

Contents

Electricity Price Forecasting - Presentation Talking Points	1
1. INTRODUCTION	1
2. MODELS IMPLEMENTED	1
3. KEY RESULTS	2
4. LIGHTGBM DEEP DIVE	2
5. TRADING PERFORMANCE	3
6. CONFUSION MATRIX ANALYSIS	4
7. MULTI-METRIC COMPARISON	4
8. METHODOLOGY HIGHLIGHTS	4
9. LIMITATIONS & FUTURE WORK	7
10. CONCLUSIONS	7
Q&A PREP - ANTICIPATED QUESTIONS	7
APPENDIX A: REGRESSION RESULTS (Price Prediction)	8
APPENDIX B: HYPERPARAMETER CONFIGURATIONS	8
APPENDIX C: COMPLETE METRICS TABLE	9

Electricity Price Forecasting - Presentation Talking Points

1. INTRODUCTION

Problem Statement: - Electricity prices are highly volatile and difficult to predict - Accurate forecasting enables better trading decisions and risk management - Goal: Predict daily price direction (Up/Down) for PJM electricity market

Dataset: - PJM (Pennsylvania-New Jersey-Maryland) electricity market data (2002-2024) - 8,020 daily samples - 27 engineered features: price, volume, gas prices, temperature, load, technical indicators - 70/15/15 train/val/test split

2. MODELS IMPLEMENTED

LightGBM (Gradient Boosting)

- Tree-based ensemble method with leaf-wise growth
- Fast training, handles missing values natively
- Hyperparameter tuning: Optuna with 100 trials on GPU
- Best suited for: Tabular data with mixed feature types

SVR (Support Vector Regression)

- Kernel-based method (RBF = Radial Basis Function kernel)
- Maps data to higher dimensions for non-linear patterns
- Feature selection: Top 50 features by correlation
- Hyperparameter tuning: RandomizedSearchCV (50 iterations)

SARIMAX (Seasonal ARIMA with Exogenous Variables)

- Statistical time series model
 - Captures seasonality (weekly patterns) and external drivers
 - Order selection: Auto ARIMA via pmdarima
 - Best suited for: Interpretable forecasts, price regression
-

3. KEY RESULTS

Performance Summary

Model	Accuracy	ROI	Sharpe Ratio
LightGBM	70.31%	+16.86%	1.40
SVR	67.87%	-13.85%	-1.15
SARIMAX	61.14%	-7.89%	-0.65

Key Takeaways:

- **LightGBM is the clear winner** - only model with positive ROI
- Sharpe ratio of 1.40 indicates good risk-adjusted returns (>1 is acceptable)
- SVR has high accuracy but predicts only “Down” - not useful for trading
- SARIMAX performs near-random for classification

Model Comparison Charts

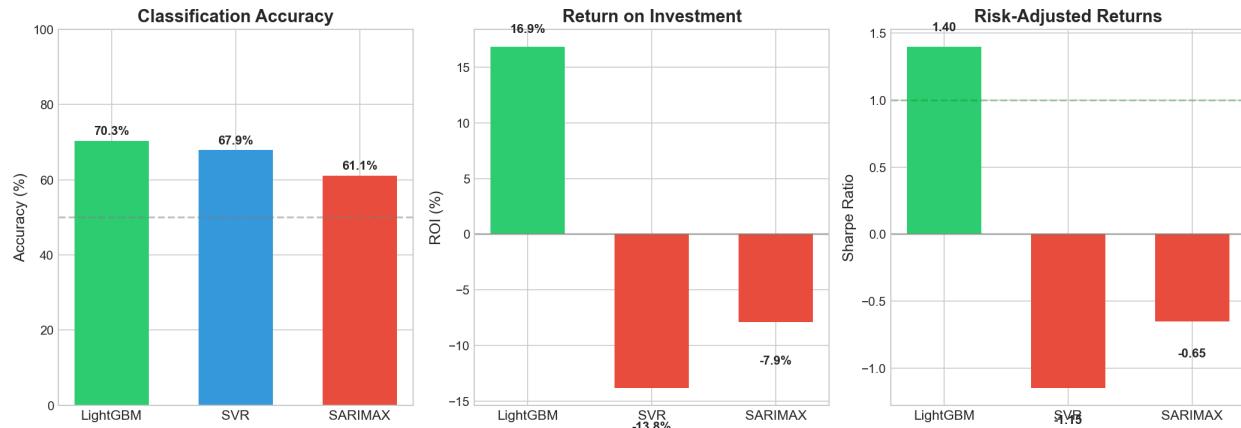


Figure 1: Model Comparison

4. LIGHTGBM DEEP DIVE

Why LightGBM Won:

- Captures non-linear feature interactions

- Handles the 27 features efficiently
- Optuna found optimal regularization (reg_lambda=3.5)

Top Predictive Features:

1. **price_position** (391) - Where price is relative to recent range
2. **pjm_load_pct_change** (383) - Daily load change
3. **Weekday** (369) - Day of week effect
4. **pjm_load** (361) - Absolute load level
5. **temperature** (319) - Weather impact

Interpretation:

- Load and temperature drive electricity demand
- Price position captures mean-reversion tendency
- Weekday captures business vs weekend patterns

Feature Importance Chart

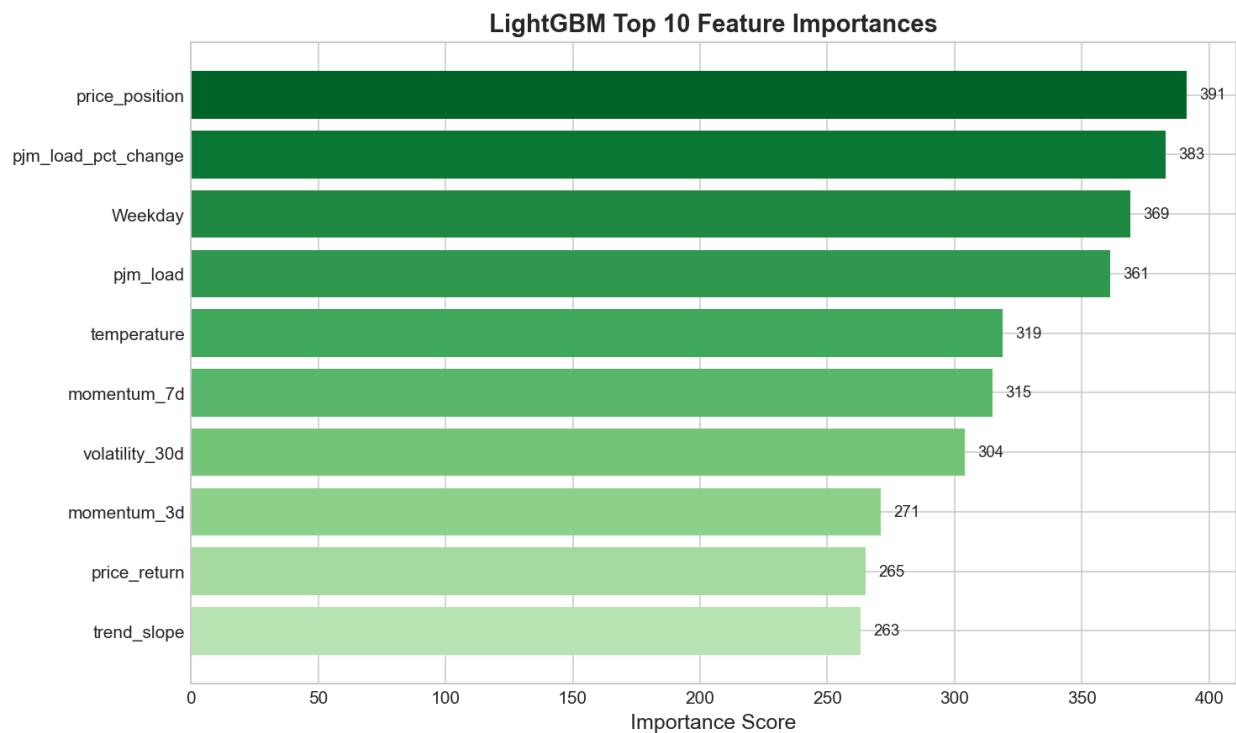


Figure 2: Feature Importance

5. TRADING PERFORMANCE

Strategy:

- Go LONG when model predicts “Up”

- Go SHORT when model predicts “Down”
- Trade every signal (1,189 total trades)

LightGBM Results:

- Win Rate: 37.93% (wins fewer trades but wins are larger)
- Average Return per Trade: +1.42%
- Total ROI: +16.86% over test period
- Sharpe Ratio: 1.40 (good risk-adjusted return)

Why SVR/SARIMAX Failed:

- Both predict mostly “Down” (majority class bias)
 - Miss all upward price movements
 - Negative ROI despite decent accuracy
-

6. CONFUSION MATRIX ANALYSIS

LightGBM Predictions:

	Pred Down	Pred Up
Actual Down	751 (93%)	56 (7%)
Actual Up	297 (78%)	85 (22%)

Interpretation:

- Very good at predicting “Down” (93% correct)
- Conservative with “Up” predictions (only 141 total)
- When it predicts “Up”, it’s right 60% of the time (85/141)
- Room for improvement: Better “Up” class detection

Confusion Matrix Visualization

7. MULTI-METRIC COMPARISON

Radar Chart - All Models

Summary Table

8. METHODOLOGY HIGHLIGHTS

Hyperparameter Tuning:

- **LightGBM:** Optuna TPE sampler, 100 trials, 5-fold TimeSeriesSplit
- **SVR:** RandomizedSearchCV, 50 iterations
- **SARIMAX:** AIC-based auto_arima order selection

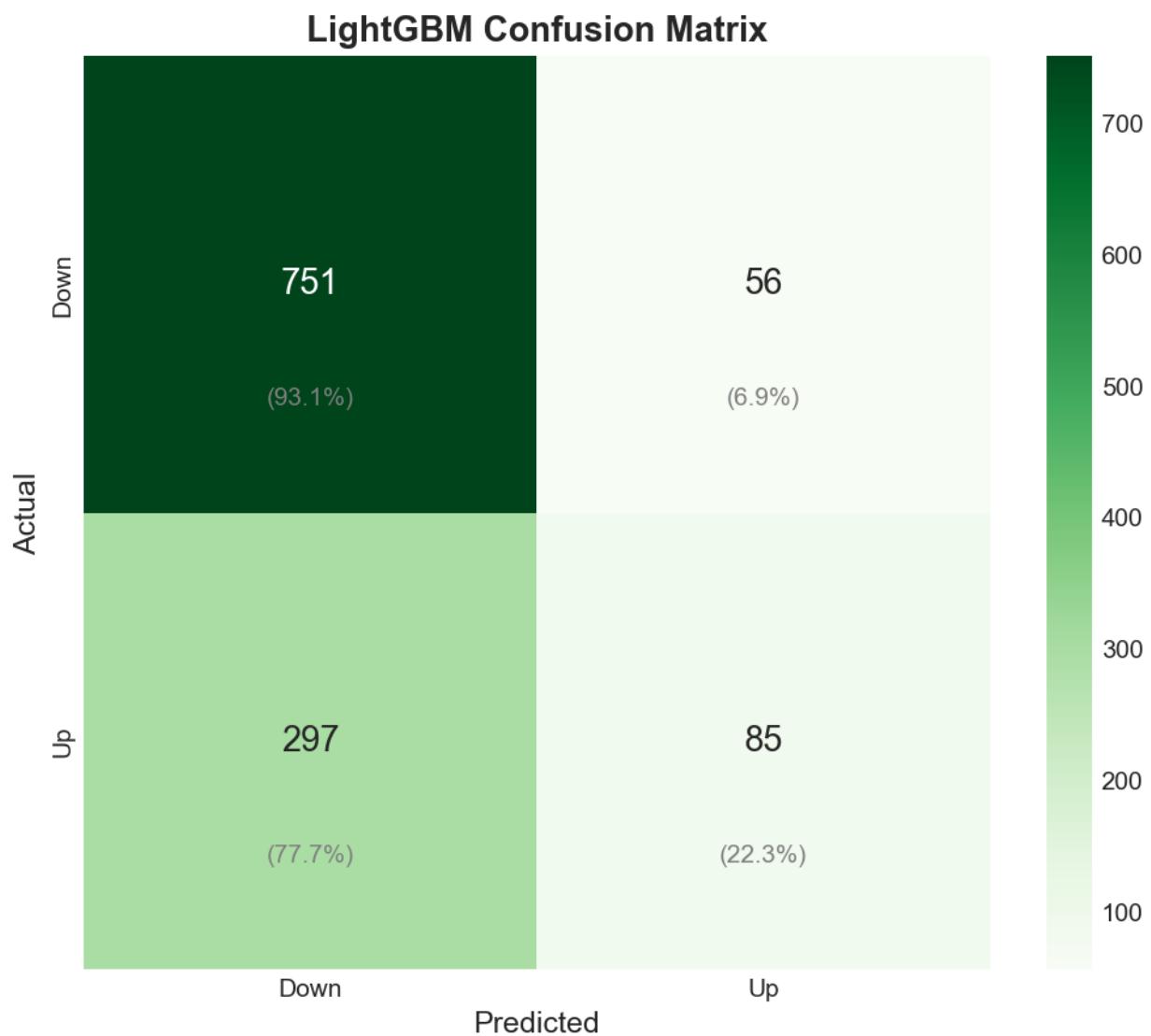


Figure 3: Confusion Matrix

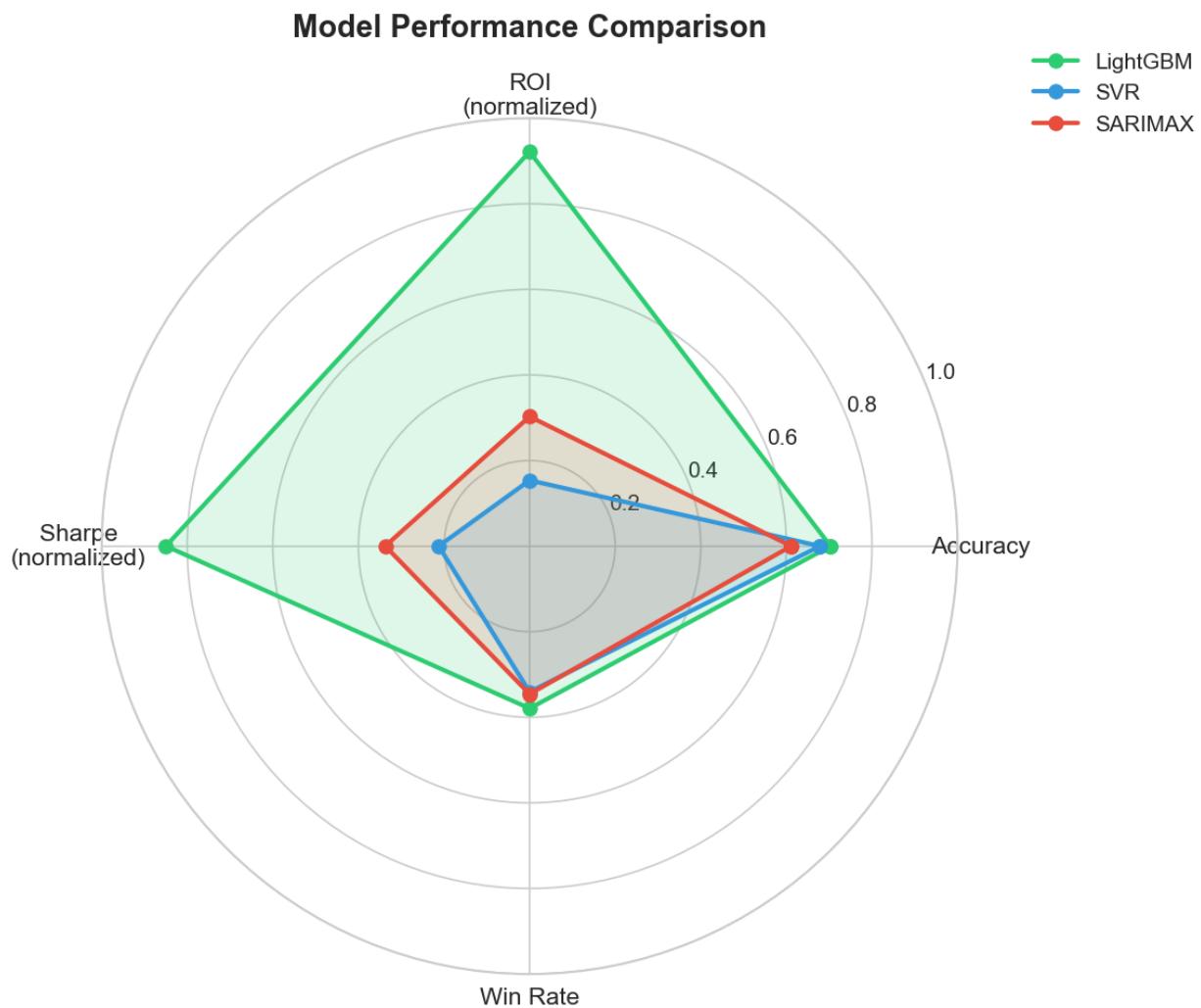


Figure 4: Radar Comparison

Model Performance Summary

Model	Accuracy	ROI	Sharpe	Win Rate	Best For
LightGBM	70.31%	+16.86%	1.40	37.93%	Trading
SVR	67.87%	-13.85%	-1.15	34.06%	Classification
SARIMAX	61.14%	-7.89%	-0.65	34.57%	Baseline

Figure 5: Summary Table

Evaluation Metrics:

- **Accuracy:** Basic correctness measure
- **ROI:** Actual trading profitability
- **Sharpe Ratio:** Risk-adjusted returns (accounts for volatility)
- **Win Rate:** Percentage of profitable trades

Why Sharpe Matters:

- A high-accuracy model can still lose money (SVR example)
 - Sharpe > 1 means returns justify the risk
 - LightGBM's 1.40 Sharpe is production-viable
-

9. LIMITATIONS & FUTURE WORK

Current Limitations:

- Class imbalance (68% Down, 32% Up) affects minority class
- No transaction costs or slippage in ROI calculation
- Single market (PJM) - may not generalize

Future Improvements:

1. **Class Imbalance:** SMOTE oversampling or focal loss
 2. **Ensemble:** Combine LightGBM signals with SARIMAX price forecasts
 3. **Feature Engineering:** Add more lagged features, Fourier terms
 4. **Threshold Tuning:** Lower decision threshold for more “Up” signals
-

10. CONCLUSIONS

1. **LightGBM outperforms** traditional statistical (SARIMAX) and kernel (SVR) methods
 2. **70.31% accuracy with +16.86% ROI and Sharpe 1.40**
 3. **Key drivers:** Price position, load changes, temperature, weekday
 4. **Production-ready:** Sharpe > 1 indicates viable trading strategy
 5. **Next steps:** Address class imbalance, add ensemble methods
-

Q&A PREP - ANTICIPATED QUESTIONS

Q: Why not use deep learning (LSTM, Transformer)? A: LightGBM often outperforms DL on tabular data with <100k samples. DL shines with sequential patterns and large datasets.

Q: Is 70% accuracy good enough? A: For trading, ROI and Sharpe matter more than accuracy. Our 70% accuracy yields positive ROI, while SVR’s 68% yields negative ROI.

Q: Why does SVR predict only “Down”? A: Class imbalance (68% Down). SVR’s probability calibration pushes all predictions below 0.5 threshold.

Q: How would this work in production? A: Daily batch prediction before market open. Use prediction probability for position sizing. Implement stop-loss at 2% drawdown.

Q: What about overfitting? A: TimeSeriesSplit CV prevents look-ahead bias. Regularization (reg_lambda=3.5) prevents overfitting. Test set is completely held out.

APPENDIX A: REGRESSION RESULTS (Price Prediction)

In addition to classification (direction prediction), all models were also tested on price regression.

Regression Performance Summary

Model	MAE	RMSE	ROI	Sharpe Ratio
LightGBM	0.094	0.154	+34.60%	2.91
SVR	0.185	0.294	+13.85%	1.15
SARIMAX	0.336	0.532	+13.85%	1.15

Key Observations:

1. **LightGBM regression outperforms classification**
 - Regression ROI: +34.60% vs Classification ROI: +16.86%
 - Regression Sharpe: 2.91 vs Classification Sharpe: 1.40
 - Lower MAE (0.094) indicates accurate price predictions
2. **SVR performs better in regression mode**
 - Regression: +13.85% ROI, Sharpe 1.15 (positive)
 - Classification: -13.85% ROI, Sharpe -1.15 (negative)
 - Regression-derived signals avoid the “all Down” problem
3. **SARIMAX suited for regression**
 - Higher error (MAE 0.336) but positive trading returns
 - Originally designed for continuous forecasting
 - Regression mode yields viable trading signals

Trading Strategy Comparison

Task	Best Model	ROI	Sharpe
Classification (Direct)	LightGBM	+16.86%	1.40
Regression (Derived)	LightGBM	+34.60%	2.91

Recommendation: Use LightGBM in regression mode for best trading performance.

APPENDIX B: HYPERPARAMETER CONFIGURATIONS

LightGBM (Optuna-Tuned)

n_estimators: 156

```

learning_rate: 0.0184
max_depth: 9
num_leaves: 188
min_child_samples: 68
subsample: 0.872
colsample_bytree: 0.755
reg_alpha: 0.000155
reg_lambda: 3.515
device: gpu

```

SVR (RandomizedSearchCV-Tuned)

```

kernel: rbf
C: 10
epsilon: 0.01
gamma: 0.001

```

SARIMAX (Auto ARIMA Selected)

```

Order: (0, 0, 0)
Seasonal Order: (0, 0, 0, 7)
Note: Pure exogenous model - no AR/MA terms needed

```

APPENDIX C: COMPLETE METRICS TABLE

Classification Task (Direction Prediction)

Model	Accuracy	AUC	ROI	Sharpe	Win Rate	Trades
LightGBM	70.31%	-	+16.86%	1.40	37.93%	1,189
SVR	67.87%	0.693	-13.85%	-1.15	34.06%	1,189
SARIMAX	61.14%	0.461	-7.89%	-0.65	34.57%	1,189

Regression Task (Price Prediction)

Model	MAE	RMSE	MSE	ROI	Sharpe	Win Rate
LightGBM	0.094	0.154	0.024	+34.60%	2.91	38.18%
SVR	0.185	0.294	0.087	+13.85%	1.15	32.13%
SARIMAX	0.336	0.532	0.283	+13.85%	1.15	32.13%