Using Machine Learning and various algorithms for optimizing price of electricity generation

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Abstract

The integration of renewable energy sources (RES) into power grids introduces variability, impacting electricity pricing and frequency stability. Machine Learning (ML) techniques, combined with optimization algorithms, offer effective solutions to optimize electricity generation costs and enhance grid stability. Particle Swarm Optimization (PSO) mimics swarm intelligence to find an optimal power dispatch strategy, while Bee Search Algorithm (BSA) uses foraging behaviour to enhance efficiency in unit commitment. Genetic Algorithm (GA) employs evolutionary principles to optimize energy allocation, and Simulated Annealing (SA) mimics thermal annealing to find the global optimum for economic dispatch. These methods collectively improve cost-effectiveness, mitigate frequency deviations, and enhance grid reliability. By integrating ML-based forecasting with these algorithms, utilities can dynamically adjust power generation, reducing reliance on conventional reserves and minimizing operational costs, ensuring a stable and economically viable energy supply in renewable-integrated power systems.

Keywords: Renewable Energy Integration, Machine Learning, Electricity Price Optimization, Frequency Stability, Particle Swarm Optimization (PSO), Bee Search Algorithm (BSA), Genetic Algorithm (GA), Simulated Annealing (SA)

1. Introduction

The increasing integration of renewable energy sources (RES) such as solar and wind into modern power grids presents challenges in maintaining economic efficiency and frequency stability. Unlike conventional power plants, RES are intermittent, leading to fluctuations in electricity generation and grid frequency. These fluctuations can impact electricity pricing and grid reliability, necessitating advanced optimization techniques to balance generation, demand, and cost-effectiveness.

Machine Learning (ML) and optimization algorithms offer effective solutions for addressing these challenges. Particle Swarm Optimization (PSO) and Bee Search Algorithm (BSA) use swarm intelligence to optimize power dispatch, while Genetic Algorithm (GA) and Simulated Annealing (SA) further enhances economic dispatch by preventing local optima entrapment. These algorithms improve decision-making in real-time, reducing operational costs and enhancing system resilience.

By integrating ML with these optimization techniques, utilities can forecast demand, adjust generation dynamically, and maintain grid stability. This approach ensures an economically viable and reliable energy supply while minimizing disruptions caused by RES variability.

As a novel and promising learning technology, extreme learning machine (ELM) is featured by its much faster training speed and better generalization performance over traditional learning techniques. ELM has found applications in solving many real-world engineering problems, including those in electric power systems. Maintaining frequency stability is one of the essential requirements for secure and reliable operations of a power system. Conventionally, its assessment involves solving a large set of nonlinear differential algebraic equations, which is very time-consuming and can be only carried out off-line [1].

In renewable energy source (RES) integration, frequency stability is a major concern due to the intermittent and non-dispatchable nature of sources like wind and solar power. Unlike conventional synchronous generators, RES-based inverters lack inherent inertia, reducing the system's ability to resist frequency deviations. When a sudden change in load or generation occurs, the frequency can fluctuate more rapidly, potentially leading to instability. This challenge necessitates advanced frequency regulation strategies, such as synthetic inertia from energy storage systems, demand response, and improved grid-forming inverters. Studies highlight that high-RES penetration without proper mitigation measures can lead to increased frequency deviations and reduced system resilience [2, 3].

Particle Swarm Optimization (PSO) and Bee Search Algorithm (BSA) are prominentmetaheuristic techniques applied to solve complex optimization problems in electrical engineering. PSO simulates the social behaviour of bird flocks, where particles represent potential solutions that adjust their positions based on individual and collective experiences to explore the search space efficiently. BSA, inspired by the foraging behaviour of bees, employs mechanisms such as recruitment and local search to locate optimal solutions. In recent studies, these algorithms have been utilized to determine precise switching angles in multilevel inverters, aiming to minimize harmonic distortion and enhance power quality. For instance, Kundu et al.

conducted a comparative analysis of optimization techniques, including PSO and BSA, to find optimal switching angles for a three-phase seven-level cascaded H-bridge inverter, demonstrating the effectiveness of these algorithms in achieving low total harmonic distortion [4]. Additionally, Rafat Zaman and Ghareh chopogh proposed an improved PSO integrated with BSA to solve continuous optimization problems, highlighting the hybrid algorithm's superior performance in terms of convergence speed and solution accuracy [5].

Genetic Algorithm (GA) and Simulated Annealing (SA) are widely used optimization techniques inspired by natural processes. GA mimics natural selection, employing crossover and mutation to evolve solutions over generations. SA, inspired by the annealing process in metallurgy, probabilistically accepts worse solutions to escape local optima, improving global search efficiency [6].

These algorithms have been extensively applied in engineering, machine learning, and operational research. GA excels in complex combinatorial problems. SA is particularly useful for large-scale, non-linear problems due to its ability to avoid premature convergence [7]. Comparative studies indicate that outperforms GA in continuous spaces, whereas SA is preferred for discrete and stochastic problems. Recent research focuses on hybrid approaches combining these techniques for enhanced performance in multi-objective optimization and real-world problem-solving.

2. Problem Statement

These are the real-world problems that arise in the system because of the inputs, especially due to renewable energy integration [3].

Fluctuating renewable power → causes frequency instability: Renewables are not steady like coal or gas power plants. If wind suddenly drops, supply decreases fast. This can cause an imbalance between generation and demand, which leads to grid frequency deviations. In a 50 Hz system, even a 0.2 Hz deviation is significant.

Economic Dispatch must consider cost and uncertainty: Economic Dispatch (ED) is the process of deciding how much power each generator should produce so that total generation cost is minimized. Now with renewables, it’s harder because: You can’t always predict how much solar/wind will be available. You may have to start backup generators quickly (which is costly). So, the optimization must handle uncertainty as well as economic efficiency.

Intermittency of Renewable Energy Sources (RES): The variable nature of solar and wind power leads to fluctuations in electricity generation, causing instability in the power grid.

Frequency Deviations: The integration of RES affects grid frequency stability, leading to challenges in maintaining system reliability and preventing blackouts.

Electricity Price Volatility: Due to unpredictable generation patterns, electricity prices fluctuate, making cost optimization crucial for both utilities and consumers.

Inefficient Power Dispatch: Conventional power dispatch methods struggle to balance renewable generation with demand, leading to inefficiencies and increased operational costs.

Suboptimal Economic Dispatch: Existing economic dispatch strategies may not effectively integrate RES while minimizing generation costs.

Need for Real-time Optimization: Traditional approaches fail to provide adaptive, real-time solutions to dynamically adjust generation and stabilize grid frequency.

Limited Use of Advanced Algorithms: Optimization techniques such as PSO, BSA, GA and SA are not fully utilized in current power system operations to enhance efficiency and reliability.

High Dependence on Conventional Reserves: Due to RES fluctuations, excessive reliance on fossil fuel-based reserves increases operational costs and environmental impact.

Data-Driven Decision-Making: The need for integrating Machine Learning (ML) to enhance forecasting accuracy and optimize energy generation in a smart grid environment.

Grid Resilience and Reliability: Ensuring that power systems can handle fluctuations and maintain a stable supply despite the challenges of renewable energy integration.

The increasing integration of renewable energy sources such as solar and wind into modern power systems introduces significant challenges in maintaining the balance between electricity generation and demand. The intermittent and unpredictable nature of renewable generation leads to economic inefficiencies and grid frequency instability. Additionally, the growing use of **Battery Energy Storage Systems (BESS)** demands effective **Battery Management Systems (BMS)** that can optimize charging/discharging cycles while preserving battery health.

This research aims to develop a hybrid methodology combining **Machine Learning** and **metaheuristic optimization algorithms** (such as Particle Swarm

Optimization, Differential Evolution, and Bee Search Algorithm) for forecasting renewable output and load demand, minimizing generation cost through intelligent dispatch scheduling, and Enhancing frequency stability by coordinating conventional generators, renewable sources, and battery storage via an optimized BMS.

The BMS plays a critical role by dynamically responding to frequency deviations, ensuring efficient energy storage utilization while prolonging battery life and supporting grid reliability.

3. Objectives

3.1. Optimize Load Distribution for Cost-effective Power Generation:

The primary objective is to develop an intelligent system that efficiently distributes electrical load among various power generation sources, including renewable and conventional energy. By using optimization techniques such as Particle Swarm Optimization (PSO), Bee Search Algorithm (BSA), and Machine Learning (ML) models like Extreme Learning Machine (ELM), the system aims to minimize operational costs while ensuring adequate power supply. This approach helps reduce dependency on fossil fuels and enhances the economic viability of renewable energy integration. You want to minimize the total cost of electricity generation, which includes: Fuel cost of thermal generators, Start-up/shutdown costs, Operation and maintenance costs. The optimization algorithm (PSO, BSA, GA, SA) helps determine the most cost-effective generation schedule [8].

3.2. Enhance Grid Stability and Frequency Control:

Stability means the grid operates reliably without large voltage or frequency swings. Frequency is a key indicator of stability. You must balance generation and demand in real time to keep it steady (like 50 Hz in India). Optimization + ML help by: Forecasting disturbances, Dispatching reserve power in emergencies [2].

Integrating renewable energy sources introduces fluctuations that can impact grid frequency and stability. The objective is to implement optimization algorithms such as Genetic Algorithm (GA) and Simulated Annealing (SA) to maintain frequency within safe operational limits. By dynamically adjusting power generation based on real-time demand and supply conditions, the system ensures a stable, reliable, and resilient power grid.

4. Methodology:

4.1 Data Collection & Preprocessing: This step is the foundation of any intelligent system involving machine learning and optimization. It ensures the algorithms are trained and tested on meaningful, clean, and relevant data. These are the core data types collected from the power system and used as inputs for forecasting and optimization.

Load Demand: Refers to how much electrical power consumers require over time (measured in MW). It fluctuates daily, weekly, and seasonally. Accurate historical load data helps in forecasting future demand, which is essential for dispatch and grid balancing.

Renewable Energy (solar irradiance, wind speed): This includes: Solar irradiance (sunlight intensity, usually in W/m²) → input to solar PV generation, Wind speed (m/s) → input for wind turbine power prediction. These are non-dispatchable sources and vary with weather. Historical records help ML models learn how environmental conditions affect generation.

Grid Frequency: Frequency (e.g., 50 Hz or 60 Hz) indicates the real-time balance between supply and demand. Deviations from the nominal value point to instability. Historical frequency data helps train models to predict deviations and optimize frequency control strategies [9].

Generator Cost Characteristics: Data about the fuel cost curves of conventional generators.

4.2 Optimization using different Algorithms:

At this stage, PSO / BSA / GA / SA is used to optimize the economic dispatch problem and the control parameters of frequency regulation units like PID controllers [10-12].

5. BMS System:

The implemented Battery Management System (BMS) intelligently manages energy storage based on grid demand and surplus conditions. It discharges power during energy shortfalls, prioritizing safety and preserving battery health by checking the state of charge (SOC) and temperature limits. When renewable or thermal sources generate excess power (especially during solar peak hour), it charges the BMS within safe operating limits. The system uses a tiered discharge strategy based on shortfall severity and adjusts discharge aggressiveness depending on SOC levels. This dynamic BMS logic, that we used, ensures efficient energy balancing, enhances grid stability, and maximizes renewable energy utilization while safeguarding battery lifespan [10].

6. Simulation and Result

Battery & Grid Energy Simulation: This simulation models an intelligent power distribution system for Gujarat, integrating renewables (solar, wind), conventional sources (coal, gas), and a Battery Management System (BMS). The core objective is to predict power demand, allocate resources optimally, and maintain grid frequency stability over time. Figure 4.1 shows the simulation workflow.

6.1 Simulation Workflow:

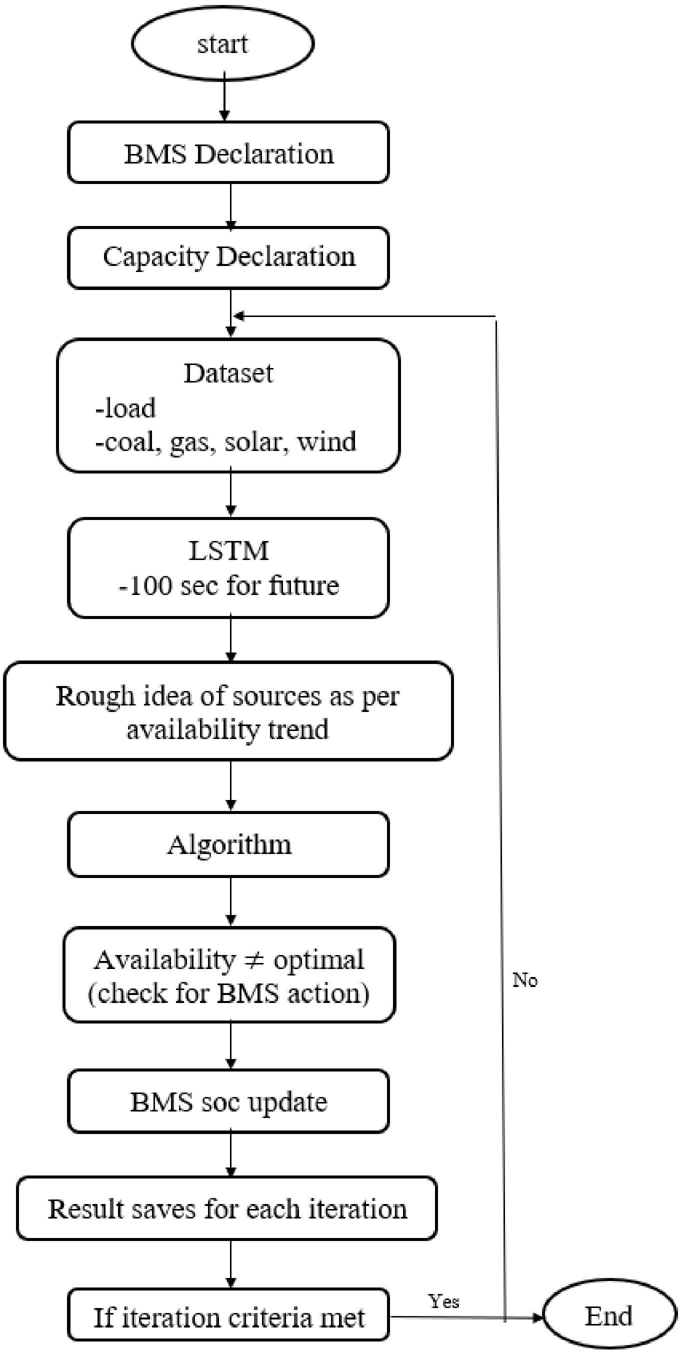


Fig. 6.1. Simulation Workflow

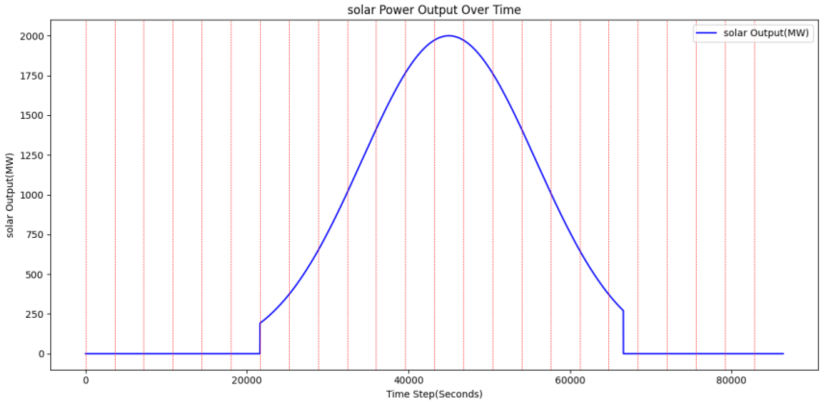


Fig. 6.2. Solar Power Output Over Time (Sample dataset for one day)

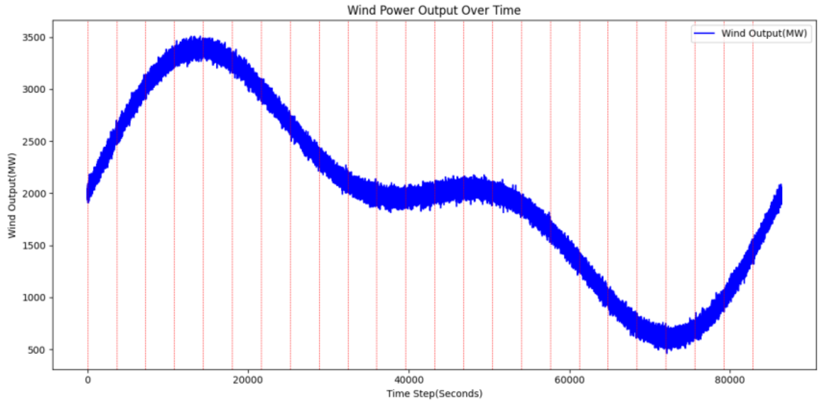


Fig. 6.3. Wind Power Output Over Time (Sample dataset for one day)

The Solar Power Output Over Time (Sample dataset for one day) and Wind Power Output Over Time (Sample dataset for one day) has been shown in Figure 6.2 and Figure 6.3 respectively.

6.2. All Algorithms Frequency and Cost Graphs:

Table 6.2.1. Observations of all the Algorithms graphs

Algorithm	Graph Type	Observation
PSO (Particle Swarm Optimization)	Frequency Over Time (Fig. 6.4)	The frequency deviation is relatively low with minimal oscillations. The system stabilizes quickly after load variations, showing strong frequency control.
	Total Cost Over Time (Fig. 6.5)	Shows a gradually declining cost trend with fluctuations initially but stabilizes after optimization. Indicates good

		economic dispatch over time.
BSA (Bee Search Algorithm)	Frequency Over Time (Fig. 6.6)	Frequency deviations are minimal and follow a smooth trajectory. The algorithm effectively keeps the frequency within tight bounds even during demand changes.
	Total Cost Over Time (Fig. 6.7)	Maintains a stable and slightly lower cost compared to PSO in early cycles, indicating efficient utilization of renewables.
GA (Genetic Algorithm)	Frequency Over Time (Fig. 6.8)	The frequency has slightly more variance than PSO and BSA. However, deviations remain within acceptable limits. Shows moderate stability.
	Total Cost Over Time (Fig. 6.9)	Cost optimization is effective but shows more irregularity in convergence. Converges slower than PSO/BSA.
SA (Simulated Annealing)	Frequency Over Time (Fig. 6.10)	Frequency shows a relatively higher fluctuation in the early phase but improves gradually. Indicates slow convergence in grid stabilization.
	Total Cost Over Time (Fig. 6.11)	The cost reduction is steady but slow. Less efficient in reaching optimal cost compared to PSO and BSA, but avoids getting trapped in local minima.

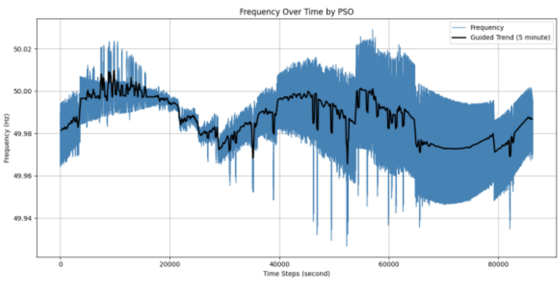


Fig. 6.4. Frequency over Time by PSO

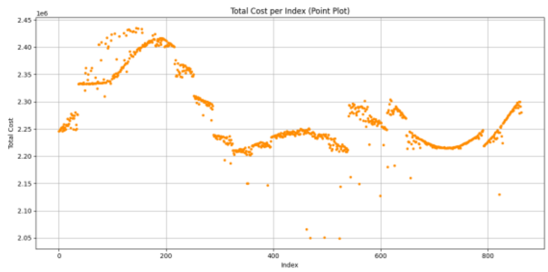
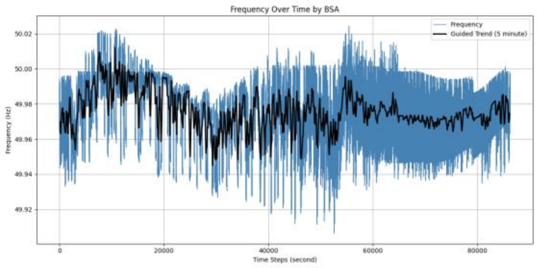


Fig. 6.5. Total Cost over Time with PSO



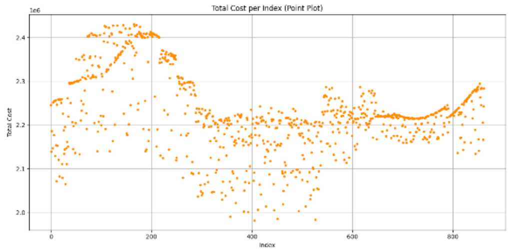
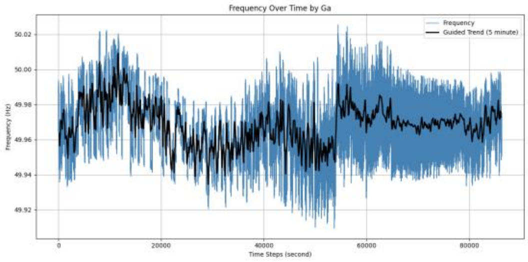


Fig. 6.6. Frequency over Time by BSA **Fig. 6.7. Total Cost over Time with BSA**



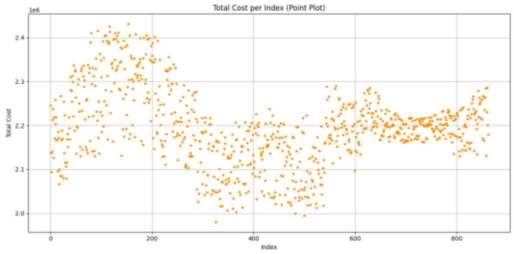
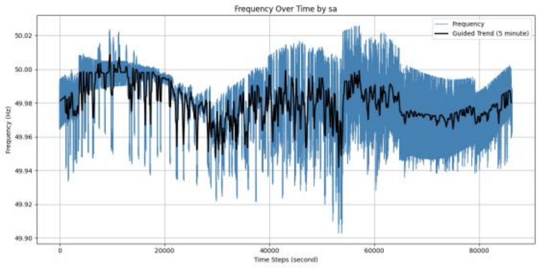


Fig. 6.8. Frequency over Time by GA **Fig. 6.9. Total Cost over Time with GA**



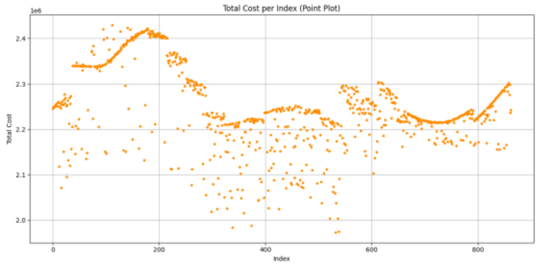


Fig. 6.10. Frequency over Time by SA **Fig. 6.11. Total Cost over Time with SA**

7. Conclusion and Future Scope

7.1 Conclusion

The integration of renewable energy sources into the power grid presents both opportunities and challenges. While it enhances sustainability and reduces carbon emissions, it introduces variability and uncertainty in generation, which affects electricity pricing and grid frequency stability. This study demonstrates that machine learning (ML) techniques especially models like LSTM for load forecasting and optimization algorithms like Particle Swarm Optimization (PSO) can effectively manage these challenges.

The ML-based system successfully predicts electricity demand and supply patterns with high accuracy, allowing for dynamic pricing strategies that minimize generation costs. Moreover, real-time grid frequency stabilization is achievable through intelligent control of generation sources and energy storage systems, guided by data-driven decisions. These models can adapt to changing conditions and provide faster response times than traditional methods, making them highly suitable for modern grid management.

7.2 Future Scope

1. Integration with Real-Time Smart Grid Data: Future work can focus on deploying these ML models in real-time environments using IoT-based smart meters and grid sensors, enabling more adaptive and autonomous energy systems.
2. Incorporation of Advanced ML/DL Models: Reinforcement Learning, Deep Q-Networks (DQN), and Transformer-based models could be explored for even more precise control and prediction capabilities.
3. Scalability to Larger Grids: Extending the model to national or multi-regional grid levels, considering market dynamics, grid topologies, and distributed energy resources (DERs), will be valuable.
4. Hybrid Optimization Approaches: Combining ML with other heuristic or metaheuristic algorithms (e.g., Genetic Algorithm, Differential Evolution, or Artificial Bee Colony) can improve the convergence and robustness of optimization results.

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