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PROMISING APPLICATIONS OF MACHINE LEARNING IN POWER SYSTEMS: A REVIEW

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Why review machine learning in power systems?

Operating data are growing
equipment, loads, networks, renewables

Engineering decisions repeat
estimation, scheduling, control, OPF

ML can help — but evidence differs
simulation ≠ field readiness

Review focus: what ML actually contributes, what evidence supports it, and what should be tested next.

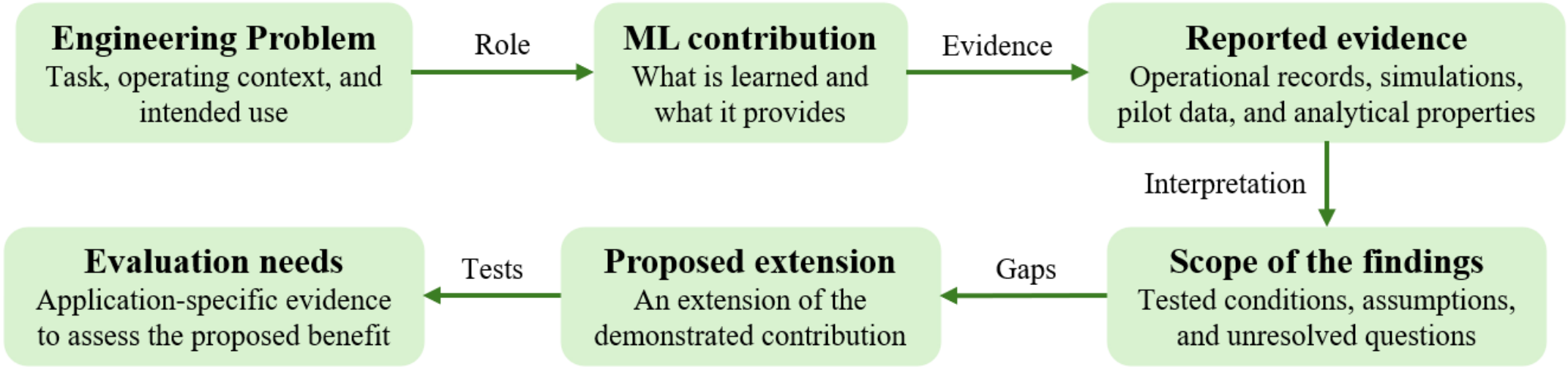
Six applications were selected because each addresses a clear engineering need and has a credible research basis.

The paper separates demonstrated capability from proposed future benefit.

Central question: where is machine learning genuinely promising, and what evidence is still missing?

Review framework

Engineering problem → ML contribution → evidence → proposed extension



The same logic is applied to all six applications so that unlike metrics are not ranked against one another.

Evidence includes operational records, simulation, pilot data, and analytical properties.

Future directions are kept separate from findings already demonstrated in the literature.

Six promising applications

Different tasks, different ML roles, different evidence

Equipment monitoring
Context-aware alarms & explained diagnoses

State estimation
Electrical structure inside learned models

Forecasting
Temporal patterns & uncertainty

Flexible loads
Scheduling & resource flexibility

RL control
Structured feedback policies

ML for OPF
Faster candidates, feasibility & scale

Monitoring and estimation interpret information; forecasting anticipates it; coordination, control and OPF use it to guide actions.

1–2. Monitoring and state estimation

Learning can extract information while retaining engineering structure

Equipment condition monitoring

Normal-behavior models provide context for wind-turbine SCADA deviations.

Glass-box transformer classifiers make diagnostic reasoning inspectable.

Next step: connect alarms and diagnoses to confirmed inspections and maintenance outcomes.

Network state estimation

Physics-aware, unfolded, and graph-based estimators embed electrical relationships in different ways.

Potential advantages: repeated computation and incomplete measurement coverage.

Next step: test sensing changes, missing measurements, local errors, and unreliable-output flags.

3–4. Forecasting and flexible-load management

Demand & renewable forecasting

Point forecasts and probabilistic forecasts answer different planning questions.

Evidence should include calibration/distributional accuracy, not only point-error metrics.

Next step: pass forecasts through the same scheduler and compare cost and limit violations.

Demand response & flexible loads

Learning can schedule loads, approximate flexibility envelopes, or learn resource behavior.

Pilot-data studies show promise but do not automatically prove dependable delivery.

Next step: measure delivered power, duration, rebound, comfort and feeder-level effects.

5–6. Reinforcement learning and machine learning for OPF

RL for feedback control

Analytical stability conditions can constrain the learned policy class.

This gives an engineering basis beyond training reward alone.

Next step: test estimation error, delays, saturation, missing measurements and fallback control.

ML for optimal power flow

Predict-and-reconstruct, physics-informed and graph-based models can reduce repeated OPF effort.

Feasibility, generalization and scale are distinct requirements.

Next step: evaluate unseen networks, full reconstruction/check/repair time, cost and violations.

What does the evidence actually support?

The six areas are promising, but not equally mature

Evidence type	Example	What it supports	Main limitation
Operational records	Condition monitoring	Real operating behavior; known failures	Does not prove maintenance benefit or transfer
Simulation	Flexible loads / community control	Controlled comparison	Depends on modeled dynamics and scenarios
Pilot data	Building flexibility	Potential use-case benefit	Does not prove savings in operation
Formal analysis	Structured RL / verification	Properties under stated assumptions	Limited to analyzed model/domain

A strong result in one evidence class should not be presented as equivalent evidence of deployment readiness.

Future research directions

Extend demonstrated capabilities toward decision-relevant engineering outcomes

Condition assessment and explained diagnoses	Link diagnoses to inspections and maintenance outcomes
Estimation guided by electrical structure	Adapt to sensing changes and flag unreliable estimates
Demand and generation forecasts with uncertainty estimates	Evaluate forecast uncertainty through scheduling outcomes
Learning schedules and resource flexibility	Assess delivered flexibility, rebound, and comfort
Control policies with analytical stability conditions	Evaluate noise, delays, and saturation and revisit stability assumptions
Learned operating candidates and structured OPF models	Combine feasibility, transfer, and scale with full solution-time assessment

The proposed extensions are not claimed achievements

Monitoring → maintenance outcomes

Estimation → sensing changes + reliability flags

Forecasting → scheduling outcomes

Flexible loads → dependable delivered service

RL → realistic implementation conditions

OPF → feasibility + transfer + scale

Cross-cutting research agenda

What should future evaluations do differently?

Transfer	Unseen assets, feeders, networks and operating regimes
Uncertainty	Flag unreliable estimates and propagate uncertainty into decisions
Decision value	Evaluate the schedule, maintenance, control or OPF outcome—not only the ML score
Feasibility & safety	Include constraints, fallback behavior and implementation conditions
Full cost	Count data, reconstruction, checking, repair and computation—not inference time alone

Conclusions

Six applications are genuinely promising
Each addresses a clear engineering need and has demonstrated ML contributions.

Evidence must stay application-specific
Operational records, simulations, pilot data and formal analysis answer different questions.

The next step is engineering integration
Future work should show that learned information improves maintenance, scheduling, control or feasible OPF decisions.

research is strongest when the learned capability is tied to a clearly defined power-system decision and tested under the conditions th