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A Novel Hybrid Model for Dynamic Line Rating Using Artificial Neural Networks

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Abstract. Dynamic Line Rating (DLR) is a smart grid technology that calculates the real-time, maximum power capacity (ampacity) of transmission lines based on current environmental conditions. DLR allows higher, safe power flows, making a better use of the line's actual capacity and thus allowing for the integration of more renewables.

This document presents a hybrid architecture that combines the physical IEEE 738 standard with advanced deep learning techniques, Long Short-Term Memory Neural Networks (LSTM) and Physics-Informed Neural Networks (PINNs), to predict the thermal ampacity of overhead transmission lines.

The architecture of the neural networks is capable of learning complex patterns from historical climatological data. This enables the model to capture the temporal and stochastic evolution of environmental conditions. Through this data-driven learning process, the DLR system can significantly reduce the reliance on field sensors, and in some cases even operate with minimal or no sensing infrastructure, by inferring the necessary conditions directly from historical and meteorological inputs.

While the traditional IEEE 738 approach is deterministic and static, providing only point estimates under fixed conditions, modern power system operation demands dynamic forecasts, uncertainty management, and physical consistency, motivating the integration of physical models with deep learning.

Key words. Ampacity, Climatological Conditions, Sensorless, Grid congestions.

1. Introduction

IEEE Standard 738 [1] has been the fundamental reference for calculating the thermal ampacity of overhead transmission conductors for more than four decades. It relies on a deterministic, steady-state heat balance that links the thermophysical properties of the conductor with environmental conditions, accounting for Joule heating, convective cooling, thermal radiation, and solar gain. However, each term in this balance depends nonlinearly on conductor temperature and weather variables, making the model inherently complex.

Despite its physical rigor, the deterministic nature of IEEE 738 presents key limitations for modern grid operations. First, it assumes thermal equilibrium, ignoring the conductor's thermal inertia—which allows typical conductors to tolerate short-term overloads due to thermal time constants of 10–40 minutes. Second, the model treats weather inputs as fixed values, overlooking their stochastic behaviour, such as the inherent variability and cyclic patterns of wind speed. This prevents proper characterization of uncertainty and leads to overly conservative operational limits. Finally, IEEE 738 lacks any predictive capability; it requires instantaneous meteorological inputs and cannot forecast ampacity. In real-world operation, grid operators increasingly need 1- to 24-hour capacity forecasts to support maintenance planning, economic dispatch, renewable integration, and proactive contingency management.

The shift towards a hybrid modelling approach that integrates Physics-Informed Neural Networks (PINNs) with Long Short-Term Memory (LSTM) architectures represents a methodological synthesis that preserves the physical rigor of IEEE 738 while adding advanced predictive capabilities. PINNs incorporate prior physical knowledge directly into the learning process by enforcing the governing equations as constraints, transforming the training procedure into a constrained optimization problem. This allows the model to remain physically consistent while leveraging the flexibility and expressive power of deep learning.

LSTM networks are designed to capture long-term temporal dependencies in sequential data, which is essential for modeling meteorological time series. Their gated architecture—comprising forget, input, and output gates—prevents the vanishing-gradient problem and allows the network to selectively retain or discard information over time. This enables LSTMs to learn complex temporal patterns such as daily temperature and solar cycles, seasonal wind behavior, cross-correlations between weather variables, and the persistence of atmospheric conditions.

The hybrid modelling offers several complementary advantages. PINN-based constraints ensure that the model's predictions remain physically consistent and do not violate fundamental thermodynamic principles, which is essential for maintaining operator trust [2]. At the same time, the LSTM [3] component provides adaptive predictive capability by learning location-specific and conductor-specific behavior that traditional IEEE 738 methods cannot capture. Because the training process incorporates probabilistic elements, the model can also quantify uncertainty and produce confidence intervals, enabling more informed, risk-aware decision-making. Altogether, these capabilities support more efficient grid operation by allowing temporal forecasts that reduce overly conservative safety margins while preserving reliability.

2. Methodology

The methodology is built on three main pillars:

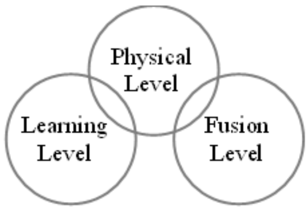

Fig. 1. Conceptual model of integration

1. Physical level

An IEEE 738-based data oracle that generates physically consistent synthetic datasets using Latin Hypercube sampling and thermodynamic validation [4].

The ranges of meteorological variables are defined based on historical climatological records, climate-change projections, and extreme weather events. The data oracle applies multiple layers of validation to ensure thermodynamic consistency and calculates numerical sensitivities to detect artificial discontinuities. These sensitivities must exhibit continuity, physical consistency, and reasonable magnitudes. The quality of the resulting synthetic dataset is then assessed using three key metrics: coverage, uniformity, and physical consistency.

2. Learning Level

LSTM-based temporal prediction models that learn multivariate meteorological patterns, incorporating temporal encoding, attention mechanisms, and multi-objective loss functions. Meteorological time series exhibit multiple temporal scales that require specific treatment, including long-term trends, daily cyclic patterns, and stochastic variability. These trends are modelled as:

$$T_{long-term}(t) = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + + \sum_{1}^{K} \beta_k \sin\left(\frac{2\pi kt}{P_{yearly}}\right) + \gamma_k \cos\left(\frac{2\pi kt}{P_{yearly}}\right) \quad [1]$$

Where:

$\alpha_0, \alpha_1, \alpha_2$: Polynomial coefficients for the trend.

β_k, γ_k: Coefficients of the harmonic components.

P_{yearly}: Annual period to capture seasonality.

$$T_{daily}(t) = A_d + \sin\left(\frac{2\pi t}{24} + \varphi_d\right) + B_d \cos\left(\frac{2\pi t}{24} + \vartheta_d\right) [2]$$

Where:

A_d, B_d: Amplitudes of the daily components.

$\boldsymbol{\varphi}_d, \vartheta_d$: Phases of the daily components.

And the stochastic variability is modelled as:

$$\epsilon(t) = \sum_{i=1}^{p} \rho_i \epsilon(t-i) + \sum_{j=1}^{q} \theta_i \mu(t-j) + \mu(t) \; [3]$$

Where:

ρ, θ : Autoregressive and moving average coefficients (similar to ARMA models).

$\mu(t) \sim \mathcal{N}(0, \sigma^2)$: White noise or random error term.

The Learning Level utilizes Long Short-Term Memory (LSTM) networks, specifically designed to model the thermal inertia and stochastic patterns inherent in meteorological variables. Unlike static models, this architecture manages a flow of temporal information through two internal states: the long-term memory, which preserves seasonal dependencies and trends, and the short-term hidden state.

To streamline the representation of the internal gating mechanisms (forget, input, and output gates), the recursive update process is defined by the following compact transition function:

$$(h_t, C_t) = \mathrm{LSTM}\left(x_t^{encoded}, h_{t-1}, C_{t-1}, \theta\right) [4]$$

Where θ represents the trainable weight matrices (W) and bias vectors (b).

The architecture processes input data through a dense encoding stage that integrates cyclical variables (time of day, day of year) using trigonometric transformations to preserve their temporal continuity:

$$x_t^{encoded} = \mathrm{Dense}(x_t) + \mathrm{Embedding}\left(\mathrm{hour}_t, \mathrm{day}_t\right) + \mathrm{Location}(t) \; [5]$$

Information propagates through stacked LSTM layers, followed by a temporal attention mechanism. This mechanism weights the historical relevance of hidden states to the current prediction, allowing the model to focus on the most significant past time steps:

$$\begin{aligned} h_1^t &= LSTM_1\left(x_t^{encoded}, h_1^{t-1}, C_1^{t-1}\right) \\ h_2^t &= LSTM_2\left(h_1^t, h_2^{t-1}, C_2^{t-1}\right) \end{aligned} \; [5]$$

The context vector (C_t) is computed using attention weights $(\alpha_{t,i})$ derived from an alignment score $(e_{t,i})$:

$$\alpha_{t,i} = \frac{\exp(e_{t,i})}{\sum_{j=1}^{T} \exp(e_{t,j})}; \; C_t = \sum_{i=1}^{T} \alpha_{t,i} h_2^i \; [6]$$

Finally, the output layer projects the current prediction for the horizon H :

$I_{t+1:t+H} = W_{\text{out}}[h_2^t; C_t] + b_{\text{out}}$ [7]

Hybrid Loss Function and Uncertainty Training is formulated as a multi-objective optimization problem that balances data accuracy with temporal and physical coherence. The total loss function is defined as:

$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{prediction}} + \lambda_1 \mathcal{L}_{\text{smoothness}} + \lambda_2 \mathcal{L}_{\text{consistence}} + \lambda_3 \mathcal{L}_{\text{physics}}$ [8]

Each term addresses a critical aspect of Dynamic Line Rating modeling:

- Prediction $(\mathcal{L}_{\text{prediction}})$: Minimizes the weighted error (w_h) relative to the true values (I_{true}).
- Smoothness ($\mathcal{L}_{\text{smoothness}}$): Penalizes unrealistic abrupt changes between consecutive time steps ($\sum |I^h - I^{h-1}|^2$).
- Consistency ($\mathcal{L}_{\text{consistence}}$): Ensures coherence with the mean of recent historical values (I_{hist}).
- Physics $(\mathcal{L}_{\text{physics}})$: Integrates constraints from the Physics Layer to penalize violations of the thermal balance.

To quantify uncertainty and generate confidence intervals $(I_{\text{lower}}, I_{\text{upper}})$, the model implements approximate Bayesian inference via Monte Carlo Dropout during the prediction phase:

$p(I_{t+h} \mid D) \approx \frac{1}{M}\sum_{m=1}^{M} f(x_{t-L+1:t}, \theta_m)$ [9]

3. Fusion Level

To ensure that the model's predictions adhere to the laws of thermodynamics, the Fusion Level implements a Physics-Informed Neural Network (PINN). This approach addresses the fundamental trade-off in deep learning: balancing the flexibility to learn from data against the strict guarantees of physical consistency required by grid operators.

The network utilizes a dual-output architecture that simultaneously predicts the conductor current (I) and its surface temperature (T_s):

$[I_\theta(x_t), T_{s,\theta}(x_t)] = \text{Network}_\theta(x_t)$ [10]

Where the inputs x_t include ambient temperature, wind velocity, wind direction, and solar radiation. By predicting both variables, the model can fully resolve the energy balance equation required by the IEEE 738 standard.

Unlike standard neural networks that minimize only prediction error, the PINN is trained using a composite loss function that enforces physical laws as soft constraints. The training objective is to minimize the total loss $\mathcal{L}_{\text{PINN}}$:

$\mathcal{L}_{\text{PINN}}(\theta) = \mathcal{L}_{\text{data}} + \lambda_1 \mathcal{L}_{\text{physics}} + \lambda_2 \mathcal{L}_{\text{bounds}} + \lambda_3 \mathcal{L}_{\text{monotony}}$ [11]

Each component serves a distinct regulatory function:

1. Data Fidelity ($\mathcal{L}_{\text{data}}$): Minimizes the mean squared error between the model predictions and observed ampacity data.
2. Physical Residual ($\mathcal{L}_{\text{physics}}$): Penalizes violations of the steady-state thermal balance. It is computed by evaluating the IEEE 738 governing equations with the predicted current and temperature; any non-zero residual indicates a violation of the first law of thermodynamics.
3. Boundary Constraints ($\mathcal{L}_{\text{bounds}}$): Enforces critical physical limits using rectified linear units (ReLU) to penalize impossible states. Specifically, it ensures that current remains non-negative and that surface temperature does not exceed realistic material limits.
4. Monotonicity ($\mathcal{L}_{\text{monotony}}$): Regularizes the gradients to ensure consistent physical behavior-for instance, verifying that the derivative relationships between current and temperature maintain the correct sign, preventing the model from learning physically invalid correlations.

This formulation transforms the training into a constrained optimization problem, guaranteeing that the model captures the stochastic nature of weather while respecting the deterministic boundaries of physics.

4. Meteorological data integration

Meteorological data are multivariate time series with complex stochastic characteristics that require specialized treatment for their effective integration into predictive models [5], [6].

There are multiple sources with different spatiotemporal resolutions and levels of reliability:

Level 1: In-Situ Observations

- Local meteorological stations: High accuracy, temporal resolution of 1–10 minutes
- Sensors on transmission lines: Provide microclimate data specific to the conductor
- Anemometric towers: Vertical wind profiles at the height of the conductors

Level 2: Atmospheric Reanalyses

- ERA5 (ECMWF): 0.25° × 0.25° resolution, hourly data since 1940
- MERRA-2 (NASA): 0.5° × 0.625° resolution, hourly data since 1980
- NCEP/NCAR: 2.5° × 2.5° resolution, 6-hourly data since 1948

Level 3: Numerical Weather Prediction Models

- GFS (NOAA): 0.25° resolution, forecasts up to 384 hours
- ECMWF IFS: 0.1° resolution, forecasts up to 240 hours
- WRF mesoscale model: 1–10 km resolution, forecasts up to 72 hours

The Preprocessing of Meteorological Time Series is carried out through the following pipeline:

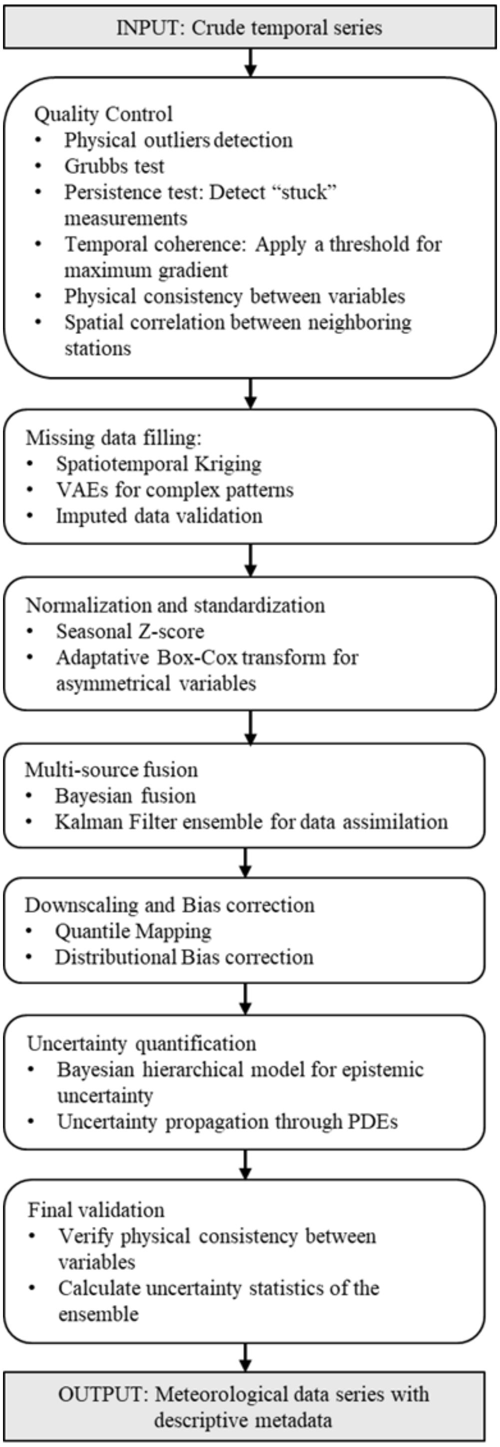

Fig. 2. Preprocessing of Meteorological Time Series pipeline

3. Results

The trained model is able to calculate line ampacity given line coordinates and time of calculation by:

- Querying the necessary meteorological data and conductor characteristics
- Inferring the Physical Level to obtain line behavior
- Inferring the Learning Level
- Inputting the results of the Physical and Learning Levels, alongside the uncertainty

The inference of the complete stack results in the prediction of the admissible current to flow in the horizon of time length T. By default, the system is tuned to calculate the maximum current admissible during the next hour, but as described in 2.2., this can be adjusted to calculate the capacity for more extreme, short-lived currents.

After gaining access to the necessary conductor characteristics and grid layout, a web application was developed, which consistently monitored the current flowing through high-voltage overhead lines and calculated the available ampacity in the next hour. A time horizon was selected in alignment with the Market Time Units (MTUs), although a more detailed 2 minute ampacity was also provided.

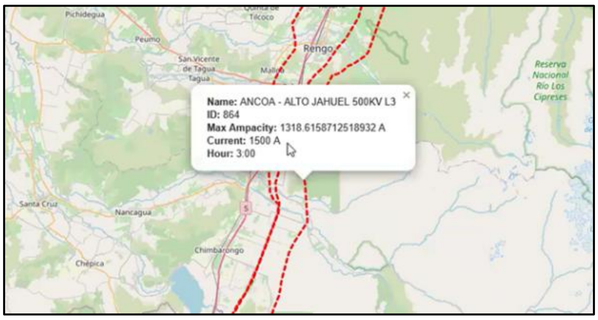

Fig. 3. Web application

4. Conclusion

The successful implementation of this hybrid system has the potential to significantly transform transmission-grid operations. Quantifiable benefits include a 10–25% increase in usable capacity, deferred investment in new infrastructure, reduced curtailment of variable renewable generation, and improved reliability through proactive prediction of critical conditions. Operational practices would also evolve, shifting from reactive to fully forecast-based decision-making, enabling continuous dynamic optimization of operating limits, risk-informed planning, and early detection of asset degradation through predictive maintenance.

Hybrid models enable admissible-current forecasts over horizons ranging from 1 to 24 hours, providing uncertainty intervals while maintaining physical consistency even under extreme weather conditions. Experimental results show average line-utilization increases of 15–25%, with peaks reaching 40–60% in favourable conditions. In addition, the system reduces operational reserves and improves renewable-energy integration through dynamic allocation of thermal capacity. The architecture also supports post-training physical validation and adaptive correction of predictions that violate IEEE 738 constraints.

Deep learning represents a significant advancement in ampacity calculation. The hybrid approach preserves the physical robustness of IEEE 738 while enabling reliable temporal forecasting, uncertainty quantification, and optimized power-system operation. The resulting benefits include increased asset utilization, deferred infrastructure investments, enhanced renewable-energy integration, and a shift toward predictive, risk-based grid management.

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