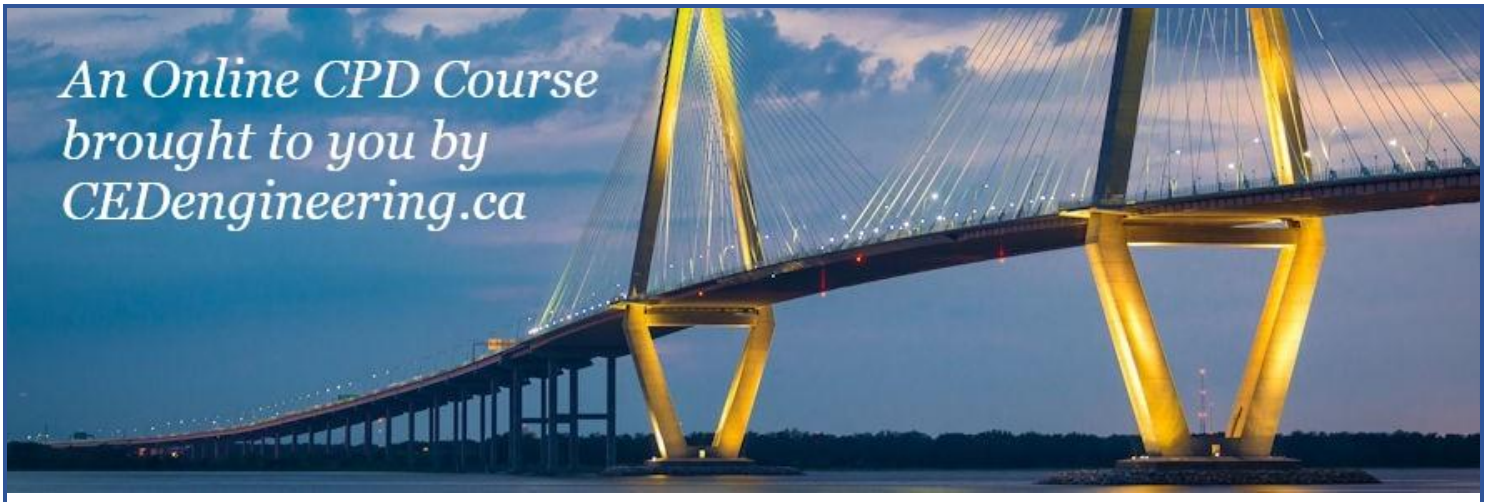


AI For Load Forecasting, DER Hosting Capacity & Distribution Planning

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Module 1: Introduction — AI as Advisory, PE Accountability & Ethics

In modern grid planning, **AI-driven models** can process vast amounts of data and highlight trends, but **the Professional Engineer is ultimately responsible** for ensuring that any AI-informed decisions are safe, reliable, and code-compliant. This opening module sets the stage by underscoring that AI/ML tools are **advisory aids** to human engineers. **Public safety and grid reliability** remain paramount — any automated prediction or recommendation must be **verified by the engineer** before adoption. The NSPE Code of Ethics and other professional guidelines emphasize that **technology does not diminish the engineer's obligation** to protect the public and ensure standards are met.

1.1 PE's Role

The engineer defines the problem, chooses appropriate AI methods, **reviews outputs critically**, and approves only those solutions that meet all design and safety criteria. For example, if an ML model forecasts modest load growth but the engineer expects potential high DER adoption, the engineer must exercise judgment — perhaps adjusting the forecast or running scenario sensitivities to cover that risk. **Engineers must never rubber-stamp an AI output without understanding and validation**. Research echoes this notion: integration of AI in power systems demands maintaining **transparency, security, and human trust** — humans must validate AI solutions and remain actively engaged in decisions.

1.2 Ethical Use of AI

Transparency and fairness are key. This means clearly documenting model assumptions (e.g., stating if a forecast assumes historical weather repeats) and being honest about model uncertainty. It also means **avoiding over-confidence** in AI: an ML model might fit historical data extremely well, but that does not guarantee future accuracy, particularly if conditions change (such as new DER patterns or economic shifts). As a safeguard, engineers often incorporate **safety margins** or conservative adjustments to AI-informed plans, and ensure **manual oversight for critical cases**.

1.3 AI Success Stories & Boundaries

AI's potential is significant — for instance, machine learning can quickly evaluate **feeder hosting capacity** for DER across thousands of nodes, providing near real-time interconnection insights where manual studies took weeks. However, certain tasks still require human engineering judgment: for example, designing a protection scheme for a reverse power flow scenario requires a skilled engineer's assessment. This course highlights both the **opportunities and limits** of AI in distribution planning, reinforcing where the **human-in-the-loop** remains indispensable.

1.4 Configuration Control

As part of professional practice, any AI models used should be under strict **configuration management**. The engineer should track model versions, training datasets, and parameter changes as rigorously as changes to physical designs. This ensures that the planning process is auditable and that when an AI model is updated (new data, new algorithm), the change is recorded and re-validated.

Module 2: Forecasting Fundamentals — Load Drivers & Features

Accurate load forecasting is the foundation of reliable distribution planning. This module covers how traditional and AI-enhanced methods forecast demand, focusing on **key drivers and features** that influence load. For distribution systems, forecasts must incorporate **local factors** beyond system-wide trends.

2.1 Load Drivers

Weather is the dominant short-term driver for electric load — temperature, humidity, cloud cover, and wind heavily affect daily peaks. **Day-type** (weekday versus weekend or holiday) and seasonality also shape usage patterns. At the feeder level, **customer composition** (residential versus commercial versus industrial mix) and **special loads** (such as EV chargers or large data centers) introduce unique patterns. AI models can ingest a wide array of features capturing these drivers: for example, a neural network might take temperature forecasts, day-of-week, sun position, and recent load data as inputs to predict tomorrow's feeder load profile.

2.2 Feature Engineering

To use these drivers effectively, the following features are commonly constructed for model input — for example:" or simply "Practitioners construct features from these drivers — for example:

- **Cooling Degree Days (CDD)**: a weather feature that aggregates the number of degrees by which daily mean temperature exceeded a comfort baseline (typically 65°F), used to estimate cumulative cooling load.
- **Holiday Flags**: a binary feature indicating holidays or special events for which typical demand patterns deviate from the norm.
- **Recent Load Lags**: including the load from the previous day or week as a model input (because load exhibits autocorrelation).

2.3 Weather Normalization

The concept of **weather normalization** is important for long-term planning. Planners often adjust historical load data to typical weather conditions (e.g., average year or design weather scenarios) to separate underlying growth from weather volatility. For instance, if last summer was unusually mild and resulted in lower peaks, the planner will normalize it to an average summer (slightly higher) before projecting next year. AI models can perform weather normalization automatically by learning the weather-load relationship and then simulating load under standard conditions.

2.4 Short-Term versus Long-Term Forecasting

Short-term forecasts (hours to a few days ahead) are typically used for operations — scheduling switching or demand response. These emphasize granular time-series patterns and often rely on ML or time-series combinations for high precision. Long-term forecasts (years or decades) feed **capacity planning and scenario analysis**; they incorporate **economic and demographic trends** (population growth, EV adoption

forecasts, efficiency trends) as well as weather and climate trends. Long-term forecasting is usually scenario-based rather than purely statistical, because uncertainty rises over time. Forecasts often combine bottom-up build-ups of known future projects (new developments, electrification plans) with top-down econometric or machine learning models for base growth.

2.5 Operational versus Planning Granularity

Distribution system planning increasingly demands **spatially and temporally granular forecasts**. Instead of one system peak value per year, utilities are moving toward forecasting loads at each substation or feeder hourly. This granular approach better captures **diversity** across circuits and identifies local issues that a system-average forecast would mask.

Module 3: Short-Term vs. Long-Term Forecasting — Methods & Applications

3.1 Short-Term Load Forecasting (STLF)

STLF generally refers to predictions from an hour ahead up to a week or month ahead. Utilities use STLF for **near-term operations** — controlling voltage regulators, scheduling dispatchable resources, or short-term market positions. Traditional STLF methods include time-series analysis (ARIMA models) and regression on weather variables; now, **AI approaches** such as neural networks, gradient boosting trees, and advanced methods (LSTM networks, XGBoost, or Transformer-based models) are common and often yield improved accuracy. These models can capture non-linear relationships and multiple features simultaneously. For well-tuned day-ahead models with weather inputs, mean absolute percentage errors (MAPE) of 1–3% are achievable at the bulk system level with well-tuned weather inputs.; **feeder-level models typically carry higher error (often 5–15%) due to lower demand diversity and DER variability**. **Validation** is straightforward: model predictions are continually compared to actual load as it comes in, with error statistics tracked. If errors grow or bias appears (e.g., consistently overpredicting morning ramp), the model is retrained or adjusted.

At the **feeder or substation level**, STLF is more challenging due to more volatile behavior (less demand aggregation). AI can identify patterns that might be too subtle for linear methods — such as a particular industrial customer's weekly cycle or how solar PV on a feeder shifts net load shape. For example, an ML model might learn that a feeder's late-afternoon net load spike only occurs on weekdays if it was sunny all midday (a scenario of PV drop-off coinciding with AC load increase). Including such nuance can help engineers manage **feeder-specific equipment** (such as scheduling capacitor switching or battery dispatch on that feeder).

3.2 Long-Term Load Forecasting (LTLF)

LTLF is used for **capacity planning and capital investment decisions**, spanning typically 5, 10, or 20-year horizons. These forecasts incorporate large-scale trends:

- **Economic and demographic growth**: correlation of load growth with GDP, population, and development projects. ML can support this (e.g., a regression that learns load versus economic indicators), but engineering judgment often governs scenario design.
- **Energy efficiency and DSM programs**: energy efficiency improvements tend to dampen base load growth; utility- or regulator-mandated Demand-Side Management (DSM) programs must be modeled as a separate downward adjustment to the base load growth trajectory.
- **DER adoption projections**: expected numbers of rooftop PV installations, EV chargers, and heat pumps (electrification). These can be scenario-driven or output of technology-adoption models (e.g., logistic growth models (e.g., Bass diffusion) or agent-based models to project EV uptake regionally).
- **Climate change effects**: gradually rising temperatures could increase air conditioning loads in summer and reduce heating loads in winter — a factor some LTLF processes now include via scenario or statistical extrapolation.

Most utilities develop **multiple scenarios** (e.g., base case, high DER case, low economy case) to span uncertainty, rather than relying on a single point long-term forecast. AI can assist by automating some scenario computations (like quickly recalculating feeder loads if EV adoption is twice the base case), but human planners set the scenario definitions and review plausibility.

3.3 Feeder-Level and Spatial Forecasting

Historically, long-term forecasts were done at system or substation level, but with **high DER variability** and local capacity issues, there is a push to develop feeder-level spatial forecasts. Techniques such as **spatial load forecasting** use customer-level or feeder-level data and ML clustering to produce growth forecasts by location. For instance, a planning team might cluster feeders by type (urban residential, rural mixed, etc.) and apply ML to predict growth on each cluster differently, then assign that growth to specific feeders. This yields a more detailed distribution of future loads across the network rather than simply applying a uniform growth factor to all feeders, which might miss local hotspots or areas of decline.

3.4 Use in Distribution Planning

Short-term forecasts help estimate **peak shifting or new peak timings** due to PV — for example, net load peaks in late afternoon instead of mid-afternoon. This information feeds into the design of solutions like storage or demand response programs. Long-term forecasts feed into **capital plans**: deciding if and when to upgrade a substation transformer depends on when its peak load is expected to exceed capacity with safety margins. Utilities often apply **threshold criteria** (e.g., plan an upgrade when forecasted peak within five years exceeds 95% of equipment rating) to ensure reliability.

Module 4: DER Impacts & Hosting Capacity — AI in Scenario Planning

The rapid growth of **Distributed Energy Resources (DERs)** — such as solar PV, battery storage, and electric vehicles — is transforming distribution planning. This module explores how AI-assisted analysis helps evaluate DER impacts on feeders, including **hosting capacity** (how much DER a feeder can accommodate without issues) and **scenario planning** for DER adoption.

4.1 Hosting Capacity Analysis (HCA)

Traditionally, engineers performed HCA manually or with deterministic tools: injecting incremental DER on a feeder until thermal or voltage limits are violated. This process is repeated for each feeder and scenario, which was time-consuming. **AI/ML** can speed up HCA by learning relationships from prior detailed simulations or using power flow data to predict violation points, effectively mapping feeder headroom in near real-time. ML-based HCA can process real feeder data (loads, impedances, topology, and conductor ratings) and output an approximate maximum DER level for each section of a feeder almost instantly, facilitating **interactive planning** and proactive identification of feeders with low capacity. However, such ML models must be validated against actual power flow results to ensure they remain conservative and do not overestimate capacity. ML can also support **dynamic hosting capacity**: forecasting how hosting capacity might change with time-varying conditions (such as midday when PV output is high versus evening peaks) and with control strategies (such as smart inverters or curtailment) — a complex problem where ML's pattern recognition adds value.

4.2 DER Scenario Planning

Long-term distribution planning now incorporates scenarios of **high DER adoption**. Instead of forecasting load growth alone, planners forecast **net load** (load minus local DER generation) under various DER penetration trajectories. AI can assist by:

- **Forecasting DER adoption**: ML can analyze historical adoption trends of PV or EVs based on demographics, economics, or incentives to predict future installations in different areas.
- **Integrating DER profiles into load shapes**: tools can create composite feeder load profiles that include solar output curves and EV charging profiles superimposed on the baseline load. This yields more accurate predictions of issues such as **midday reverse power flow (back feed)** or **evening rebound peaks** due to solar.
- **Evaluating mitigation measures**: with ML-driven simulations, planners can test solutions such as advanced volt/VAR control, storage dispatch, or demand response under DER scenarios to evaluate improvements in hosting capacity.

4.3 Example — Feeder DER Scenario

Consider a suburban feeder with moderate load growth but rapidly increasing rooftop PV and EV adoption. In a high DER scenario, daytime minimum net load might become negative (export), risking voltage rise beyond limits per **ANSI C84.1 Range A** (upper limit of 105% of nominal). Evening peak might spike due to

EV charging. By running an AI-augmented power flow or surrogate model and applying **IEEE 1547-2018** interconnection requirements, planners evaluate when such issues appear and how severe they become. They can then simulate mitigations: adding a regulator, using time-of-use rates to spread EV charging, or requiring smart inverter settings. AI helps by quickly evaluating many combinations and identifying which feeders face constraints under each scenario.

4.4 Safety and Reliability Considerations

Even as AI speeds up these analyses, **engineers must ensure reliability margins are maintained**. If an ML model suggests a feeder can handle an additional 2 MW of solar DER before overloading, an engineer might impose a buffer (planning for only 1.5 MW) because of model uncertainty or because rare conditions not present in historical training data might not be captured. This is where the **risk-based approach** is critical — incorporate uncertainty in DER performance and **quantify risk** if the model is wrong. Probabilistic hosting capacity analysis (Monte Carlo simulation of DER placements and outputs), which AI can accelerate, is recommended. Planning decisions should lean conservative unless validated by robust analysis, including **power-flow verification of AI predictions for extreme cases** and compliance with voltage limits, thermal ratings per IEEE and ANSI standards.

Module 5: Validation, Uncertainty & Metrics — Ensuring Credibility

Using AI in grid planning introduces questions of **trust and accuracy**. This module focuses on how to validate AI-based forecasts and analyses, handle uncertainty, and set decision criteria. Any AI output must be as credible as traditional results, and that requires careful measurement and control.

5.1 Validation Metrics

For forecasting models, common metrics include:

- **MAE (Mean Absolute Error)** and **MAPE (Mean Absolute Percentage Error)**: these indicate how far off predictions are on average. For example, a feeder load forecast might have a daily MAPE of 4%, meaning predictions are on average 4% off actual values. Planners may require the yearly peak forecast to be biased high (toward the safe side) if MAPE is significant.
- **RMSE (Root Mean Square Error)**: weighted toward larger errors, important when occasional large errors are a concern.
- **Coverage Probability** for probabilistic forecasts: whether actual values fall within the model's stated prediction intervals at the claimed confidence level. For example, in a 90% prediction interval, approximately 90% of actual values should fall within the bounds. A model where only 70% of actuals fall in the 90% interval is mis calibrated and needs recalibration.

Engineers should verify that models meet accuracy targets on **out-of-sample data** (data not used to train the model) before trusting them for decisions.

5.2 Handling Uncertainty

Even after training and testing, forecasting and DER impact analysis will have uncertainty — particularly in long-range planning. PEs should incorporate this into decision-making:

- **Short-term operational use**: incorporate error bands (such as prediction intervals) and plan for worst-case scenarios in addition to the point forecast. If the day-ahead forecast says 100 MW ± 5 MW for a substation, an operator might schedule resources for 105 MW to be secure.
- **Long-term planning**: use scenario analysis to bracket uncertainty. If one scenario shows a substation over capacity by Year 5 and another not until Year 10, the utility might prepare a contingency plan by Year 5 but delay actual investment until trends clarify, depending on risk tolerance.
- **Model drift and re-validation**: over time, models may become less accurate if trends shift (e.g., post-pandemic load pattern changes, or new DER behavior). Establish processes to **monitor model performance** and retrain or recalibrate models periodically. If changes are made (such as adding new input features or altering the algorithm), treat it as a new version and validate it before using it in production planning — consistent with **ISO 9001** continuous improvement cycles.

5.3 Decision Thresholds & Criteria

In planning, decisions often hinge on forecasts crossing thresholds (e.g., a project triggers when forecasted load exceeds 95% of equipment rating within a set number of years). With ML forecasts, an engineer might implement a **more conservative threshold** to account for uncertainty. Alternatively, the engineer can feed the model's uncertainty into a **risk calculation**. For example, if a transformer loading is forecasted at 90% in five years with a ±10% prediction interval, the probability of actually hitting ~100% should prompt starting an upgrade earlier (since consequences of overloading are severe). By quantifying these probabilities through ensemble forecasts or statistical models, planners can rank projects by risk rather than deterministic dates.

5.4 Calibration of AI Models

If a model consistently mis predicts certain events (say it underestimates load on extremely humid days), that bias should be incorporated into the model or workflow. A crucial part of any AI deployment is a **feedback loop**: compare predictions with outcomes and calibrate. For instance, if an ML-based hosting capacity estimate is found to overestimate actual capacity in some feeders after field data is available, adjust the model or add a buffer factor for those conditions. Treat AI models as you would protection relay settings — something to be tested, tuned, and documented through a formal process.

5.5 Governance & Transparency

Treat AI models and algorithms as part of the design documentation. Keep records of training data sources, model parameters, and test results. If an external AI tool is used, understand its workings sufficiently to explain results. Stakeholders (regulators, clients, or the public) may require such explanation. Modern practice in utilities calls for **explainable AI** — results should be interpretable in engineering terms so that decision-makers trust them. For example, if an ML model identifies that a certain combination of high solar output and low load drives a voltage violation, the planner should be able to articulate that physical reasoning — not just say 'the model said so.' This fosters confidence and ensures the engineer can **defend the decisions** if challenged.

Module 6: Governance, Model Risk & FMEA — Managing the Process

This module addresses **how to govern AI models and manage risks** associated with their use in planning. Introducing AI can be seen as adding a new component to the planning process — one that requires its own oversight to ensure it does not inadvertently lead to errors.

6.1 Model Risk Management

Many large utilities treat critical models (like long-term forecast models) under a model risk management framework, which means:

- **Model documentation**: comprehensive documentation of model purpose, structure, assumptions, data sources, and known limitations.
- **Independent validation**: another engineer or a dedicated model validation team may review the model and its output as a check.
- **Periodic review**: the model is periodically re-validated and updated as needed. Treat an AI model as a piece of infrastructure — it requires maintenance and oversight.

Good governance ensures continuity too — if a key employee leaves, the knowledge of the model does not leave with them because it is documented within the organization.

6.2 FMEA for AI in Planning

Performing a **Failure Modes and Effects Analysis (FMEA)** can identify how AI modeling might go wrong and what controls to put in place. Some potential failure modes and mitigations are shown in the table below.

Potential AI-related issue	Impact	Mitigation approach
Missing key constraint or scenario in the AI model (e.g., not training on extreme weather or neglecting a DER growth scenario)	Could yield a design that fails under unconsidered conditions, risking overload or outage in real operation	Conduct thorough upfront reviews of load cases and scenarios (include extreme stress conditions); perform sensitivity analysis on model inputs; maintain human review of outputs against established engineering criteria and planning standards.
Data quality problem (bad or biased input data used for ML training)	Model may be systematically biased (e.g., forecasting too low due to underreported past load) — leading to under-built capacity	Implement data validation before model training; use techniques to detect anomalies and outliers; if data is limited or noisy, err on the side of conservative planning.
Model overfitting or bias (model fits historical idiosyncrasies but does not generalize)	Unreliable predictions under new conditions (e.g., load forecast fails if customer behavior changes)	Use hold-out validation and cross-validation to test generalization; simplify model if needed (Occam's razor); incorporate explainability checks to ensure model factors make sense physically.
Over-reliance on AI outputs by staff without understanding them	Risk of taking incorrect actions — e.g., approving DER interconnections that violate standards — because 'the model said so'	Institute formal review procedures: require engineer approval for all AI-driven decisions, provide planner training on model use, and build checks into tools (e.g., flags when predictions are outside training range or unusual conditions arise).

By identifying such risks early through FMEA or similar processes, organizations can implement robust controls and **avoid black-box syndrome**. For instance, a utility might automatically flag any forecast scenario requiring an unprecedented growth rate or any AI suggestion that pushes equipment beyond nameplate ratings, forcing an engineer to review it.

6.3 ISO 9001 & Continuous Improvement

Align the AI usage process with your enterprise's quality management system. That means having documented procedures for model updates, recordkeeping of inputs and outputs, and feedback loops for improvement. Essentially, treat the AI model as part of your planning process that falls under QA oversight. Many utilities are developing internal **AI governance committees** or guidelines — often borrowing from finance and medical fields — to ensure ML model use is controlled and traceable. Applying **risk-based**

thinking, each time an AI-enabled study is performed, consider the risk if it is wrong and mitigate appropriately through margins, further analysis, or conservative design choices.

6.4 Communication with Stakeholders

Part of governance is being able to communicate to executives, regulators, or the public how AI was used in planning. If a capacity upgrade is deferred because an AI-enhanced forecast predicts slower growth, be prepared to explain why the forecast is credible and what measures are in place if reality diverges. Being transparent about uncertainty (e.g., 'This project can be safely deferred three years with only a 5% risk of overload based on multiple scenarios') is better than presenting a false sense of precision. Decision-makers appreciate knowing the range of possible outcomes and the **reasoning** behind any recommended plan.

Module 7: Documentation, Communication & Professional Defensibility

Implementing AI in load forecasting and distribution planning must be accompanied by **strong documentation and communication**, to ensure professional accountability and confidence in the results. This module provides guidelines for documenting the modeling process and effectively conveying findings to stakeholders.

7.1 Document the Modeling Process

Every step, from data collection to model selection to results, should be well-documented:

- **Data provenance and preparation**: record sources of data (e.g., weather data from NOAA, SCADA load data from the past five years) and any cleaning or normalization performed. This is part of **data lineage** — knowing what is feeding your AI.
- **Model details**: note the type of model (e.g., random forest with X decision trees, or neural network architecture) and the rationale for choosing it. Include key hyperparameters and how they were determined (e.g., grid search) where relevant.
- **Constraints and assumptions**: list explicit constraints used (such as 'maximum loading set at 95% of rating to incorporate margin' or 'EV adoption follows state IRP scenario B') as well as implicit assumptions. These form the specs of the analysis that a peer reviewer or regulator might scrutinize.
- **Versioning and updates**: if the model will be reused periodically, maintain a log of versions — for example, 'Forecast Model v2.0 includes updated weather data through 2026 and a new feature for remote work impacts.' This ensures clarity when model outputs change.

7.2 Presenting Results to Stakeholders

Many stakeholders are not interested in algorithmic details — they care about outcomes and reliability. Recommended practices:

- **Focus on outcomes and actions**: for example, 'Based on advanced forecasting, we project substation ABC will reach 100% of capacity by 2028 in the high DER scenario, so we recommend initiating design of a new substation by 2026.' Present the range of outcomes or a few scenario graphs for context.
- **Use visuals and summaries**: graphical representations (load curves, hosting capacity heat maps) help convey complex data quickly. A hosting capacity map can communicate which areas can accept more DER and which are at their limit, using simple color codes.
- **Acknowledge uncertainty openly**: it is better to say 'The AI model predicts 3.5% annual growth, but considering uncertainties (±1%), we are planning for up to 5% to stay on the safe side' than to claim the model is exact. Regulators and utility managers understand that forecasting is not perfect; they want to know how risk is being managed.

7.3 Professional Defensibility

In a regulatory or legal setting, using AI does not excuse the engineer from explaining the basis of decisions. If anything, more explanation may be needed because of AI's complexity. Ensure that all usage of AI in the planning process can be explained in plain engineering terms:

- If ML identified that temperature-humidity index was the top feature influencing peak load, the planner should articulate how high humidity impedes nighttime cooling leading to higher next-day air conditioning load — connecting the ML insight to physical reasoning.
- If an AI algorithm suggested an unusual network reconfiguration to accommodate DER, the engineer should confirm it with a load flow study and explain the physics of why it is beneficial (e.g., offloading a heavily loaded segment to an adjacent lightly loaded feeder).
- If a forecast led to deferring an upgrade, be prepared to show the data and calculations — i.e., the projected load versus capacity chart with baseline and high-case scenarios — and how it will be monitored and revisited annually as needed.

7.4 Auditability

Treat the AI-augmented planning study like any other engineering document. Save all relevant files (data, models, analysis results). If questioned later about why an upgrade was not initiated earlier, you should be able to produce documentation showing the forecast and scenario analysis performed — demonstrating that the decision was reasonable given the available information. Because AI is data-driven, **keep raw data and diagnostic plots** for at least critical feeders or system-level forecasts. They can provide evidence that you did not rely on flawed data (e.g., you might show that after weather normalization, the underlying load trend was flat for three years, leading to a decision not to invest, and that subsequent data confirms that trend still holds).

7.5 Conclusion

By blending AI tools with sound engineering practice — thorough validation, prudent risk management, continuous monitoring, and clear documentation — PEs can confidently utilize AI for smarter, more flexible distribution planning while upholding the high standards of safety and reliability that the electric grid demands.

References

1. Pacific Northwest National Laboratory (PNNL). Artificial Intelligence and Machine Learning for Grid Operations: Findings and Recommendations. Report No. PNNL-35735. Richland, WA: U.S. Department of Energy, 2022. https://www.pnnl.gov/main/publications/external/technical_reports/PNNL-35735.pdf

2. National Association of Regulatory Utility Commissioners (NARUC). Distribution System Planning Reference Book: Second Edition. Washington, DC: NARUC, 2022. https://pubs.naruc.org/pub/67991367-1866-DAAC-99FB-BB8E84FFB258

3. Naecker, T. et al. Machine Learning Applications for DER Hosting Capacity Analysis on Electric Distribution Systems. The AI Translation: Energy Distribution Series, 2023. https://www.theaitranslation.org/mapping/energy-dist-01

4. Hashmi, M.U., et al. "A Review of Hosting Capacity Enhancement Methods for Renewable and Sustainable Energy," IEEE Access, vol. 11, 2023. Also available as arXiv preprint arXiv:2312.06582. https://arxiv.org/pdf/2312.06582

5. IEEE Std 1547-2018. Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces. New York, NY: IEEE, 2018.

6. ANSI C84.1-2020. Electric Power Systems and Equipment — Voltage Ratings (60 Hz). Washington, DC: American National Standards Institute / NEMA, 2020.

7. National Society of Professional Engineers (NSPE). Code of Ethics for Engineers. Alexandria, VA: NSPE, 2023. https://www.nspe.org/resources/ethics/code-ethics

8. International Organization for Standardization. ISO 9001:2015 — Quality Management Systems: Requirements. Geneva: ISO, 2015.