Integrating Renewable Energy and Demand Response Strategies for Cost-Effective Industrial Energy Management

Leila Mohammadian
Department of Electrical Engineering, Shab.C., Islamic Azad University, Shabestar, Iran
Le.mohammadian@iau.ac.ir

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Abstract

This study presents a cost-minimization framework for energy procurement in large industrial consumers, incorporating alternative energy sources such as micro-turbines, bilateral contracts, power markets, and renewable energy systems—namely wind turbines and photovoltaic systems. Battery storage is integrated to enhance energy efficiency. Additionally, the impacts of real-time pricing demand response programs (RTP-DRP) and time-of-use demand response programs (TOU-DRP) on load profile smoothing and cost reduction are examined. A scenario-based probabilistic programming approach is employed to model uncertainties in electricity price fluctuations, consumer demand, wind speed variations, solar irradiation, and temperature changes. The optimization problem is formulated as a mixed-integer linear programming (MILP) model, ensuring global optimal solutions via GAMS software. Comparative analysis indicates that RTP-DRP achieves a 12.33% reduction in energy procurement costs, while TOU-DRP leads to a 6.23% reduction, demonstrating the superior effectiveness of RTP-DRP in cost savings and load stabilization.

Keywords: Energy Procurement, Large Industrial Consumers, Real-time Pricing, Time-Of-Use Pricing.

1. Introduction

In many electricity markets, consumers exert minimal influence over market design, with key decisions predominantly made by market entities such as producers, transmission operators, distribution companies, and retailers. One of the central objectives of power system restructuring is to enhance consumer monitoring capabilities, ensuring long-term benefits. Despite these efforts, most consumers remain passive participants in market dynamics due to a lack of economic incentives to engage in complex and time-intensive transactions, except for large industrial consumers. These entities are often granted direct access to electricity procurement via pool markets, which operate either as centralized trading platforms or through bilateral contracts [1].

This study analyzes and compares the effects of RTP-DRP and TOU-DRP on industrial energy supply strategies. Several prior works have explored demand response programs, including [2], which propose methodologies for assessing participation impacts across different market structures. Market-clearing mechanisms that incorporate price-sensitive consumer bidding strategies have also been examined [3]. Furthermore, the challenge of cost-optimal electricity procurement for large consumers—balancing shared facilities, bilateral contracts, and local generation while managing associated risks—has been addressed in [6]. Various demand response mechanisms, such as interruptible loads and capacity market programs, have been developed to enhance load characteristics and consumer satisfaction [8].

Another optimization model [9] introduces a framework for adjusting consumers' hourly load profiles in response to dynamic electricity prices while maximizing economic benefits. This model incorporates constraints on daily energy consumption, load variations, and production adjustments and utilizes robust optimization techniques to account for price uncertainty. A novel demand response exchange platform is presented in [10], where DR resources are traded between buyers and vendors as commodities. This market structure aims to enhance independent trading reliability while enabling vendors to adjust consumption in response to real-time system needs. The impacts of battery storage integration and TOU-DRP on large consumers' energy procurement have been separately examined in [11] and [12]. In contrast, this study extends previous research by analyzing both TOU-DRP and RTP-DRP, evaluating their combined effects on industrial load profiles and cost optimization.

The organization of this paper is as follows: Section 2 formulates the problem of energy procurement for large industrial consumers with market access, incorporating distributed generation units such as wind turbines, photovoltaic systems, and battery storage alongside RTP-DRP and TOU-DRP frameworks. Section 3 presents numerical case studies exploring the performance of the proposed model across different operational scenarios, comparing the cost-saving potential of TOU-DRP and RTP-DRP strategies. Finally, Section 4 provides concluding remarks.

2. Modeling the Proposed Problem

This section details the formulation of energy procurement optimization for large industrial consumers, accounting for uncertainties in ambient temperature, solar irradiation, wind speed, electricity market prices, and demand variations. To ensure adaptability, decision variables are modeled as scenario-dependent functions, allowing robust procurement planning under diverse conditions.

2.1. Objective function

The optimization framework considers eight distinct energy sources for industrial procurement under various scenarios: power grid supply, bilateral contracts, micro-turbines, wind turbines, photovoltaic systems, and battery storage. Additionally, RTP-DRP and TOU-DRP are incorporated as virtual power sources to enhance cost efficiency. The objective function, given in Equation (1), seeks to minimize procurement costs while ensuring compliance with technical and operational constraints across multiple scenarios.

$$O.F. = Minimize \sum_{l=1}^{B} \sum_{t=1}^{T} \lambda_{l,t} P_{l,t}^{BC} + \sum_{t=1}^{T} \sum_{s=1}^{Ns} P_s \times \left\{ \begin{array}{l} \lambda_{t,s} P_{t,s}^{p} + \sum_{j=1}^{N_j} \sum_{h=1}^{N_h} S_{j,h}^{MT} P_{j,h,t,s}^{MT} \\ + C_t^{B} \times (\chi \times P_{t,s}^{charge} + \frac{P_{t,s}^{disc}}{\eta}) \\ + C_t^{wind} \times P_{t,s}^{wind} + C_t^{PV} \times P_{t,s}^{PV} \end{array} \right\} \quad (1)$$

The proposed objective function is designed to optimize the energy procurement strategy for large industrial consumers by considering multiple cost components. The first segment of the function models the procurement cost associated with bilateral contracts, ensuring economic feasibility in long-term agreements. The second segment incorporates the costs of electricity acquisition from the upstream grid, as well as the operational expenditures of distributed energy resources, including micro-turbines, battery storage systems, wind turbines, and photovoltaic arrays.

To ensure an accurate representation of micro-turbine operational costs, a triplex piecewise linear function is implemented within a linear optimization framework, enabling optimal response determination. Additionally, uncertainties in key parameters—such as electricity market prices, consumer demand, and environmental variables (wind speed, ambient temperature, and solar irradiation)—are integrated into the model to dynamically assess wind and photovoltaic generation outputs [11, 12]. The objective function is designed for minimization, subject to a range of technical and physical constraints, which are further detailed in the following sections.

2.2.Constraint of power balancing

The objective function is designed to be minimized while ensuring that the power balance constraint is maintained under varying operational conditions and across different scenarios at each time interval. This constraint, represented in Equation (2), mandates that the total power supply, comprising electricity procured from the upstream grid, bilateral contracts, micro-turbines, wind turbines, photovoltaic systems, and the discharge capacity of battery storage, must equal the adjusted load of the large industrial consumer.

In this study, the adjusted consumer load accounts for standard consumption patterns and modifications introduced by demand response programs. Specifically, it incorporates RTP-DRP and TOU-DRP, influencing load variations. Additionally, the power allocated for battery charging is factored into the load equation, ensuring accurate representation of energy storage dynamics within the procurement model.

$$\begin{aligned}&\sum_{l=1}^{B} P_{l,t}^{BC} + P_{t,s}^{p}\\&+\sum_{j=1}^{N_j}\sum_{h=1}^{N_h} P_{j,h,t,s}^{MT} + P_{t,s}^{wind}\\&+P_{t,s}^{PV} + P_{t,s}^{disc} =\\&load_{t,s} + P_{t,s}^{ch\,arg\,e}\end{aligned} \tag{2}$$

2.3.Constraints of bilateral contracts

The procurement of electricity through bilateral contracts is subject to predefined limitations to ensure contractual compliance and economic feasibility. Constraint (3) establishes an upper limit on the energy procured from each individual bilateral contract, preventing overcommitment beyond agreed thresholds. Additionally, Constraint (4) represents the cumulative power purchased across all bilateral agreements, ensuring that the total contracted energy remains within the allowable range dictated by procurement strategies and operational requirements. These constraints play a critical role in optimizing energy sourcing while maintaining financial efficiency and operational stability within the industrial consumer's energy portfolio.

$$P_{l,t}^{min_{l\,l,t}^{BC\;max_l}{}_{l,t}} \tag{3}$$

$$P_t^{BC} = \sum_{l=1}^{N_l} P_{l,t}^{BC} \quad (4)$$

2.4.Constraints of micro-turbine models

To model the operational cost of micro-turbines, a triplex piecewise linear cost function is formulated, as represented in Equation (5). This function enables precise cost evaluation while maintaining computational efficiency within the optimization framework. Equations (6)–(11) define the key technical constraints governing micro-turbine operation:

- **Capacity Constraints (Equations 6 & 7):** These equations impose upper limits on the power dispatch from micro-turbines, ensuring that generation remains within the predefined capacity of the system's available blocks.
- **Ramp Rate Constraints (Equations 8 & 9):** These constraints regulate the permissible rates of increase and decrease in micro-turbine generation, maintaining operational stability and preventing abrupt power fluctuations.
- **Minimum On/Off Time Constraints (Equation 10):** The operational duration of each micro-turbine unit must satisfy predefined minimum on and off time requirements, preventing inefficient cycling and optimizing resource utilization.
- **Auxiliary Variable Definitions (Equation 11):** The auxiliary variables $Up_{i,j}$,$Dn_{i,j}$introduced in Equation (10) are formally defined in Equation (11), ensuring accurate linear modeling of minimum uptime and downtime constraints.

By integrating these constraints, the optimization model ensures reliable micro-turbine operation while maintaining economic and technical feasibility under varying energy procurement scenarios [13-15].

$$Cost^{MT} = \sum_{t=1}^{T}\sum_{j=1}^{N_j}\sum_{h=1}^{N_h}\sum_{s=1}^{Ns} P_s \times S_{j,h}^{MT} P_{j,h,t,s}^{MT} \quad (5)$$

$$0 \le P_{j,h,t,s}^{MT} \le (P_{j,h}^{MAX} - P_{j,h-1}^{MAX}) \times U_{j,t}^{MT} \quad (6)$$

$$0 \le P_{j,1,t,s}^{MT} \le P_{j,1}^{MAX} \times U_{j,t}^{MT} \quad (7)$$

$$\sum_{h=1}^{N_h} P_{j,h,t}^{MT} - \sum_{h=1}^{N_h} P_{j,h,t-1}^{MT} \le R_j^{up} \times U_{j,t}^{MT} \quad (8)$$

$$\sum_{h=1}^{N_h} P_{j,h,t-1}^{MT} - \sum_{h=1}^{N_h} P_{j,h,t}^{MT} \le R_j^{down} \times U_{j,t-1}^{MT} \quad (9)$$

$$U_{j,t}^{MT} - U_{j,t-1}^{MT} \le U_{j,t+Up_{j,i}}^{MT}$$
$$U_{j,t-1}^{MT} - U_{j,t}^{MT} \le 1 - U_{j,t+Dn_{j,i}}^{MT} \quad (10)$$

$$\mathrm{Up}_{j,i} = \begin{Bmatrix} i i \le \mathrm{MUT}_j \\ 0 i > \mathrm{MUT}_j \end{Bmatrix}$$
$$\mathrm{Dn}_{j,i} = \begin{Bmatrix} i i \le \mathrm{MDT}_j \\ 0 i > \mathrm{MDT}_j \end{Bmatrix} \quad (11)$$

2.5.Constraints of wind turbine models

The amount of power generated by the wind turbine can be expressed by Equation (12) at any time and for any scenario [16].

$$P_{t,s}^{wind,max} \begin{cases} 0 & V_{t,s}^{w} < V_{ci} \\ p_r \times \left(\frac{V_{t,s}^{w} - V_{ci}}{V_r - V_{ci}}\right) & V_{ci} < V_{t,s}^{w} < V_{cr} \\ p_r & V_r < V_{t,s}^{w} < V_{c0} \\ 0 & V_{t,s}^{w} > V_{c0} \end{cases} \quad (12)$$

The power drawn from wind turbines by the industrial consumer is subject to predefined limits to ensure efficient utilization and system reliability. At any given time and across all scenarios, the maximum allowable power consumption from wind turbines must satisfy the constraint outlined in Equation (13). This condition accounts for variations in wind energy generation while maintaining a balanced and optimized energy procurement strategy.

$$P_{t,s}^{wind} \leq P_{t,s}^{wind,max} \tag{13}$$

2.6.Constraints of photovoltaic system models

PV systems directly convert solar energy into electricity, and their generated power is fully utilized by consumers to maximize efficiency. In this study, uncertainties related to ambient temperature and solar irradiation are incorporated into the model using a normal distribution function. Various operational scenarios are generated based on this probabilistic framework, ensuring a realistic representation of fluctuating environmental conditions. Consequently, the available power from PV systems at any given time and across different scenarios is mathematically formulated in Equation (14) [17].

$$P_{t,s}^{M,max} \frac{G_{t,s}^{a}}{G_{a_0}} \left\{ P_{Max,0}^{M} + \mu \; {}_{t,s}^{a} \; {}_{t,s}^{a} \frac{NOCT-20}{800} \; {}_{M,0} \; P_{max} \{\} \right\} \tag{14}$$

The consumption of electricity generated by PV systems is subject to predefined constraints to ensure operational feasibility and efficiency. At any given time and across all scenarios, the industrial consumer's maximum allowable utilization of PV-generated power must comply with the limitations established in Equation (15). This constraint is designed to maintain energy procurement within technical and operational boundaries while accounting for fluctuations in solar energy generation.

$$P_{t,s}^{PV} \leq P_{t,s}^{M,max} \tag{15}$$

2.7.Constraints of battery storage models

The battery storage system is governed by a series of equations that define its operational constraints and dynamic behavior.

- **Initial Energy Condition (Equation 16):** Establishes the battery's initial state of charge, serving as a reference for subsequent calculations.
- **Charge and Discharge Constraints (Equations 17 & 18):** These equations impose limits on the charging and discharging power, ensuring the battery operates within its physical and technical capabilities.
- **State-of-Charge Representation (Equation 19):** Defines the battery's state-of-charge (SOC), tracking energy levels throughout the optimization process.
- **Charge-Discharge Exclusivity Constraint (Equation 20):** Prevents simultaneous charging and discharging operations, enforcing a logical operational constraint to maintain system integrity.
- **Dynamic Energy Model (Equation 21):** Describes the evolution of stored energy over time as a function of previous SOC, charging power, and discharging power, ensuring accurate modeling of battery behavior.

$$X_{t_0}^{b} = X_{0}^{b} \tag{16}$$

$$P_{t,s}^{charge} \leq P_{charge}^{max_{t,s}^{charge}} \tag{17}$$

$$P_{t,s}^{disc} \leq P_{disc}^{max_{t,s}^{disc}} \tag{18}$$

$$X_{b}^{min_{t,s}^{b}{}_{b}^{max}} \tag{19}$$

$$U_{t,s}^{charge} + U_{t,s}^{disc} \leq 1 \quad (20)$$

$$X_{t,s}^{b} = X_{t-1,s}^{b} + \chi \times P_{t,s}^{charge} - \frac{P_{t,s}^{disc}}{\eta} \quad (21)$$

2.8.TOU-DRP model

The primary objective of TOU-DRP is to enhance load curve stability by shifting electricity consumption from peak hours to off-peak periods, thereby reducing overall operational costs [19-21]. Given its structure, TOU-DRP allows only partial load transfer, meaning that certain segments of demand can be rescheduled while maintaining system reliability. The mathematical representation of this load shift mechanism is formulated in Equation (22) [22]. Additionally, the technical constraints governing the load response program—including limitations on transferable loads, scheduling boundaries, and consumer participation conditions—are formally defined in Equations (23) through (26) [23].

$$load_{t,s} = (1 - DR_{t,s}).load_{t,s}^{0} + ldr_{t,s} \quad (22)$$

$$\sum_{t=1}^{T} ldr_{t,s} = \sum_{t=1}^{T} DR_{t,s}.load_{t,s}^{0} \quad (23)$$

$$load_{t,s}^{inc} \leq inc_{t,s}.load_{t,s}^{0} \quad (24)$$

$$DR_{t,s} \leq DRmax \quad (25)$$

$$inc_{t,s} \leq incmax \quad (26)$$

Equation (23) establishes the fundamental principle of load shifting under the time-of-use demand response program (TOU-DRP), ensuring that total energy consumption remains unchanged. Rather than reducing or increasing overall load, consumption is redistributed from peak periods to off-peak times, maintaining system balance. This means that the decrease in load during peak hours must be precisely offset by an equivalent increase in other periods.

Furthermore, Equation (24) constrains the maximum permissible incremental load, limiting it to a specific percentage of the base load to prevent excessive shifts that may disrupt operational stability. Equations (25) and (26) impose additional restrictions on load variation, ensuring that percentage changes remain within predefined boundaries. For this study, the allowable percentage for load reduction and increase is set at 20% [17], maintaining feasibility while optimizing cost efficiency.

2.9.RTP-DRP model

This study employs the proposed RTP-DRP model [18] to analyze its impact on load curve smoothing and cost reductions in comparison to TOU-DRP. The RTP-DRP framework follows a systematic approach:

1. **Average Daily Load Calculation (Equation 27):** The baseline energy consumption is computed to establish a reference for demand responsiveness.
2. **Real-Time Pricing Determination (Equation 28):** The RTP is dynamically adjusted based on TOU rates, the average load, and real-time demand fluctuations at each time interval.
3. **New Load Curve Adjustment (Equation 29):** The updated load profile is derived by integrating RTP-DRP effects, optimizing consumer response to price signals.

Additionally, the load elasticity parameter E is set to −0.5 [24], capturing the sensitivity of demand changes in response to real-time pricing variations. This formulation ensures a realistic and effective demand response strategy while enhancing cost efficiency and load stability.

$$P_{av,s} = \frac{\sum_{t=1}^{24} load_{t,s}^{0}}{24} \quad (27)$$

$$\lambda_{RTP}^{t} = \frac{load_{t,s}^{0}}{P_{av}} . \lambda_{TOU}^{t} \quad (28)$$

$$load_{t,s}^{RTP} = load_{t,s}^{0} + E \times load_{t,s}^{0} \times \left(\frac{\lambda_{RTP}^{t} - \lambda_{TOU}^{t}}{\lambda_{TOU}^{t}} \right) \quad (29)$$

3. Numerical Studies

In this section, the proposed model is evaluated through multiple scenarios within a case study framework, where results under different operational modes are systematically presented and compared. The optimization problem is formulated as an MILP model, ensuring computational efficiency and global optimality. To solve the model, the CPLEX solver [25] is employed within the GAMS environment [26], enabling precise numerical analysis and scenario-based assessments.

3.1.Data

The daily load profile is structured over a 24-hour period, encompassing peak, medium, and low consumption intervals, as described in [11]. The dataset includes information on bilateral contracts, covering 12 distinct agreements, each specifying minimum and maximum power limits along with corresponding prices [12]. Additionally, operational details of the industrial consumer's micro-turbine units are provided in [12], offering insights into local generation capacities. Environmental parameters—including daily solar irradiation, air temperature, and wind speed forecasts—are presented for a sample day in [11], facilitating scenario-based modeling of renewable energy generation. Moreover, the technical specifications for wind turbines, PV systems, and battery storage technologies are outlined in [12], ensuring accurate representation within the optimization framework. The projected consumer load profile is reported in [11], while the upstream grid price curve for the studied hours is illustrated in Figure 1. Lastly, the generated power from wind turbines and PV systems is depicted within the third scenario [12], providing a comparative assessment of renewable integration under varying conditions.

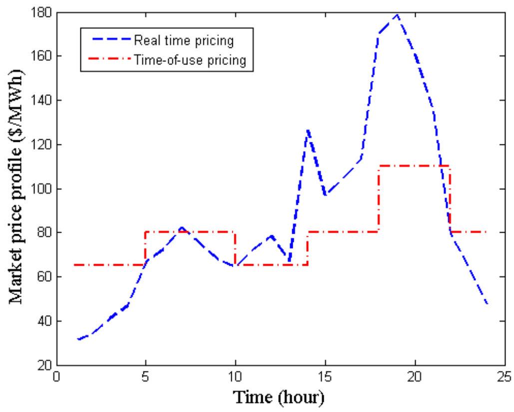

Fig.1. TOU and RTP for upstream grid

4. Comparing the results in three different models

To evaluate the effects of different energy sources and demand response programs (DRPs) on industrial energy procurement, three distinct operational modes are examined:

- **Mode 1:** Energy supply without any DRP, serving as a baseline scenario.
- **Mode 2:** Energy supply incorporating time-of-use demand response (TOU-DRP) to assess its influence on load curve stabilization and cost reduction.
- **Mode 3:** Energy supply optimized through

the proposed real-time pricing demand response (RTP-DRP) to evaluate its impact on load curve dynamics and total procurement costs.

The comparative results, presented in Table 1, illustrate the financial benefits associated with DRP implementation:

- In **Mode 1**, where no DRP is applied, the total procurement cost is $39,907.
- In **Mode 2**, incorporating TOU-DRP, the total cost is $38,461, demonstrating a cost reduction of $1,446, equivalent to 6.23% savings.
- **Mode 3**, which integrates RTP-DRP, is expected to yield further cost advantages, though its detailed impact remains to be discussed in subsequent results.

Table.1. Comparison of operation costs for large industrial consumer

Parameters	Case 1	Case 2	Case 3
Purchased cost from power market ($)	15922	13831	8747
Purchased cost from bilateral contracts ($)	9322	9322	9322
Purchased cost from micro-turbines ($)	14664	15308	16914
Total cost ($)	39907	38461	34983
Reduced total cost (%)	0	3.62	12.33

The observed cost reduction is primarily attributed to the implementation of TOU-DRP, which redistributes electricity consumption from peak to off-peak periods, thereby minimizing purchases from the upstream grid during high-priced intervals.

To further demonstrate the benefits of RTP-DRP, the proposed model was applied in Mode 3, where RTP-based load management was introduced. The results indicate a total energy procurement cost of $34,983, reflecting a $4,924 reduction compared to Mode 1—equivalent to a 12.33% cost savings. This improvement stems from the dynamic optimization of consumer load responses through RTP-DRP, enabling real-time adjustments based on market fluctuations.

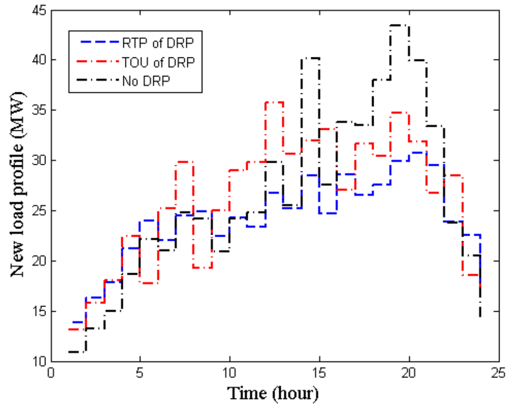

Fig.2. Consumer's load curve

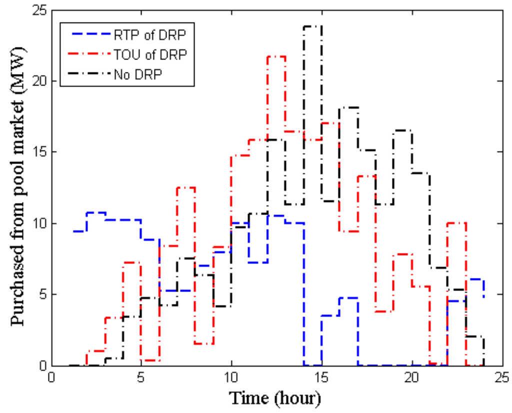

Fig.3. Power supplied from the upstream grid in the third scenario and three different modes

A key distinction between Mode 2 (TOU-DRP) and Mode 3 (RTP-DRP) lies in the level of load curve smoothing achieved. As depicted in Figure 2, RTP-DRP facilitates a more substantial shift in consumption away from peak hours, further enhancing curve stabilization compared to TOU-DRP. Additionally, the influence of RTP-DRP on grid electricity procurement is illustrated in Figure 3, demonstrating a significant reduction in peak-hour purchases relative to Modes 1 and 2. This reduction in reliance on high-cost grid power directly contributes to greater overall cost efficiency in Mode 3.

5. Conclusion

This study presents a comprehensive energy procurement model aimed at ensuring a sustainable and stable electricity supply for large industrial consumers. The framework integrates multiple energy sources—including the upstream grid, bilateral contracts, micro-turbines, wind turbines, photovoltaic systems, and battery storage—while incorporating TOU-DRP and RTP-DRP. To account for uncertainties in electricity prices, consumer demand, and environmental conditions (such as wind speed, solar irradiation, and ambient temperature), a scenario-based probabilistic approach is employed. The model differentiates between bilateral contract variables, which remain deterministic, and other decision variables, which adapt dynamically across scenarios. The effectiveness of the proposed framework is demonstrated through three comparative operational modes:

- Mode 1: Standard energy procurement without demand response programs.
- Mode 2: Implementation of TOU-DRP to assess its impact on load curve smoothing and cost reduction.
- Mode 3: Application of RTP-DRP to evaluate its enhanced capabilities in optimizing energy costs and stability.

Results indicate that Mode 3 achieves the most significant cost reduction, with a 12.33% decrease compared to Mode 1, attributed to dynamic load management and efficient battery storage utilization. Additionally, RTP-DRP facilitates greater load curve smoothing than TOU-DRP, further stabilizing energy consumption patterns and optimizing procurement strategies. Ultimately, Mode 3 proves to be the most effective approach, demonstrating superior economic and operational performance. These findings highlight the efficiency of RTP-DRP in reducing energy costs and ensuring a stable, optimized power supply for industrial consumers.

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