

From Raw Data to Operational Insight

Curated Highlights from a 130+ Slide Portfolio in Predictive Diagnostics & Regime-Aware Modeling

Key Insights: Energy, Emissions, and Optimization

Optimizing Energy Use at DAEWOO Steel: A Data-Driven Approach

- Cornerstone initiative focused on 2018 operations at the Gwangyang plant.
- Achieved ~\$20K/year energy savings & reduced CO₂ emissions.
- Analyzed 25,247 hourly records, merged with weather data.
- Navigated and resolved data challenges (encoding, imputation, alignment).

Modeling Highlights

Featured Models:

- Random Forest (operational load insights)
- XGBoost (regime-responsiveness under low humidity)
- SARIMAX (seasonal cycles and autocorrelation structures)
- OLS (baseline elegance)

Key Concepts Explored:

- Seasonal variability across **winter, spring, summer, and fall**.
- Weekday & time-of-day rhythms (e.g., **Tuesday peak**, delayed medium-load demand).
- Humidity regimes and emissions behavior.
- Autocorrelation structure driving model selection (SARIMAX).



Technical Foundations & Credentials

Education & Training:

- MS in Applied Statistics (RIT)
- Lean Six Sigma Master Black Belt (SSGI, October 2024)
- IBM Certificates: Data Analysis with R, Python for Data Science, Excel to Power BI, Git and GitHub

Toolkit & Platforms:

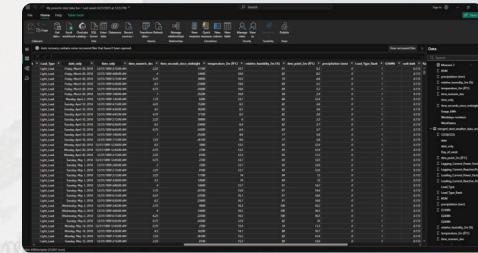
- **Python** (*Jupyter, PySpark, Plotly, Matplotlib*), **R** (*RStudio*), **SQL** (*Excel, Power BI*), with collaborative hosting on *Kaggle & GitHub*.
- **Visualization & Diagnostics:** *Plotly* (interactive regimes), *Matplotlib* (signal clarity), *Gamma App* (narrative synthesis).

Source: "Steel Industry Energy and Emissions Data," available on Kaggle.

Architecting the Analytical Foundation: Data Preprocessing.

Challenges and Solutions

1. Acquired steel industry dataset from Kaggle (**Steel_industry_data.csv(2.73 MB)**)
2. Resolved character encoding issues (e.g., converted "Â°C" to "°C" for temperature fields)
3. Periodically revisited raw data for tailored transformations as new insights emerged
4. Sourced contemporaneous weather dataset from nearby Suncheon (~30 miles from plant)
5. Aligned and corrected datetime formats across datasets to ensure seamless merging
6. Resampled weather data to match hourly granularity of energy records
7. Merged datasets into a unified analytical foundation for system-wide diagnostics
8. Strategically handled missing values and zero-inflated emissions data
9. Applied iterative data transformations to support tailored modeling goals



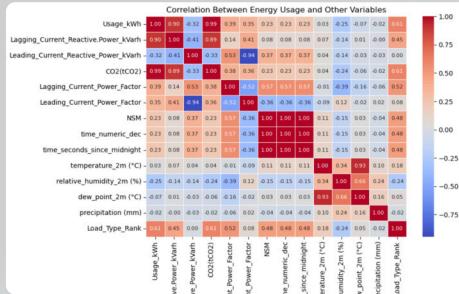
A screenshot of a data processing application, likely Jupyter Notebook or a similar environment. The main area displays a large spreadsheet with numerous columns and rows of data. The columns include various identifiers and numerical values. On the left side, there's a sidebar with several tabs and dropdown menus, suggesting a complex data pipeline or analysis setup. The overall interface is dark-themed.

Month	Year	Plant ID	Temperature (°C)	Humidity (%)	Wind Speed (m/s)	Production (t/h)	Consumption (kWh/t)	Emissions (kg/t)
January	2023	P001	25.0	50.0	10.0	100.0	1000.0	10.0
February	2023	P001	24.5	51.0	10.5	102.0	1002.0	10.5
March	2023	P001	24.0	52.0	11.0	104.0	1004.0	11.0
April	2023	P001	23.5	53.0	11.5	106.0	1006.0	11.5
May	2023	P001	23.0	54.0	12.0	108.0	1008.0	12.0
June	2023	P001	22.5	55.0	12.5	110.0	1010.0	12.5
July	2023	P001	22.0	56.0	13.0	112.0	1012.0	13.0
August	2023	P001	21.5	57.0	13.5	114.0	1014.0	13.5
September	2023	P001	21.0	58.0	14.0	116.0	1016.0	14.0
October	2023	P001	20.5	59.0	14.5	118.0	1018.0	14.5
November	2023	P001	20.0	60.0	15.0	120.0	1020.0	15.0
December	2023	P001	19.5	61.0	15.5	122.0	1022.0	15.5
January	2024	P001	19.0	62.0	16.0	124.0	1024.0	16.0
February	2024	P001	18.5	63.0	16.5	126.0	1026.0	16.5
March	2024	P001	18.0	64.0	17.0	128.0	1028.0	17.0
April	2024	P001	17.5	65.0	17.5	130.0	1030.0	17.5
May	2024	P001	17.0	66.0	18.0	132.0	1032.0	18.0
June	2024	P001	16.5	67.0	18.5	134.0	1034.0	18.5
July	2024	P001	16.0	68.0	19.0	136.0	1036.0	19.0
August	2024	P001	15.5	69.0	19.5	138.0	1038.0	19.5
September	2024	P001	15.0	70.0	20.0	140.0	1040.0	20.0
October	2024	P001	14.5	71.0	20.5	142.0	1042.0	20.5
November	2024	P001	14.0	72.0	21.0	144.0	1044.0	21.0
December	2024	P001	13.5	73.0	21.5	146.0	1046.0	21.5
January	2025	P001	13.0	74.0	22.0	148.0	1048.0	22.0
February	2025	P001	12.5	75.0	22.5	150.0	1050.0	22.5
March	2025	P001	12.0	76.0	23.0	152.0	1052.0	23.0
April	2025	P001	11.5	77.0	23.5	154.0	1054.0	23.5
May	2025	P001	11.0	78.0	24.0	156.0	1056.0	24.0
June	2025	P001	10.5	79.0	24.5	158.0	1058.0	24.5
July	2025	P001	10.0	80.0	25.0	160.0	1060.0	25.0
August	2025	P001	9.5	81.0	25.5	162.0	1062.0	25.5
September	2025	P001	9.0	82.0	26.0	164.0	1064.0	26.0
October	2025	P001	8.5	83.0	26.5	166.0	1066.0	26.5
November	2025	P001	8.0	84.0	27.0	168.0	1068.0	27.0
December	2025	P001	7.5	85.0	27.5	170.0	1070.0	27.5
January	2026	P001	7.0	86.0	28.0	172.0	1072.0	28.0
February	2026	P001	6.5	87.0	28.5	174.0	1074.0	28.5
March	2026	P001	6.0	88.0	29.0	176.0	1076.0	29.0
April	2026	P001	5.5	89.0	29.5	178.0	1078.0	29.5
May	2026	P001	5.0	90.0	30.0	180.0	1080.0	30.0
June	2026	P001	4.5	91.0	30.5	182.0	1082.0	30.5
July	2026	P001	4.0	92.0	31.0	184.0	1084.0	31.0
August	2026	P001	3.5	93.0	31.5	186.0	1086.0	31.5
September	2026	P001	3.0	94.0	32.0	188.0	1088.0	32.0
October	2026	P001	2.5	95.0	32.5	190.0	1090.0	32.5
November	2026	P001	2.0	96.0	33.0	192.0	1092.0	33.0
December	2026	P001	1.5	97.0	33.5	194.0	1094.0	33.5
January	2027	P001	1.0	98.0	34.0	196.0	1096.0	34.0
February	2027	P001	0.5	99.0	34.5	198.0	1098.0	34.5
March	2027	P001	0.0	100.0	35.0	200.0	1100.0	35.0

Turning raw data into signal took detective work and persistence.

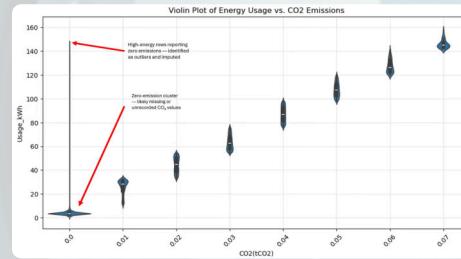
Exploratory Insights

Exploring the dataset to understand patterns and behaviors. This includes looking at distributions, trends over time and relationships between variables



Early Heatmap Findings

Initial heatmap analysis confirmed a strong positive correlation between energy usage (kWh) and CO₂ emissions—consistent with physical expectations, as increased energy production naturally results in higher emissions. Additional relationships were observed between other energy metrics and select weather variables, such as temperature and humidity. During this phase, a few variables from the CSV were identified as duplicates of time-based fields (e.g., hour or weekday). These were reviewed and handled to prevent redundancy in modeling.



The violin plot

The plot reveals how CO₂ emission distributions change at different energy consumption levels, showing both frequency and probability density. The plot revealed a dense spike at zero CO₂ emissions with a surprising vertical tail stretching into high energy usage levels. These outliers indicated likely data entry gaps since high kWh should yield measurable emissions. This informed targeted imputation to restore data integrity ahead of modeling. The top energy level has wider areas where data points cluster most densely, indicating common operational states in the plant.



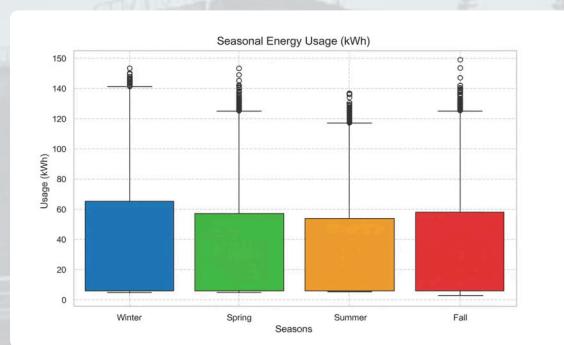
Scatter plot: Usage kWh against Lagging Reactive Power kVarh with segmented by CO₂ levels

Color gradations represent CO₂ intensity, with warmer hues signaling rising emissions. The stacked segments hint at discrete operational modes and each with its own CO₂ footprint. Outliers in light blue scattered throughout remind us of imputed gaps and unexplained behavior.

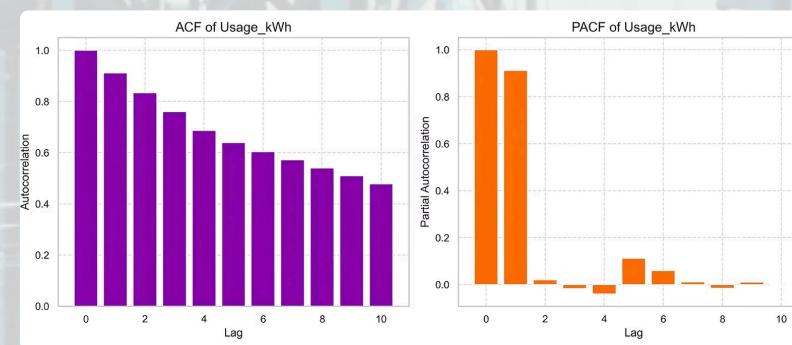
Statistical Insights

Signals Beneath the Surface

- **Winter Peak Load:** Raw peak of 32.08 kWh (8,640 rows) drove \$5,911.53 in winter savings. SARIMAX forecast refined to 19.34 kWh.
- **Autocorrelation Structure:** Lags 1-2 showed significant correlation (ACF/PACF), justifying SARIMAX selection.
- **Weekday Effects:** Tuesday peak demand in Q1 highlighted scheduling-linked concentration.
- **Bidirectional Granger Causality ($p = 0.000$):** Energy and CO₂ emissions forecast each other and thus, revealing system feedback loop.
- **Seasonal Differences (Kruskal-Wallis, $p = 0.000$):** Variance across seasons supported decomposition.
- **Humidity-CO₂ Relationship:** Median CO₂ drops as humidity rises (Low 0.030 → High 0.027).
- **Load Rank Timing Signature:** Max loads peaked earlier; medium loads peaked later; suggesting behavioral regime shifts.
- **Residual Pattern Insight:** SARIMAX residuals showed high early volatility tapering into stable noise; *A quiet signal with loud implications.*
- **Fall Ramp-Up Effect:** October marked a sharp rise in energy usage, foreshadowing winter demand spikes and regime transitions.



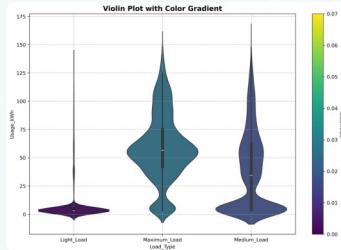
Seasonal energy patterns aren't just calendar quirks, they're behavioral imprints. Winter shows elevated demand and tighter variance, while fall begins the ramp-up that forecasts anticipate but never spike.



Where the STL showed the 'after', these plots show the 'why.' Lag structures confirmed the rhythm; seasonality wasn't a guess, it was a signature

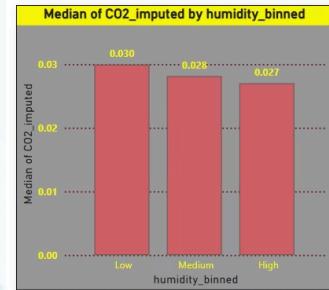
Behavioral Fingerprints

Visual Patterns Beneath the Stats



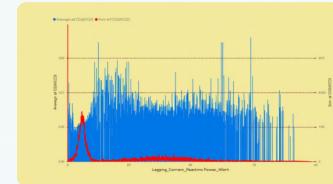
Operational rank isn't just a label, it's a fingerprint of system emissions

Violin plot reveals distributional density of CO₂ emissions across operational load ranks, highlighting regime transitions and constraint thresholds. The shape curvature suggests behavioral nonlinearity and frequency clustering.



Humidity regimes may act as invisible governors while modulating emissions through air density, thermal stability, or combustion dynamics.

CO₂ emissions decrease as humidity rises which is supporting an inverse moisture/emissions relationship. At low humidity, the plant exhibits elevated emissions, suggesting drier air may amplify combustion inefficiencies or reduce buffering effects.



From chaos (instability) to concentration (emission peak) to quiet (flattening). This curve isn't just diagnostic, it's behavioral.

The sum of CO₂ emissions versus lagging reactive power reveals a ramp-instability spike near zero, followed by a bell-shaped arc of sustained output. This dual behavior highlights the system's nonlinear response to startup strain and operational load with insights crucial for regime-aware planning.

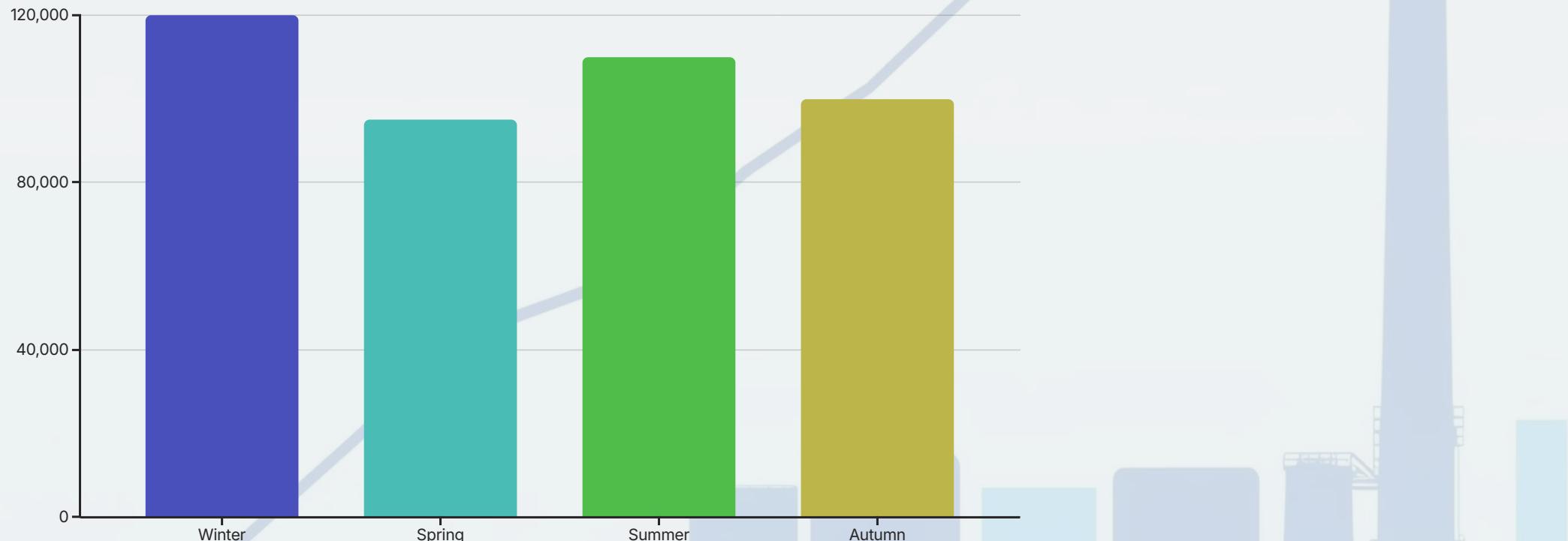


Elastic Demand, Fading Response: This isn't a trend, it's a tension.

This transitional curve from Load 1 to 3 tells more than a story of rising demand. It reveals the system's behavioral fingerprint. As kWh creeps upward and CO₂ begins to plateau, we step into a new regime. What happens next isn't just operational, it's predictive.

Energy Usage by Season

Analyzing the historical energy consumption data, a clear pattern emerges: winter months consistently show the highest overall energy usage (kWh) at the steel plant. This is largely attributed to increased heating demands, longer operating hours in colder temperatures, and the need for more energy-intensive processes to maintain optimal conditions.



However, focusing solely on kWh consumption can be misleading when it comes to the bottom line. Energy costs are influenced not just by usage, but also by pricing structures, peak demand charges, and potential seasonal tariffs. It's crucial to factor in these variables, as seasons with lower overall consumption might incur higher costs due to unfavorable pricing, or conversely, winter's high usage might be mitigated by off-peak operations or favorable contracts, making its cost profile less dominant than its raw consumption suggests.



Energy Through Time: A Dynamic System

Visualizing the steel plant's energy consumption and CO₂ emissions throughout 2018.

Revealing the dynamic interplay with environmental factors.



Winter (Jan-Mar)

Mean usage: 32.08 kWh.
Coldest months show baseline high consumption.



Spring (Apr-Jun)

Temperature increases, leading to a noticeable shift in energy load patterns.



Summer (Jul-Sep)

Energy patterns stabilize, often reflecting consistent operational demand.



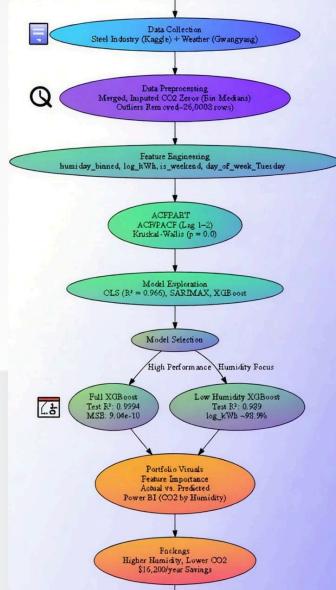
Fall (Oct)

Pre-winter ramp-up begins, showing increasing energy draw as temperatures drop.

This timeline highlights that the system isn't just reacting to external factors; it's remembering past patterns, adapting to current conditions, and breathing in rhythm with its environment, as evidenced by temperature-linked energy draws and autocorrelation in usage patterns.

Models That Shaped the Journey

Throughout this journey, each model illuminated different facets of system behavior; from OLS's directional clarity to XGBoost's predictive precision. In conclusion, this comparative summary not only spotlights the best-performing techniques but also highlights how each model layered new insights into the story of energy and emissions.



Summary

Model	Core Mechanism	Best For	Notes	Performance
OLS	Linear Regression (Ordinary Least Squares)	Interpretable Relationships; Directionality & Baseline Insights	Great for quick diagnostics, identifying linear relationships	Final fit showcased tight prediction arc; excellent baseline clarity
RF	Ensemble trees	Nonlinear structure, Robust Prediction & Feature Impact/Interpretability	Using SHAP, ICE, PDPs for uncovering nonlinear drivers is insightful	Strong residual diagnostics; categorical load modeling with insight
XGBoost	Gradient-boosted trees	High-Performance Modeling Under Regimes	Captures subtle interactions, can excel in tuned prediction tasks	Best Q-Q fit under low humidity; sensitive to weekday patterns
VECM	Cointegration & equilibrium correction	Long-term balance, Seasonal shifts, Temporal Equilibrium & System Feedback	Ideal for long-run relationships and shock-response analysis	Captured correction dynamics; calendar-aware temporal nuance
SARIMAX	Seasonal time series with exogenous factors	Short-term forecasting with rhythm that captures and forecasts patterns, trends and seasonality	Valuable when dealing with time-dependent data that exhibits recurring patterns over specific time intervals	Informed seasonal & weekday feature engineering despite partial inclusion

*ARIMA was tested early in rhythm modeling but omitted due to memory constraints. Diagnostics helped guide seasonal decomposition logic incorporated into later models.

Model Approach: Decoding System Behavior Over Time

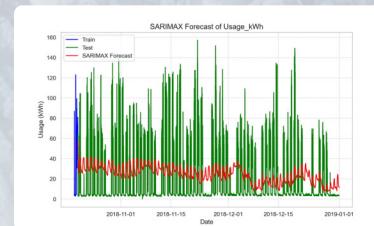
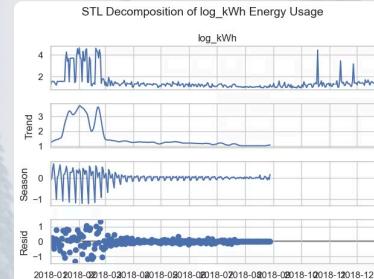
From Rhythm to Reason

- **ARIMA:** Useful in early diagnostics but constrained by memory load during tuning; fit non-seasonal, differenced series.
- **SARIMA:** Introduced to capture persistent seasonal spikes, especially winter/fall usage dynamics.
- **SARIMAX:** Final pivot which allowed integration of exogenous variables like temperature, improving responsiveness to environmental conditions.

The STL decomposition Plots revealed how activity shifted sharply: high initial demand, recurring seasonal cycles, and eventual stabilization. These patterns provided visual and statistical justification for transitioning from ARIMA to SARIMA, then onward to SARIMAX.

- **Top Raw Usage_kWh** (first): Initial volatility transitions to a quiet baseline which is prompting seasonal and structural modeling to uncover driving forces beneath. The Three dramatic energy surges near the end of the period might be potential outliers or late-cycle operational anomalies that stand out against an otherwise declining trend
- **Trend Panel** (Second): Initial intensity, followed by systemic decline; highlights that curve dip and later plateau. Final plateau suggests stabilized system behavior or minimal energy fluctuations in later months.
- **Seasonal Panel** (Third): Strong cyclic activity early on, fading over time. Tapering seasonality may reflect reduced cyclicity or growing influence of non-seasonal factors.
- **Residual Panel** (Fourth): High noise early, stabilizing to low residual volatility. Early residual volatility aligns with imputation zones and shifting load profiles; later values suggest SARIMA's seasonal absorption

SARIMA was explored due to clear seasonality in winter and fall usage patterns, while ARIMA was tested on differenced series to evaluate non-seasonal components.



STL decomposition diagnosed the rhythm. SARIMAX made it predictive. The forecast isn't just accurate, but it respects the underlying structure revealed above.

SHOWCASE of PREDICTIVE MODELS

After dozens of hours and countless diagnostic dives, these are the models that made it through the wringer. Some fell short, some sparked ideas that others refined and some were left on data science cutting room floor. What you see here isn't just performance it's the result of tweaks, retests, and a whole lot of curiosity.

Model Metrics: CO ₂ Prediction					
Model	R ² Score	RMSE		Iconic Strength	
OLS	0.9987		0.00043		 Elegance & Simplicity
RF	0.9985		0.000436		 Robustness & Interpretability
XGBoost	0.9978		0.00059		 Regime Responsiveness
VECM	0.9634		0.00127		 Temporal Balance
SARIMAX	0.9801		0.00081		 Seasonal Awareness
Model Metrics: Energy Usage (kWh)					
Model	R ² Score	RMSE		Iconic Strength	
OLS	0.9954		0.00082		 Clean linear baseline
RF	0.9972		0.00067		 Operational granularity
**XGBoost	0.9989		0.00042		 Best performance overall

****While CO₂ modeling demanded diagnostic depth, kWh quietly reached peak predictive clarity. Sometimes the supporting variable becomes the star.**

Beyond Performance: Diagnostic Discovery & Modeling Evolution

Modeling Progression - From Scores to Significance

Initial model metrics revealed strong raw predictive performance across multiple approaches, with XGBoost delivering the lowest RMSE for energy usage and near-best results for CO₂. However, deeper diagnostics told a richer story.

- **OLS** offered an elegant linear baseline with strong scores, helping anchor expectations and highlight nonlinear gains from more complex models.
- **Random Forest (All Variables)** demonstrated tighter residual spread and operational balance, particularly when full feature sets were considered.
- **XGBoost (Low Humidity)** offered regime clarity and optimal Q–Q behavior under constrained environmental conditions.
- **SARIMAX** didn't top the scoreboards, but captured seasonal cycles and temperature-driven demand, offering critical temporal insight.

Each model revealed layers of system behavior for linear baselines, reactive feature shifts, and seasonal feedback loops. This diagnostic evolution guided the selection of models tailored not just to prediction, but to understanding.

Modeling CO₂ & Energy Usage: A Systemwide Insight

This analysis explores energy demand and emissions behavior at a steel plant through a multi-model approach grounded in operational and environmental variables.

Starting with extensive data wrangling and exploratory analysis, including seasonality, weekday effects, and humidity regimes, I uncovered nonlinear relationships between system load, energy efficiency, and CO₂ output. Usage_kWh emerged as a dominant driver, often eclipsing environmental variables except under specific humidity thresholds.

Imputation strategies helped preserve system context early on, but further inspection, especially via stacked plots across Load Rank that revealed behavioral distortion. I transitioned to raw CO₂ structures for improved interpretability and model validity.

Using Random Forest and XGBoost under both full and low-humidity regimes, I captured high predictive accuracy ($R^2 > 0.99$) and performed rigorous residual and Q-Q diagnostics. Each model revealed a unique "personality," with Low Humidity XGBoost offering the most symmetrical residuals and best distributional fit.

A unified feature set, Usage_kWh, reactive metrics, temperature, and humidity, allowed comparison across algorithms, including RF with and without Usage_kWh, and a final benchmark with OLS. Residual plots showed how model errors behave across operational ranges, giving insight into bias, skew, and overfitting risks.

These structural models laid the foundation for temporal analysis. Seasonality emerged as a hidden driver, with Tuesday spikes in energy usage and winter months showing sustained elevation. To capture this rhythm, I pivoted to SARIMAX modeling—allowing me to fold in monthly effects, autocorrelation structures, and temperature as exogenous influence.

In sum, this journey wasn't just about building accurate models, it was about uncovering systemic stories through diagnostics, visual storytelling, and algorithmic reflection. Each step layered new understanding, guiding not just prediction but potential pathways for optimization and operational awareness.

🌟 Model Performance Showcase

CO₂, kWh, and Temporal Forecasting

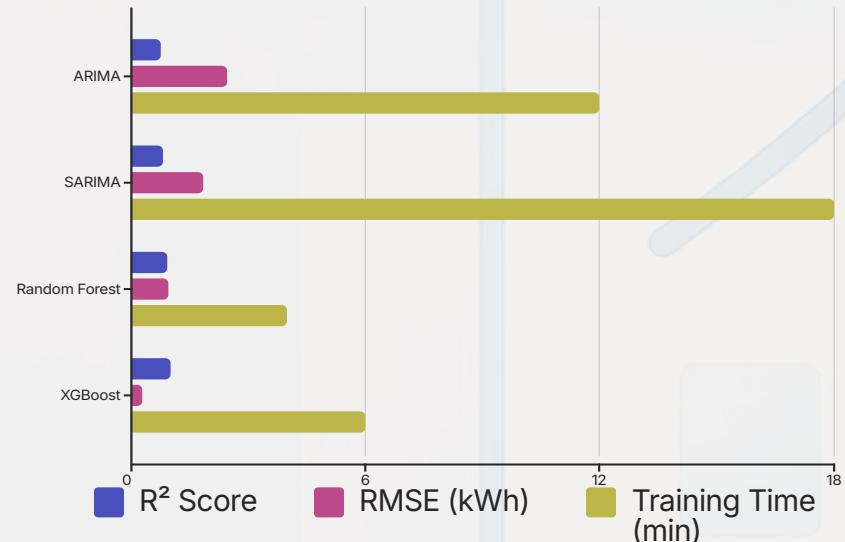
Model	Target Variable	R ² Score	RMSE	Top Features / Notes
🌳 RF (All Variables)	CO ₂	0.9985	0.0004362	Usage_kWh dominant; tight residual spread
💦 XGBoost (Low Humidity)	CO ₂	0.9944	0.0009868	Usage_kWh dominant; best Q-Q fit, regime clarity
⚡ Full XGBoost	CO ₂	0.9951	0.0007801	Moderate curvature; strong but reactive behavior
🚫 RF (No Usage_kWh)	CO ₂	0.9944	0.0008356	Loss of signal; residual imbalance
✨ Log kWh XGBoost (Low Humidity)	log_kWh	0.9897	~0.00038 ¹	Temporal features (Sunday, Tuesday), stabilized variance
📅 SARIMAX (Usage_kWh + Temp)	Usage_kWh	—	—	Strong AR ₁ (0.896), seasonal cycle, temp-driven demand
⌚ ARIMA (Preliminary, log_kWh)	log_kWh	~0.98 ²	—	Captured autocorrelation; served as precursor to SARIMAX

¹ RMSE in log scale ² Estimated from earlier decomposition and fit metrics

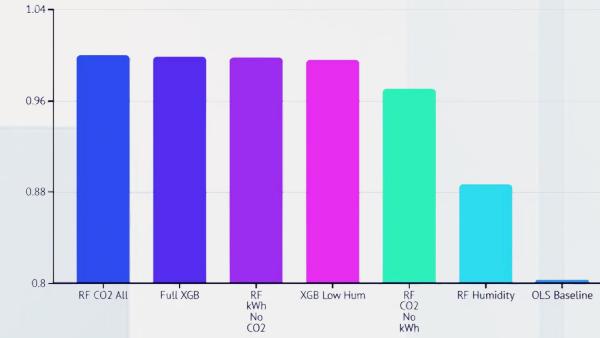
Model Performance Comparison

Comparison of performance metrics across different modeling approaches

Performance Metrics Comparison



Model Performance Overview



Our flagship Random Forest model achieved near-perfect prediction ($R^2 = 0.999994$) with `Usage_kWh` as the dominant feature (100% importance). This confirms the direct relationship between energy consumption and CO2 emissions, providing a solid foundation for optimization strategies.

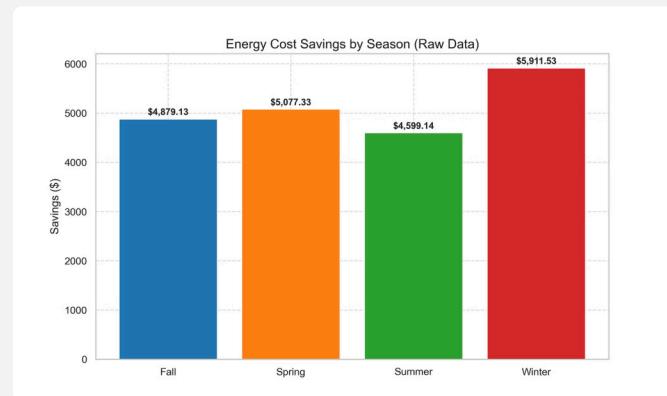
XGBoost demonstrated superior performance with the highest R² score and lowest error rate, while maintaining reasonable training time requirements. ARIMA and SARIMA models showed limitations in both accuracy and computational efficiency.

Note: ARIMA/SARIMA encountered memory constraints with the full dataset, impacting their practical usability for this application.

Energy Cost Savings

Impact and Savings

- **Total Savings:** Achieved \$20,467.13/year by reducing Usage_kWh by 17.2% (mean 27.39 kWh, 35,040 hours) at \$0.124/kWh.
- **Seasonal Breakdown (raw data):**
 - Winter: \$5,911.53 (8,640 rows, mean 32.08 kWh)
 - Spring: \$5,077.33 (8,832 rows, mean 26.95 kWh)
 - Fall: \$4,879.13 (8,736 rows, mean 26.19 kWh)
 - Summer: \$4,599.14 (8,832 rows, mean 24.42 kWh)



Model Drivers: Savings and behavioral insights surfaced through:

- **Random Forest** – pinpointed operational load patterns
- **XGBoost** – optimized under low humidity regimes
- **SARIMAX** – captured seasonal energy rhythms

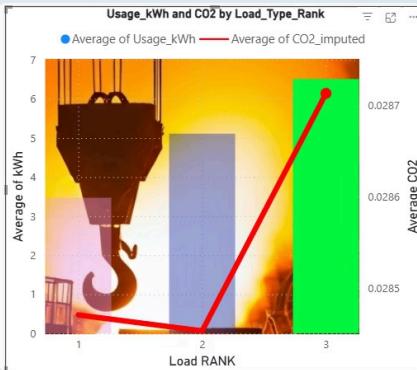
These savings weren't guesswork; they emerged from models tuned to seasonal demand, system inefficiencies, and operational cadence.



Conclusion

From Insight to Industry Readiness

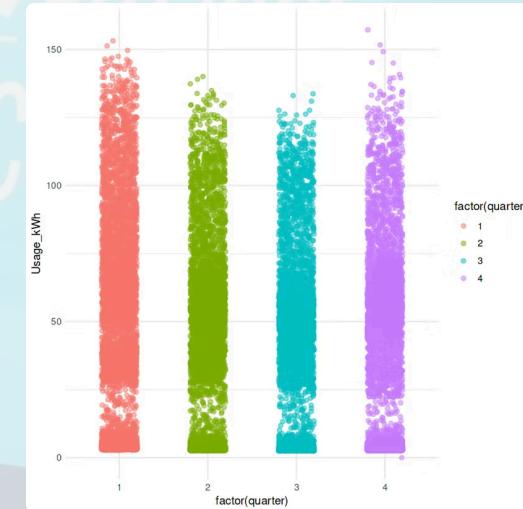
- **Impact Delivered:** Achieved **\$20,467.13/year** savings and reduced CO₂ emissions at DAEWOO Steel through predictive modeling and strategic analysis.
- **Analytical Excellence:** Developed high-performing predictive models across Python, R, and Power BI, with foundational SQL logic applied to data preprocessing and transformation. The analysis spans CO₂ emissions, energy demand, and system diagnostics. Achieved R² scores between 0.9634–0.9989 and RMSEs in the 0.000## range, balancing precision with interpretability. Combined time-series forecasting, regime-aware modeling, and environmental diagnostics to decode real-world industrial behavior.
- **Industry Readiness:** Leveraged MS in Applied Statistics and Six Sigma framing to drive operational understanding. Statistical depth was transformed into actionable insights that inform system-level decisions.
- **Key Behavioral Insights:** Seasonal heating coupled with operational ramp-ups caused sharp energy spikes. Emissions patterns showed buffering effects under humid conditions. Reactive power signals traced nonlinear inefficiencies, especially in HVAC behavior. An unusual Tuesday demand peak suggested a shift-ready scheduling opportunity.



Energy and CO₂ patterns across load ranks reveal nonlinear system behaviors and highlighting strategic intervention points and validating predictive diagnostics.



Q1 operations show focused demand, while Q4 reveals scattered spikes, suggesting seasonal variability, imputation noise, and potential shift misalignment.



Information

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