,t}$ —Signal-to-noise ratio, dB; $g_{j,m}$ —The channel gain between base station j and user m , dB; σ^2 —Noise power, kW; A —Channel gain fixed loss. $0 \leq B_{j,m,t} \leq x_{j,m,t} b^{\max}, \forall j \in \Omega^{BS}, m \in \Omega^{User}, t \in \Omega^T$ (9)

$$\sum_{m \in \Omega^{User}} x_{j,m,t} B_{j,m,t} \leq b^{\max}, \forall j \in \Omega^{BS}, t \in \Omega^T \quad (10)$$

$$b_{j,t}^{tr} = \sum_{m \in \Omega^{User}} B_{j,m,t}, \forall j \in \Omega^{BS}, t \in \Omega^T \quad (11)$$

$$L_j = \frac{\sum_{m \in \Omega^{User}} x_{j,m,t} B_{j,m,t}}{b^{\max}} \leq A_T, \forall j \in \Omega^{BS}, t \in \Omega^T \quad (12)$$

In the Formula: A_T —the bandwidth utilization limit of the load distribution that the base station can perform. Base stations select base stations that have high load rates but still have enough resources to access new users for load transfer.

3 COLLABORATIVE MODEL FOR VIRTUAL POWER PLANTS AND DISTRIBUTION NETWORKS WITH 5G BASE STATIONS

This paper considers the collaboration of distribution network and virtual power plant, aiming at the optimal economic and environmental benefits respectively, that is, the lowest carbon emissions, and builds a multi-objective interval optimization model.

Objective function 1: The operating cost of facilities including distribution network, distributed power supply, virtual power plants and RC are minimum, that is:

$$\min y_1 = C^{OPT} - E^{OPT} \quad (13)$$

In the Formula: C^{OPT} —Annual operating cost of the system, Ten thousand yuan. E^{OPT} —Annual operating revenue of the system, Ten thousand yuan. System operation cost includes 5G base station maintenance and operation cost in virtual power plants, fuel cost of diesel generator set, main network power purchase cost, and optical abandonment cost. The expression is as follows:

$$C^{OPT} = \tau \sum_{j \in \Omega^{BS}} \sum_{t \in \Omega^T} c^{BS-opt} P_{j,t}^{BS} \Delta t + \tau \sum_{j \in \Omega^{BS}} \sum_{t \in \Omega^T} c^{Gen} P_{j,t}^{Gen} \Delta t + \tau \sum_{t \in \Omega^T} c_t^e P_t^{Grid} \Delta t + \tau \sum_{i \in \Omega^{PV}} c^{aban} (P_{i,t}^w - P_{i,t}^{PV}) \Delta t \quad (14)$$

In the Formula: τ —Days of the year; Ω^T —Interval set; c^{BS-opt} —Base station communication equipment maintenance costs, Ten thousand yuan /kW; c_t^e —Electricity purchase price from the main network, RMB/kW; c_t^{Gen} —Diesel generator electricity price, RMB/kW; c^{aban} —Abandonment of light punishment factor; Δt —The duration of a single session, Take 1h; $P_{j,t}^{BS}$ —Base station j power consumption, kW; P_t^{Grid} —Purchase electricity from the main network, kW; P_t^{Gen} —The amount of electricity generated by a diesel generator, kW; $\tilde{P}_{i,t}^w$ —Predicted value of photovoltaic cell output, $P_{i,t}^w = [P_{i,t}^w, \bar{P}_{i,t}^w]$, kW; $P_{i,t}^{PV}$ —Active power output of photovoltaic cells, kW.

Objective function 2: minimum system carbon emission.

$$\min y_2 = \tau \omega f \sum_{t \in \Omega^T} P_t^{Grid} \Delta t \quad (15)$$

In the Formula: ω —Carbon emissions corresponding to power generation per unit of coal consumption; f —Coal consumption coefficient corresponding to unit power generation in external power grid, kg/kW.

4 SOLUTION PROCESS

In this paper, combined with the model interval deterministic transformation, the proposed multi-objective interval

optimization model was solved using the non-dominated sorting genetic (NSGA-II) algorithm^[7]. The overall solution process is shown in Fig. 2.

The main steps are as follows:

- 1) Initialize the data. Parameters such as population size N , crossover probability a_1 , mutation probability a_2 and iteration number ν were set to read the basic data of the model.
- 2) Generate initial population. Randomly generate N individuals as population P_0 .
- 3) Deterministic transformation. The upper and lower limits of the interval affected by uncertain factors are calculated, and the objective function and constraint conditions are transformed by the interval order relation and the interval possibility.
- 4) The population was selected, crossed and mutated.
- 5) Population fitness calculation. A new generation of population was formed by using non-dominant ordering and crowding distance calculation.
- 6) Convergence condition determination. If the number of iterations meets the set value, the process is terminated and Pareto frontier set is output. Otherwise, increase the number of iterations by 1 and return to step 3).

5 EXAMPLE ANALYSIS

To validate the effectiveness of the proposed method in this paper, a simulation analysis is conducted using the modified IEEE-33 node distribution system^[8] as an example. The distribution network structure and the spatial distribution of communication loads are shown in Fig 1. This system consists of 33 nodes, 32 lines, and operates at a voltage level of 12.66 kV.

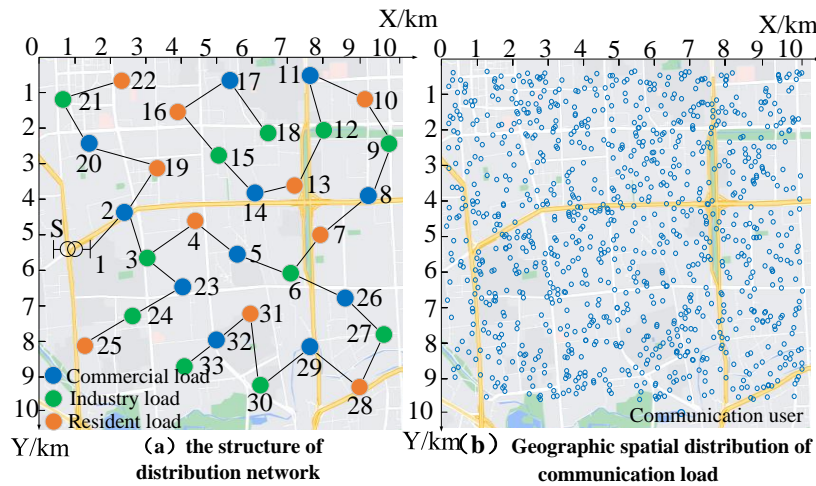


Fig 1: Simulation system architecture (a)Distribution network structure (b)Communication load distribution

It is assumed that the load types in this distribution network can be categorized as commercial load, residential load, and industrial load. The forecast errors for electric load, communication load, and photovoltaic (PV) output are assumed to be 15%, 15%, and 20% of their respective forecast values. The daily output prediction curve for PV cells can be found in reference [9].

By adopting the method described to handle uncertain factors and using the NSGA-II algorithm to solve the multi-objective optimization model that incorporates economic and environmental benefits, the resulting Pareto optimal solution set is shown in Fig. 2.

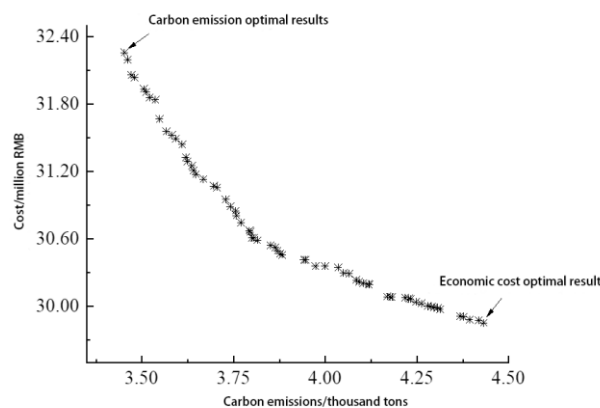


Fig 2: Pareto frontier set

From the above figure, it can be seen that the obtained Pareto front solution set covers a wide range and is evenly distributed, ensuring the diversity of optimal solutions. This can effectively guide the formulation of collaborative strategies for 5G base stations and distribution networks.

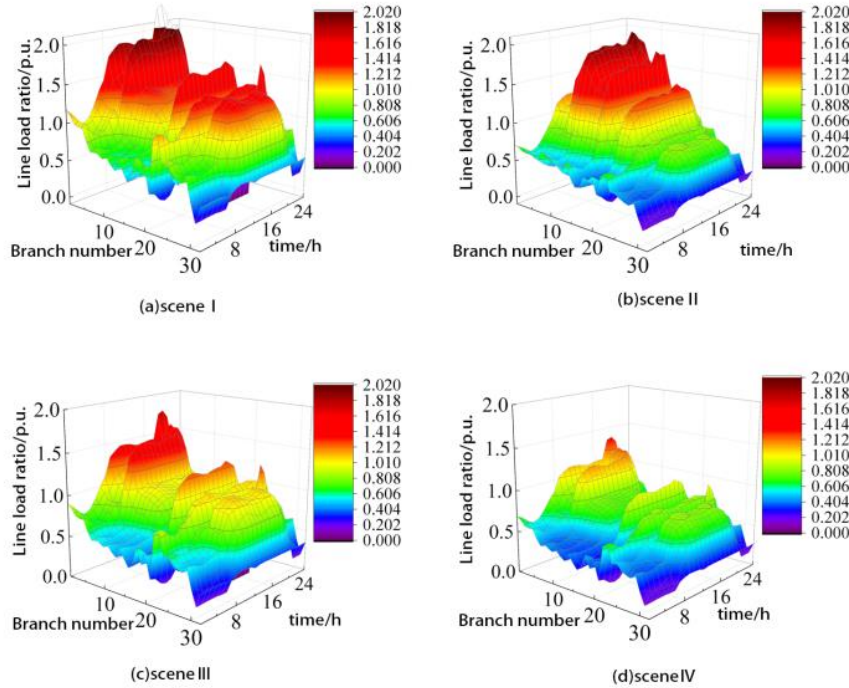


Fig. 3: Line carrying capacity under different cases

According to Fig. 3, lines 6-10, 12, and 14 experience severe line overload. The uncoordinated 5G base stations leads to congestion and blockage in certain sections of the distribution network. The bandwidth utilization before and after the implementation of flexible bandwidth allocation for base stations at 11:00 and 21:00 is shown in Fig. 4. Load types 1, 2, and 3 correspond to commercial load, residential load, and industrial load, respectively. It can be observed that during the peak solar energy generation at 12:00, the overall bandwidth utilization of the base stations shows a decreasing trend. At 21:00, when there is no solar power generation, the base stations adjust their bandwidth to reduce power consumption and minimize electricity purchases from the main grid.

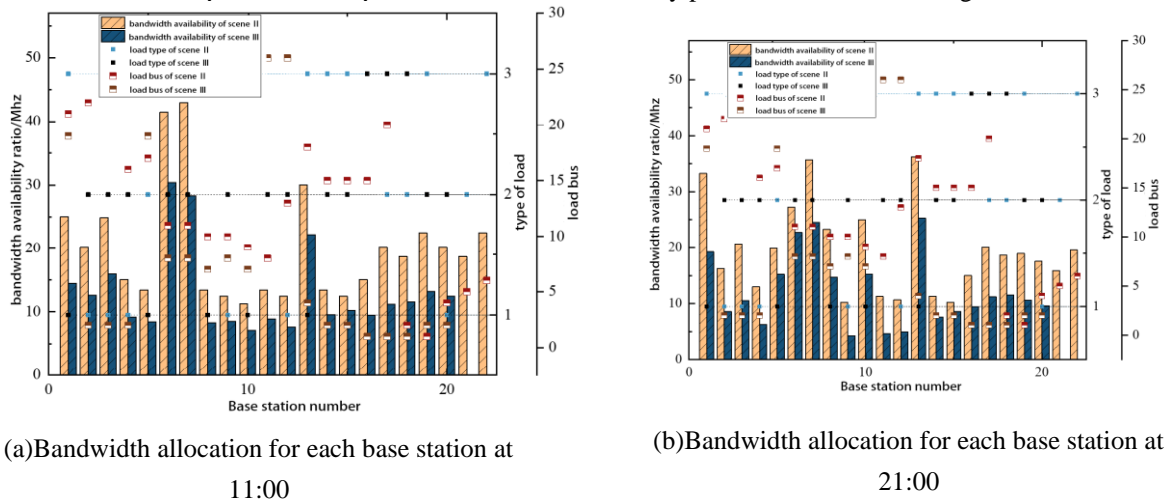


Fig. 4: Bandwidth allocation of each base station at a typical time

6 CONCLUSION

Based on the perspective of power communication coupling, a multi-objective collaboration model considering communication flexibility between virtual power plants, 5G base stations, and distribution networks was established. The interval method was used to analyze and handle uncertain factors. The main conclusions are as follows:

The multi-objective collaboration model between virtual power plants and distribution networks proposed in this article can effectively promote the coordinated development of power communication systems and fully tap into the communication flexibility of 5G base stations; The demand response potential for developing 5G base stations is influenced by both the individual base station level and the base station group level; Interval optimization methods can effectively handle the uncertainty of communication and power loads in collaborative planning, adapting to the subjective preferences of different users.

Author Contributions: The authors confirm contribution to the paper as follows: study conception and design: Dawei Zhang, Xvdong Cui; data collection: Changbao Xv, Shigao Lv; analysis and interpretation of results: Dawei Zhang, Lianhe Zhao; draft manuscript preparation: Dawei Zhang. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study”.

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