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**| RESEARCH ARTICLE**

# Advanced Computational Methods, State Estimation, and Control Strategies for Enhancing Efficiency in Modern Power Systems and Clean Energy Technologies

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**| ABSTRACT**

The power systems are changing quickly, with more and more incorporation of renewable energy resources, distributed energy resources, energy storage devices, and intelligent communication technology. The complexity of these developments has resulted in the need for sophisticated computational techniques, accurate state estimation and intelligent control strategies for reliable and efficient grid operation. This review discusses the latest developments of computation methods such as optimization algorithms, Model Predictive Control, Volt/Var Optimization, and data driven methods for enhancing power system monitoring and decision making. The role of state estimation in the context of EMS is explained as the backbone of the Energy Management Systems and how the integration of SCADA with PMS units can improve network observability, accuracy of estimation and real-time situational awareness. The advanced voltage regulation, reactive power management, renewable energy coordination and energy storage control strategies are also assessed. Additionally, applications, software tools, measurement technologies, benchmarking frameworks and industrial implementations are identified which support intelligent grid operation. The current measurement uncertainty, cybersecurity threats, communication delay, data fusion, scalability, distributed computation and uncertainty caused by renewable generation are thoroughly discussed concerning the emerging research directions. The results show the substantial gains in grid efficiency, reliability, power quality and renewable energy integration that can be achieved by integrating advanced computational techniques with advanced state estimation and predictive control. The next steps involve the implementation of AI, machine learning to create adaptive and sustainable electricity networks that can deliver the energy required to support global energy transitions and growth.

**| KEYWORDS**

Advanced computational methods, state estimation, model predictive control (MPC), volt/VAR optimization (VVO), modern power systems.

**| ARTICLE INFORMATION**

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## 1. Introduction

Advanced computational methods, state estimation and control strategies are increasingly becoming key elements of modern power systems and clean energy technologies, facilitating reliable operation, efficient energy management and seamless integration of renewable energy resources [Parhizi, 2015]. Distributed energy resources (DERs), energy storage, electric vehicles and hybrid AC/DC networks are growing rapidly, making power system operation even more complex. Consequently, the traditional monitoring and control methods are not enough to deal with the increasingly dynamic and decentralized electrical grid. Therefore, modern power systems depend on sophisticated mathematical models, optimization methods, statistical estimation methods, and real time data analytics to observe the power network conditions, predict the power system behavior, optimize the operational performance and ensure reliability and stability of the power network [Al-Imon, 2024]. The state estimation is the key to modern energy management systems that fuse data from Supervisory Control and Data Acquisition (SCADA) systems, Phasor Measurement Units (PMUs), Wide Area Monitoring Systems (WAMS), and other sensors with physics-based network models to estimate important state variables, including bus voltage magnitudes and voltage phase angles [Fang, 2012]. However, since the practical measurement systems are only able to measure a subset of variables in the network, statistical estimation techniques, such as Weighted Least Squares (WLS), are common methods used to calculate the most likely operating state, robust to the uncertainty of measurements and the redundancy of the system. The quality of measurements, observability of the network, redundancy and the capability of rejecting erroneous or corrupted measurements with residual analysis, chi square testing, Principal Component Analysis (PCA), and hypothesis testing are a few of the key factors that influence the effectiveness of state estimation [Beaudin, 2010]. The computational tools for modern state estimation and control have several closely coupled mathematical components: the measurement matrix (H), measurement error covariance matrix (R), gain matrix (G), hat matrix (K), sensitivity matrix (S), and residual covariance matrix, all of which allow for data assimilation, uncertainty quantification, bad data detection, and robust estimation in complex power networks [Dunn, 2011]. In practice, the measurement configurations used can vary according to the available sensing infrastructure and the diagnostic needs and may include active and reactive power injections or line flow measurements, with a strong integration of the conventional load flow analysis. Intelligent power systems is based on advanced computational methods, statistical state estimation and optimization based control strategies [Al-Imon, 2025]. The combination of these helps to monitor, adapt, utilize resources efficiently, and operate modern electricity networks resiliently and reliably, which aids in the transition to sustainable low carbon, renewables dominated energy systems. Despite this, Weighted Least Squares (WLS) is still the most popular estimation algorithm since it minimizes the weighted residuals between measured and predicted values, and considers the uncertainty in the measurement [Chen, 2009]. Under noisy measurements, rapidly changing operating conditions, and incomplete network observability, forecast assisted estimation, machine learning assisted initialization, and adaptive estimation techniques further enhance the performance of estimation. These strategies enable scenario analysis, predictive monitoring, and resilient operation of increasingly data-rich power systems. In all, the combination of sophisticated computational and state estimation techniques, optimization based control strategies, and statistical techniques forms the analytical basis for intelligent power system operation.

## 2. Problem Formulation, Advanced Computational Methods, and State Estimation

The main goal of modern power systems is to enhance the efficiency, reliability, stability and resilience of power systems by voltage and reactive power optimization based control using accurate modeling, state estimation and optimization for transmission and distribution networks [Ali, 2025]. The aim is to integrate data driven observations, physics based system models, advanced optimization algorithms and intelligent control strategies to ensure reliable performance of the system while satisfying operation and physical constraints. Distributed generation, battery energy storage systems, electric vehicles, and renewable energy sources are growing in the percentage of their penetration into the power grid, creating a high dynamic cyber physical system that demands constant monitoring and adaptive decision-making [Al-Ali, 2025]. One of the basic problems in the power system operation of the modern era is state estimation. The goal is to determine the entire state of the system, such as values of voltage magnitudes, voltage phase angles and other operating variables from a few known measurements. Multiple formulations have been created based on the types of measurement(s) available and topology of the network. Those systems that heavily depend on the active and reactive power injected into the system can be formulated as reduced state estimation problems and make use of specially structured Jacobians which facilitate the use of iterative algorithms [Borges, 2025]. Other configurations use the measurements of power flow through transmission line or a combination of injections and line flow to increase measurement redundancy, network observability, and the robustness of the estimation process. With appropriate placement of the measurements and network configuration, these formulations allow for decoupled or nearly decoupled estimation methods which result in a reduction of the computational burden with the same estimation accuracy [Ojo, 2025]. In today's distribution network, the measurement infrastructure is often incomplete, customer privacy requires protection, and the geographical aspect makes it difficult to deploy sensors. Thus, some parts of the network are not known and only communicate with visible parts via boundary variables like injected currents and power flows. This has encouraged the development of the highest level estimation approaches in which unknown areas of the network are modeled as external inputs to the observable subsystem [Newman, 2022]. These techniques rely on the fact that network conditions can be inferred from their measurable effects, and thus they can provide better situational awareness, even in the presence of limited measurement availability (Table 1). State estimation is also the basis for advanced control strategies. Many optimization methods are available, and one of the most popular is Model Predictive Control (MPC), which uses a mathematical model to predict how a system will behave into the future, and then decides on an optimal sequence of control actions over a finite prediction horizon [Elalfy, 2024]. MPC can incorporate information on electricity demand, renewable generation, and network constraints to control the voltage, provide reactive power compensation, and manage network congestion while maintaining operational security in a proactive way. Modern state estimation has also been enhanced by the use of data driven computational methods, combining statistical learning and traditional physics based methods [Oyebode, 2024]. These technologies work together to help curb the need for large infrastructure investments, improve the resilience of the grid and ensure reliable operation of modern clean energy systems, while also allowing for scalable real time monitoring, adaptive control, and efficient use of renewable energy resources.

Table 1. Advanced Computational Methods and Their Applications in Modern Power Systems

| Computational Method | Primary Function | Advantages | Major Applications | References |
|---|---|---|---|---|
| Weighted Least Squares (WLS) | Estimates system states from noisy measurements | High estimation accuracy, robust statistical framework | Static and dynamic state estimation | [1], [3], [4] |
| Distribution System State Estimation (DSSE) | Estimates operating conditions in distribution networks | Improved observability, active distribution management | Distribution automation, DER integration | [1], [73] |
| Model Predictive Control (MPC) | Predicts future system behavior and optimizes control actions | Proactive control, constraint handling | Voltage regulation, energy management, hybrid AC/DC systems | [11], [24], [34] |
| PMU and SCADA Data Fusion | Combines synchronized and conventional measurements | Higher estimation accuracy and observability | Wide area monitoring, real time operation | [6], [7], [16], [77] |
| Machine Learning and AI | Learns system behavior from historical data | Adaptive prediction, anomaly detection | Load forecasting, fault diagnosis, predictive maintenance | [44], [45] |

## 3. Control Strategies, Integration of Estimation and Control, and Efficiency Performance Analysis

A key challenge to modern power systems is the efficient operation based on coordinated control strategies, which aim at optimizing voltage regulation, reactive power management, resource scheduling and system stability across the transmission and distribution network [Georgious, 2024]. As the use of renewable energy resources continues to grow, the traditional approaches to control are being replaced by intelligent, adaptive and predictive schemes which can cope with the changing operating conditions. The strategies utilize the latest measurement and optimization technologies and real-time communication systems to optimize energy use, minimise loss, maintain power quality and increase grid reliability [Chaudhary, 2021]. Volt/Var Optimization (VVO) is one of the most critical strategies, which optimizes the voltage profile and Reactive Power Compensation over the whole distribution network. Reactive power support is typically offered using capacitor banks, voltage regulators, transformer tap changers and automatic control devices controlled by Supervisory Control and Data Acquisition (SCADA) systems [Taabodi, 2025]. These devices are continuously monitored and automatically adjusted, allowing utilities to optimize voltage levels, improve power factor, limit overcurrent, minimize transmission and distribution losses and enable reliable integration of renewable energy resources. VVO has been successfully deployed in various practical cases, achieving proven energy, operational cost, stress reduction, and enhancement of the overall power quality and network stability [Li, 2022]. Another important factor of demand management and conservation is voltage optimization. DVR can help reduce peak loads and conserve voltage, while maintaining voltage stability, by adjusting feeder voltages in real time based on demand. The system further optimizes the use of reactive power, resulting in more efficient use of energy, through automatic power factor correction, coordinated capacitor switching, and intelligent load management [Liu, 2025]. Both short term and long term load forecasting helps the operators to plan the generation resources, postpone expansion of the infrastructure and make better operational planning in different load conditions. Advanced Measurement Technologies are being utilized more and more in modern Control Systems to enhance situational awareness. Phasor measurement units (PMUs) offer high frequency measurements of voltage and current phasors with a degree of synchronization that is more accurate than traditional monitoring methods to capture fast dynamics of the system [20]. When used with Distribution Supervisory Control and Data Acquisition (DSCADA), intelligent communication networks and advanced information technology infrastructure, PMU measurements greatly enhance system observability, allowing for more accurate voltage control, quicker detection of disturbances and better decision making for operating the system. Model Predictive Control (MPC) has proven to be one of the most powerful optimization frameworks for today's power system control due to the fact that it takes into account multiple operating constraints, forecast uncertainties and future system behavior simultaneously [Howlader, 2026]. MPC can anticipate future operating conditions to make optimal control decisions, ensuring voltage stability, balancing generation and demand, coordinating energy storage resources and controlling distributed energy resources. It has applications like voltage stabilization, energy management, coordinated generation scheduling, flexible load control, and hybrid AC/DC network operation (Figure 1). To attain stable and economically efficient operation under very variable conditions, advanced MPC formulations include static capacitor banks, demand side management, forecasting of renewable generation and nonlinear system constraints [Adeyinka, 2024]. Forecast driven coordination has gained significance in recent years with the introduction of uncertainties in the operation of the power system by renewable energy sources. Predictive algorithms rely on historical measurements, weather forecasts and operation data to estimate future grid conditions and allow grid system operators to proactively schedule controllable resources in advance of disturbances. Intelligent co-ordination of electricity generation, battery storage and electricity consumption is also beneficial to system flexibility, minimises electricity curtailment of renewables and optimises overall system efficiency [Alzahrani 2023]. The predictive capabilities are the building blocks for adaptive grid management in contemporary smart grid.

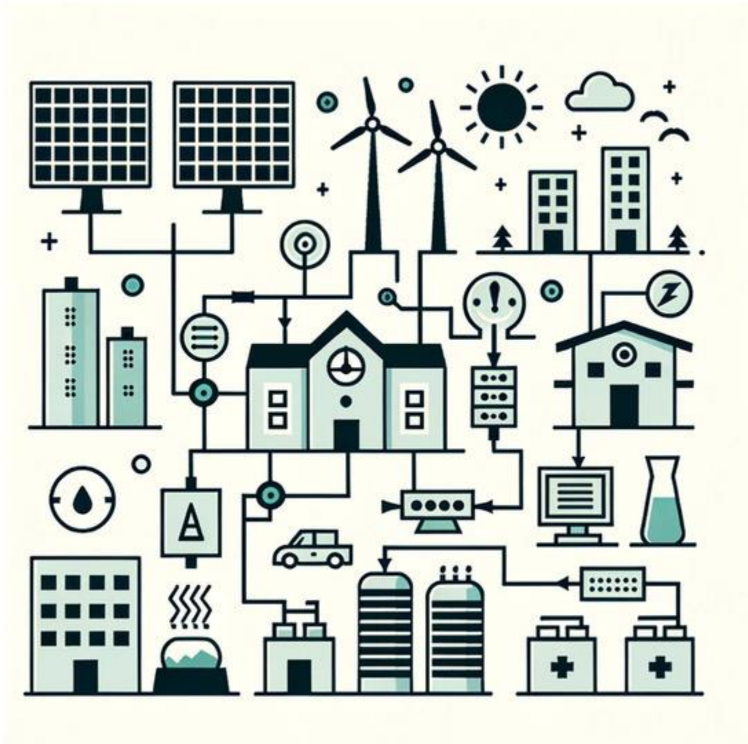

Figure 1. Schematic of an integrated smart grid connecting renewable energy sources to urban infrastructure, residential housing, and industrial storage systems [50]

**4. Applications, Standards, Tools, and Benchmarks**

Advanced computational techniques, state estimation and intelligent control strategies are now basic technologies for the operation of modern power systems and clean energy infrastructures [Ullah, 2025]. They are used in various applications, including transmission and distribution networks, where they play a key role in ensuring grid stability, efficiency, and awareness. They are also used in renewable energy integration, providing a seamless and stable way to integrate renewables into the grid. They also have applications in energy storage systems, where they can be used to store energy for later use. They can also be used in smart meters and sensors, which can provide real-time data on energy consumption and usage patterns [Lim, 2025]. The modern electrical system is getting more and more decentralized, data-rich, and intelligent, and these technologies enable real-time monitoring, automated decision-making and adaptive control across all of the power system (Figure 2). One of the most popular applications in today's power systems is state estimation. The transmission system state estimation (TSSE) is a vital application in the transmission control centers that has been a part of the operations for a long time now and has been playing an important role in providing information for secure system operation, contingency analysis, energy management using solar cells [Kaiss, 2025]. More recently, Distribution System State Estimation (DSSE) has become as important as distribution networks have changed from passive energy delivery systems to actively managed networks with distributed generation, battery energy storage systems, EV's and flexible loads. Such developments demand ongoing estimation of the operating conditions of the networks for reliable and efficient management of the system [Akteruzzaman, 2026]. The capabilities of state estimation have been greatly enhanced with high precision measurement technologies, especially Phasor Measurement Units (PMUs). Their synchronized high speed measurements give details about fast changing network conditions and thus operators are able to get coherent real time images of voltage profiles, phase angles and power flows across the electrical grid. These measurements facilitate system observability, speed the detection of disturbances, and supply the information for advanced control applications [Li, 2025]. Real time operational decision making is also based on state estimation. The reliable estimation of system states allows supervisory control systems and automated controllers to keep the voltage level stable, control the power flow, detect abnormal operating conditions and react quickly to disturbances. In today's distributed system, state estimation is used for active voltage control, feeder management, congestion management, and coordinated control of distributed energy resources. Thus, precise state information becomes the fundamental data source for energy management systems that are intelligent and aim to keep the grid stable and efficient [Minai, 2025]. These are amplified by advanced optimization techniques, which enable predictive control applications. MPC is based on mathematical models, which predict the future operating conditions and optimized control to be taken based on the system limitations and uncertainty in the prediction. This functions enable operators to control the voltage profiles, manage DERs, optimise battery storage operation, and keep the system stable amidst rapidly varying demand and renewable energy output. Offline training, predictive modeling and adaptive optimization further enhance the efficiency and responsiveness of real time control systems [Almihat, 2025]. New benchmarking systems also consider advanced optimization and control techniques used in conjunction with state estimation. These evaluations enable the understanding of the suitability of various algorithms for large scale interconnected power systems in uncertain conditions.

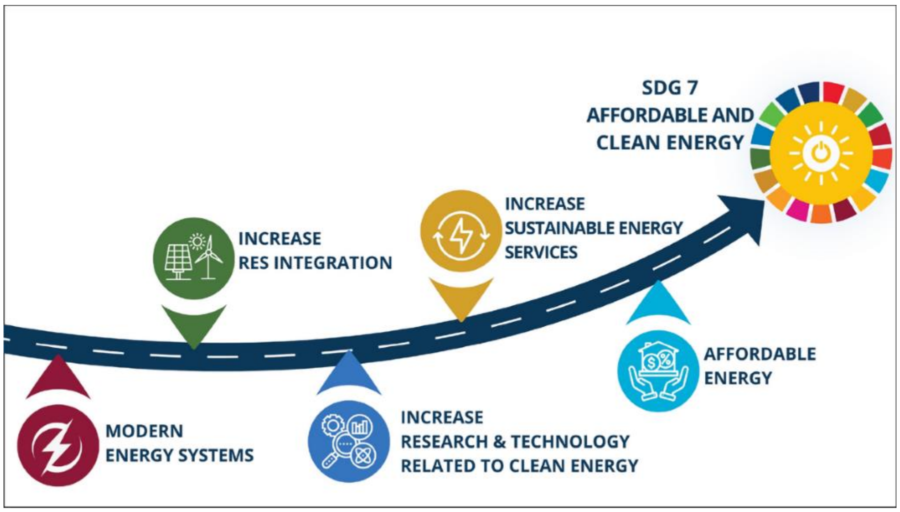


Figure 2. Strategic roadmap illustrating key milestones and objectives required to achieve United Nations Sustainable Development Goal (SDG 7) [Shrivastav, 2021].

**5. Challenges and Future Research Directions**

Despite considerable advances in sophisticated computational techniques, state estimation and intelligent control strategies for modern power systems, there are still many technical issues that hinder their widespread application to the growing complexity of electricity networks dominated by electricity generation from renewables [Huang, 2008]. The demand for innovations and new research and engineering solutions has grown as more distributed energy resources, energy storage systems, electric vehicles and digital communication technologies have entered the realm of the grid [Castañeda 2025]. One of the most basic problems is that of data quality, measurement integrity and outlier detection. Accurate measurements from sensor devices such as Supervisory Control and Data Acquisition (SCADA) and Phasor Measurement Units (PMUs) and other monitoring devices play a key role in state estimation. The measurements are, however, often affected by noise, missing information, communication failures, sensor failures, calibration errors, and malicious cyberattacks [Al-Imon, 2025]. Estimation algorithms that can detect, isolate and correct errors in measurements while maintaining estimation accuracy, are an ongoing research area and current challenge. The improvement of bad data detection, statistical residual analysis, anomaly detection and cyber resilient estimation techniques will be critical for the operation in real time. Another big challenge is time synchronization and the integration of heterogeneous sensors. In today's power systems, synchronized measurements from PMUs are combined with traditional SCADA systems, smart meters, and distributed sensors with a variety of sampling frequencies and reporting periods [Khan, 2024]. The fusion of heterogeneous measurement sources is complicated due to differences in communication latency, measurement time, synchronization accuracy and data quality. Further research is needed to estimate the accuracy of synchronization algorithms, advanced data fusion techniques and resilient communication architectures that enable reliable state estimation in the presence of timing errors and even synchronization failure [Benitez, 2025]. In the wake of more decentralized and distributed electrical networks, distributed and asynchrony estimation frameworks are taking on greater significance. Centralized estimation methods are generally difficult to satisfy the high computation and communication demands of the large scale smart grid with thousands of distributed energy resources. Distributed estimation algorithms offer several advantages, such as enhanced scalability, computational efficiency, and data privacy, by enabling the processing of data at a local level and facilitating decentralized information sharing (Table 2) [Waqas, 2020]. But under asynchronous operation to guarantee convergence, stability, communication efficiency, and accuracy in estimation is still a big challenge in research. Integrated energy systems also add multiple interacting uncertain inputs that make the optimization and control in real time challenging [Tuncar, 2024]. Operational decision making must take into consideration the variability of renewable generation, electricity demand, market dynamics, weather uncertainty, equipment failures, and communication delays at the same time. One of the most difficult research directions in intelligent power system management is to be able to model these uncertainties jointly for computational efficiency and to ensure real-time performance.

Table 2. Major Challenges, Research Opportunities, and Potential Future Directions

| Challenge | Impact on Power Systems | Potential Research Direction | References |
|---|---|---|---|
| Measurement uncertainty and bad data | Reduced estimation accuracy | AI based anomaly detection and robust estimation | [14], [18], [47] |
| Time synchronization and heterogeneous sensors | Data inconsistency | Advanced sensor synchronization and data fusion | [6], [7], [81], [82] |
| Distributed and asynchronous estimation | Communication and convergence issues | Scalable decentralized estimation algorithms | [11] |
| Model uncertainty and topology changes | Reduced control performance | Adaptive and self learning estimation models | [14], [15], [77] |
| Renewable generation uncertainty | Difficulty in real time optimization | Stochastic optimization and probabilistic forecasting | [67] |
| Cybersecurity and data privacy | Vulnerability to cyber attacks | Secure communication, intrusion detection, resilient control | [8], [14] |
| Integration of estimation and control | Increased computational complexity | Joint estimation and predictive control frameworks | [1], [77] |

## 6. Discussion

Power system modernization has revolutionized monitoring, control and optimization of power systems. Traditional electrical grids were built on a basis of centralized power generation, predictable usage patterns, and sparse communication networks [Ying, 2023]. The near-exponential deployment of renewable energy resources, distributed energy resources (DERs), battery energy storage systems, electric vehicles and intelligent sensing technologies, however, has created a very dynamic operating environment that requires more advanced computational methods. It has, therefore, become imperative that the next generation of power systems is reliable and is able to incorporate and enable low carbon energy systems; advanced computational methods, state estimation and intelligent control strategies have thus become the foundation of next generation power systems [Imon, 2025]. One of the most important points that emerged during this review is that state estimation is the basis for almost all applications at a higher level of power system applications. The effectiveness of modern Energy Management Systems (EMS) depends on the accuracy of the estimated bus voltages, voltage phase angles, power flows, and network operating conditions, before higher level applications like contingency analysis, optimal power flow, voltage regulation and economic dispatch are performed [Indrajith, 2025]. The traditional Weighted Least Squares (WLS) estimation still gives a robust mathematical framework as a solution to the problem of reconciling noisy measurements with physical network models, taking into account the uncertainty in measuring processes. But to achieve good integration, the data fusion procedure must be complex enough to handle the various delays, inaccuracies, and frequencies between the system components. Hence, the focus of research has moved from gathering more measurements to creating computational algorithms that are able to extract meaningful information from heterogeneous and continuously changing sets of data. Alongside, advanced computational methods are becoming crucial in solving more complex optimization problems within reasonable computational time [Cerpa, 2007].

Optimization of traditional power systems is typically a complex task that can be difficult to solve for large-scale networks with thousands of buses, renewable generators, distributed storage, and controllable loads. Recent progress in the fields of sparse optimization, warm start methods, iterative nonlinear programming and distributed optimization has significantly decreased the computational cost without compromising solution quality. Model Predictive Control (MPC) is one of the most promising developments, in particular, since it predicts future operating conditions and optimizes the current control actions [Zheng, 2025]. MPC enables systems to be operated proactively, not reactively, by determining optimal operation by integrating demand forecasts, uncertainty in renewable generation and network constraints. This forecasting ability is particularly important as renewable energy contributes increasing variability to electricity generation. Although technological progress has been achieved, there are still some significant issues that need to be addressed. One of the biggest drawbacks for the accuracy of the state estimation is the data quality that is present [Hossain, 2025]. Uncertainty exists in estimation processes due to measurement errors, communication delay, missing measurements, degradation of sensors and malicious cyber-attacks. Therefore, emerging challenges should be addressed in future work through the incorporation of AI, anomaly detection, and cybersecurity technologies into estimation frameworks, enhancing the systems' resilience against more complex attacks. Likewise, electricity use is becoming ever more unpredictable, with the rise of electric vehicles, demand response programs and distributed generation changing historical patterns of electricity use [Ansari, 2023]. State estimation, optimization and control are all equally impacted by these uncertainties. The next generation of computational systems, however, should integrate probabilistic forecast, stochastic optimization, machine learning and adaptive control into centralized decision making frameworks that are robust to the interactions of multiple sources of uncertainty. Computational performance in real time is also a key factor to consider [Liang, 2025]. As the algorithms for making decisions become more sophisticated, so does the computational power that is needed to execute them. The operators of power systems often have a few seconds to detect the disturbance, estimate the power system conditions, and take corrective actions. In future, parallel computing, cloud based optimization, edge computing, distributed processing and hardware acceleration should continue to be used to stress the importance of computational efficiency. These ever-growing computational needs will likely be met by advances in high performance computing and artificial intelligence. AI and machine learning are likely to play a significant role in almost every area of intelligent power system management in the future [Hossain, 2024]. Data based estimation methods can be used to uncover relationships that are not captured in a physics based model and can be used alongside it. Indeed, machine learning algorithms have already proved to deliver satisfactory results in load forecasting, renewable energy generation forecasting, fault diagnosis, anomaly detection, voltage stability assessment, and predictive maintenance. But data-driven methods do not always have an explanatory edge and can not necessarily be successful when deployed outside of the scope of the training data [Islam, 2021]. Thus, hybrid approaches of physical system knowledge and artificial intelligence are most likely to be able to give the most reliable solutions for future power system applications. With greater electricity infrastructure digitization, cybersecurity has become another important factor. Today's smart grids rely on a wide range of communication between sensors, substations, distributed generators, control centers and market operators. This multi-layered design can expose the system to much greater risk for cyber attacks that can impact the accuracy of measurement, communications, or control functions [Negi, 2026]. Therefore, future estimation and control systems need to include secure communication protocols, encrypted data transmission, intrusion detection systems, resilient control architectures, and privacy preserving computational methods to guarantee reliable operation in hostile environments. The presence of DERs continues to grow and drive the need for smart computational approaches. BESS, microgrids, EVs, demand response and renewable generation will have bidirectional flows, which are quite different from the unidirectional flows of traditional power networks [He, 2025]. Future power systems will have to manage these various resources, while ensuring frequency regulation, voltage stability, power quality and economic efficiency. To realize this goal, there is a need to have tight coupling between the forecasting, optimization, estimation, and adaptive control algorithms at various temporal and spatial scales. The overall evidence showed that advanced computational methods, state estimation and intelligent control strategies have collectively constituted the technology of modern power system. Significant advances have been made in accuracy of estimation, computational speed, optimization and reliability in operation.

## 7. Conclusion

Advanced computational methods, state estimation, and intelligent control strategies have become indispensable for the reliable and efficient operation of modern power systems and clean energy technologies. Their integration enhances real time monitoring, improves voltage regulation, optimizes energy management, and supports large scale renewable energy integration while maintaining system stability and resilience. Although significant progress has been achieved in computational efficiency, predictive control, and measurement technologies, challenges related to uncertainty, cybersecurity, data quality, and scalability remain. Continued interdisciplinary research, supported by artificial intelligence, advanced optimization, and resilient cyber physical systems, will drive the development of sustainable, secure, and intelligent future electricity networks.

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