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## Interval-Based Multi-Objective optimization for communication Base Stations allocation in Virtual Power System



**Abstract:** - This article introduces a multi-objective interval-based collaborative planning approach for virtual power plants and distribution networks. After thoroughly analyzing the operational dynamics and communication load transmission characteristics of 5G base stations, a demand response model involving virtual power plants and 5G base stations in the cellular respiration process was developed. A multi-objective interval optimization model was then formulated for the joint planning of virtual power plants and distribution networks. The results of the calculations confirm the method's effectiveness.

**Keywords:** virtual power plants; distribution networks; planning; communication flexibility; multi-objective interval optimization

### 1 INTRODUCTION

As 5G digitization and its applications rapidly expand, the construction of 5G base stations, is experiencing unprecedented growth. To facilitate the extensive grid integration, numerous studies have been carried out on related issues. As a novel type, base stations of 5G are considered standard dispersed assets [1], gaining considerable attention from both domestic and international scholars, leading to several research findings. For instance, reference [2] introduced a cost optimization model for base station clusters; reference [3] explored aspects like waste heat utilization, base station sleep, and "water/energy production and sales"; and reference [4] suggested an approach for analyzing the energy storage possible of 5G base station allocation while considering communication load. However, these studies regarding the involvement of 5G base station adaptability in power grid interactions remains exhibit certain limitations: they primarily focus on partial aspects of base station flexibility and do not fully account for the impact of various uncertainties on system decision-making. Additionally, there is a lack of research on the changes in renewable energy consumption levels after integrating station loads into virtual power plants (VPP).

Many current research on uncertainty utilize random or resilient optimization methods. For instance, reference [5] presents a two-stage robust model for dynamic distribution networks. However, stochastic optimization depends heavily on extensive and reliable historical data, and its effectiveness is limited by the challenges in accurately obtaining data related to communication users, power loads, and renewable energy output [6]. On the other hand, robust optimization typically focuses only on worst-case scenarios when aiming to meet system objectives, leading to results that are often too conservative. As a result, these approaches are not well-suited for the collaborative decision-making required between distributed networks and 5G base stations.

In response to these challenges, this article introduces a multi-objective interval cooperation framework for distribution networks and virtual power plants, incorporating the flexibility of 5G base station communication. The model begins with a thorough analysis of the interaction mechanisms between distribution networks and virtual power plants, followed by the establishment of a demand response model for 5G base stations. Subsequently, the model addresses uncertainties by employing the interval method, considering factors such as the configuration of 5G base station equipment, the selection of access nodes during the operation phase of the virtual power plant, and the expansion of distribution network capacity. This approach aims to achieve a coordinated balance between economic and environmental objectives.

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## 2 5G BASE STATION MODELING IN VIRTUAL POWER PLANTS

### 2.1 Energy sector limitation

The constraints in the energy field mainly describe the power consumption patterns of various devices within 5G base stations throughout the transmission.

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

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

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

In the given formula, the set of 5G base stations is denoted by  $j(\Omega^{BS})$ ; the collection of time intervals is represented  $t(\Omega^T)$ . The total power consumption for base station  $j$  at time  $t$  is indicated by  $P_{j,t}^{BS}$ , measured in kilowatts (kW). The variable power consumption, which changes with the load, is  $P_{j,t}^{out}$ , also in kW. The constant or static power draw, regardless of activity, is  $P_{j,t}^{fixed}$ , in kW. The power consumption when the system is idle or without traffic is  $P^0$ , in kW. The power used when the base station is in sleep mode to conserve energy is  $P^{sleep}$ , in kW. The power transmitted by the transceiver of base station  $j$  at time  $t$  is  $P_{j,t}^{TR}$ , in kW, with  $P^{TRmax}$  being the maximum possible transmission power consumption by the transceiver, in kW. The rate at which the transceiver's power consumption changes with the dynamic load is given by the slope  $\Delta p$ . The operating state of the transceiver is represented by the binary variable  $I_{j,t}$  which is either 0 (off) or 1 (on). The ratio of the fixed overhead signaling power to the transmitted power is denoted by  $p^{OH}$ . The maximum bandwidth utilization capacity of the transceiver is  $b_{max}$ , in megahertz (MHz), and the actual bandwidth usage is represented by  $b_{j,t}^{tr}$ , with  $k$  being a weighting factor introduced for proportional adjustments [7].

### 2.2 Communication field constraint

To ensure the normal operation of 5G base stations and satisfy the data needs of end-users, the communication field constraint focuses on the adaptive variations in telecommunications operations and the connectivity within these stations.

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

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

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

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

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

Within the formula presented, the collection of communication users is represented by  $m(\Omega^{User})$ . The connectivity status between the base station  $j$  and user  $m$  at time  $t$  is denoted by  $x_{j,m,t}$ , The signal-to-noise ratio (SNR) experienced by the user at the base station is given by  $\varphi_{j,m,t}$ , measured in decibels (dB). The channel gain from base station  $j$  to user  $m$  is expressed as  $g_{j,m}$ , also in dB. The power of the background noise impacting the signal

is quantified by  $\sigma^2$ , with the unit being kilowatts (kW). Lastly,  $A$  signifies the fixed loss in channel gain that is consistently present during transmission.

$$0 \leq B_{j,m,t} \leq x_{j,m,t} b^{\max}, \forall j \in \Omega^{\text{BS}}, m \in \Omega^{\text{User}}, t \in \Omega^{\text{T}} \quad (9)$$

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

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

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

Within the equation,  $A_T$  represents the maximum capacity of bandwidth that a base station can allocate for traffic distribution. The objective is for base stations to identify peers with a high traffic load yet possessing surplus capacity to accommodate additional users, thereby facilitating the offloading of traffic.

### 3 INTEGRATED MODEL FOR VIRTUAL POWER PLANTS DISTRIBUTION NETWORKS AND 5G BASE STATIONS

This study focuses on the collaboration between the virtual power plant and distribution network, with the goal of optimizing both economic and environmental benefits, particularly minimizing carbon emissions. To achieve this, a multi-objective interval optimization framework is developed.

Objective function 1: Minimize the operating costs associated with facilities such as the virtual power plants, distributed energy resources, distribution network, and RC, expressed as:

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

Within the equation,  $C^{\text{OPT}}$  refers to the yearly operational expenses of the system, valued in ten thousand yuan. This includes the maintenance and operational costs for 5G base stations in virtual power plants, the fuel expenses for diesel generator sets, the cost of purchasing power from the main grid, and the costs associated with energy that is not utilized, such as through optical power. The annual operational revenue of the system is denoted by  $E^{\text{OPT}}$ , also in ten thousand yuan. This revenue accounts for the earnings derived from the system's operations, including profits from the 5G infrastructure services and other related operational activities. The formula for calculating the system's operational cost is presented as follows:

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

Within the formula, " $\tau$ " symbolizes the complete tally of days encompassing a year. The set  $\Omega^{\text{T}}$  encapsulates a series of discrete intervals. The variable  $c^{\text{BS-opt}}$  signifies the maintenance costs for base station communication equipment, priced in ten thousand yuan per kilowatt (kW). The electricity procurement cost from the main grid is indicated by  $c_t^e$ , in yuan per kilowatt (RMB/kW). The cost for electricity generated by diesel generators is expressed by  $c_t^{\text{Gen}}$ , also in yuan per kilowatt (RMB/kW). The  $c^{\text{aban}}$  factor accounts for the penalty associated with the abandonment of light, serving as a punitive measure.

The duration of each time session is represented by  $\Delta t$ , which is considered to be one hour. The power consumption of base station  $j$  is denoted by  $P_{j,t}^{\text{BS}}$  measured in kilowatts (kW). The electricity purchased from the main grid is represented by  $P_t^{\text{Grid}}$ , in kilowatts (kW), while the electricity generated by a diesel generator is given by  $P_t^{\text{Gen}}$ , in the same unit. The predicted output of the photovoltaic cells is indicated by  $\tilde{P}_{i,t}^{\text{w}}$ , in kilowatts (kW). Lastly, the

active power output from the photovoltaic cells is denoted by  $\tilde{P}_{i,t}^w = [P_{i,t}^w, \bar{P}_{i,t}^w], kW; P_{i,t}^{PV}$  also measured in kilowatts (kW).

Objective function 2: minimizing system carbon emissions.

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

Within the equation, the symbol  $\omega$  denotes the quantity of carbon emissions that are emitted per unit of coal burned for electricity generation. The term  $f$  represents the rate of coal usage required to produce a unit of electricity in the external power grid, measured in kilograms per kilowatt (kg/kW).

#### 4 SOLUTION PROCESS

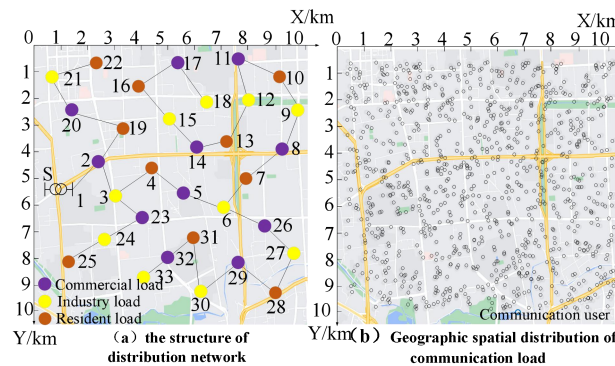
In this study, we employed the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to tackle the multi-objective interval optimization problem using a certain transformation model interval. The overall methodology is illustrated in Figure 2.

The process involves the following key steps:

- 1) Data Initialization: Set up variables such as group size NNN, recombination likelihood  $a1a_1a1$ , mutation chance  $a2a_2a2$ , and the quantity of iterations vvv, and prepare the model's basic data.
- 2) Initial Population Generation: Create the initial population P0P\_0P0 by randomly generating NNN individuals.
- 3) Deterministic Transformation: Compute the upper and lower bounds of the intervals influenced due to unpredictable factors. Transform the objective functions and constraints based on interval order relations and interval possibility measures.
- 4) Selection, Crossover, and Mutation: Apply selection, crossover, and mutation operations to the population.
- 5) Fitness Evaluation: Assess the fitness of the new generation using non-dominant sorting and crowding distance measures to form the next generation of the population.
- 6) Convergence Check: Determine if the algorithm has reached the specified number of iterations. If not, increment the iteration count by 1 and return to step 3. If the iteration limit is reached, output the Pareto front.

#### 5 EXAMPLE ANALYSIS

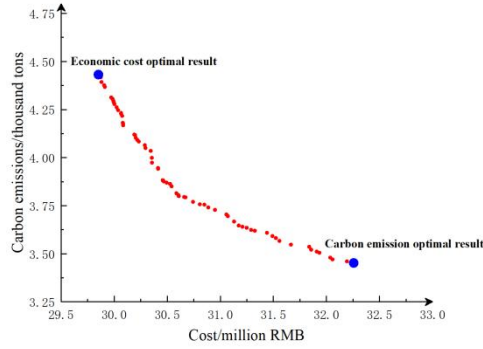
To assess the effectiveness of the proposed method, a simulation analysis was performed using the adapted [8] as a case study. The distribution network configuration and the layout of the communication loads are depicted in Figure 1. This system features 33 nodes, 32 connecting lines, and operates at a nominal voltage of 12.66 kV.



**Fig 1:** Simulation system architecture (a) Distribution network topology (b) Communication load layout

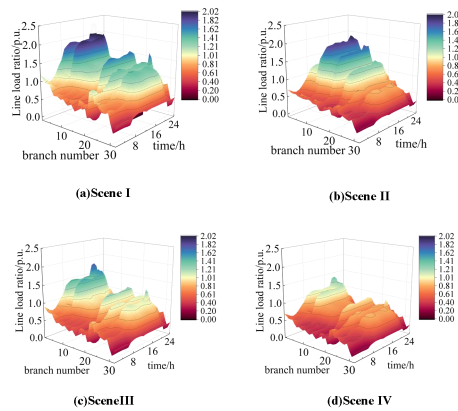
In this analysis, the distribution network's loads are categorized into commercial, residential, and industrial types. It is assumed that forecast errors are 15% for electrical and communication loads, and 20% for photovoltaic (PV) outputs. The daily production forecast for solar panels is detailed in reference [9].

By applying the proposed approach to manage these uncertainties and employing the NSGA-II to address the optimization model, which considers both economic and environmental factors, the Pareto optimal solutions obtained are illustrated in Figure 2.



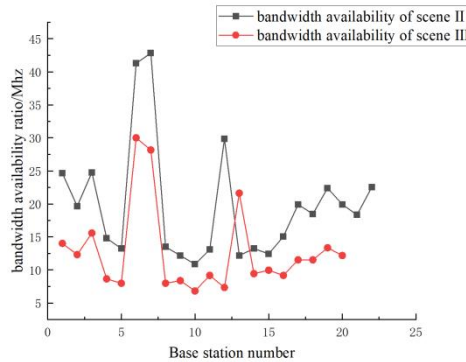
**Fig 2: Pareto frontier set**

The Pareto front shown in the figure demonstrates a broad and well-distributed range of solutions, reflecting a diverse set of optimal outcomes. This comprehensive distribution is advantageous for developing collaborative approaches between distribution networks and 5G base stations.

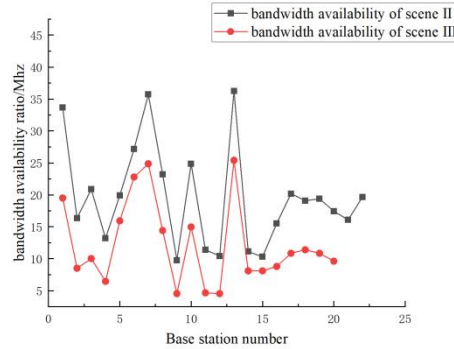


**Fig. 3: Transmission line capacity in various scenarios**

Figure 3 indicates that lines 6-10, 12, and 14 are experiencing significant overload issues. This overload is attributed to the uncoordinated operation of 5G base stations, which causes bottlenecks in certain segments. Figure 4 illustrates the data throughput utilization prior to and following implementing adaptive bandwidth distribution for the base stations at 11:00 and 21:00. The load types are categorized as follows: Type 1 for commercial loads, Type 2 for residential loads, and Type 3 for industrial loads. Notably, during maximum solar energy output production at 12:00, the total bandwidth utilization by base stations tends to decrease. Conversely, at 21:00, when solar power production is absent, the base stations modulate their bandwidth to reduce power consumption and reduce reliance on the main grid.



(a) The distribution of data transmission capacity at the 11:00 hour for each base station.



(b) The distribution of data transmission capacity at the 21:00 hour for each base station.

**Fig. 4:** Typical time Bandwidth allocation of each base station

## 6 CONCLUSION

From the perspective of power communication integration, a multi-objective collaboration model was developed, addressing the interplay between virtual power plants, distribution networks, and 5G base stations with an emphasis on communication flexibility. The model employs interval methods to manage and analyze uncertainties. The key findings are outlined below:

The proposed multi-objective collaboration model enhances the harmonized advancement of energy resources and communication systems and leverages the communication flexibility of 5G base stations effectively.

The possible for demand response in the context of 5G base stations is influenced by factors at both the aggregate level of base station groups and the individual base station level.

Interval optimization techniques prove effective in managing uncertainties related to communication and power loads in collaborative planning, accommodating diverse user preferences.

**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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