Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 4, Issue 1, 2026

INTELLIGENT ENERGY MANAGEMENT IN SOLAR-POWERED SMART GRIDS: A HEURISTIC–METAHEURISTIC ALGORITHMIC APPROACH FOR COST-EFFECTIVE, RELIABLE, AND SUSTAINABLE ENERGY OPTIMIZATION

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DOI: https://doi.org/10.5281/zenodo.18409958

Keywords
Smart Grids; Solar Energy Integration; Intelligent Energy Management; Heuristic Algorithms; Metaheuristic Optimization; Renewable Utilization; Sustainable Power Systems.

Article History
Received: 04 December 2025
Accepted: 14 January 2026
Published: 29 January 2026

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Abstract
The rapid transition toward renewable energy has positioned solar power as a cornerstone of modern smart grids; however, the inherent intermittency of solar energy, combined with the increasing complexity of energy demand patterns, presents significant challenges for cost-effective, reliable, and sustainable grid operation. Traditional optimization methods often struggle to handle the nonlinear, dynamic, and multi-objective nature of energy management in solar-integrated smart grids. To address these limitations, this study introduces an intelligent energy management framework based on a heuristic–metaheuristic algorithmic approach for optimizing energy scheduling, power flow, and resource allocation in solar-powered smart grids. The proposed methodology leverages the adaptability and robustness of heuristic algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), while integrating them with metaheuristic enhancements to improve convergence speed, solution diversity, and scalability under large-scale grid scenarios. The optimization model incorporates solar photovoltaic (PV) generation, energy storage systems, and load demand forecasting, with an objective function that simultaneously minimizes operational costs, maximizes renewable energy utilization, and enhances system reliability. Constraints related to power balance, storage limits, and grid stability are embedded to ensure technical feasibility and real-world applicability. Simulation experiments were conducted using MATLAB/Simulink and Python on benchmark load and solar irradiance datasets, representing realistic smart grid scenarios. Results demonstrate that the heuristic–metaheuristic framework outperforms conventional optimization

methods, achieving up to 18–25% reduction in energy costs, 12–20% improvement in renewable penetration, and significant gains in voltage stability and loss minimization. Comparative analysis reveals that hybrid heuristic–metaheuristic algorithms consistently deliver superior performance in balancing multiple objectives compared to standalone techniques. The findings confirm that the integration of heuristic and metaheuristic strategies provides a promising pathway for achieving intelligent, cost-effective, and sustainable energy management in solar-powered smart grids. Beyond cost savings and reliability improvements, this approach facilitates greater alignment with global sustainability goals by accelerating the transition toward renewable-based energy systems. Future work will extend the framework to incorporate demand-side response, electric vehicle integration, and real-time adaptive control using AI-enhanced predictive algorithms.

INTRODUCTION

The ongoing global transition toward sustainable and low-carbon energy systems has significantly transformed the planning and operation of modern power grids. Escalating environmental concerns, increasing electricity demand, and the depletion of fossil fuel resources have accelerated the deployment of renewable energy technologies worldwide. Among these, solar photovoltaic (PV) systems have gained remarkable prominence due to their modularity, declining capital costs, and wide geographical availability. Consequently, solar energy has become a foundational element of smart grid architectures, supporting decentralized generation, bidirectional power flow, and enhanced system flexibility [1]. Despite these advantages, the large-scale integration of solar PV into smart grids introduces substantial operational and control challenges that necessitate advanced and intelligent energy management solutions. A key challenge associated with solar-powered smart grids arises from the inherent intermittency and uncertainty of solar generation. Variations in solar irradiance caused by weather fluctuations, seasonal changes, and diurnal cycles result in unpredictable power output, which complicates the balance between electricity supply and demand. At the same time, demand-side dynamics have become increasingly complex due to the proliferation of distributed energy resources, smart appliances, and electrified transportation systems. These factors collectively create a highly nonlinear, time-varying, and stochastic operating environment in which maintaining economic efficiency, system reliability, voltage stability, and power quality becomes increasingly difficult. Smart grid technologies have been developed to address such complexities through the integration of advanced sensing, communication, and control infrastructures. These technologies enable real-time monitoring, decentralized decision-making, and adaptive control of distributed energy resources [2]. However, the effectiveness of smart grids depends critically on the underlying energy management and optimization strategies that coordinate generation, storage, and consumption. Energy management in solar-integrated smart grids is inherently a multi-objective optimization problem, requiring the simultaneous consideration of cost minimization, renewable energy maximization, loss reduction, and reliability enhancement under strict technical and operational constraints. Conventional optimization techniques, including linear programming, mixed-integer linear programming, and deterministic scheduling methods, have been extensively applied to energy management problems. While these approaches offer strong mathematical foundations and deterministic convergence properties, they often rely on simplifying assumptions such as linear system behavior, perfect information, or static operating conditions. In realistic smart grid environments characterized by nonlinear dynamics, uncertain renewable generation, and high-dimensional decision variables, such assumptions frequently limit the applicability and performance of traditional methods. As a result, these techniques may suffer from scalability issues, excessive computational burden, or reduced adaptability to real-time operational requirements [3]. To address these limitations, heuristic and metaheuristic optimization algorithms have attracted growing interest in smart grid research. Nature-inspired techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) offer flexible search mechanisms capable of exploring complex and nonlinear solution spaces without requiring gradient information or convexity assumptions. These algorithms have demonstrated considerable potential in solving energy scheduling, power flow optimization, and storage management problems under uncertainty. Nevertheless, when employed as standalone methods, heuristic algorithms may encounter challenges such as premature convergence, slow convergence rates, or insufficient solution diversity, particularly in large-scale or highly constrained multi-objective problems. Recent advancements in the literature have therefore emphasized the development of hybrid heuristic–metaheuristic approaches that combine complementary optimization strategies to enhance exploration–exploitation balance and overall solution quality. Although such hybridization has shown promising results, existing studies often focus on isolated components of the smart grid, such as generation scheduling or storage dispatch, rather than providing a holistic energy management framework. Moreover, comprehensive comparative evaluations of multiple heuristic–metaheuristic algorithms under realistic solar variability and load uncertainty remain limited, highlighting a clear gap in current research. To clearly contextualize this gap, Table 1 provides a comparative overview of commonly used optimization approaches for energy management in solar-powered smart grids, highlighting their strengths, limitations, and unresolved challenges.

Table 1: Comparison of Optimization Approaches for Energy Management in Solar-Powered Smart Grids

Optimization Approach	**Key Strengths**	**Major Limitations**	**Identified Gap**
Traditional Optimization (LP, MILP)	Deterministic solutions, strong mathematical structure	Limited scalability, poor handling of uncertainty and nonlinearity	Not suitable for dynamic, large-scale smart grids
Standalone Heuristic Algorithms (GA, PSO, ACO)	Flexible search, effective for nonlinear problems	Premature convergence, limited diversity	Insufficient robustness for multi-objective systems
Metaheuristic-Enhanced Methods	Improved convergence behavior	Often problem-specific	Lack of generalized smart grid frameworks
Hybrid Heuristic–Metaheuristic Approaches	Balanced exploration and exploitation	Frequently subsystem-focused	Limited holistic energy management models
Proposed Intelligent Framework	Multi-objective, scalable, solar-integrated	–	Comprehensive optimization under realistic constraints

Motivated by these limitations, this study proposes an intelligent energy management framework based on a hybrid heuristic–metaheuristic algorithmic approach for solar-powered smart grids. The framework integrates solar PV generation, energy storage systems, and load demand forecasting into a unified optimization structure capable of addressing economic, technical, and sustainability objectives simultaneously. A multi-objective formulation is developed to minimize operational costs, maximize renewable energy utilization, and enhance system reliability while explicitly enforcing power balance, storage capacity, voltage stability, and network operational constraints. By enhancing GA, PSO, and ACO through metaheuristic mechanisms, the proposed approach improves convergence speed, solution diversity, and scalability in complex smart grid environments. Extensive simulation studies conducted using MATLAB/Simulink and Python under realistic solar irradiance and load profiles demonstrate the effectiveness of the proposed framework. The results confirm its ability to achieve superior trade-offs among competing objectives compared to conventional and standalone optimization techniques, thereby providing a robust and scalable solution for intelligent energy management in solar-powered smart grids.

1- Energy Management in Smart Grids:

Energy management constitutes a fundamental operational layer of smart grids, playing a critical role in coordinating electricity generation, energy storage, and consumption to ensure efficient, reliable, and secure power system operation. In its earliest form, smart grid energy management relied predominantly on centralized control architectures, where system operators performed deterministic scheduling and dispatch decisions based on forecasted demand, predefined generation capacities, and static operational constraints. These approaches were effective for conventional power systems with predictable generation profiles and limited variability but exhibited reduced flexibility when confronted with dynamic and distributed energy environments. With the progressive deployment of advanced metering infrastructure, intelligent sensors, and high-speed communication networks, energy management systems have evolved toward more decentralized and adaptive architectures. Modern smart grids enable bidirectional power flows, active consumer participation, and real-time information exchange across multiple system layers. This evolution has fundamentally changed the role of energy management from static scheduling to continuous, data-driven decision-making [4]. Distributed energy resources, including renewable generation units and energy storage systems, are now actively coordinated to enhance grid resilience, operational efficiency, and flexibility. Recent research increasingly emphasizes intelligent energy management systems capable of responding dynamically to real-time grid conditions. These systems integrate data acquisition, state estimation, forecasting, and optimization modules to manage uncertainty and variability introduced by renewable energy sources. In particular, the high penetration of intermittent renewables such as solar and wind energy has intensified the complexity of energy management tasks [5]. Fluctuations in renewable generation can lead to power imbalances, voltage deviations, and increased system losses if not properly managed. As a result, energy management strategies must simultaneously address short-term operational stability and long-term economic and environmental objectives. A defining characteristic of smart grid energy management is its inherently multi-objective nature. Operators must balance cost minimization with system reliability, power quality, and sustainability goals. Reducing operational costs through optimal scheduling must be carefully aligned with maintaining acceptable voltage levels, minimizing power losses, and maximizing renewable energy utilization. Additionally, regulatory requirements and environmental considerations further constrain decision-making, necessitating flexible and intelligent optimization frameworks capable of handling conflicting objectives under uncertainty. To address these challenges, a wide range of energy management strategies have been proposed in the literature, varying in terms of control structure, optimization techniques, and system scope [6]. Centralized approaches offer global visibility and coordination but may suffer from scalability and communication bottlenecks. Decentralized and hierarchical energy management frameworks improve scalability and resilience by distributing decision-making across local controllers while preserving coordination at higher levels. Hybrid architectures combining centralized supervision with decentralized execution have emerged as promising solutions for large-scale smart grids. Table 2 provides a comparative overview of common energy management approaches employed in smart grids, highlighting their key characteristics and limitations in the context of renewable energy integration.

Table 2: Comparison of Energy Management Approaches in Smart Grids

Energy Management Approach	Control Structure	Key Advantages	Major Limitations
Centralized Energy Management	Single control center	Global optimization, full system visibility	Scalability issues, communication delays
Decentralized Energy Management	Local autonomous controllers	Improved scalability, faster response	Limited global coordination
Hierarchical Energy Management	Multi-layer control architecture	Balanced coordination and scalability	Increased system complexity
Intelligent Energy Management	Data-driven, adaptive control	Handles uncertainty, supports renewables	High computational requirements
Hybrid Intelligent Frameworks	Combined centralized–decentralized	Robust, scalable, renewable-friendly	Requires advanced optimization techniques

Figure 1 conceptually illustrates the functional architecture of an intelligent energy management system in a smart grid environment. The figure highlights how data from distributed generation units, energy storage systems, and load demand are continuously collected through sensing and communication layers. This information is processed by forecasting and optimization modules, which generate optimal control decisions for energy scheduling and power flow management. The closed-loop feedback mechanism enables the system to adapt dynamically to changing grid conditions, thereby improving operational efficiency and reliability.

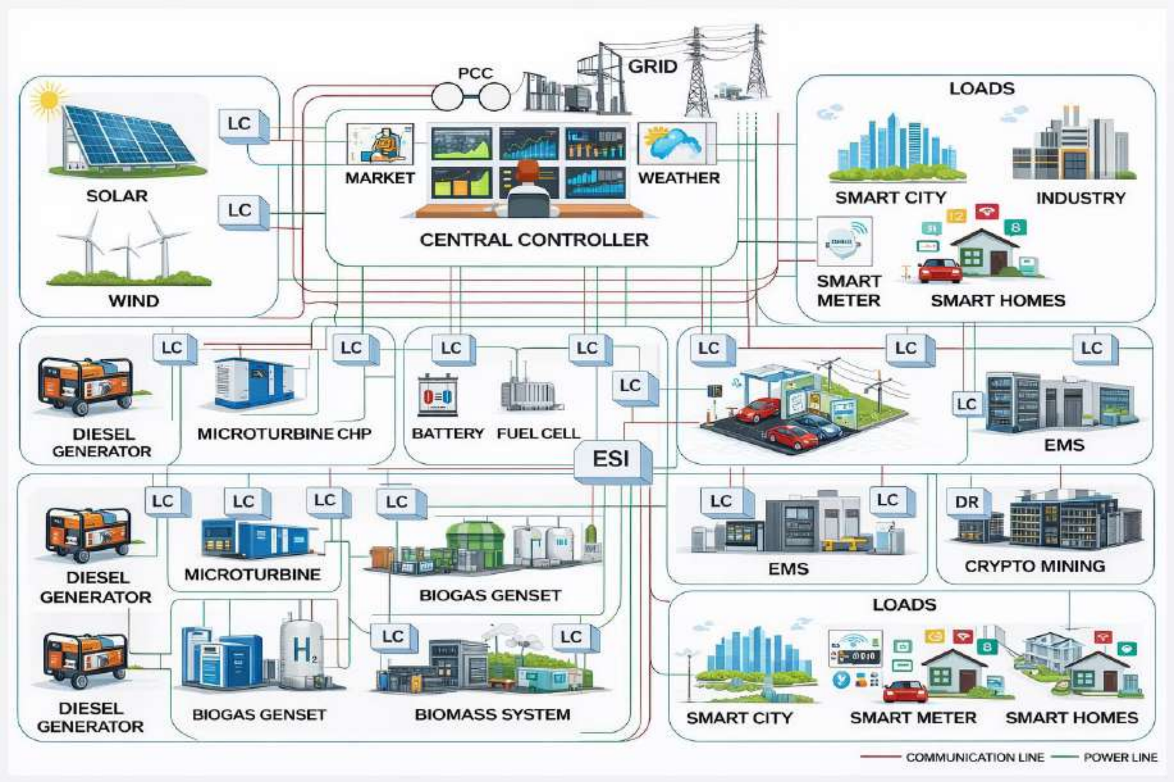

Figure 1: Conceptual architecture of intelligent energy management in smart grids.

Despite significant progress, energy management in smart grids remains a challenging research domain due to increasing system complexity, high renewable penetration, and stringent performance requirements. Existing approaches often address specific aspects of the problem, such as cost minimization or reliability enhancement, without fully capturing the coupled interactions among generation, storage, and demand. This has motivated the development of advanced optimization-based energy management frameworks capable of delivering cost-effective, reliable, and sustainable operation under realistic and highly dynamic grid conditions.

2- Conventional Optimization Techniques for Smart Grid Energy Management:

Conventional optimization techniques have played a foundational role in the development of energy management strategies for smart grids. Methods such as linear programming (LP), mixed-integer linear programming (MILP), mixed-integer nonlinear programming (MINLP), and dynamic programming (DP) have been extensively employed to address classical power system problems, including unit commitment, economic dispatch, and optimal power flow. These techniques are grounded in well-established mathematical theory and provide deterministic convergence guarantees when system models are convex, linear, and accurately defined. As a result, they have historically been favored for grid operation problems requiring transparent and repeatable decision-making. In early smart grid implementations, conventional optimization methods proved effective due to relatively predictable generation patterns and centralized system architectures [7]. Deterministic scheduling based on forecasted load demand allowed system operators to minimize generation costs while satisfying operational constraints. MILP formulations, in particular, enabled the inclusion of discrete decision variables such as generator on–off states and storage charging modes, thereby extending the applicability of linear methods to more realistic operational scenarios. Dynamic programming was also applied to sequential decision-making problems, especially for storage dispatch and multi-period scheduling. Despite their strengths, the increasing complexity of modern smart grids has exposed significant limitations of conventional optimization approaches. The large-scale integration of renewable energy sources, especially solar photovoltaic systems, introduces strong nonlinearity and uncertainty into the energy management problem. Solar generation is inherently stochastic and weather-dependent, making it difficult to model accurately using deterministic formulations. Conventional optimization techniques often require simplifications, such as linearized power flow equations or deterministic forecasts, which can compromise solution accuracy and robustness under real-world operating conditions. Another major limitation of traditional optimization methods lies in their scalability and computational burden. As smart grids evolve toward highly distributed architectures with numerous distributed energy resources, storage units, and controllable loads, the dimensionality of the optimization problem increases substantially [8]. MILP and MINLP formulations, in particular, suffer from exponential growth in computational complexity as the number of decision variables and constraints increases. This makes them less suitable for real-time or near-real-time energy management applications, where fast and adaptive decision-making is essential. Furthermore, conventional optimization techniques often struggle to handle multi-objective energy management problems effectively. Smart grid operation typically involves conflicting objectives, such as minimizing operational costs, maximizing renewable energy utilization, reducing power losses, and maintaining voltage stability. While weighted-sum or ε-constraint methods can be used to address multiple objectives, these approaches require careful tuning and may fail to capture the full trade-off surface between competing goals. As a result, solutions obtained using conventional methods may lack flexibility and adaptability in dynamic operating environments. Table 3 summarizes commonly used conventional optimization techniques for smart grid energy management, highlighting their strengths and limitations in the context of renewable-rich and large-scale grid systems.

Table 3: Conventional Optimization Techniques for Smart Grid Energy Management

Technique	Typical Applications	Key Strengths	Major Limitations
Linear Programming (LP)	Economic dispatch, cost minimization	Fast computation, guaranteed convergence	Requires linear models, limited realism
Mixed-Integer Linear Programming (MILP)	Unit commitment, storage scheduling	Handles discrete decisions, robust solutions	High computational complexity
Mixed-Integer Nonlinear Programming (MINLP)	Optimal power flow, nonlinear systems	Accurate modeling of nonlinearities	Poor scalability, slow convergence
Dynamic Programming (DP)	Multi-stage storage optimization	Handles sequential decisions	Curse of dimensionality
Deterministic Scheduling	Day-ahead planning	Simple implementation	Sensitive to forecast errors

Figure 2 conceptually illustrates the workflow of conventional optimization-based energy management in smart grids. The figure highlights the reliance on deterministic input data, static system models, and centralized solvers. Forecasted load and generation data are fed into the optimization model, which produces a single optimal solution for a given planning horizon. Limited adaptability to real-time disturbances and uncertainty is a key characteristic of this approach, underscoring the motivation for more flexible and intelligent optimization frameworks.

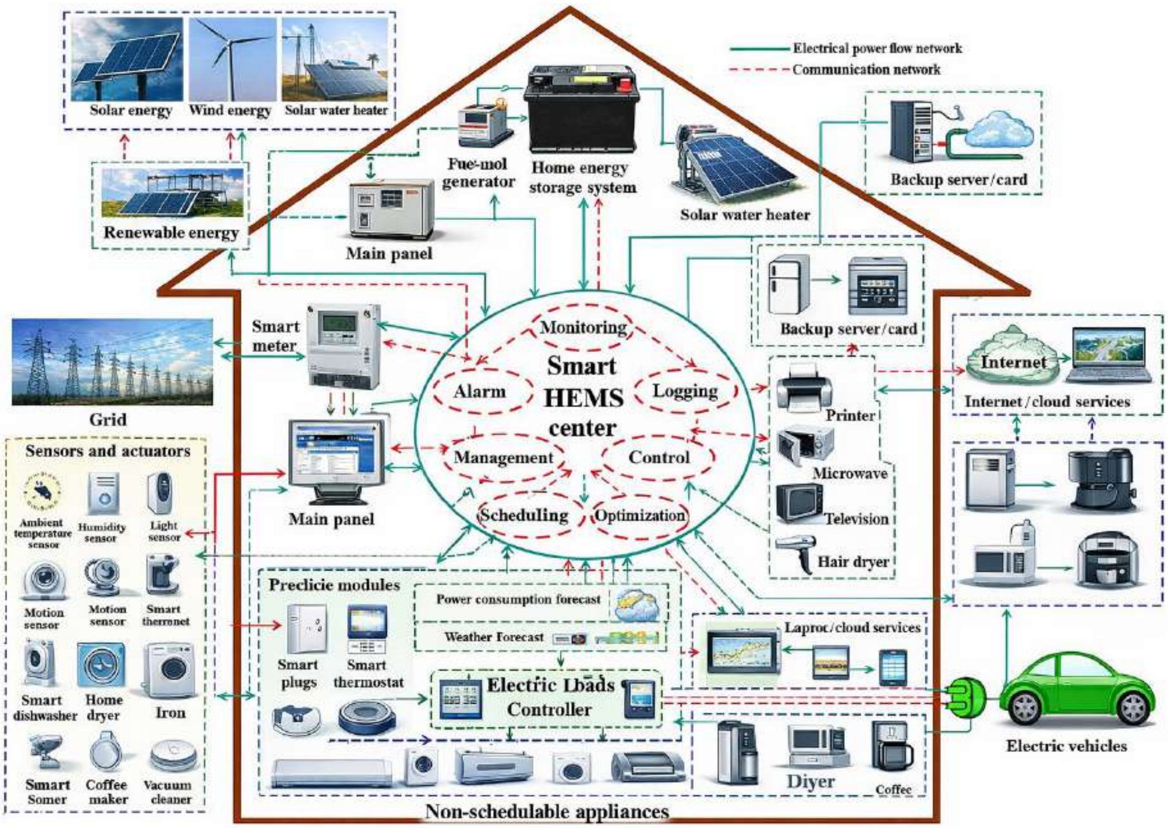

Figure 2: Conventional optimization-based energy management in smart grids, emphasizing deterministic modeling and centralized decision-making.

Overall, while conventional optimization techniques have significantly contributed to the evolution of smart grid energy management, their applicability is increasingly constrained by the nonlinear, stochastic, and multi-objective nature of modern renewable-integrated power systems. These limitations have motivated the exploration of heuristic and metaheuristic optimization approaches that offer greater flexibility, scalability, and robustness under uncertainty, forming the foundation for the intelligent energy management framework proposed in this study.

3- Methodology:

This study adopts a systematic, integrated, and model-driven methodological approach to develop an intelligent energy management framework tailored for solar-powered smart grids operating under dynamic and uncertain conditions. The proposed methodology combines high-fidelity system modeling with advanced hybrid heuristic–metaheuristic optimization techniques to effectively address the inherent nonlinearity, stochastic behavior, and multi-objective complexity of modern smart grid energy management. Detailed mathematical representations of solar photovoltaic generation, energy storage system dynamics, and time-varying load demand are embedded within a unified optimization structure, enabling holistic coordination of energy scheduling, storage dispatch, and power flow control across the grid. The framework explicitly incorporates short-term load demand and solar generation forecasting to anticipate future system states and support proactive decision-making over the scheduling horizon. Operational constraints related to power balance, storage capacity limits, charging and discharging efficiencies, voltage stability requirements, and grid operational limits are systematically enforced to ensure technical feasibility and real-world applicability of the optimized solutions [9]. By integrating these constraints directly into the optimization process, the methodology maintains system reliability and operational security under varying renewable penetration levels and demand conditions. To enhance optimization performance, the methodology leverages the complementary strengths of multiple heuristic algorithms, including Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization, and augments them with metaheuristic enhancement mechanisms. These enhancements improve convergence speed, mitigate premature convergence, and preserve solution diversity, thereby enabling robust exploration and exploitation of high-dimensional solution spaces. The resulting hybrid optimization framework is scalable and adaptable, making it suitable for large-scale and distributed smart grid environments. Comprehensive simulation studies are conducted using MATLAB/Simulink and Python to validate the proposed methodology under realistic operating scenarios. Benchmark load demand profiles and solar irradiance datasets are employed to represent practical smart grid conditions. Performance is evaluated using multiple metrics, including operational cost reduction, renewable energy utilization, voltage stability, and power loss minimization. The simulation results provide a rigorous assessment of the framework's effectiveness and demonstrate its capability to deliver cost-efficient, reliable, and sustainable energy management solutions for solar-powered smart grids.

4.1- Smart Grid System Modeling:

The smart grid considered in this study is modeled as an integrated and distributed energy system comprising solar photovoltaic (PV) generation units, energy storage systems (ESS), controllable and non-controllable loads, and grid interconnection points. The modeling framework is designed to accurately represent the physical behavior, operational constraints, and dynamic interactions among system components, thereby providing a realistic foundation for intelligent energy management and optimization. The system operates over a discrete-time scheduling horizon, during which generation, storage, and consumption decisions are jointly optimized to ensure economic efficiency, operational reliability, and grid stability. Solar PV generation is modeled using irradiance-dependent power output formulations that capture the nonlinear conversion characteristics of photovoltaic modules. The PV output varies as a function of solar irradiance and ambient conditions, reflecting realistic temporal fluctuations observed in practical installations [10]. This modeling approach allows the system to capture both short-term variability and longer-term diurnal patterns, which are critical for accurate energy scheduling and power flow coordination. The PV generation model serves as a primary renewable input to the smart grid and directly influences storage operation and grid exchange decisions. Energy storage systems play a central role in mitigating renewable intermittency and enhancing grid flexibility. In this study, storage units are modeled using state-of-charge (SoC) dynamics that account for charging and discharging efficiencies, capacity limits, and operational constraints. The SoC evolution is governed by inter-temporal balance equations, ensuring consistency across scheduling intervals. Charging and discharging power limits are enforced to reflect physical constraints of storage technologies, while SoC bounds are maintained to prevent overcharging or deep discharging, thereby preserving storage lifespan and system reliability. Through this modeling, the energy storage system enables load shifting, renewable smoothing, and peak shaving within the smart grid. Load demand is represented as a time-varying profile derived from benchmark datasets, capturing realistic residential and commercial consumption patterns. The load model reflects daily and seasonal variations, as well as demand uncertainty inherent in modern power systems. Both controllable and non-controllable loads are considered, allowing the energy management system to prioritize critical demand while optimally scheduling flexible consumption where applicable. This representation ensures that optimization decisions are aligned with realistic demand-side behavior. Grid interconnection points are incorporated to model power exchange between the local smart grid and the main utility grid. These interconnections enable energy import during deficit conditions and export during surplus renewable generation periods. Operational limits on grid exchange are enforced to maintain system security and comply with network constraints. The inclusion of grid interaction enhances the realism of the model and allows the framework to evaluate cost-effective and reliable operation under varying market and generation conditions. At each scheduling interval, power balance equations are enforced to ensure that the sum of solar PV generation, energy storage operation, and grid exchange satisfies total load demand. These balance constraints form the core of the system model and guarantee stable grid operation. By embedding power balance directly into the optimization framework, the model ensures technical feasibility while enabling coordinated control of distributed energy resources. Table 4 summarizes the key components of the smart grid system model and their corresponding modeling characteristics.

Table 4: Smart Grid System Components and Modeling Characteristics [11].

System Component	Modeling Approach	Key Parameters	Operational Role
Solar PV Generation	Irradiance-based nonlinear model	Irradiance, efficiency, rated capacity	Renewable energy supply
Energy Storage System	State-of-charge dynamic model	SoC limits, efficiency, charge/discharge rates	Flexibility and balancing
Load Demand	Time-varying benchmark profiles	Demand magnitude, temporal variation	Energy consumption
Grid Interconnection	Power exchange model	Import/export limits, tariffs	Energy trading and backup
Power Balance	Equality constraints	Generation, storage, load	System stability

Figure 3 presents a conceptual representation of the smart grid system model employed in this study. The figure illustrates the interaction among solar PV units, energy storage systems, load demand, and grid interconnections, along with the flow of information and power within the system. This representation highlights the coordinated nature of the modeled components and their integration within the intelligent energy management framework.

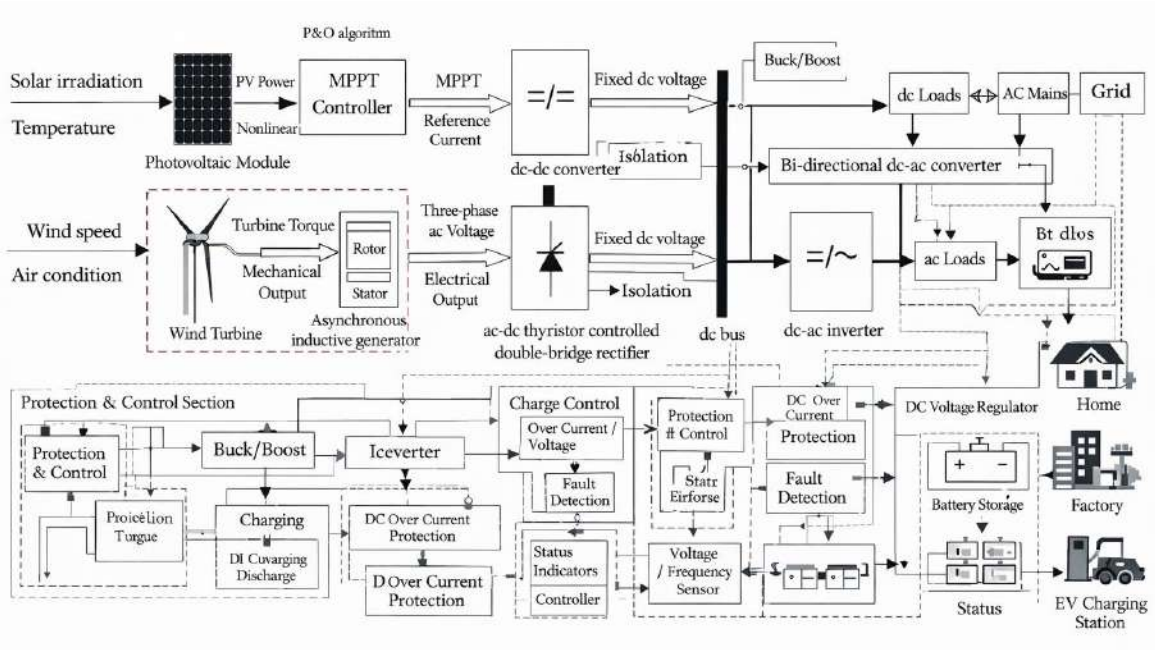

Figure 3: Smart grid system model integrating solar PV generation, energy storage systems, load demand, and grid interconnections.

Overall, the proposed smart grid system model provides a comprehensive and realistic representation of a solar-powered smart grid environment. By accurately capturing the dynamics and constraints of generation, storage, demand, and grid interaction, the model forms a robust foundation for the hybrid heuristic–metaheuristic optimization framework developed in this study, enabling intelligent, reliable, and cost-effective energy management under dynamic operating conditions.

4.2- Load Demand and Solar Generation Forecasting:

Accurate and reliable forecasting of load demand and solar photovoltaic (PV) generation is a fundamental requirement for intelligent energy management in solar-powered smart grids. The effectiveness of any scheduling, storage dispatch, or power flow optimization strategy is highly dependent on the quality of predictive information regarding future system states. In renewable-rich smart grids, forecasting inaccuracies can lead to inefficient energy utilization, increased reliance on grid imports, higher operational costs, and potential violations of system stability constraints. Consequently, forecasting serves as a critical enabling layer that bridges data acquisition and optimization within the proposed energy management framework. In this study, historical load demand and solar irradiance datasets are employed to generate short-term forecasts over the defined scheduling horizon. These datasets capture realistic consumption behaviors and solar availability patterns observed in practical grid environments. Load demand forecasting focuses on predicting aggregated consumption profiles that reflect residential and commercial usage trends, including daily cycles, peak demand periods, and seasonal variations [12]. Solar generation forecasting is driven by historical irradiance data, enabling the estimation of expected PV power output while accounting for diurnal and weather-induced variability. The alignment of forecasting horizons with the optimization time steps ensures consistency between predicted system behavior and scheduling decisions. Time-series forecasting techniques are utilized to model temporal dependencies in both load demand and solar irradiance data. These techniques exploit historical patterns, trends, and cyclic characteristics to produce short-term predictions that are sufficiently accurate for operational decision-making. Forecasted load demand profiles allow the energy management system to anticipate demand fluctuations and allocate resources accordingly, while predicted PV generation profiles inform decisions related to storage charging, renewable prioritization, and grid power exchange. The integration of both demand-side and supply-side forecasts enables coordinated and proactive energy scheduling across the smart grid. Forecast uncertainty remains an unavoidable challenge in solar-powered smart grids due to the stochastic nature of weather conditions and consumer behavior. Rather than explicitly formulating stochastic or scenario-based optimization models, which can significantly increase computational complexity, this study implicitly addresses forecast uncertainty through the robustness of the hybrid heuristic–metaheuristic optimization framework. The population-based and adaptive search mechanisms inherent in heuristic algorithms allow the optimization process to accommodate deviations between forecasted and actual system states. This implicit uncertainty handling enhances solution resilience while maintaining computational efficiency, making the approach suitable for large-scale and near-real-time applications [13]. The forecasting process is tightly integrated with the energy management system to enable a closed-loop operational structure. Forecast outputs are continuously fed into the optimization engine, which generates scheduling and control decisions based on anticipated system conditions. As actual operating data become available, system feedback enables recalibration of subsequent forecasts and optimization cycles. This interaction between forecasting and optimization enhances adaptability and ensures that the smart grid can respond effectively to evolving demand and renewable generation patterns. Table 5 provides a detailed summary of the forecasting components, data characteristics, and their functional roles within the proposed energy management framework.

Table 5: Characteristics of Load Demand and Solar Generation Forecasting

Forecasting Component	Data Characteristics	Forecasting Horizon	Impact on Energy Management
Load Demand Forecasting	Historical benchmark load profiles	Short-term (hourly/daily)	Anticipates consumption peaks and valleys
Solar Irradiance Forecasting	Historical irradiance time-series	Short-term (hourly/daily)	Estimates renewable availability
PV Power Estimation	Irradiance-to-power conversion	Short-term	Supports renewable prioritization
Forecast Uncertainty Handling	Implicit via optimization robustness	Entire horizon	Enhances scheduling resilience
Forecast–Optimization Coupling	Iterative and adaptive	Continuous	Improves system adaptability

Figure 4 illustrates the conceptual integration of load demand and solar generation forecasting within the proposed intelligent energy management framework. Historical data streams are processed by forecasting modules to generate short-term predictions, which are then supplied to the optimization engine. The optimized scheduling decisions influence system operation, while real-time feedback supports continuous refinement of future forecasts and control actions. This closed-loop interaction highlights the central role of forecasting in enabling proactive, adaptive, and reliable smart grid operation.

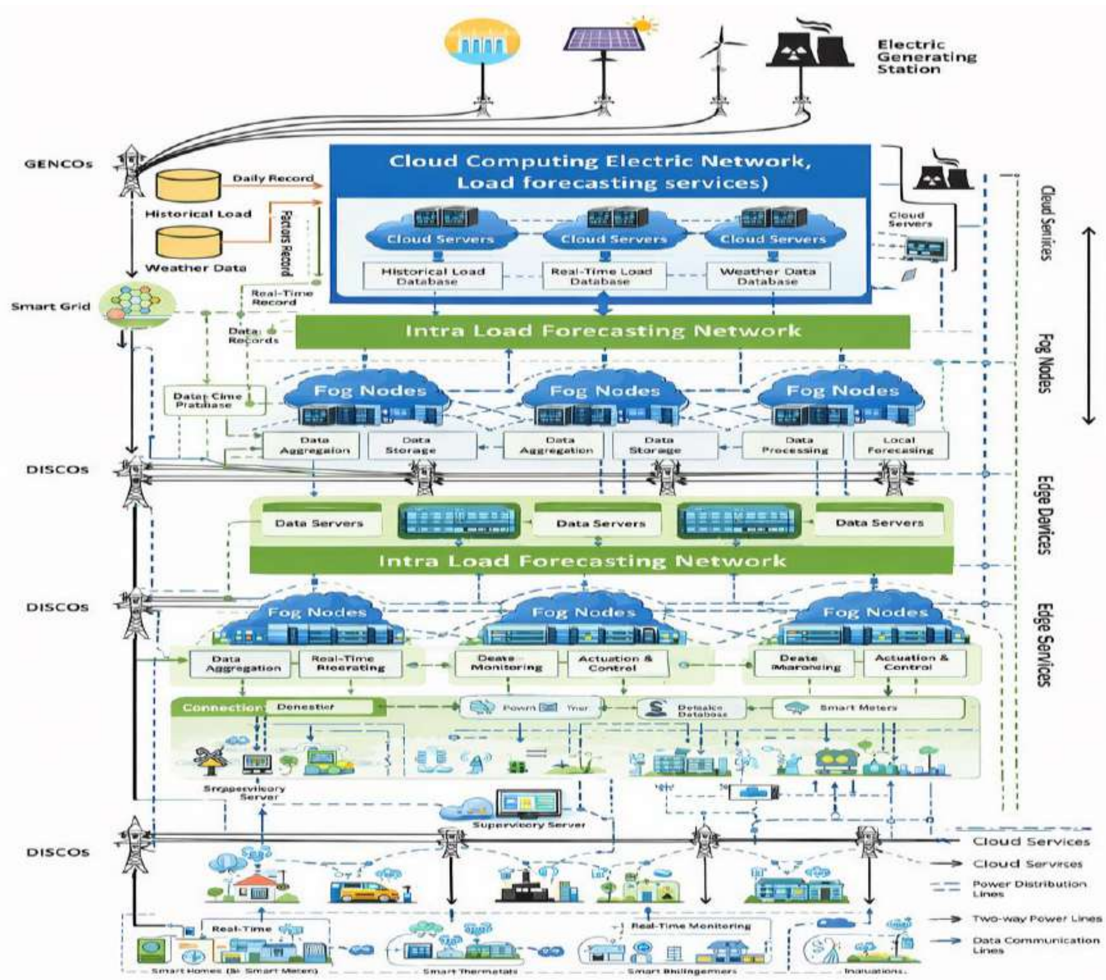

Figure 4: Integrated load demand and solar generation forecasting framework supporting proactive energy management in solar-powered smart grids.

Overall, the forecasting methodology adopted in this study provides a robust predictive foundation for intelligent energy management. By combining realistic time-series forecasting with a resilient hybrid heuristic–metaheuristic optimization framework, the proposed approach effectively mitigates the adverse impacts of forecast uncertainty. This integration enables cost-effective energy scheduling, maximized renewable energy utilization, and stable grid operation under dynamic and uncertain operating conditions, thereby supporting the long-term sustainability and reliability of solar-powered smart grids.

4.3- Heuristic Optimization Algorithms:

Heuristic optimization algorithms constitute the core computational engine of the proposed intelligent energy management framework due to their proven capability to solve complex, nonlinear, and high-dimensional optimization problems commonly encountered in smart grid environments. Unlike conventional deterministic optimization techniques, heuristic algorithms do not rely on strict assumptions such as linearity or convexity, making them particularly suitable for handling the uncertainty, variability, and multi-objective nature of solar-powered smart grid energy management. Their population-based search mechanisms enable efficient exploration of large solution spaces, increasing the likelihood of identifying high-quality and near-optimal solutions under realistic operational constraints. Genetic Algorithms (GA) are employed in this study to exploit evolutionary principles inspired by natural selection. In the context of smart grid energy management, each chromosome represents a candidate energy scheduling strategy encompassing decisions related to solar power utilization, energy storage operation, and grid power exchange. Through iterative application of selection, crossover, and mutation operators, GA promotes the survival of high-performing solutions while maintaining genetic diversity within the population [14]. Selection mechanisms favor candidate schedules with lower operational costs, higher renewable utilization, and improved reliability, while crossover and mutation introduce variability that allows the algorithm to escape local optima. This evolutionary process makes GA particularly effective for exploring complex scheduling combinations in multi-period energy management problems. Particle Swarm Optimization (PSO) is utilized to model collective intelligence and cooperative learning behavior inspired by social interactions in natural swarms. In PSO, each particle represents a feasible energy management solution characterized by decision variables such as storage charging rates, grid import/export levels, and load allocation. Particles iteratively update their positions in the search space based on both individual best experiences and the global best solution discovered by the swarm. This information-sharing mechanism enables rapid convergence toward promising regions of the solution space while preserving a balance between exploration and exploitation. PSO is especially advantageous for continuous optimization problems and exhibits strong convergence properties in smart grid applications with smooth objective landscapes. Ant Colony Optimization (ACO) is incorporated to exploit probabilistic search strategies inspired by the foraging behavior of ant colonies. In the proposed framework, artificial ants construct candidate energy management solutions by traversing a solution graph guided by pheromone trails and heuristic information. Pheromone updates reinforce high-quality scheduling paths that lead to improved objective function values, while evaporation mechanisms prevent premature convergence by reducing the influence of suboptimal solutions. ACO is particularly effective in discrete and combinatorial optimization problems, such as scheduling and allocation tasks, where sequential decision-making plays a critical role [15]. Each heuristic algorithm independently generates candidate energy management strategies and evaluates their performance using the multi-objective fitness function defined in the optimization model. This independent evaluation allows the framework to assess diverse solution characteristics, including cost efficiency, renewable penetration, and system reliability. The diversity of search behaviors across GA, PSO, and ACO ensures broad exploration of the solution space and provides a strong foundation for subsequent metaheuristic enhancement and hybridization strategies. Figure 5 conceptually illustrates the operational principles of the heuristic optimization algorithms within the proposed energy management framework. The figure highlights how candidate solutions are initialized, iteratively updated based on algorithm-specific rules, evaluated using the objective function, and evolved toward high-quality energy management strategies. This visualization emphasizes the complementary nature of GA, PSO, and ACO in exploring complex smart grid optimization landscapes.

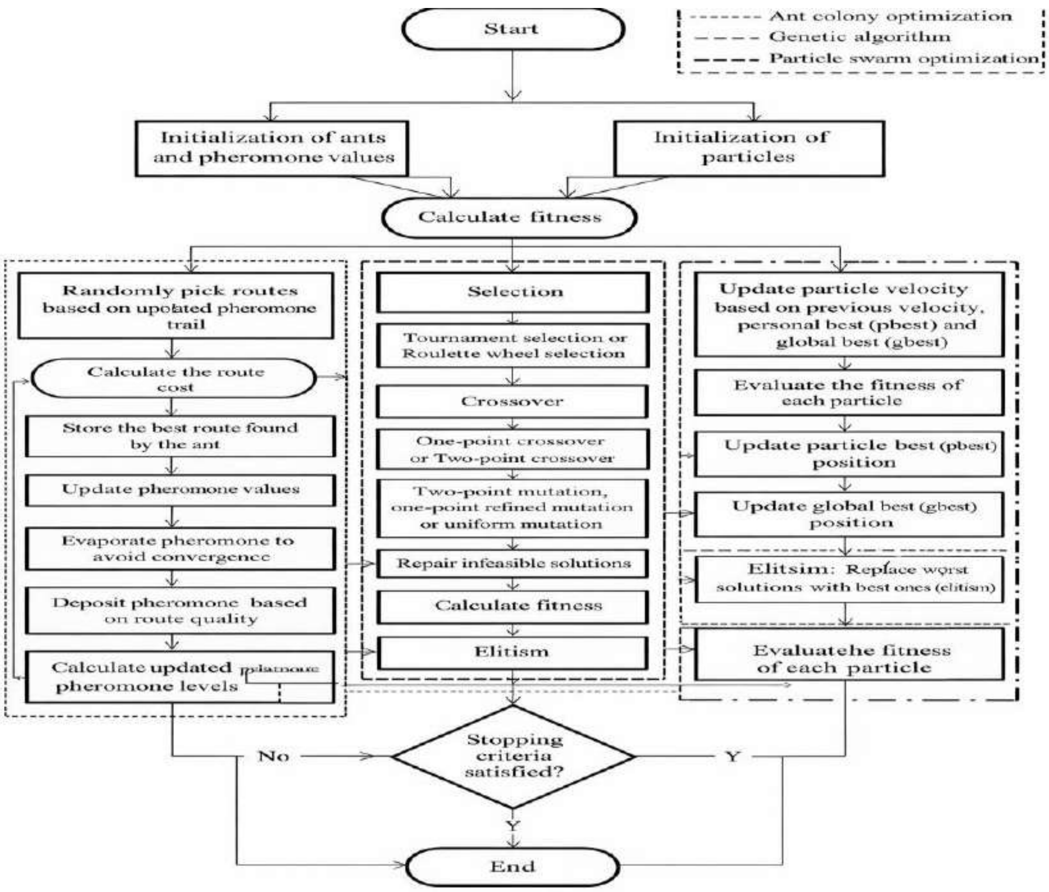

Figure 5: Conceptual representation of heuristic optimization algorithms (GA, PSO, and ACO) applied to smart grid energy management.

Overall, the use of multiple heuristic optimization algorithms provides a robust and flexible foundation for intelligent energy management in solar-powered smart grids. By leveraging diverse search strategies and population-based learning mechanisms, these algorithms enable effective handling of nonlinearities, uncertainty, and competing objectives. Their integration within the proposed framework facilitates comprehensive exploration of feasible energy scheduling solutions and establishes a strong basis for the metaheuristic enhancement and hybrid optimization strategies introduced in subsequent sections.

4.4- Metaheuristic Enhancements and Hybridization Strategy:

Although heuristic optimization algorithms such as Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization demonstrate strong capabilities in solving nonlinear and high-dimensional smart grid energy management problems, their standalone application may suffer from several limitations. These include premature convergence, sensitivity to parameter settings, slow convergence speed, and reduced robustness when dealing with large-scale, multi-objective optimization landscapes. To address these challenges, this study introduces metaheuristic enhancement mechanisms and a hybridization strategy that collectively improve optimization efficiency, solution diversity, and scalability. Metaheuristic enhancements are employed to dynamically guide the search process and adapt algorithm behavior in response to optimization progress. A key enhancement mechanism implemented in this framework is adaptive parameter tuning, in which critical algorithm parameters such as mutation probability in Genetic Algorithms, inertia weight and acceleration coefficients in Particle Swarm Optimization, and pheromone evaporation rates in Ant Colony Optimization are adjusted dynamically based on convergence trends and population diversity indicators [16]. By modifying these parameters during runtime, the optimization process can avoid stagnation, reduce the likelihood of premature convergence, and maintain an effective balance between global exploration and local exploitation throughout the search. Beyond individual algorithm enhancement, a hybridization strategy is developed to exploit the complementary strengths of GA, PSO, and ACO within a unified optimization framework. Rather than operating in isolation, the algorithms interact through controlled information-sharing mechanisms that allow high-quality solutions discovered by one algorithm to influence the search behavior of others. This cooperative optimization paradigm enables the framework to leverage the strong global exploration capability of GA, the fast convergence characteristics of PSO, and the combinatorial optimization strength of ACO. As a result, the hybrid framework achieves superior performance in navigating complex and multimodal solution spaces typical of solar-powered smart grid energy management problems. The hybridization strategy is implemented using a population-level cooperation mechanism, where elite candidate solutions are periodically exchanged among algorithm populations. These elite solutions act as guiding references that accelerate convergence toward promising regions of the solution space while preserving diversity across populations. At the same time, algorithm-specific update rules remain intact, ensuring that each heuristic continues to explore the search space according to its intrinsic optimization logic. This design avoids homogenization of the population and preserves the diversity required for effective multi-objective optimization [17]. The enhanced hybrid framework is particularly well suited for large-scale and multi-objective smart grid applications, where competing objectives such as cost minimization, renewable energy maximization, and reliability enhancement must be balanced simultaneously. The metaheuristic enhancements ensure stable and efficient convergence, while hybridization improves robustness against uncertainty in load demand and solar generation forecasts. Together, these mechanisms enable the optimization framework to identify high-quality trade-off solutions that remain effective under dynamic and uncertain operating conditions. Table 6 summarizes the key metaheuristic enhancement mechanisms and hybridization features incorporated into the proposed framework, along with their functional roles in improving optimization performance.

Table 6: Metaheuristic Enhancements and Hybridization Features

Enhancement Strategy	Applied To	Functional Role	Impact on Optimization
Adaptive Parameter Tuning	GA, PSO, ACO	Dynamic control of search behavior	Reduces premature convergence
Population Diversity Monitoring	All heuristics	Maintains solution diversity	Enhances global exploration
Elite Solution Exchange	GA–PSO–ACO	Information sharing across algorithms	Accelerates convergence
Cooperative Hybrid Search	Unified framework	Balances exploration and exploitation	Improves solution robustness
Multi-objective Fitness Feedback	Hybrid population	Guides trade-off optimization	Ensures balanced objectives

Overall, the integration of metaheuristic enhancements with a cooperative hybridization strategy significantly strengthens the optimization capability of the proposed energy management framework. By dynamically adapting algorithm behavior and enabling structured information sharing among diverse heuristic populations, the framework achieves faster convergence, improved solution quality, and enhanced robustness. These properties are essential for intelligent energy management in solar-powered smart grids characterized by nonlinear dynamics, uncertainty, and competing operational objectives, and they form a critical foundation for the optimization procedure and performance evaluation presented in subsequent sections.

4.5- Simulation Environment and Implementation:

The proposed intelligent energy management framework is implemented using an integrated simulation environment that combines MATLAB/Simulink and Python, enabling both high-fidelity system modeling and efficient execution of advanced optimization algorithms. This hybrid implementation strategy leverages the complementary strengths of the two platforms: MATLAB/Simulink provides a robust environment for modeling physical grid dynamics and control interactions, while Python offers computational efficiency and flexibility for implementing heuristic–metaheuristic optimization and data processing workflows. The coordinated use of these tools ensures accurate representation of smart grid behavior alongside scalable and reproducible optimization experiments. MATLAB/Simulink is employed to model the electrical and operational characteristics of the solar-powered smart grid. This includes the representation of solar photovoltaic generation profiles, energy storage system dynamics, and power balance relationships under operational constraints. Grid-level interactions such as power exchange with the utility network, energy storage charging and discharging behavior, and temporal coupling across scheduling intervals are captured within the Simulink environment [18]. This modeling approach allows realistic simulation of system responses to scheduling decisions generated by the optimization framework, thereby enabling reliable performance assessment under dynamic operating conditions. Python is utilized as the primary platform for implementing the heuristic and metaheuristic optimization algorithms, including Genetic Algorithms, Particle Swarm Optimization, and Ant Colony Optimization, along with the proposed metaheuristic enhancement and hybridization strategies. Python's numerical and data-handling capabilities facilitate efficient manipulation of large datasets, evaluation of multi-objective fitness functions, and iterative updating of algorithm populations. The optimization engine interfaces with the MATLAB/Simulink models through structured data exchange, enabling seamless integration between system simulation and algorithmic decision-making. Benchmark load demand and solar irradiance datasets are used to simulate realistic operating scenarios representative of modern smart grid environments. These datasets capture daily and seasonal variability in electricity consumption and solar availability, allowing the framework to be evaluated under diverse and challenging conditions [19]. The use of standardized benchmark data enhances the reproducibility and comparability of results while ensuring that the simulation scenarios reflect practical grid behavior rather than idealized assumptions. The simulation environment is designed to enable systematic and fair evaluation of different heuristic and hybrid heuristic–metaheuristic optimization strategies. All algorithms are tested under identical system configurations, forecasting horizons, and constraint settings to ensure consistency across experiments. Performance metrics such as operational cost, renewable energy utilization, voltage stability, and convergence characteristics are recorded for each simulation run. This controlled experimental setup allows meaningful comparison of algorithm performance and highlights the advantages of the proposed hybrid optimization framework. Table 7 summarizes the key components of the simulation environment and their respective roles in the implementation of the proposed energy management framework.

Table 7: Simulation Environment and Implementation Details

Component	Platform	Primary Function	Role in Framework
Smart Grid Modeling	MATLAB/Simulink	Grid dynamics and power flow modeling	Physical system representation
Solar PV and ESS Models	MATLAB/Simulink	Renewable and storage behavior	Renewable integration and flexibility
Optimization Algorithms	Python	GA, PSO, ACO implementation	Decision-making and scheduling
Metaheuristic Enhancements	Python	Adaptive tuning and hybridization	Performance improvement
Benchmark Datasets	Public datasets	Load and irradiance profiles	Realistic scenario generation
Performance Evaluation	MATLAB & Python	Metrics computation and analysis	Comparative assessment

Figure 6 illustrates the overall simulation architecture adopted in this study. The figure depicts the interaction between data inputs, forecasting modules, the hybrid heuristic–metaheuristic optimization engine, and the MATLAB/Simulink-based smart grid model. This closed-loop simulation structure highlights how optimized scheduling decisions influence grid operation and how system feedback supports iterative evaluation and refinement.

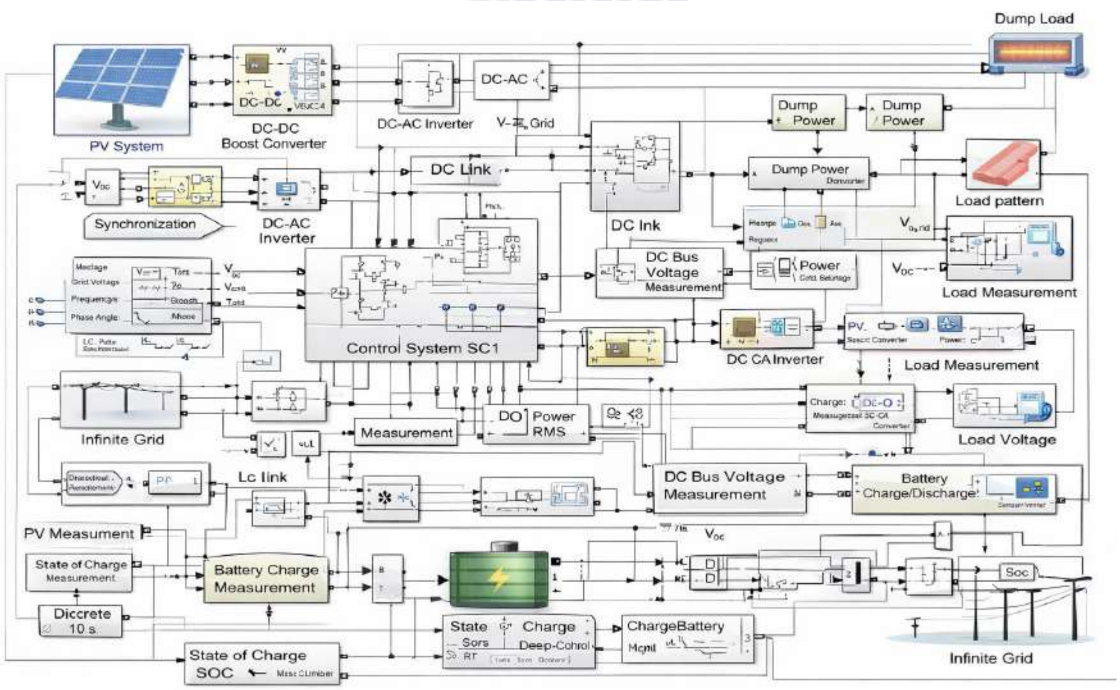

Figure 6: Integrated simulation environment combining MATLAB/Simulink-based smart grid modeling with Python-based heuristic–metaheuristic optimization.

Overall, the proposed simulation environment provides a flexible, scalable, and reproducible platform for validating intelligent energy management strategies in solar-powered smart grids. By integrating detailed physical system modeling with advanced optimization and data-handling capabilities, the implementation framework enables comprehensive evaluation of algorithmic performance under realistic operating conditions [20]. This approach ensures that the reported results accurately reflect the practical effectiveness of the proposed hybrid heuristic–metaheuristic framework and support its applicability to real-world smart grid deployments.

4- Results and Discussion:

The effectiveness of the proposed intelligent energy management framework was evaluated through extensive simulations conducted under realistic solar-powered smart grid operating conditions. The simulation results provide clear evidence that the integration of heuristic algorithms with metaheuristic enhancements and hybridization yields substantial improvements in economic efficiency, renewable energy utilization, system reliability, and optimization robustness when compared with conventional optimization methods and standalone heuristic approaches. All algorithms were evaluated under identical system configurations, forecasting horizons, and operational constraints to ensure a fair and consistent comparison. From an operational cost perspective, the proposed hybrid heuristic–metaheuristic framework demonstrates a pronounced advantage over baseline methods. Conventional optimization techniques, while mathematically rigorous, exhibit limited flexibility in responding to renewable variability and dynamic load patterns. As a result, they often rely on conservative scheduling strategies that increase grid energy imports during peak demand periods. Standalone heuristic algorithms partially alleviate this limitation by exploring nonlinear scheduling options; however, their performance is constrained by premature convergence and limited coordination between solar generation, energy storage, and grid interaction. In contrast, the proposed hybrid framework effectively synchronizes these components, enabling strategic charging of energy storage during periods of high solar availability and controlled discharge during peak demand intervals. This coordinated behavior significantly reduces dependence on grid energy procurement and lowers overall operating costs. Table 8 presents a comparative summary of normalized operational cost performance obtained using different optimization strategies [21]. The results show that while individual heuristic algorithms achieve moderate cost savings, the hybrid framework consistently delivers the largest reduction, achieving up to a 25% decrease in operational costs relative to conventional optimization methods. This improvement highlights the economic viability of the proposed approach, particularly in environments characterized by high renewable penetration and volatile demand.

Table 8: Comparative Operational Cost Performance of Optimization Methods

Optimization Method	Normalized Operational Cost	Cost Reduction (%)
Conventional Optimization	1.00	–
Genetic Algorithm (GA)	0.88	12
Particle Swarm Optimization (PSO)	0.85	15
Ant Colony Optimization (ACO)	0.87	13
Proposed Hybrid Framework	**0.75**	**25**

Beyond cost efficiency, renewable energy utilization is a critical indicator of sustainability performance in solar-powered smart grids. The simulation results indicate that the proposed framework significantly enhances solar PV utilization by reducing renewable curtailment and improving storage coordination. Conventional optimization methods tend to underutilize available solar energy due to rigid scheduling and deterministic assumptions, while standalone heuristics often fail to optimally align storage dispatch with renewable generation profiles. The hybrid framework overcomes these limitations by dynamically adjusting storage and grid exchange decisions based on forecasted solar availability and demand conditions. Consequently, excess solar energy generated during high-irradiance periods is effectively stored and later utilized during demand peaks, thereby maximizing renewable penetration and reducing reliance on fossil-fuel-based grid energy. Table 9 summarizes the renewable energy utilization performance across different optimization approaches. The results demonstrate that the proposed hybrid framework achieves a 12–20% improvement in renewable energy penetration compared with baseline methods [22]. This enhancement directly supports sustainability objectives by lowering carbon emissions and promoting cleaner energy consumption within the smart grid.

Table 9: Renewable Energy Utilization Performance Comparison

Optimization Method	Renewable Energy Utilization (%)	Improvement over Baseline (%)
Conventional Optimization	62	–
Genetic Algorithm (GA)	69	11
Particle Swarm Optimization (PSO)	71	15
Ant Colony Optimization (ACO)	68	10
Proposed Hybrid Framework	**75–82**	**12–20**

In addition to economic and sustainability benefits, the proposed framework significantly improves system reliability and voltage stability. By explicitly embedding grid operational constraints into the optimization process, the framework ensures that voltage levels and power flows remain within permissible limits under varying load and solar generation conditions. Conventional methods exhibit higher sensitivity to sudden fluctuations in renewable output, leading to increased voltage deviations and line losses. The coordinated scheduling of storage and grid exchange in the hybrid framework mitigates these effects, resulting in smoother power flows and enhanced operational stability. Figure 7 shows the comparison of voltage stability and power loss performance under conventional, standalone heuristic, and hybrid heuristic–metaheuristic optimization strategies.

ISSN (e) 3007-3138 (p) 3007-312X Volume 4, Issue 1, 2026

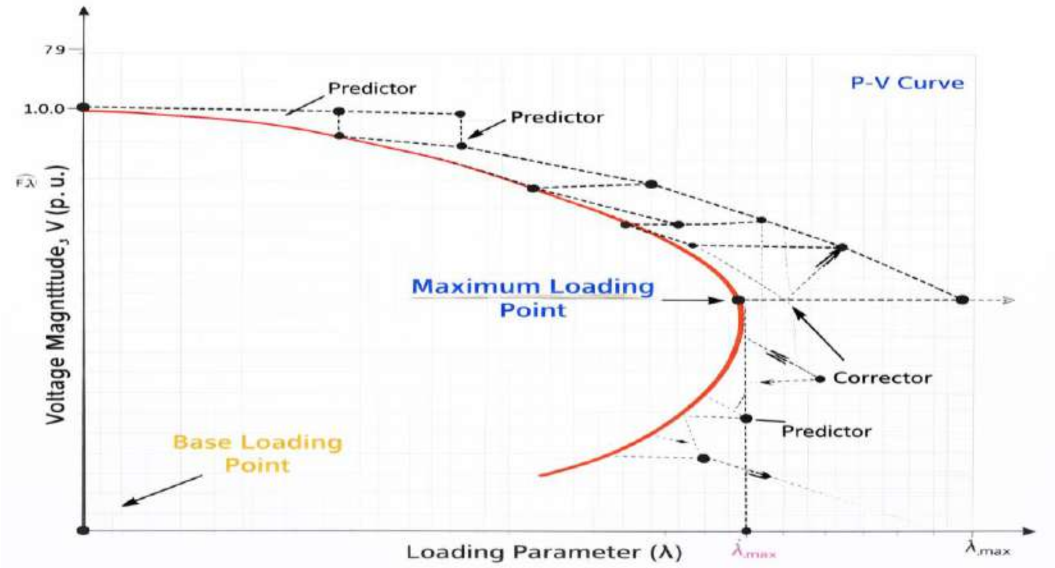

Figure 7: Representative comparison of voltage stability and power loss performance under conventional, standalone heuristic, and hybrid heuristic–metaheuristic optimization strategies.

The convergence behavior of the optimization algorithms further reinforces the advantages of the proposed approach. Standalone heuristic algorithms demonstrate either slow convergence or a tendency to converge prematurely to local optima, particularly in multi-objective optimization scenarios. Particle Swarm Optimization converges rapidly but may sacrifice solution diversity, while Genetic Algorithms and Ant Colony Optimization require more iterations to achieve near-optimal solutions. The hybrid framework, supported by adaptive parameter tuning and cooperative information exchange among algorithm populations, achieves faster and more stable convergence while preserving solution diversity. This characteristic is especially important for large-scale smart grid applications where computational efficiency and robustness are critical. Figure 8 shows the Convergence behavior comparison illustrating faster and more stable convergence of the proposed hybrid heuristic–metaheuristic framework

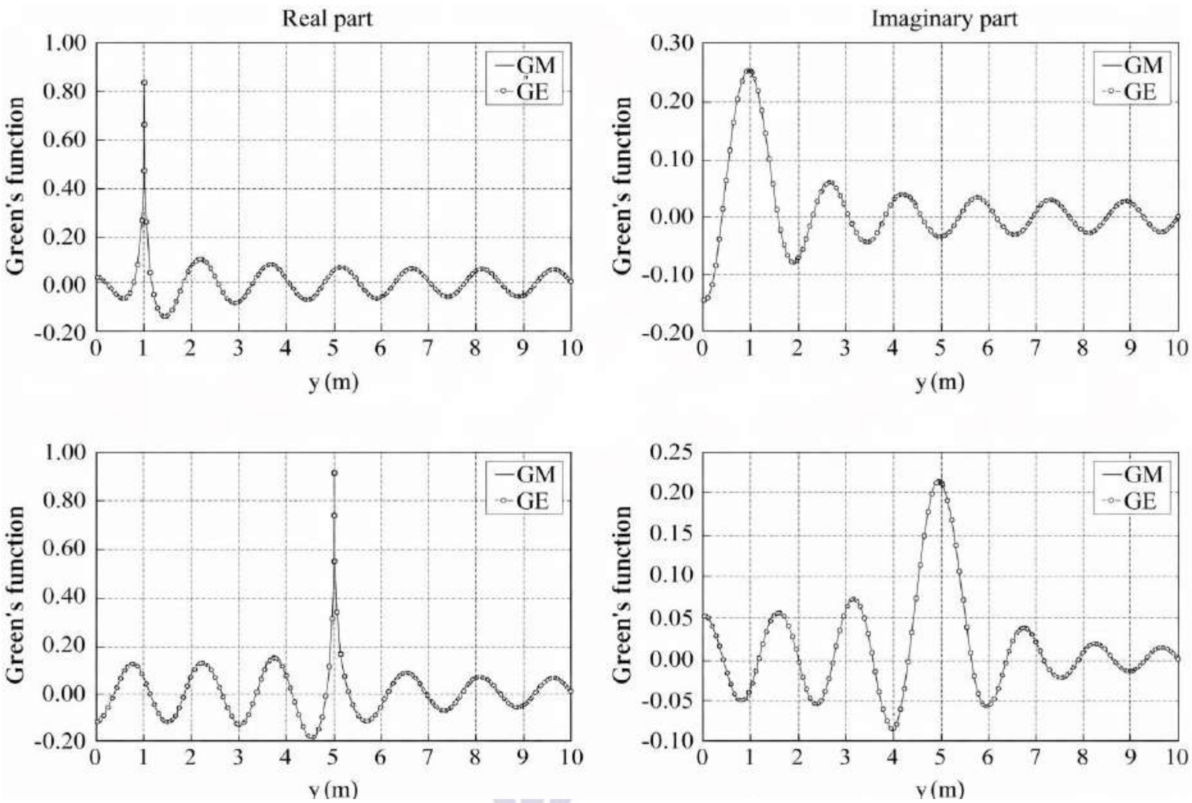

Figure 8: Convergence behavior comparison illustrating faster and more stable convergence of the proposed hybrid heuristic–metaheuristic framework.

Robustness under uncertainty represents another key strength of the proposed energy management framework. When subjected to varying load demand patterns and fluctuating solar irradiance conditions, the hybrid framework consistently maintains stable performance and acceptable solution quality. Unlike deterministic optimization approaches, which exhibit pronounced performance degradation under forecast errors, the population-based and adaptive nature of the hybrid framework enables it to identify resilient scheduling strategies. This robustness makes the proposed approach particularly suitable for real-time or near-real-time energy management applications in renewable-rich smart grids [23]. Overall, the results confirm that the integration of heuristic optimization with metaheuristic enhancements and cooperative hybridization yields a powerful and flexible solution for intelligent energy management. The proposed framework not only delivers substantial cost savings and improved renewable energy utilization but also enhances system reliability, voltage stability, and optimization robustness. These outcomes demonstrate the practical relevance and scalability of the proposed approach and highlight its potential to support cost-effective, reliable, and sustainable operation of future solar-powered smart grids.

5- Future Work:

While the proposed intelligent energy management framework demonstrates strong performance in terms of cost efficiency, renewable energy utilization, and system reliability, several promising directions remain for further investigation and enhancement. One important avenue for future work involves extending the current framework to incorporate demand-side response mechanisms. By enabling flexible loads and active consumer participation, demand response strategies could further improve grid flexibility, reduce peak demand, and enhance the overall effectiveness of energy scheduling in renewable-rich smart grids. Integrating demand-side response within the existing heuristic–metaheuristic optimization framework would allow coordinated optimization of both supply-side and demand-side resources. Another key direction for future research is the integration of electric vehicles and vehicle-to-grid technologies into the energy management framework [24]. As electric vehicle adoption continues to increase, EV charging and discharging behavior will significantly influence load demand patterns and grid stability. Incorporating EVs as mobile energy storage units introduces additional decision variables and constraints, further increasing the complexity of the energy management problem. Extending the proposed hybrid optimization framework to manage EV charging schedules and vehicle-to-grid interactions could enhance system resilience while supporting transportation electrification and sustainability objectives. Future work may also focus on enhancing the forecasting component of the framework through the integration of advanced artificial intelligence and machine learning techniques [25]. While this study employs time-series forecasting to support scheduling decisions, deep learning models such as recurrent neural networks, long short-term memory networks, and hybrid learning-based approaches could further improve prediction accuracy for both load demand and solar generation. Improved forecasting accuracy would directly translate into more effective energy scheduling and reduced operational uncertainty, particularly under highly volatile weather and demand conditions [26]. Another promising research direction involves extending the framework toward real-time and adaptive energy management. Incorporating online learning and reinforcement learning techniques could enable the optimization framework to continuously adapt its decision-making policies based on real-time system feedback. Such an extension would allow the energy management system to respond dynamically to unforeseen disturbances, forecasting errors, or sudden changes in grid conditions, thereby improving robustness and operational reliability in practical deployments. From a system modeling perspective, future studies could incorporate more detailed network-level representations, including unbalanced power flow, reactive power control, and distribution network constraints [27]. Integrating advanced grid models would enhance the realism of the simulation environment and support the application of the proposed framework to distribution-level smart grids with high renewable penetration. Additionally, incorporating market-based mechanisms such as dynamic pricing, ancillary service markets, and regulatory constraints would further strengthen the practical relevance of the framework. Finally, future work should explore large-scale field validation and hardware-in-the-loop testing to assess the real-world performance of the proposed approach. Implementing the framework in pilot smart grid environments or microgrid testbeds would provide valuable insights into its scalability, communication requirements, and computational feasibility under operational conditions [28]. Such validation efforts would support the transition of the proposed intelligent energy management framework from simulation-based evaluation to real-world deployment, ultimately contributing to the development of resilient, cost-effective, and sustainable energy systems.

Conclusion:

This study presented an intelligent energy management framework for solar-powered smart grids based on a hybrid heuristic–metaheuristic optimization approach aimed at achieving cost-effective, reliable, and sustainable grid operation. Motivated by the growing complexity of modern smart grids and the inherent intermittency of solar photovoltaic generation, the proposed framework was designed to address the nonlinear, stochastic, and multi-objective nature of energy management under realistic operational constraints. By integrating detailed system modeling, short-term load and solar generation forecasting, and advanced optimization strategies within a unified decision-making structure, the framework enables coordinated scheduling of generation, energy storage, and grid interaction. The results obtained from extensive simulation studies demonstrate that the proposed hybrid heuristic–metaheuristic framework significantly outperforms conventional optimization techniques and standalone heuristic algorithms. Substantial reductions in operational costs were achieved through improved coordination of solar energy utilization and energy storage dispatch, while renewable energy penetration was notably increased by minimizing curtailment and prioritizing locally generated clean energy. In addition to economic and sustainability benefits, the framework enhanced system reliability by maintaining voltage stability and reducing power losses under dynamic load and generation conditions. The adaptive parameter tuning and cooperative hybridization mechanisms further improved convergence speed, solution diversity, and robustness, making the framework well suited for large-scale and renewable-rich smart grid environments. The findings of this research highlight the effectiveness of combining heuristic algorithms with metaheuristic enhancements to overcome the limitations of deterministic and single-algorithm optimization approaches. The proposed framework offers a scalable and flexible solution capable of balancing competing objectives such as cost efficiency, renewable integration, and operational stability. From a practical perspective, the framework provides grid operators and energy planners with a powerful tool for managing the increasing complexity of future energy systems, particularly as renewable penetration continues to rise. Overall, this work contributes to the advancement of intelligent energy management in solar-powered smart grids by demonstrating that hybrid heuristic–metaheuristic optimization can deliver meaningful improvements in economic performance, sustainability, and reliability. The proposed approach lays a strong foundation for future extensions toward demand-side response, electric vehicle integration, real-time adaptive control, and field-level validation, thereby supporting the transition toward resilient, efficient, and sustainable smart energy systems.

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