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Editorial

Optimization and Machine Learning Approaches for Power Systems: Progress and Research Priorities

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Power system planning and operation must account for uncertainty in renewable generation and electricity demand. The models used to support these decisions must also respect network limits and consider how flexible resources can respond to changing conditions. Probabilistic forecasting, robust scheduling and machine-learning-assisted optimal power flow can help address these challenges [1–3]. The key question is whether these methods help planners and operators maintain a reliable electricity supply at an acceptable cost as operating conditions change.

The nine papers in this Special Issue, "Optimization and Machine Learning Approaches for Power Systems", connect uncertainty representation, computational tractability and operational flexibility. Their contributions encompass relay coordination, industrial power-to-heat control, probabilistic resource deliverability, multimodal demand forecasting, multi-agent optimal power flow and energy-hub risk assessment. Complementary reviews address planning under uncertainty, storage intelligence and broader artificial intelligence applications. An important remaining question is how improvements in these individual tasks translate into sustained system-level benefits. This requires evaluating forecasting, optimization and control together.

Future research should focus on whether better forecasts lead to better decisions in power-system operation. Task-based learning and smart predict-then-optimize methods train forecasting models to improve the decisions they support [4,5]. Forecasting methods should therefore be compared not only by their prediction errors, but also by their effects on operating costs, energy curtailment and unmet electricity demand. Proper scoring rules help evaluate probabilistic forecasts, which describe possible outcomes and their probabilities. Conformal calibration helps construct ranges or sets of possible outcomes that reflect prediction uncertainty [6,7]. Researchers should clearly state the assumptions behind these methods, especially when applying them to conditions that differ from those used for training. They should also ensure that each forecast uses only information that would have been available when it was made.

A further priority is to ensure that machine learning-based optimization respects physical limits and supports stable power-system operation. Lagrangian learning and feasibility-restoration methods can help find or adjust solutions to meet operating constraints [8,9]. Neural-network verification checks whether a model meets specified requirements, while stability-constrained reinforcement learning aims to maintain system stability [10,11]. Researchers should distinguish between methods that respect operating limits during testing and those that offer mathematical guarantees under clearly defined conditions. Testing should cover changes in network connections, equipment outages, measurement errors and operating conditions not encountered during training.

Planning research should connect these operational advances to investment decisions.

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Decisions. Stochastic valuation of smart-grid options and joint investment in energy storage and soft open points show how flexibility can preserve choices under uncertain distributed-generation expansion [12,13]. Distributionally robust optimization provides a complementary approach when the underlying probability distribution is imperfectly known [14]. A research priority is to quantify the value of additional information and adaptive investment, while accounting for implementation delays, controllability and regulatory constraints. Comparisons should distinguish the value of flexible assets from the value of the information and control policies used to operate them.

Cross-sector applications also require consistent reliability assessment. Reinforcement learning for hydrogen-integrated microgrids illustrates the interaction between storage capacity and control [15], while the F-factor methodology offers a complementary measure of storage's network-security contribution [16]. Future comparisons should separate controller improvements from capacity effects and jointly assess degradation, conversion losses, investment costs and service reliability. Controllers should be compared under the same information set, with perfect-foresight solutions reported separately as benchmarks.

Finally, researchers should design their studies so that others can repeat the experiments. Established simulation tools, the updated IEEE Reliability Test System and PowerGym provide a basis for comparing methods [17–19]. Studies should use common tests of challenging operating conditions, evaluate models on data from periods after those used for training, clearly report solver settings and state the computing resources required for training. Results should show how costs and operating-limit violations vary across test cases, rather than reporting only averages. Sharing code, data-processing steps and unsuccessful test cases would help establish whether a method performs well in new conditions or only under favourable test conditions. Independent testing in real power systems remains necessary before improved results on test systems can be considered evidence that a method is ready for practical use.

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