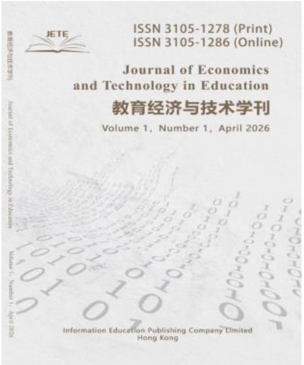

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A Distribution Network Planning Method for Coordinated Optimization of Electricity Pricing Mechanisms

Yin Xuanyi, Liu Run

Abstract: This study investigates the electricity price game problem in demand response by analyzing how real-time electricity price optimization influences both grid revenue and user demand. A Stackelberg game framework is adopted to characterize the leader–follower interaction between the grid operator and electricity users. User demand behavior is modeled using a Logistic demand response function, which captures the nonlinear relationship between price signals and load adjustment. To ensure practical applicability, grid operational constraints and electric vehicle (EV) charging constraints are incorporated through penalty terms, and the resulting constrained optimization problem is solved using the Sequential Least Squares Programming (SLSQP) algorithm. Demand elasticity coefficients, which critically affect optimization outcomes, are estimated using both historical load data and external commercial data. Comparative experiments are conducted to evaluate how different elasticity coefficients influence pricing results and load regulation performance. The results demonstrate that iterative Stackelberg-based optimization can effectively balance grid revenue and load stability, while elasticity

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coefficients derived from local load data yield better alignment with actual demand behavior. These findings provide theoretical and practical support for real-time electricity pricing strategies.

Keywords: Demand response; Real-time electricity pricing; Stackelberg game; Demand elasticity; Electric vehicle charging; SLSQP optimization

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标题：面向电价机制协同优化的配电网规划方法

摘要：本研究通过分析实时电价优化如何同时影响电网收益和用户需求，研究了需求响应中的电价博弈问题。采用 Stackelberg 博弈框架来刻画电网运营商与电力用户之间的领导者—跟随者互动关系。用户需求行为采用 Logistic 需求响应函数进行建模，该函数能够描述价格信号与负荷调整之间的非线性关系。为确保研究具有实际应用价值，在模型中通过惩罚项引入了电网运行约束和电动汽车（EV）充电约束，并利用序列最小二乘规划（Sequential Least Squares Programming，SLSQP）算法求解由此形成的约束优化问题。需求弹性系数是影响优化结果的重要参数，本研究利用历史负荷数据以及外部商业数据对其进行估计。通过对比实验分析不同弹性系数对电价结果及负荷调节性能的影响。研究结果表明，基于迭代 Stackelberg 博弈的优化方法能够有效平衡电网收益与负荷稳定性，而基于本地负荷数据获得的弹性系数与实际需求行为具有更好的匹配度。研究结果为实时电价制定策略提供了理论依据和实践参考。

关键词：需求响应；实时电价；Stackelberg 博弈模型；需求弹性系数；电动汽车充电约束；序列最小二乘规划（SLSQP）算法

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1.Introduction

With the increasing penetration of distributed energy resources, demand response has become an essential mechanism for improving power system flexibility and operational efficiency (Albadi and El-

Saadany, 2008). Electricity pricing plays a central role in demand response, as it directly influences user consumption behavior while determining grid revenue. Consequently, the design of effective pricing mechanisms requires a careful balance between economic efficiency, system security, and user acceptance.

Existing studies have explored price-based demand response using game-theoretic approaches, particularly Stackelberg models, to describe the interaction between electricity retailers and users (Xu et al., 2021). However, most existing works focus on single objectives or simplified constraints, and the influence of demand elasticity estimation on pricing outcomes is often insufficiently examined. In practice, elasticity coefficients are difficult to estimate accurately and may vary significantly across datasets and regions.

To address these issues, this study proposes a real-time electricity pricing optimization framework based on a Stackelberg game model. By integrating a Logistic demand response function, multiple operational constraints, and data-driven elasticity estimation, the proposed approach aims to answer the following questions:

How can grid revenue be maximized through price-based game strategies?

How can system security and user satisfaction be ensured under multiple operational constraints?

How do elasticity coefficients derived from different data sources affect optimization results?

Which elasticity estimation approach better reflects actual demand behavior?

In this research project, the study was conducted through a collaborative workflow involving two components. One component focused on data acquisition, preprocessing, and elasticity coefficient estimation, while another part concentrated on model construction and optimization. Specifically, in first component, researchers collected multi-day time-series datasets of electricity price and demand from public platforms such as Uber demand datasets and academic databases. These datasets were normalized and processed to eliminate regional differences and to ensure comparability across different samples. Machine learning–based regression models were then applied to fit the relationship between electricity price and demand. Among several candidate models, including random forest regression, polynomial regression, and ensemble models, Gaussian Process Regression demonstrated the highest fitting accuracy and was therefore selected for further analysis. Based on the fitted demand curves, elasticity coefficients for peak, flat, and valley periods were calculated and provided as key parameters for the optimization model developed by the junior research group.

2. Demand Response Model

Electricity user demand is modeled using a Logistic demand response function, which reflects the nonlinear adjustment of electricity consumption in response to price signals (Palensky and Dietrich, 2011). Compared with linear demand models, the Logistic function can capture saturation effects and diminishing sensitivity at extreme price levels, making it more suitable for real-world demand response analysis.

For each time period (i), the electricity demand is expressed as:

$$D_i(P_i) = \frac{Q_{max,i}}{1 + e^{k(P_i - P_{0,i})}}$$

where $D_i(P_i)$ denotes the electricity demand in time period i, Qmax, i represents the maximum transferable load, $P_{0,i}$ is the baseline price, and k is the price sensitivity coefficient. Through this formulation, users respond to electricity prices in a smooth and continuous manner, providing a foundation for subsequent elasticity analysis and pricing optimization.

3. Calculation of Demand Elasticity Coefficient

To quantify the sensitivity of demand to price variation, the demand elasticity coefficient is calculated based on baseline electricity price and baseline load.

The elasticity is defined as:

$$E = \left(\frac{P_{base}}{P - P_{base}} \frac{Q - Q_{base}}{Q_{base}} \right)$$

Based on the elasticity value, the demand elasticity coefficient b is defined as:

$$b = \frac{|elasticity|}{Q_{base} \cdot P_{base}}$$

where Q_{base} and P_{base} are obtained by calculating the average load and average electricity price during peak, flat, and valley periods.

The coefficient b represents the degree of user demand sensitivity to electricity price changes and serves as a key parameter in the optimization model (Borenstein, 2005).

The elasticity coefficients used in the optimization model were obtained through a data-driven estimation process. Multiple days of hourly electricity price and demand data were collected from public datasets and commercial platforms. Because the data were obtained from different geographical regions and time periods, normalization was performed to reduce the influence of regional scale differences. Specifically, the demand and price values of each day were divided by the daily maximum value, allowing the model to capture relative variation patterns rather than absolute magnitude differences. After preprocessing, regression analysis was performed using machine learning tools. The regression models were evaluated using performance metrics including the coefficient of determination (R^2), mean squared error (MSE), and root mean squared error (RMSE). The Gaussian Process Regression model achieved the best fitting performance and was therefore selected to derive the elasticity coefficients used in the optimization framework.

4. Introduction of External Elasticity Coefficients

To enhance the robustness of elasticity estimation and evaluate its influence on pricing outcomes, external commercial data are introduced for comparative analysis. In addition to elasticity coefficients derived from local load data, elasticity values obtained from commercial datasets and literature are also considered.

The estimation procedure consists of data import, regression model training, demand prediction, and performance evaluation using R^2 and MSE metrics. Among the tested models, Gaussian process regression demonstrates superior fitting accuracy and is therefore selected for elasticity extraction. By comparing elasticity coefficients derived from different sources under the same optimization framework, the sensitivity of pricing strategies to elasticity estimation is systematically examined.

Using 2018 data from a specific region, multiple regression models are tested. Based on fitting accuracy comparison, Gaussian process regression achieves the best performance, with higher R2 and lower MSE compared to other models. Elasticity coefficients are then calculated for peak, flat, and valley periods to support optimization.

Optimization	Model Number	Model Type	RMSE	MSE	R^2	MAE
1	2.18	Gassion process Regresion	0.121639	0.014796	0.844193	0.076417
2	2.2	Gassion process Regresion	0.121739	0.01482	0.843936	0.073994
3	2.16	integration	0.122054	0.014897	0.843128	0.088143

Fig. 1 The Parameter of Different Models

```
---Model parameters---
MSE: 0.0121
RMSE: 0.1101
MAE: 0.0757
MAPE: 21.9596%
Explained Variance: 0.8747
Median AE: 0.0521
R²: 0.8747

---Time-based Price Elasticity Analysis---
morning/evening peak: 0.0988
middle of the night/wee hours: 1.7478
off-peak hours: -0.3253
```

Fig. 2 The Parameter Calculation Using Python

5. Optimization Objectives and Constraints

5.1 Objective Function

The optimization objective is to maximize the net revenue of the grid operator while incorporating user demand response behavior and system security considerations. The objective function is defined as:

$$\max\left(\sum_{i}(P_i - C_i)\,D_i(P_i) - \lambda \cdot \text{Penalty}\right)$$

Where Pi is the electricity price in time period i, Ci is the grid-side cost price, and λ is the penalty weight.

5.2 Constraints and Penalty Terms

The penalty term includes the following constraints:

5.2.1 Load balance constraint:

Preventing excessive deviation from baseline load;

5.2.2 Peak/valley constraints:

Peak demand shall not exceed 90% of peak load;

Valley demand shall not be lower than 110% of valley load;

5.2.3 Price smoothing constraint:

The difference between the maximum and minimum electricity prices shall not exceed 0.6 CNY/kWh;

5.2.4 Electric vehicle (EV) charging constraints:

Total EV charging energy is close to 500 kWh; Valley-period charging accounts for no less than 40%; Single-period charging power does not exceed 200 kW.

6. Optimization Algorithm

The Sequential Least Squares Programming (SLSQP) algorithm is employed to solve the constrained optimization problem (Mohsenian-Rad et al., 2010). The electricity price in each time period is constrained within the following range:

$$Ci \leq Pi \leq ai$$

where ai denotes the user-acceptable maximum price and Ci represents the grid-side cost price.

A dynamic Stackelberg game framework is adopted (Wan et al., 2024), and the optimization process is carried out through iterative updating. Stable optimization results are obtained after 3000 iterations.

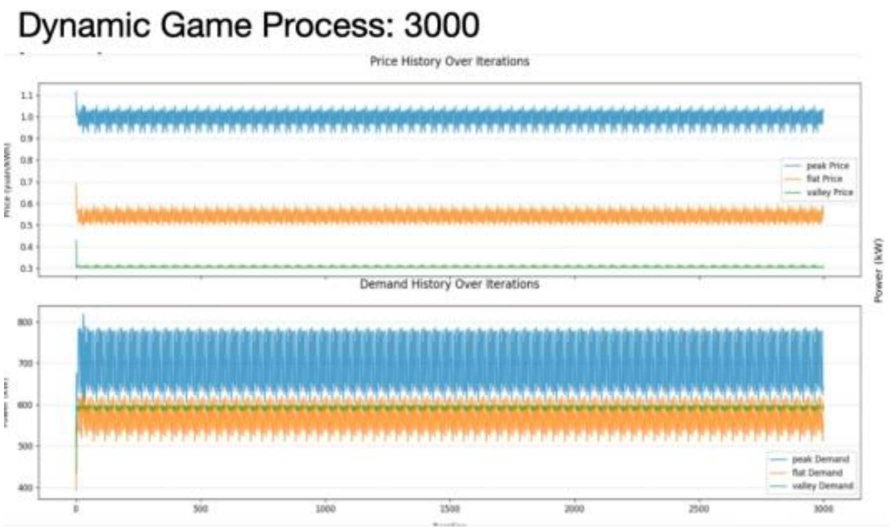

Fig. 3 Iterative Evolution of Electricity Price and Demand in the Dynamic Game Process

7. Results and Comparative Analysis

The experimental procedure follows a multi-stage workflow. First, the elasticity coefficients calculated from historical load datasets and external commercial datasets were imported into the optimization framework. Second, the Stackelberg game-based pricing model was solved using the SLSQP algorithm under multiple operational constraints. Third, iterative optimization was conducted for 3000 rounds to obtain stable electricity price and demand responses. Finally, the optimized pricing results were compared with baseline results and with results derived from different elasticity coefficients to evaluate the effectiveness of the proposed method.

Comparative experiments are conducted by substituting different elasticity coefficients into the optimization model, including coefficients calculated from load datasets, coefficients derived from Uber data, and coefficients obtained from other literature. Datasets from 2018 and 2019 are used for cross-year comparison.

The results indicate that elasticity coefficients calculated from historical load data better align with actual demand curves, reducing deviations in peak, flat, and valley periods. Compared to non-optimized baseline methods, the SLSQP-based iterative pricing mechanism significantly improves prediction accuracy and peak shaving effects.

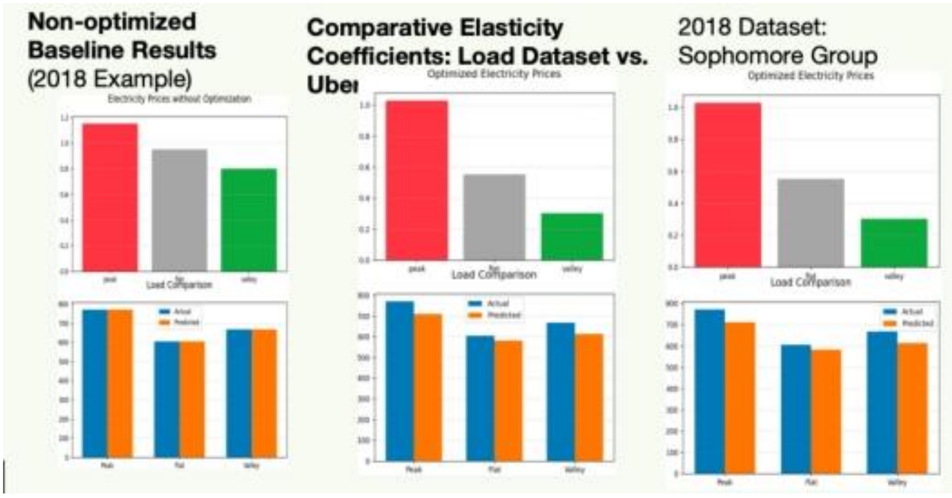

Fig. 4 Load Comparison under Baseline and Optimized Electricity Pricing with Different Elasticity Coefficients

Additionally, based on the load data used to calculate elasticity coefficients and the predictions made for both load and electricity prices, the results indicate that future electricity prices are projected to be:

Peak period: 0.95–1.05 CNY/kWh

Flat period: 0.5–0.6 CNY/kWh

Valley period: approximately 0.35 CNY/kWh

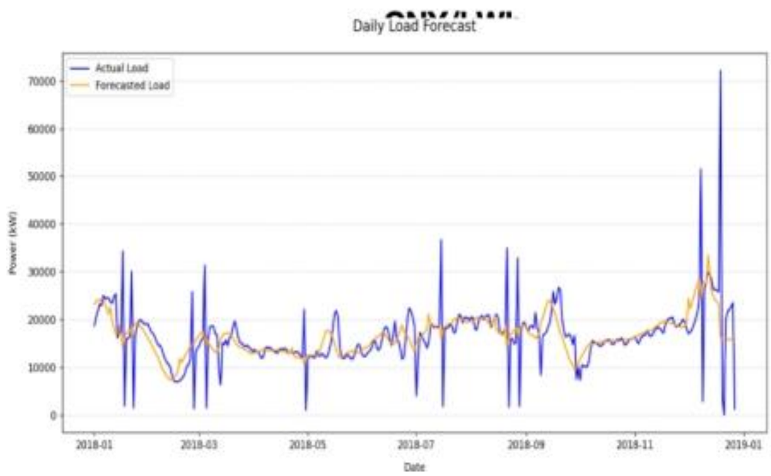

Fig. 5 Daily Load Forecast Results for the 2018 Dataset

8.Conclusion

The results demonstrate that multi-constraint balancing, including load balance, energy conservation, peak and valley limits, price smoothing, and electric vehicle (EV) charging constraints, effectively enhances both grid revenue and system security. The incorporation of soft constraints, such as load balance and EV charging, enables the model to balance economic benefits and operational safety, although the selection of penalty weights still requires further sensitivity analysis.

The elasticity coefficients calculated from historical load data are shown to better align with actual demand curves, reducing deviations during peak, flat, and valley periods. Compared with non-optimized methods, the SLSQP-based optimization and iterative pricing mechanism significantly improve prediction accuracy and peak shaving performance.

Overall, the proposed Stackelberg game-based model effectively optimizes real-time electricity prices, enhancing grid revenue while ensuring system security. By comparing elasticity coefficients derived from grid load data and Uber commercial data, the study validates the importance of local load data for accurate parameter calibration. By combining mathematical optimization using SLSQP and iterative pricing with multi-constraint balancing, the proposed approach outperforms non-optimized methods in both prediction accuracy and load regulation. This work provides theoretical support for electricity market pricing strategies and demonstrates strong practical implementation potential. Future extensions could include multi-agent game models or machine learning techniques for parameter optimization.

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