Climate Informed Transmission Expansion Planning Using Predictive Analytics

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Abstract: Transmission expansion planning (TEP) traditionally optimizes investments in new lines, reconductoring, or grid-enhancing technologies to meet future demand and renewable integration goals under relatively stable historical assumptions. However, climate change introduces non-stationary uncertainties through rising ambient temperatures, more frequent and intense heatwaves, altered wind and solar patterns, and compound extreme events that derate generation and transmission capacities while spiking cooling-driven demand. Predictive analytics leveraging machine learning, high-resolution climate projections (e.g., Thermodynamic Global Warming or TGW datasets), historical weather reanalysis, SCADA/PMU data, and outage records enable climate-informed TEP by generating accurate forecasts of temperature-dependent parameters such as dynamic line ratings (DLR), load profiles, renewable availability, and outage risks. This research paper develops a comprehensive framework that integrates predictive analytics into multi-stage, stochastic or robust TEP models. It employs predictive models (LSTM, graph neural networks, or hybrid physics-informed networks) for multi-horizon DLR forecasting, load under heat stress, and extreme event probabilities, feeding these outputs into capacity expansion optimization that co-optimizes transmission, generation, and storage under climate ensembles. Formulations use mixed-integer linear programming (MILP) with data-driven uncertainty sets or scenario reduction, explicitly incorporating conductor heat balance equations for ambient-adjusted or dynamic ratings.

Introduction

Transmission systems must evolve rapidly to accommodate surging demand from electrification, massive renewable deployment in remote zones, and decarbonization targets. Conventional TEP minimizes the net present value of investment plus operational costs subject to power flow, reliability (N-1 or N-k), and capacity constraints, often relying on deterministic load/generation forecasts or a handful of scenarios. Climate change renders these approaches insufficient: rising temperatures and heatwaves simultaneously increase cooling loads (30–50%+ peaks) and degrade infrastructure performance through thermal derating, while altering renewable resource patterns and elevating outage probabilities.

Predictive analytics bridge this gap by transforming raw climate, weather, and operational data into actionable forecasts that inform planning parameters. High-resolution datasets like TGW provide hourly meteorology at fine spatial scales for historical and projected periods under various warming levels. Machine learning models Long Short-Term Memory (LSTM) networks, graph neural networks (GNNs) respecting grid topology, or physics-informed variants embedding heat balance equations predict dynamic line ratings , temperature-adjusted loads, renewable capacity factors, and risk of heat-induced faults or outages. These predictions feed into robust or stochastic optimization frameworks that generate plans robust across plausible climate futures rather than a single nominal case.

This paper presents a detailed climate-informed TEP framework powered by predictive analytics. It reviews physical impacts of temperature rise on transmission, describes predictive modeling techniques for key variables formulates enhanced mathematical models incorporating analytics outputs, discusses uncertainty characterization and flexibility integration, explores computational methods, presents empirical insights from cooperative Western Interconnection studies and DLR analytics, and outlines challenges with policy recommendations. By embedding predictive forecasts of heatwave stresses and dynamic capacities, the framework enables proactive investments in transmission corridors, reconductoring with high-temperature low-sag (HTLS) conductors, and non-wires alternatives that enhance resilience while supporting high-renewable penetration.

Demand surges and generation deratings (thermal plants lose efficiency; solar output drops with panel temperature) compound transmission bottlenecks, increasing congestion and contingency risks. Compound events—heat plus drought or low wind—further erode reliability. Traditional planning struggles with these non-stationarities because historical data no longer represent future conditions.

Predictive analytics address this by learning complex mappings from multivariate inputs (ambient temperature, wind speed/direction at multiple points along corridors, solar irradiance, humidity, historical loadings) to outputs such as conductor temperature, ampacity (DLR), load multipliers, and outage/fault probabilities. LSTM or temporal convolutional networks capture temporal dynamics and thermal inertia, while GNNs incorporate spatial topology and inter-line dependencies. Physics-informed losses enforce heat balance or Kirchhoff laws, improving generalization to unseen warming levels or extremes. Ensemble or probabilistic models quantify uncertainty for robust planning inputs.

These forecasts enable climate-informed parameters in TEP: scenario-dependent DLR or ambient-adjusted ratings (AAR), temperature-scaled loads, climate-adjusted effective load carrying capability (ELCC) for renewables and storage, and risk-weighted contingencies. Predictive DLR models have demonstrated mean absolute percentage errors below 3% in some applications, supporting safer exploitation of latent capacity.

Predictive Analytics Techniques for Climate-Informed Parameters

Effective predictive models require rich data: weather reanalysis or numerical weather prediction (NWP) downscaled to corridor level, SCADA/PMU telemetry, direct conductor sensors (temperature, tension, sag), and outage databases. For DLR forecasting, inputs include lagged weather variables, current loading, and NWP outputs; outputs are probabilistic ampacity or T_c over horizons from hours to days ahead. Hybrid GAT-LSTM architectures fuse graph attention for spatial correlations with temporal modeling.

For load forecasting under heat stress, models incorporate cooling degree hours, urban heat island effects, and behavioral responses, often using gradient boosting or deep networks. Renewable forecasts integrate temperature effects on solar efficiency and potential wind lulls. Outage risk prediction treats heat as a driver in classification or regression models (e.g., Poisson for counts), linking maximum temperature, heat index, and prior loading to failure modes like vegetation contact from sag.

Climate projections (ensembles with warming deltas applied to historical reanalysis) generate long-term scenarios or synthetic extremes via generative adversarial networks (GANs) while preserving spatiotemporal correlations. Scenario reduction via clustering or principal component analysis maintains tractability while retaining tail risks. These analytics outputs feed directly into TEP as time-series or distribution parameters, replacing static assumptions.

Cooperative multi-area formulations optimize shared investments and tie-line flows, capturing benefits during spatially varying heatwaves. Objectives may incorporate resilience metrics such as CVaR of unserved energy or emissions. Predictive analytics reduce conservatism by providing tighter, better-calibrated uncertainty sets compared to simple intervals.

Solution uses decomposition (Benders, column-and-constraint generation), commercial MILP solvers, or ML surrogates for power flow/heat evaluations to handle scale. Digital twins integrate real-time predictive updates for adaptive planning loops.

Integration of Flexibility, DLR, and Predictive Insights

Predictive DLR analytics are particularly valuable, often unlocking 10–40% additional capacity under favorable conditions while issuing timely derating alerts. In TEP, this values non-wires alternatives (sensors, advanced conductors) explicitly against new builds. Flexibility resources—demand response, storage, virtual power plants—enter with climate-adjusted performance (e.g., temperature effects on battery efficiency or DR participation during heat).

Cooperative planning, informed by predictive heatwave replays, demonstrates substantial gains: in Western Interconnection studies replaying 2019 events under 2059 warming, collaboration reduces prices and costs significantly, with benefits persisting (though diminished) during widespread events, especially benefiting solar-heavy regions like California. Predictive analytics enhance these by providing granular, corridor-specific forecasts that guide strategic siting of new lines or reconductoring.

Case Studies and Empirical Insights

Western Interconnection analyses using advanced modeling chains and climate-replayed heatwaves show cooperative TEP lowers wholesale prices by up to 64%, total costs by ~35%, and emissions via better renewable utilization. Benefits are pronounced for localized events but remain positive under widespread stress when combined with storage. Data-driven robust TEP formulations using predictive outputs outperform deterministic baselines in worst-case performance, reducing curtailment and enhancing resilience.

DLR predictive models in various systems achieve low errors and support higher renewable hosting capacity. Quasi-dynamic or probabilistic ratings incorporating climate projections quantify long-term rating reductions (e.g., 1.5–5% in Europe under different RCPs), informing reconductoring priorities. National and regional studies emphasize integrating predictive analytics for extreme event stress testing, probabilistic planning, and adaptive pathways.

These cases confirm that replacing static assumptions with predictive, climate-informed parameters yields more efficient, resilient plans, particularly when valuing DLR and interregional coordination.

Challenges, Future Directions, and Policy Implications

Challenges include data scarcity for extremes (addressed via synthetic generation or transfer learning), model drift under evolving climate or grid topologies, computational scalability for nodal stochastic TEP with many scenarios, and regulatory acceptance of probabilistic or ML-augmented planning. Equity—ensuring resilience benefits reach vulnerable communities—and cost allocation for cooperative projects require attention.

Future directions encompass hybrid predictive-optimization digital twins for continuous planning updates, standardization of climate stress testing with predictive DLR in resource adequacy, multi-energy extensions (power-gas-heat), and decision-making under deep uncertainty frameworks. Advances in explainable AI and federated learning support collaborative, privacy-preserving analytics.

Policy should mandate climate-informed probabilistic planning per emerging guidance (e.g., EPRI, FERC), incentivize DLR/sensor deployment and predictive analytics through performance-based regulation, streamline interregional permitting and cost allocation, and fund high-resolution downscaling and data platforms. Alignment with decarbonization accelerates transmission buildout needed by 2035.

Conclusion

Climate-informed transmission expansion planning using predictive analytics marks a paradigm shift toward adaptive, uncertainty-aware, and resilient infrastructure development. By leveraging ML-driven forecasts of DLR, loads, renewables, and risks within robust or stochastic optimization, planners can optimize investments that perform well across warming scenarios, unlock latent capacity on existing assets, and support high-renewable grids amid intensifying heatwaves. Empirical evidence from cooperative Western studies and DLR analytics confirms significant economic, reliability, and environmental gains. Realizing full potential demands integrated data pipelines, advanced computation, stakeholder-validated metrics, and enabling policies. As climate risks and clean energy ambitions grow, predictive analytics-powered TEP will be indispensable for affordable, secure, and sustainable power systems capable of withstanding future stresses.

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