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Review

Investigating Intelligent Forecasting and Optimization in Electrical Power Systems: A Comprehensive Review of Techniques and Applications

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Abstract: Electrical power systems are the lifeblood of modern civilization, providing the essential energy infrastructure that powers our homes, industries, and technologies. As our world increasingly relies on electricity, and modern power systems incorporate renewable energy sources, the challenges have become more complex, necessitating advanced forecasting and optimization to ensure effective operation and sustainability. This review paper provides a comprehensive overview of electrical power systems and delves into the crucial roles that forecasting and optimization play in ensuring future sustainability. The paper examines various forecasting methodologies from traditional statistical approaches to advanced machine learning techniques, and it explores the challenges and importance of renewable energy forecasting. Additionally, the paper offers an in-depth look at various optimization problems in power systems including economic dispatch, unit commitment, optimal power flow, and network reconfiguration. Classical optimization methods and newer approaches such as meta-heuristic algorithms and artificial intelligence-based techniques are discussed. Furthermore, the review paper examines the integration of forecasting and optimization, demonstrating how accurate forecasts can enhance the effectiveness of optimization algorithms. This review serves as a reference for electrical engineers developing sophisticated forecasting and optimization techniques, leading to changing consumer behaviors, addressing environmental concerns, and ensuring a reliable, efficient, and sustainable energy future.

Keywords: forecasting; machine learning; meta-heuristic algorithms; optimization; power systems; renewable energy sources

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1. Introduction

The rapid evolution of power systems, driven by the integration of renewable energy sources (RESs) and the increasing complexity of grid operations, necessitates developing and implementing advanced forecasting and optimization techniques to ensure grid stability, efficiency, and sustainability. As we move towards a more sustainable and resilient energy future, the role of intelligent forecasting and optimization in electrical power systems will grow in importance. Therefore, intelligent forecasting and optimization techniques have emerged as essential tools for effectively managing and operating electrical power systems. These advanced computational methods, rooted in artificial intelligence (AI)—with machine learning (ML) as a key subset—and data science, enable navigation of the complexity of modern power systems with improved accuracy and efficiency [1,2].

AI encompasses a broad range of computational approaches that aim to mimic human intelligence, while ML is a crucial subset focused on algorithms that can learn and improve from data without explicit programming.

Intelligent forecasting in power systems encompasses a wide array of predictive techniques aimed at forecasting various system parameters and states [3]. The forecasting concept is crucial for maintaining system stability [4], optimizing resource allocation [5], and improving overall efficiency [6]. Load forecasting, for instance, has long been a critical component of power system planning and operation. Traditional methods relied heavily on historical data and simple statistical models. However, the advent of machine learning (ML) [7] and AI has revolutionized this field. Advanced algorithms such as Artificial Neural Networks (ANNs) [8], Support Vector Machines (SVMs) [9], and, more recently, deep learning (DL) models [10] can capture complex non-linear relationships in data, leading to more accurate predictions of electricity demand across different time horizons—from short-term (hours to days ahead) [11,12] to long-term (years ahead) [13] forecasts. Similarly, renewable energy forecasting has become increasingly vital with the growing penetration of wind [14,15] and solar power [16,17]. These forecasting models often combine Numerical Weather Prediction (NWP) data with ML techniques to predict the power output of RESs. For instance, ensemble methods that aggregate multiple forecasting models have shown promising results in capturing the uncertainty inherent in renewable generation [18]. Moreover, price forecasting in electricity markets has gained significance with the deregulation of power sectors in many countries. Accurate price predictions are essential for (1) market participants to optimize their bidding strategies and (2) for system operators to ensure market efficiency [19,20].

On the other hand, the optimization applications in electrical power systems are diverse and challenging. Unit commitment [21–23] and economic dispatch [24–26] problems, which involve determining the optimal scheduling and output power of generating units, have been traditionally solved using mathematical programming techniques. However, as power systems become more complex with the integration of renewables and the consideration of multiple objectives (e.g., cost minimization, emission pollution reduction, and reliability maximization) [27], more advanced optimization algorithms are required. Meta-heuristic algorithms such as Genetic Algorithms (GAs) [28], Particle Swarm Optimization (PSO) [29], and Ant Colony Optimization (ACO) [30], etc., have shown remarkable effectiveness in solving these complex, non-linear, and often non-convex optimization problems. These nature-inspired algorithms can efficiently explore vast solution spaces to find near-optimal solutions, even in highly constrained environments. Furthermore, reinforcement learning (RL), a branch of ML, is gaining traction in power system optimization. RL algorithms, which learn optimal strategies through interaction with the environment, are particularly well-suited in power systems [31]. Applications range from optimal energy management in microgrids (MGs) to adaptive control of power electronic devices [32].

The incorporation of forecasting and optimization techniques is particularly advantageous in the context of power systems. For instance, stochastic optimization methods that incorporate forecasting uncertainties can lead to more robust decision-making [33]. Model predictive control (MPC) frameworks, which use forecasts to optimize system operation over a rolling time horizon, are increasingly being applied to various power system problems, from energy storage management to demand response programs [34]. The implementation of these intelligent techniques is facilitating the development of advanced energy management systems (EMSs). Modern EMSs leverage real-time data, forecasts, and optimization algorithms to make proactive decisions, enhancing system efficiency and reliability [35]. Intelligent EMSs can optimize utilizing local generation [36], energy storage systems [37], and flexible loads [38] in MG operations based on forecasts of renewable generation and electricity prices, ensuring cost-effective and reliable operation. Moreover, demand response programs, which encourage consumers to adjust their electricity usage in response to grid conditions, are benefiting from these advanced techniques [39]. Also, ML algorithms can predict consumer behavior and optimize incentive structures [40], while optimization algorithms can determine the best strategies for load shifting and peak reduction [41].

2. Literature Survey

It is essential to first acknowledge the body of literature that has contributed significantly to the domains of forecasting and optimization in electrical power systems. Several surveys have been published over the years focusing on specific aspects of these topics. For instance, some reviews have focused solely on optimization algorithms used in power systems, including classical techniques like linear programming, as well as modern metaheuristic approaches such as PSO, GA, and ACO. Other surveys have concentrated on forecasting techniques, exploring the evolution from traditional statistical models like ARIMA (Auto-Regressive Integrated Moving Average) to advanced ML-based models like ANN and SVMs. While these reviews offer valuable insights into specific areas, they often lack a holistic approach that addresses the growing complexity and interconnectedness of modern power systems, especially with the integration of RESs. One notable gap in the existing literature is the lack of integration between intelligent forecasting and optimization. Existing reviews tend to focus either on forecasting methodologies or on optimization techniques, treating them as separate entities. This approach may have been sufficient in the past, but as power systems become more complex, it is no longer enough to treat forecasting and optimization in isolation. With the increasing penetration of RESs like wind and solar power, there is an urgent need for methodologies that integrate both accurate forecasting and efficient optimization to ensure grid stability, operational efficiency, and cost-effectiveness. For these reasons, this review paper aims to fill that gap by providing a comprehensive survey that not only covers the latest advancements in forecasting and optimization but also demonstrates how these two critical areas are intertwined. For example, renewable energy forecasting, which has seen significant progress with the use of ML and DL models, directly impacts optimization processes like economic dispatch and unit commitment. Accurate forecasting of wind and solar power output can enhance the performance of optimization algorithms, ensuring that decisions made regarding power generation and distribution are based on reliable data. This integration is essential for improving the efficiency and sustainability of modern power systems, yet it is a topic that has not been adequately covered in existing review papers.

The necessity for this updated and comprehensive review stems from several factors. First, the rapid advancements in AI and ML have dramatically transformed both forecasting and optimization in recent years. Techniques such as DL, reinforcement learning (RL), and hybrid models are now being applied to solve highly complex problems in power systems. These methods are capable of handling non-linear relationships, processing large volumes of data, and adapting to the dynamic nature of modern grids, particularly with the integration of renewable energy. Previous reviews often focused on earlier statistical methods or classical optimization techniques, which, while still valuable, are not fully equipped to handle the complexities of today's power systems. Therefore, a new review that includes recent AI-driven approaches is necessary to provide researchers and engineers with the most up-to-date knowledge on these advanced techniques.

Moreover, several key characteristics set this review apart from previous works. First, the scope of this paper is broader than most existing reviews, as it covers both traditional and advanced methods in both forecasting and optimization. While earlier papers might focus on specific techniques such as time series forecasting and metaheuristic optimization, this review encompasses a wide range of methodologies, from traditional methods like econometric models and trend analysis to cutting-edge AI-based techniques like DL and RL. This comprehensive approach ensures that readers gain a thorough understanding of the full spectrum of techniques available for managing power systems. Second, this review goes beyond theoretical discussions by offering insights into real-world applications. Many existing reviews tend to be highly theoretical, discussing methods in abstract terms without providing concrete examples of how these methods are being used in practice. In contrast, this paper includes case studies and practical applications of intelligent forecasting and optimization techniques in areas such as energy storage management, demand response, and electricity price forecasting. By doing so, it provides valuable insights for both academics and practitioners who are working to apply these techniques in real-world settings.

In conclusion, this review paper addresses a critical gap in the literature by providing a comprehensive, up-to-date overview of both forecasting and optimization techniques in electrical power systems, with a particular focus on their integration. While existing reviews may have provided valuable insights into specific aspects of these topics, they often treat forecasting and optimization as separate entities and fail to address the challenges posed by modern power systems, particularly with the rise of renewable energy. By combining these two areas and exploring the latest advancements in AI and ML, this paper provides a unique and necessary contribution to the field, offering both theoretical insights and practical applications that are essential for the future of electrical power systems.

3. Intelligent Forecasting Techniques

The practice of intelligent forecasting within electrical power systems employs sophisticated computational methodologies, incorporating AI and ML, to anticipate electricity consumption and production. This forecasting is crucial for preserving grid stability and security in intricate power networks. The approach forecasts variables that affect electricity supply and demand, thereby facilitating utility companies in making well-informed decisions regarding mixed-energy optimization, management of energy storage, and assurance of system security. In competitive markets, accurate forecasting has financial rewards through the provision of clear price signals. Extensive datasets are analyzed using AI techniques, particularly ML algorithms, in this approach. These advanced computational methods can identify complex patterns that would not normally be perceptible with conventional methods. ML, as a subset of AI, excels at learning from data to improve forecasting accuracy over time. This approach yields superior accuracy in predictions. Intelligent forecasting is applicable to both large-scale power systems and MGs by optimizing the resource utilization and energy storage management. The importance of this domain grows with the increasing integration of RESs and expansion of MGs. Traditional statistical methods and advanced AI algorithms are some of the methodologies under this discipline. As the power systems continuously evolve, ongoing research on intelligent forecasting is very much necessary to enhance system efficiency and reliability. Since intelligent forecasting plays a vital role in ensuring the efficient and reliable operation of both large and small electrical power systems, this paper covers all the different methodologies employed in predictive analytics, from traditional statistical models up to advanced AI and ML algorithms.

3.1. Traditional Methods

The concept of intelligent forecasting in electrical power systems has a rich historical background, being found in many developed methodologies for predicting electricity consumption and maintaining stability and reliability in power grids. This development has grown from simple trend analysis to sophisticated ML methods, each further refining accuracy and efficiency of forecasting. In the following subsections, the traditional methods of intelligent forecasting are explained.

3.1.1. Trend Analysis

Trend analysis, one of the pioneering methods in intelligent forecasting, involves a precise examination of historical data to uncover discernible patterns and trends. These identified trends are then extrapolated to forecast future electricity demand. By leveraging past consumption data, forecasters can pinpoint seasonal fluctuations in demand, trace growth trends, and identify other outstanding features to predict future demand with high accuracy. The simplicity of trend analysis provides a foundational understanding of the variations in electricity demand over time, making it an essential tool for initial assessments. Additionally, trend analysis can be further enhanced by decomposing time series data into seasonal, trend, and residual components, offering a clearer picture of demand fluctuations. However, while effective for short-term forecasting, the trend analysis may fail to capture sudden changes or anomalies in demand, highlighting the need for more sophisticated methods for long-term predictions [42,43].

3.1.2. Econometric Models

As the need for more accurate forecasts intensified, econometric models emerged as a vital tool. These models employ statistical techniques to forecast electricity demand based on a plethora of economic indicators, including but not limited to GDP, population growth, and industrial activity. By considering the intricate relationships between electricity demand and various economic variables, econometric models provide more accurate forecasts. For instance, surges in industrial activity or population growth are typically correlated with increased electricity demand, insights that can be effectively captured and analyzed through these models. The choice of econometric model (e.g., linear, nonlinear) depends on the complexity of the relationships between the variables and the available data. Moreover, the accuracy of forecasts heavily relies on the quality and granularity of the economic data, underscoring the importance of robust data collection frameworks [44,45].

3.1.3. End-Use Approach

The end-use approach represents another pivotal method in intelligent forecasting, focusing on the precise analysis of consumption patterns across different end-user sectors, including residential, commercial, and industrial. By gaining a profound understanding of how various sectors utilize electricity, forecasters can make more accurate predictions regarding overall demand. For example, residential electricity consumption often peaks during evening hours when individuals return home from work, whereas industrial consumption may exhibit higher levels during the daytime. This sector-specific insight facilitated by the end-use approach is crucial for capturing accurate demand patterns. Furthermore, analyzing end-use patterns can also inform strategies for improving energy efficiency in each sector. Incorporating behavioral studies can enhance forecasts by accounting for how policy changes or awareness campaigns might influence consumption patterns [46,47].

3.1.4. Time Series Analysis

Time series analysis is another widely employed method in intelligent forecasting, involving the utilization of historical data to identify seasonal patterns, trends, and other temporal dependencies that can inform predictions about future electricity demand. Techniques within time series analysis, such as Auto Regressive Integrated Moving Average (ARIMA) models, Exponential Smoothing (ES), and Seasonal Decomposition (SD), are particularly adept at capturing complex temporal dynamics in electricity demand data. These models are especially valuable for short-term forecasting, where understanding the immediate past's influence on the near future is crucial for operational efficiency and resource allocation. For instance, ARIMA models can effectively predict daily peak demand hours based on historical patterns, enabling grid operators to make informed decisions about supply management [48,49].

The traditional forecasting methods applied to power systems, though useful, have several limitations. Trend analysis often has problems in handling non-linear trends and sudden changes in consumption patterns. Econometric models can be overly sensitive to economic variable fluctuations and may not capture complex interdependencies in the power sector. The end-use approach, while detailed, requires extensive data collection, which is often time-consuming and costly to carry out accurately. Time series analysis may fail to account for external factors, and its effectiveness might be lower when being used for a long-term forecast. These methods also generally lack the ability to handle big data and adapt to rapid changes in power consumption patterns caused by factors like renewable energy integration, electric vehicle adoption, and smart grid technologies.

They often struggle with incorporating real-time data and may not capture the impact of extreme weather events or sudden policy changes effectively. Moreover, these traditional approaches may not fully leverage the potential of newer technologies like (Internet of Things) IoT devices and smart meters, which provide vast amounts of granular data. Therefore, in order to solve the problem of intelligent forecasting, either researchers move for more advanced methods or combine them with traditional methods. Further, this paper discusses more advanced methods for solving intelligent predictions.

Traditional forecasting methods in electrical power systems have evolved significantly over time, adapting to the increasing complexity and data availability in modern grids. These methods form the foundation upon which more advanced techniques are built and continue to play a crucial role in many forecasting applications. Understanding these traditional approaches is essential for appreciating the advancements brought by newer methods and for recognizing situations where simpler techniques may still be preferable. Traditional methods encompass a range of statistical and analytical approaches that have been refined over decades of application in power system planning and operations. They vary in their complexity, data requirements, and applicability to different forecasting horizons and scenarios. While each method has its strengths, they also have limitations, particularly in dealing with the high dimensionality and non-linearity characteristic of modern power systems with high renewable energy penetration. In summary, Figure 1 provides a concise overview of the traditional methods employed in intelligent forecasting. These traditional methods are foundational to understanding the evolution and application of forecasting in electrical power systems. Therefore, the figure serves as a roadmap for understanding the evolution of forecasting techniques in power systems, from simple trend analysis to more sophisticated time series approaches.

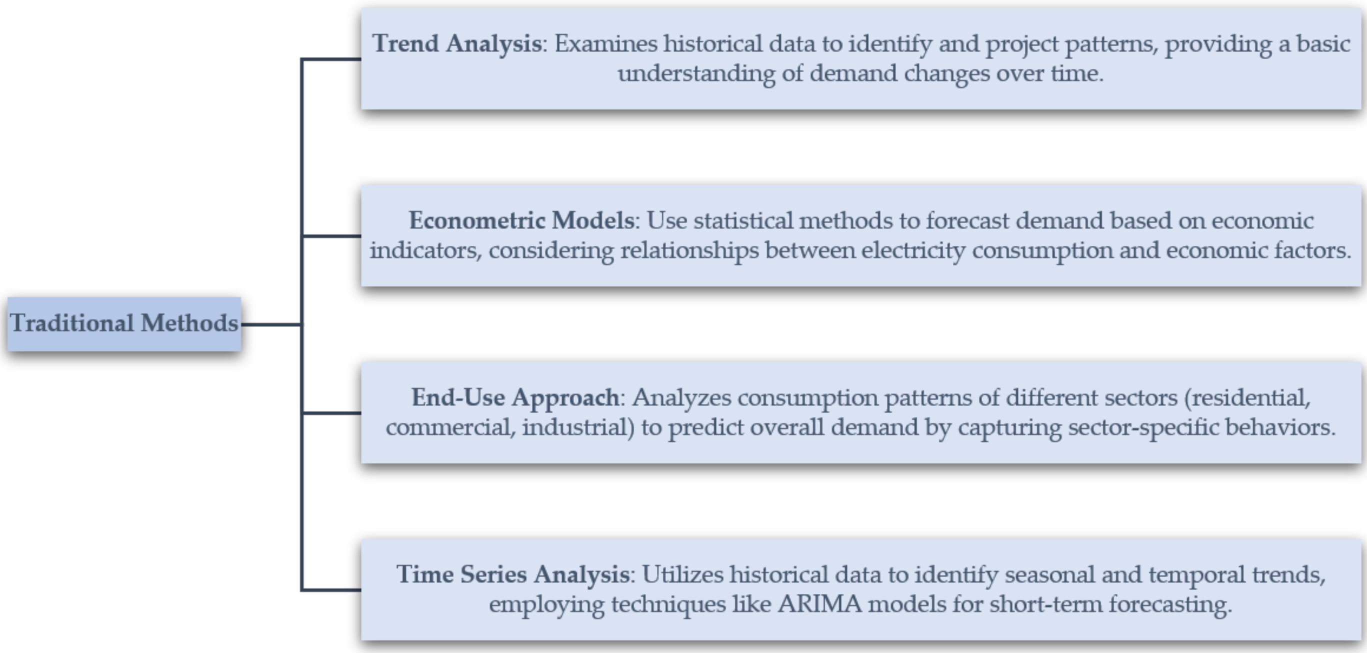

Figure 1. Traditional methods of forecasting.

3.2. Advanced Methods

State-of-the-art intelligent forecasting techniques have become very important in power systems due to their ability to handle complex, non-linear relationships and large data volumes. ML-based methods, such as those using ANN and SVM, can effectively uncover hidden patterns and have the flexibility that is in demand by changing conditions of power consumption [50]. DL frameworks, with their characteristic multiple layers, are able to detect complex temporal and spatial correlations in load data [51]. Hybrid models integrate various methodologies to utilize their specific advantages, frequently enhancing the overall precision of forecasts. Ensemble techniques combine predictions from several models, thereby minimizing errors and augmenting robustness. RL modifies forecasting approaches in response to ongoing feedback, rendering it appropriate for dynamic power systems [52]. Probabilistic techniques facilitate the quantification of uncertainty, which is essential for risk evaluation and decision-making within unstable energy markets [53]. These newer techniques are especially relevant to current power systems, where growing renewable integration, demand response programs, and smart grid technologies yield some complex forecasting problems that traditional methods cannot handle very well.

3.2.1. Artificial Intelligence

Undoubtedly, methods of ML and DL introduced a revolution in intelligent forecasting within electrical power systems. Enormous volumes of data are used for training models to identify complex patterns and enable the models to predict correctly. Neural networks, inspired by the human brain, are particularly effective for time series forecasting. Variants like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) are widely used. LSTM networks are adept at capturing long-term dependencies in data, making them suitable for predicting electricity demand over extended periods. CNNs, on the other hand, excel at identifying spatial patterns in data. SVMs are another example of supervised learning models that handle non-linear relationships in data effectively. Moreover, DL models have demonstrated superior performance in handling large datasets and non-linear relationships, often outperforming traditional statistical methods. For instance, in solar and wind power forecasting, DL models have achieved notably lower Mean Absolute Percentage Errors (MAPE) compared to conventional techniques. Recent innovations in DL architectures include the following: (1) Transformer models, which have shown remarkable results in capturing both short-term and long-term patterns in energy consumption and generation data. (2) Graph Neural Networks (GNNs), which are increasingly being used to model the complex topology of power grids, improving forecasts that depend on network structure. (3) Attention mechanisms, which have enhanced the interpretability and performance of deep learning models in energy forecasting tasks. (4) Transfer learning techniques, allowing for models trained on data-rich regions to be adapted for use in areas with limited historical data. These models can be trained to predict electricity demand based on various input features, such as historical consumption data, weather conditions, and economic indicators.

3.2.2. Hybrid Models

These models incorporate some forecasting methods to take advantage of the merits of each approach. For instance, the hybrid model may combine time series analysis with ML for the purpose of precise analysis of temporal patterns and complex relationships in the data set. Thus, overcoming the limits set by each methodology allows for these types of models to make better and more reliable forecasts. In fact, various studies have identified that hybrid models, regarding performance, outperform traditional models, positioning them as the most sought-after when high-level forecasting is wanted.

3.2.3. Ensemble Methods

Ensemble methods involve combining the predictions of multiple models to improve accuracy. Common techniques for ensembling include bagging, boosting, and stacking, and are commonly used in ensemble methods. Bagging (Bootstrap Aggregating) involves training multiple models on different subsets of the data and averaging their predictions. This reduces variance and helps prevent overfitting. Boosting sequentially trains models, with each new model focusing on the errors made by the previous ones. This approach reduces bias and further improves the general accuracy of predictions. Stacking is the process of designing a meta-model that combines forecasts from several base models, taking advantage of their individual strengths. Ensemble methods have been widely adopted in power systems forecasting due to their ability to enhance prediction accuracy and robustness.

3.2.4. Reinforcement Method

RL is a class of ML in which an agent learns to make decisions through interaction with the environment. Within power systems, RL can improve the functioning of power grids through learning from historical datasets and obtaining real-time evaluations. Deep reinforcement learning (DRL), which combines RL with DL methods, has been able to handle the complexities associated with modern power systems. DRL algorithms learn to make optimal decisions in dynamic and uncertain environments. That feature justifies the applications of potential interest in demand response, energy storage management, and control of grid stability.

3.2.5. Probabilistic Method

While traditional deterministic methods yield a single point estimate, the probabilistic forecasting represents a range of possible outcomes along with their respective probability. This technique is particularly useful in tackling the uncertainties related to power systems, including the variability of RESs. This method helps operators make informed decisions by quantifying the risks and uncertainties associated with different scenarios.

3.2.6. Fuzzy Logic Approaches

Fuzzy logic has emerged as a valuable advanced technique in power system forecasting, offering a way to handle uncertainty and imprecision in data. Unlike traditional binary logic, fuzzy logic allows for degrees of truth, making it well-suited for complex systems with ambiguous or incomplete information. Recent studies have demonstrated the effectiveness of fuzzy logic in various forecasting tasks within electrical power systems. Some researchers have proposed using fuzzy logic to improve electricity consumption forecasting and optimize power network efficiency based on consumer satisfaction and efficient consumption mode assessment. This approach shows promise in balancing consumption and generation, potentially reducing energy losses in power networks. In the realm of short-term load forecasting, novel combinations of neural networks and type-2 fuzzy systems have been introduced. These methods, which incorporate feedback into fuzzy neural networks, have achieved impressive accuracy levels in predicting next-day electrical loads for urban areas. Such high levels of accuracy underscore the potential of fuzzy logic in enhancing forecasting precision.

Table 1 provides a comprehensive overview of advanced intelligent forecasting methods. It details their unique characteristics, strengths, and weaknesses. This summary aims to facilitate a deeper understanding of each method's applicability and potential limitations within the context of electrical power systems.

Table 1. Overview of advanced methods of intelligent forecasting.

Method Category	Key	Techniques	Unique Strengths	Limitations	Typical Tasks	Lowest Error Reported	Ref.
Machine Learning, Deep Learning, ANN and SVM	• **Strong fitting ability** • **Can handle nonlinear characteristics** • **High prediction accuracy with sufficient data**	• Long Short-term Memory Networks (LSTMs) • Convolutional Neural Networks (CNNs) • Transformer models • Graph Neural Networks (GNNs) • Support Vector Machines • Random Forests	• Excellent at capturing complex patterns • Adaptable to various time horizons • Can handle large datasets • Superior performance in spatial-temporal forecasting	• Require large amounts of training data • Can be computationally intensive • May overfit if not properly regularized • Limited interpretability (especially deep learning)	• Short-term load forecasting • Renewable energy generation prediction • Electricity price forecasting • Grid stability assessment	• MAPE: 1.5–5% for short-term load forecasting • RMSE: 2.5–3.5% for solar power forecasting	[54–64]
Reinforcement Learning	• **Learns optimal strategies through interaction with the environment** • **Can handle dynamic and uncertain environments**	• Deep Q-networks • Policy Gradient methods • Actor–222Critic methods	• Adaptable to changing environments • Can optimize for long-term outcomes • Suitable for real-time decision-making and control	• Requires careful design of reward functions • May be unstable during training • Can be data-inefficient • Challenging to apply in safety-critical systems	• Demand response management • Energy storage optimization • Microgrid control • Adaptive grid stability control	• Not typically reported in error metrics; often measured in terms of cumulative reward or policy performance	[52,58,65]
Probabilistic Methods	• **Provides a range of possible outcomes with probabilities** • **Helps in managing uncertainties**	• Bayesian Probabilistic Technique • Copula-augmented state space models • Quantile Regression	• Quantifies uncertainty in predictions • Useful for risk assessment • Can incorporate prior knowledge	• Can be computationally expensive • Requires careful selection of prior distributions • May be sensitive to model misspecification • Can be challenging to interpret for non-experts	• Wind and solar power forecasting • Load forecasting with uncertainty quantification • Price forecasting in volatile markets	• Typically reported in probabilistic metrics; e.g., 90% prediction intervals with 5–10% average width for renewable forecasting	[53,66–68]
Ensemble Methods	• **Combines multiple models to improve accuracy** • **Reduces errors compared to individual methods**	• Bagging • Boosting • Stacking • Voting regression	• Often outperforms individual models • Reduces overfitting • More robust to noise and outliers	• Can be computationally expensive • May be complex to implement and tune • Can be challenging to interpret • Potential for increased model complexity	• Load forecasting • Renewable energy prediction • Comprehensive power system state forecasting	• MAPE: 1–3% for short-term load forecasting • RMSE: 2–4% for wind power forecasting	[69–73]
Hybrid Models	• **Combines strengths of multiple techniques** • **Often outperforms individual models**	• CNN-LSTM combinations • Physics-informed neural networks • ANN-SVM hybrids	• Can leverage strengths of different methods • Potentially more accurate than single models • Flexible and adaptable to various scenarios	• Increased complexity in model design and implementation • May require more expertise to develop and maintain • Risk of overfitting if not properly designed • Can be computationally intensive	• Long-term load forecasting • Integrated renewable energy forecasting • Complex system-wide predictions	• MAPE: 1–2% for day-ahead load forecasting • RMSE: 1.5–3% for solar power forecasting	[74–77]
Fuzzy Logic Approaches	• **Handles uncertainty and imprecision** • **Allows for degrees of truth** • **Can incorporate expert knowledge**	• Fuzzy regression • Interval type-2 fuzzy logic systems • Fuzzy time series • Adaptive neuro-fuzzy inference systems (ANFIS)	• Effective in handling linguistic variables • Robust performance with uncertain data • Can integrate expert knowledge easily • Suitable for complex, non-linear systems	• May require careful tuning of membership functions • Can be computationally intensive for large rule bases • Performance depends on quality of fuzzy rules	• Long-term load forecasting • Short-term load forecasting • Electricity price forecasting • Renewable energy forecasting	• MAPE: 2–6% for short-term load forecasting • RMSE: 3–7% for electricity price forecasting	[78–81]

4. Applications of Intelligent Forecasting

The various intelligent techniques for forecasting in electrical power systems find wide applications in energy mix optimization, management of energy storage, and coordination of hydro-thermal operations. These techniques increase the predictability of electricity demand and pre-informed conditions for renewable energy generation, thus further facilitating power system operations with efficiency and reliability. They are also expected to reduce costs and enhance market competitiveness. The subsequent sections delve into these applications in greater detail.

4.1. Load Forecasting

Load forecasting is a critical application of intelligent forecasting techniques in electrical power systems, playing a vital role in supporting the transition to more sustainable and efficient energy infrastructure. As highlighted by Ibrahim et al. in [82], load forecasting is particularly crucial in the context of smart grids, where concerns for power system reliability and security are paramount. The increasing complexity of modern power systems, driven by the integration of RESs and the deregulation of power sectors, has made accurate load forecasting more challenging and important than ever. The applications of load forecasting extend to various operational and planning activities in power systems. For instance, Giap et al. emphasize that accurate load forecasting is crucial for ensuring sufficient power supply and preventing economic losses due to either power shortages or excess capacity [83]. This is particularly relevant in developing regions, as demonstrated by their study in the IA-Grai District of Gia Lai Province, Vietnam. In more advanced power systems, such as in Europe, the demands on load forecasting have become even more stringent. Esclapez et al. note that prediction systems in Europe now need to operate on a quarter-hour basis, significantly increasing the computational burden. This situation has led to innovative approaches in load forecasting, such as algorithms that selectively update forecasts to optimize computational resources while maintaining or even improving accuracy [84]. The Greek electricity system provides another interesting case study. Stamatellos and Stamatelos demonstrated that even relatively simple forecasting models, when robustly designed, can achieve performance levels comparable to those of system operators [85]. Their study, using public domain electric load data and typical climatic data, showed that a simple feed-forward ANN could make 24-h-ahead hourly electricity load forecasts with an accuracy close to that of the Greek system operator. Short-term load forecasting (STLF), typically covering periods from a few hours to a week ahead, has emerged as an active area of research and application. STLF is essential for day-to-day operations of power systems, enabling energy planners to use advanced methods and technologies for sustainable expansion [82]. In practical terms, STLF helps utilities and system operators manage energy operations more efficiently, indirectly saving money and reducing CO_2 emissions [84]. These applications highlight the versatility of load forecasting techniques across different power system contexts. From supporting the transition to smart grids and renewable energy integration to optimizing day-to-day operations and long-term planning, load forecasting continues to be a cornerstone of modern power system management.

4.2. Renewable Energy Generation Forecasting

Renewable energy generation forecasting has become increasingly crucial in the evolving landscape of electrical power systems. As the integration of RESs into power grids continues to grow, accurate forecasting of their generation becomes essential for maintaining grid stability, optimizing energy management, and supporting the transition to sustainable energy systems. The Smart4RES project, as described by Camal et al. in [86], exemplifies the cutting-edge efforts in this field. The project aims to improve the performance of short-term forecasting models for RESs and associated weather forecasting, while also optimizing decisions in power systems and electricity markets. This initiative is particularly focused on distribution grids, addressing challenges such as grid congestion, voltage deviations, and power quality issues that arise from the intermittent nature of renewables. One of the key applications of renewable energy forecasting is in the day-ahead and real-time operation of wind and solar farms. Camal et al. highlight the development of accurate forecasting systems for these purposes, which are crucial for grid operators and energy traders. Additionally, they mention methods for predicting short-term wind power fluctuations and their impact on grid stability, showcasing how forecasting directly contributes to maintaining a reliable power supply. The integration of renewable energy forecasting with consumption patterns offers innovative approaches to energy management. Vinagre et al. explored the correlation between solar radiation and electrical consumption of lights to improve energy consumption forecasting. Their study, conducted at the Polytechnic of Porto campus, employed multiple forecasting methods including multi-layer perceptron ANNs, support vector regression, and linear regression [87]. This application demonstrates how renewable energy forecasting can be coupled with load forecasting to enhance overall energy system management. The application of AI algorithms in renewable energy forecasting is a growing trend. Szczepaniuk provides a comprehensive overview of AI applications in the energy sector, including renewable energy sources. Their research indicates that AI algorithms can significantly improve processes in energy generation, distribution, storage, consumption, and trading. For renewable energy forecasting, these algorithms offer enhanced capabilities in handling the complex, non-linear relationships inherent in weather-dependent energy sources [88]. As highlighted by Klyuev et al., the urgent task of balancing electricity production and consumption becomes even more critical with the increasing share of renewables. Their review of forecasting methods emphasizes the importance of considering the forecasting horizon, which is particularly relevant for RESs given their variability across different timescales [58].

4.3. Electricity Price Forecasting

Electricity price forecasting has emerged as a critical application of intelligent forecasting techniques in the modern electricity market. As power systems become increasingly complex and dynamic, accurate price predictions are essential for market participants, system operators, and consumers to make informed decisions and optimize their strategies.

The volatility and unpredictability of electricity prices, influenced by factors such as usage patterns, weather conditions, outages, location, and economic variables, underscore the importance of sophisticated forecasting methods. Corippo et al. highlight this complexity, emphasizing that the ability to predict these prices presents great value to both consumers and utility companies [89]. Their research demonstrates the effectiveness of computational intelligence and neural networks in analyzing historical electrical pricing data to predict future prices, achieving impressive accuracy with a Root Mean Square Error (RMSE) of 0.476 and a Mean Absolute Percentage Error (MAPE) of 3.61%. In the context of smart grid and demand response programs, electricity price forecasting plays a crucial role in reducing investment and operation costs. Rezaei et al. proposed an innovative approach using Gated Recurrent Units (GRUs) for price forecasting [90]. Their methodology incorporates electrical load consumption as an input variable and integrates an adaptive noise reducer to enhance model performance. This approach not only improves the efficiency of demand response programs but also provides producers with effective tools to make informed decisions in the electricity market, potentially leading to significant cost savings through optimal resource utilization. The importance of long-term electricity price forecasting is emphasized by Ortiz et al., who present two methodologies specifically for the Spanish electricity market [91]. Their study, using real data, underscores the necessity of price forecasting for all market participants. Long-term forecasts are particularly valuable for strategic planning, investment decisions, and policy-making in the energy sector. Advancements in DL techniques have further enhanced the accuracy and reliability of electricity price forecasting. Pourdaryaei et al. introduced a novel framework combining multi-head self-attention and CNN techniques. Their approach, which includes a feature selection method using mutual information and neural networks, demonstrated superior performance across different seasons. The proposed model achieved the lowest average MAPE of 1.75% and RMSE of 0.0085, outperforming other DL models and setting a new benchmark in forecasting accuracy [92]. The application of electricity price forecasting extends beyond mere prediction. As highlighted by Klyuev et al. in their literature review, various forecasting methods, including regression, autoregressive models, probabilistic forecasting techniques, and deep machine learning algorithms, can be applied to electricity price forecasting. The choice of method often depends on the specific forecasting horizon and the unique characteristics of the electricity market in question [58].

Figure 2 provides a comprehensive overview of the various applications of intelligent forecasting methods in predicting electricity prices and their subsequent impact on the market. This figure concisely illustrates how these advanced techniques can enhance the accuracy of price predictions, thereby influencing market dynamics and decision-making processes.

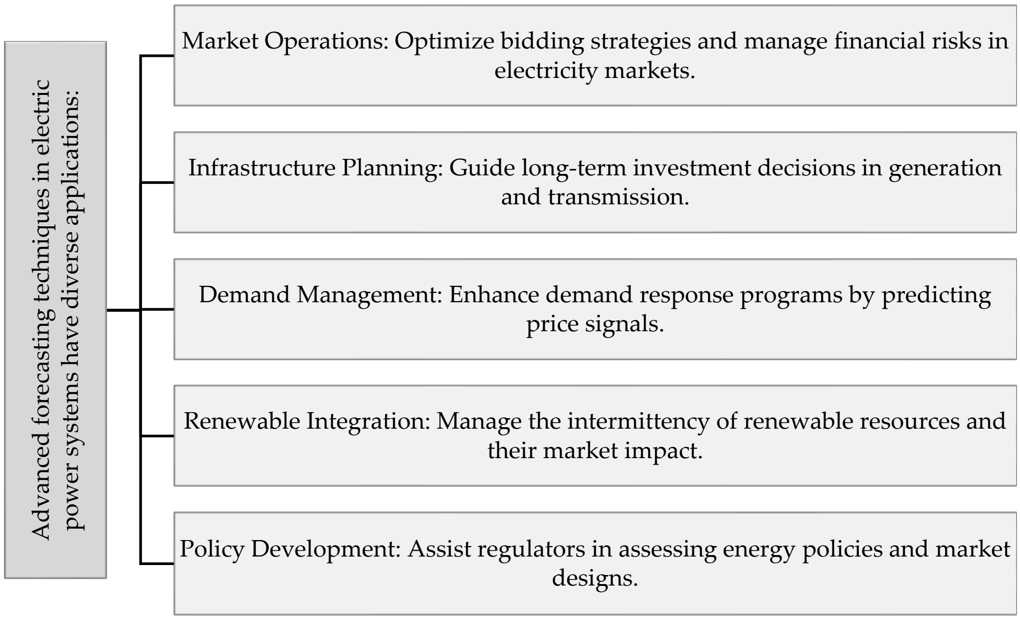

Figure 2. Implementations of advanced forecasting methods to predict electricity prices.

4.4. Demand Response Forecasting

Demand response forecasting has emerged as a critical application of intelligent forecasting techniques in modern smart grids. As power systems evolve to accommodate increasing renewable energy integration and dynamic consumer behavior, accurate prediction of demand response becomes essential for maintaining grid stability, optimizing energy resources, and enhancing overall system efficiency.

The importance of demand response prediction is underscored by the vast amounts of data generated in smart grids. Kumari et al. highlight that the preprocessing and integration of these extensive data are crucial steps in the load forecasting process [93]. Their research demonstrates the effectiveness of the Prophet technique in predicting future demand response based on historical data. This method shows resilience even when faced with missing values, fluctuations, trends, and abnormal variations, making it particularly valuable in real-world applications where data quality can be inconsistent. DL models have shown significant promise in demand forecasting for smart grids. Aguiar-Pérez and Pérez-Juárez emphasize that these models are adept at learning patterns from customer data and forecasting demand across various time horizons [94]. They specifically point out the effectiveness of LSTM networks in this domain. The application of such advanced techniques is crucial for efficient power systems, helping to balance supply and demand, particularly in the context of demand response programs and maintaining power system stability. The integration of AI in demand response has opened new avenues for enhancing energy system reliability. Ali et al. discuss the significant growth of demand response as a cost-effective technique for improving energy system dependability [95]. AI's ability to handle complex tasks and provide near-real-time decisions makes it a key technology for enabling demand-side management. The authors highlight various applications of optimization algorithms in demand response, including consumer selection, attribute and preference learning, dynamic pricing, device scheduling and control, and incentive design. In the context of STLF, which is crucial for demand response, Ibrahim et al. demonstrate the superiority of DL regression models. Their research shows that such models can achieve high accuracy, with an R-squared value of 0.93 and a MAPE of 2.9%. This level of accuracy is vital for effective demand response strategies, as it allows for more precise matching of supply with anticipated demand [82]. The application of demand response prediction extends to various scenarios in smart grids [96]:

- Grid Stability Management: Accurate demand response prediction helps system operators anticipate and manage potential imbalances between supply and demand, especially with the increasing integration of intermittent renewable energy sources.
- Optimized Resource Allocation: Utilities can use demand response forecasting to optimize the scheduling of generation resources, reducing the need for expensive peaking plants and minimizing operational costs.
- Dynamic Pricing Strategies: Demand response forecasting enables the implementation of more effective dynamic pricing schemes, encouraging consumers to shift their energy usage to off-peak hours.
- Consumer Engagement: By predicting demand response patterns, utilities can develop more targeted and effective consumer engagement programs, enhancing participation in demand response initiatives.
- Renewable Energy Integration: demand response forecasting aids in managing the variability of renewable energy sources by anticipating when demand can be shifted to match renewable generation peaks.
- Smart Home and Building Management: Advanced demand response forecasting techniques can be integrated into smart home and building management systems, automatically adjusting energy consumption based on predicted grid conditions and prices.
- Electric Vehicle (EV) Charging Management: As EV adoption increases, demand response forecasting becomes crucial for managing the significant load they represent, optimizing charging schedules to benefit both the grid and vehicle owners.

However, challenges remain in the field of demand response prediction. Assad et al. point out the limitations of current intelligent algorithms and suggest that quantum algorithms could potentially optimize the computational burden in future smart grid applications. This highlights the ongoing need for research and development in this field to address the increasing complexity of smart grids and demand response scenarios [96].

5. Optimization

Optimization refers to the process of identifying the most effective solution to a problem within a set of given constraints. In this context, a mathematical expression is optimized when the values of its variables are determined in such a way that the expression's value is either maximized or minimized. Optimization can also be described as a mathematical tool used to find the best strategy for executing a specific task among several possible methods. To achieve this goal, a criterion must be established to compare different feasible designs and select the optimal one. This criterion is expressed as a function of the problem variables and is known as the objective function. In certain scenarios, it is necessary to satisfy multiple criteria simultaneously, leading to a multi-objective optimization problem. These functions are often non-homogeneous and non-proportional, which increases the complexity of the problem. The following sections delve into the details of single-objective and multi-objective optimization, along with various optimization algorithms. This comprehensive exploration provides insights into the methodologies and applications of optimization in the electric power systems field. But, before exploring specific optimization algorithms, it is essential to understand non-convex optimization problems, which are prevalent in power system applications. While some problems can be formulated as convex, many real-world power system scenarios lead to non-convex problems characterized by multiple local optima, making global optimum discovery challenging. Non-convexity in power systems often stems from nonlinear relationships between variables (e.g., quadratic relationship between power flow and voltage magnitudes), discrete decision variables (like generator on/off status), inherently non-convex AC power flow equations, and non-convex feasible regions introduced by system stability and security constraints. This non-convexity significantly complicates the optimization process, as traditional gradient-based methods may converge to local rather than global optima. Consequently, advanced optimization techniques, including heuristic and metaheuristic algorithms, have been developed to better navigate non-convex solution spaces. Understanding the non-convex nature of many power system optimization problems is crucial for appreciating the need for sophisticated algorithms and the challenges in finding optimal solutions for complex power system operations.

5.1. Single-Objective Optimization Problem

The basic form of a single-objective problem in electrical power systems is focused on meeting a particular goal; for example, the goal could be to minimize the total generation cost, minimize the power losses, or maximize the efficiency of the system. This process involves determining the optimal settings for various control variables such as the generator outputs, voltage levels, and transformer taps to an acceptable level to achieve the desired objective. The optimization must meet many constraints like power flow balance equations, generator capacities, voltage profile, and network security. Once the problem is set mathematically, it can be solved using a variety of optimization algorithms in order to find the best solution as explained in the following sections. This optimization process is very crucial for grid operators to be able to schedule the generation and distribution of electricity in a way that is efficient and meets the demand, and this has to be performed at the least cost possible as well as fulfilling the regulatory and environmental requirements [97]. By continuously improving these optimization techniques, the power industry can better handle the complexities of modern electrical grids, integrating RESs and adapting to changing consumption patterns.

5.2. Multi-Objective Optimization Problem

Multi-objective problems in electric power systems may be defined as a problem in which two or more conflicting objectives must be attained. These objectives often include minimizing costs, reducing emissions, enhancing reliability, and maximizing efficiency. The complexity arises because improving one objective may negatively impact another, creating the need for trade-offs. Some of the important entities involved here include generation units, transmission networks, and demand loads, all of which interconnect in a complex manner. To manage these trade-offs, the decision-makers employ multi-objective algorithms of optimization, most especially the Pareto optimization. This method optimizes a number of objectives and defines a set of equally optimal solutions called the Pareto front, from which a decision-maker can choose the best option in terms of priorities [98]. The importance of multi-objective optimization in sustainable energy management cannot be overstated. Ultimately, effectively addressing multi-objective problems leads to a more sustainable and resilient energy future, balancing environmental concerns with operational and economic needs.

6. Optimization Algorithms

Optimization algorithms have been an integral part of developing and functioning electrical power systems. Historically, these methods have evolved from simple linear programming (LP) techniques to more sophisticated approaches like mixed-integer programming, dynamic programming (DP), and heuristic algorithms. It was originally considered that optimization applies to solving economic dispatch and unit commitment problems to meet power generation and demand at minimum cost. The advent of RESs and smart grids increased the complexity of the power systems, thereby calling for more advanced optimization techniques. GA, PSO, ACO, TLBO, and ML-based techniques are a few of the many methods used nowadays to deal with uncertainties and variability related to the integration of renewable energies. These methods are employed in many power system planning, operation, and control aspects. The primary goal is to minimize costs, reduce losses, improve stability, and enhance overall system performance while satisfying various constraints related to power flow, voltage limits, and equipment capacities. Figure 3 demonstrates the optimization algorithms considered in this study.

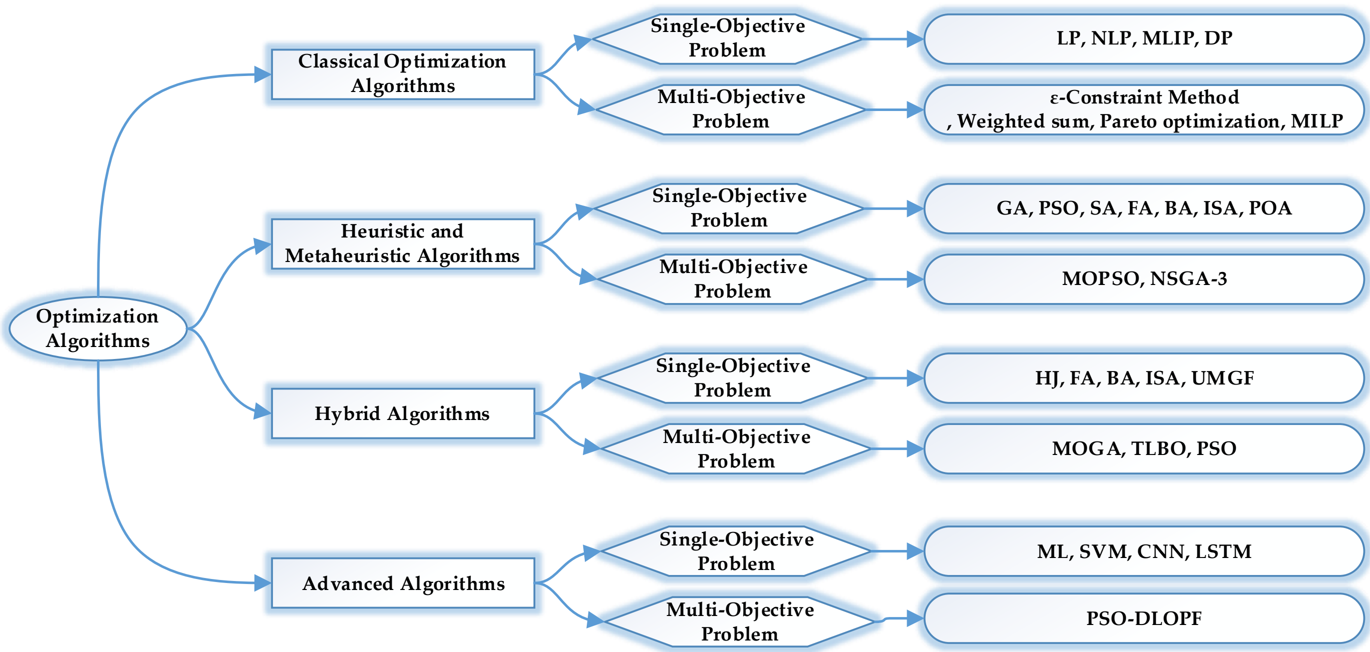

Figure 3. Overview of various optimization algorithms.

6.1. Classical Optimization Algorithms

Classical optimization algorithms, including Linear Programming (LP), Nonlinear Programming (NLP), Mixed Integer Linear Programming (MILP), and Dynamic Programming (DP), form the foundation of many optimization problems in electrical power systems. These methods have been instrumental in addressing challenges in power system planning, operation, and control.

6.1.1. Single-Objective Problem

Classical optimization algorithms aim to find the optimal solution for a single-objective function while satisfying a set of constraints. In the recent literature, several key approaches and applications have emerged, demonstrating the continued relevance and evolution of classical optimization techniques.

LP appears as a basic optimization algorithm of interpretation for power systems. Tsvettsykh et al. used LP as a component of the optimization strategy for predicting and improving the sustainable innovation growth in the enterprise of the electric power industry. Their approach incorporates LP with multi-criteria decision-making, applying the AMPL language. This method was useful in power industry enterprises in their decision-making regarding strategic directions for achieving the goals of sustainable innovative development [99]. This was followed by an approach developed by Fan et al. using the finite cost constraint theory as a basis for an improved flexible response capability of power systems. This method involves the creation of a bidding function with a monthly quotation at its heart, calculation of a demand response inhibition factor, one-dimensional feature recognition vector calculation influenced by length waveform, and finally, an analysis of the credibility of the feature points under varying conditions. The approach then leads to the formulation of a power emergency demand response model using the limited cost constrained approach with a view of minimizing operating costs [100]. The formulation of objective functions is crucial in addressing specific power system challenges. Hamouda Ali et al. introduced three single-objective functions for the Optimal Reactive Power Dispatch (ORPD) problem: voltage deviation, system operating cost, and real power loss. Additionally, they considered transmission power loss minimization as a key objective, highlighting the diverse goals that can be pursued within the framework of classical optimization [101]. The effectiveness of these classical methods is often evaluated through comparison with more advanced techniques. For example, Manikandan et al. stated that although methods like the Conventional Lagrange method can be used to solve the economic dispatch problem in renewable integrated MGs, the Sparrow Search Algorithm is usually more effective [102].

6.1.2. Multi-Objective Problem

Classical optimization algorithms for multi-objective problems in electrical power systems have evolved to address the complex challenges of balancing multiple, often conflicting objectives. The recent literature highlights several key approaches and applications in this domain.

In [103], Mallégol et al. suggest the possible approach to address non-linearities in Multi-Energy System (MES) mathematical models. Their approach represents an MES as a multi-objective MILP corresponding to the dual objectives of maximum cost reduction and the rate of RESs. This method enables a relatively intricate operation and an accurate system configuration in comparison to traditional approaches, yet it maintains lower levels of complexity compared to the latter. The efficiency of this approach was shown by solving a permanent MES optimization problem with hourly time steps through the year with acceptable computation times. In the context of DC networks with high photovoltaic (PV) penetration, Montoya et al. formulated an EMS as a multi-objective optimization problem. Their approach considers economic, technical, and environmental objective functions simultaneously. To solve this complex problem, they implemented a weighted optimization method for each pair of conflicting objective functions. Additionally, they proposed an iterative solution methodology (ISM) to eliminate errors introduced by linearization. This methodology proved effective in reaching the optimal global solution for each objective function, as demonstrated in simulations using the monopolar version of the IEEE 33-bus grid [104]. The OPF problem has also seen advancements in multi-objective optimization. To cope with the difficulties of solving OPF problems in large-scale power systems, Wu et al. developed an improved decomposition-based multi-objective algorithm called IMOEA/D. Their approach aims to accelerate algorithm convergence and increase species diversity through three key strategies: (1) the barnacle optimization algorithm against the differential evolution algorithms: a competition strategy. (2) An adaptive mutation strategy. (3) Selective candidate with similarity selection to balance exploration and exploitation capabilities. These improvements indeed enhanced the population diversity and, thereby, established the superiority and efficiency of the proposed algorithm for solving the multi-objective OPF problems confirmed on IEEE 30-bus and IEEE 57-bus test systems [105].

Moreover, algorithms such as ε-constraint, Weighted sum, and Pareto optimization are other classic algorithms have been employed to solve optimization problems. The ε-constraint method is aimed at maximizing one of the objectives while putting others to be constraints having some bounds. It systematically changes these constraints to generate a pareto optimal solution that enables one to undertake a trade-off analysis of the conflicting objectives. Villacrés and Carrión proposed a methodology for solving the real and reactive power dispatch problem with more than one objective in order to minimize the active power losses and generation costs based on MINLP using the ε-constraint method and fuzzy satisficing approach, demonstrating its superiority to the one available in Digsilent Power Factory [106]. The Weighted Sum Method combines multiple objectives into a single objective by assigning weights to each criterion. The overall performance is evaluated based on these weighted criteria, making it easier to identify optimal solutions across different objectives. Marler presented a method using this approach to solve complex optimization problems in power systems, highlighting its advantages in achieving balanced solutions [107]. Pareto Optimization, also known as multi-objective optimization, seeks solutions where no objective can be improved without worsening another. The set of all such non-dominated solutions forms the Pareto front, representing the best trade-offs among objectives. Fettah et al. proposed an optimization framework employing the Multi-Objective Multi-Verse Optimization (MOMVO) algorithm to optimize the integration of DGs and Capacitor Banks (CBs) into electrical distribution networks [108].

These studies collectively highlight the evolving nature of classical optimization methods in addressing multi-objective problems in power systems. Key trends include the following: (1) the integration of linearization techniques to handle non-linear aspects of power systems while maintaining computational efficiency. (2) The development of weighted optimization methods to balance multiple objectives. (3) The use of iterative solution methodologies to refine solutions and eliminate errors introduced by simplification techniques. (4) The incorporation of nature-inspired algorithms and adaptive strategies to enhance solution diversity and convergence in complex, large-scale systems.

6.2. Heuristic and Metaheuristic Algorithms

Heuristic and metaheuristic algorithms have gained significant attention in solving complex optimization problems in electric power systems. These techniques offer practical solutions to challenges that are often difficult or time-consuming to solve using classical optimization methods. Heuristic methods are problem-specific algorithms that use practical rules or educated guesses to find good, but not necessarily optimal, solutions. Metaheuristics, on the other hand, are higher-level procedures designed to find, generate, or select a heuristic that may provide a sufficiently good solution to an optimization problem, especially with incomplete or imperfect information or limited computation capacity.

6.2.1. Single-Objective Problem

Heuristic and metaheuristic algorithms have gained significant traction in solving single-objective optimization problems in electrical power systems. These methods offer powerful alternatives to classical optimization techniques, especially when dealing with complex, non-linear problems that are characteristic of modern power systems. The recent literature highlights several key approaches and applications in this domain.

Guerraiche et al. proposed an innovative approach to the techno-economic green optimization of MGs using swarm metaheuristics. Their study focused on optimizing the series–parallel power energy system using three distinct algorithms: Firefly Algorithm (FA), Bat Algorithm (BA), and Interior Search Algorithm (ISA). The objective function considered both the total cost of the system and emission gases, taking into account device dependability, performance, capital costs, and maintenance costs. The authors demonstrated through numeric simulations that these swarm metaheuristic algorithms could lead to significant reductions in costs while maintaining an acceptable level of reliability in MGs [109]. In the context of OPF problems, Hamouda Ali et al. introduced the Peafowl Optimization Algorithm (POA) as an effective method for load dispatch and power flow in power grids. Their research showed that POA outperformed various other optimization techniques, including COOT, GJO, HPO, LSMA, RSA, SCSO, and SOA. The POA demonstrated significant potential in identifying the most appropriate global solutions, investigating preferred search locations, and ensuring fast convergence speed. This makes it a promising approach to solving complex OPF problems in electric power systems [110]. While not strictly a metaheuristic method, Carreras and Kirchsteiger proposed an empirical approach to optimize non-linear problems in domestic energy management systems. Their method, which considers the non-linear behavior of battery inverters, involves iterations of linear optimization problems to determine the optimal charging and discharging strategy. This approach, although not a traditional metaheuristic, demonstrates the importance of considering non-linearities in power system optimization and could potentially be integrated with metaheuristic methods for more comprehensive solutions [111]. Sousa et al. evaluated different initial solution algorithms to be used in heuristic optimization for solving energy resource scheduling in smart grids. They proposed two initial solution algorithms for use with the Simulated Annealing (SA) metaheuristic. Their findings showed that an adequate algorithm for generating a good initial solution could significantly improve the metaheuristic's performance in finding a final solution close to the optimal, compared to using a random initial solution. The proposed approach achieved results within 0.1% of the optimal solution in just one minute, whereas a deterministic technique, while obtaining the optimal result, required around 26 h [112].

6.2.2. Multi-Objective Problem

Heuristic and metaheuristic algorithms are particularly effective in addressing complex scenarios where multiple, often conflicting objectives need to be balanced. The recent literature highlights several key approaches and applications in this domain. Mallégol et al. in [113] proposed a fast heuristic algorithm for MESs design optimization. Their approach addresses the complexity of optimizing MESs over long time periods with a high temporal resolution, which is typically infeasible using traditional methods. The algorithm was applied to a district-scale MES with five types of generation units, including combined heat and power (CHP). The results showed that the heuristic was up to 99.9% faster than state-of-the-art MILP solvers for smaller time periods, with a mean error of just 2.3×10^{-4}%. Shi et al. introduced an innovative multi-objective optimization model for a three-phase transformer design. They proposed a hybrid algorithm termed MOPSO-NSGA3, combining Multi-Objective Particle Swarm Optimization (MOPSO) and Non-Dominated Sorting Genetic Algorithm-3 (NSGA-3). This approach effectively minimized short-circuit deviation, operating loss, and manufacturing costs while satisfying various design parameter constraints. The algorithm was tested on 50 MVA/110 kV and 63 MVA/110 kV prototypes, demonstrating a maximum error of less than 7% [114]. Borges et al. developed a multi-objective PSO methodology for energy resource management in systems with high penetration of Distributed Generation (DG) and EVs. Their approach aimed to maximize profit while minimizing CO_2 emissions, applied to a real Spanish electric network in Zaragoza with 1300 EVs and 70% DG penetration. The study normalized cost and CO_2 emissions by subtracting the minimum value and dividing by the range, providing a balanced approach to these conflicting objectives [115].

6.3. Hybrid Algorithms

Hybrid optimization algorithms use several sub-algorithms to take advantage of one technique while avoiding the drawbacks of the other techniques. Due to this, these approaches can efficiently solve difficult problems that cannot be solved effectively by a single algorithm involved in the approach. They are especially valuable in large-scale combinatorial optimization where all known algorithms improve solution quality and reduce computational time. This hybridization is used widely in various sectors such as data analysis, transportation, and communication networks.

6.3.1. Single-Objective Problem

Hybrid optimization algorithms combine different optimization techniques to leverage their respective strengths and overcome individual limitations. The recent literature highlights several innovative approaches in this domain. Li et al. proposed a hybrid optimization algorithm for capacity optimization in integrated energy systems. This approach combines PSO algorithms with the Hooke-Jeeves (HJ) method. The hybrid algorithm demonstrated significant improvements in both optimization speed and accuracy compared to traditional single optimization methods. Notably, it reduced the number of iteration steps by approximately 31% compared to the PSO alone and by about 48% compared to the HJ algorithm. This efficiency gain translated into substantial cost savings, with the hybrid approach reducing overall system costs by approximately 60% compared to traditional methods [116]. Guerraiche et al. demonstrated a techno-economic green optimization model for MGs using a swarm metaheuristic-based approach. While developed with an emphasis on multi-objective problems, their method shows that the use of hybrids can be effective in single-objective cases. In the study, three optimization techniques, Firefly FA, BA, and ISA, were used while Ushakov algorithm (UMGF) was applied to estimate reliability. The conventional as well as modernistic control-suitable strategy used in this study was more efficient in managing the power flow whilst minimizing the costs of energy consumption and without compromising the reliability of the system [109].

6.3.2. Multi-Objective Problem

Addressing power quality issues in renewable energy systems, Hooda and Saini presented a power quality control strategy for a 3-bus solar-based hybrid system. Their approach employs a Multi-Objective Genetic Algorithm (MOGA) for reactive power planning, combined with a PWM and PID controller for frequency control and STATCOM for reactive var compensation. Simulations conducted in MATLAB/Simulink 9.1 demonstrated the effectiveness of this hybrid method, showing an average reactive power saving of 5.88 kVAR and significant improvements in power quality. This study showcases the capability of hybrid methods in simultaneously addressing multiple objectives, such as power factor improvement and reactive power loss reduction in renewable energy-based systems [117]. In the context of distributed resource allocation, Ansari and Byalihal applied a hybrid optimization algorithm combining TLBO and PSO for the optimal placement of DG and STATCOM in power systems. Their multi-objective formulation aimed to maximize cost–benefit and voltage stability factors while minimizing the network security index and power losses. The hybrid TLBO-PSO algorithm demonstrated superior convergence performance compared to individual optimization techniques, highlighting the potential of hybrid methods in tackling complex, multi-objective optimization problems in power system planning and operation [118]. The ability of hybrid methods to balance multiple, often conflicting objectives while maintaining or improving the solution quality and computational efficiency is a significant advantage. These methods can effectively handle the complexity and conflicting objectives inherent in modern power system design and operation, demonstrating superior performance in terms of solution quality, convergence speed, and adaptability to various problem domains.

6.4. Advanced Algorithms

Advanced optimization algorithms leverage cutting-edge computational techniques and novel algorithmic approaches such as AI-based methods and emerging methods to overcome the limitations of traditional optimization methods. AI-based methods have shown significant promise in enhancing decision-making and system performance, while the emerging optimization methods combine traditional techniques with new computational paradigms, often leveraging AI and advanced heuristics. The recent literature demonstrates significant improvements in solution quality, computational efficiency, and applicability to real-world power system challenges.

6.4.1. Single-Objective Problem

A comprehensive approach to power system optimization was presented by Zhao, leveraging both mathematical techniques and AI. The research focused on developing methods for system optimal operation and faulty status detection, utilizing linear approximation and convex relaxation techniques to address non-convex AC Optimal Power Flow (ACOPF) problems. Additionally, the study incorporated DL models, specifically CNN and LSTM networks, for fault recognition and Sub-Synchronous Oscillation (SSO) detection. This integration of traditional optimization techniques with advanced ML approaches represents a significant step forward in power system management, demonstrating substantial improvements in system performance through simulation results [119]. Peng highlights four main models used in power system stability assessment: (1) SVM, (2) Multilayer Perceptron (MLP), (3) CNN, and (4) LSTM. These models, along with Principal Components

Analysis (PCA), have been employed to analyze and predict system stability, with metrics such as accuracy, recall rate, mean absolute error, and mean squared error being used to evaluate their performance [120].

6.4.2. Multi-Objective Problem

Advanced optimization algorithms are one significant area of development in the optimization of CCHP systems within the context of smart grids. Chen et al. proposed a novel approach that employs heuristic algorithms, specifically SA and GA, in conjunction with Model Predictive Control (MPC) for operation optimization. This method aims to improve energy efficiency, reduce environmental impact, and enhance system resilience. Simulation studies verified significant improvements in both energy efficiency and system resilience, demonstrating the potential of combining heuristic algorithms with advanced control techniques in power system optimization [121]. Fakih et al. presented a bi-level multi-objective optimization model for designing and operating RESs and battery energy storage (BES) systems in existing electrical grids. Their approach combines PSO with Dynamic Linear AC-Optimal Power Flow (DLOPF) to minimize costs while limiting carbon emissions. This sophisticated model addresses the complex interplay between CO_2 constraints, RES and BES installations, and overall system costs. The study revealed that achieving stricter CO_2 limits (up to a 30% reduction) required more RES and BES installations, increasing the overall cost by USD 15 million but reaching storage limits. This research highlights the trade-offs between environmental goals and economic considerations in power system planning [122]. AI's application extends to smart home energy management as well. Radke et al. discuss the use of AI technology for optimal utilization of solar resources and reducing energy consumption for load management. Their proposed method aims to minimize peak load during peak hours, reduce electricity consumption, and lower electricity bills for domestic loads [123].

However, it is important to note that the effectiveness of these AI methods often depends on the quality and quantity of available data, as well as the specific characteristics of the power system under consideration. Furthermore, these emerging optimization methods are designed to handle the dynamic and complex nature of modern power systems, including the integration of RESs and smart grid technologies. There is a strong focus on developing methods that can provide high-quality solutions within reasonable computational timeframes, which is crucial for real-time power system operations. Many of these methods are capable of handling multiple, often conflicting objectives simultaneously, reflecting the complex nature of power system management.

7. Optimization Application in Power Systems

Optimization algorithms are employed in various applications such as OPF, where they help determine the most efficient operating conditions for power generation and distribution. These algorithms are also applied in unit commitment to determine the schedule of electricity generation plants to meet demand in the most efficient way. In addition, optimization algorithms are vital for economic load dispatch, which aims to minimize the total generation cost while satisfying all operational constraints. They are also used in demand response management, which involves controlling the consumer demand to correspond to the supply conditions, improving the stability of the grid. Furthermore, optimization algorithms assist in the integration of RESs by managing the variability and uncertainty associated with these resources. They are essential in planning and operation tasks, such as transmission network expansion and maintenance scheduling, ensuring a reliable and cost-effective power supply. The mentioned applications are explained in general and discussed in detail in terms of the strengths and weaknesses of the applications in Table 2.

Table 2. Summary of different uses of optimization algorithms in electric power systems.

Application	Advantages	Disadvantages	References
Generation Dispatch and Unit Commitment	• Minimizes operational costs • Balances supply and demand • Can incorporate environmental objectives (e.g., CO_2 reduction)	• Computationally intensive for large systems • Requires accurate load and renewable generation forecasts	[115,124]
Optimal Power Flow (OPF)	• Improves system efficiency • Reduces transmission losses • Can be adapted for distributed systems	• Non-convex problem, challenging to solve • May require simplifications for real-time applications	[125,126]
Transmission Network Planning and Expansion	• Supports long-term grid reliability • Facilitates integration of renewable energy sources • Can consider multiple objectives (cost, reliability, environmental impact)	• Involves significant uncertainty in long-term planning • High investment costs associated with decisions	[127–129]
Renewable Energy Integration	• Enhances grid stability with high renewable penetration • Improves economic efficiency of renewable resources • Supports energy transition goals	• Requires handling of uncertainties in renewable generation • May need advanced forecasting techniques • Complexity increases with system size	[111,130,131]
Demand Response and Load Management	• Reduces peak demand • Improves system reliability • Can lead to significant cost savings for consumers	• Requires consumer participation and education • Privacy concerns with data collection • May face regulatory challenges	[100,132,133]
Microgrid Operation and Control	• Improves system reliability and efficiency • Reduces operational costs • Facilitates integration of renewable energy sources • Enhances energy management flexibility	• Complexity in coordinating multiple energy sources • Requires advanced control systems • Potential high initial investment costs	[134–136]
Voltage and Reactive Power Control	• Improves voltage stability • Reduces power losses • Enhances power quality • Supports integration of electric vehicles and renewable sources	• Requires complex modeling of system components • May face challenges in real-time implementation • Potential conflicts between multiple optimization objectives	[117,137,138]

7.1. Generation Dispatch and Unit Commitment

Generation dispatch and unit commitment are fundamental optimization problems in power system operations. These applications focus on determining the optimal scheduling and output levels of generating units to meet forecasted demand while minimizing operational costs and satisfying various system constraints. Recent research in this area includes the work by Naderi et al., who proposed a hybrid fuzzy-based improved comprehensive learning PSO-DE algorithm to solve the Optimal Active Power Dispatch (OAPD) problem. Their approach considers the Unified Power Flow Controller (UPFC) device, demonstrating significant cost savings in simulations on the IEEE 30-bus system over a 365-day horizon [124]. Borges et al. presented a multi-objective PSO methodology for energy resource management in systems with high penetration of DG and EVs. Their approach aimed to maximize profit while minimizing CO_2 emissions and was applied to a real Spanish electric network in Zaragoza with 1300 EVs and 70% DG penetration [115].

7.2. Optimal Power Flow (OPF)

OPF is an optimization problem in power systems that aims to determine the best operating levels for electric power plants to meet system load at the lowest possible cost while maintaining system security. Sadnan proposed a scalable Distributed Optimal Power Flow (D-OPF) method based on Equivalent Network Approximation (ENApp) for efficient power distribution system operation. This method addresses the computational complexities faced by centralized optimization methods and is more resilient to single points of failure [125]. Forouzandeh et al. presented a novel business model for smart buildings using intelligent energy management. They formulated a mixed binary optimization problem to determine the optimal contract power capacity and schedule for electric vehicle/battery storage charge and discharge, achieving a significant electricity cost reduction of 47% in their simulations [126].

7.3. Transmission Network Planning and Expansion

Optimization techniques are also employed in long-term planning of transmission networks, determining the most cost-effective way to expand or reinforce the grid to meet future demand and reliability requirements. Refaat et al. introduced a new decision-making strategy for the techno-economic assessment of generation and transmission expansion planning in modern power systems. Their approach efficiently integrates RESs by controlling and enhancing the Hosting Capacity (HC) level. The proposed model demonstrated its ability to select appropriate projects precisely in simulations on the Garver network and the 118-bus system [127]. Huang et al. proposed a method to optimize the total capacity of substations in distribution networks, considering renewable energy penetration rate and load variations. Their economic analysis model simultaneously optimizes the capacity and quantity of substation transformers, taking into account the effects of reducing net load and enhancing the reliability of distribution feeders [128]. Pradilla-Rozo et al. developed a hybrid optimization methodology based on the modified gradient-based metaheuristic optimizer (MGbMO) and the successive approximation power flow method to solve the optimal conductor selection problem in medium-voltage distribution networks. Their approach achieved significant reductions in annual investment and operating costs compared to traditional methods [129].

7.4. Renewable Energy Integration

With the increasing penetration of RESs, optimization becomes a vital context in managing their variability and uncertainty in power systems. Khan et al. proposed an optimal decision model for the electric power market considering renewable energy units, loads, energy storage systems, and the involvement of new energy and EVs in market bidding. Their model takes into account the technological limits of new energy units and storages, demonstrating that renewable energy systems can achieve greater energy production efficiency and higher bids for the market with a virtual power plant (VPP) structure [130]. Oriza et al. introduced a bi-level optimization model for optimal energy trading between MGs and distribution companies (Discos), considering renewable energies and a demand management strategy. Their approach, solved using PSO, showed an optimal solution for energy consumption and trading [131]. Carreras and Kirchsteiger proposed an improved method to solve non-linear optimization problems in domestic energy management systems, considering the non-linear behavior of battery inverters. Their iterative approach to linear optimization problems determined the most adequate charging and discharging strategy, leading to cost savings and reduced emissions [111].

7.5. Demand Response and Load Management

Optimization techniques are employed to design and implement effective demand response programs and load management strategies, aiming to optimize the timing of flexible loads and determine optimal pricing strategies. Priolkar and Sreeraj proposed an optimal scheduling of loads based on dynamic tariffs and implementation of a Direct Load Control (DLC)-based demand response program for domestic consumers. They used binary PSO and a discrete elephant herd optimization algorithm to minimize cost and peak-to-average ratio, resulting in significant energy cost savings and improved Peak-to-Average Ratio (PAR) [132]. Fan et al. designed an optimization method for the flexible response capability of power systems under limited cost constraints. Their approach incorporated a bidding function with a monthly quotation, demand response inhibition factor, and feature point credibility under different conditions to minimize operating costs [100]. Dwijendra et al. proposed an optimal management of energy demand in the electrical distribution grid using an interval optimization approach and incentive-based modeling of demand response programs with a reserve scheduling mechanism. Their ε-constraint method for a solution demonstrated positive effects under uncertainties [133].

7.6. MG Operation and Control

MGs have emerged as a promising solution for the future of power generation and distribution systems, offering flexibility, reliability, and resilience. The optimization of MG operations is crucial for balancing economic and energy issues while integrating RESs. Di Somma et al. presented an optimization approach to a residential MG using MILP in MATLAB. Their method achieved significant reductions in both costs and primary energy use compared to traditional scenarios, with cost reductions ranging from 2 to 4 times and primary energy use reductions ranging from 2 to 5 times during the winter season for both the electricity and heating sectors [134]. Zhang et al. proposed an optimized strategy for MGs using the Promoted Remora Optimization (PRO) algorithm. Their approach aimed to meet load power requirements, ensure a constant DC bus voltage, and minimize operational costs. The study demonstrated a high system efficiency (average 87.99%) and optimizer efficiency (average 86.46%), with daily operational costs ranging from USD 1,379,595 to USD 1,479,998 [135]. Muzzammel et al. conducted a comparative analysis of OPF in renewable energy-based MGs. They simulated two cases of battery charging and discharging using the IEEE-14 bus system in MATLAB/Simulink. Their results showed that PSO was more promising than the Newton–Raphson method, reducing transmission line losses by 17% in the battery charging case and 19–20% in the battery discharging case, while also improving the voltage profile [136].

7.7. Voltage and Reactive Power Control

Voltage and reactive power control are essential aspects of power system operation, particularly with the increasing penetration of RESs and the integration of EVs. Chen et al. proposed a reactive power optimization method considering EV discharging/charging support. Their approach analyzed the charger's reactive power regulation principle, established a charger state constraint model, and integrated a reactive power optimization target function for the distribution system. The method employed PSO for charger power factor angle optimization. The results showed that the orderly discharging/charging method increased the voltage profile and decreased the loss rate of the network by 40%, while also reducing customer expenditure by 13% [137]. Chi et al. introduced an adaptive many-objective robust optimization model for the deployment of dynamic reactive power sources to improve voltage stability in power systems with wind power penetration and induction loads. Their model simultaneously optimized five objectives: (1) total equipment investment, (2) adaptive short-term voltage stability evaluation, (3) tie-line power flow evaluation, (4) prioritized steady-state voltage stability evaluation, and (5) robustness evaluation. They developed an angle-based adaptive many-objective evolutionary algorithm (MaOEA) with improvements in adaptive mutation rate and elimination procedure [138]. Hooda and Saini presented a power quality control strategy for a 3-bus solar-based hybrid system to improve power quality and reduce power losses. Their approach employed a PWM with PID controller for frequency control and STATCOM for reactive var compensation. Using MOGA for reactive power planning, they achieved an average reactive power saving of 5.88 kVAR and significant improvements in power quality [117].

Overall, these studies demonstrate the diverse approaches and techniques being applied to optimize MG operations and voltage and reactive power control in modern power systems, addressing the challenges posed by renewable energy integration and evolving grid technologies. Table 2 offers an in-depth overview of the various applications of optimization techniques in electric power systems. It outlines each application, emphasizing both the benefits and potential drawbacks associated with these techniques.

8. Integration of Forecasting and Optimization

As power grids evolve into intricate and dynamic networks, the integration of intelligent forecasting and optimization has become not just important, but absolutely essential. Several theoretical frameworks have emerged to address this integration, aiming to enhance system efficiency, reliability, and adaptability. This section explores key frameworks that have been proposed in the recent literature.

8.1. Theoretical Frameworks

Probabilistic approaches have gained significant attention in addressing the uncertainties inherent in power system operations. Telle et al. proposed a comprehensive probabilistic day-ahead forecasting framework for distributed integrated energy systems. Their approach combines several advanced techniques, including personalized standard load profiles (PSLPs) for electricity and heat demand as well as PV generation, quantile regression for profile refinement, and PCHIP (Piecewise Cubic Hermite Interpolating Polynomial) interpolation for approximating empirical cumulative distribution functions. A key innovation in their framework is the use of discrete convolution to determine joint probability density functions of distributed net loads. This probabilistic framework makes it easier to understand likely system states, enabling optimization algorithms to make decisions that account for possible outcomes rather than relying on point forecasts [139]. The integration of Machine Learning Operations (MLOps) with forecasting and optimization processes represents another important theoretical framework. Gürses-Tran and Monti explored this concept, emphasizing the critical need to translate forecast method quality into tangible business value within the power system wholesale market [140]. As the computational demands of integrated forecasting and optimization increase, frameworks focusing on computational efficiency have become essential. Candela Esclapez et al. addressed this challenge by proposing an innovative algorithm that optimizes the use of previously calculated forecasts to enhance computational efficiency in STLF. Their approach is particularly relevant in the European context, where prediction systems need to operate on a quarter-hour basis, significantly increasing computational requirements [84]. These frameworks are not mutually exclusive and often overlap in their approaches. For instance, the probabilistic framework proposed in [139] could potentially be integrated with the computational efficiency techniques in [84] to create a more robust and efficient system. Similarly, the MLOps approach explored in [140] could incorporate probabilistic elements to enhance its ability to handle uncertainties in the power system.

8.2. Applications of Integration

The integration of intelligent forecasting and optimization techniques has revolutionized power system operations. Recent research has demonstrated the wide-ranging applications of these integrated approaches, from STLF to comprehensive decision-making enhancement in the electric power sector. At the forefront of these applications is STLF, a critical component in managing energy operations efficiently. Candela Esclapez et al. made significant strides in this area by developing an innovative algorithm that not only improves forecasting accuracy but also reduces computational burden [84]. Building on the theme of computational efficiency, the application of ML operations in power systems has emerged as a promising avenue for integrating forecasting and optimization. Gürses-Tran and Monti explored this concept, emphasizing the importance of aligning model development with business value in the power system wholesale market [140]. The integration of intelligent forecasting and optimization extends beyond load forecasting and operational efficiency. Eikeland presented a comprehensive study showcasing a broad spectrum of applications in the electric power sector. These applications form a cohesive framework for enhancing decision-making processes across various aspects of power system operations [141]. Eikeland's research highlights several key areas in electricity demand forecasting and grid stability. ML methods have proven more accurate than traditional statistical approaches for short- and medium-term predictions, enhancing resource allocation and operational planning. Integrated gradients were used to interpret DL models, identifying variables causing grid disturbances and improving reliability. Advanced forecasting techniques, particularly for wind power, provide accurate day-ahead probabilistic forecasts, which are crucial for balancing RESs with grid stability. Additionally, optimizing Thermal Energy Grid Storage (TEGS) helps balance solar energy generation and reduce decarbonization costs, contributing to sustainability goals. These diverse applications collectively contribute to enhancing decision-making processes for decarbonization targets, integration of RESs, cost savings, and maintaining a reliable power supply. They represent a holistic approach to power system operations, where improvements in one area, such as load forecasting, can have cascading benefits across the entire system. These studies point towards a future where integrated intelligent forecasting and optimization techniques are fundamental to addressing the complex challenges of modern power systems. Future research may focus on exploring new areas where these integrated approaches can be applied to address emerging challenges in the power sector.

In recent years, since incorporating physics-informed methods is a growing research direction, the application of physics-informed methods to problems that combine forecasting and optimization in electrical power systems has gained significant attention. These approaches offer a promising solution to enhance the accuracy and reliability of decision-making processes in complex power system operations. Physics-informed methods in this context involve the integration of fundamental physical laws and engineering principles into ML models and optimization algorithms. By doing so, they create a synergy between data-driven forecasting and physics-based optimization, leading to more robust and realistic solutions [142]. One key application area is in the domain of renewable energy integration and grid management. For instance, physics-informed neural networks (PINNs) have been employed to forecast renewable energy generation while simultaneously optimizing power dispatch. These models incorporate physical constraints such as power flow equations and generation limits directly into the neural network architecture. This allows for more accurate predictions of renewable energy output while ensuring that the optimized dispatch solutions remain feasible within the physical constraints of the power system [143]. Another important application is in demand response and load management. Physics-informed methods have been used to develop integrated forecasting and optimization frameworks that predict load profiles while optimizing demand response strategies. These approaches typically combine traditional time series forecasting techniques with optimization algorithms, constrained by physical models of building energy consumption and grid dynamics. The resulting solutions not only provide accurate load forecasts but also optimal demand response strategies that respect the physical limitations of both consumer devices and the power grid [144]. The advantages of using physics-informed methods for integrated forecasting and optimization are manifold. They provide more realistic and implementable solutions by ensuring that forecasts and optimization results adhere to physical laws. They also tend to generalize better to unseen scenarios, as the incorporated physical knowledge provides a form of regularization. Additionally, these methods often require less data for training compared to purely data-driven approaches, as they leverage domain knowledge to supplement the learning process. However, challenges remain in the widespread adoption of these methods. The integration of complex physical models can increase computational complexity, and there is often a need to balance the trade-off between model accuracy and computational efficiency. Moreover, as power systems become increasingly complex with the integration of diverse energy resources and smart grid technologies, developing accurate and comprehensive physics-informed models becomes more challenging. Despite these challenges, the potential of physics-informed methods for integrated forecasting and optimization in power systems is significant. As research in this field progresses, we can expect to see more sophisticated algorithms that can handle increasingly complex power system scenarios, potentially revolutionizing how we approach planning and operation in modern electrical grids.

8.3. Challenges and Solutions of the Integration

The integration of intelligent forecasting and optimization in electrical power systems, while promising, faces several challenges. Recent research has identified these challenges and proposed innovative solutions, paving the way for more efficient and effective power system operations. One of the primary challenges in this field is the computational burden associated with forecasting, particularly in STLF. Candela Esclapez et al. highlighted this issue in the context of European power systems, where prediction systems need to operate on a quarter-hour basis. This frequent updating requirement significantly increases the computational load, potentially leading to delays in decision-making processes. To address this challenge, Candela Esclapez et al. proposed an innovative algorithm that optimizes the use of previously calculated forecasts. Their solution involves prioritizing the usage of previous forecasts to save computational resources and implementing an algorithm to identify which forecasts are more accurate. The researchers suggest that this algorithm could be applied to other forecasting systems to speed up computation times and reduce forecasting errors, offering a scalable solution to the challenge of computational efficiency in power system forecasting [84].

Another significant challenge in the field is the disconnect between model development and business value in forecasting tasks. Gürses-Tran and Monti observed that forecasters predominantly evaluate model quality using residuals and error statistics during development, often neglecting the costs or rewards associated with business applications. This oversight can lead to models that perform well in theoretical scenarios but fail to deliver tangible business value in real-world applications. To bridge this gap, the study proposed a ML operations framework for power systems. Their approach involves analyzing the wholesale power market to translate forecast quality into business value and using ProLoaF, a data-driven forecasting tool, to address near-real-time capacity procurement tasks that are challenging for traditional model-driven approaches. The results showed that ProLoaF significantly outperformed these models in terms of both RMSE and procurement cost reduction. This demonstrates the potential of a ML operations framework to create a more seamless integration between model development, deployment, and business outcomes in power system operations [140]. The challenges of computational burden and business value alignment are interconnected. As power systems become more complex and data-intensive, the need for computationally efficient models that deliver real-world value becomes increasingly critical. The solutions proposed in [84,140] address these challenges from different angles, but both contribute to the overall goal of creating more effective and efficient power system operations.

Moreover, as power systems continue to evolve with the integration of RESs and smart grid technologies, new challenges are likely to emerge. Future research may need to address issues such as the following:

- Handling increased uncertainty and variability in power generation due to RESs.
- Integrating forecasting and optimization across different time scales, from real-time operations to long-term planning.
- Developing models that can adapt to changing system conditions and learn from new data in real time.

9. Discussion and Future Direction

The landscape of intelligent forecasting and optimization in electrical power systems is undergoing a rapid and profound transformation, primarily driven by remarkable advancements in AI and ML. As modern power grids become increasingly complex and dynamic, particularly with the widespread integration of RESs, the demand for sophisticated forecasting and optimization techniques has reached unprecedented levels.

In the realm of intelligent forecasting, researchers are focusing on integrating diverse data sources for more accurate predictions and enhancing real-time predictive analytics for quicker responses to changing conditions. Improving the flexibility of forecasting models is essential to manage the complexity and variability of modern power systems. The rise of

RESs introduces unique challenges, requiring innovative methods to handle uncertainties from RESs and demand fluctuations. Developing robust algorithms to manage these uncertainties is crucial for reliable power system operations, necessitating adaptive models with probabilistic forecasts. The advent of big data analytics offers immense potential for enhancing power system forecasting and optimization. Leveraging large datasets can enhance prediction accuracy and decision-making, with advanced ML techniques providing valuable insights for better load forecasting, fault detection, and resource allocation. However, real-time data processing demands sophisticated computational infrastructure and algorithms.

Turning our attention to optimization techniques, we encounter a diverse array of approaches, each with unique strengths and applications. Classical optimization algorithms, applicable to both single-objective and multi-objective problems, remain foundational in power system optimization. These established methods provide robust frameworks for balancing objectives such as cost reduction, environmental impact mitigation, and system efficiency enhancement. This versatility makes them particularly effective in addressing the complexities of modern power systems, especially in integrating renewable energy and promoting sustainable development. Building on this foundation, heuristic and metaheuristic methods have emerged as powerful tools for single-objective and multi-objective optimization. These innovative approaches consistently demonstrate superior performance in solution quality and computational efficiency, particularly for the complex, non-linear problems characteristic of contemporary power grids. Their value is especially evident in scenarios where traditional optimization methods struggle due to problem complexity or computational demands. Taking this evolution further, hybrid optimization methods offer a versatile and potent approach to the multifaceted challenges in modern power system design and operation. By combining different optimization techniques, these methods effectively address a wide range of issues, from transformer optimization to reactive power planning and distributed resource allocation. Their superior performance in solution quality, computational efficiency, and adaptability makes them invaluable across various domains, including integrated energy systems, domestic energy management, and MG optimization.

The integration of intelligent forecasting and optimization in power system operations marks a significant advancement, enhancing STLF accuracy and overall decision-making in the electric power sector. Theoretical frameworks supporting this integration are diverse and evolving, including probabilistic approaches for handling uncertainties, ML operations frameworks aligned with business objectives, and computational efficiency techniques to meet growing processing demands. These frameworks collectively enable more effective and adaptable power system management. Emerging technologies like the IoT and blockchain have the potential to revolutionize power systems. IoT devices provide real-time data, improving situational awareness and operational efficiency, which benefits demand response programs, predictive maintenance, and system resilience. Blockchain technology ensures secure and transparent transactions within the power grid, facilitating peer-to-peer energy trading and enhancing cybersecurity. However, these advancements necessitate addressing interoperability issues and ensuring data privacy and security. Establishing common standards and protocols is crucial for seamless communication and data exchange, while robust encryption methods and stringent data governance frameworks are essential to protect sensitive information and critical infrastructure.

The future of intelligent forecasting and optimization in electrical power systems is poised for significant advancements, driven by the rapid evolution of AI, ML, and data analytics technologies. As power grids become increasingly complex and dynamic, particularly with the widespread integration of RESs, the demand for more sophisticated forecasting and optimization techniques continues to grow. One of the primary areas of focus for future research will be the development of more adaptive and robust forecasting models. These models will need to handle the increasing variability and uncertainty introduced by RESs such as wind and solar power. Researchers are likely to explore advanced DL architectures, including attention mechanisms and transformer models, which have shown promise in capturing long-term dependencies and complex patterns in time series data. Additionally, the integration of physics-informed neural networks may help bridge the gap between data-driven approaches and domain-specific knowledge, potentially leading to more accurate and interpretable forecasts. The field of optimization is expected to see advancements in multi-objective optimization techniques, as power system operators grapple with balancing multiple, often conflicting goals such as cost minimization, emissions reduction, and reliability maximization. Future research may focus on developing more efficient algorithms for solving large-scale, non-convex optimization problems in real time, potentially leveraging quantum computing technologies as they mature. Hybrid optimization approaches, combining classical methods with metaheuristics and ML, are likely to gain prominence, offering improved solution quality and computational efficiency. The integration of forecasting and optimization will likely become more seamless, with researchers developing holistic frameworks that can handle end-to-end decision-making processes in power systems. This may include the development of RL agents capable of making complex decisions in highly dynamic environments, considering both short-term operational constraints and long-term strategic objectives. Additionally, the incorporation of explainable AI techniques will be crucial to build trust and transparency in these decision-making systems, especially in critical infrastructure like power grids. As the volume and variety of data available to power system operators continue to grow, future research will need to address challenges related to big data analytics and real-time processing. This may involve the development of distributed and federated learning approaches that can leverage decentralized data sources while maintaining data privacy and security. Edge computing and IoT technologies are likely to play a significant role in enabling real-time data processing and decision-making at the grid edge. The rise of prosumers and peer-to-peer energy trading will necessitate the development of new forecasting and optimization techniques that can handle decentralized and highly dynamic market structures. This may include the use of blockchain technology for secure and transparent energy transactions, as well as the development of game-theoretic approaches to model and optimize interactions between multiple autonomous agents in the energy market. Cybersecurity will become an increasingly important consideration in the development of intelligent forecasting and optimization systems. Future research will need to focus on developing robust and resilient algorithms that can withstand potential cyber-attacks and maintain the integrity of power system operations. This may involve the integration of adversarial ML techniques to improve the robustness of forecasting models and the development of secure multi-party computation methods for distributed optimization. As climate change continues to impact weather patterns and energy demand, future forecasting models will need to adapt to these changing conditions. This may involve the development of transfer learning techniques that can quickly adapt pre-trained models to new environments or the integration of climate models into long-term energy forecasting systems. The human-AI interaction in power system operations is another area ripe for future research. As intelligent systems become more prevalent, there will be a need to develop intuitive interfaces and decision-support tools that can effectively communicate complex information to human operators and policymakers. This may involve advancements in data visualization techniques and the development of collaborative AI systems that can work seamlessly alongside human experts. Lastly, as the energy sector moves towards greater electrification of transportation and heating, future forecasting and optimization techniques will need to account for these new sources of demand and potential flexibility. This may involve the development of integrated models that can simultaneously optimize across multiple energy vectors (electricity, heat, and transportation) and time scales. In summary, the future of intelligent forecasting and optimization in electrical power systems is bright, with numerous opportunities for groundbreaking research and innovation. As these technologies continue to evolve, they will play a crucial role in enabling the transition to a more sustainable, reliable, and efficient energy future. However, realizing this potential will require interdisciplinary collaboration between researchers in power systems, computer science, data analytics, and other related fields, as well as close cooperation between academia, industry, and policymakers.

10. Conclusions

In the dynamic world of electrical engineering, accurate forecasting and optimization are the backbones that ensure efficient and reliable power delivery. Intelligent forecasting and optimization have been highlighted in this review as being critical to present-day electrical power systems. However, due to new configurations introduced by the integration of RESs and smart technologies, these complex techniques have become vital in managing intricate power grids. Forecasting methodologies, ranging from traditional statistical approaches to sophisticated ML models, have significantly enhanced the forecast for load, renewable generation, electricity price, and demand response. Meanwhile, optimization algorithms have evolved from classical to new heuristic, meta-heuristic, and hybrid ones that truly fit the highly complex and non-linear nature of contemporary power systems. Moreover, the integration of forecasting and optimization has led to the development of emerging structures that support systems' stability and efficiency. However, some challenges still exist such as increased variability of renewable sources, real-time processing of big data, and integration of multiple goals. Looking ahead, the field is poised for further advancements, potentially leveraging emerging technologies like quantum computing and RL. As the energy sector progresses towards sustainability and decentralization, these intelligent techniques will again play primary roles in achieving optimal, reliable, and green power systems at distributed levels. Future research should focus on developing more adaptive and computationally efficient methods to address the evolving complexities of modern power grids, ultimately contributing to a more sustainable and resilient energy future.

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