Electricity Price Forecasting in Singapore (Group 18)

NUS ISEM IE3100R Systems Design Project

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1. Background

Concord New Energy Group Limited (CNE), headquartered in Singapore, is a growing player in global renewables. This project supports CNE's entry into the Singapore wholesale electricity market as a renewable energy provider and an energy storage system operator. To enable electricity arbitrage, we developed a short-term price forecasting model using time-series and deep learning methods.

2. Problem Definition

Although the Energy Market Company (EMC) provides price (USEP) forecasts based on privileged market data and a Linear Programming model, their approach does not incorporate time-series or ML techniques. We saw an opportunity to build a competitive model using publicly available data and reputable third-party sources — leveraging EMC's demand forecasts, commodity prices, and historical USEP trends — to extract latent supply-side signals without access to market bids.

Skills Used

Programming (Python, R), Data Wrangling

Statistics, Machine Learning

3. Methodologies

Gathering Data

- **3 Main Data Sources**:
  (1) EMC: historical and forecast USEP/Demand
  (2) Platts for commodity prices
  (3) Data.gov.sg for weather

Energy Market Company — Forging A Resilient Energy Market

S&P Global Platts

data.gov.sg

Feature Selection + Feature Engineering

- **Statistical Tests:** Kruskal-Wallis Test, adjusted R^2, Spearman's Correlation
- **Time-Series Tools:** ACF/PACF plots
- **Engineered Features:** lags, moving average, rate of change

Model Training

- **LSTM-based** model with stacked and bi-directional layers
- **Hyperparameter tuning** over evaluation set

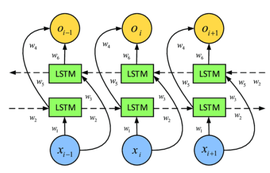


Image Credit: DOI:10.3390/math10071022

Evaluation + Testing

- **Recursive forecasting**
- **Metrics**: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE)

4. Training, Evaluating, and Testing Splits

We selected the longest clean, continuous stretch of data (Feb–Oct 2024) for model training and evaluation. Testing was conducted on recent data windows (Jan–Feb 2025), during which manual collection of EMC forecasts enabled realistic benchmarking.

- Train Set: Start of Feb 2024 to End of Aug 2024 (6 months)
- Evaluation Set: Start of Sep 2024 to End of Oct 2024 (2 months)

Cleanest continuous stretch

- Test Set 1: 13 Jan 2025 to 21 Jan 2025 (effective: 5 days)
- Test Set 2: 23 Jan 2025 to 31 Jan 2025 (effective: 5 days)
- Test Set 3: 10 Feb 2025 to 20 Feb 2025 (effective: 7 days)

Manual data collection period

5. Feature Selection

1 Categorical Features

Kruskal – Wallis Test on USEP: Significant → Temporarily Kept

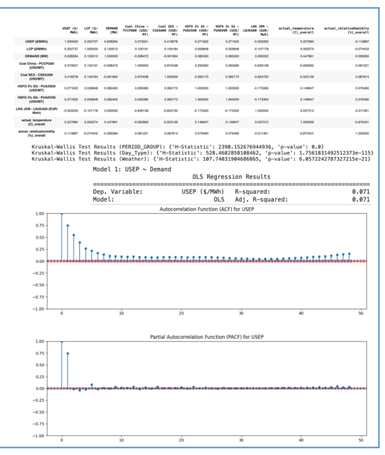
→ Kruskal – Wallis Test on Demand + Adjusted R^2: No added value → Dropped All

2 Numerical Features

Spearman's Correlation on USEP:
Kept: Demand, Coal SEA, HSFO, LNG
Dropped: Temp., R. Humidity, etc.

3 Lagged Features

ACF/PACF on USEP
Kept: t-1, t-5, t-48, t-96



6. Feature Engineering

Finalized list of features for the model:

1) USEP
2) USEP t-1
3) USEP t-5
4) USEP t-48
5) USEP t-96
6) USEP MA_3
7) USEP MA_6
8) USEP MA_12
9) USEP MA_24
10) Demand MA_3
11) Demand MA_6
12) Demand MA_12
13) Demand MA_24
14) Demand ROC_1
15) Demand ROC_5
16) Demand ROC_12
17) Demand ROC_24
18) Demand (MW)
19) Coal SEA – CSEA00
20) HSFO 2% SG – PUAXS00
21) LNG JKM – LNJKA00

7. Model Architecture

Architecture chosen based on trial, literature, and validation performance. Bi-directional LSTM captures time dependencies in both directions; stacked LSTMs enable hierarchical feature extraction; dense layers map learned features to final USEP prediction; activation (Tanh/ReLU), L2 regularization, dropout, learning rate learned obtained by optimising hyperparameters.

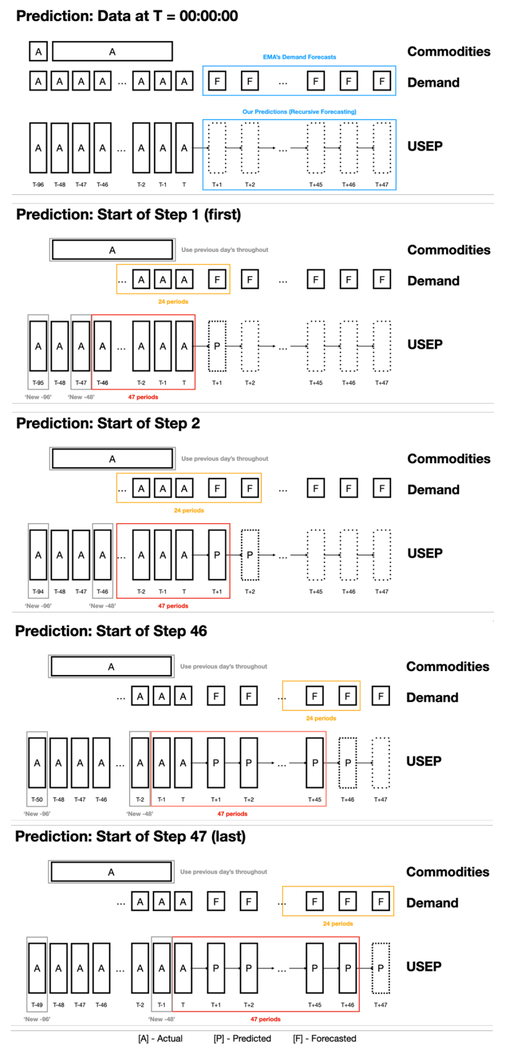
Data → Bi-LSTM (128) *+ tanh & L2 reg* → LSTM (16) *+ tanh & L2 reg* → LSTM (16) *+ tanh & L2 reg* → Dense (16) *+ ReLU* → Dense (8) *+ ReLU* → Dense (1) → **Prediction**

8. Evaluation and Testing

- **Recursive Forecasting** – At **T00:00**, the model predicts USEP for t+1 using all known values, then recursively predicts t+2 to t+47 using its own outputs.
- **Realistic Deployment Simulation**
  - **Evaluation**: Used **actual demand** (forecasts not available)
  - **Testing**: Used **EMC's demand forecasts** to simulate real-world deployment
- **Fair Comparison during Testing** – Both models use the same input conditions (forecast demand). We then compared our predictions against forecast USEP.

Results

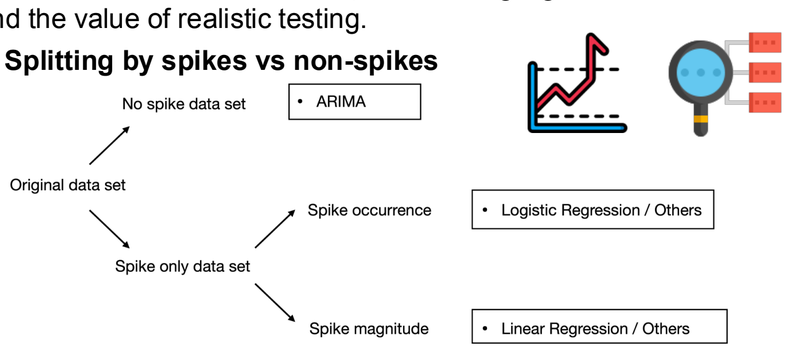
	Our Forecast	EMC's Forecast
Test Set 1	Overall MAE: 11.52 Overall MAPE: 10.18% Daily Errors: 2025-01-16: MAE = 10.44, MAPE = 10.07% 2025-01-17: MAE = 8.42, MAPE = 7.80% 2025-01-18: MAE = 10.46, MAPE = 9.77% 2025-01-19: MAE = 10.42, MAPE = 9.92% 2025-01-20: MAE = 8.67, MAPE = 7.90% 2025-01-21: MAE = 20.69, MAPE = 15.61%	Overall MAE: 7.06 Overall MAPE: 6.52% Daily Errors: 2025-01-16: MAE = 5.82, MAPE = 5.84% 2025-01-17: MAE = 6.80, MAPE = 6.56% 2025-01-18: MAE = 6.16, MAPE = 5.95% 2025-01-19: MAE = 8.17, MAPE = 7.73% 2025-01-20: MAE = 3.64, MAPE = 3.87% 2025-01-21: MAE = 11.77, MAPE = 9.15%
Test Set 2	Overall MAE: 9.94 Overall MAPE: 8.13% Daily Errors: 2025-01-26: MAE = 9.70, MAPE = 8.64% 2025-01-27: MAE = 31.93, MAPE = 19.75% 2025-01-28: MAE = 4.09, MAPE = 4.58% 2025-01-29: MAE = 3.62, MAPE = 3.91% 2025-01-30: MAE = 5.13, MAPE = 5.85% 2025-01-31: MAE = 5.18, MAPE = 6.03%	Overall MAE: 15.21 Overall MAPE: 13.71% Daily Errors: 2025-01-26: MAE = 18.90, MAPE = 16.06% 2025-01-27: MAE = 27.67, MAPE = 17.81% 2025-01-28: MAE = 4.49, MAPE = 4.96% 2025-01-29: MAE = 11.78, MAPE = 12.67% 2025-01-30: MAE = 15.17, MAPE = 16.11% 2025-01-31: MAE = 13.27, MAPE = 14.66%
Test Set 3	Overall MAE: 44.28 Overall MAPE: 19.20% Daily Errors: 2025-02-14: MAE = 14.06, MAPE = 12.10% 2025-02-15: MAE = 21.43, MAPE = 15.12% 2025-02-16: MAE = 16.82, MAPE = 17.69% 2025-02-17: MAE = 181.18, MAPE = 34.19% 2025-02-18: MAE = 33.93, MAPE = 24.05% 2025-02-19: MAE = 29.79, MAPE = 20.53% 2025-02-20: MAE = 12.73, MAPE = 10.74%	Overall MAE: 32.01 Overall MAPE: 10.48% Daily Errors: 2025-02-14: MAE = 6.18, MAPE = 5.26% 2025-02-15: MAE = 23.00, MAPE = 17.30% 2025-02-16: MAE = 9.47, MAPE = 9.31% 2025-02-17: MAE = 161.54, MAPE = 22.96% 2025-02-18: MAE = 10.23, MAPE = 7.58% 2025-02-19: MAE = 10.69, MAPE = 8.28% 2025-02-20: MAE = 2.94, MAPE = 2.64%



9. Alternative Models

Before adopting the LSTM-based model, we tested various simpler approaches under earlier setups. While not directly comparable due to different evaluation methods, the trials highlighted their limitations and the value of realistic testing.

1) Splitting by spikes vs non-spikes



2) Splitting by category labels

10. Limitations

- **Manual forecast collection** at midnight led to occasional data gaps and hence limited forecast data
- **Limited forecast data** meant it was not used in training
- **Evaluation limited to daily comparisons** (EMC updates every 30 min)

11. Future Directions

- **Automate data collection** (e.g. via web scraping, if allowed)
- **Train time-specific models** to reduce recursive error accumulation
- **Explore transformer models/reinforcement learning/other AI models** as a potential upgrade over LSTMs
- **Improve spike handling** (e.g. with anomaly-aware loss functions)

12. Conclusion

Accurate electricity price forecasting may be possible without privileged bid/offer data.
Our LSTM-based model showed promise in stable conditions, with room to improve on extreme price spikes.