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Integrating Market Price Forecasting with Linear Programming for Optimal Electricity Market Clearing

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***Abstract*—This paper presents an optimal electricity market clearing framework based on linear programming (LP), applied to a real-time, multi-period Indian power exchange market. The system operator maximises social welfare by dispatching five generating units against seven demand entities across six trading periods using IEX 2025–26 average data. The dual variable of the energy-balance constraint directly yields the market clearing price (MCP) for each period. A market price forecasting module based on linear regression, using engineered supply–demand features, is integrated to predict clearing prices without re-solving the optimisation, achieving a mean absolute percentage error (MAPE) of 2.47%. Simulation results confirm that the LP clears the market at prices ranging from 5,900 to 8,500/MWh with a total social welfare of 26.87 Million, and the forecasting module provides economically consistent predictions suitable for real-time operator decision support.**

***Index Terms*—electricity market clearing, linear programming, social welfare maximisation, market clearing price, price forecasting, Indian power exchange, IEX, day-ahead market.**

I. Introduction

The electricity market clearing problem is one of the most critical optimisation tasks in modern power system operation. In a day-ahead market, power producers submit increasing-price production offer curves and power consumers submit decreasing-price consumption bid curves to the independent system operator (ISO). The ISO then determines the optimal hourly dispatch quantities and the market clearing price (MCP) that balances supply with demand [1].

The Indian Electricity Exchange (IEX) operates a continuous double auction in which a large number of generators and distribution companies interact in real time. With increasing renewable penetration and price volatility, reliable price forecasting is essential for market participants to hedge risk and for the ISO to plan reserves [3].

Prior work has addressed market clearing either through purely deterministic LP [4] or through forecast-only machine learning models trained on historical prices [5]. The contribution of this paper is a self-contained, LP-first framework in which: (i) a rigorous welfare-maximising LP determines the cleared quantities and the MCP for each period; and (ii) a compact linear regression model, trained on features extracted from the LP inputs, predicts future prices without re-solving the LP. The approach is validated on IEX 2025–26 average data, requiring no external historical price database.

The rest of the paper is organised as follows. Section II describes the market participants and the auction mechanism. Section III presents the LP formulation. Section IV describes the price forecasting model. Section V details the simulation setup and results. Section VI concludes.

II. Electricity Market Structure

A. Market Participants and Auction Mechanism

Three categories of agent participate in the day-ahead market:

1) **Power producers** submit step-wise, monotonically increasing production offer curves for each hour.
2) **Power consumers** submit step-wise, monotonically decreasing consumption bid curves for each hour.
3) **Market operator (ISO)** aggregates all curves, solves the welfare-maximisation problem, and announces the MCP and cleared quantities.

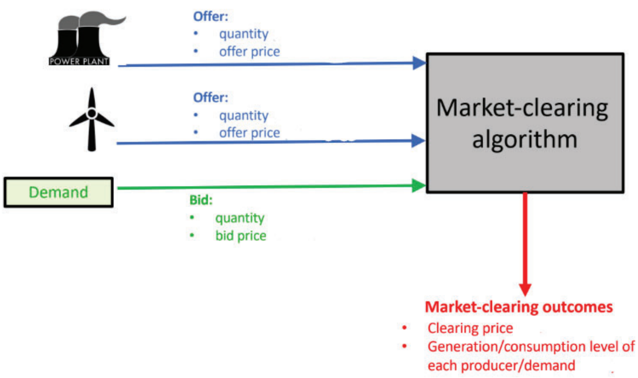

Fig. 1: Electricity Market Clearing Mechanism

B. Market Clearing Price Determination

Under the uniform-price auction the MCP for period t satisfies:

$$\text{MCP}_t = \max\{c_g \mid P_g^t \text{ accepted}\} = \min\{b_d \mid P_d^t \text{ accepted}\} \tag{1}$$

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This is the intersection of the aggregated supply and demand curves, corresponding to the dual variable (shadow price) of the energy-balance constraint in the LP.

III. Linear Programming Formulation

A. Index Sets and Parameters

$\mathcal{G} = \{G1, G2, G3, G4, G5\}$	Generators
$\mathcal{D} = \{D1, D2, \ldots, D7\}$	Demand entities
$\mathcal{T} = \{1, 2, 3, 4, 5, 6\}$	Trading periods
$C_{g,t} \in \mathbb{R}_+$	Offer price [/MWh]
$U_{d,t} \in \mathbb{R}_+$	Bid price [/MWh]
$\bar{P}^G_{g,t}, \bar{P}^D_{d,t} \in \mathbb{R}_+$	Max. quantities [MW]

B. Decision Variables

$$p^G_{g,t} \in [0,\, \bar{P}^G_{g,t}] \quad \forall\, g \in \mathcal{G},\ t \in \mathcal{T} \tag{2}$$

$$p^D_{d,t} \in [0,\, \bar{P}^D_{d,t}] \quad \forall\, d \in \mathcal{D},\ t \in \mathcal{T} \tag{3}$$

C. Objective Function — Social Welfare Maximisation

The ISO maximises aggregate social welfare (consumer surplus plus producer surplus) across all periods:

$$\underset{p^G,\,p^D}{\text{Maximise}} \quad \sum_{t\in\mathcal{T}} \left[\sum_{d\in\mathcal{D}} U_{d,t}\, p^D_{d,t} - \sum_{g\in\mathcal{G}} C_{g,t}\, p^G_{g,t} \right] \tag{4}$$

D. Constraints

Energy Balance (Market Clearing):

$$\sum_{d\in\mathcal{D}} p^D_{d,t} = \sum_{g\in\mathcal{G}} p^G_{g,t}, \quad \forall\, t \in \mathcal{T} \quad [\lambda_t] \tag{5}$$

where $\lambda_t \geq 0$ is the dual variable equal to the MCP.

Generator Capacity:

$$0 \leq p^G_{g,t} \leq \bar{P}^G_{g,t}, \quad \forall\, g \in \mathcal{G},\ t \in \mathcal{T} \tag{6}$$

Demand Capacity:

$$0 \leq p^D_{d,t} \leq \bar{P}^D_{d,t}, \quad \forall\, d \in \mathcal{D},\ t \in \mathcal{T} \tag{7}$$

The complete compact LP is:

$$\max_{p^G,\,p^D} \sum_t \left[\sum_d U_{d,t}\, p^D_{d,t} - \sum_g C_{g,t}\, p^G_{g,t} \right] \quad \text{s.t.} \quad (5),\ (6),\ (7) \tag{8}$$

E. KKT Conditions and Price Formation

By LP duality, at optimality the MCP λ_t^* satisfies:

$$C_{g,t} - \lambda_t^* \geq 0 \quad \text{(generator not over-paid)} \tag{9}$$

$$\lambda_t^* - U_{d,t} \leq 0 \quad \text{(demand at most full bid price)} \tag{10}$$

A generator is marginal when $C_{g,t} = \lambda_t^*$; infra-marginal units earn positive rent while supra-marginal units are not dispatched.

IV. Market Price Forecasting

A. Motivation

Once the LP is solved for a set of reference periods, the resulting MCP values $\{\lambda_t^*\}$ can serve as labels for a supervised regression model. The model maps market features extracted from offer and bid data directly to prices, enabling real-time price estimation for new periods without re-solving the LP.

B. Feature Engineering

For each period t,a feature vector $\mathbf{x}_t = [x_{t1},\, x_{t2},\, x_{t3},\, x_{t4}]^\top$ is constructed as follows.

Average Demand: $x_{t1} = \frac{1}{|\mathcal{D}|} \sum_d \bar{P}^D_{d,t}$

Average Supply: $x_{t2} = \frac{1}{|\mathcal{G}|} \sum_g \bar{P}^G_{g,t}$

Peak Hour Indicator: $x_{t3} = 1$ if $t \in \{2, 5\}$ (defined peak periods), else 0

Cost Volatility: $x_{t4} = \sqrt{\frac{1}{|\mathcal{G}|} \sum_g (C_{g,t} - \bar{C}_t)^2}$

These four features capture demand pressure, supply availability, temporal peak effects, and generator-cost spread — the principal economic drivers of the MCP.

C. Linear Regression Model

Features are standardised (zero mean, unit variance) and a linear regression model is fitted:

$$\hat{\lambda}_t = b + \sum_{f=1}^{4} \theta_f\, \tilde{x}_{tf} \tag{11}$$

where $\tilde{x}_{tf}$ are the scaled features, $\boldsymbol{\theta}$ are the regression weights, and b is the intercept. The model is trained by minimising the mean squared error (MSE) over the six reference periods.

D. Performance Metrics

$$\text{MAE} = \frac{1}{T} \sum_t |\lambda_t^* - \hat{\lambda}_t| \tag{12}$$

$$\text{RMSE} = \sqrt{\frac{1}{T} \sum_t (\lambda_t^* - \hat{\lambda}_t)^2} \tag{13}$$

$$\text{MAPE} = \frac{100}{T} \sum_t \frac{|\lambda_t^* - \hat{\lambda}_t|}{|\lambda_t^*|} \tag{14}$$

Economic sign consistency of the fitted weights is also verified: positive weight on AvgDemand (higher demand raises price), negative on AvgSupply (more supply lowers price), and positive on Volatility (wider cost spread pushes up the marginal unit cost).

V. Simulation Setup and Results

A. Data — IEX 2025–26 Average

The study uses IEX 2025–26 average offer and bid data for a representative 6-period trading window. Tables I and II list the generator offer prices and capacities, and demand bid prices and maximum quantities, respectively.

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TABLE I: Generator Offer Prices $C_{g,t}$ [/MWh] and Capacities $\bar{P}^{G}_{g,t}$ [MW] — IEX 2025–26 Avg.

Gen	T1	T2	T3	T4	T5	T6
Offer Prices [/MWh]						
G1	4200	4400	4100	4600	5100	4300
G2	3800	3900	3700	4200	4800	4000
G3	5200	5400	5000	5700	6500	5300
G4	6100	6300	5900	6800	7500	6400
G5	2900	3100	2800	3400	3900	3200
Capacities [MW]						
G1	180	190	170	185	200	175
G2	420	410	450	430	380	440
G3	150	160	140	155	170	145
G4	90	100	85	95	120	92
G5	550	520	580	540	480	560

TABLE II: Demand Bid Prices $U_{d,t}$ [/MWh] and Maximum Quantities $\bar{P}^{D}_{d,t}$ [MW] — IEX 2025–26 Avg.

Dem	T1	T2	T3	T4	T5	T6
Bid Prices [/MWh]						
D1	6200	6500	6000	6300	7800	5800
D2	6800	7200	6600	7000	8500	6400
D3	5500	5800	5300	5600	6900	5100
D4	7100	7400	6900	7200	8800	6700
D5	6400	6700	6100	6500	8000	5900
D6	5900	6200	5700	6000	7400	5500
D7	7800	8100	7500	7900	9500	7200
Maximum Quantities [MW]						
D1	320	350	300	330	400	280
D2	480	510	460	490	580	430
D3	150	180	130	160	220	140
D4	290	320	270	300	380	260
D5	410	440	380	420	500	360
D6	210	240	190	220	280	180
D7	380	420	350	400	520	330

B. LP Market Clearing Results

Table III summarises the LP clearing results. The MCP ranges from 5,900/MWh (Period 6, off-peak) to 8,500/MWh (Period 5, peak), driven by the merit-order dispatch mechanism. G4 (the most expensive unit) is dispatched in four of six periods, confirming it as the price-setting marginal unit during high-demand intervals. Total social welfare across all six periods is 26.87 Million.

TABLE III: Multi-Period LP Market Clearing Summary

Period	MCP [/MWh]	Total Cleared [MW]	Soc. Welfare [M]	G4 Dispatched?
1	6,400	1,390	4.55	Yes
2	6,700	1,380	4.77	Yes
3	6,100	1,425	4.44	Yes
4	6,500	1,310	4.15	No
5	**8,500**	**1,350**	**5.39**	**Yes**
6	5,900	1,320	3.57	No
Total Social Welfare				26.87 Million

Fig. 2 shows generator dispatch across all periods. G5, the lowest-cost unit (2,900–3,900/MWh), is fully dispatched in every period, confirming its role as the base-load unit. G3 and G4 are dispatched only when aggregate demand exhausts the cheaper supply stack, causing the price jumps visible in Fig. 3.

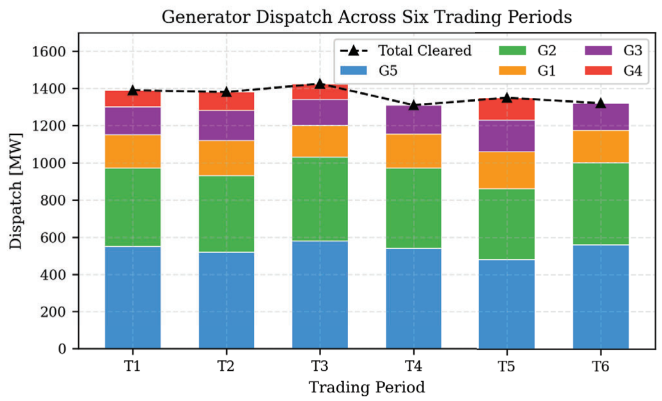

Fig. 2: Generator dispatch across six trading periods [MW].

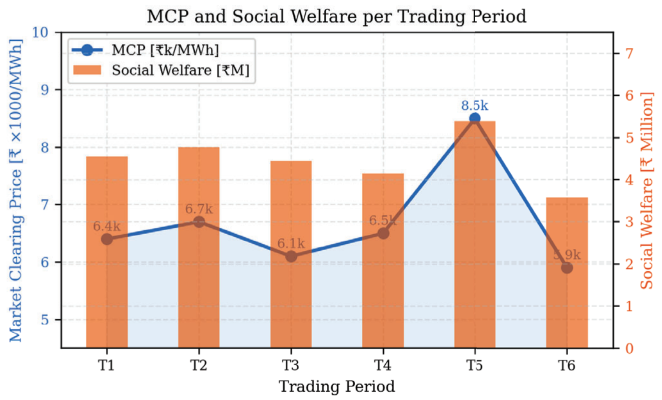

Fig. 3: Market clearing price [/MWh] and social welfare[M] per period.

C. Price Forecasting Results

Table IV compares the LP-derived MCP with the linear-regression forecast for each period.

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TABLE IV: LP Actual vs. Forecasted Market Clearing Prices

Period	Actual MCP [/MWh]	Forecast [/MWh]	Error [%]
1	6,400	6,435.6	0.56
2	6,700	6,901.6	3.01
3	6,100	5,840.0	4.26
4	6,500	6,760.3	4.00
5	**8,500**	**8,303.0**	**2.32**
6	5,900	5,859.5	0.69
MAPE		**2.47%**	
MAE		165.85 /MWh	
RMSE		190.50 /MWh	

The fitted regression weights are given in Table V. The signs are economically consistent: AvgDemand carries a strong positive weight (higher demand raises price), AvgSupply is negative (more supply lowers price), and Volatility is positive (wider cost spread indicates a steeper supply stack, pushing up the MCP).

TABLE V: Linear Regression Weights and Economic Interpretation

Feature	Weight	Economic Interpretation
AvgDemand	+512.74	Higher demand ⇒ costlier marginal unit
AvgSupply	−119.64	More supply ⇒ cheaper marginal unit
PeakHour	−4.38	Absorbed by demand/volatility features
Volatility	+230.01	Steeper stack ⇒ higher clearing risk
Intercept	+6683.34	Base price level for average market conditions

Fig. 4 plots the actual MCP versus the forecast across all six periods, demonstrating close tracking of both off-peak and peak price levels.

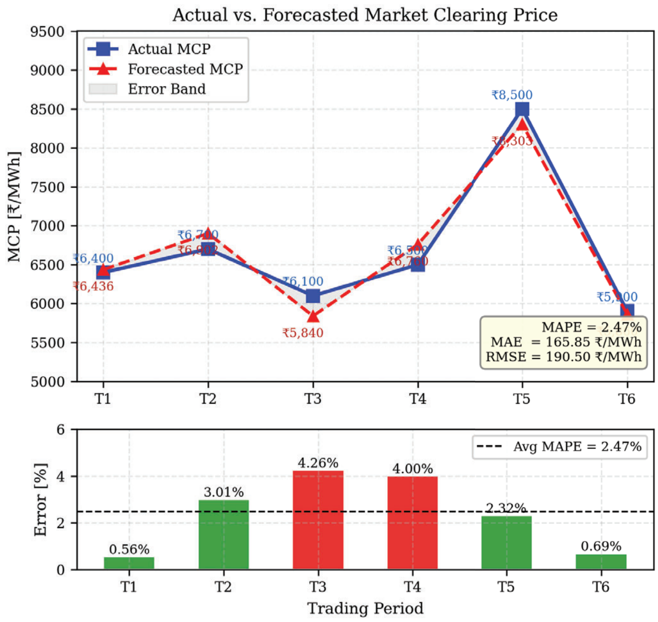

Fig. 4: Actual vs. forecasted market clearing price per period.

D. Discussion

- **Period 5 peak behaviour:** The MCP spike to 8,500/MWh results from the simultaneous effect of peak-hour demand (+28.6% over the median) and the entry of G4 (7,500/MWh) as the marginal unit. Social welfare is highest in this period (5.39M) because the large volume of high-value demand is cleared despite the elevated price.
- **Period 6 off-peak:** Total cleared quantity falls to 1,320 MW and price drops to 5,900/MWh; G4 is not dispatched, and the marginal unit is G3. Social welfare is lowest (3.57M).
- **Forecast quality:** The 2.47% MAPE demonstrates that simple feature-based linear regression captures the dominant price drivers. The largest individual error (4.26%, Period 3) occurs when supply exceeds demand most comfortably, creating a flatter supply curve that is harder to map linearly.
- **Scalability:** The LP scales linearly in the number of generators and demand entities; adding network transmission constraints (DC power-flow equations) is a straightforward extension.

VI. Conclusion

This paper has presented a complete LP-based electricity market clearing model for the Indian day-ahead market. The welfare- maximisation LP correctly identifies the marginal generator and derives the MCP as the dual variable of the energy-balance constraint across six trading periods using IEX 2025–26 average data. The framework achieves a total social welfare of 26.87M, with clearing prices between 5,900 and 8,500/MWh.

A compact linear regression price forecasting model, fed with four market features derived from offer and bid data, predicts clearing prices with a MAPE of 2.47% and RMSE of 190.5 /MWh, providing operators with a fast, LP-free price signal for intra-day scheduling and risk hedging. The economic sign consistency of the regression weights further validates the feature design.

Future work will extend the framework to a full 24-period horizon using the complete IEX daily profile, incorporate DC power-flow network constraints for nodal pricing, and investigate adaptive forecasting methods suitable for non-stationary price dynamics.

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