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Optimal Scheduling of Integrated Distributed Generation with Battery Energy Storage System

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Abstract: As the global shift toward cleaner energy accelerates, the adoption of Hybrid Renewable Energy Systems (HRES) which integrate solar photovoltaics (PV), wind power, thermal generators, and battery energy storage systems (BESS) has become increasingly prevalent. One of the foremost challenges in managing these systems lies in optimizing their operation amid variable weather patterns and fluctuating energy demand, particularly across different seasons. This review provides an in-depth exploration of optimal power flow (OPF) strategies for HRES, focusing on advanced optimization techniques such as Mixed-Integer Linear Programming (MILP) and Particle Swarm Optimization (PSO). The study also highlights the complementary role of demand response (DR) in improving system adaptability and cost-effectiveness. The operational value of BESS is underscored in applications like energy arbitrage, peak demand management, and renewable energy stabilization during periods of intermittency. Furthermore, the review discusses the application of simulation platforms like MATLAB/Simulink to model and analyze real-time control scenarios. Results from reviewed studies demonstrate that integrating intelligent control algorithms for coordinating renewable and conventional sources significantly enhances system performance, improves reliability, and lowers operational expenses.

Index Terms **-** Hybrid Renewable Energy System, Battery Energy Storage System, Optimal Power Flow, Mixed-Integer Linear Programming, Particle Swarm Optimization, Seasonal Variation.

I. INTRODUCTION

Managing energy demand is becoming increasingly crucial, as current decisions will significantly influence the sustainability of future energy systems. Today's energy strategies must focus on the efficient and optimized use of all available resources. This necessitates a thorough understanding of both traditional and renewable energy types, including their environmental impacts, reliability, and long-term availability. With recent shifts in global climate patterns, there is growing momentum toward adopting renewable energy technologies. These sources such as solar, wind, and other naturally replenished systems—are now favored for their sustainability, minimal environmental footprint, and clean operation. To support sustainable growth and energy security, countries must adopt integrated energy management practices that combine resource efficiency with environmental responsibility [1].

The growing urgency to reduce carbon emissions and build resilient energy infrastructures has accelerated the adoption of hybrid energy systems that blend renewable and conventional sources. Among these, Hybrid Renewable Energy Systems (HRES) have emerged as a practical solution, offering a balanced approach by utilizing solar, wind, thermal, and storage technologies. Their integrated structure allows for enhanced reliability and flexibility, especially in the face of variable weather conditions and fluctuating demand. By minimizing dependence on fossil fuels and supporting grid stability, HRES not only promote environmental sustainability but also support long-term energy planning goals. The combination of generation diversity and intelligent control strategies positions these systems as a cornerstone for future energy frameworks. [2], [3].

One of the foremost challenges in the efficient operation of Hybrid Renewable Energy Systems (HRES) lies in formulating optimal scheduling strategies that account for year-round variability. Seasonal shifts significantly affect the performance of renewable energy sources, as solar output is typically highest during longer summer days, while wind energy potential often increases in winter or during transitional weather periods. These fluctuations, driven by geographic and climatic influences, necessitate the use of advanced control methods capable of adapting energy dispatch schedules in real time. Achieving an effective balance between resource availability and consumer demand throughout the year requires intelligent planning that is responsive to both environmental conditions and dynamic load behaviors. [4].

Addressing the integration challenges of hybrid renewable energy systems, researchers have introduced advanced strategies combining improved Optimal Power Flow (OPF) models with comprehensive long-term scheduling methodologies. These solutions ensure seamless coordination among solar photovoltaic systems, wind energy units, thermal power plants, and battery energy storage. Within this framework, Battery Energy Storage Systems (BESS) are essential for grid flexibility, storing surplus electricity during periods of low consumption or high renewable output, and releasing it during energy deficits. This function supports grid stability, reduces peak load stress, and enhances overall system resilience. Meanwhile, thermal power plants serve as dependable backup sources, compensating for the intermittent nature of renewables and maintaining continuous energy supply and voltage quality. [5].

Advanced optimization techniques have been employed to enhance the operational efficiency of hybrid energy systems. Among these, Mixed-Integer Linear Programming (MILP) stands out for effectively handling binary variables and rigid operational constraints, making it particularly suitable for discrete and long-term scheduling applications. On the other hand, Particle Swarm Optimization (PSO) is widely recognized for its flexibility and strong performance in addressing complex, non-linear, and multi-objective scenarios. Moreover, the incorporation of demand response (DR) strategies helps synchronize energy consumption with generation availability, contributing to lower operational expenditures and increased system adaptability [8].

This study presents a comprehensive analysis of cutting-edge approaches for optimizing the annual scheduling of Hybrid Renewable Energy Systems (HRES). Emphasis is placed on examining the influence of seasonal variations in energy resources, the integration of demand-side management strategies, and a performance comparison between Mixed-Integer Linear Programming (MILP) and Particle Swarm Optimization (PSO) methods. Furthermore, the review highlights the use of modeling platforms such as MATLAB/Simulink, which offer dynamic simulation environments for assessing system performance and validating optimization techniques under practical, real-world scenarios.

II. System Components

Hybrid energy systems integrate multiple renewable and conventional power sources, typically including photovoltaic arrays, wind energy converters, and thermally driven generators, all supported by battery-based energy storage. This combination enables a more stable power supply and enhances the contribution of clean energy. These systems can function in parallel with the electrical grid. However, because renewable resource availability varies with the seasons, the system's operational approach must be dynamically adjusted throughout the year to ensure optimal functionality and energy balance.

2.1 Solar Energy System

Solar power stems from the immense energy continuously emitted by the sun, making it the most abundant and eco-friendly energy resource available. Among renewable technologies, solar energy stands out due to its wide availability, low environmental impact, and decreasing costs. Through photovoltaic (PV) technology, sunlight can be transformed directly into electrical energy [9]. Historically, PV systems have served as a practical power solution for residential, off-grid, and medium-scale uses, and have increasingly been adopted in commercial applications. The large-scale deployment of solar infrastructure in the 1980s played a key role in reducing electricity generation costs, leading to a surge in grid-connected PV systems. Presently, solar energy contributes around 5% to the global electricity supply [10]. Solar energy production is typically highest in summer due to extended daylight and clearer skies. In contrast, winter months see a significant drop in solar yield, which can challenge energy supply stability unless managed with appropriate planning.

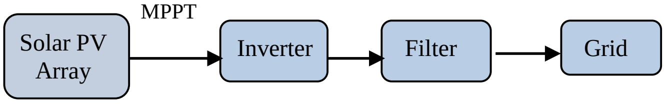

Fig. 1. Block Diagram of Solar PV system

2.2 Wind Energy Conservation System

Systems designed to capture wind power known as Wind Energy Conversion Systems (WECS) convert moving air into electricity that can be used in power networks [11]. Each system generally includes three essential parts: spinning blades (the rotor), an electricity-generating component, and circuitry that manages power flow. To connect to the electric grid, the generated power must be adapted to meet specific voltage and frequency levels. This adaptation is achieved through the use of specialized electronic devices, like inverters and rectifiers [12]. Although the core idea behind wind energy is relatively simple capturing motion to produce electricity, the engineering behind turbines is often highly advanced [13]. Modern wind turbines are usually built with a horizontal-axis setup, featuring a pair or trio of blades, a mechanical assembly with gears, and a generator, all mounted on a tall supporting tower. Wind strength isn't consistent year-round; it shifts depending on geography and season. Some areas see stronger winds in the colder months or during transitional periods like spring and fall, while others experience better wind conditions in summer. Because of these fluctuations, wind power systems must be designed to adapt their output accordingly.

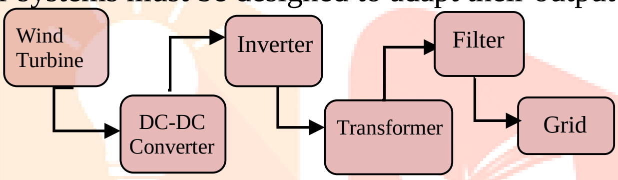

Fig. 2. Block Diagram of W.E.C.S

2.3 Thermal Power System

Steam acts as the primary driving force in thermal power generation. Water, typically sourced externally, is first processed through a treatment system where it undergoes purification using specific chemicals. These additives help minimize corrosion and prevent the accumulation of unwanted substances within the system's pipelines. Once treated, the water is directed to the boiler and superheater, where it is converted into high-temperature, high-pressure steam. This steam then drives a turbine, which is mechanically connected to an electrical generator, converting thermal energy into electricity. After energy extraction, the steam is cooled and condensed back into water via a condenser linked to a cooling tower, and is then cycled back into the system. The plant's efficiency and output can vary based on the type of fuel employed, with coal and kerosene being among the most commonly used. Because thermal units can be dispatched on demand, they play a vital role in balancing the variability of renewable sources. They are especially important during periods of low solar irradiance, calm wind conditions, or increased winter demand.

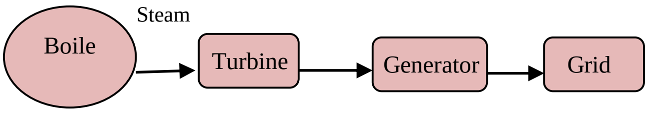

Fig. 3. Block Diagram of Thermal Power Plant

2.4 Battery Energy Storage System

In modern decentralized power architectures, energy storage especially battery banks serve as the system's balancing mechanism, absorbing the natural ebb and flow of solar and wind generation [14]. These systems operate like energy reservoirs, filling up when production exceeds needs and releasing energy back into the system during times of shortfall [15]. Instead of letting surplus renewable energy go to waste, these smart storage units stockpile it for later use, especially when sunlight fades or wind calms. This dynamic response not only cushions the grid against instability but also enables smarter consumption strategies flattening high-demand periods and redistributing load across more favorable times.

III. Seasonal Variation and Its Impact on HRES

Seasonal dynamics play a pivotal role in shaping how Hybrid Renewable Energy Systems (HRES) perform and are managed. These temporal shifts not only influence how much energy can be harvested from nature but also alter consumption behavior, depending on environmental and societal factors. To keep systems running efficiently throughout the year, energy strategies must be agile, responsive, and season-aware.

3.1 Seasonal Variability of Renewable and Thermal Sources

3.1.1 Solar Energy

The effectiveness of solar installations is strongly influenced by seasonal sunlight patterns. Longer, sunnier days in summer often lead to heightened energy yields from photovoltaic (PV) modules. On the flip side, during winter, reduced daylight hours and persistent cloud coverage can significantly hamper solar performance. In some northern regions, the disparity is dramatic PV systems may deliver up to 70% less electricity in winter than during peak summer months, underscoring the need for seasonal system planning.

3.1.2 Wind Energy

Wind resources also vary with the seasons but in a more complex, location-specific manner. In many temperate and coastal areas, wind speeds tend to be stronger in winter due to larger differences in atmospheric pressure, offering a valuable complement to reduced solar availability. However, because wind behavior is highly unpredictable and varies widely between regions, accurate local data is necessary for dependable system modeling and forecasting.

3.1.3 Thermal Energy

Thermal units serve as dependable backups, stepping in when renewable output is insufficient. Their flexibility makes them especially useful during cold seasons or extreme weather, when energy demand rises and solar or wind contributions are limited. Nevertheless, frequent use of thermal sources is discouraged due to their fuel costs and environmental footprint, making it crucial to schedule their operation as efficiently as possible.

3.2 Influence of Seasonal Load Patterns

Energy consumption patterns vary significantly with the seasons, influenced by regional climate conditions. In colder environments, winter demand tends to rise due to the increased use of heating systems, extended lighting needs from reduced daylight hours, and, in some areas, the operation of snow-clearing or snowmelt infrastructure. On the other hand, in hotter climates, energy usage surges during summer months as air conditioning and cooling appliances operate at full capacity. These seasonal dynamics lead to fluctuating demand profiles marked by pronounced peaks during extreme temperatures. To ensure system efficiency and reliability, energy management strategies must be responsive to these changes. Therefore, incorporating precise load forecasting into energy scheduling models is essential for optimizing system performance throughout the year.

3.3 Challenges in Supply-Demand Balance

A persistent issue in renewable-based energy systems is the seasonal disconnect between electricity supply and consumption patterns. Solar resources are most abundant in the summer, a period with relatively low heating requirements. In contrast, wind power tends to peak in the colder months, yet this may not coincide with the timing or intensity of heating demand, particularly in the evenings. Bridging this temporal divide requires a multi-faceted approach, deploying large-scale storage systems, such as batteries, to retain surplus energy for use during periods of higher demand. Keeping dispatchable energy units, like thermal generators, available to support the grid when renewable output falls short. Engaging end-users through demand-side flexibility programs that shift consumption to periods of higher renewable availability.

As renewable penetration increases, coordinating generation, storage, and consumption becomes more complex, demanding innovative strategies to ensure reliable power delivery.

3.4 Need for Seasonal Forecasting and Adaptive Scheduling

Effectively managing the fluctuations in renewable energy generation and consumption requires robust seasonal forecasting methods. These predictive tools estimate key variables such as solar irradiance, wind velocity, and temperature-sensitive load trends. Leveraging such forecasts allows for the development of flexible scheduling frameworks, which can be optimized using advanced techniques like Mixed-Integer Linear Programming (MILP) and Particle Swarm Optimization (PSO). These approaches facilitate dynamic control over generation dispatch, energy storage operations, and demand-side management in response to seasonal trends. By incorporating real-time weather data, past consumption records, and intelligent predictive models often powered by machine learning these systems can significantly improve forecasting accuracy and operational reliability. In the absence of such adaptive mechanisms, energy systems risk inefficiencies such as underuse of renewable sources or excessive reliance on conventional power generation.

IV. Optimization Techniques

Running Hybrid Renewable Energy Systems (HRES) efficiently demands intelligent control strategies that can navigate technical limitations and unpredictable inputs. To meet this challenge, advanced optimization algorithms play a critical role. Two notable examples are Particle Swarm Optimization (PSO), known for its adaptability and efficiency in navigating complex solution spaces, and Mixed-Integer Linear Programming (MILP), valued for its precision in decision-making under strict system constraints. While PSO mimics natural behavior to explore a wide range of possible outcomes, MILP provides exact solutions for well-defined, structured problems. Their differing capabilities make them highly effective either separately or in tandem for optimizing hybrid systems under varying operational conditions.

4.1 Mixed-Integer Linear Programming (MILP)

Mixed-Integer Linear Programming (MILP) serves as a structured decision-making tool tailored for energy systems that must juggle both measurable quantities like output levels or storage capacities and yes/no choices, such as activating specific units. It translates scheduling tasks into a logical framework governed by strict operational guidelines, including how fast generators can ramp up or down, how long they must stay on or off once switched, and the need to keep supply and demand balanced at all times. MILP is particularly well-suited to environments where operations follow rigid rules, such as dispatching thermal plants or enforcing battery safety limits. Its major advantage is the ability to consistently find the best possible solution within these predefined constraints, which is why it's widely used for forward-looking planning. However, this precision comes at a cost MILP assumes a simplified, linear view of system behavior, which may not reflect real-world complexities, and its solution time can grow rapidly as systems become larger or more detailed. This makes it less ideal for quick, real-time decisions in expansive hybrid setups.

4.2 Particle Swarm Optimization (PSO)

Inspired by the behavior of flocks of birds and schools of fish, Particle Swarm Optimization (PSO) is a metaheuristic approach designed to tackle intricate optimization challenges. Unlike traditional methods such as MILP, which may struggle with problems that are non-linear, multi-dimensional, or have complex constraints, PSO uses a population of solution candidates referred to as particles that navigate the solution space. Each particle adjusts its position based on its past performance and the best-performing solutions found by the group, creating a dynamic process of collective learning. This collaborative exploration allows PSO to quickly converge to optimal or near-optimal solutions, making it highly effective in unpredictable and constantly changing environments. PSO's ability to work without the need for linear assumptions or derivative-based methods makes it particularly valuable for real-time decision-making and for handling systems with intricate, time-varying constraints. Moreover, PSO's ease of implementation and adaptability make it an appealing option for operational scheduling in distributed energy systems, smart grids, and energy management in homes or microgrids. MILP excels in environments that require detailed planning with stringent rules, offering high precision and ensuring that strict operational constraints are met. In contrast, PSO is well-suited for situations where flexibility, rapid response, and the ability to handle complex, unpredictable factors are paramount. Future work is increasingly focusing on integrating MILP and PSO in hybrid algorithms, using MILP for foundational scheduling and PSO for real-time adjustments, thereby combining the strengths of both approaches.

V. System Workflow

5.1 Seasonal Forecasting and Data Collection

The model initiates by examining past weather trends and annual electricity consumption patterns. Key parameters such as solar irradiance, wind velocity distributions, and temperature-related demand shifts are analyzed in detail. These variables play a vital role in forecasting both seasonal energy resource availability and the corresponding load demands. For instance, solar output typically reaches its maximum during the summer, whereas wind energy generation may be more substantial in the winter months, depending on the specific characteristics of the location.

5.2 Dynamic Resource Allocation

Using the projected seasonal trends, the system orchestrates the dispatch of power from solar photovoltaic panels, wind turbines, and thermal units, while also optimizing the operation of the battery energy storage system (BESS). In the summer months, the model prioritizes solar generation, taking advantage of extended daylight hours and high irradiance levels. Conversely, during the winter season when solar availability declines wind energy and thermal power sources become the primary contributors. The BESS is strategically employed to absorb surplus energy and discharge it during high-demand periods or when renewable inputs fall short.

5.3 Optimization with MILP and PSO

The model employs a dual-layered optimization framework to optimize energy generation and consumption effectively. For strategic, long-term, and day-ahead planning, Mixed-Integer Linear Programming (MILP) is utilized. This technique addresses key operational constraints, including generator startup and shutdown states, mandatory minimum on/off durations, ramp rate limitations, and storage capacity bounds. MILP enables cost-efficient system scheduling while maintaining compliance with technical and operational requirements. Complementing this, Particle Swarm Optimization (PSO) is deployed for real-time, adaptive system control. PSO is well-suited for handling the system's nonlinear and uncertain characteristics, such as intermittent wind energy, dynamic battery charge-discharge behavior, and unpredictable load variations. By combining MILP for high-level scheduling with PSO for responsive control, the model achieves a balance between optimal long-term planning and agile adaptation to real-time conditions across all seasons.

5.4 Demand Response Integration

To enhance system adaptability and maintain grid reliability, the model integrates seasonal Demand Response (DR) strategies. Through Price-Based DR, consumer load is shifted to periods with lower electricity prices, such as late-night hours or midday intervals when solar output is abundant. Meanwhile, Incentive-Based DR motivates users to curtail energy usage during peak load times or grid stress events by offering financial compensation. These demand-side management techniques play a vital role in aligning energy consumption with available supply, minimizing operational expenses, and addressing seasonal demand challenges particularly during high-load seasons like summer, due to air conditioning, and winter, due to heating demands.

5.5 Yearly Optimization Outcomes

Implementing a seasonally adaptive scheduling framework throughout the year enables the model to deliver several key benefits. Firstly, it maximizes the efficiency of energy use by prioritizing renewable sources and reducing dependence on conventional fossil-fueled generation. Secondly, operational expenditures are lowered through optimized resource allocation and proactive demand-side strategies. Thirdly, the model strengthens energy supply reliability by anticipating seasonal fluctuations and adjusting operations accordingly to maintain a consistent balance between supply and demand. Additionally, overall system resilience is significantly improved through the incorporation of Battery Energy Storage Systems (BESS) and Particle Swarm Optimization (PSO), which together offer real-time responsiveness in the face of unpredictability. This holistic, seasonally-aware approach ensures that the hybrid renewable energy setup functions at optimal performance year-round, effectively aligning generation with consumption trends and mitigating the variability inherent in renewable resources.

VI. RESULTS AND DISCUSSION

A seasonally adaptive control strategy is proposed to enhance the performance and cost-efficiency of Hybrid Renewable Energy Systems (HRES), combining a rule-based long-term planning engine with a real-time controller based on swarm intelligence. Mixed-Integer Linear Programming (MILP) establishes optimal energy dispatch schedules within technical and operational limits, while Particle Swarm Optimization (PSO) dynamically adapts system responses to short-term variability. Simulations conducted over an annual cycle demonstrate that this dual-layered framework improves renewable energy penetration, reduces operational costs, and enhances supply-demand balancing by forecasting and adjusting to seasonal fluctuations in both generation and load. To further strengthen system resilience, targeted load-shifting incentives and a strategically sized Battery Energy Storage System (BESS) are incorporated. Instead of oversizing storage to cover the full load thereby avoiding excessive capital investment the BESS is optimized to support critical operations during periods of low renewable output or grid outages. An intelligent energy management system (EMS) oversees battery utilization, prioritizing essential loads while automatically shedding non-critical ones to preserve stored energy. This integrated approach minimizes infrastructure costs, reduces asset degradation, and ensures dependable system operation under varying and uncertain conditions.

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