Qualifying Exam: Modeling and Simulation of Renewable Energy and Electrical Power Infrastructure — Computational Challenges and Opportunities

ALEXANDER BARAJAS-RITCHIE, Oregon State University, USA

This paper provides a comprehensive survey of the literature on the modeling and simulation of renewable energy and electrical power infrastructure, focusing on the computational challenges and opportunities in the context of societal inequality and climate change. We delve into the formal computational description of power flow problems through Quasi-Steady-State (QSS) simulation and address the complexities of computing with wide-area time-series data, highlighting scaling and storage issues. Further, we examine the integration of renewable energy resources into power flow and QSS simulations, spotlighting the modern generation's prospects, including hybrid plants. This paper discusses the computational intricacies of modeling and simulating microgrids and regional grids. Looking ahead, we evaluate the potential of emerging technologies and paradigms, such as open-source software, forecasting time-series resources, control and optimization integration, high-performance computing, and quantum-based optimization, to revolutionize power system computing.

Additional Key Words and Phrases: Renewable Energy Integration, Power Grid Simulation, Computational Challenges, Time-series Data, Grid Optimization, High-Performance Computing

ACM Reference Format:
Alexander Barajas-Ritchie. 2023. Qualifying Exam: Modeling and Simulation of Renewable Energy and Electrical Power Infrastructure — Computational Challenges and Opportunities. 1, 1 (November 2023), 11 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

As the world grapples with the realities of climate change and a pressing need for sustainable solutions, the energy sector finds itself at the forefront of this global transition. Renewable energy sources are now central to discussions on the future of energy. We can see a growing trend of renewable energy characterized in Figure 1 and predicts a significant grid penetration [41]. However, their integration into traditional power systems poses challenges. From ensuring consistent power flow amidst the inherent variability of renewables to modeling a rapidly evolving electrical infrastructure, the landscape of power and energy engineering is undergoing a major change.

Modeling and simulation play a critical role in navigating this new terrain. They serve as the compass, helping us understand, predict, and optimize the behavior of these complex systems. But with new sources of energy come new computational challenges. The rise of renewable energy introduces unpredictability and variability, demanding advanced methodologies that can capture these dynamics accurately [27]. Quantum optimization, machine learning, real-time data acquisition, forecasting, and open-source toolboxes are just a few techniques researchers and professionals employ to address these challenges.

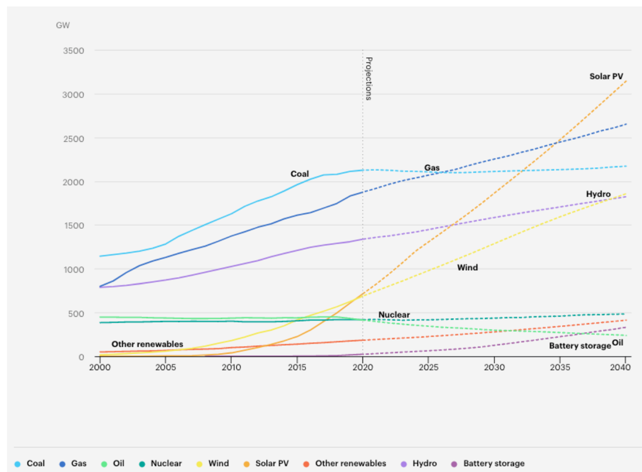

Fig. 1. IEA, Installed power generation capacity by source in the Stated Policies Scenario, 2000-2040, IEA, Paris https://www.iea.org/data-and-statistics/charts/installed-power-generation-capacity-by-source-in-the-stated-policies-scenario-2000-2040, IEA. License: CC BY 4.0

California Independent System Operator (CAISO)

To illustrate and contextualize the intermittency of renewable power and electrical demand, a recent day of CAISO data was analyzed. Figure 2 presents the demand curve (or demand profile) for October 10th, 2023, alongside renewable energy generation. This visualization demonstrates the mismatch between demand and renewable generation, underscoring the challenges in integrating renewable energy sources [44]. On this particular day, the total demand was 6,795,087 MWh, with renewable energy sources contributing 3,001,210 MWh, accounting for 44.17% of the total demand.

The large ramping observed is predominantly due to solar generation, which becomes significantly active during the day, contributing to 58.31% of the demand (7:00 AM to 6:00 PM). This daily cycle, while predictable, highlights the inherent variability in renewable generation. Although the contribution of renewable sources drops to 28.99% in the morning (12:00 AM to 7:00 AM) and 35.49% at night (6:00 PM to 12:00 AM), the overall energy deficit of 3,793,877 MWh

Author's address: Alexander Barajas-Ritchie, barajale@oregonstate.edu, Oregon State University, 1691 SW Campus Way, Corvallis, Oregon, USA, 97330.

XXXX-XXXX/2023/11-ART $15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

Time of Day	Total Demand (MWh)	Total RE Generation (MWh)	% of Demand Met by RE	Total Energy Deficit (MWh)
Morning	1,796,201	520,718	28.99%	1,275,483
Day	3,095,479	1,805,011	58.31%	1,290,468
Night	1,903,407	675,481	35.49%	1,227,926
Total	6,795,087	3,001,210	44.17%	3,793,877

Table 1. Metrics of Demand and Renewable Energy Generation for CAISO Data on 10/24/2023

for the entire day indicates a substantial reliance on other energy sources during periods of low renewable generation, Table 1. This pattern emphasizes the crux of the problem with non-dispatchable, unpredictable renewable generation. While there is a clear and predictable pattern of increased solar output during the day, the overall variability and the challenge of predicting renewable generation availability remain a significant hurdle [41]. The goal is to maximize the utilization of these renewable resources whenever available, but the uncertainty of availability poses a key challenge in energy planning and grid management.

This paper aims to survey the literature, methodologies, and solutions in modeling and simulation of renewable energy and electrical power infrastructure. Understanding these computational challenges and opportunities becomes paramount as society faces the pressures of climate change and inequality. Through a detailed examination of key research papers and methodologies, this paper will shed light on the current landscape, the challenges ahead, and the promising solutions on the horizon.

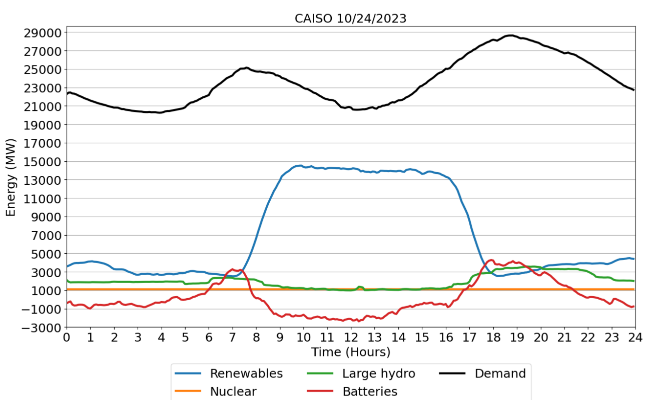

Fig. 2. The graph shows the demand and renewable generation time series of California Independent System Operator (CAISO) on Oct 24th, 2023. The data was pulled from the CAISO website via their open data portal. link: https://www.caiso.com/TodaysOutlook/Pages/supply.html

2 EVOLUTION OF POWER SYSTEM MODELING AND SIMULATION: BRIEF HISTORY AND DEVELOPMENT

Modeling and simulation in power systems have evolved significantly, adapting to the changing landscapes of technology and energy demands. This evolution mirrors broader shifts in energy production, management, and consumption strategies.

The history of power system modeling traces back to the late 19th century with the earliest electrical networks. Initial models were fundamental, focusing mainly on direct current (DC) systems, and aimed at the basic transmission of electricity [59]. The late 1880s witnessed the advent of alternating current (AC) systems, which brought a new layer of complexity, necessitating more sophisticated models to address alternating phases, variable voltage levels, and the intricacies of power factors [3].

As electrical grids expanded in the early to mid-20th century, introducing numerous generators and diverse load centers, modeling started to reflect this increased complexity. Developments during this era in long-distance transmission, load flow analysis, and three-phase systems marked critical advancements [28]. The need to address dynamic stability, fault management, and the behaviors of interconnected grid systems became more prominent. This period was crucial in transitioning from manual calculation methods to the early stages of computer-aided simulations.

The digital revolution, particularly from the 1970s onward, massively influenced power system modeling. The shift to digital computation facilitated handling complex calculations, large-scale simulations, and the incorporation of various operational scenarios [43]. Optimization techniques and statistical methods for managing uncertainties became more integrated, marking a substantial leap in simulation capabilities [3].

The turn of the 21st century brought a greater emphasis on network reliability, economic efficiency, and environmental impacts in power system operations. The increasing importance of understanding power market dynamics, regulatory frameworks, and consumer behavior patterns began to influence modeling approaches.

3 QUASI-STEADY-STATE SIMULATION

Exploring and understanding electrical power grids' dynamic behaviors has increasingly centered around Quasi-Steady-State (QSS). QSS modeling is pivotal in power system analysis, mainly when high-frequency dynamics are not the primary focus. In the realm of long-term stability analysis, QSS models are essential. These models allow for a more granular examination of how the grid reacts to various operational conditions and disturbances over time, emphasizing phenomena like cascading failures and overall system stability [21].

QSS models provide a practical alternative in large-scale power grids, where dynamic simulations can be excessively time-consuming. These models study grid stability over small intervals, such as every 5 minutes, to ensure that the dynamic behaviors of the grid are within acceptable limits. This approach is crucial in balancing the need for accurate system analysis against the computational demand of solving large, complex grid models [39].

3.1 The Power Flow Problem in Power System Analysis

Understanding the Power Flow Problem is crucial in analyzing and ensuring the efficient operation of power systems in generation and demand configurations. This problem involves calculating the steady-state voltage at various buses in a power grid under a specific set of loads and generation conditions. It aims to provide a snapshot of the electrical system's operating condition, serving as a foundation for many critical analyses in power system engineering [26].

The Power Flow Problem is formulated based on non-linear algebraic equations derived from Kirchhoff's Laws [20]. These equations relate the bus voltage magnitudes and angles to system parameters such as line impedance, power injections, and demand. The core challenge lies in its non-linear nature, primarily due to the power-voltage relationship. This nonlinearity introduces complexities in the analytical understanding and the numerical solution of these equations [60].

The primary goal is determining the voltage magnitude and phase angle at each bus, ensuring that the power generation equals the load demand and system losses. Solving this problem allows engineers to determine the operating point of the power system under specific load and generation conditions, assess the system limits like voltage levels and line loading to ensure reliable operation and assist in strategic decision-making processes such as economic dispatch, contingency analysis, and planning for system expansion with the inclusion of renewable sources like wave, wind, and solar.

Various numerical methods are employed to solve the Power Flow Problem, each with its strengths and limitations [5]. The Newton-Raphson Method is highly efficient and widely used due to its quadratic convergence properties, making it particularly effective in systems with numerous buses. It is well-suited for advanced grids with sophisticated monitoring and control systems that can handle computational demands. However, it does require an accurate initial guess and can struggle with the nonlinearity introduced by high renewable integration [20].

In contrast, the Gauss-Seidel Method, while simpler and requiring less computational power, is generally slower to converge and is more suited for smaller or less complex grids. It may not perform as well in the grid complexity often presented by modern power systems with diverse generation sources [60].

Lastly, the Fast Decoupled Load Flow approximates the Newton-Raphson method that decouples the real and reactive power calculations. This method is less accurate but significantly faster, making it useful for iterative studies where speed is crucial, such as in large grids or during the initial stages of the planning process [61]. However, it may not be reliable for systems with atypical operating conditions, such as those with a high degree of renewable generation, due to the assumptions made during the decoupling process [50].

The complexity and size of real-world power grids can make the Power Flow Problem particularly challenging. Large interconnected systems demand significant computational resources, and the problem's non-linear nature means solutions are not always guaranteed to converge. These challenges are compounded in unique operational scenarios, such as low load conditions or high renewable generation, presenting non-standard system states where traditional solutions may struggle.

Beyond determining operational feasibility and system limits, solving the Power Flow Problem is integral for dynamic and stability studies. It forms the baseline condition for transient stability analysis, voltage stability studies, and fault analysis, all essential for modern power systems' secure and reliable operation.

3.2 Computational Challenges in Quasi-Steady-State (QSS) Models

A primary issue with QSS models is their inconsistent ability to offer correct approximations and stability assessments. This inconsistency becomes particularly evident when comparing the performance of QSS models against long-term stability models. For instance, a study highlighted that while QSS models might inaccurately indicate stability, a developed hybrid model successfully captured unstable behaviors that the QSS model failed to detect. This failure of the QSS model to identify instability could potentially lead to an oversight in crucial stability planning and intervention strategies [61].

Another significant challenge in QSS models is their limited capability to model the dynamics of power systems accurately. This limitation stands out when juxtaposed with full-time-domain simulators, which provide a more detailed and precise depiction of system controls and dynamics [39]. Time-domain simulators capture a wider range of system responses and interactions, essential for reliable power system operation and planning [24].

3.3 Model Simplifications in Quasi-Steady-State Analysis

Model simplifications aim to maintain the essence of a system's behavior and dynamics, balancing accuracy with computational efficiency, which allows for less computationally intensive QSS modeling. These simplifications include linearization, Fast Decoupled Load Flow, Aggregation, and Reduced-Order Modeling. Many of these simplifications have both benefits and trade-offs [61].

In the context of power systems, the non-linear equations that describe system behavior are inherently complex and pose significant challenges regarding computational solvability. Linearization offers a practical simplification, wherein these equations are linearized around a specific, usually stable, operating point to provide a manageable approximation for the system's response to small disturbances. This linear approach eases the computational burden and can be quite effective when the system's operation remains close to the chosen point. However, it is imperative to acknowledge that this method is limited to small-signal stability analysis and may not be sufficient to capture the true dynamics during more significant disturbances, such as faults, sudden load changes, or the integration of intermittent renewable energy sources. In such scenarios, the linearized model may not accurately reflect the system's behavior, potentially leading to inadequate or incorrect system stability and performance assessments. This limitation necessitates caution in the reliance on linearization, particularly when assessing the robustness of the power system under a wide range of operating conditions [32].

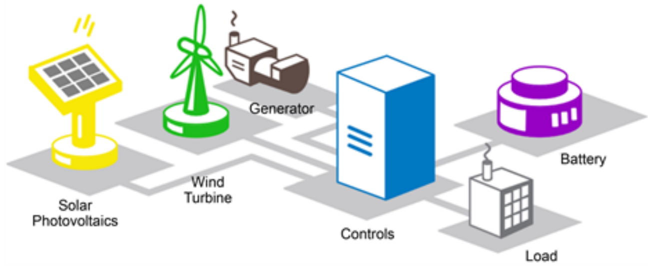

Fig. 3. Renewable Energy grid

Aggregation in power system analysis groups similar elements into composite entities, condensing the complexity of the grid into manageable sections. The cellular aggregation technique clusters components based on geographic or electrical characteristics, simplifying large-scale analysis and reducing computational demands. While efficient, this method can obscure finer dynamics, so maintaining an accurate representation of the system's critical behaviors is vital, especially when integrating diverse energy sources or during atypical operating conditions [33].

Reduced-order modeling (ROM) in power system analysis is a method that simplifies the modeling process. It aims to retain the critical dynamics of the system while reducing the computational complexity by minimizing the number of equations. For instance, a study by Takeda 1978 addressed steady-state stability challenges by reducing the number of generators in the model to simplify the system without significantly affecting the short-circuit capacity at specific points [52]. ROM techniques like modal truncation keep only the most significant modes, streamlining the analysis for large-scale systems where detailed modeling is computationally intensive [52].

Through these simplifications, QSS models achieve a balance between the need for detailed, accurate modeling and the limitations imposed by computational resources. However, it is crucial to recognize the trade-offs involved, as oversimplification can lead to inaccurate predictions and inadequate system analysis. Combined with QSS sometimes not being reliable, adding a non-inertia generation source (RE) adds a layer of complexity discussed in section 4.

4 INTEGRATING RENEWABLE ENERGY SOURCES INTO POWER GRIDS

Integrating renewable energy sources (RES) into existing power grids represents a critical transition towards sustainable energy systems. This challenge extends beyond the technical domain, demanding innovative computational models and simulation techniques to predict and manage the variability and uncertainty inherent in RES.

4.1 Simulation and Modeling Techniques

Hybrid renewable energy systems (Figure 3) that amalgamate multiple generation sources with storage technologies are increasingly common [11]. The installation of *Internet of Things* (IoT) devices in smart grids, used for real-time data collection and monitoring, necessitates robust data analytics and control algorithms, vital for optimizing energy distribution [10]. Advanced modeling techniques, like PNNL's Global Change Analysis Model (GCAM), are essential for simulating the interplay between energy, water, land, climate, and economic systems over time. GCAM's comprehensive framework help to assess the impacts of demographic and technological shifts on resource use and environmental outcomes. It is developed by a multidisciplinary team, integrating human decision-making with Earth system science for global policy and climate analysis [2, 13]

Similarly, NREL's HOMER Pro software, now maintained by UL Solutions, sets the standard for optimizing hybrid microgrid designs. It simulates myriad combinations of energy solutions over yearlong periods, with time steps down to a minute, to identify the most cost-effective and efficient system configurations. HOMER Pro's simulation capabilities are complemented by an optimization algorithm designed to handle complex, multi-variable problems, making it a powerful tool for answering "What if?" questions in microgrid design under variable conditions such as fluctuating fuel costs and renewable resource availability [7].

4.2 Computational Challenges in Renewable Energy Integration

The influx of RES, like solar and wind, introduces unprecedented variability, compelling a paradigm shift to advanced computational models for predicting and managing generation patterns, which are crucial to grid stability and power quality [22]. The inadequacy of QSS models in this new dynamic landscape necessitates the adoption of real-time simulation platforms such as CyDER, which offers scalable, high-fidelity grid simulations accommodating millions of individual customers renewable systems [1]. Leveraging high-performance computing, CyDER's parallelized simulations enable extensive modeling of state-wide energy systems, enhancing the real-time processing of complex data sets [1]. These computational strides are exemplified by LBNL's comprehensive studies, like the state-wide DER impact analysis in Indiana, that assess infrastructure, economic, and reliability impacts under varied renewable adoption scenarios, highlighting the critical role of advanced modeling for energy system transitions.

4.3 Future Directions and Opportunities

Advancements in high-performance computing and quantum-based optimization promise to revolutionize the modeling and simulation of renewable energy systems [18]. In section 8, the paper will discuss the advancements in quantum-based optimization methods in power systems. Open-source software frameworks catalyze the collaborative development of computational tools, thus stimulating innovation and expanding accessibility. Moreover, integrating forecasting models with control mechanisms will be imperative for navigating the complexities of future smart grids with high RES penetration [58]

The computational aspect of integrating renewable energy into power grids presents significant challenges and opportunities. Progress in developing real-time simulation tools and computational methods is ongoing, and continuous research is necessary. The ability to effectively incorporate RES is crucial for the future of energy systems, where computational science stands at the forefront of this transformative endeavor [12].

5 COMPUTATIONAL CHALLENGES OF MODELING AND SIMULATING MICROGRIDS AND REGIONAL GRIDS

Effective integration of renewable energy into microgrids and regional power systems is vital for enhancing the resilience and reliability of our energy infrastructure. However, modeling and simulating these systems present substantial computational challenges. These challenges stem from the complexity of the systems, the necessity for real-time operational capabilities, and the unpredictable nature of renewable energy sources.

5.1 Microgrids

Integrating renewable energy sources (RES) such as solar and wind into microgrids introduces significant variability, necessitating advanced computational models for dynamic simulation of power flow and transient stability analysis. These models are crucial for understanding the power quality issues and the minimal inertia of microgrids due to high RES penetration. Sophisticated modeling ensures interoperability with the main grid and is essential for the real-time control and management of variable renewable energy sources, maintaining stability and efficiency.

Agent-based models and co-simulation platforms excel in simulating the distributed nature of microgrids, allowing for the detailed study of individual component behaviors and their impacts on the overall system. Optimization algorithms, particularly those based on metaheuristic approaches, are vital for efficient load management and energy cost minimization. These include population-based algorithms like PSO, differential evolution, GSA, BSA, and harmony search algorithm, which address scheduling and operational optimization within microgrids [45, 54].

Heuristic algorithms have been developed to enhance energy management in standalone microgrids, reducing the wastage of renewable energy potential and optimizing usage for each time interval. Similarly, metaheuristic optimization techniques are applied to the economic dispatch problem, ensuring cost-effective generation dispatch in line with a microgrid's operational parameters [51, 55].

Energy storage management is also optimized using algorithms like PSO-based heuristics, which consider daily generation and load forecasts for economic optimization. These strategies aim to minimize energy costs and maximize profits against fluctuating market prices and distributor tariffs, underscoring the importance of intelligent management systems for industrial microgrids [29].

5.2 Regional Grids

As regional grids expand, the complexity of managing disparate data sources grows. Accurate state estimation and interdependency modeling are critical for operational reliability. Increasing renewable energy installations intensify interactions between transmission and distribution systems, complicating stability and power quality assessments. Scalability concerns, as illustrated by the CROSSBOW project, revolve around adapting smart grid solutions to diverse conditions and ensuring economic viability and technical feasibility on a broader scale [37].

High-fidelity simulations are vital for capturing the nuanced behaviors of regional grids and preparing for various levels of renewable integration and changing demand patterns. The methodologies developed by the NHERI SimCenter for regional hazard simulation demonstrate the potential for similar high-resolution modeling in regional power grids, underscoring the need for simulations that integrate complex system interactions and multi-fidelity models [16].

Integrating microgrids requires careful network reconfiguration and impact analysis for maintaining stability and addressing line constraints in high-renewable penetration systems. The CROSSBOW project's energy management strategies for balancing renewable energy and storage illustrate the importance of flexibility and robustness for grid resilience, which is crucial for regions with a significant mix of renewable energy sources [37].

6 OPEN SOURCE SOFTWARE IN POWER SYSTEM ANALYSIS

Integrating renewable energy sources into existing power grids introduces complex challenges, demanding robust simulation tools for analysis and optimization. Open-source software (OSS) has become a significant player in this domain, providing flexibility and fostering innovation through community-driven development. These OSS tools enable the simulation of intricate renewable energy models and serve as a testbed for novel optimization algorithms, significantly contributing to the field's advancement.

6.1 Challenges in Open-source Development

Developing OSS for power systems entails intricate difficulties, particularly in ensuring accuracy and reliability within electrical and physical grid behavior simulations. The variable nature of renewable energy sources amplifies these challenges, demanding OSS that can adapt to various conditions. Furthermore, open-source developers must address cybersecurity, given the critical infrastructure status of power grids, and maintain a collaborative environment to keep pace with rapid technological changes.

6.2 OSS Tools: A Catalyst for Renewable Integration

The National Renewable Energy Laboratory (NREL) suite of OSS tools has proven indispensable for simulating grid behaviors with high renewable energy penetration. These tools are critical in evaluating renewable integration strategies and enhancing system resilience. The OSS landscape, outlined in Table 2, illustrates a variety of tools available for power system analysis and renewable energy integration.

6.3 Existing Open Source Tools and Frameworks

The diversity and applicability of OSS tools for power system analysis are extensive, each offering tailored features for integrating and managing renewable energy within the grid. Tools such as pyPSA, OpenDSS, and GridLAB-D exemplify the range of capabilities available, from the optimization of electricity networks to in-depth power distribution analysis and smart grid technologies support. The versatility of these tools in accommodating renewable energy sources, such as solar and wind, and their storage solutions is instrumental for modern power systems. A detailed overview of these and other significant OSS tools is provided in Table 1, which outlines their main features and specific uses in renewable energy systems. This table serves as a resource for understanding the strengths and applications of various OSS solutions in the context of renewable energy integration.

6.4 Enhancing Power System Models with OSS

OSS's computational capabilities are crucial for modeling the integration of renewable energy into power grids. These tools facilitate the processing of large datasets, such as time-series data. They can be integrated with traditional power flow models, enhancing the analysis and planning capabilities for grids with significant renewable energy contributions.

OSS is indispensable in the evolution of power systems towards greater renewable energy integration. OSS's reliability, interoperability, and user-friendliness will become increasingly important as the energy sector advances. The continuous refinement of OSS, driven by the collaborative efforts of a global community, is vital for tackling the complexities of today's energy challenges and promoting sustainable energy solutions.

7 FORECASTING IN POWER SYSTEMS

Integrating renewable energy sources into power systems has transformed the landscape of electricity generation, with the inherent variability of renewables like wind and solar power demanding robust forecasting techniques. These techniques are necessary for grid stability, optimization of operations, and efficient resource allocation. As Variable Renewable Energies (VREs) become more prevalent, the capability to predict their output accurately becomes increasingly crucial for power system operators and renewable generators alike.

7.1 The Importance of Forecasting

Balancing supply and demand in real-time is a quintessential task for power systems, made more intricate by integrating renewables. Their output is intermittent, and precise forecasting is crucial for anticipating energy production fluctuations. Such forecasting is also central to maintaining the grid's stability, where variations in voltage and frequency can lead to unreliability. Moreover, effective forecasting helps minimize costs associated with energy storage and peak load management, enhancing the economic efficiency of the power system [19, 46].

7.2 Challenges of Renewable Energy Forecasting

The output from renewable sources can fluctuate significantly due to weather, time of day, and seasonal changes. Therefore, advanced forecasting techniques that can adapt to swift shifts in energy availability are necessary. These complexities are magnified in marine energy forecasting, where the complexity of marine dynamics adds another layer of intricacy [31, 47].

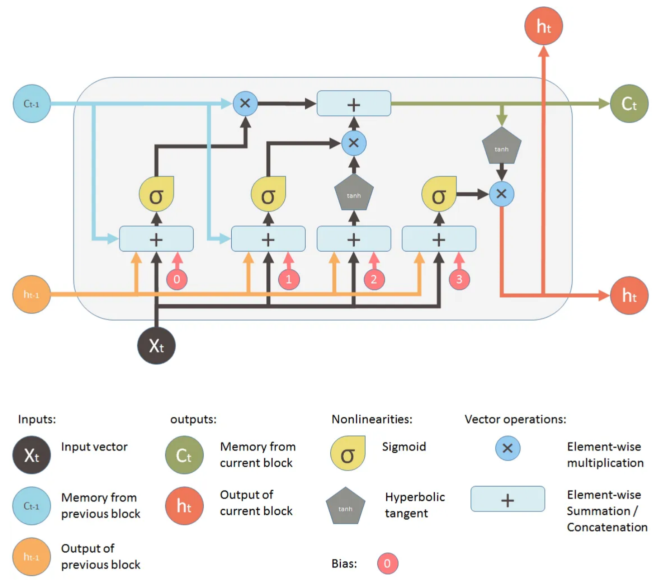

Fig. 4. LSTM Network Architecture

7.3 Advanced Forecasting Methodologies

The surging integration of renewables has spurred the development of advanced forecasting methodologies. This includes traditional time series models like AutoRegressive Integrated Moving Average (ARIMA), which is essential for capturing linear trends and seasonality in renewable outputs. Moreover, probabilistic models such as Gaussian Processes and Bayesian regression are increasingly utilized to manage uncertainty and incorporate prior knowledge into predictions, with the understanding that they often sacrifice interpretability. Machine learning-based forecasters, including Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), Support Vector Machines (SVMs), and Extreme Learning Machines (ELMs), alongside metaheuristic algorithms, have also shown promising results in accurately predicting wind and solar power outputs [6].

Demand Forecasting with LSTM. LSTM networks (figure 4) are particularly suited for demand time-series forecasting in smart grids. Their ability to capture temporal dependencies in energy consumption patterns makes them ideal for modeling and predicting the load in the presence of the variability introduced by renewables [6].

Probabilistic Power Flow Prediction. Probabilistic forecasting models offer a spectrum of potential outcomes essential for decision-making under uncertainty. These models, especially when based on advanced ML techniques like LSTMs, provide grid operators with valuable insights into possible future states of the power system [31].

7.4 Comparative Methodologies

A critical and systematic review of existing ML methodologies for renewable power prediction has highlighted the importance of categorizing these techniques. This categorization is based on their

Software	**Main Features**	**Use in Renewable Energy**
pyPSA	Python-based simulation and optimization for power systems with renewable integration features.	optimization of electricity and other energy networks, addressing renewable integration challenges.
OpenDSS	flexibility and depth in power distribution analysis, supporting smart grid technologies.	analysis of power grids with renewable energy sources and storage system integration.
PowerModels.jl	Julia/JuMP package for power system optimization with a focus on renewable energy.	Supports novel power system models and scenarios with renewables.
GridLAB-D	simulation of distributed generation and smart grid technologies in power systems.	Modeling the impact of renewable integration on power system operations.
MATPOWER	Matlab toolbox for steady-state power system simulation and optimization.	Enabling research and education in power grids, focusing on economic and environmental aspects.
PowSyBl	Java framework for grid modeling and simulation with modular design and plugin support.	Facilitates the creation of applications for power flow simulations and analyses with renewables.
PSAT	Matlab and GNU/Octave toolbox for power system analysis and design.	Suitable for small to medium size power system analysis, including renewable energy scenarios.

Table 2. Summary of Open-Source Software for Power System Analysis

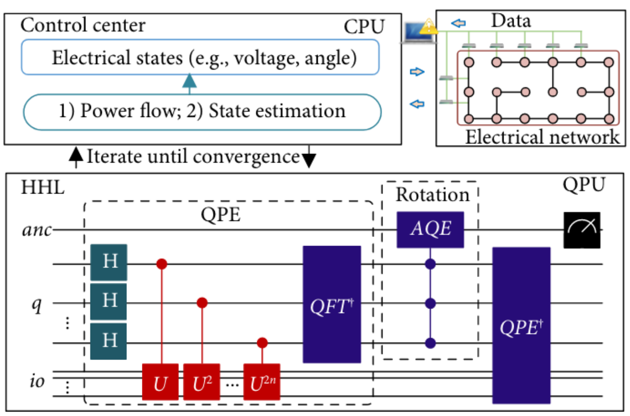

Fig. 5. Quantum circuit architecture for quantum-inspired power grid static analytics

characteristics and the type of forecasted renewable energy, providing a framework for selecting the most appropriate tools for specific applications [6].

7.5 The Horizon of Forecasting

Emerging trends, such as the incorporation of real-time data from IoT devices and satellites and the utilization of big data analytics and cloud computing, are set to significantly enhance the precision of forecasting models. Moreover, adaptive and self-learning systems, which adjust based on forecasting performance, are the cutting edge of forecasting technology [62]. These advancements will likely be critical in transitioning to a sustainable and resilient power infrastructure, supporting the projected growth of renewable energy's contribution to electricity generation to reach 85% by 2050. [6].

8 QUANTUM-BASED OPTIMIZATION

8.1 Quantum Computing in Power Systems

Quantum Computing harnesses quantum mechanics principles, notably quantum superposition and entanglement, allowing qubits to represent multiple states simultaneously. This extraordinary computational power is crucial in power systems for handling complex, dynamic problems like power flow optimization, solving the Unit Commitment Problem, and enhancing analytics, especially in grids with renewable energy and varying demand[63]. The architecture of such a quantum computing model is depicted in Figure 5 [63], demonstrating the potential for quantum-inspired solutions in power grid analytics.

8.2 Power Flow Optimization

Power flow optimization is essential for efficient and reliable grid functioning, especially amidst growing complexity due to renewable integration. Classical algorithms, limited by the non-linear nature of power flow equations in vast networks, often lag in performance. Quantum computing provides innovative and effective solutions, mainly through Quantum Annealing and the Quantum Approximate Optimization Algorithm (QAOA). Quantum Annealing is adept at finding global minima in complex energy landscapes, an essential aspect of power flow optimization[38]. QAOA improves solutions iteratively, adapting well to the evolving needs of modern power grids[17].

8.3 Unit Commitment Problem

The Unit Commitment Problem is a complex decision-making process in power systems, aiming to optimize the operation of various power generation units under multiple constraints. It is an NP-hard problem difficult for classical computing to solve efficiently. Quantum computing, with its parallel processing abilities, offers a promising new approach. QAOA, for instance, encodes the problem into a quantum state and evolves it to find optimal solutions rapidly, a technique more efficient than traditional sequential approaches[25].

8.4 Analytics in Power Systems with Quantum Computing

Analytics tasks like N-k contingency analysis, state estimation, and transient stability assessment are crucial in power systems. These require handling complex combinations and permutations that classical computing can find challenging. Quantum computing, with its superior data processing and complex algorithm execution capabilities, provides faster, more accurate solutions. For example, quantum-enhanced state estimation can swiftly manage large data sets and complex calculations, essential in grids with high renewable integration [63]. Transient stability analysis, crucial for predicting system behavior after disturbances, benefits significantly from quantum computing's ability to quickly model and analyze complex scenarios [63].

9 WIDE-AREA TIME-SERIES DATA

Our modern power systems are marked by a transformation trajectory driven by technological innovations, evolving energy demands, and the imperative for sustainable energy solutions. Central to this transformation is the position of wide-area time-series data, which is instrumental in aiding the operational efficiency, stability, and resilience of power systems and the grid. The addition of Wide Area Measurement Systems (WAMS) has heralded an era of enhanced data accessibility, enabling time-series data analysis [49]. As shown in Figure 6, synchrophasor technology, using GPS technology to synchronize measurements, plays a pivotal role in the functioning of WAMS, offering high-precision monitoring of the electrical grid. As power systems evolve in complexity due to the integration of distributed intermittent renewable generation, the need for total grid monitoring through wide area monitoring (WAM) to ensure power availability and quality becomes clear [49].

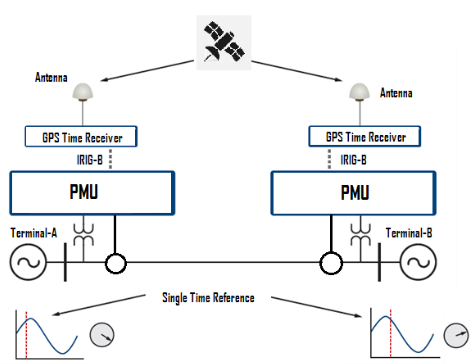

Fig. 6. Synchrophasor Technology with two buses and a line showcasing GPS technology integration

9.1 Challenges with Time-Series Data

The growing amount of time-series data in power systems, mainly from using WAMS and other monitoring technologies, brings about various barriers, particularly in real-time processing and analysis. This data's high resolution and volume necessitate robust and adaptable systems capable of handling high data flow and ensuring quick processing for useful insights [23]. Advanced tools and algorithms are needed to process streaming time-series data, spot unusual patterns, and provide real-time forecasts crucial for grid stability and efficient operation [34]. The infrastructure must be scalable to manage the increasing data volume and the computational demands of real-time analytics [56]. It must be designed to ensure smooth data processing and analysis as time-series data grows. Wrong or missing data can significantly affect the analysis results, possibly harming decisions in power grid operations [9]. Latency, the delay in processing, is a critical factor, especially during significant grid disturbances. The need for low latency in data processing is highlighted to ensure quick decisions are made to maintain grid stability and address adverse events. Efficient storage solutions and fast data retrieval mechanisms are crucial for practical real-time analysis. This includes using suitable databases and storage systems that allow quick data access and analysis, crucial for real-time decision-making processes [23]. Integrating real-time analytics solutions with existing monitoring and control infrastructure in power systems is a significant task. Ensuring smooth data flow between different systems is crucial for fully utilizing real-time analysis of time-series data. The challenges with time-series data in real-time processing and analysis highlight the need for strong, adaptable, and efficient systems. Addressing these challenges is not just a technical need but a strategic effort to use time-series data for improving grid monitoring, control, and decision-making processes, moving power systems toward a model of enhanced reliability and resilience.

9.2 Data Accessibility and Analysis

The emergence of WAMS has brought about a significant transformation in the accessibility and availability of data within power systems and the grid. By leveraging synchronized measurements across a wide geographical expanse, WAMS has enabled real-time monitoring and collection of time-series data, enriching the information pool available for analysis and decision-making processes [4]. This enhanced data accessibility is indispensable for comprehending and adapting to the dynamic behavior of modern power grids, especially among evolving energy demands and the incorporation of renewable energy sources. One of the essential roles of time-series data is its utility during significant disturbances in the grid. Such disturbances, whether caused by natural disasters, equipment failures, or sudden changes in energy demand or supply, can cause cascading failures and widespread outages if not promptly identified. Time-series data offers invaluable insights into the grid's response to these disturbances [8]. Through analysis, operators and engineers can find the causes of disturbances, assess the system's resilience, and devise requisite countermeasures to restore grid stability [30]. A significant application of time-series data analysis in power systems is the assessment of system-equivalent inertia. System-equivalent inertia is pivotal for maintaining system frequency stability, particularly in grids with a high penetration of renewable energy resources [48]. The cited source shows how time-series data pulled from widespread synchronized measurements helped the estimation of system-equivalent inertia [14]. This estimation is quintessential for ensuring that the grid can withstand frequency deviations and promptly recover from disturbances, fostering enhanced grid reliability and resilience in the face of burgeoning renewable energy integration.

9.3 Evolving Complexity in Modern Power Systems

Modern power systems face increasing complexity due to integrating varied renewable energy sources, Electric Vehicle (EV) charging stations, and energy storage solutions. This complexity is brought about by the diverse energy sources, changing generation patterns, and evolving demand due to electric mobility and other new technologies [36]. Power systems now need to handle more distributed renewable energy while also meeting the demands of EV charging stations and managing energy storage solutions. These changes call for a stronger and more adaptable grid infrastructure capable of handling dynamic operational challenges and ensuring reliable power availability and quality [35].

The introduction of Wide Area Monitoring (WAM) has been vital in navigating the complex landscape of modern power systems. WAM provides a comprehensive view, enabling real-time monitoring and control over large areas. Through synchronized measurements and advanced sensor systems, WAM offers valuable insights into the dynamic behavior of power systems, improving operational efficiency and reliability [15]. Also, the data collected through WAM is crucial for accurate forecasting, real-time decision-making, and proactive strategies, especially during significant disturbances or sudden changes in load and generation profiles [40].

The congestion and complexity in modern grid networks highlight the importance of Wide Area Monitoring Protection and Control (WAMPAC). WAMPAC, a feature of the Smart Grid, supports a two-way network capable of self-recovery in case of failures. By using the capabilities of WAMPAC, grid operators and planners can effectively address the challenges posed by congestion, promoting a more resilient and reliable power system infrastructure [57].

The growing integration of renewables, electric mobility, and storage solutions, combined with the need for enhanced grid monitoring and control, showcases the evolving complexity of modern power systems. A combined effort towards comprehensive grid monitoring through WAM and smart grid technologies is essential for navigating the dynamic operational landscape, ensuring power availability and quality amidst the increasing complexity of modern power systems.

9.4 Data Management and Security

Adopting big data technologies is essential for handling the large volumes of time-series data generated by modern power systems. Ensuring the security and privacy of this data is paramount [57]. Effective communication protocols and standards are crucial for the seamless exchange of information between different parts of the grid [42]. As the grid evolves into a cyber-physical system, security considerations become increasingly critical to protect against cyber threats [53].

10 CONCLUSION

In this paper, we've tackled the complex computational challenges that come with bringing renewable energy into our electrical power systems. Our analysis has underscored the importance of Quasi-Steady-State (QSS) simulations for accurate power flow in grids and pinpointed the issues with handling extensive time-series data. The promise of renewable energy, particularly from hybrid plants, to revolutionize our energy infrastructure is evident, and there's a pressing need for improved computational methods for managing microgrids and regional grids.

Climate change is amplifying societal inequities, with the most vulnerable communities facing the greatest risks and having the least resources to cope. Renewable energy advancements have not reached everyone equally, highlighting a gap that we must close for a fair transition to greener power.

Our computational efforts can help predict and even out energy resource distribution, ensuring fairness. Microgrid development, informed by simulation, can provide much-needed resilience against climate change for those in the most precarious situations.

As we advance, the fusion of open-source tools, refined forecasting techniques, and the potential of high-performance and quantum computing offers a path to a more just and resilient energy future. It's crucial that our work addresses both technical and social challenges, pushing for a future where innovation leads to widespread benefit.

REFERENCES

[1] 2023. Cyber Physical Co-simulation Platform for Distributed Energy Resources (CyDER). https://github.com/LBNL-ETA/CyDER original-date: 2016-12-12T17:45:39Z.

[2] 2023. Global Change Analysis Model (GCAM). https://github.com/JGCRI/gcam-core original-date: 2016-01-29T15:57:28Z.

[3] Omar H. Abdalla, Hilal Al-Hadi, and Hisham Al-Riyami. 2009. Development of a digital model for Oman electrical transmission main grid. In *2009 International Conference on Advances in Computational Tools for Engineering Applications*. 451–456. https://doi.org/10.1109/ACTEA.2009.5227914

[4] Uttam Adhikari, Thomas Morris, and Shengyi Pan. 2017. WAMS Cyber-Physical Test Bed for Power System, Cybersecurity Study, and Data Mining. *IEEE Transactions on Smart Grid* 8, 6 (Nov. 2017), 2744–2753. https://doi.org/10.1109/TSG.2016.2537210 Conference Name: IEEE Transactions on Smart Grid.

[5] Olukayode A. Afolabi, Warsame H. Ali, Penrose Cofie, John Fuller, Pamela Obiomon, and Emmanuel S. Kolawole. 2015. Analysis of the Load Flow Problem in Power System Planning Studies. *Energy and Power Engineering* 07, 10 (2015), 509–523. https://doi.org/10.4236/epe.2015.710048

[6] Hanin Alkabbani, Ali Ahmadian, Qinqin Zhu, and Ali Elkamel. 2021. Machine Learning and Metaheuristic Methods for Renewable Power Forecasting: A Recent Review. *Frontiers in Chemical Engineering* 3 (2021). https://www.frontiersin.org/articles/10.3389/fceng.2021.665415

[7] Jyoti Ranjan Baral, Smruti Ranjan Behera, and Twinkle Kisku. 2022. Design and Economic Optimization of Community Load Based Microgrid System Using HOMER Pro. In *2022 International Conference on Intelligent Controller and Computing for Smart Power (ICICCSP)*. 1–5. https://doi.org/10.1109/ICICCSP53532.2022.9862479

[8] Petr Bartolomey and Sergey Semenenko. 2017. Super-accelerated power systems power flow and state estimation calculations within the WAMS environment. In *2017 14th International Conference on Engineering of Modern Electric Systems (EMES)*. 55–58. https://doi.org/10.1109/EMES.2017.7980380

[9] P. I. Bartolomey, S. A. Eroshenko, E. M. Lebedev, and A. A. Suvorov. 2012. New information technologies for state estimation of power systems with FACTS. In *2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe)*. 1–8. https://doi.org/10.1109/ISGTEurope.2012.6465686 ISSN: 2165-4824.

[10] Ramesh Kumar C and Ram Kumar Sharma. 2023. Renewable Energy Systems with Improved Power Quality in Smart Grid using Fuzzy Logic Method. In *2023 2nd International Conference for Innovation in Technology (INOCON)*. 1–7. https://doi.org/10.1109/INOCON57975.2023.10101322

[11] Wenchao Cai, Chenglong Li, Kodjo Agbossou, Pierre Bénard, and Jinsheng Xiao. 2022. A review of hydrogen-based hybrid renewable energy systems: Simulation and optimization with artificial intelligence. *Journal of Physics: Conference Series* 2208, 1 (March 2022), 012012. https://doi.org/10.1088/1742-6596/2208/1/012012 Publisher: IOP Publishing.

[12] J.M. Carrasco, L.G. Franquelo, J.T. Bialasiewicz, E. Galvan, R.C. PortilloGuisado, M.A.M. Prats, J.I. Leon, and N. Moreno-Alfonso. 2006. Power-Electronic Systems for the Grid Integration of Renewable Energy Sources: A Survey. *IEEE Transactions on Industrial Electronics* 53, 4 (June 2006), 1002–1016. https://doi.org/10.1109/TIE.2006.878356 Conference Name: IEEE Transactions on Industrial Electronics.

[13] David P. Chassin, Jason C. Fuller, and Ned Djilali. 2014. GridLAB-D: An Agent-Based Simulation Framework for Smart Grids. *Journal of Applied Mathematics* 2014 (June 2014), e492320. https://doi.org/10.1155/2014/492320 Publisher: Hindawi.

[14] Ugyen Chophel and Samten. 2022. Practical Experience on WAMS Technology Implementation in Bhutan Power System. In *2022 International Conference on Power, Energy and Innovations (ICPEI)*. 1–4. https://doi.org/10.1109/ICPEI55293.2022.9986911

[15] Elodie Ciciriello. 2017. Integration of heat demand and demand response in power systems to cover the flexibility requirements linked to high shares of variable renewable energy. https://www.semanticscholar.org/paper/Integration-of-heat-demand-and-demand-response-in-Ciciriello/52200e8bc98538920388c4f28a8d72ccf7e0c4ba

[16] Gregory G. Deierlein, Frank McKenna, Adam Zsarnóczay, Tracy Kijewski-Correa, Ahsan Kareem, Wael Elhaddad, Laura Lowes, Matthew J. Schoettler, and Sanjay Govindjee. 2020. A Cloud-Enabled Application Framework for Simulating Regional-Scale Impacts of Natural Hazards on the Built Environment. *Frontiers in Built Environment* 6 (2020). https://www.frontiersin.org/articles/10.3389/fbuil.2020.558706

[17] Edward Farhi, Jeffrey Goldstone, and Sam Gutmann. 2014. A Quantum Approximate Optimization Algorithm. https://doi.org/10.48550/arXiv.1411.4028 arXiv:1411.4028 [quant-ph].

[18] G. Ferrari-Trecate, E. Gallestey, P. Letizia, M. Spedicato, M. Morari, and M. Antoine. 2004. Modeling and control of co-generation power plants: a hybrid system approach. *IEEE Transactions on Control Systems Technology* 12, 5 (Sept. 2004), 694–705. https://doi.org/10.1109/TCST.2004.826958 Conference Name: IEEE Transactions on Control Systems Technology.

[19] Jwaone Gaboitaolelwe, Adamu Murtala Zungeru, Abid Yahya, Caspar K. Lebekwe, Dasari Naga Vinod, and Ayodeji Olalekan Salau. 2023. Machine Learning Based Solar Photovoltaic Power Forecasting: A Review and Comparison. *IEEE Access* 11 (2023), 40820–40845. https://doi.org/10.1109/ACCESS.2023.3270041 Conference Name: IEEE Access.

[20] Frederik Geth, Sander Claeys, and Geert Deconinck. 2020. Current-Voltage Formulation of the Unbalanced Optimal Power Flow Problem. In *2020 8th Workshop on Modeling and Simulation of Cyber-Physical Energy Systems*. 1–6. https://doi.org/10.1109/MSCPES49613.2020.9133699

[21] Mohammad Ghiasi. 2018. A comparative study on common power flow techniques in the power distribution system of the Tehran metro. *Tehnički glasnik* 12, 4 (Dec. 2018), 244–250. https://doi.org/10.31803/tg-20180630204718

[22] Sudipta Ghosh, Younes J. Isbeih, and Mohamed Shawky El Moursi. 2023. Assessment of Bus Inertia to Enhance Dynamic Flexibility of Hybrid Power Systems With Renewable Energy Integration. *IEEE Transactions on Power Delivery* 38, 4 (Aug. 2023), 2372–2386. https://doi.org/10.1109/TPWRD.2023.3241721 Conference Name: IEEE Transactions on Power Delivery.

[23] Lin Guan, Junbo Zhang, Linshu Zhong, Xiaohua Li, and Yan Xu. 2017. Enhancing security and resilience of bulk power systems via multisource big data learning. In *2017 IEEE Power & Energy Society General Meeting*. 1–5. https://doi.org/10.1109/PESGM.2017.8274002 ISSN: 1944-9933.

[24] Hengdao Guo, Ciyan Zheng, Herbert Ho-Ching Iu, and Tyrone Fernando. 2017. A critical review of cascading failure analysis and modeling of power system. *Renewable and Sustainable Energy Reviews* 80 (Dec. 2017), 9–22. https://doi.org/10.1016/j.rser.2017.05.206

[25] Pascal Halffmann, Patrick Holzer, Kai Plociennik, and Michael Trebing. 2022. A Quantum Computing Approach for the Unit Commitment Problem. https://doi.org/10.48550/arXiv.2212.06480 arXiv:2212.06480 [quant-ph].

[26] Dr. Chandrashekhar S. Hiwarkar, Abhay M. Halmare, Anurag A. Belsare, Nitin B. Mohriya, and Roshan Milmile. 2022. Load Flow Analysis on IEEE 14 Bus System. *International Journal for Research in Applied Science and Engineering Technology* 10, 4 (April 2022), 1572–1574. https://doi.org/10.22214/ijraset.2022.41590

[27] Yuan Huang, Yimeng Sun, and Zhaohao Ding. 2022. Renewable Energy Integration Driven Charging Scheme for Electric Vehicle Based Large Scale Delivery System. In *2022 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia)*. 1251–1256. https://doi.org/10.1109/ICPSAsia55496.2022.9949661

[28] Juan C. Jimenez and Chika O. Nwankpa. 2011. Circuit model of a phase-shifting transformer for analog power flow emulation. In *2011 IEEE International Symposium of Circuits and Systems (ISCAS)*. 1864–1867. https://doi.org/10.1109/ISCAS.2011.5937950 ISSN: 2158-1525.

[29] Dominika Kaczorowska, Jacek Rezmer, Vishnu Suresh, and Tomasz Sikorski. 2023. Smart Management of Energy Storage in Microgrid: Adapting the Control Algorithm to Specific Industrial Facility Conditions. *Sustainability* 15, 21 (Jan. 2023), 15576. https://doi.org/10.3390/su152115576 Number: 21 Publisher: Multidisciplinary Digital Publishing Institute.

[30] Aleksey Y. Koshlakov, Ekaterina I. Zharikova, Nikita G. Furtsev, and Andrey N. Belyaev. 2022. Identification of Power Systems Parameters Based on Wide Area Measurement Data. In *2022 Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus)*. 1204–1209. https://doi.org/10.1109/ElConRus54750.2022.9755468 ISSN: 2376-6565.

[31] Binghui Li and Jie Zhang. 2020. A review on the integration of probabilistic solar forecasting in power systems. *Solar Energy* 210, C (Sept. 2020). https://doi.org/10.1016/j.solener.2020.07.066 Institution: Johns Hopkins Univ., Baltimore, MD (United States) Publisher: Elsevier.

[32] P. Li, B.H. Zhang, J. Shu, Z.Q. Bo, and A. Klimek. 2010. Research on order reduction of power system modeling for dynamic voltage stability analysis. In *IEEE PES T&D 2010*. 1–5. https://doi.org/10.1109/TDC.2010.5484388 ISSN: 2160-8563.

[33] Peng Li, Baohui Zhang, Jin Shu, Zhiguo Hao, Andrew Klimek, Zhiqian Bo, Chenggen Wang, and Yuting Wang. 2009. Research of reduced-order modeling for dynamic voltage stability analysis of power system. In *2009 Transmission & Distribution Conference & Exposition: Asia and Pacific*. 1–4. https://doi.org/10.1109/TD-ASIA.2009.5356822 ISSN: 2160-8644.

[34] Qianmu Li, Shunmei Meng, Sainan Zhang, Ming Wu, Jing Zhang, Milad Taleby Ahvanooey, and Muhammad Shamrooz Aslam. 2019. Safety Risk Monitoring of Cyber-Physical Power Systems Based on Ensemble Learning Algorithm. *IEEE Access* 7 (2019), 24788–24805. https://doi.org/10.1109/ACCESS.2019.2896129 Conference Name: IEEE Access.

[35] Jiaping Liao and Cheng He. 2014. Wide-area monitoring protection and control of future power system networks. In *2014 IEEE Workshop on Advanced Research and Technology in Industry Applications (WARTIA)*. 903–905. https://doi.org/10.1109/WARTIA.2014.6976419

[36] Huan Ma, Dong Yang, Hao Qin, Yongji Cao, Dingyi Cheng, Bing Zhang, Xudong Hao, and Ning Zhou. 2022. Power System Equivalent Inertia Estimation Method Using System Identification. In *2022 IEEE 5th International Conference on Electronics Technology (ICET)*. 360–365. https://doi.org/10.1109/ICET55676.2022.9824227 ISSN: 2768-6515.

[37] Despoina I. Makrygiorgou, Nikos Andriopoulos, Ioannis Georgantas, Jun Rong, Ioannis Moraitis, Esteban Pastor Calatayud, and Manuel Serrano Matoses. 2023. Scalability and replicability analysis of smart grid projects: Insights from the H2020 CROSSBOW project. *Frontiers in Energy Research* 11 (2023). https://www.frontiersin.org/articles/10.3389/fenrg.2023.1167517

[38] Thomas Morstyn. 2023. Annealing-Based Quantum Computing for Combinatorial Optimal Power Flow. *IEEE Transactions on Smart Grid* 14, 2 (March 2023), 1093–1102. https://doi.org/10.1109/TSG.2022.3200590 Conference Name: IEEE Transactions on Smart Grid.

[39] An Ning, Zhou Shuangxi, and Zhu Lingzhi. 2006. Power System Voltage Stability Limits Estimation based on Quasi-Steady-State Simulation. In *2006 International Conference on Power System Technology*. 1–7. https://doi.org/10.1109/ICPST.2006.321470

[40] Khaled Nusair and Lina Alhmoud. 2020. Application of Equilibrium Optimizer Algorithm for Optimal Power Flow with High Penetration of Renewable Energy. *Energies* 13, 22 (Jan. 2020), 6066. https://doi.org/10.3390/en13226066 Number: 22 Publisher: Multidisciplinary Digital Publishing Institute.

[41] S. Rajendra Prasad and M. Gopichand Naik. 2022. A Review on Wind Power Forecasting Models for improved Renewable Energy Integration. *Proceeding of International Conference on Information Science and Technology Innovation (ICoSTEC)* 1, 1 (Feb. 2022), 113–118. https://doi.org/10.35842/icostec.v1i1.19 Number: 1.

[42] Feng Qi, Peng Yu, Bin Chen, WenJing Li, Qiang Zhang, Dan Jin, Geng Zhang, and Yang Wang. 2018. Optimal Planning of Smart Grid Communication Network for Interregional Wide-Area Monitoring Protection and Control System. In *2018 IEEE International Conference on Energy Internet (ICEI)*. 190–195. https://doi.org/10.1109/ICEI.2018.00042

[43] Nariman Rahmanov, Viktor Kurbatskiy, Huseyngulu Guliyev, Nikita Tomin, and Zaur Mammadov. 2017. Probabilistic assessment of power system mode with a varying degree of wind sources integration. *E3S Web of Conferences* 25 (2017), 02003. https://doi.org/10.1051/e3sconf/20172502003 Publisher: EDP Sciences.

[44] Ali Rezaei, Afshin Balal, and Yaser Pakzad Jafarabadi. 2023. Using machine learning prediction to design an optimized renewable energy system for a remote area in Italy. *International Journal of Applied Power Engineering (IJAPE)* 12, 3 (Sept. 2023), 331–340. https://doi.org/10.11591/ijape.v12.i3.pp331-340 Number: 3.

[45] M. F. Roslan, M. A. Hannan, P. J. Ker, K. M. Muttaqi, and T. M. I. Mahlia. 2021. Optimization algorithms for energy storage integrated microgrid performance enhancement. *Journal of Energy Storage* 43 (Nov. 2021), 103182. https://doi.org/10.1016/j.est.2021.103182

[46] Olena Rubanenko, Sree Lakshmi Gundebommu, Marijana Cosovic, and Vladislav Lesko. 2021. Predicting the Power Generation from Renewable Energy Sources

by using ANN. In *2021 20th International Symposium INFOTEH-JAHORINA (INFOTEH)*. 1–6. https://doi.org/10.1109/INFOTEH51037.2021.9400527

[47] Elissaios Sarmas, Nikos Dimitropoulos, Vangelis Marinakis, Zoi Mylona, and Haris Doukas. 2022. Transfer learning strategies for solar power forecasting under data scarcity. *Scientific Reports* 12, 1 (Aug. 2022), 14643. https://doi.org/10.1038/s41598-022-18516-x Number: 1 Publisher: Nature Publishing Group.

[48] V. Siyoi, M. Nthontho, S. Chowdhury, and S.P. Chowdhury. 2012. Wide area monitoring for power system protection - a review. In *2012 IEEE International Conference on Power System Technology (POWERCON)*. 1–6. https://doi.org/10.1109/PowerCon.2012.6401410

[49] Jiyu Song, Xinhang Zhou, Zhiquan Zhou, Yang Wang, Yifan Wang, and Xutao Wang. 2023. Review of Low Inertia in Power Systems Caused by High Proportion of Renewable Energy Grid Integration. *Energies* 16, 16 (Jan. 2023), 6042. https://doi.org/10.3390/en16166042 Number: 16 Publisher: Multidisciplinary Digital Publishing Institute.

[50] B. Stott and O. Alsac. 1974. Fast Decoupled Load Flow. *IEEE Transactions on Power Apparatus and Systems* PAS-93, 3 (May 1974), 859–869. https://doi.org/10.1109/TPAS.1974.293985 Conference Name: IEEE Transactions on Power Apparatus and Systems.

[51] Vishnu Suresh, Przemyslaw Janik, Michal Jasinski, Josep M. Guerrero, and Zbigniew Leonowicz. 2023. Microgrid energy management using metaheuristic optimization algorithms. *Applied Soft Computing* 134 (Feb. 2023), 109981. https://doi.org/10.1016/j.asoc.2022.109981

[52] S. Takeda. 1978. Reduced order modeling for power system transient analysis. *Electr. Eng. Jpn. (Engl. Transl.); (United States)* 98:2 (Jan. 1978). https://doi.org/10.1002/eej.4390980208

[53] Vladimir TERZIJA and Yutian LIU. 2016. Guest editorial: special issue on wide area monitoring, protection and control in smart grid. *Journal of Modern Power Systems and Clean Energy* 4, 3 (July 2016), 317–318. https://doi.org/10.1007/s40565-016-0221-8

[54] Gokul Sidarth Thirunavukkarasu, Mehdi Seyedmahmoudian, Elmira Jamei, Ben Horan, Saad Mekhilef, and Alex Stojcevski. 2022. Role of optimization techniques in microgrid energy management systems—A review. *Energy Strategy Reviews* 43 (Sept. 2022), 100899. https://doi.org/10.1016/j.esr.2022.100899

[55] Bogdan Tomoiaga, Mircea Chindris, Andreas Sumper, and Mousa Marzband. 2013. The Optimization of Microgrids Operation through a Heuristic Energy Management Algorithm. *Advanced Engineering Forum* 8-9 (June 2013), 185–194. https://doi.org/10.4028/www.scientific.net/AEF.8-9.185

[56] Gabriel Tudor, Cornel-Cristian Andrei, Madalina Arhip-Calin, and Valentina Rohat. 2021. Edge data processing using Kalman filter. In *2021 9th International Conference on Modern Power Systems (MPS)*. 1–4. https://doi.org/10.1109/MPS52805.2021.9492575

[57] Saghar Vahidi, Mohsen Ghafouri, Minh Au, Marthe Kassouf, Arash Mohammadi, and Mourad Debbabi. 2023. Security of Wide-Area Monitoring, Protection, and Control (WAMPAC) Systems of the Smart Grid: A Survey on Challenges and Opportunities. *IEEE Communications Surveys & Tutorials* 25, 2 (2023), 1294–1335. https://doi.org/10.1109/COMST.2023.3251899 Conference Name: IEEE Communications Surveys & Tutorials.

[58] Ganesh K. Venayagamoorthy. 2009. Potentials and promises of computational intelligence for smart grids. In *2009 IEEE Power & Energy Society General Meeting*. 1–6. https://doi.org/10.1109/PES.2009.5275224 ISSN: 1932-5517.

[59] Danko Vidović, Elis Sutlović, and Matislav Majstrović. 2021. A Unique Electrical Model for the Steady-State Analysis of a Multi-Energy System. *Energies* 14, 18 (Jan. 2021), 5753. https://doi.org/10.3390/en14185753 Number: 18 Publisher: Multidisciplinary Digital Publishing Institute.

[60] Xiaozhe Wang and Hsiao-Dong Chiang. 2014. Analytical Studies of Quasi Steady-State Model in Power System Long-Term Stability Analysis. *IEEE Transactions on Circuits and Systems I: Regular Papers* 61, 3 (March 2014), 943–956. https://doi.org/10.1109/TCSI.2013.2284171 Conference Name: IEEE Transactions on Circuits and Systems I: Regular Papers.

[61] Xiaozhe Wang and Hsiao-Dong Chiang. 2014. Quasi steady-state model for power system stability: Limitations, analysis and a remedy. In *2014 Power Systems Computation Conference*. 1–7. https://doi.org/10.1109/PSCC.2014.7038362

[62] Ziqiang Zhang, Jinxiong Zhao, and Zhiru Li. 2021. Preliminary Analysis of The Application and Development of Big Data, Cloud Computing, IoT, Mobile Internet, AI, and Blockchain In The Power Scene. In *Proceedings of the 3rd International Conference on Information Technologies and Electrical Engineering (ICITEE '20)*. Association for Computing Machinery, New York, NY, USA, 526–530. https://doi.org/10.1145/3452940.3453043

[63] Yifan Zhou, Zefan Tang, Nima Nikmehr, Pouya Babahajiani, Fei Feng, Tzu-Chieh Wei, Honghao Zheng, and Peng Zhang. 2022. Quantum computing in power systems. *iEnergy* 1, 2 (June 2022), 170–187. https://doi.org/10.23919/IEN.2022.0021

Received 08 November 2023