

# Modern Power Systems and Clean Energy Technologies: Advanced Computational Methods, State Estimation, and High-Efficiency Control Strategies

Farhana Afrin Risa <sup>1\*</sup>, Ashok Kumar Chowdhury <sup>2</sup>

<sup>1</sup> Department of Computer and Communication Engineering, International Islamic University Chittagong, Bangladesh.

<sup>2</sup> Department of Electrical and Electronics Engineering, Bangladesh Power Development Board, Chattogram, Bangladesh

\*Email: [risaaftrin1008@gmail.com](mailto:risaaftrin1008@gmail.com)

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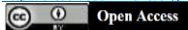
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## ABSTRACT

The power system landscape is changing dramatically as more renewable energy, inverter based resources, energy storage, hybrid AC/DC systems, and digitally enabled control technologies are integrated into the system. The review focuses on complex computational techniques, dynamic state estimation and high-efficiency control techniques that facilitate reliable and flexible operation of the grid in the future under the growing conditions of variable loads and low grid inertia. The concepts of model predictive control are introduced as a potential framework for real time frequency regulation, voltage management, renewable coordination and storage optimization and the centralized, decentralized and explicit approaches are discussed with respect to their different coordination, scalability and computational efficiency. Advanced filtering and phasor measurement data are explored to enhance real time system awareness and observability analysis is used to determine the placement of sensors for reliable state reconstruction. For converter dominated systems the dynamics of the DC side is taken into account which has important implications for the coordinated modeling of the AC and DC side during fast disturbances in order to ensure stable energy transfer. In the context of renewable integration and grid flexibility, clean energy interfaces such as photovoltaic systems, wind generation, HVDC transmission, microgrids and storage are also discussed. To deploy this practically, laboratory and hardware in the loop validation, efficient computation, secure communication and adherence to changing grid codes and interoperability standards are required.

## Introduction

Inverter based resources, renewable energy and energy storage, and optimizing operation are now all prevalent in modern power systems, representing a fundamental change in the way that the electrical grid is managed. This transition demands increased reliability and efficiency, more flexibility and a more aware system with high penetration of low carbon generation. The field is focused on the interaction between power engineering, control theory, computational methods and energy policy, with a special interest in the securing of a power grid and an efficient power market in new and more challenging operating conditions [1]. This change is very much driven by advanced computational methods which allow real-time analysis, planning, estimation and control in the presence of uncertainty and in a rapidly changing environment. For grid forming converters, and integrated energy systems, model predictive control has become an important method that allows all operating decisions to be optimized continuously with respect to the current system states and to new forecasts [2]. Various MPC methods have been explored to achieve a balance between the control accuracy and computational demand, namely centralized, decentralized and explicit MPCs. Explicit MPC can be used in relatively hardware-limited controllers as it can precompute a map of optimal control actions over various operating conditions.

With the addition of high penetrations of inverter based resources and hybrid AC/DC networks, state estimation has also gained growing significance [3]. Dynamically estimating state and parameters, combined with PIs and WWS, can enhance the visibility of voltage, frequency, power flow and other system conditions. It is especially crucial for low inertia systems where frequency changes can be very quick after disturbances. Including inertia and primary frequency response in the frequency model can enhance predictive control and speed up the response of converter based resources. The control architectures are also being integrated with new technologies like edge computing, blockchain for energy trading, and newer optimization techniques [4]. Yet some challenges remain in the practical implementation such as computational complexity, observability restrictions, estimator stability, sensor placement, communication and interoperability, cybersecurity, and laboratory and field testing.

### Computational Foundations and Advanced Methods for Grid Operations and Planning

The grid is increasingly reliant on sophisticated computational techniques for analyzing, forecasting and managing grid performance with high levels of renewable energy, inverter based resources, Distributed Generation, and changing market parameters [5]. State estimation and forecasting are the basis for real time grid awareness, allowing the operating conditions to be understood and control decisions to be made based on that understanding. The phasor measurement unit data and advanced estimation methods provide enhanced visibility in hybrid AC/DC networks, while machine learning enabled forecasting assists in providing short term renewable energy generation, usage and system state predictions. MPC is an important real-time computation and planning tool [6]. MPC has to design future control actions optimally, taking into account constraints, storage dynamics, renewable variability, and changing system parameters, based on current conditions and forecasts. MPC based supervisory control is able to predict the frequency behavior and govern the response of the converter for disturbance events in grid forming converter applications [7]. Centralized MPC relies on information that's available system-wide to optimise overall performance, while decentralised MPC relies on distributing the computation across local controllers, thereby reducing the amount of communication needed and the load demanded on the computation. Explicit MPC can also be even more efficient from a computational perspective, by precomputing the optimal control actions for the various operating regions defined by the problem. Real time models can predict the evolution of frequency and the rates of change, and grey box models are the integration of physical system representation and stochastic elements to deal with uncertainties arising out of measurements and processes [8]. However, parameter sensitivity analysis also shows that uncertainties in resources based on a converter can have an effect on the size and timing of frequency responses. When dealing with complex and dynamic grids, robust identification, estimation and adaptation is required when using computational methods (Table 1) [9]. Overall, computational efficiency is a major factor. Stiffer dynamic models may be more stable at the expense of higher computational cost by using numerical methods like backward Euler. Low rank state estimation, reduced order modeling and decentralized computation are scalable alternatives for real time applications. So the choice of computational architecture must be a compromise between the accuracy of the model, the number of required communications, the computational complexity of the software, numerical stability, and response time [10].

Table 1: Comparison of Model Predictive Control (MPC) Architectures

| MPC Architecture | Description & Key Features | Computational & Communication Characteristics | References |
|------------------|----------------------------|-----------------------------------------------|------------|
|------------------|----------------------------|-----------------------------------------------|------------|

|                          |                                                                                  |                                                                                                     |     |
|--------------------------|----------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------|-----|
| <b>Centralized MPC</b>   | Relies on system-wide information to optimize overall grid performance.          | Demands high computational load and extensive system-wide communication.                            | [2] |
| <b>Decentralized MPC</b> | Distributes computation across local controllers focusing on local disturbances. | Reduces communication requirements and lowers online computational load.                            | [5] |
| <b>Explicit MPC</b>      | Precomputes optimal control actions offline across various operating regions.    | Highly efficient online; ideal for hardware-limited controllers with minimal real-time computation. | [6] |

### Dynamic State Estimation, Observability, and High Efficiency Control Strategies

Dynamic state estimation is an important issue in modern power systems since it can supply the changing system conditions information based on nonlinear and time varying measurements in real time. Extended Kalman Filter (EKF) and other estimation methods are able to estimate varying states of a system, even if the system is nonlinear, while also handling uncertainty in measurements [11]. Dynamic state estimation is very relevant to rapidly changing grids with high penetration of inverter based resources, as opposed to static estimation which uses a set of measurements at a specific point in time to estimate the state of the grid. The key to reliable state estimation is to ensure there is enough information to identify and recover the state of the system. The observability of the system may be state and input dependent in nonlinear systems, and may need to be assessed both analytically and empirically [12]. Analytical observability is the ability of measurements and inputs of the system, taken over some finite time period, to uniquely determine the state, while weak observability is the ability to distinguish different initial states using the available measurements. Singular values, eigenvalues and condition numbers of observability matrices can be used to assess the observability of the conditions where the observability matrix is poorly conditioned and to characterize the quality of estimation [13]. These measures also aid with the numerical conditioning and trustworthiness of state reconstruction. In power system applications, different network conditions and renewable generation, loads, and converter behavior mean dynamic observability is paramount. Measurement uncertainty and nonlinear measurement relationships may compromise the fidelity of estimation, and poor sensor placement may result in the absence of good observation of key system states [14]. Therefore, analysis of observability can be used for sensor placement, measurement configuration and estimator design. Other methods include active sensing and state trajectory planning, in which the configuration of the sensors used and/or the input to the system are chosen to enhance the distinguishability of various states. These are more important if the available measurement resources are restricted and the required state awareness has to be maintained under varying operating conditions [15]. As the power system gets more and more dominated by converter interfaced generation, high efficiency control strategies are now more and more demanded. Grid forming Voltage Source Converters are able to operate quickly and provide frequency support in low inertia systems. An approach to control coordination is model predictive control that takes advantage of the measurements of systems and prediction models to set active power setpoints that take into account operational and hardware requirements [16]. After a disturbance has occurred, a supervisory

MPC layer can utilize multiple converters and provide guidance to the system towards a stable operating point, thereby controlling the frequency deviation and frequency rate of change.

### DC Side Dynamics, Clean Energy Technologies, and Grid Integration

When addressing high efficiency control in converter dominated power systems, the AC side dynamics must be taken into consideration in addition to DC side dynamics. Traditional control methods have tended to be based on AC system dynamics, but the increased penetration of converter interfaced resources has introduced DC link dynamics as a key component of the overall stability. An introduction of DC side behaviour into the control design can aid in avoiding over-acceleration of the converter, energy transfer ratios and converter based resources' response to rapid disturbances [17]. A coordinated representation of AC and DC dynamics can then be effectively used to improve converter capabilities and system stability. The model predictive control approach offers a practical framework with which these dynamics can be added to high efficiency operation (Table 2). Explicit and decentralized MPC methods can be helpful for scalability in systems with many converter interfaced resources. The distributed control approach eliminates communication requirements since the local controllers only communicate with the local disturbances, and explicit MPC decreases the online computational requirements by precomputing the control laws (Figure 1) [18]. The following features facilitate plug-and-play implementation and help minimize the hardware and computational requirements for high speed control. The simulation studies have shown good stability characteristics but formal stability analysis and validation for a broader range of operating conditions is still important development areas. Power transfer capability by HVDC can be controlled and is suitable to complement existing AC power system in renewable power system. It can be used to integrate remote renewable resources, enable cross regional electricity exchanges and decrease reliance on congested AC transmission corridors [19]. The precise control of power flows also offers extra flexibility for managing power fluctuations from variable generation and maintaining system stability. Combining the dynamics at the DC side, the HVDC transmission, smart grid technologies, storage and predictive control, therefore, provides a more coordinated system for modern clean energy systems [20]. The application of both of them can enhance the operational flexibility, and help ensure reliable electricity supply when the share of renewables increases, but computational needs, stability validation, interoperability, and suitable regulatory frameworks are also relevant matters to be addressed for implementation.

Table 2: State Estimation, Clean Energy Technologies, and Grid Integration Challenges

| Category / Component            | Key Techniques & Features                                             | Operational Role & Impact                                                                                   | References |
|---------------------------------|-----------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------|------------|
| <b>Dynamic State Estimation</b> | Extended Kalman Filter (EKF) and time-varying measurement processing. | Estimates nonlinear states and handles uncertainty in low-inertia grids with high inverter-based resources. | [12]       |
| <b>Observability Analysis</b>   | Singular values, eigenvalues, and condition numbers.                  | Evaluates sensor placement, measurement configuration, and numerical conditioning for state reconstruction. | [15]       |

|                                |                                                                                    |                                                                                                            |      |
|--------------------------------|------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|------|
| <b>Clean Energy Interfaces</b> | Solar PV, wind generation, HVDC transmission, battery storage, and microgrids.     | Enables flexible AC/DC integration, cross-regional power exchange, and rapid voltage/frequency support.    | [17] |
| <b>Deployment Challenges</b>   | Computational complexity, cybersecurity, observability limits, and HIL validation. | Addresses practical hurdles in meeting evolving grid codes, interoperability standards, and field testing. | [18] |

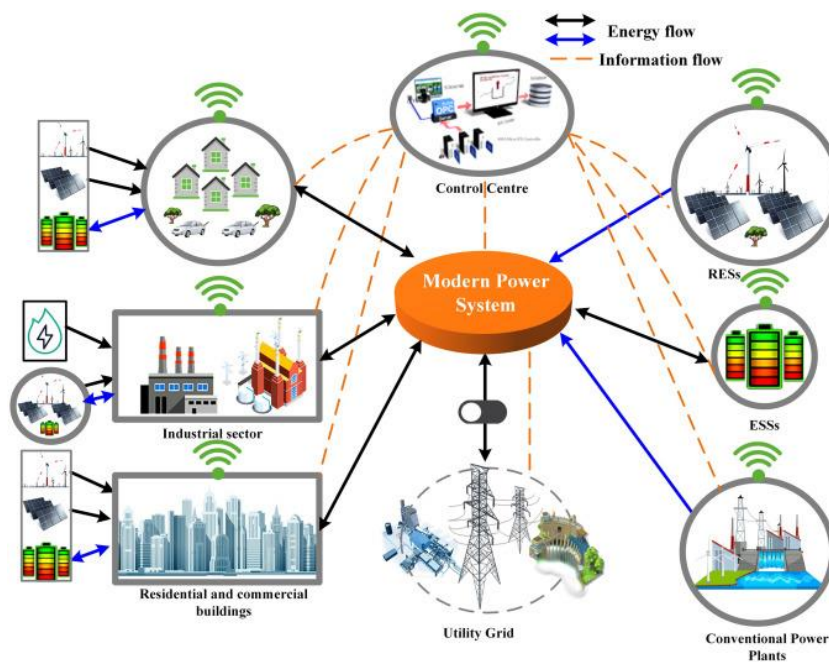


Figure 1. Closed Loop Estimation and Predictive Control for Converted Dominated Power Systems [42]

### Renewable Integration, Grid Codes, and Economic Considerations

With the advent of integration of renewable energy, flexible AC and DC interfaces and advanced control strategies are emerging. Hybrid AC/DC configurations can take the best of both worlds, offering more flexibility in the operation of variable renewable energy sources, energy storage, and power flows (Figure 2). With the growing share of renewables, grid codes are also evolving to meet the technical needs of inverter based resources [21]. The design and operation of MPC and other advanced control systems are more and more affected by the requirements for frequency response, voltage regulation, fault response, and system stability. Typically, renewable generation sources are interfaced with existing electrical networks using power electronics. Both solar PV and wind generation can be DC generation and can need to be converted and conditioned for grid connections [22]. It is then obvious that power electronic converters are needed to serve as the interface between renewable generation and conventional AC transmission and distribution infrastructure. With inverter control, voltage, frequency, active power, reactive power can be controlled with grid requirements maintained. DC AC conversion technologies are also vital for energy storage systems and microgrids to help manage energy use, ensure voltage regulation and provide system stability during disturbances or power outages [23]. The integration of advanced grid interfacing technologies must also take economic factors into account. It will require initial investment in power electronic equipment, communication infrastructure, monitoring systems,

control platforms and the upgrading of the associated grid. As operating time is extended, better control may result in lower operating costs, less curtailment of renewable energy generation, increased reliability, and increased utilization of existing network capacity. Economic value of these benefits will vary with renewable penetration, system characteristics, electricity market structures, infrastructure conditions and regulatory requirements [24].

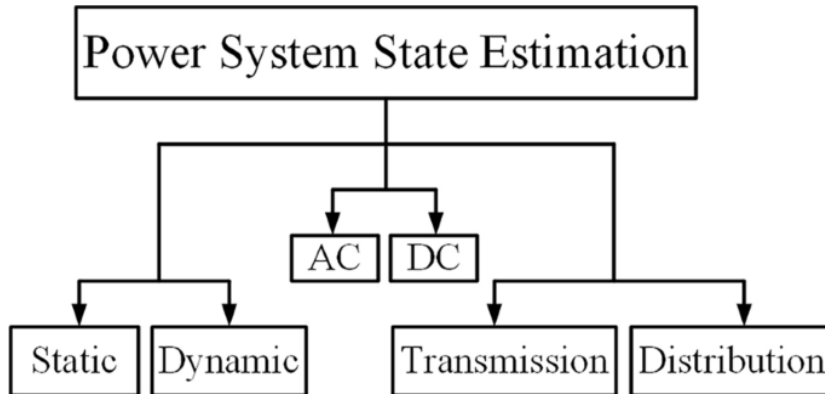


Figure 2. Clean Energy Interfaces Hybrid AC and DC Grid Integration [43]

### Applications, Standards, Regulation, and Interoperability

The advancement of computational techniques, dynamic state estimation and highly efficient control techniques is used in modern power systems for protection, monitoring, control, systems planning and market oriented operations. Dynamic state estimation, protection coordination, data supervision and real time control can be supported by digital fault recorders, merging units, and intelligent electronic devices that are connected to processing platforms [25]. Hybrid protection and control architectures are able to link process and substation buses, thereby monitoring system conditions continuously and initiating a protection action in a timely fashion. Advanced control platforms are often simulated in the laboratory or in the hardware in the loop environment prior to deployment in the utility network. Buses in the process and substation scenarios can be simulated, fiber connected merging units can be tested and real time tests can be performed under representative operating conditions to assess the performance of state estimation and model based control [26]. The factory testing and laboratory validation offer a practical way to find computational, communication and control limitations before installing the system into the field, offering opportunities to identify the limitations before they are encountered in the field, before deployment. Predictive control technologies are more and more regulated by regulations and grid codes. There are opportunities to incentivize utilities to enhance reliability, integration of renewables, and operational efficiency through performance based approaches. Grid developments in Europe have encouraged grid flexibility and demand response, and non-wire alternatives have been considered; in other regions, grid requirements are evolving to incorporate fast frequency response and voltage and frequency control [27]. These requirements have implications for advanced MPC systems in terms of the technical conditions they need to meet for coordination of renewable and converter based resources. Advanced grid technologies are also affected by market and regional conditions. Grid integration and control systems are crucial to use in major applications, such as utilities, and growing in other applications, such as industrial microgrids and commercial energy management systems [28]. Demand for adaptive and robust control approaches stems from renewable deployment, decarbonization goals, reliability needs, and technology cost reductions. The explicit MPC and associated model based strategies are especially powerful tools for high renewable systems due to the ability to satisfy reduced inertia, rapid dynamics, and operational constraints without becoming impractical for computational requirements.

## Discussion

Modern power systems are undergoing change due to the growing deployment of renewable energy, inverter based resources, energy storage, flexible loads, and digitally enabled control systems. Today's power systems are not the traditional power system where the main asset is the synchronous generator, but rather have reduced rotational inertia, faster electrical dynamics, bidirectional power flows, distributed generation, and increased generation and demand uncertainty [29]. The changes have made the computational technologies that offer accurate system awareness and quick control decisions even more important. The inclusion of the state estimation, forecasting, model predictive control, advanced power electronics, and intelligent communication, it can therefore be said that the grid management has undergone a paradigm change from mostly static and centralized to mostly dynamic and increasingly adaptive grid operation. As any kind of dependable control relies upon the availability of precise details regarding system conditions, computational procedures serve as the base for this change. State estimation and forecasting enable the continuous assessment of voltage, frequency, power flows, renewable generation, etc [30]. Phasor measurement units and other high speed measurement technologies deliver information at a temporal resolution that can be useful in monitoring the rapidly changing grid conditions. They can be used in conjunction with dynamic estimation to enhance visibility in complex AC and hybrid AC/DC systems. Machine learning based forecasting can be used to supplement physical models to detect patterns in renewable generation, demand, and system behavior [31]. However, quality of the data, operating conditions, and the capacity of the model to represent unusual disturbances remain as factors of prediction accuracy. Therefore, data driven methods are best used in a broader physical and computational context, not to replace the existing models of the systems. Model predictive control is an important link between prediction and real time decision making. MPC relies on a model of the system and observations and predictions of the system to inform the control actions for a future period [32]. Only the immediate control action is executed; the optimization is then repeated with the new information. MPC is well suited for renewable rich systems, where operating conditions might change significantly, because of this rolling structure. They can be used to regulate frequency, control voltage, coordinate renewable generation, manage storage, and schedule integrated energy systems [33]. The ability to include constraints is especially useful as this is one of the most important features needed in modern grids, which must meet power flow, equipment, energy management and stability requirements. The success of any MPC is highly dependent on the quality and complexity of the prediction model. High fidelity models can accurately capture dynamics of the converter and the interaction of the networks, but can also require significant computing resources. Reduced order models can increase computational efficiency, but can also neglect dynamics that enter into severe disturbances [34]. Grey box models offer an alternative, as they are a combination of physical models and statistical descriptions of uncertainty. In real time applications where control decisions might need to be made within very short time, this accuracy/tractability balance becomes crucial. Implicit integration is one of the numerical techniques that can be used to increase the stability of simulations of stiff dynamic models, but because of its higher numerical complexity, it may not be directly applied to high speed control [35]. However, that need a lot of communication infrastructure and computing power. Decentralized control involves handling the decision-making process at a local level and can minimize communication needs and enhance scalability. Local controllers can react quickly to disturbances in the vicinity of particular converter interfaced resources. Explicit MPC also has a further computational benefit due to the ability to compute the optimum control actions offline for various regions of the operating space [36]. In real time operation, the appropriate action can be decided in a short time with the ability to just compute the precomputed control law. Another important aspect of the reliable

operation of the modern grid is dynamic state estimation. In some cases, when the states of the system vary quickly or when the converter dynamics contribute to the system behavior, conventional static estimation may not be adequate [37]. Dynamic estimation is an estimation that relies on a series of measurements to monitor the evolution of the state vector and includes the nonlinear behavior of the system. Extended Kalman filtering and similar methods offer means for forecasting and assigning the state of the system when the measurements or processes are uncertain. However, a reliable estimation is hard to be achieved without enough observability. Observability analysis therefore has direct implications on the placement of sensors and the reliability of the estimation [38]. The numerical quality of state reconstruction can be assessed using singular values, eigenvalues and condition numbers and poorly conditioned estimation conditions can be identified. The assessment of observability in a power system may be complicated in practice due to measurement uncertainty, limited number of available sensors, non-linearity in the measurement relationship, and changing network configuration [39]. These limitations can be mitigated by active sensing and by using improved sensor configuration, to further increase the distinguishability of system states. Thus the PMUs, conventional measurement data, intelligent electronic devices, and advanced estimation algorithms can collectively offer a better picture of changing states on a grid, especially in real time. The performance of the converter in fast transients and the energy available to the converter is affected by the dynamics of the direct current link [40]. Failure to consider these dynamics could lead to control decisions that may be theoretically correct from an AC perspective, but physically incorrect for the converter system. Therefore, the inclusion of DC side behavior in the design of a controller can lead to a better representation of the energy transfer and can avoid unwanted converter responses. The integrated perspective of AC/DC is becoming more and more important, as battery storage, PV generation, HVDC transmission and power electronic interfaces are becoming more dominant [41].

### Conclusion

Modern power systems are being reshaped by renewable generation, inverter based resources, energy storage, and advanced digital control. Computational methods, dynamic state estimation, forecasting, and model predictive control provide essential capabilities for maintaining stability, flexibility, and efficient operation under increasingly variable conditions. Integration of AC and DC technologies, including HVDC and converter based interfaces, further strengthens renewable energy integration. However, computational complexity, observability limitations, uncertainty, cybersecurity, interoperability, and regulatory requirements remain important challenges. Continued development of efficient control algorithms, reliable estimation methods, realistic validation, and compatible standards will be essential for achieving secure, flexible, economical, and low-carbon power systems.

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