Artificial Intelligence for the Improvement of Transmission Line Performance: A Review

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***Abstract*:**
These instructions provide you guidelines for preparing papers for NIELIT- International Journal of Digital Technologies [IJDT. Use this document as a template and as an instruction set. Overhead transmission lines run for hundreds of kilometers through open terrain, which is exactly why they cause so much trouble: they are hard to watch continuously, exposed to whatever the weather does, and slow to inspect by hand. Utilities have historically dealt with these using conservative rules — fixed thermal ratings, threshold-based relays, and inspection crews sent out on a schedule rather than as needed. Those methods work, but they leave capacity and information on the table. Over the last decade, artificial intelligence has started to close that gap. This review looks at where AI has actually made a difference in transmission line performance, organized around four areas that keep coming up in the literature: detecting and locating faults, rating lines dynamically instead of statically, inspecting hardware and vegetation from drone imagery, and forecasting load or optimizing power flow at the network level. It also looks at the problems that keep these systems from being deployed more widely — not enough real fault data, models that don't transfer well from one utility's lines to another's, a general discomfort with black-box decisions in safety-critical systems, and the practical headache of bolting new AI tools onto decades-old SCADA infrastructure. The goal here is less to declare a winner among techniques and more to give a grounded picture of what is working, what isn't yet, and where the field seems to be heading.

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I. INTRODUCTION

Transmission lines are the part of the grid that gets the least sympathy and the most punishment. They carry bulk power over long distances, they're almost always overhead and exposed, and they run through terrain that's often difficult to reach — mountains, farmland, forest corridors. That combination means transmission lines account for a disproportionate share of power-system disturbances, and because a single fault on a major line can ripple outward into a much larger outage, speed and accuracy in detecting problems matter far more here than on shorter, better-protected distribution feeders.

At the same time, utilities are under pressure from two directions that pull in opposite ways. On one side, there's a real reluctance to build new transmission corridors — permitting alone can take a decade — so operators are being asked to squeeze more capacity out of the lines they already have. On the other side, renewable generation is adding variability that the grid wasn't originally designed around, and inspection budgets rarely keep pace with the number of miles that need to be walked, flown, or climbed each year. AI has found its way into transmission line management largely because it offers a practical answer to both problems at once. Machine learning models trained on current and voltage waveforms can catch and localize faults faster than conventional impedance relays [1–3]. Deep learning applied to drone footage can spot a cracked insulator or an encroaching tree branch far more consistently than a person scanning thousands of images [14–19]. And data-driven thermal

models let a line be rated against the weather it's actually experiencing, rather than the worst-case weather someone assumed decades ago [7–13].

The rest of this paper works through four areas where this shows up in the literature, then steps back to talk about what's still getting in the way of wider adoption. Figure 1 gives a rough map of how the four areas relate to each other.

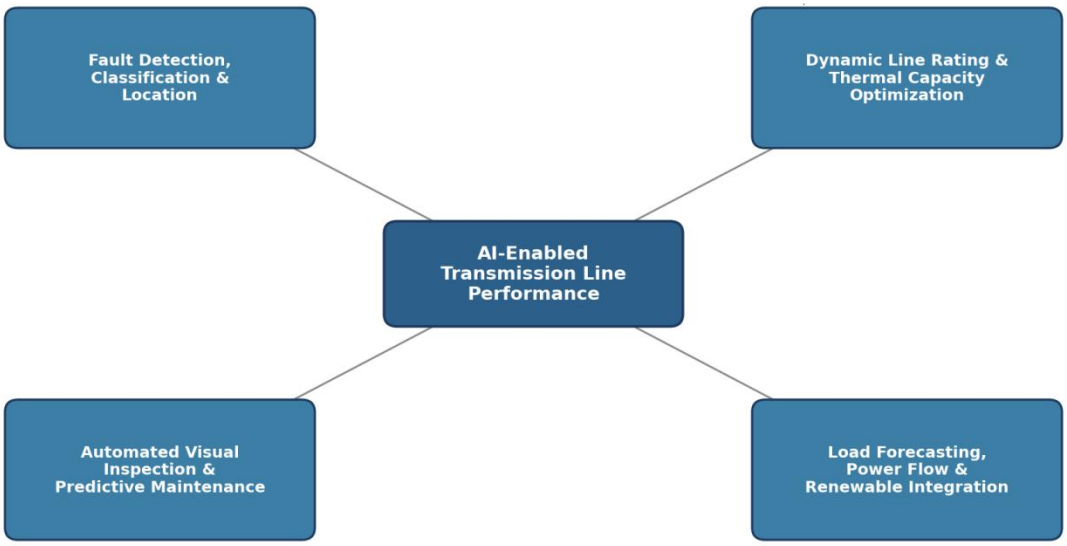


Fig. 1. AI application domains across the transmission line lifecycle

II. AI Techniques Used in Transmission Line Applications

No single algorithm dominates this space — which technique shows up depends heavily on the problem being solved and how much labeled data is realistically available. A few families recur often enough to be worth naming up front.

I. Classical machine learning — SVMs, random forests, k-nearest neighbors, decision trees — still gets used a lot for fault classification and DLR regression, mostly because it doesn't demand huge datasets or GPU budgets [1, 8].

II. ANNs and adaptive neuro-fuzzy inference systems (ANFIS) remain popular for fault diagnosis specifically because ANFIS keeps some of the rule-based structure engineers are used to, which makes the output easier to trust [2, 6].

III. Deep learning — CNNs, and object detectors like YOLO and Faster R-CNN in particular — is where almost all the recent inspection work lives, since insulator and hardware defects are fundamentally an image recognition problem [14–19].

IV. LSTMs, temporal convolutional networks, and echo state networks show up wherever the problem is really a time-series forecast — dynamic line rating and load forecasting both fall into this bucket [9–11].

V. Fuzzy logic and hybrid metaheuristic methods (genetic algorithms or particle swarm optimization layered onto a neural net) tend to appear when there's real uncertainty in the inputs or more than one objective to balance at once [2, 20].

VI. Probabilistic and Bayesian methods, like natural gradient boosting, are a newer addition to the DLR literature, aimed at giving operators an actual confidence interval instead of a single forecast number [12].

III. Applications of AI in Transmission Line Performance

A. *Fault Detection, Classification, and Location*

Of the four areas discussed, fault diagnosis has the longest history of research and practical application. It is also an area of significant importance for power system reliability and protection. Overhead transmission lines extending over long distances are frequently exposed to short-circuit faults, high-impedance faults, and weather-induced disturbances. Impedance-based distance relaying is a widely used conventional technique for detecting and locating such faults. However, this method has several limitations, including reduced accuracy in detecting high-impedance faults, potential

errors caused by mutual coupling between parallel transmission lines, and degraded performance under noisy or asymmetric measurement conditions. These limitations highlight the need for more robust and reliable fault diagnosis techniques for modern power systems

The response in the literature has been to throw a fairly wide range of classifiers at the problem — ANN, ANFIS, SVM, random forest, and more recently deep architectures — trained on the voltage and current waveforms captured at line terminals, to figure out whether a fault occurred, what kind it was, and roughly where along the line it happened. One widely cited survey walks through this progression from naive Bayes and decision trees through to CNNs and ANFIS, and makes the point that the field has been moving toward deeper architectures mainly because they hold up better on noisy field data [1]. Other reviews focused specifically on identification, classification, and localization techniques land on a similar conclusion, but add that ANFIS-style hybrid systems tend to be favored in practice because they strike a better balance between accuracy and something engineers can actually interpret [2, 3].

The accuracy numbers reported in these studies are genuinely striking. One ANN trained on a simulated 330 kV line reached close to 100% fault-detection accuracy and about 99.5% localization accuracy, with detection happening in well under a millisecond — clearly ahead of the SVM and PCA-based methods it was compared against [6]. A systematic review limited to 2023–2024 papers found broadly similar results, with detection accuracy staying above 99% even when 20–30 dB of noise was added to the current signal [5]. Figure 2 pulls a few of these numbers together alongside a defect-detection result from the inspection literature discussed later in Section 3.3. That said, it's worth being a little skeptical of how far these numbers generalize — most of them come from simulated or lab-generated data, and several of the same review papers flag that validation against real, messy, imbalanced field records is still fairly thin on the ground [1, 4].

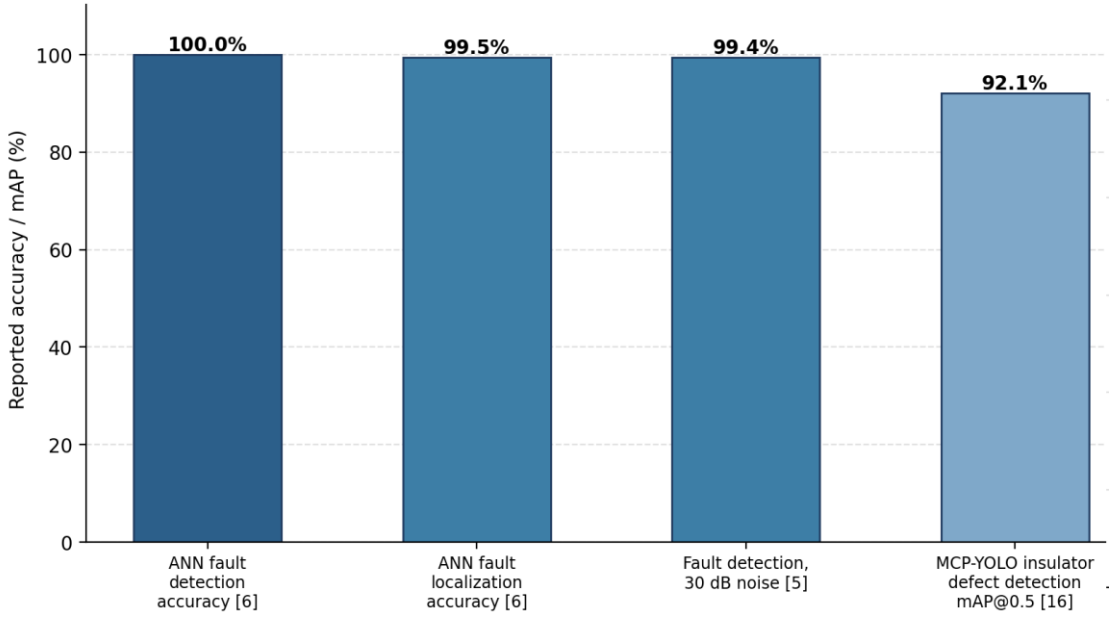


Fig 2. Selected reported performance figures from the reviewed literature [5, 6, 16].

B. Dynamic Line Rating and Thermal Capacity Optimization

Most transmission lines are still rated the old-fashioned way: pick a worst-case combination of low wind and high ambient temperature, calculate the thermal limit for that, and operate under it permanently. It's a safe approach, but it's wasteful — actual weather is usually kinder than the worst case, and a conductor cooled by real wind can often carry meaningfully more current than its static rating allows. Dynamic line rating (DLR) is the fix: estimate ampacity from the weather the line is actually experiencing, or is forecast to experience, rather than from an assumption made once and never revisited [7].

This is a genuinely hard forecasting problem, because the relationship between wind speed, wind direction, ambient temperature, solar radiation, and conductor temperature doesn't reduce to anything simple — which is exactly why AI has taken hold here. Random forest regressors trained on weather variables have been used to estimate real-time DLR in a way that specifically helps absorb renewable generation on lines that would otherwise be constrained [8]. LSTM models have been used to capture the transient thermal response of a conductor directly from field measurements [10], and more recent work using temporal convolutional networks has pushed this into actual forecasting — necessary if a line's extra capacity is going to be scheduled a day ahead — with one South Indian case study finding that DLR delivered roughly 120% of the static rating for the majority of hours studied [11]. There's also a push toward probabilistic methods: models like natural gradient boosting treat the weather inputs as distributions rather than fixed numbers, so the output is a rated capacity with some honest uncertainty attached rather than a single number presented as fact [12]. On the sensing side, echo state networks paired with fiber-optic or

laser temperature sensing have been explored as a way to keep ratings updating continuously rather than in batches [10]. AI-based DLR can unlock real transmission capacity without new construction, and that headroom turns out to matter most exactly when it's needed — during high wind or high solar output [8, 12, 13].

C. Automated Visual Inspection and Predictive Maintenance

Inspecting towers, conductors, insulators, and the surrounding right-of-way has traditionally meant a ground crew, a helicopter, or someone climbing the structure directly — none of which are fast, cheap, or particularly safe. Drones carrying decent cameras, combined with deep-learning vision models, have largely taken over this job, and it's probably the single most active area of AI research in transmission line management right now [15].

The typical pipeline uses a CNN-based detector — YOLO variants and Faster R-CNN are the most common choices — to first locate insulators, hardware, and conductors in an aerial image, and then to flag defects on those components: cracking, contamination, flashover marks, corrosion, missing pieces [14, 17, 18]. A lot of the newer work is really about making these models small enough to run on the drone itself, so defects get flagged during the flight instead of after someone reviews thousands of images back at the office — a real bottleneck once you're running inspections at scale [16]. The numbers here are also good: one lightweight, edge-optimized YOLO variant hit 92.1% mean average precision, 90.5% precision, and 89.0% recall on a real UAV-collected dataset, while staying light enough to run on limited hardware [16]. But nearly every paper in this space includes some version of the same caveat — models trained on one utility's self-collected images tend to fall apart when pointed at a different region, a different camera, or different lighting [14, 15].

Some recent papers try to get around that generalization problem by baking in physical knowledge about the equipment — known insulator geometry, standard mounting specs — directly into vision-language models rather than relying purely on learned features [16], or by using attention mechanisms and generative approaches to help the model catch small, partially hidden defects that are easy to miss otherwise [18]. The scope has also broadened past insulators alone: some systems now detect a fuller set of line components — dampers, splitters, connectors — directly from live drone video [19]. And this same idea of catching problems before they cause an outage has spread beyond lines themselves, into predictive maintenance for renewable and other grid-connected assets, nudging utilities generally toward condition-based rather than calendar-based maintenance [20].

D. Load Forecasting, Power Flow Optimization, and Renewable Integration

Not all of the useful AI work happens at the level of a single line. Load forecasting models, whether short-term or medium-term, feed directly into decisions about which corridors are likely to get loaded near their limits and when. AI-based optimal power flow and congestion-management approaches try to route power across the network in a way that avoids overloading any one line while keeping losses down — which pairs naturally with DLR, since knowing a line's real-time capacity is only half the problem; the other half is deciding how to actually use it. Renewable generation adds a layer of urgency to this, since wind and solar output swing in ways that interact directly with thermal limits, and it's not a coincidence that several of the DLR studies cited above are explicitly framed around accommodating that variability rather than curtailing generation or risking a thermal violation [8, 12, 13].

IV. CHALLENGES

There are following challenges with AI performance in Transmission system

1. Not enough real data, and what exists is imbalanced. Actual fault events and genuine defect images are rare next to normal operating data, which forces a lot of reliance on synthetic augmentation and transfer learning to train anything robust [16, 22].
2. Models don't travel well. A classifier trained on one line, one region, or one camera setup often loses accuracy fast once it's applied somewhere with different terrain, conductors, or climate [14, 15].
3. Trust is a real barrier, not just a talking point. Utilities running safety-critical protection systems are understandably wary of black-box deep learning, which is part of why ANFIS and other hybrid, more interpretable methods keep getting favored in practice [2, 3].
4. Old infrastructure doesn't make this easy. A lot of transmission assets are still tied to SCADA and protection hardware that's decades old, and retrofitting new sensing and communications around that is expensive and slow.
5. More AI dependence means more attack surface. As these models lean harder on live sensor and weather feeds, they become a more attractive target for manipulation — recent DLR datasets have started including adversarially perturbed data specifically to study this [13].

6. Everything has to run fast and cheap. Both drone inspection and real-time protection need inference that fits within tight latency and power budgets, which is driving a lot of the current work on smaller, pruned model architectures [16].

V. Future Scope and Research Opportunities

- Hybrid, physics-informed models that combine learned patterns with established thermal standards like IEEE 738 and CIGRE, aiming for better generalization without giving up interpretability [12].
- More onboard intelligence — lightweight CNNs running directly on drones or line-mounted sensors rather than sending everything back to a data center first [16].
- Digital twins that tie weather, imagery, sensor data, and fault history together into one model instead of treating DLR and predictive maintenance as separate problems.
- Federated and transfer learning across utilities, so the data-scarcity problem can be addressed without individual utilities having to hand over raw operational data.
- More probabilistic forecasting generally — extending the uncertainty-aware approach already showing up in DLR work toward fault risk and maintenance prioritization [12].
- Reinforcement learning applied at the network level, moving past single-line diagnostics toward coordinated congestion management and renewable integration across the whole system.

VI. Conclusion

AI has quietly become a working part of transmission line management rather than a research curiosity — it shows up in real-time fault detection, in how lines get rated, in how they get inspected, and increasingly in how the wider network gets optimized. The literature is fairly consistent in showing that AI-based methods outperform the static, rule-based approaches they're replacing, especially once conditions get noisy or resources get tight. What's less settled is how well any of this scales past the lab: limited real-world data, models that don't transfer across sites, justified caution around black-box decisions, and the sheer inertia of legacy infrastructure are all still real obstacles. The next round of progress probably won't come from squeezing another percentage point of accuracy out of any one technique, it will come from addressing these shared problems, through physics-informed modeling, smarter edge deployment, and utilities actually finding ways to share data with each other.

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