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Research on Active Distribution Network User-side Resource Mining and Scheduling Optimization Methods

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Abstract: The installed capacity and electricity production from renewable energy sources, including wind power and photovoltaics, have been consistently rising, facilitating the ecological transformation of the energy framework. Nonetheless, the unpredictability and variability of renewable energy sources provide problems to the power system, necessitating the evolution of the contemporary power system into a smart and efficient framework to harness the potential of demand-side resources. This study focuses on the load of electric vehicles (EVs) and analyzes their usage and charging habits through surveys. A demand response model that takes into account users' travel and battery degradation is established. This model aims to reduce the grid peak-to-valley difference, improve system stability, and reduce operating costs. Meanwhile, this paper also pays attention to electric vehicle aggregators and establishes a demand response model to refine the charging power curve, maximizing their interests. The results show that electric vehicles, as a high-quality demand response resource, can effectively promote the stability of the power system and the consumption of renewable energy. Electric vehicle aggregators can also obtain greater benefits by optimizing their scheduling, providing users with higher-quality demand response services.

Keywords: Demand response, Electric vehicl, Optimized scheduling

1. Introduction

According to *Renewables 2024* published by the International Energy Agency (IEA), by 2030, global renewable energy capacity is expected to exceed the current targets set by various countries by about 25%. The main driver of this growth in global renewable energy capacity is China [1]. With enhanced power demand-side management and improved end-use electricity efficiency, controllable resources on the demand side, like those on the supply side, have become dispatchable resources in power system planning and operation. This aims to equilibrate the variability of wind and solar generation on the supply side with the unpredictable nature of demand, referred to as demand response. Nevertheless, numerous unexploited potential resources in demand response remain, and an authorized uniform classification system is currently absent. In terms of active distribution network scheduling, dispersed demand-side resources find it difficult to participate directly in grid control. To facilitate the integration of demand-side resources into electricity market transactions and power system planning, it is necessary to aggregate and regulate them. For resource exploration, this study focuses on electric vehicles (EVs) and storage modules. In terms of scheduling optimization, the study focuses on electric vehicle aggregators. Meeting user demands for electric vehicle travel while

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scheduling demand-side resources like electric vehicles plays a significant role in peak shaving, stable operation of the power system, and the integration of new energy sources.

2. Literature review

Scholars around the world have conducted extensive research on establishing mechanisms for demand response potential assessment. On a macro level, from 2006 to 2022, studies by the U.S. Federal Energy Regulatory Commission indicated that the available demand response potential in the U.S. steadily increased from 2006 to 2016 but has slightly decreased since 2017. The reasons for this fluctuation are diverse, with demand response policies being a key factor. From a micro perspective, Ye Ersen Sai Like et al. focused on developing an integrated probability prediction model for the potential of demand response by load aggregators, which demonstrated better prediction accuracy and generalizability than single prediction models [2].

Upon user confirmation of involvement in demand response, demand-side controllable resources may be scheduled to fulfill diverse requirements. Yuhao Ding et al. suggested a day-ahead integrated energy scheduling method aimed at minimizing economic costs and carbon emissions. This method efficiently diminishes economic expenses and carbon emissions of the system [3]. To mitigate the unpredictability of wind and solar energy in active distribution networks, Q. Luo et al. introduced a two-stage optimal scheduling model for day-ahead and real-time demand response resources. Simultaneously integrating price-based and incentive-based demand response has been demonstrated to enhance the optimization of user load distribution [4]. In practical applications, Yingying Zheng et al. focused on electric vehicle aggregators, constructing an optimized scheduling model from the perspectives of system operation optimization and economic benefits [5]. This study focuses on electric vehicle loads, taking into account their dual load and storage characteristics, as well as user demands, to explore the impact of their demand response potential on the grid and validate their ability to aid in peak shaving and valley filling. For optimizing the scheduling of demand response resources, the study focuses on electric vehicle aggregators, modeling the aggregation as a whole while considering vehicle users' needs. It aims to maximize the benefits for the aggregators and explores their potential profits and contributions to the grid when participating in demand response.

3. Electric vehicle demand response resource exploration

3.1. Conceptual definition

The definition of demand response in this article is: in response to real-time changes in electricity prices or economic incentives provided by the grid or its suppliers during high prices or when system reliability is threatened, end-users alter their consumption patterns compared to their normal electricity usage [6]. Demand response participants can be individual users or load aggregators.

Demand response can be categorized based on different dimensions: From the electrical characteristics dimension, demand-side resources can be divided into motor loads, temperature-controlled loads, electric vehicle loads, and multi-energy coupled loads. From the user dimension, it mainly includes industrial, commercial, and residential users.

Beyond the traditional ‘electrical perspective’, the ‘carbon perspective’ on low-carbon demand response resources includes new energy sources from the system, such as wind, solar, hydro, and nuclear power, and electricity usage behaviors from the user's perspective [7]. The article characterizes demand response potential as the user's capacity to modulate load—either by reducing or increasing it—under specific operating conditions, relative to the load that would be consumed in the absence of demand response participation [8]. It can be further divided into three categories—theoretical demand response potential, economic demand response potential, and available demand response potential.

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3.2. Model establishment

The article aims to establish a demand response model for private electric vehicles that takes user travel requirements and battery degradation into account. The model constraints include maximum battery capacity and maximum charging/discharging power, with the goal of minimizing the grid's peak-to-valley difference. This illustrates how electric car involvement in demand response can improve the stability of the power system.

1) Electric Vehicle to Grid State Analysis

In this study, electric vehicles participating in demand response can be categorized into two situations:

- Off-grid state: When electric vehicles have travel needs and are not connected to the grid, or are connected but not participating in demand response, they are considered off-grid.
- On-grid state: When electric vehicles do not have travel needs, are connected to the grid and participate in demand response, they are considered on-grid. In this state, they can respond to grid dispatch commands.

2) Objective Function

This section aims to illustrate the peak shaving potential of electric vehicles by minimizing the peak-to-valley discrepancy in grid demand on a typical day. First, calculate the total load curve considering the peak shaving capability of electric vehicles, as shown in Equation (1):

$$P_{NL}(t) = P_L(t) + P_c(t) - P_{dc}(t) \tag{1}$$

Where $P_L(t)$ is the original load without peak shaving. $P_c(t)$ and $P_{dc}(t)$ represent the electric vehicle aggregation charging and discharging power at time t, respectively. $P_{NL}(t)$ is the load optimized by the electric vehicle aggregation peak shaving.

The objective function is:

$$\min[\max P_{NL}(t) - \min P_{NL}(t)] \tag{2}$$

3) EV Schedulable Ability Model Constraints

With the development of automobile batteries and smart grid technology, the factors constraining the demand response capability of electric vehicles and their modeling are as follows.

State of Charge (SOC): When an electric vehicle is off-grid, it's unable to adjust the state of charge (SOC). When the electric vehicle is on-grid, the SOC condition is met:

$$SOC_t = SOC_{t-1} + \frac{nP_C(t)}{E_{max}} \tag{3}$$

$$SOC_t = SOC_{t-1} - \frac{P_{dc}(t)}{nE_{max}} \tag{4}$$

Where SOC_t and SOC_{t-1} denote the state of charge capacity at times t and $t-1$ respectively; $P_c(t)$ and $P_{dc}(t)$ represent the charging and discharging power at time t; n is the efficiency coefficient and E_{max} indicates the maximum battery capacity.

Additionally, as an electric vehicle, it must meet the user's travel requirements. Before an electric vehicle reaches the off-grid state, its capacity must be charged above a specified level to ensure usability. This is met if:

$$SOC_{t-leave} \geq SOC_{leave} \tag{5}$$

Where SOC_{leave} indicates the required charge level when the user leaves, and $SOC_{t-leave}$ represents the charge level at the off-grid time.

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Deep discharges of the electric vehicle can severely impact battery lifespan. To minimize the effect of charging and discharging on battery life, a minimum discharge level should also be set:

$$\mathrm{SOC_t} \geq \mathrm{SOC_{low}} \tag{6}$$

Where $\mathrm{SOC_{low}}$ represents the minimum discharge level.

Battery charging and discharging power: When an electric vehicle is on-grid, it can choose to charge or discharge according to demand response requirements, but it cannot do both simultaneously. The charging power cannot exceed the maximum charging power of the electric vehicle's battery, and the same applies to discharging. This is described by equations (7) and (8):

$$0 \leq \mathrm{P_c(t)} \leq \mathrm{P_{cmax}} \tag{7}$$

$$0 \leq \mathrm{P_{dc}(t)} \leq \mathrm{P_{dcmax}} \tag{8}$$

Where $\mathrm{P_{cmax}}$ and $\mathrm{P_{dcmax}}$represent the maximum charging and discharging power respectively;

When the electric vehicle is off-grid, it cannot respond to grid scheduling requests. Thus both charging and discharging power are set to zero:

$$\mathrm{P_c(t)} = \mathrm{P_{dc}(t)} = 0 \tag{9}$$

3.3. Case study

1) Model Analysis

Based on usage and ownership, existing electric vehicles can mainly be divided into private electric vehicles, electric taxis, and electric buses.

Private electric vehicles are linked to the grid on weekdays, serving as effective demand response resources, except for morning and afternoon commutes. Their charge can be adjusted more assertively to augment demand response capability during transit. During rest days, their travel patterns become more unpredictable, complicating the formation of large-scale clusters for demand response scheduling [9]. For electric taxis, regardless of weekdays or rest days, they are on the road most of the time. Even at night, due to driver shift changes, they continue operating without charging. Charging usually happens during meal breaks at the fastest possible speed to resume work, which limits their participation in demand response and makes unified grid scheduling challenging. For electric buses, on both weekdays and rest days, they start the first service in the early morning. After completing each route, they have a 30 to 60-minute break for charging and driver changes before starting the next route. After the last service, they return to the bus depot for charging, making them less suited for daytime clustering but excellent demand response resources at night. In conclusion, this article chooses to model weekday private electric vehicles, which have strong demand response capabilities, as they are highly representative.

2) Model Setting

To simulate the peak shaving capability of electric private vehicles in a city in 2025, the following parameters are set for modeling:

- - Battery Capacity per Vehicle: 100 kWh
- - Maximum Charging Power: 80 kW
- - Maximum Discharging Power: 80 kW

Studies show that deep discharges affect battery lifespan, and without protection, it may discourage user participation in demand response. To protect lithium battery lifespan, the discharge depth should not exceed 80% [10].

In the context of electric private vehicles addressing urban commuting requirements, where average distances are under 50 km, and taking into account the necessity for the battery level to

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remain above 20% while accommodating additional user demands, the minimum battery capacity required during operation is established at 50 kWh. Based on current electric vehicle consumption, the battery can last for 200 km before dropping to 20% charge. The off-grid times are set from 7:00-9:00 for the morning commute and from 16:00-18:00 for the evening commute. At other times, the cars are connected to the grid for demand response.

Due to model scale, the number of participating vehicles is set at 800, which is 0.1% of the 2025 EV ownership in Guangzhou city. Details are shown in Table 1.

Table 1: Example model setting

Item	Value
Number of electric vehicles	800
Unit electric vehicle battery capacity/kW·h	100
Total battery capacity/MWh	80
Maximum charging power/kW	80
Maximum discharge power/kW	80
Maximum discharge depth	80%
Minimum battery capacity before travel/kW·h	50
Charge/discharge efficiency	95%
On-grid time slot	10am – 3pm & 7pm – 6am (next day)

The private electric vehicles case is analyzed using the CPLEX solver through the YALMIP toolbox in MATLAB R2023a. A set of typical summer load data provided by the Guangzhou Power Supply Bureau is applied. We divide the day into 24 periods and plot the daily load graph $P_L(t)$ for each period. Then the load graph considering electric vehicle demand response is plotted for comparison. The electric vehicle aggregation discharging load curve is given for reference(Figure 2), where values greater than 0 indicate charging and less than 0 indicate discharging.

3) Results Analysis

In this case, electric vehicles of the number of 800 participate in demand response over a 24-hour period. The battery capacity is set at 80 kWh, with charging and discharging power limited to 80 kW. The battery capacity ranges from 20% to 100%. The charge reserved for traveling for users is set at 50%. Before demand response, the typical daily load curve has a maximum of 1563 MW and a minimum of 982 MW, with a difference of 581 MW. After optimization with electric vehicles participating in demand response, the load curve's maximum is 1516.1 MW and the minimum is 1044.64 MW, reducing the difference to 471.46 MW, an 18.85% reduction in peak-valley difference (Figure 1). This demonstrates the significant role of electric vehicles in smoothing load curves, reducing peak-valley differences, and enhancing the stability of the power system.

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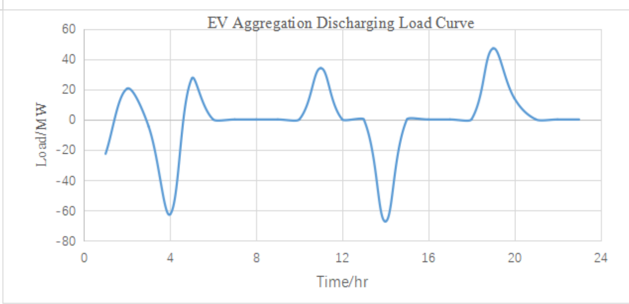

Figure 1: Peak load shaving result

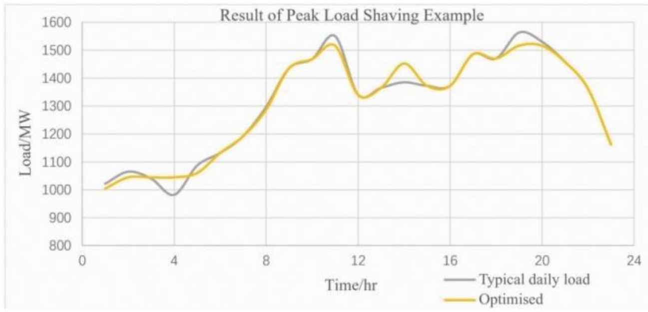

Figure 2: EV aggregation charging/discharging result

4. Optimization scheduling of electric vehicles considering aggregators

4.1. Modelling

1) Charging and discharging mode of electric vehicles

There are three modes of charging and discharging for EVs within the grid:

Absence of Participation in Charging/Discharging Scheduling: In this mode, upon connection to the grid, the electric vehicle (EV) charges at a power limited by both the charging station and the vehicle until fully charged, then ceasing to charge until disconnection from the grid occurs. Throughout this interval, the electric vehicle does not adhere to grid scheduling.

Partial Participation in Charging/Discharging Scheduling: In this mode, the charging time of the EV can be controlled, but it only charges and does not discharge. Aggregators can choose to charge these EVs when electricity prices are low to gain economic benefits. In this mode, the EV partially participates in demand response.

Full Participation in Charging/Discharging Scheduling: From the moment the EV connects to the grid, it fully follows charging and discharging arrangements. Aggregators can choose to charge when prices are low and discharge when prices are high, leading to greater economic benefits compared to partial participation. In this mode, the EV fully participates in demand response.

Among these methods, full participation in charging/discharging scheduling is given lots of attention due to its high flexibility and economic advantages. Based on current research, this article also adopts a model that considers full participation in charging/discharging scheduling with aggregators for optimizing electric vehicle networks.

2) Objective function

To guarantee that electric car aggregators possess the market motivation to perform peak shaving functions for the power system and effectively serve customers, it is imperative to prioritize their profitability. This research seeks to optimize the revenue of electric car aggregators, constrained by the following parameters:

$$max(\mathrm{F} = \sum_{j=1}^{N} \sum_{t=1}^{T} f_{j,t}) \tag{10}$$

$$f_{j,t} = nP_{c,j,t} i_{c,j,t} r_{c,t} - \frac{P_{dc,j,t} i_{dc,j,t}}{n} r_{d,t} \tag{11}$$

$$i_{c,j,t} + i_{dc,j,t} \leq 1 \tag{12}$$

Where F represents the total income for the electric vehicle aggregator managing N vehicles over T time periods. $f_{j,t}$ is the income from the j-th vehicle participating in demand response during the t-th period. $P_{d,j,t}$ and $P_{c,j,t}$ denote the discharge and charge power for the j-th vehicle during the t-th period, respectively. The indicators $i_{c,j,t}$ and $i_{dc,j,t}$ define the charging and discharging state of the

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j-th vehicle during the t-th period, both being binary variables, where they cannot be 1 simultaneously. $r_{c,t}$ and $r_{d,t}$ are the charging and discharging prices for the t-th period, respectively.

3) Constraints

Power constraints: For any vehicle at any time, the charging and discharging power must not exceed their respective maximum limits and cannot occur simultaneously. More importantly, as the battery industry develops, using a single value after taking the average for charging power doesn't accurately depict the real situation. In reality, the charging power of electric vehicles when the battery is at 0%-80% state of charge (SOC) is several times that of when it is at 80%-100% SOC. Averaging the charging power into a single value loses the demand response potential of electric vehicles.

This paper employs a novel approach by delineating the charging power of electric vehicles over time as capacity fluctuates, hence considerably broadening the possible domain in contrast to conventional modeling techniques that average the charging rate.The specific formulas are as follows:

The study period is divided into T intervals, assuming constant power within each interval. The actual charging power is:

$$P_{j,t} = P_{c,j,t} i_{c,j,t} n - \frac{P_{dc,j,t} i_{dc,j,t}}{n} \tag{13}$$

$$i_{c,j,t} + i_{dc,j,t} \leq 1 \tag{14}$$

Where $P_{c,j,t}$ and $P_{dc,j,t}$ represents the charging and discharging power of j-th EV in the t-th time interval respectively; The indicators $i_{c,j,t}$ and $i_{dc,j,t}$ define the charging and discharging state of the j-th vehicle during the t-th period, both being binary variables, where they cannot be 1 but can be 0 simultaneously, meaning EVs can’t charge and discharge at the same time but can neither be charging or discharging; n is the charging/discharging efficiency.

Electric vehicle charging power should meet:

$$0 \leq P_{j,t} \leq P_{cmax} \tag{15}$$

$$0 \leq P_{j,t} \leq P_{dcmax} \tag{16}$$

Where P_{cmax} is the maximum charging power, P_{dcmax} is the maximum discharging power.

Charge level constraints: Set a minimum charge level. When the electric vehicle's charge falls below this level, it charges at maximum power until it reaches the minimum. This minimum level is determined by the user based on daily driving needs and the vehicle's range. Establish a goal charge level. The aggregator must guarantee that the vehicle attains this level before disconnecting from the grid. The target level is determined by the user's minimum energy requirements at the time of disconnection. Users can modify it based on their usage patterns. When the charge is above the minimum level, the aggregator implements more complex optimization strategies. These include charging when electricity prices are low to reduce costs while ensuring the target charge is met and discharging during peak price periods to sell power back to the grid for profit and potentially alleviate peak loads.

The specific formulas are as follows:

$$SOC_{MAX} \geq SOC_{j,t} \geq SOC_{base} \tag{17}$$

Where SOC_{MAX} represents the maximum battery charge level, SOC_{base} represents the minimum charge level, and $SOC_{j,t}$ represents the battery charge level of the j-th EV at time t.

$$SOC_{j,exp} \geq SOC_{EXP} \tag{18}$$

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Where $\mathrm{SOC}_{j,exp}$ indicates the charge level of the j-th vehicle at the user-specified time exp. SOC_{EXP} is the expected charge level set by the user.

4.2. Case study

According to the analysis in Section 2.2.1, due to the demand response time and capacity of private EVs, this section continues to focus on private EVs as the subject of study.

1) Model Setting

In this example, private electric vehicles engage in demand response with aggregators from 8:00 PM to 8:00 AM. Specific parameters are shown in Table 2.

The battery capacity of each vehicle is set at 120 kWh. The maximum charging/discharging power for 0-100 kWh is 160 kW, and for 100-120 kWh, it is 40 kW. To ensure unexpected driving needs, the minimum charge level is set at 24 kWh, sufficient for driving 150 km. The vehicle's off-grid time is set to 8:00 AM for the morning commute, and on-grid time is 8:00 PM for post-work hours. During 8:00 PM - 8:00 AM, vehicles are connected to the grid for demand response.

Due to model scale, the number of participating vehicles is set at 80, which is 0.01% of the 2025 EV ownership in Guangzhou city. Details are shown in Table 2.

Table 2: Example Model setting

Item	Value
Number of electric vehicles	80
Unit electric vehicle battery capacity /kW·h	120
Total battery capacity /kW·h	9600
0-100kW·hMaximum charge and discharge power/kW	160
Maximum charging/discharging power for 100-120kW·h/kW	40
User-set minimum charge level /kW·h	24
User-set expected charge level/kW·h	100
Charge/discharge efficiency	95%

The case of private electric automobiles is examined utilizing the CPLEX solver via the YALMIP toolbox in MATLAB R2023a. Utilizing time-of-use price data, the timeframe is segmented into 24 intervals to analyze the 80 private electric vehicles within these segments. The target function is to optimize the economic advantages for the EV aggregator, taking into account the daily utilization of electric car owners.

2) Results Analysis

In this innovative modeling approach, charging power is dynamically adjusted based on battery capacity. Here's a case scenario: 80 electric vehicles participate in demand response over 24 time segments. Battery capacity is set to 120 kWh. The maximum charging/discharging power limit is 160 kW for 0-100 kWh and 40 kW for 100-120 kWh. The battery capacity range is [20%, 100%]. The expected charge level set by users is 100 kWh.

According to Figure 3, the total aggregator profit is $1374.

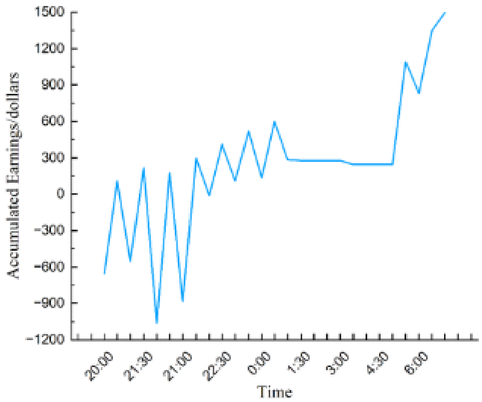

Figure 3: EV aggregator detailed power profit

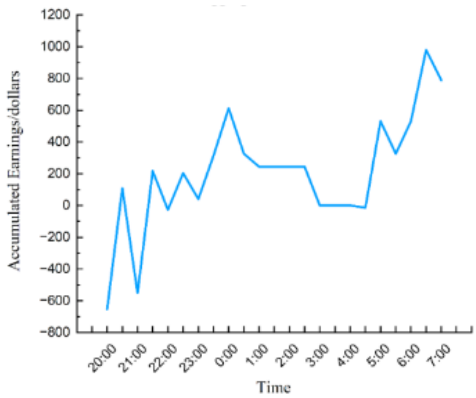

Figure 4: EV aggregator average power profit

In a traditional modeling approach, the charging power is set to a constant average value. In the case scenario: 80 electric vehicles participate in demand response over 24 time segments. Battery capacity is set to 120 kWh. The average maximum charging/discharging power is 100 kW. The battery capacity range is [20%, 100%]. The expected charge level set by users is 100 kWh.

According to Figure 4, the total aggregator profit is $785.96. This indicates that in the demand response scenario for EV aggregators, the model generates $1374 in 12 hours. By using a more detailed approach to model EV charging power, as opposed to the traditional average method, the aggregator's profit increases by approximately 74.82%.

5. Conclusion

The model demonstrates that electric vehicles, as a valuable demand response resource, contribute significantly to peak shaving and enhancing power system stability. The study formulates a demand response model for private electric car aggregators to optimize dispatching, taking into account journey requirements and battery degradation. It aims to optimize the aggregator's revenues, limited by the maximum battery capacity and the maximum charging and discharging power thresholds. A novel approach to enhance the EV maximum charging power curve is suggested to broaden the viable area for demand response capabilities, resulting in increased advantages. The optimized scheduling strategy and refined charging model for electric car aggregators are proved to significantly boost profits, enabling them to offer more attractive demand response products to users. User acceptance and willingness to participate are assumed to be ideal, without accounting for more realistic scenarios, and there are several constraints in the model that need further consideration. Future research will focus on improving algorithms for better fitting results.

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