



Power and Energy Machine Learning Data Management Course

26 – 30 September 2027
Toronto

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Ref: 313_126380 **Date:** 26 – 30 September 2027 **Location:** Toronto **Fees:** 16000 Euro

Overview

Power and Energy Machine Learning Data Management Course is a five-day intermediate course for power-generation, grid, utility, renewable-energy, asset, reliability, data, and operations professionals, who leave with a Power and Energy ML Data-to-Decision Pack. Participants connect operational data, quality, time-series preparation, forecasting, anomaly detection, predictive maintenance, monitoring, and human decisions without building production models. The course supports evidence-based use of machine learning in energy operations. Agile Leaders Training Center provides training in power and energy machine learning data management.

Who Should Attend

- Teams responsible for generation, grid, utility, or renewable-energy operations
- Teams responsible for asset reliability and predictive maintenance decisions
- Teams responsible for operational data, historians, meters, and sensors
- Teams responsible for forecasting, planning, and performance analysis
- Teams responsible for analytics governance, monitoring, and operational risk

The course assumes participants work with energy operations or data and leaves out model coding, control-system configuration, protection engineering, market trading, certification, and autonomous operational control.

Departments and Industries

The course supports machine-learning evaluation across power generation, transmission, distribution, renewable energy, utilities, industrial energy, and asset services.

- Generation operations, performance, and maintenance
- Transmission, distribution, and grid control support
- Renewable forecasting and integration planning
- Asset management, reliability, and condition monitoring
- Data engineering, analytics, cybersecurity liaison, and governance

Learning Objectives

By the end of this course, participants will be able to:



- Analyze energy data sources, context, quality, and ownership
- Build time-series preparation and data-readiness profiles
- Evaluate forecasting, anomaly, and predictive-maintenance evidence
- Compare model uncertainty, errors, drift, and operational impacts
- Apply monitoring, governance, and human decision controls
- Build a Power and Energy ML Data-to-Decision Pack

Course Agenda

Day 1: Energy Data and ML Use Cases

- Power and Energy ML Use Case Canvas
- Generation, Grid, Meter, Weather, and Asset Data Map
- Operational Technology and Information Technology Boundary
- Forecast, Detect, Diagnose, Prioritize, and Optimize Task Matrix
- Human Decision Authority and Accountability Canvas

Day 2: Data Quality and Time Series

- Time-Series Timestamp, Interval, and Alignment Check
- Missing Measurement and Bad-Data Treatment Guide
- Data Provenance, Context, Units, and Lineage Profile
- Seasonality, Weather, Load, and Event Feature Map
- Energy ML Data-Readiness Scorecard

Day 3: Forecasting and Anomaly Evidence

- Load and Renewable Forecast Evaluation Sheet
- Baseline, Horizon, and Forecast Error Comparison
- Anomaly and Fault Detection Signal Review
- False Alarm and Missed Event Impact Matrix
- State Estimation and Situational Awareness Questions

Day 4: Predictive Maintenance and Model Control

- Asset Condition and Failure Mode Data Link
- Predictive Maintenance Lead-Time Decision Map
- Uncertainty, Generalization, and Operational Limitations
- Model Drift and Performance Monitoring Plan
- Cybersecurity, Change, Escalation, and Human Override Controls



Day 5: Energy ML Decision Practice

- Suggested Exercise: Profile an Energy Time-Series Dataset
- Suggested Exercise: Review a Forecast and Error Pattern
- Suggested Exercise: Triage Anomaly and Maintenance Signals
- Suggested Exercise: Define Monitoring and Escalation Controls
- Capstone Exercise: Power and Energy ML Data-to-Decision Pack

Practical Exercises

The course uses suggested activities to connect energy data and model outputs to accountable operational decisions.

- Suggested activity: frame an energy use case with the decision, data sources, operational context, owners, and exclusions
- Suggested activity: profile time-series data for timestamps, gaps, units, seasonality, events, lineage, and readiness
- Suggested activity: review forecast or anomaly evidence with baselines, errors, uncertainty, and operational consequences
- Suggested activity: assemble a decision pack covering maintenance action, model monitoring, cybersecurity, change, override, and escalation

FAQs

Who suits power and energy machine learning data management training, and what does it assume?

The course suits generation, grid, utility, renewable, reliability, asset, data, and operations teams. It assumes familiarity with energy processes or operational data but not programming or machine-learning development.

How does energy machine learning data management differ from data science training?

Energy machine learning data management focuses on operational context, data readiness, forecast and anomaly evidence, maintenance decisions, monitoring, and governance. Data science training focuses on coding, algorithms, feature engineering, model tuning, and deployment.

What data supports machine learning in power and energy operations?

Relevant sources may include plant historians, supervisory systems, meters, sensors, weather, maintenance records, asset registries, alarms, outages, market or demand data, and operator logs, subject to quality, access, context, and security controls.



Why must energy ML models be monitored after deployment?

Operating conditions, assets, sensors, data pipelines, weather, demand, and maintenance practices change. Monitoring detects declining performance, drift, data failures, unreliable alerts, and conditions that require investigation, retraining, restriction, or human override.

Conclusion

Participants take back a Power and Energy ML Data-to-Decision Pack linking use cases, sources, time-series readiness, forecasting, anomaly evidence, maintenance signals, uncertainty, monitoring, cybersecurity, decision authority, and escalation. It improves collaboration between operational and data teams. It preserves accountable human control over energy decisions.