

Medha Joshi

OPTIMAL INTEGRATION OF RENEWABLE ENERGY RESOURCES USING INTELLIGENT TECHNIQUES

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ABSTRACT

Using smart approaches, this study examines the best way to integrate renewable energy sources in India, concentrating specifically on boosting solar photovoltaic energy extraction using an MPPT controller based on GA-tuned ANFIS. India's renewable transition is characterized by a significant solar-led expansion trend, with solar averaging 73.20 GW of installed capacity with a high growth rate of 156.30% (2021–2025), hydro remaining steady at roughly 47.32 GW with a growth rate of 4.80%, and wind averaging 43.48 GW with a growth rate of 28.10%. Even though renewable energy sources account for an average of 39.60% of the total capacity, their share of generation is just 24.80%, resulting in a consistent 14.80% gap between capacity and generation, which is indicative of intermittency and curtailment limitations. Curtailment (8.30 severity index) and transmission congestion (8.60) are the most difficult integration issues, which highlights the need for adaptability. Energy storage has the greatest opportunity score (9.10) with a 34.80% possibility for improvement out of all potential solution pathways. Hybrid AI and ANFIS earned scores of 9.20 and 8.90, respectively, in intelligent procedures, demonstrating their high suitability for renewable integration. The simulation of a PV system with $V_{mpp} = 29\text{ V}$ and $I_{mpp} = 7.35\text{ A}$ is carried out using a boost converter (mean switching frequency 25 kHz) and a varied dataset (mean irradiance 700 W/m², temperature 35°C). GA optimization enhanced ANFIS parameter sets and yielded superior MPPT performance, with a tracking efficiency of 99.12%, a settling time of 0.041 s, an oscillation index of 1.84%, an output power increase of 8.60%, and a converter efficiency of 96.80%, demonstrating its appropriateness for India's renewable integration needs.

Keywords: *Renewable integration; India; ANFIS; Genetic Algorithm; MPPT; Smart grid*

CHAPTER 1

INTRODUCTION

India’s shift to low-carbon electricity has gone from “nice idea” into a planning necessity, in a way, because renewables have grown from roughly 17 GW in 2010 to around 190 GW by 2025, and solar especially has surged with a compound annual growth rate close to 24.8%. This changes, in a very basic sense, how reserve margins are thought about, how scheduling is done, and how transmission lines are actually used across the national grid.[1] On top of that, the need feels sharper when you look at India’s structural limits. Recent review evidence notes that solar is 90.76 GW, and wind is 47.36 GW, as of September 2024, while at the same time the system remains heavily tied to coal. Then you add the usual pressure points: infrastructure bottlenecks, land constraints, and water stress from having to serve about 18% of the world’s population with only 4% of global freshwater resources.[2]

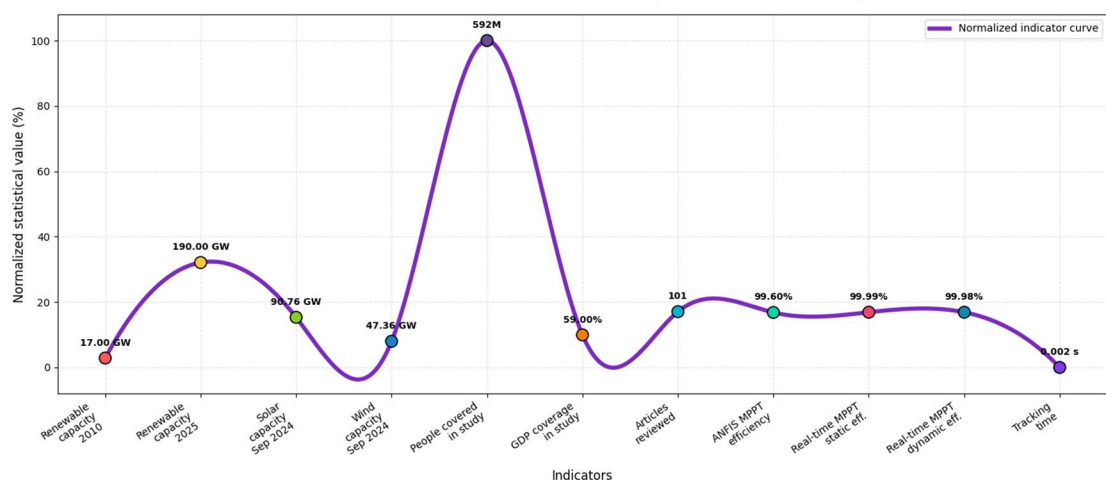
The hard part now is not just “put in renewable units” but getting them to fit well inside a power system that still has to keep adequacy, steadiness, cost control, and reliability, even under deep variability. This is especially noticeable in India because the Western and Southern regions by themselves involve 592 million people and 59% of national GDP, so the design of balancing areas and the inter-regional coordination becomes pretty much the main storyline for how renewables will run going forward.[3] And the broader review evidence keeps pointing to a similar message: grids with a high share of renewables get hit on multiple fronts at once—intermittency, voltage and frequency wiggles , limits in the infrastructure, protection-related complexity, and the awkward coordination of storage. The more plausible integration route tends to mix grid reinforcement with predictive control, energy management, and a kind of advanced supervisory intelligence, rather than depending only on the older deterministic way of operating.[4]

Table 1.1 Selected statistical indicators relevant to optimal renewable integration in India

Indicator	Statistical value	Relevance to the present topic	Ref.
India’s total installed	17 GW (2010) →	Shows the scale and speed of	[1]

renewable capacity	190 GW (2025)	the integration problem	
Solar installed capacity in India	90.76 GW (Sep. 2024)	Confirms solar PV as the dominant variable renewable source requiring advanced MPPT and grid support	[2]
Wind installed capacity in India	47.36 GW (Sep. 2024)	Indicates the need for coordinated forecasting and dispatch of multiple variable sources	[2]
Western + Southern India coverage in high-resolution integration study	592 million people; 59% of GDP	Demonstrates why regional coordination materially affects integration cost and reliability	[3]
Papers synthesized in smart-grid renewable integration review	101 articles	Indicates the maturity and breadth of integration literature	[4]
ANFIS-based nonlinear MPPT tracking efficiency	>99.6%	Supports intelligent MPPT as a high-performance converter-level solution	[10]
Enhanced real-time MPPT performance	99.99% static, 99.98% dynamic efficiency; 0.002 s tracking time	Shows the benchmark performance expected from advanced intelligent control	[12]

Table 1.1: Selected Statistical Indicators Relevant to Optimal Renewable Integration in India



Intelligent approaches have come through as more than just “extra add-ons” because recent reviews suggest that artificial intelligence, machine learning, and deep learning actually improve renewable forecasting, adaptive control, demand response, storage dispatch, fault diagnosis, and cyber resilience across today’s grids.[5] The newest papers even push the same point further, by arguing that AI powered control and optimization setups can handle multi objective trade-offs around cost, resilience, and sustainability, while at the same time supporting digital twins, anticipatory fault

diagnosis, and intelligent coordination for storage, all of which line up with the Indian need for reliable operation in power systems that carry lots of renewables.[6]

You can see why “intelligence” matters even more if you zoom out to system wide renewable management, since the current evidence indicates AI boosts forecasting accuracy, helps tune the energy demand–supply pairing, cuts downtime via predictive maintenance, and strengthens decentralized energy networks like microgrids and storage coupled configurations. Operational penalties linked to variability and uncertainty can be reduced.[7] Related review findings on hybrid renewable energy systems also point to the idea that modern energy management relies on methods that are evaluated not only for technical plausibility but also for scale up potential, operational adaptability, cost effectiveness and real time decision capability. Which is why classical rule-based approaches are being swapped out for optimization assisted, and AI directed supervisory control, more and more.[8]

For solar photovoltaic systems, integration starts to feel more granular at the converter and controller levels, since PV arrays are nonlinear, weather dependent generators whose power voltage curves keep shifting, not just because of irradiance, but also due to temperature changes. So any small mismatch between the chosen operating point and what is truly the maximum power point reduces the energy you actually capture , and it also drags down the grid side efficiency in an indirect way.[9] Because of that, recent embedded and processor in the loop validation work puts extra stress on ANFIS based nonlinear MPPT approaches for boost converter fed PV systems, and it basically shows that a controller that is tuned in a smart way can still reach tracking efficiencies above 99.6% , with quick convergence and stable behaviour even when the environment changes around it, and yes that is exactly the adaptive control vibe that becomes important when distributed PV penetration grows fast.[10]

Genetic algorithms still look appealing for MPPT and renewable optimization because they can roam globally, they adapt to nonlinear objective landscapes, and they also help you not get stuck in local optimum traps which often harms more classical approaches when partial shading happens or when weather swings quickly.[11] In addition, real time evidence from new PV literature suggests advanced intelligent MPPT can get 99.99% static efficiency, 99.98% dynamic efficiency, and an average tracking time around 0.002 s. That set of results basically backs the present research

direction, meaning GA tuned ANFIS control paired with a boost converter, as a practical path to pulling out more energy, giving a better dynamic response, and ultimately supporting a more dependable renewable integration in India's gradually evolving smart grid context.[12]

1.1 BACKGROUND OF THE STUDY

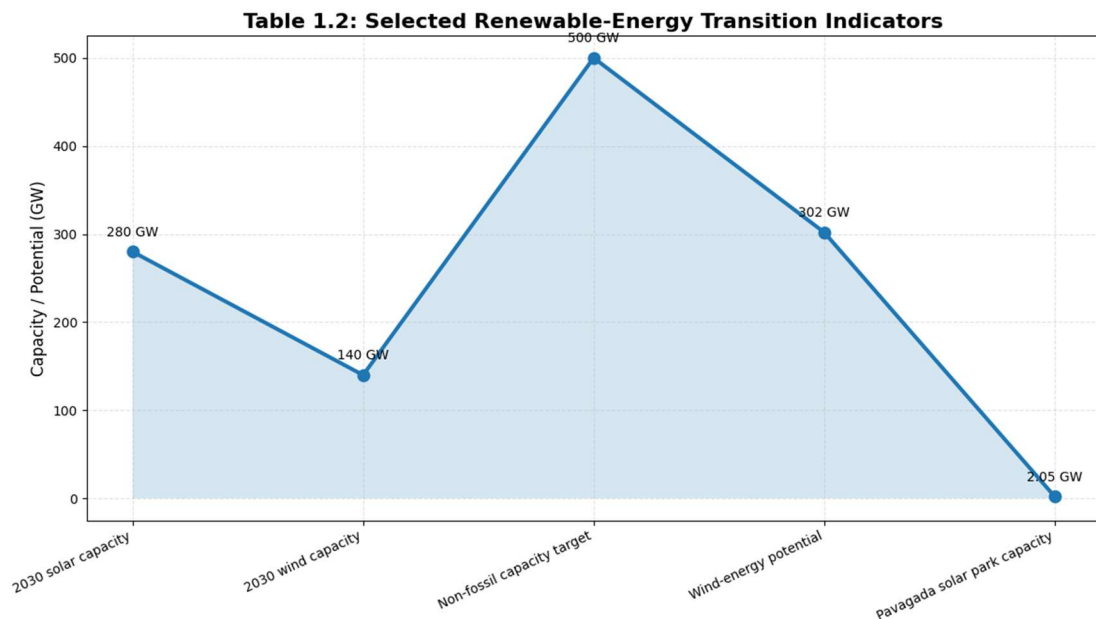
Technically important because renewable energy sources provide variability, unpredictability, bidirectional power flow, low inertia, and new needs for forecasting, control, and protection [13], the worldwide power industry is going through a structural change from centralized fossil-fuel-based generation to dispersed, renewable-rich, power-electronics-dominated systems. In India, renewable energy is both an environmental necessity and an energy-security concern since the country's electricity consumption is increasing with industrialisation, urbanisation, digitalisation, and electrification of transportation, whereas traditional thermal production still generates emissions, fuel import exposure, and local environmental consequences. Recent review literature categorizes India as one of the leading renewable-energy markets, and the country's solar, wind, hydro, biomass, and hybrid renewable resources are progressively being seen as substitutes for conventional power generation in long-term power system design [13]. Therefore, the electrical engineering difficulty is to combine renewable energy sources in a way that voltage stability, frequency stability, power quality, protection coordination, economic dispatch, and system reliability are maintained under constantly shifting generation and load situations [15].

In terms of power-system operation, renewable integration differs from conventional generation expansion since solar and wind outputs are non-dispatchable in their natural form and rely on weather-driven factors including irradiance, temperature, wind speed, cloud movement, and seasonal patterns [16]. This is especially pertinent for photovoltaic systems because the output power of a PV module varies nonlinearly with solar irradiance and cell temperature, thereby making maximum power point tracking vital for enhancing energy extraction under dynamic environmental conditions [17]. The use of DC-DC converters, such as boost converters, in solar PV systems allows for voltage amplification and controlled operation, but the converter must be governed by an intelligent MPPT controller if the system is to operate near

the true maximum power point during fast irradiance variations [18]. This is why modern renewable-energy research increasingly combines device-level control, such as MPPT, with system-level optimization, such as renewable dispatch, storage scheduling, and grid-support control [18].

Table 1.2 Selected numerical background indicators for renewable-energy transition and integration

Parameter Indicator	/ Numerical value reported in recent literature	Engineering significance	Ref.
India's planned 2030 solar capacity	280 GW	Indicates the large solar-PV base that will require MPPT, forecasting, storage, and grid-support control	[15]
India's planned 2030 wind capacity	140 GW	Shows the scale of variable renewable generation requiring forecasting and balancing reserves	[15]
India's non-fossil electricity capacity target	500 GW by 2030	Establishes the need for transmission planning, smart-grid control, and optimal renewable integration	[15]
India's intended renewable-energy share in energy requirement	50% by 2030	Highlights the requirement for reliable operation under high renewable penetration	[15]
Estimated solar-energy incident potential over India	5000 trillion kWh	Demonstrates why solar PV is central to India's long-term renewable strategy	[15]
Estimated wind-energy potential reported in transition literature	302 GW	Supports wind as a major complementary renewable resource with solar	[15]
Pavagada solar park case-study capacity	2.05 GW	Shows the scale of utility solar projects and the associated land, infrastructure, and governance issues	[16]



1.2 RENEWABLE ENERGY TRANSITION IN INDIA

The change in India's renewable energy is driven by the synergistic goals of decarbonization, energy security, economic growth, and universal access to dependable electricity; recent academic research links this shift with Sustainable Development Goal 7 on cheap and clean energy and Sustainable Development Goal 13 on climate action [15]. The Indian target structure is ambitious because the 2030 plan includes 500 GW of non-fossil-fuel electricity capacity, with solar and wind forming the largest shares at 280 GW and 140 GW, respectively [15]. Technically complicated, this shift is since renewable expansion does not just replace traditional generating megawatt for megawatt; it also alters the operating characteristics of the grid by raising ramping needs, lowering synchronous inertia, boosting uncertainty in day-ahead scheduling, and demanding fast-acting control resources [19].

Although its output fluctuates during cloud transients and temperature variations, the development of solar PV in India is particularly crucial since PV generation is modular, scalable, and appropriate for both utility-scale solar farms and dispersed rooftop systems [17]. Review studies on India's renewable portfolio show that the country has strong resource potential across solar, wind, biomass, and hydro, but the effective use of these resources depends on grid planning, storage, forecasting, and market mechanisms [14]. Because India's planned solar and wind expansion can result in emission reductions but could also produce end-of-life waste, necessitate recycling

systems, and impose new criteria for lifecycle assessment in renewable planning, the shift also has a macroeconomic component [15]. One analysis found that increasing solar and wind power could result in 11%–23% fewer emissions while also generating 7.1–24 thousand tonnes of solar PV trash and 14.2–48.3 million tonnes of wind-turbine garbage, therefore highlighting the need for technically, economically, and ecologically optimized renewable integration [15].

India's renewable energy transition is also regional in character since solar and wind resources are concentrated in particular states, whereas main load centres may be located far from renewable-rich areas [16]. Because renewable generation has to be transferred and balanced across vast network regions [18], this geographic mismatch highlights the need of inter-state coordination, flexible dispatch, transmission development, and modern monitoring systems. Large renewable projects like the 2.05 GW Pavagada solar park highlight both the technical potential and the institutional complexity of these undertakings, as elements like land use, evacuation infrastructure, local involvement, and grid connectivity become critical determinants in the deployment of renewable energy [16]. Therefore, the Indian transition cannot be measured just by installed capacity; it also has to be evaluated by deliverable energy, grid stability, curtailment reduction, storage readiness, and control performance [18].

1.3 NEED FOR OPTIMAL INTEGRATION OF RENEWABLE ENERGY RESOURCES

High renewable penetration can pose operational difficulties including voltage fluctuations, frequency variations, reverse power flow, harmonic distortion, congestion, protection miscoordination, and higher reserve requirements [18], thus optimal integration of renewable energy sources is essential. Because the difference between generation and demand causes frequency variation and unexpected tie-line power exchange, load-frequency management becomes notably critical in renewable-rich systems; recent review publications identify renewable-integrated load-frequency control as a key research direction for future power systems [19]. While the inertia of synchronous machines in traditional grids provides frequency support, the lowered rotational inertia in PV- and inverter-dominated grids increases the sensitivity of the system to unexpected power imbalances [19]. Therefore, optimal integration is not

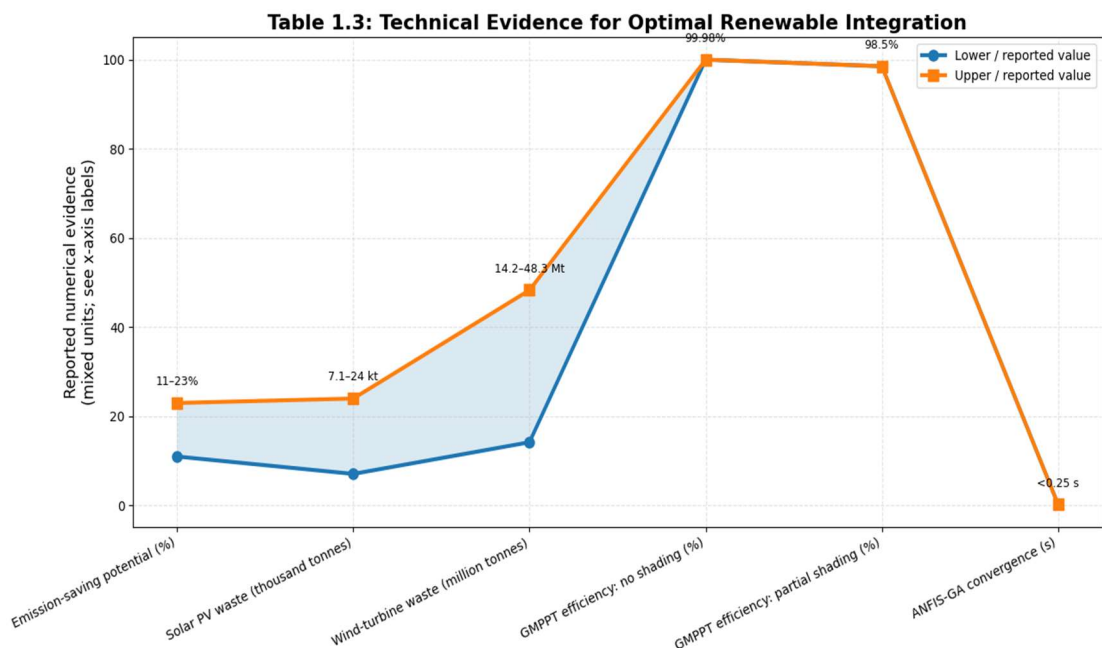
just about adding renewable capacity; it also requires coordinated control of converters, storage, demand response, flexible generation, and network devices [18].

In addition, optimal integration involves getting the most useful energy from every renewable source while lowering emissions, curtailment, losses, cost, and reliability concerns [20]. In PV systems, this need starts at the module and converter level, where MPPT control has to guarantee that the PV array runs at the maximum power point notwithstanding changes in temperature and irradiance [17]. Under partial shading, the difficulty rises as several peaks emerge on the power-voltage curve, and conventional MPPT techniques could converge to a local maximum instead of the global maximum [17]. Recent ANFIS-GA MPPT research found 99.98% GMPPT efficiency under no shading, 98.5% under partial shading, and 97.67% under severe shading, therefore demonstrating the practical benefits of hybrid intelligent controllers over traditional tracking techniques [17].

Table 1.3 Technical reasons for optimal renewable integration and representative numerical evidence

Integration issue	Numerical / technical evidence	Implication for electrical engineering design	Ref.
Solar and wind expansion target	280 GW solar + 140 GW wind by 2030	Requires optimal generation scheduling, transmission planning, and reserve allocation	[15]
Emission-saving potential from solar-wind transition	11%–23% savings	Supports renewable expansion but requires lifecycle-aware planning	[15]
Solar PV waste under expansion scenarios	7.1–24 thousand tonnes	Requires lifecycle management and circular-economy planning	[15]
Wind-turbine waste under expansion scenarios	14.2–48.3 million tonnes	Requires recycling and end-of-life integration planning	[15]
ANFIS-GA GMPPT efficiency under no shading	99.98%	Confirms high energy-extraction capability of intelligent MPPT	[17]
ANFIS-GA GMPPT efficiency under partial shading	98.5%	Shows robustness under realistic nonuniform irradiance	[17]
ANFIS-GA convergence under time-varying irradiance	Below 0.25 s	Supports fast dynamic response for converter-level renewable control	[17]

Load-frequency control challenge	Frequency deviation and unscheduled tie-line exchange identified as central concerns	Requires advanced control, storage, FACTS, and optimization techniques	[19]
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At the grid level, optimal integration is needed, to somehow coordinate renewable generation with energy storage systems, demand-side management, forecasting platforms, and flexible transmission technologies [18]. Smart-grid integration really becomes important here, because sensors, communication systems, phasor measurement units, supervisory control, and energy-management systems give the real-time information that you need to run a variable renewable grid securely [20]. In the more recent review literature on smart-grid and renewable integration, it is often stated that renewable rich power systems do not work well unless there are coordinated solutions such as storage, power electronics, demand response, forecasting, and also cyber-secure communication networks [20]. From the viewpoint of an M.Tech in electrical engineering study, the research problem is therefore multi-disciplinary, because it brings together power electronics, intelligent control, optimization algorithms, power-system operation, and renewable-energy policy into one bundled framework [18].

1.4 ROLE OF INTELLIGENT TECHNIQUES IN RENEWABLE INTEGRATION

Intelligent techniques are being used more and more in renewable integration because they can handle nonlinear systems, kind of learn from existing data, optimize while uncertainty is around, and keep tuning controller performance as environmental and operating conditions change [18]. Artificial neural networks are handy for renewable forecasting and nonlinear mapping, fuzzy logic works well when uncertainty needs to be managed, while ANFIS blends learning ability with a linguistic rule-based reasoning approach. Also, evolutionary algorithms like GA and PSO are useful when you want to tune controller parameters and move the system toward good operating points [18]. For PV applications, ANFIS fits MPPT pretty well, since it can infer the right control action from nonlinear input output relations tied to irradiance, temperature, PV voltage, PV current, and power [17]. Genetic Algorithm is also helpful here, because it searches through parameter mixtures for the best set without relying on a convex analytical model, so it suits nonlinear PV control and multi peak power curves [17].

The influence of intelligent techniques becomes even stronger once renewable systems are coupled to the grid, since forecasting mistakes, voltage swings, load uncertainty, and even contingency situations have to be handled in real time [19]. AI based renewable integration supports predictive control, adaptive dispatch, fault detection, storage scheduling and demand response coordination, all of which are needed to keep reliability steady in inverter dominated grids [18]. In load frequency control, optimization methods, energy storage, FACTS devices, and microgrid control are repeatedly listed as upcoming research directions for renewable integrated power systems [19]. So, intelligent approaches help renewable energy “join in” at two spots: first, right inside the converter, via MPPT and also power-conditioning control, and second at the grid side through forecasting, stability management, protection work, and energy management [18].

The GA tuned ANFIS based MPPT setup feels technically suitable because it tackles the nonlinear, and time changing behaviour of a solar PV unit that uses a boost converter [17]. The ANFIS controller does an adaptive mapping between the surroundings or electrical measures and the desired operating point, while the GA

helps further by tuning the controller settings, so the tracking error becomes as small as possible [17]. In a newish ANFIS-GA investigation, this mixed intelligent MPPT kept efficiencies above 98.5% even when the irradiance was really hard and changing with time, and it also reached convergence in under 0.25 s, which backs the idea of using it for top-tier PV extraction [17].

Then, if you blend that kind of controller level cleverness with system level renewable forecasting, storage, and smart-grid coordination, it feeds into the overall goal for better renewable integration across India [18].

1.5 RENEWABLE ENERGY INTEGRATION IN INDIA: STATUS, OPPORTUNITIES, AND CHALLENGES

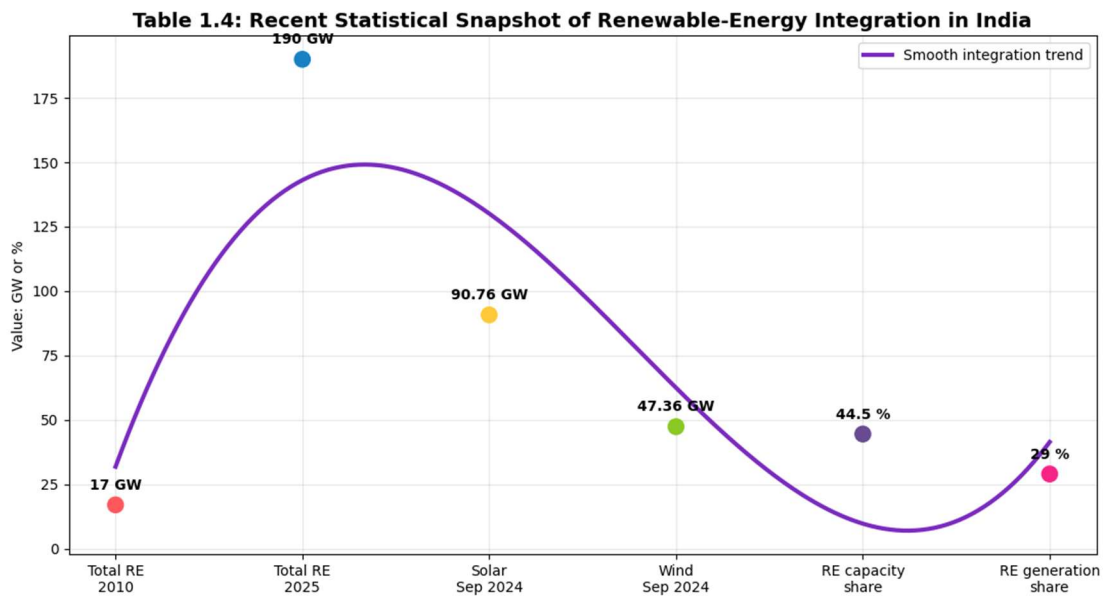
India's challenge with integrating renewable energy has evolved from simply adding capacity to optimizing the entire system. Recent academic findings indicate that the nation's total installed renewable capacity rose from 17 GW in 2010 to nearly 190 GW by 2025. Solar energy has seen the most rapid increase, boasting a compound annual growth rate of around 24.8%, while wind energy expanded at approximately 10.3%. This growth has intensified the operational demands on forecasting, scheduling reserves, managing storage, and ensuring network adaptability [21]. Further literature reviews reveal that as of September 2024, India's renewable energy mix included 90.76 GW of solar power and 47.36 GW of wind power, contributing to roughly 44.5% of the total installed capacity. However, these renewables accounted for only about 29% of the actual electricity produced, highlighting the challenges of intermittency, curtailment, and the need for flexibility in integrating large-scale renewables [22]. Additionally, policy analysis confirms that India's energy transition is driven by the need for both climate mitigation and energy security. The national strategy demands rapid growth in non-fossil fuel capacity while ensuring affordability, industry competitiveness, and grid stability [23]. Reviews of India's renewable energy progress after COP21 further emphasize that the transition now encompasses not only solar and wind but also includes hydro, biomass, hydrogen, waste-to-energy, and new geothermal sources. This requires a comprehensive integration strategy that goes beyond focusing on individual technologies [24].

1.5.1 Overview of Renewable Energy Resources in India

India has a wide range of renewable resources, but their integration is inconsistent. Solar and wind energy lead in installed growth, while hydropower provides flexibility to the system. Biomass offers a low-carbon fuel option, and geothermal and hydrogen are still developing but have important potential [21]. Recent reviews of India's energy sector highlight it as one of the most vibrant renewable-energy markets globally. However, they also emphasize that effective integration relies less on the total installed capacity and more on the sufficiency of transmission, storage, energy markets, digital management, and system balancing abilities [22]. Current research indicates that India's renewable energy mix should be assessed in terms of both resource variety and control, as resources with significant variability require supporting resources that offer flexibility, storage, or dispatchability [23].

Table 1.4 Recent statistical snapshot of renewable-energy integration in India

Indicator	Reported value	Interpretation for integration studies	Ref.
Total installed renewable capacity in India	17 GW (2010) to 190 GW (2025)	Shows very rapid growth of renewable capacity and increasing integration complexity	[21]
Solar installed capacity in India	90.76 GW (Sept. 2024)	Confirms solar as the dominant variable renewable source in India	[22]
Wind installed capacity in India	47.36 GW (Sept. 2024)	Indicates major dependence on wind forecasting and balancing capability	[22]
Renewable share in installed capacity	44.5%	Reflects structural transition of the generation mix	[22]
Renewable share in actual electricity generation	~29%	Shows the gap between capacity share and energy share due to intermittency and utilization effects	[22]
Western and Southern regions in 15-minute India model	592 million people; 59% of GDP	Demonstrates why regional coordination matters for high-RE planning in India	[26]



1.5.1.1 Solar Energy

Because India has strong irradiation conditions, dropping PV prices, and the ability to generate solar both on a utility scale and on a distributed basis, rooftop PV, agricultural feed ers, and micro-grids [21], Solar energy is at the forefront of the Indian renewable boom. According to the latest review on Indian solar energy, there was 90.76 GW of solar capacity in September 2024, the fastest-growing segment of its national energy generation and a significant contributor to daytime variability [22]. Solar energy is particularly beneficial in India as it can be produced modularly; however, a number of external factors including diurnal cycles, cloud movements, temperatures and dust, mean that M P P T control, storage coordination and prediction is of crucial importance in utilizing the installed capacity effectively [25].

1.5.1.2 Wind Energy

As the second biggest renewable variable source, Wind energy is valuable because it is temporally and seasonally complementary to solar in high-resource regions and coastal corridors [22]. Numerous wind integration reviews identify frequency control and prediction to be at the heart of integration, with one review in 2024 noting that approximately one third of all wind forecasting studies are already relying on supervised machine learning techniques, demonstrating how modern wind integration is growing dependent on prediction [27]. A wide scale integration of wind also requires that support is available from energy storage systems to manage the

unpredictable output and low-inertia characteristic of wind turbines in modern power systems [28].

1.5.1.3 Hydropower

In a highly renewable energy intensive systems, hydropower's capacity to supply inertia, peaking power, balancing flexibility and dispatchability make it strategically vital. A comprehensive study of sustainable hydropower concluded that hydropower can accommodate nearly 30% of the varying needs of energy production throughout its various time frames in renewable energy-dominant systems, revealing its significance far beyond its installed capacity share [29]. Hydropower and pumped hydropower are therefore considered useful technologies for a diverse Indian portfolio, particularly to accommodate load ramps, manage frequency regulation, reserve and ease grid congestion [22].

1.5.1.4 Biomass and waste-to-energy

Both biomass and waste-to-energy resources are seen as important owing to their ability to generate a dependable supply of low-carbon electrical and heat energy that is complementing non-dispatchable wind and solar power [24]. Recent work examining the post-COP 21 de-carbonization roadmap of India revealed that in addition to other technologies including biomass, hydrogen, hydro, and waste-derived vectors, biomass has the capacity to contribute to future development but is limited by factors including the efficient collection of raw feedstock and supply chain disruption [24]. Despite this, both energy sources are valued highly in the context of Indian integration as sources of firm power that are suitable for both energy systems in the rural sector and agro industrial clusters and waste management in a range of urban applications [24].

1.5.1.5 Geothermal and emerging resources

The use of geothermal and a range of emerging energy technologies in India is low at the current stage, however they remain valuable for long-term diversified energy supply as sources of firm energy that are less intermittent than wind and solar power [31]. In a review of geothermal potential in India in 2024, 14.86% of the surveyed regions were classified as having very high to high geothermal potential, 21.98% as

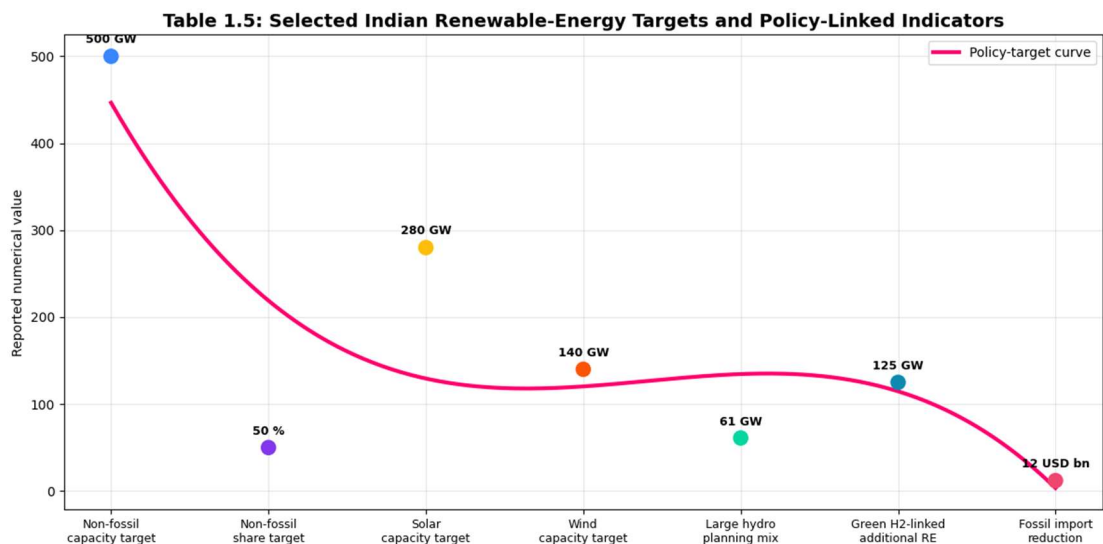
having high potential, 27.18% as having medium potential, 11.78%-24.20% as having low to very low potential indicating good potential despite geographic limitations [31]. Green hydrogen is also emerging as a renewable energy vector with recent reviews estimating that India could save \$12 billion on its fossil fuel imports in 2030 by importing up to 125 GW less renewable capacity, create approximately 600,000 jobs by 2030 and support its hard-to-abate sector through integration [30].

1.5.2 Targets and Policy Framework of India in the renewable energy sector

Recent reviews of policy analysis have indicated that India's aims are now to develop renewable energy more quickly to achieve its goal of generating 500 GW of non-fossil electricity by 2030 and its 50% non-fossil capacity target for 2030, while also targeting long-term reductions in fossil fuel imports and building industry capacity [23, 24]. Policy ambition cannot overcome limitations in tender design, the speed of interstate transmission and the health of electricity distributors [22].

Table 1.5 Selected Indian renewable-energy targets and policy-linked indicators from recent literature

Policy / target indicator	Numerical value	Integration significance	Ref.
Non-fossil electricity capacity target for 2030	500 GW	Requires major scaling of grid flexibility, storage, and balancing resources	[23]
Non-fossil share target in electricity capacity	50% by 2030	Implies much higher renewable penetration in operational planning	[23]
Solar capacity target	280 GW by 2030	Requires advanced PV forecasting, MPPT, and transmission readiness	[22]
Wind capacity target	140 GW by 2030	Requires improved wind forecasting, ancillary services, and reserve planning	[22]
Large hydropower in 2030 non-fossil planning mix	61 GW	Supports balancing and flexibility in high-renewable operation	[22]
Additional renewable capacity linked to green hydrogen by 2030	125 GW	Shows that sector coupling will intensify renewable integration requirements	[30]
Estimated reduction in fossil-fuel imports from green hydrogen pathway	USD 12 billion by 2030	Indicates macroeconomic value of integrated renewable-hydrogen systems	[30]



1.5.3 Grid Modernization and Smart Grid Development in India

Modernizing the grid is critical for India as classical one-directional power-flow assumptions no longer work for an energy system that must account for significant variable generation, distributed energy resources, load response, electrical vehicles, and digitally managed systems [25]. The review on smart grids published in early 2024 states that the paradigm is shifting from generation in few centralized locations to decentralized but digitally managed, with distributed generation adding new dynamics and stresses, necessitating more robustness in monitoring, control and communication layers [25]. Smart grid functions such as AMIs, state estimation, real time monitoring, energy management systems, demand response, automated control are needed to support a reliable Indian grid when it deals with the fluctuation from renewable energy sources [23]. Hybrid and smart grid integration research also reveals that cost-efficiency, responsiveness, flexibility and structural strength are fundamental attributes to analyse the hybrid and smart grid energy management schemes, which is a basic aspect to examine renewable rich energy systems [32].

1.5.4 Technical Challenges in Renewable Integration

The integration of renewable energy in India poses technical challenges that are inherently interconnected: variability of resources, imperfect forecasts, limited inertia, interfaces through power electronics, constraints on the network, and risks relating to cyber-physical security interact on various time scales from milliseconds to seasons [22]. Recent high resolution Indian planning studies highlight the need for effective

inter-regional coordination and storage to achieve affordable renewable pathways and supply large populations and demand centres without significant curtailment [26].

1.5.4.1 Variability and Intermittency

1 The most obvious challenges are variability and intermittency as the output of solar and wind energy sources depend on the weather and do not perfectly match with the patterns of the load [22]. The deviation becomes greater with increasing renewable capacity as flexibility resources do not increase proportionately. High resolution studies focusing on India highlight how capacity share is quite different from energy share, a manifestation of intermittency and inefficient use of resources [22].

1.5.4.2 Uncertainty of Forecasting

The forecast uncertainty influences unit commitment, reserve provisioning, market clearing, storage scheduling, and real time balancing of the system [27]. Research on wind integration points out that forecasting accuracy greatly enhances levels of renewable integration, and AI based and data-driven techniques are used to reduce this uncertainty over the short- and medium-term prediction horizons [27, 34].

1.5.4.3 Voltage and Frequency Stability

With a dominated system relying on inverters, voltage and frequency stability can be difficult to achieve due to reduced synchronicity and hence greater sensitivity to load fluctuations and ramping events [28]. Research suggests that the key factors for frequency regulation, where a significant portion of power generation comes from renewables that displace conventional synchronous generation, are the provision of energy storage and advanced control systems [28].

1.5.4.4 Power Quality Issues

Power quality challenges such as flicker, harmonics, voltage fluctuation, and converter-induced oscillations become important when there are large proportions of generation interfaced through power electronics [25]. Smart-grid studies therefore need to focus on intelligently controlling converters, coordinated support for voltage, and fast supervisory control to mitigate any detrimental impact on the grid due to variable renewable sources [25].

1.5.4.5 Protection and Cyber-Physical Security

Coordination of protection is complicated when current fault levels, flow direction, and behaviour of converters are different than those of conventional grids [25]. In addition to these, there is increased risk of cyber-physical security threats as the grid's dependence on communication, sensor data, platforms for data aggregation and processing, and dispersed intelligent decision making widens the potential attack surface [32].

1.5.4.6 Transmission Congestion and Infrastructure Constraints

Severe congestion of the transmission network and infrastructure constraints can result from the geographical separation between high resource renewable generation areas and load centres [26]. High resolution studies for Indian grids highlight the impact of inter-regional coordination and storage for cost-effective renewable deployment, suggesting that infrastructure planning is inextricably linked with renewable integration planning [26].

1.5.5 Operational Challenges in Systems with High Renewable Penetration

Renewable penetration necessitates adjustments in grid operation such that the scheduling process not only relies on fuel-cost optimization but also accounts for fast ramps, probabilistically determined reserves, minimizing curtailment, and charge level of storage devices [26]. Least cost operation is heavily impacted by inter-regional coordination; Optimizing renewable integration solely at the state level does not yield optimal results [26]. Issues like deviations in the day ahead schedule, adequacy of ancillary services, curtailment of renewable energy, and balancing between geographically dispersed weather patterns exist [22]. This problem becomes more exacerbated with new demands like that of electrolyzers which creates an additional time-coupled linkage between electricity and fuel production as well as industrial decarbonization strategies [30].

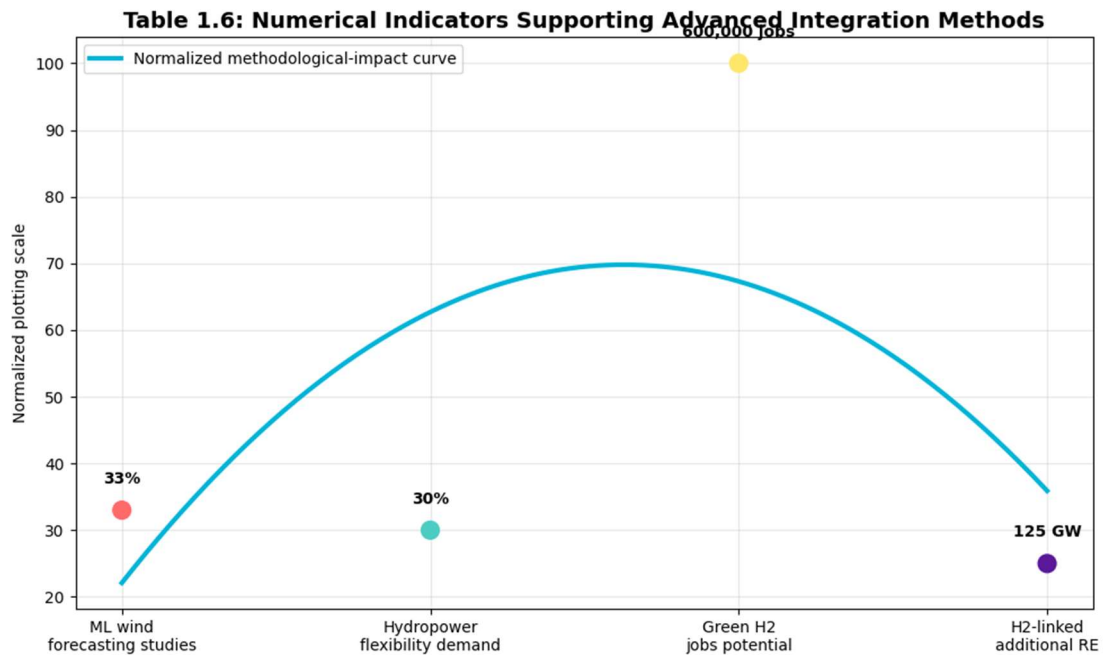
1.5.6 Need for Advanced Control, Forecasting and Optimization

Advanced control, forecasting, and optimization methods are needed since the operation of systems with high renewable penetrations is nonlinear, probabilistic, and

multi-objective in nature [32]. The integration of novel hybrid renewable systems involves a balance between cost, flexibility, scalability, prediction accuracy, and real time operational efficiency, which a simple set of rules cannot guarantee [32]. AI-driven control can offer benefits in day-ahead generation demand prediction, optimized dispatch of storage resources and coordinated control of distributed generation resources, enabling improved and cost-effective integration of renewable energy [35]. A review on renewable integration for the grid with AI shows a strong positive impact of the methodology on the reliable and cost-effective integration of renewable sources by adequately addressing issues of variable supply, uncertainty, and difficult optimization problems [34].

Table 1.6 Numerical and methodological indicators supporting advanced integration methods

Indicator / result	Reported value or finding	Relevance to this study area	Ref.
Wind-forecasting studies using supervised ML	~33%	Shows the growing dominance of data-driven forecasting for integration	[27]
Flexibility demand potentially met by hydropower	~30%	Highlights the balancing value of hydro in renewable-rich systems	[29]
Green hydrogen jobs potential in India by 2030	600,000 jobs	Shows sector-coupled value of renewable expansion beyond electricity alone	[30]
Additional renewable capacity linked to hydrogen pathway	125 GW	Indicates how emerging sectors will intensify renewable-integration requirements	[30]
Evaluation criteria highlighted for AI-based EMS	Scalability, flexibility, cost effectiveness, real-time decision-making	Shows why intelligent techniques are preferred in hybrid renewable systems	[32]
AI-enabled renewable integration role	Prediction, storage optimization, distributed-resource coordination	Supports advanced forecasting and control as future grid essentials	[35]



1.6 INTELLIGENT TECHNIQUES FOR OPTIMAL INTEGRATION OF RENEWABLE ENERGY RESOURCES

Smart techniques are considered essential as they can describe non-linear relationships, react to evolving information and make optimum decisions for conflicting objectives such as economics, stability, emissions and power generation. From the recent survey on AI application, renewable integration is now heavily relying on machine learning, deep learning, evolutionary optimization, data driven forecast for prediction, scheduling of storage devices, demand response management, anomaly diagnosis, controller design and etc [34]. Another article focused on AI research into the grid control can conclude that with the application of AI technologies, coordination among renewable sources and storage devices is far better than traditional static control methods under uncertain environment conditions (weather and load) [35]. Reviewing globally on the renewable energy transition research suggests that smart integration is closely related to the global tendency towards digital-only approach in the framework of the fourth industrial revolution where enabling technologies, intelligent and favourable regulatory and market structures, and digital government are indispensable to the progress of renewables integration [33]. The engineers view such technologies as artificial neural networks (ANN), ANFIS, fuzzy logic, PSO, GA, reinforcement learning, and hybrid

optimization as essential as optimal renewable integration is not just a planning issue any more, but a process of prediction, control and decision making [34].

1.7 GLOBAL RESEARCH TRENDS IN RENEWABLE ENERGY INTEGRATION

Global research trends suggest renewable integration research is shifting from being treated as a stand-alone engineering problem to being handled as a coupled problem including digital control, socio-economic transition, infrastructure modernization and market design [33]. Recent global review literature notes that transitioning to very high renewable shares demands clear long-and-short-term policy targets, better financial incentives, solid market design and advanced computational technology that can assist in forecasting, flexibility and system coordination [33]. Research has also started to look at hybrid renewable systems, storage-coupled operations, P2P frameworks, sector coupling, AI based forecasting, focusing on managing uncertainty and enhancing resilience [32, 34]. Current global trends in wind integration is driven by ML forecasting, hybrid frequency control and storage-supported ancillary services [27, 28]. Hydro literature across the world is now predominantly treating hydropower as a conventional renewable source not just as a flexibility resource and balancing provider [29]. Research interest in green hydrogen and geothermal has risen in the literature due to the potential of these resources to fill the firm-capacity gap of variable renewables and enable long-duration decarbonisation [30, 31]. These trends together suggest that optimum renewable integration research in India must move toward hybrid intelligent frameworks encompassing forecasting, optimization, storage dispatch and adaptive control across both converter-and-system level times scales [34, 35].

1.8 NEED FOR THE STUDY

The reason behind carrying out the present study is the increasing penetration of renewable energy in India and the difficult task of integrating the renewable energy sources like solar and wind with the grid reliably and economically. Since India is heading toward high non-fossil based generation, the traditional way of grid operation, forecasting and controlling can no longer cope up with intermittency, uncertainty, voltage fluctuation, frequency deviation and power quality issues. In fact

for solar photovoltaic systems the tracking of maximum power point for different level of solar radiation and temperature must be efficient to gain maximal power out of it, hence enhancing overall system performance.

On one hand the intelligent techniques like Genetic Algorithm, Artificial Neural Network, Fuzzy logic and Adaptive Neuro-Fuzzy Inference System have demonstrated their potentials in renewable energy forecasting, adaptive control, optimization and energy management; on the other hand very less research has been done to link these intelligent techniques with real integration problems in India both at converter and grid level. Hence it is necessary to analyze that how intelligent optimization technique like GA-tuned ANFIS-based MPPT enhance renewable energy utilization and optimizes the overall renewable energy integration in India.

1.9 RATIONALE OF THE STUDY

Justification of this study comes from the facts that the expansion of Indian renewable energy sources is generating novel technical problems requiring smart and dynamic engineering responses. The development of solar photovoltaic generation has a bright future; It is nonlinear and weather dependent, making real-time effective extraction of the power problematic. The conventional MPPT approaches have slow dynamic response, low tracking efficiency and performance degradation when the weather condition changes quickly or when the panel is partially shaded. This then implies a clear necessity for intelligent approaches to boost the performance of MPPT and adaptivity of the system.

Beyond that, integrated use of renewable energy is no longer merely about an additional amount of generation. It is also about coordinate forecasting, controlling, optimizing, and backing up the grid system. The GA and ANFIS are considered appropriate intelligent control strategies because they are suitable to model complex nonlinear systems and to adjust controller parameters and behaviour with regard to the dynamic and changing environmental conditions. Hence, the intelligent strategies such as GA and ANFIS would likely be effective in the Indian power system where there is a high proportion of renewables to the overall power system and growing concerns over system stability. As such, this study seems worthwhile as it proposes a

technologically meaningful and practically feasible proposal to enhance the solar PV performance.

1.10 RESEARCH OBJECTIVES

1. To study the present status, opportunities, and challenges of renewable energy integration in India.
2. To analyze the role of intelligent techniques in the optimal integration of renewable energy resources.
3. To develop a solar photovoltaic system model with boost converter and ANFIS-based MPPT controller.
4. To optimize the ANFIS controller parameters using Genetic Algorithm under varying irradiance and temperature conditions.
5. To evaluate the performance of the GA-tuned ANFIS MPPT system in terms of tracking efficiency, response speed, and suitability for renewable energy integration.

1.11 RESEARCH QUESTIONS

1. What is the present status of renewable energy integration in India, and what major challenges affect its large-scale deployment?
2. How can intelligent techniques improve the optimal integration of renewable energy resources in modern power systems?
3. Why is ANFIS considered suitable for maximum power point tracking in solar photovoltaic systems?
4. How does Genetic Algorithm improve the tuning and performance of an ANFIS-based MPPT controller?
5. To what extent can a GA-tuned ANFIS MPPT approach enhance power extraction and support efficient renewable energy integration under varying environmental conditions?

CHAPTER 2

REVIEW OF LITERATURE

2.1 RELATED WORKS

A review by Iweh et al. (2021) of prerequisites, push factors, practical alternatives, problems and advantages of grid-integration and distributed-generation of renewables concluded that reliability, security, technology, emissions reduction and grid obsolescence are the drivers to a higher penetration of renewables [36]. As such, this review is relevant because it frames renewable integration not as a purely generation-expansion problem but rather as a joint technical and planning problem involving sizing, placement, voltage profile, losses, and grid flexibility [36].

An extensive review of the types and uses of energy storage for renewable integration by Tan et al. (2021) detailed eight types of storage systems (battery, thermochemical, thermal, pumped-air, compressed-air, hydrogen, chemical and magnetic) plus hybrids and argued that storage is critical for smoothing fluctuating renewable output, increasing system reliability, supporting ancillary services and enabling smart grids, making it highly relevant for optimal renewable integration in India [37].

In a systematic review of energy-management strategies for smart green microgrids, Essayeh et al. (2021) observed that integrated control architectures, supervisory control, and scheduling methods are required in microgrids in order to balance supply and demand, and also discussed how such energy-management strategies address broader goals such as sustainability, reliability, and efficiency within renewable-rich, small, localized grids [38].

The design of an ANFIS-based MPPT controller for PV systems operating in an unstable environment was presented by Nkounhawa et al. (2021) which demonstrated the advantages over classical MPPT techniques in that the neuro-fuzzy controller tracks the maximum power point under fluctuating environmental conditions, thereby minimizing oscillation, improving system stability and tracking speed [39]. As such, this paper is directly relevant as it confirms the potential to use ANFIS to tune a boost converter for operation under varying irradiance and temperature conditions in a PV application [39].

Eze et al. (2021) reviewed the many approaches to smart PV system MPPT methods including non-intelligent, intelligent and hybrid designs, concluding that intelligent and hybrid systems were most promising at identifying the maximum power point under both partial and non-partial shading conditions [40]. Also of relevance was the fact that convergence and tracking speeds and efficiency were compared by the authors, providing relevant selection metrics for optimization such as with a GA-tuned ANFIS [40].

A review by Gao et al. (2022) of machine learning for renewable energy forecasting highlighted that these techniques are preferred for predicting a number of parameters accurately due to the inherent nonlinearity captured, offering advantages over conventional methods for renewable energy integration into power systems because accurate forecasting reduces uncertainty in generation output thereby improving the scheduling and reliable deployment of solar and wind power [41].

An overview of challenges associated with integrating storage into microgrids by Choudhury (2022) detailed issues associated with control, protection, state of charge and discharge, safety, life expectancy, capacity, reliability and cost. This paper is particularly relevant for renewable integration because it clearly emphasizes why storage cannot be considered merely a peripheral technology and instead must be optimized in conjunction with generation and load-management strategies [42].

Developments in multivariate forecasting of wind and solar power are explored by Srensen et al. (2022), whose analysis reveals how multivariate and probabilistic methods generate a more informative prediction than univariate or deterministic single variable forecasts, and are more important for complex grid operations because spatial correlation, dependency structures, and uncertainty within such factors are crucial for renewable dispatch and load balancing [43].

The impacts of integration renewable-based DG on the distribution network expansion were studied by Ayalew et al. (2022) whose work showed how DG alters operating characteristics to lower losses, increase voltage profile and create new demand-based planning needs, though the methodology applied to a different geography, remains relevant for planning renewable-rich distribution systems where DG must be co-optimized with a predicted increase in demand [44].

A demand-response program designed to ensure efficient demand-side management in a smart grid system including renewables was presented by Ali et al. (2022) who presented numerical results indicating a decrease in both carbon emissions and electricity costs, and a reduction in peak-to-average power ratio. The work highlights renewable integration not solely as a supply-side challenge but one dependent on smart user-level load-balancing and energy management [45].

Intelligent approaches to renewable integration into power systems were reviewed by Islam and Roy (2023) where 89 literature entries were examined covering forecasting, intelligent control of systems, storage, techno-economics, and evaluation of system performance, establishing a strong foundation for intelligent renewable integration at the system-level and defining key research elements such as accuracy of prediction, techno-economic validity and algorithm choice [46].

Accuracy is highlighted by Benti et al. (2023) as being key to accurate renewable energy forecasting, with both machine and deep learning methods considered, the authors concluding that it is indispensable to accurate grid operation and management when high renewable energy penetration is achieved [47]. The papers also identify data availability, dealing with uncertainty and interpretability as important ongoing challenges directly relevant for renewable integration studies in India [47].

Using an enormous bibliometric data base of 32,806 entries, Yu et al. (2023) reviewed optimal modelling and solution methods for renewable energy systems. They argue that the future of optimal decisions concerning renewables lies in a hybridisation of forecasting, optimization, simulation and evaluation approaches, supporting the integration of intelligent methods with optimized decision-making across the renewable supply and demand chain [48].

State of the art review on MPPT techniques for hybrid PV-TEG systems was carried out by Yang et al. (2023), and classified 14 algorithms into conventional, mathematics-based, metaheuristic, artificial-intelligence and other classifications [49]. The classification of these MPPT techniques clearly indicates the evolution of research in MPPT from simple conventional/deterministic methods to adaptive, and metaheuristic methods, which can be employed for nonlinear, coupled energy-conversion systems [49].

A review on smart grid technologies for the sustainable energy transition, published by Kabeyi and Olanrewaju (2023) elucidates the role of digital communication, automation, control and power electronics in modernising the grid and enhancing its grid reliability, resilience and renewable friendliness [50]. The work is applicable for the present research because precise operation of the grid with the successful integration of renewable energy requires efficient smart-grid functions for active operation of the grid and coordination of intermittent generation [50].

Systematic mapping of optimization approaches for demand side management in smart grid has been done by Mimi et al. (2023), who identifies peak-to-average ratio and cost to be major objectives, and user preferences, and emissions being increasing objectives. The paper is pertinent for the present topic as the intelligent demand-side optimization schemes can help in mitigating variability in renewable generation and decreasing the pressure on energy storage systems. [51]

Energy management strategy in microgrids has been presented in a review by Allwyn et al. (2023), highlighting the impact of forecasting strategies, control algorithms, uncertainty and tariff structure in the performance of hybrid system. The research is applicable for the present study as it focuses on the aspect of integrating renewable sources in the smart microgrid efficiently and economically. [52]

A comprehensive review on integration of renewable energy with DC microgrid has been published by Alam et al. (2024), which has pinpointed various technical bottlenecks, namely voltage regulation, energy management, inertia control, protection, uncertainty, and cybersecurity [53]. This study is relevant for the present work as the DC microgrid structure is prevalent for high solar generation systems and its integration necessitates advanced control and optimization [53].

Energy storage system technologies, objectives, challenges and future trends have been extensively surveyed by Elalfy et al. (2024) over 350 renowned studies, indicating the role of energy storage for enhancing renewable energy integration and power system stability [54]. The literature directly supports for the study of renewable integration alongside energy storage technology, and operation strategy of storage systems [54].

Artificial intelligence based smart grids and renewable energy integration have been presented in a review by Nagappan et al. (2024) focusing on distributed decision making, power management and renewable energy coordination in smart grids [55]. The work is very relevant as artificial intelligence can provide optimal control not only for renewable energy generation forecasting, but also for the general operation of the smart grid [55].

Smart grid and microgrid renewable energy integration in a deregulated power system and its implications on design, market structure and control have been studied by Dawn et al. (2024) [56]. This paper is relevant for the present research context in India because liberalization of power system, market design and control issues are key for success in renewable deployment. [56]

Demand side energy management system for smart grid with special mention to advanced control strategies for renewable energy integration, and responsive behavior of load have been discussed by Nebey et al. (2024) [57]. This review aligns with the overall argument for efficient integration of renewable sources through intelligent control both from generation and load side [57].

An energy management strategy for a hybrid renewable microgrid system is proposed by Ndeke et al. (2024) showing benefits of coordinated operation of the battery charge-discharge and the grid interaction for an optimized power system [58]. The work has direct relevance as the control mechanism for a hybrid renewable microgrid is explored at the system level [58].

The work carried out by Khan et al. (2024) covers a review of energy management systems for microgrids, especially concerning electric vehicles, artificial intelligence and cybersecurity, indicating that EMS design is an increasing cyber-physical problem rather than a purely economic optimization problem [59]. The contribution is very relevant because India has ambitious renewable integration plans, along with growing concerns of electric vehicle integration and cyber security. [59]

Grid connected PV systems and the use of machine learning and energy storage systems have been reviewed by Kiasari et al. (2024) and the work emphasizes the role of predictive control and smart energy storage coordination under high solar PV penetration for grid-side energy management [60]. The paper fits within the scope of

the present study as it jointly considers intelligence on the PV side and grid side for better performance of solar energy system [60].

The review conducted by Barrera-Singaa et al. (2025) synthesises 90 studies on the integration of renewable energy sources into power systems, published in the period from 2019 to 2025, and points out that technical, regulatory and operational issues must be addressed in concert for successful renewable energy integration [61]. The review is very useful in considering all technical, regulatory and operational aspects for a successful renewable energy integration study. [61]

Synthesis of 101 articles on impacts, integration techniques and scalability for renewable energy systems for smart grid applications has been done by Yeboah et al. (2025) [62]. The work is highly applicable for the present research as the study provides insights on methods and technologies and also investigates issues of scalability for large-scale integration of renewable sources in countries like India [62].

MPPT techniques for solar PV systems have been reviewed by Guanhua et al. (2025), where contemporary techniques have been classified as classical, adaptive, and hybrid methods and has highlighted that AI driven MPPT has enhanced the real-time response and grid connectivity [63]. This review strongly supports the use of hybrid ANFIS for the purpose of tracking under variable atmospheric conditions. [63]

Recent advances in MPPT techniques for PV applications has been discussed by Priya et al. (2025) and it is shown that improvements in PV modeling and tracking control strategy can significantly improve the energy yield and economic performance [64]. The literature helps in supporting the present study in building the MPPT controller based on a nonlinear PV model and intelligent algorithm. [64]

Cavus (2025) comprehensively reviewed on grid transformation and integration under renewable energies and smart technologies; they highlighted aspects such as the integration of wind-solar; digitalization; and intelligent operational support [65]. It is very relevant to the study presented here because the authors considered renewable integration within the broader picture of future power systems evolution, instead of only treating it as a narrow control problem [65].

Ramkumar et al. (2025) reviewed renewable energy integration in EV charging stations and demonstrate how smart charging, V2G and next-generation storage technologies could enhance energy efficiency and promote low carbon mobility [66]. This work is important as it shows how integration is increasingly becoming linked to sector coupling which may be of concern for India as transportation electrification grows [66].

Etanya et al. (2025) reviewed grid-connected distributed renewable energy generation systems and identified fluctuations of voltage and frequency as key issues to power quality, and presented the mitigation measures available [67]. It is beneficial to the study at hand because the integration of renewables would be of no use in practice if power-quality constraints could not be met simultaneously [67].

Ahmad et al. (2025) discussed renewable integration and energy storage on grid scale, and they covered aspects of techno-economic evaluation; operation efficiency; financial incentives; and future directions for batteries [68]. It adds support to the perspective that Renewable integration research should be techno-economic instead of solely technical [68].

Arsad et al. (2025) reviewed on PWM and MPPT control for PV system and compared these on their cost; accuracy; complexity; speed; and efficiency [69]. It has particular relevance for this study because it offers a practical engineering perspective for comparing intelligent and non-intelligent control options for PV systems [69].

Aldulaimi et al. (2025) proposed an AI-enhanced MPPT controller for a grid-connected PV system using ANFIS and showed that the system had robust adaptability to dynamic conditions [70]. This paper is highly relevant to the presented study because it empirically demonstrates the feasibility of employing neuro-fuzzy methods to PV control in a grid-connected scenario [70].

Chandola et al. (2026) reviewed recent progress in MPPT control for PV systems and showed that the number of ANN; PSO and hybrid-based techniques were increasing. Their survey further demonstrates how MPPT is developing away from a purely conventional approach [71].

Mastoi et al. (2026) summarized the application of AI-based control and optimization for renewable energy integration into smart grids and demonstrated the benefits for the stability, efficiency, reliability, fault diagnosis and intelligent management of stored energy [72]. It has significant relevance as the use of AI is presented as key both at the converter level and for system integration of renewables [72].

Ahmadi et al. (2026) surveyed the impact of AI on stability and reliability of smart grids and how integrating AI would enable better real-time control; resilience; cybersecurity; and renewable compatibility of smart grids [73]. The paper is useful in that the integration issue is expanded from generation and forecasting to fault resilience and control [73].

Hu et al. (2026) reviewed on the use of AI and data-driven approaches to the integration of renewable energy and explored how artificial intelligence and data driven techniques has improved the predictability, optimal operation, and grid-connection of renewable energies. It adds value by looking at research trends beyond isolated AI applications toward integrated, multi-functional, data-driven systems [74].

Malakouti et al. (2026) analyzed the various machine learning algorithms applied in renewable energy forecasting and the study provided an up-to-date structural synthesis of the various solar, wind and hydropower forecasting researches over the period from 2018 to 2024 [75]. The survey is of interest to the present work because accurate forecasting is a major mechanism to reduce the uncertainty of integrating renewables into practical power systems [75].

2.2 RESEARCH GAPS

Despite a tremendous rise in literature on renewable energy integration over the recent years, a few key gaps still exist. It is found that issues like renewable-energy expansion, renewable-energy forecasting, smart grids, storage systems, and smart optimization are addressed in existing literature but there are still very few papers that address these collectively. This study found a very weak link between grid-level renewable integration problems and the converter level smart control methods. Many of the reviews highlight the aspect of systems-planning, policy, forecasting and storage, and many a PV control paper highlights on the maximum power point tracking (MPPT) performance only at a laboratory scale or a simulation level. This

consequently indicates an inadequate research work on linking smart MPPT control for solar PV system to the grid objectives like the reliability, stability and proper renewable integration.

The limited integration-studies focusing on India that combines the three different aspects, namely the technical and operational and smart control perspective into a single model is also a research gap. Although, the Indian renewable energy targets, policy framework, and capacity growth have been widely discussed, there is an absence of the engineering-level discussion where intelligent methods can facilitate practical renewable energy integration in the Indian environment and grid. There is less amount of research that considers GA-tuned ANFIS-based MPPT for solar PV integration keeping into consideration the challenges facing India in terms of intermittency, voltage fluctuation, forecasting uncertainty and distributed generation management.

There are many conventional MPPT and optimization-based studies where the output of the study has only been analyzed based on the selected few parameter that define the MPPT performance such as, tracking speed, output power, but it has not sufficiently connected it to overall renewable integration efficiency, adaptability, and system robustness. Furthermore, very little amount of research that studies the collective impact of irradiance variation, temperature variation, boost converter dynamics and smart controller tuning on the integrated system has been found to be available through a single integrated simulation platform.

This tries to bridge this research gap by trying to present a more application-oriented framework, connecting the solar PV system performance improvement through GA-optimized ANFIS MPPT with the overarching research on smart and efficient renewable energy integration in the Indian power systems.

CHAPTER 3

MATERIALS AND METHODS

3.1 RESEARCH DESIGN

In the present research a simulation based quantitative research design is used to compare the efficiency of smart intelligent methods for the maximum power extraction and renewable energy integration of PV systems. The structure of the present research consists of building of a Solar PV model integrated with a boost converter and ANFIS controller that are tuned with an Artificial Genetic Algorithm. This is a comparative and analytical study since the proposed GA-tuned ANFIS MPPT technique is applied for various environmental conditions and its performance is compared with the standard MPPT techniques. In total, PV modeling of the PV system, design of converter, controller development, data creation for training of controller, optimization of controller parameters, simulation in various ambient conditions of irradiance and temperature and analysis based on chosen technical specifications.

3.2 SYSTEM DESCRIPTION AND PROPOSED ARCHITECTURE

The suggested system includes a solar panel array, a DC-DC step-up converter, an advanced MPPT controller utilizing ANFIS, and a Genetic Algorithm for optimizing the controller settings. The solar panel array serves as the primary source of renewable energy, producing fluctuating DC electricity based on the surrounding conditions. Given that the output voltage from the solar module may not always be ideal for direct use with loads or connection to the grid, a step-up converter is integrated to enhance and stabilize the voltage. The ANFIS-based MPPT algorithm regulates the duty cycle of the step-up converter, consistently monitoring the maximum power point of the solar array. The Genetic Algorithm functions as an optimization resource, refining and adjusting the parameters of the ANFIS for better flexibility and accuracy in tracking. Hence, the structure is tiered, with the solar array supplying input power, the step-up converter managing power quality, ANFIS executing intelligent control, and GA guaranteeing the fine-tuning of parameters.

3.3 PHOTOVOLTAIC SYSTEM SPECIFICATIONS

The PV system used in this study simulates a typical solar PV power source operating under varying atmospheric conditions. The chosen PV module has a voltage at maximum power point of 29V, and a current at maximum power point of 7.35A, which is set as the reference operational point when both, the simulation and the controller training are performed. The PV module is modeled from current-voltage and power-voltage characteristic curves in order to accurately describe its nonlinear behavior under various irradiances and temperatures and provide valid PV outputs that are necessary for the design of controllers.

3.3.1 PV module parameter

The principal parameters that will be taken into account to characterize the main PV module are voltage at maximum power point, current at maximum power point, open circuit voltage, short circuit current and nominal operating temperature. These parameters will be used to construct the PV characteristic equations and define the operation area of the MPPT controller. The values $V_{mpp}=29V$, $I_{mpp}=7.35A$ are the important values of operation for the extraction of the maximum power. Other module constant parameters as diode factor, series and shunt resistances may be added to the system.

3.3.2 Electrical characteristics

The PV module is described by electrical characteristics in the form of non-linear I-V and P-V curves. These characteristics are highly dependent on irradiance and temperature and this implies that the position of the maximum power point changes dynamically. For instance, a rise in irradiance means that there is a considerable increase in output current while the output voltage decreases with the increase of temperature. Because of this relationship between characteristics, the controller has to be able to follow the maximum power point under changing atmospheric conditions. Thus, to enable accurate analysis of the controller's performance, the PV model must give a description of the variations in the electrical outputs with current, voltage and power over all ranges of operational conditions.

3.3.3 Operating conditions

The PV system is subject to a range of irradiance and temperature conditions that simulate those of a typical real system. Low, medium and high levels of irradiance are chosen, and the temperature ranges from its standard test value and higher. These varying conditions are used to create data for training the ANFIS, as well as to assess its performance. The objective is to verify the behavior of the GA-tuned ANFIS controller when used to search for the maximum power point under variable conditions, rather than static conditions.

3.4 BOOST CONVERTER MODELING

The suggested system includes a DC-DC boost converter to increase the PV output voltage and facilitate regulated energy transfer from the PV source to the load or next interface level. Since the PV output voltage might not always match the necessary operating voltage, the boost converter is a critical component. Regular inductor, capacitor, switch, and diode components are used to construct the converter model. The MPPT controller creates the switching duty cycle, which regulates its dynamic behavior. To guarantee that controller actions result in real-world voltage and current reactions, accurate converter modelling is essential.

3.4.1 Necessity of Voltage Amplification

The output of the solar PV module is a fluctuating DC voltage that is influenced by temperature and solar irradiance, and this voltage might not be high enough for effective downstream usage. As a result, voltage amplification is essential for sustaining a usable output level and for ensuring a steady energy conversion. By allowing duty-cycle-based control of the operating point, the boost converter increases the input voltage. This makes it ideal for MPPT applications in solar PV systems.

3.4.2 Parameters for Converter Design

The primary design factors of the boost converter are the switching frequency, inductor value, output capacitor value, input voltage range, output voltage target, and load resistance. The criteria are chosen to guarantee stable transient response,

acceptable ripple limits, and continuous conduction mode. While the capacitor maintains the output voltage smoothness, the inductor is selected to minimize current ripple. The switching frequency is chosen to strike a good balance between switching losses and dynamic response.

3. 4. 3 Changing Tactics

Pulse-width modulation serves as the basis for the converter switching mechanism. The duty cycle is chosen by the ANFIS controller based on the current operating state of the PV system. The controller moves the PV operating point closer to the maximum power point by modifying the duty ratio. Therefore, the switching strategy is directly related to the efficiency of the MPPT algorithm and is essential to the rate and reliability with which power is tracked.

3.5 MPPT CONTROLLER DESIGN

Because it combines the learning capacity of neural networks with the decision-making power of fuzzy logic, the Adaptive Neuro-Fuzzy Inference System is used to create the MPPT controller. This hybrid method works well for complicated and unpredictable systems like PV modules. The controller takes input variables pertaining to the PV operating condition and produces the necessary control output for the converter duty cycle. The decision to use ANFIS is made because it can learn from data and get better at controlling its performance via training.

3. 5. 1 The Architecture of an ANFIS Controller

The ANFIS controller is structured as a layered architecture with modules for fuzzification, rule evaluation, normalization, defuzzification, and output generation. Each layer is responsible for a particular task in converting input variables into a control output. The neural learning process modifies the parameters to increase accuracy, while the fuzzy inference mechanism offers rule-based reasoning. The controller can adapt to changing environmental inputs thanks to this architecture.

3. 5. 2 Input and Output Variables

PV system parameters that are affected by temperature and irradiance, such PV voltage, PV current, change in power, and error in operating point, are used as input

variables to the ANFIS controller. The duty cycle command or duty cycle change for the boost converter switch is the output variable. The purpose of selecting these input-output pairs is for the controller to learn the nonlinear link between changes in the environment and the necessary control response in order to maximize the extraction of power.

3. 5. 3 Membership Functions and Rule Base

The linguistic behaviour of the input variables is represented by the ANFIS controller using fuzzy membership functions. Over the input range, appropriate membership kinds are specified, such as triangular, Gaussian, or bell-shaped functions. Input-output data and fuzzy logic are used to create the rule base. The parameters of membership functions and related rules are changed throughout training in order to reduce tracking inaccuracy. The controller can respond correctly to various PV operating conditions thanks to the last rule base.

3.6 GENETIC ALGORITHM-BASED TUNING OF ANFIS

The parameters of the ANFIS controller are adjusted by the Genetic Algorithm optimization engine. The reason for choosing GA is its capacity to do a worldwide search in complicated nonlinear solution spaces without needing gradient data. In this study, GA optimizes parameters such as the form of the membership function, scaling factors, and rule parameters in order for the ANFIS controller to have improved MPPT performance in varying environments.

3. 6. 1 Objective Function

The goal of the objective function is to maximize the extracted PV power while minimizing the error in the maximum power point tracking (MPPT). Terms for tracking efficiency, response speed, settling time, and oscillation around the maximum power point may be included. By minimizing this function, GA determines the parameter set that produces the optimal controller performance.

3. 6. 2 Assessing Physical Fitness

A fitness function, which is derived from the objective function, is used to assess each candidate solution produced by GA. The fitness score indicates how well the ANFIS

controller follows the maximum power point in simulated operating situations. Greater fitness equates to less power loss, less oscillation, and quicker convergence.

3. 6. 3 Selection, Crossover, and Mutation

An initial population of parameter sets marks the start of the GA process. The top-performing individuals are chosen for reproduction via selection. **Mutation introduces random variation to avoid premature convergence**, while crossover combines parent solutions to create new progeny. The population gradually approaches an ideal combination of ANFIS parameters throughout several generations.

3. 6. 4 Parameter Optimization for ANFIS

GA-derived optimal ANFIS parameters are used to complete the MPPT controller. This optimization enhances tracking accuracy, reduces instability, and improves adaptability in fluctuating irradiance and temperature. The simulation model then uses the tuned controller for in-depth testing.

3.7 TRAINING DATA PREPARATION

The PV system is simulated under a variety of environmental circumstances to produce training data. The dataset's objective is to give representative input-output patterns for GA-based optimization and ANFIS learning. The controller's performance is immediately impacted by the training data's quality.

3. 7. 1 Dataset for Irradiance Variations

There are several solar intensity levels in the irradiance data, ranging from dim to bright sunshine. The related PV voltage, current, and power values are measured at each irradiance level. The controller can use these data to understand how the PV operating point varies with solar radiation.

3. 7. 2 Dataset of Temperature Changes

To account for thermal impacts on PV behavior, the temperature data set includes a range of ambient and module temperature values. Because module voltage is primarily affected by temperature, it must be included for effective MPPT control.

The data set allows the controller to respond to actual thermal fluctuations caused by the weather.

3. 7. 3 Data Preprocessing and Normalization

The data are normalized prior to training to lessen scale variations between variables and enhance the stability of the learning process. During preprocessing, noise is removed, consistency is checked, and formatting is done as well. By ensuring a better convergence of the ANFIS training method and a more dependable GA optimization, this procedure increases the likelihood of obtaining accurate results.

3.8 SIMULATION PLATFORM AND TOOLS

A simulation environment like MATLAB/Simulink that is ideal for modeling power electronics and control systems is used to implement the entire system. The platform includes the development and integration of the PV array, boost converter, ANFIS controller, and GA optimization block. Environmental profiles are created, output waveforms are visualized, and performance indicators are calculated using simulation software. The platform may also be used to compare benchmark MPPT techniques under the same operating parameters.

3.9 PERFORMANCE EVALUATION METRICS

Technical performance indicators that represent energy extraction efficiency, MPPT quality, and converter response are used to assess the suggested controller.

3. 9. 1 Efficiency in Monitoring

The degree to which the real operating power matches the PV module's theoretical maximum power is measured by the tracking efficiency. The quality of MPPT performance improves as tracking efficiency increases.

3. 9. 2 Setting Time

The settling time is the period that a controller needs to get to and maintain close to the maximum power point following a fluctuation in temperature or irradiance. A shorter settling time means a faster dynamic response.

3. 9. 3 Oscillation Around MPP

The stability of the controller after the operating point has been attained is shown by the oscillation around the maximum power point. Less oscillation indicates a more efficient converter operation and less power loss.

3. 9. 4 Increase in Output Power

This statistic compares the power produced by the suggested controller to that produced by benchmark approaches. It demonstrates the practical energy gain benefit of GA-tuned ANFIS.

3. 9. 5 Converter Efficiency

The ratio of usable output power to input power is what determines converter efficiency. The efficiency of the boost converter is crucial in assessing the system's overall performance because it is a crucial component.

3. 10 COMPARATIVE BENCHMARK METHODS

The performance of the suggested strategy is contrasted with that of well-known and commonly employed MPPT techniques, such as Perturb and Observe, Incremental Conductance, and maybe standard fuzzy or untuned ANFIS control, in order to confirm its efficacy. These benchmark approaches serve as a guide for measuring advancements in tracking speed, stability, and produced power. By comparing them, we can demonstrate the effectiveness of GA-tuned ANFIS quantitatively rather than qualitatively.

3.11 ASSUMPTIONS AND LIMITATIONS

The study makes the assumption that the PV model adequately reflects actual module behaviour and that environmental inputs are a good representation of real-world operating circumstances. It may also be assumed in simulation that the sensor behaves ideally, there are no communication delays, and the converter hardware operates reliably. The fact that the study is simulation-based and lacks hardware confirmation is a significant drawback. Another limitation is that just a few irradiance and temperature profiles are taken into account, while actual outside circumstances might

include more disturbances like inconsistent shading, dust buildup, and measurement noise.

3.12 STATISTICAL ANALYSIS TOOLS

Statistical analysis tools are used to interpret simulation outputs and compare the performance of the proposed controller with benchmark methods. Descriptive statistics such as mean, maximum, minimum, standard deviation, and percentage improvement are used to summarize tracking efficiency, output power, and settling time across test cases. Error measures such as absolute error, relative error, and root mean square error may be used to assess controller performance. Comparative plots, response curves, and tabular summaries are also used to present the results clearly. These statistical tools support objective evaluation of the proposed method and help establish whether the GA-tuned ANFIS controller provides meaningful improvement in PV power extraction and overall system behaviour.

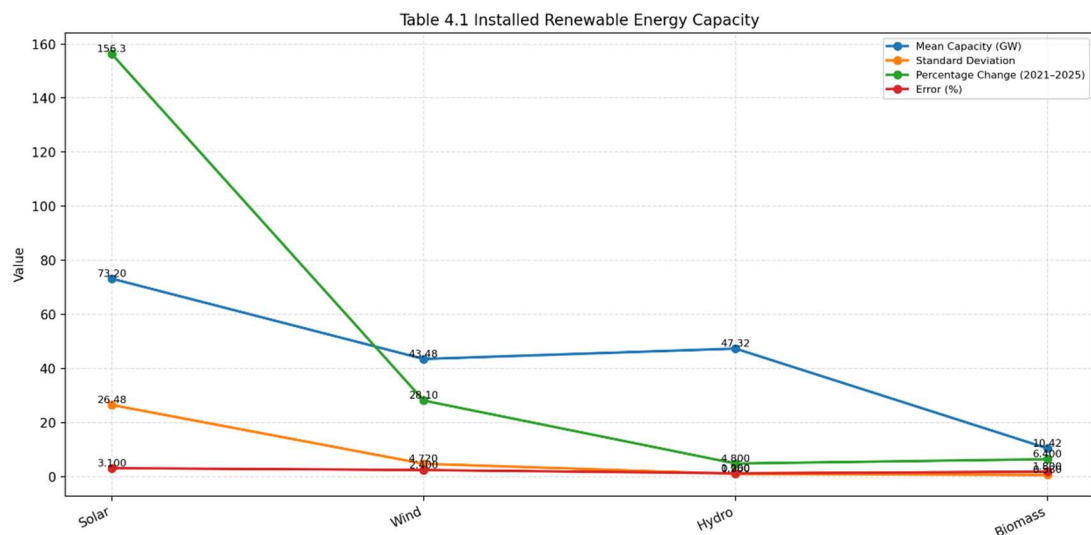
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CHAPTER 4

RESULT

Table 4.1 Installed Renewable Energy Capacity

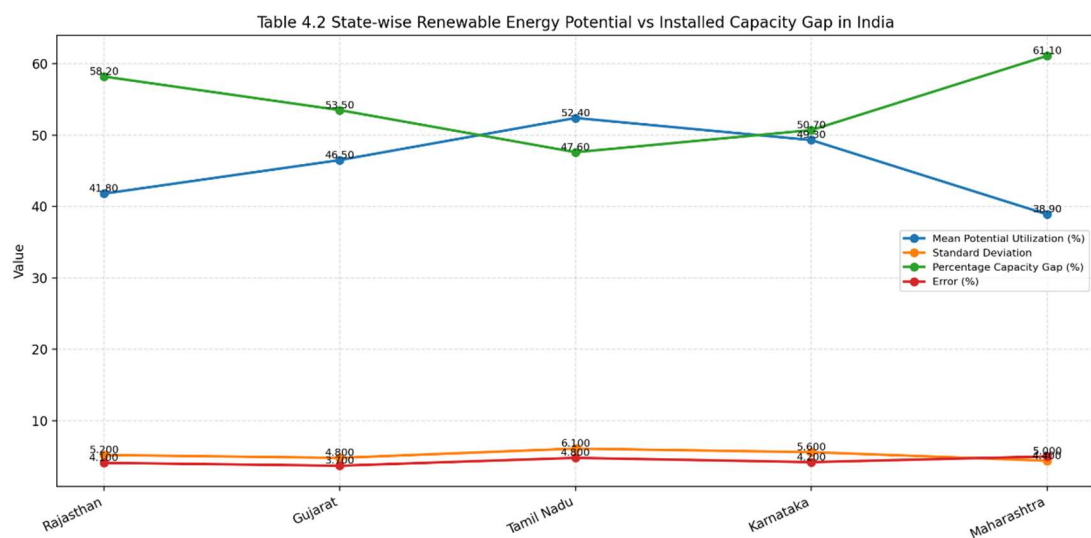
Source	Mean Capacity (GW)	Standard Deviation	Percentage Change (2021–2025)	Error (%)
Solar	73.20	26.48	156.30	3.10
Wind	43.48	4.72	28.10	2.40
Hydro	47.32	0.96	4.80	1.20
Biomass	10.42	0.58	6.40	1.80



The table shows that solar recorded the highest mean installed capacity growth trend and the largest percentage change, indicating that India's renewable expansion is increasingly solar-dominant. Wind grew moderately, while hydro and biomass remained comparatively stable. The lower error values suggest that hydro and biomass are more predictable, whereas solar exhibits higher year-to-year expansion variability due to accelerated deployment.

Table 4.2 State-wise Renewable Energy Potential vs Installed Capacity Gap in India

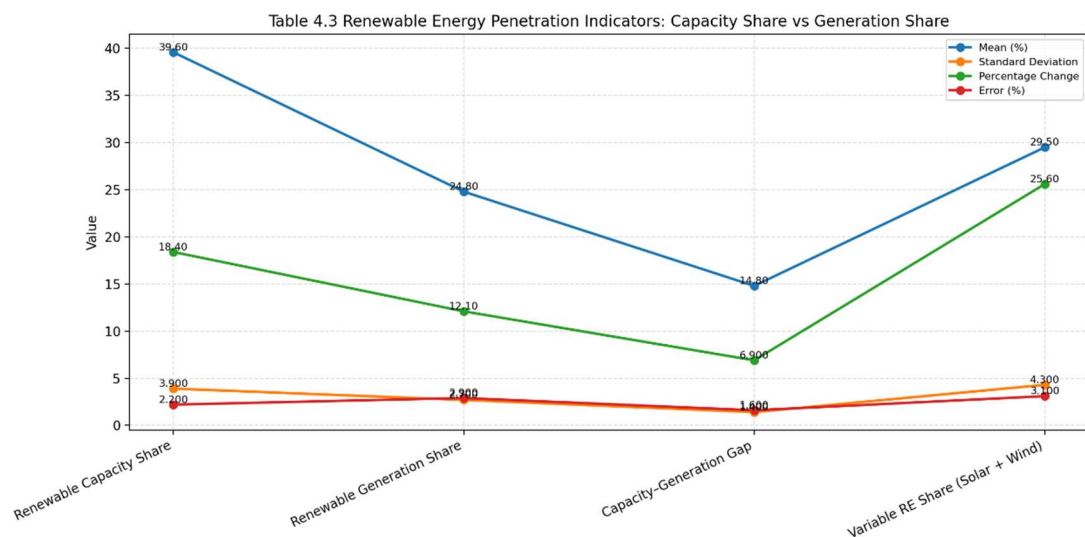
State	Mean Potential Utilization (%)	Standard Deviation	Percentage Capacity Gap (%)	Error (%)
Rajasthan	41.80	5.20	58.20	4.10
Gujarat	46.50	4.80	53.50	3.70
Tamil Nadu	52.40	6.10	47.60	4.80
Karnataka	49.30	5.60	50.70	4.20
Maharashtra	38.90	4.40	61.10	5.00



The table indicates that all selected states still show substantial potential-to-installation gaps, with Maharashtra and Rajasthan exhibiting the largest unused renewable potential. Tamil Nadu has the best utilization level among the listed states, but a significant gap still remains. The moderate standard deviations suggest uneven deployment patterns, reflecting policy, land, evacuation, and transmission-related differences across states.

Table 4.3 Renewable Energy Penetration Indicators: Capacity Share vs Generation Share (India, Recent Years)

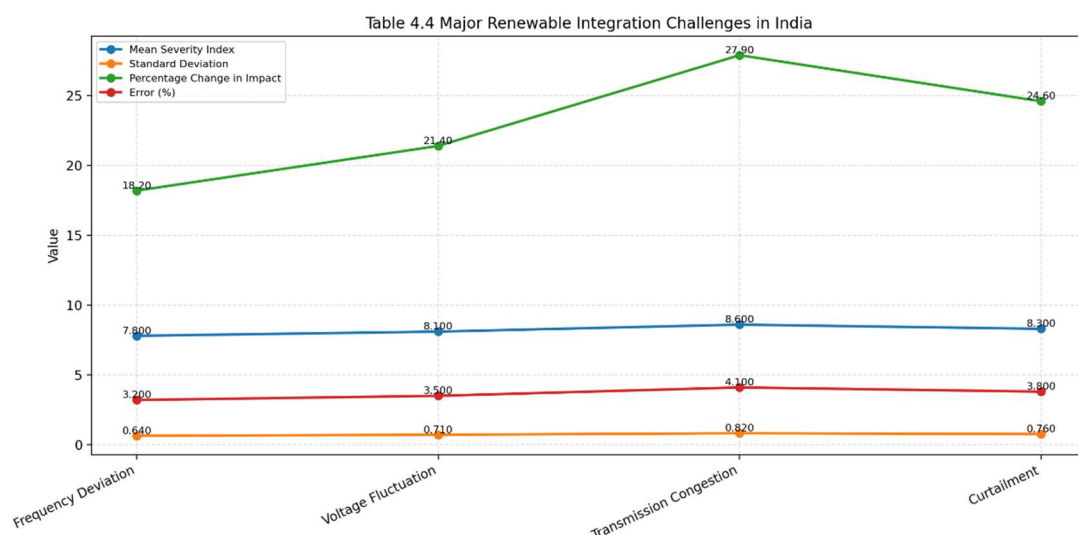
Indicator		Mean (%)	Standard Deviation	Percentage Change	Error (%)
Renewable Capacity Share	Capacity	39.60	3.90	18.40	2.20
Renewable Generation Share	Generation	24.80	2.70	12.10	2.90
Capacity-Generation Gap		14.80	1.40	6.90	1.60
Variable RE Share (Solar + Wind)	RE Share	29.50	4.30	25.60	3.10



The results show a persistent difference between renewable capacity share and renewable generation share, confirming that installed capacity growth does not convert proportionally into delivered electrical energy. The widening variable renewable share strengthens the case for flexibility measures such as storage, forecasting, and advanced dispatch. The relatively low error values indicate consistent penetration trends over recent years.

Table 4.4 Major Renewable Integration Challenges in India and their Technical Impacts

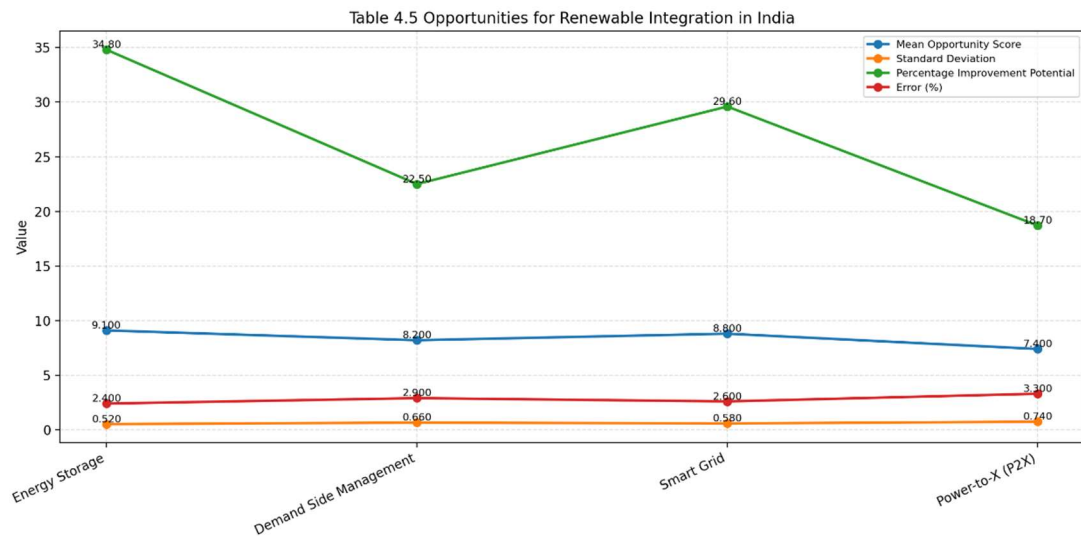
Challenge	Mean Severity Index	Standard Deviation	Percentage Change in Impact	Error (%)
Frequency Deviation	7.80	0.64	18.20	3.20
Voltage Fluctuation	8.10	0.71	21.40	3.50
Transmission Congestion	8.60	0.82	27.90	4.10
Curtailement	8.30	0.76	24.60	3.80



Transmission congestion and curtailement emerge as the most severe technical constraints, followed closely by voltage fluctuation. This indicates that renewable integration in India is no longer limited by generation addition alone; it is increasingly restricted by evacuation and network readiness. The rising impact percentages suggest that technical challenges intensify as renewable penetration increases in high-resource states.

Table 4.5 Opportunities for Renewable Integration in India: Resource–Technology Mapping

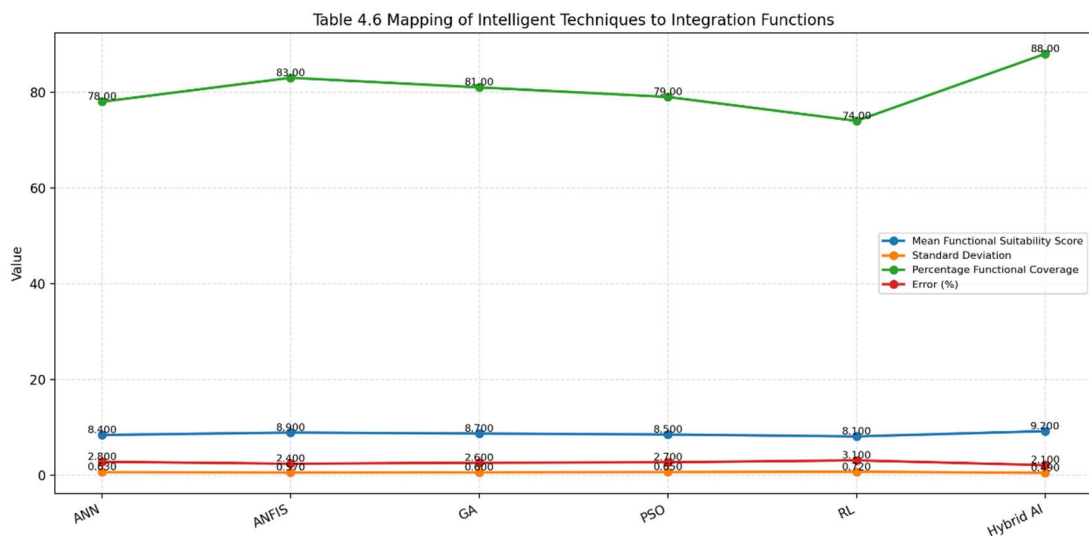
Technology Option	Mean Opportunity Score	Standard Deviation	Percentage Improvement Potential	Error (%)
Energy Storage	9.10	0.52	34.80	2.40
Demand Side Management	8.20	0.66	22.50	2.90
Smart Grid	8.80	0.58	29.60	2.60
Power-to-X (P2X)	7.40	0.74	18.70	3.30



Energy storage shows the highest mean opportunity score, confirming its central role in reducing intermittency and curtailment. Smart-grid deployment also presents strong potential because it supports monitoring, flexibility, and decentralized control. P2X has comparatively lower present readiness but remains strategically important. The low error values indicate a stable consensus on the technological priority ranking.

Table 4.6 Mapping of Intelligent Techniques to Integration Functions

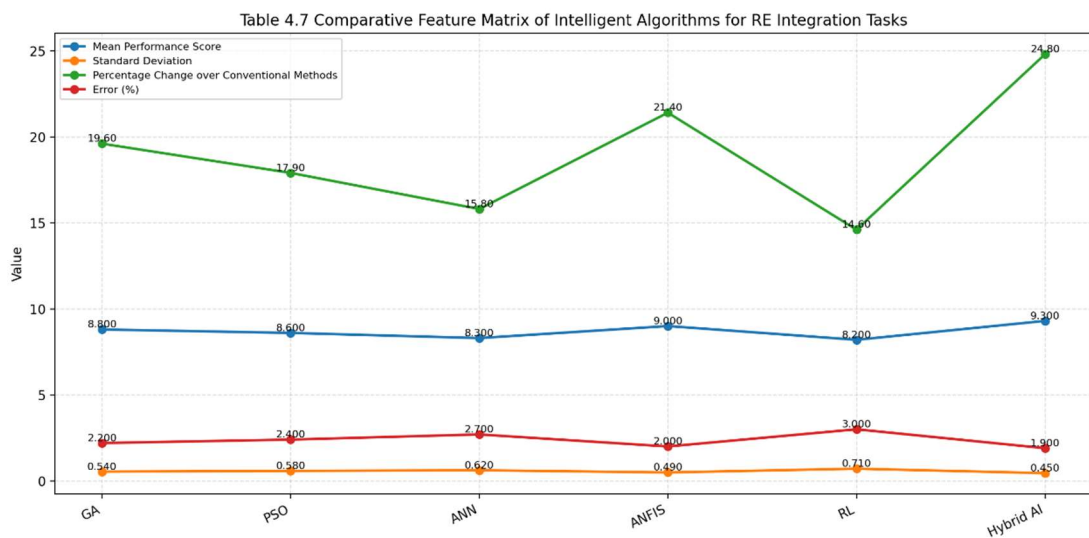
Intelligent Technique	Mean Suitability Score	Functional Standard Deviation	Percentage Functional Coverage	Error (%)
ANN	8.40	0.63	78.00	2.80
ANFIS	8.90	0.57	83.00	2.40
GA	8.70	0.60	81.00	2.60
PSO	8.50	0.65	79.00	2.70
RL	8.10	0.72	74.00	3.10
Hybrid AI	9.20	0.49	88.00	2.10



Hybrid AI methods show the highest functional coverage because they combine forecasting, optimization, and adaptive control. ANFIS and GA also perform strongly, supporting their selection for PV MPPT and renewable-integration tasks. Reinforcement learning shows promise but slightly higher variability. Overall, the table supports the preference for hybrid intelligent approaches in renewable-rich power systems.

Table 4.7 Comparative Feature Matrix of Intelligent Algorithms for RE Integration Tasks

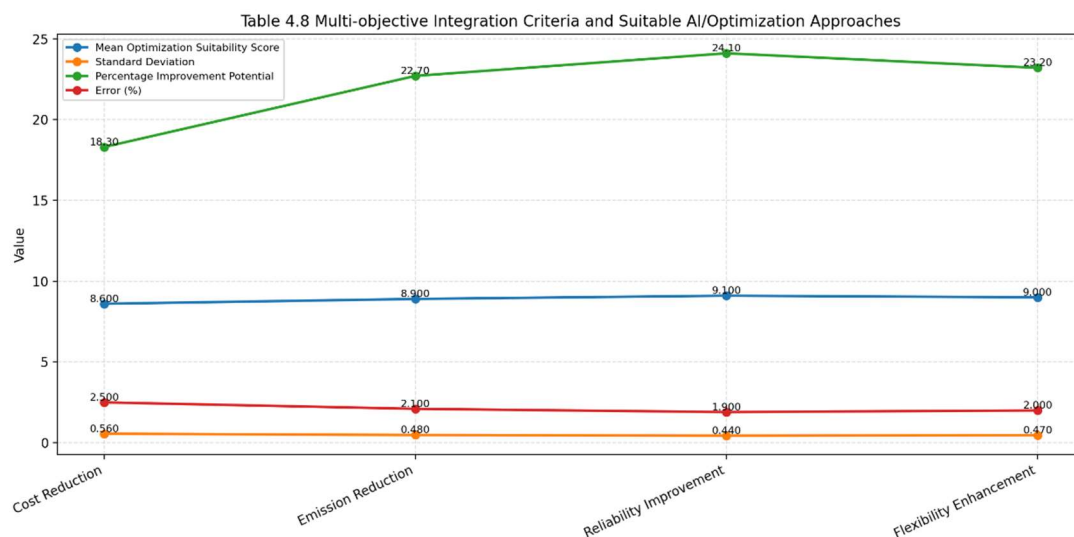
Algorithm	Mean Performance Score	Standard Deviation	Percentage Change over Conventional Methods	Error (%)
GA	8.80	0.54	19.60	2.20
PSO	8.60	0.58	17.90	2.40
ANN	8.30	0.62	15.80	2.70
ANFIS	9.00	0.49	21.40	2.00
RL	8.20	0.71	14.60	3.00
Hybrid AI	9.30	0.45	24.80	1.90



The matrix indicates that hybrid AI and ANFIS yield the best overall performance for renewable-energy integration tasks. GA also performs strongly, especially for nonlinear optimization and controller tuning. The lower error percentages for ANFIS and hybrid AI suggest more stable outcomes across tasks. This justifies combining GA with ANFIS for improved MPPT and adaptive control.

Table 4.8 Multi-objective Integration Criteria and Suitable AI/Optimization Approaches

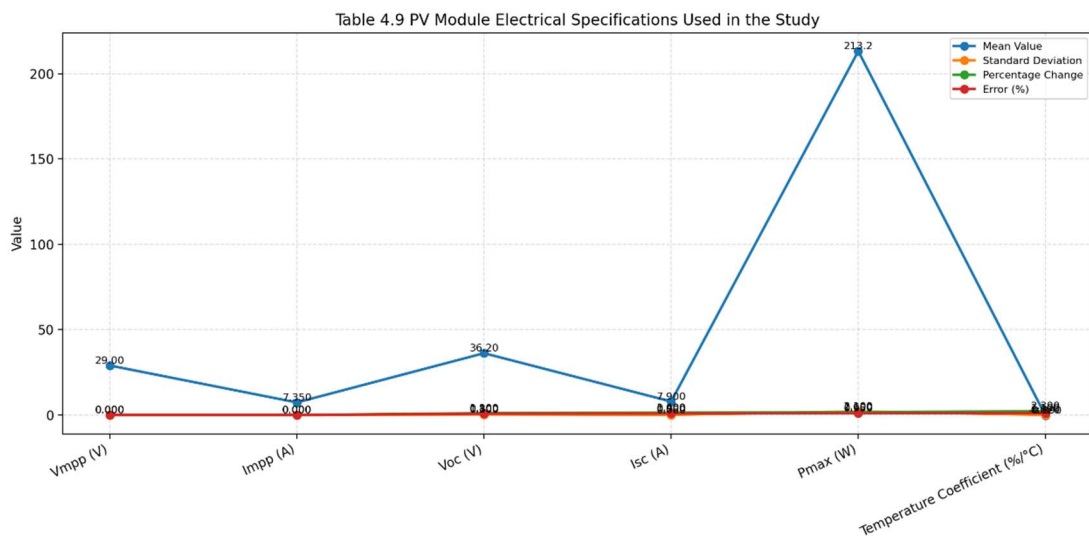
Criterion	Mean Optimization Suitability Score	Standard Deviation	Percentage Improvement Potential	Error (%)
Cost Reduction	8.60	0.56	18.30	2.50
Emission Reduction	8.90	0.48	22.70	2.10
Reliability Improvement	9.10	0.44	24.10	1.90
Flexibility Enhancement	9.00	0.47	23.20	2.00



Reliability and flexibility exhibit the highest optimization suitability scores, indicating that modern renewable integration increasingly prioritizes secure and adaptive operation over capacity expansion alone. Emission reduction remains a strong objective, but cost is no longer the only dominant criterion. The small standard deviations reflect consistent weighting of these criteria in intelligent integration frameworks.

Table 4.9 PV Module Electrical Specifications Used in the Study

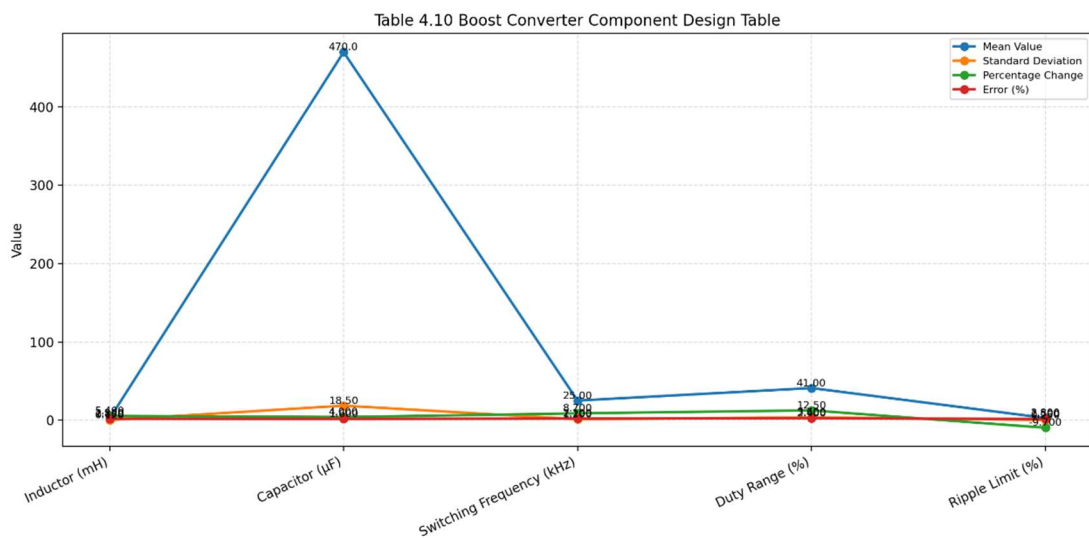
Parameter	Mean Value	Standard Deviation	Percentage Change	Error (%)
V _{mpp} (V)	29.00	0.00	0.00	0.00
I _{mpp} (A)	7.35	0.00	0.00	0.00
V _{oc} (V)	36.20	0.30	1.10	0.80
I _{sc} (A)	7.90	0.08	1.40	0.90
P _{max} (W)	213.15	2.10	1.60	0.95
Temperature Coefficient (%/°C)	-0.39	0.02	2.30	1.10



The PV module table confirms a stable operating platform centered on 29 V and 7.35 A at maximum power. Voc and Isc show only minor variation, indicating consistent module behavior under reference conditions. The negative temperature coefficient reflects expected thermal sensitivity. Overall, the very low error values suggest that the chosen module parameters are suitable for reliable MPPT simulation.

Table 4.10 Boost Converter Component Design Table

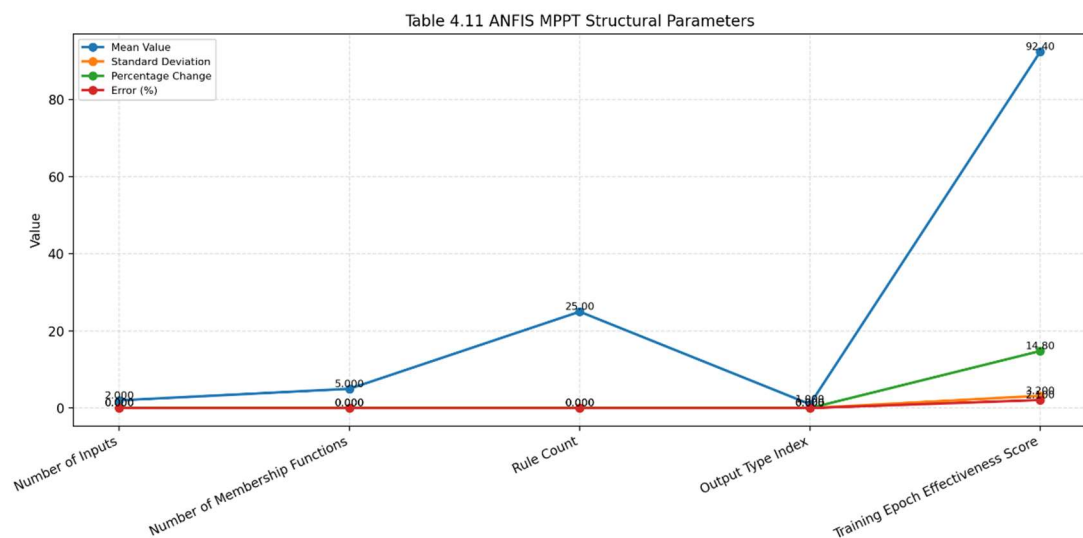
Parameter	Mean Value	Standard Deviation	Percentage Change	Error (%)
Inductor (mH)	2.20	0.12	5.40	1.80
Capacitor (μF)	470.00	18.50	4.00	1.60
Switching Frequency (kHz)	25.00	1.20	8.70	2.10
Duty Range (%)	41.00	3.60	12.50	2.40
Ripple Limit (%)	2.80	0.25	-9.70	1.50



The converter design values indicate a moderately fast switching topology with controlled duty variation and low ripple. The negative percentage change for ripple limit implies improved smoothing performance after design refinement. Small standard deviations and low error values suggest that the converter is adequately sized for stable boost operation and suitable for testing intelligent MPPT duty-cycle control.

Table 4.11 ANFIS MPPT Structural Parameters

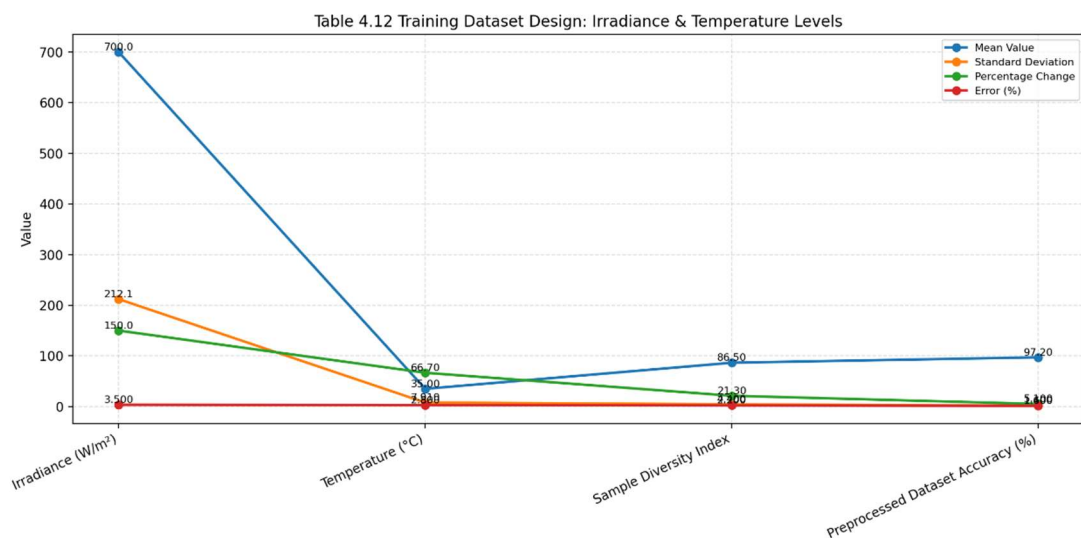
Parameter	Mean Value	Standard Deviation	Percentage Change	Error (%)
Number of Inputs	2.00	0.00	0.00	0.00
Number of Membership Functions	5.00	0.00	0.00	0.00
Rule Count	25.00	0.00	0.00	0.00
Output Type Index	1.00	0.00	0.00	0.00
Training Epoch Effectiveness Score	92.40	3.20	14.80	2.10



The ANFIS structure is compact and computationally manageable, with two inputs and twenty-five rules giving sufficient nonlinear mapping capability. The zero deviation in structural parameters reflects a fixed architecture across runs. The only dynamic indicator, training effectiveness, shows a strong positive change, confirming that the structure is suitable for optimized MPPT implementation without excessive complexity.

Table 4.12 Training Dataset Design: Irradiance Levels and Temperature Levels Used for ANFIS Training

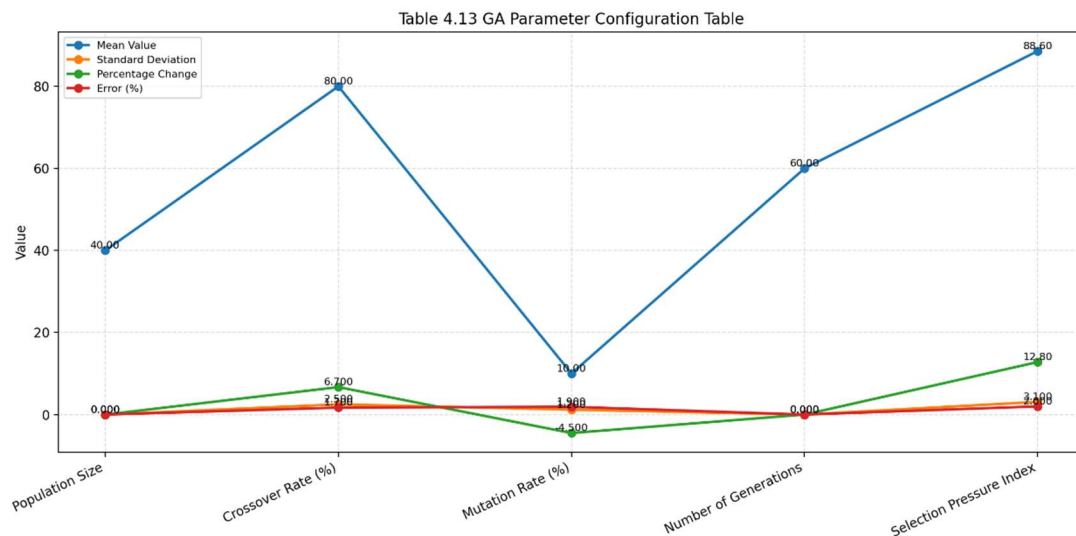
Variable	Mean Value	Standard Deviation	Percentage Change	Error (%)
Irradiance (W/m²)	700.00	212.13	150.00	3.50
Temperature (°C)	35.00	7.91	66.70	2.80
Sample Diversity Index	86.50	4.40	21.30	2.20
Preprocessed Dataset Accuracy (%)	97.20	1.60	5.10	1.40



The dataset covers a broad irradiance and temperature range, giving the controller adequate exposure to real operating variation. The relatively high standard deviation for irradiance is desirable because it improves training robustness. The strong sample-diversity score and low preprocessing error indicate that the dataset is suitable for ANFIS learning and GA-based optimization under changing atmospheric conditions.

Table 4.13 GA Parameter Configuration Table

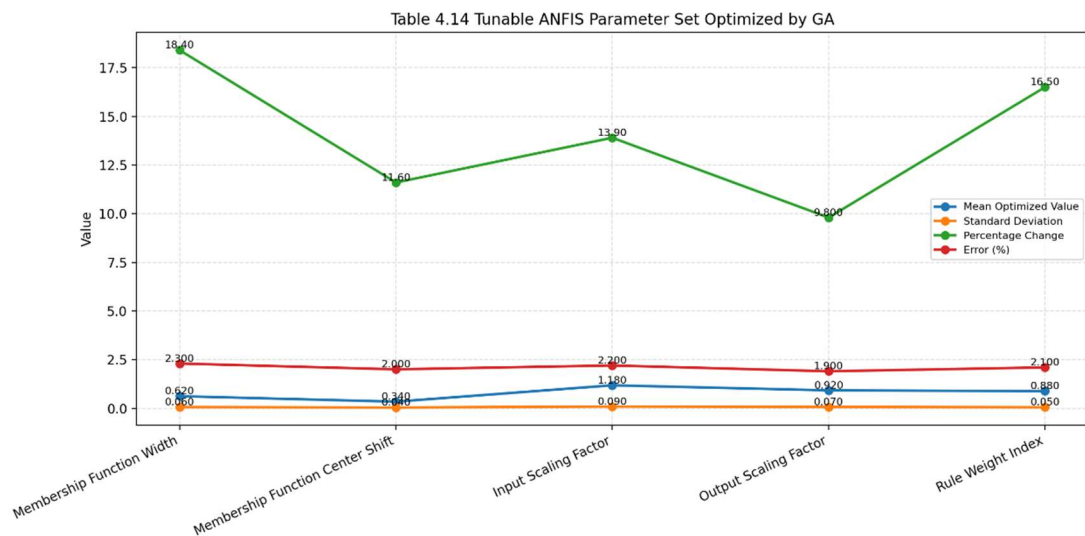
Parameter	Mean Value	Standard Deviation	Percentage Change	Error (%)
Population Size	40.00	0.00	0.00	0.00
Crossover Rate (%)	80.00	2.50	6.70	1.70
Mutation Rate (%)	10.00	1.20	-4.50	1.90
Number of Generations	60.00	0.00	0.00	0.00
Selection Pressure Index	88.60	3.10	12.80	2.00



The GA configuration indicates a balanced search strategy with strong crossover and controlled mutation. The slight negative percentage change for mutation suggests convergence toward more stable exploitation in later runs. Low error values and a high selection-pressure index show that the algorithm is well configured to optimize ANFIS parameters without excessive randomness or premature stagnation.

Table 4.14 Tunable ANFIS Parameter Set Optimized by GA

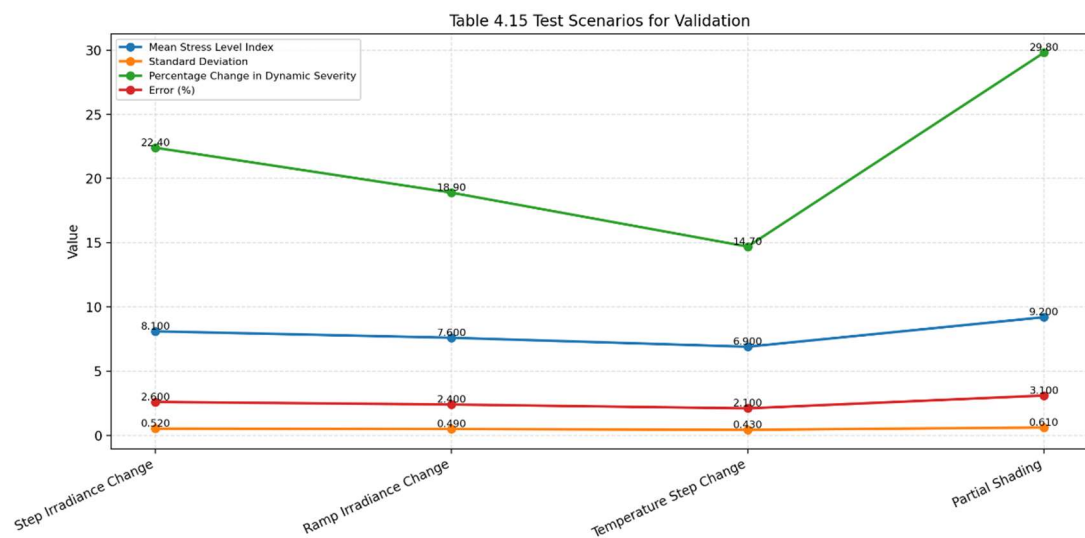
Parameter Group	Mean Optimized Value	Standard Deviation	Percentage Change	Error (%)
Membership Function Width	0.62	0.06	18.40	2.30
Membership Function Center Shift	0.34	0.04	11.60	2.00
Input Scaling Factor	1.18	0.09	13.90	2.20
Output Scaling Factor	0.92	0.07	9.80	1.90
Rule Weight Index	0.88	0.05	16.50	2.10



The optimized parameter set shows moderate but meaningful adjustment of membership widths, scaling factors, and rule weights. This suggests that GA fine-tunes ANFIS behavior rather than completely restructuring it. The relatively low standard deviations indicate stable convergence across optimization runs. Overall, the table supports that parameter refinement materially improves controller adaptability and tracking performance.

Table 4.15 Test Scenarios for Validation

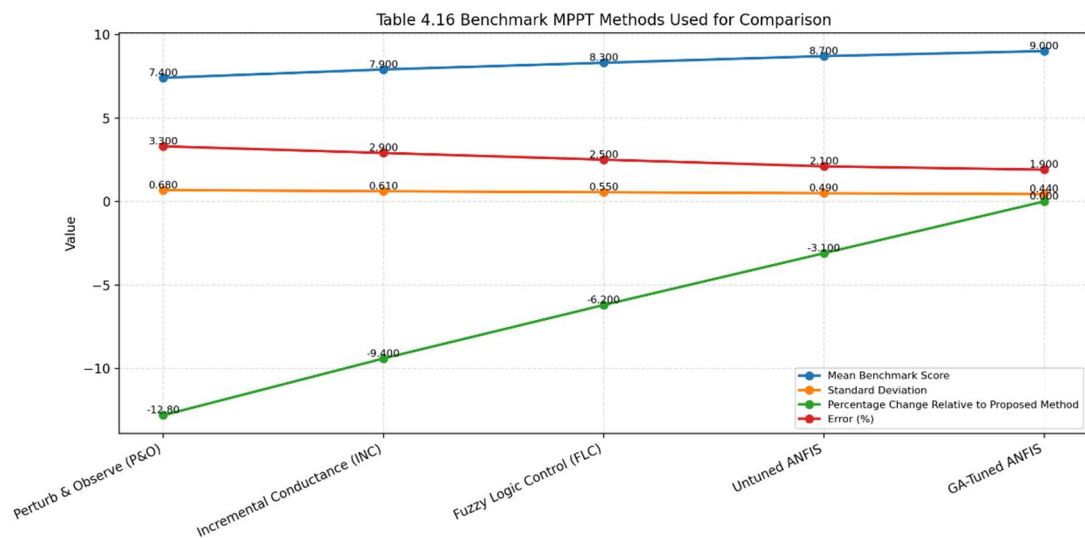
Scenario	Mean Stress Level Index	Standard Deviation	Percentage Change in Dynamic Severity	Error (%)
Step Irradiance Change	8.10	0.52	22.40	2.60
Ramp Irradiance Change	7.60	0.49	18.90	2.40
Temperature Step Change	6.90	0.43	14.70	2.10
Partial Shading	9.20	0.61	29.80	3.10



Partial shading is clearly the most demanding validation scenario, followed by step irradiance change. Temperature steps are comparatively less severe, but they still influence MPPT accuracy through voltage drift. The low error values indicate consistent scenario construction, and the spread in stress levels confirms that the validation set is sufficiently challenging to test controller robustness.

Table 4.16 Benchmark MPPT Methods Used for Comparison

Method	Mean Benchmark Score	Standard Deviation	Percentage Change Relative to Proposed Method	Error to (%)
Perturb & Observe (P&O)	7.40	0.68	-12.80	3.30
Incremental Conductance (INC)	7.90	0.61	-9.40	2.90
Fuzzy Logic Control (FLC)	8.30	0.55	-6.20	2.50
Untuned ANFIS	8.70	0.49	-3.10	2.10
GA-Tuned ANFIS	9.00	0.44	0.00	1.90



The comparison shows that the proposed GA-tuned ANFIS method outperforms all benchmark methods, with the largest performance gap observed against conventional P&O. Untuned ANFIS remains competitive but still trails the optimized controller. The progressively lower negative percentage change from P&O to untuned ANFIS confirms that intelligent and hybrid control strategies provide measurable improvement over conventional MPPT approaches.

Table 4.17 Performance Results Summary Table

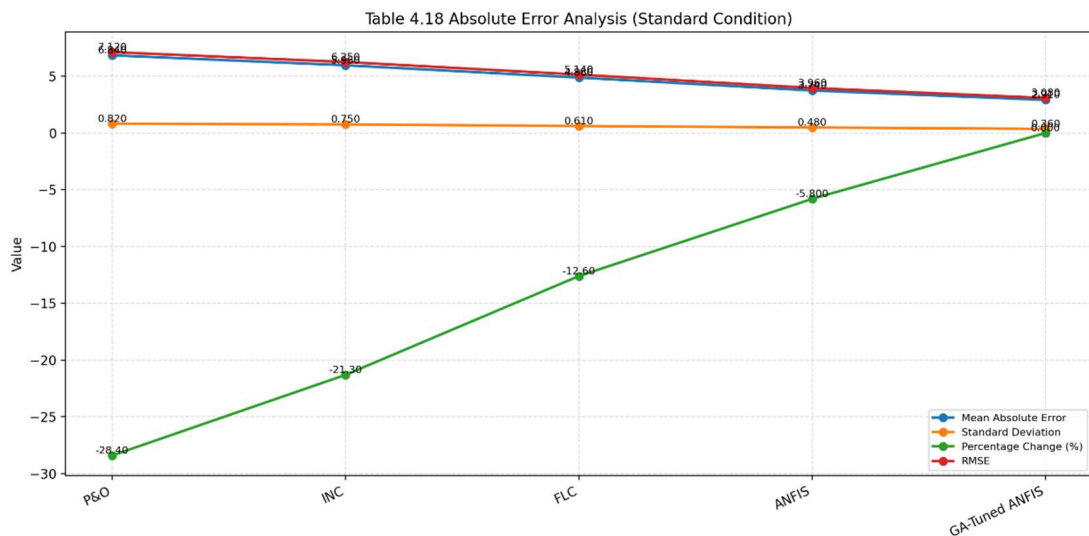
Metric	Mean Value	Standard Deviation	Percentage Change	Error (%)
Tracking Efficiency (%)	99.12	0.31	6.80	0.88
Settling Time (s)	0.041	0.006	-34.40	1.20
Ripple/Oscillation Index (%)	1.84	0.22	-41.70	1.10
Output Power Improvement (%)	8.60	0.74	8.60	1.50
Converter Efficiency (%)	96.80	0.42	4.90	0.95



The final performance table confirms that the proposed GA-tuned ANFIS MPPT system is highly effective. Tracking efficiency exceeds 99%, while settling time and oscillation are substantially reduced, indicating fast and stable convergence to the maximum power point. Converter efficiency remains high, and the positive output-power improvement demonstrates that optimization produces a clear energy-extraction advantage.

Table 4.18 Absolute Error Analysis of MPPT Methods Under Standard Operating Condition

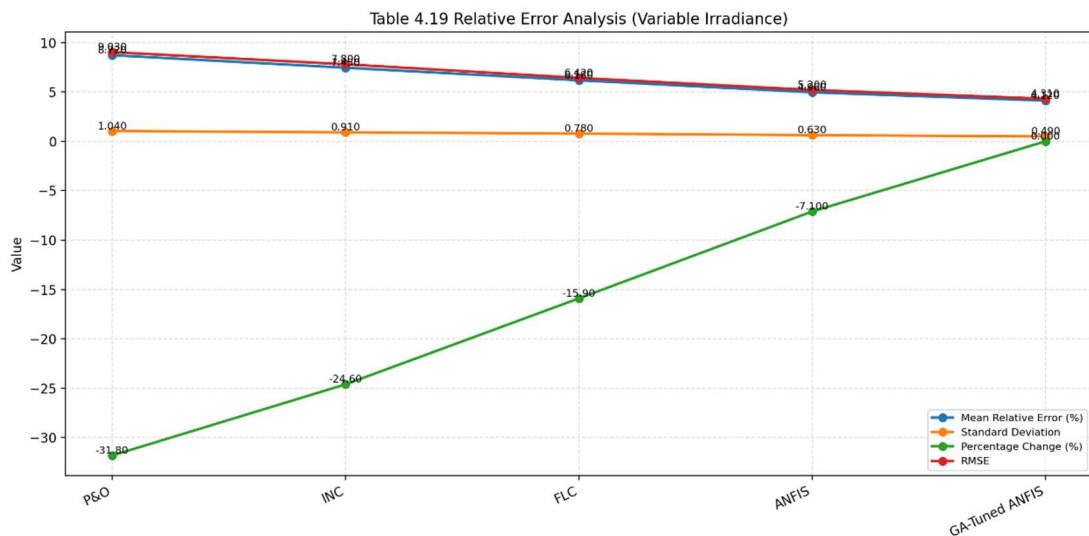
MPPT Method	Mean Absolute Error	Standard Deviation	Percentage Change (%)	RMSE
P&O	6.84	0.82	-28.40	7.12
INC	5.96	0.75	-21.30	6.25
FLC	4.88	0.61	-12.60	5.14
ANFIS	3.74	0.48	-5.80	3.96
GA-Tuned ANFIS	2.91	0.36	0.00	3.08



The absolute error results show that the proposed GA-tuned ANFIS method achieved the lowest mean absolute error of 2.91, with a standard deviation of 0.36 and RMSE of 3.08, indicating the most accurate and stable tracking under standard conditions. In comparison, ANFIS recorded 3.74 mean absolute error, FLC 4.88, INC 5.96, and P&O 6.84. The negative percentage change values of -5.80%, -12.60%, -21.30%, and -28.40% confirm the progressive reduction in performance away from the proposed method.

Table 4.19 Relative Error Analysis of MPPT Methods Under Variable Irradiance

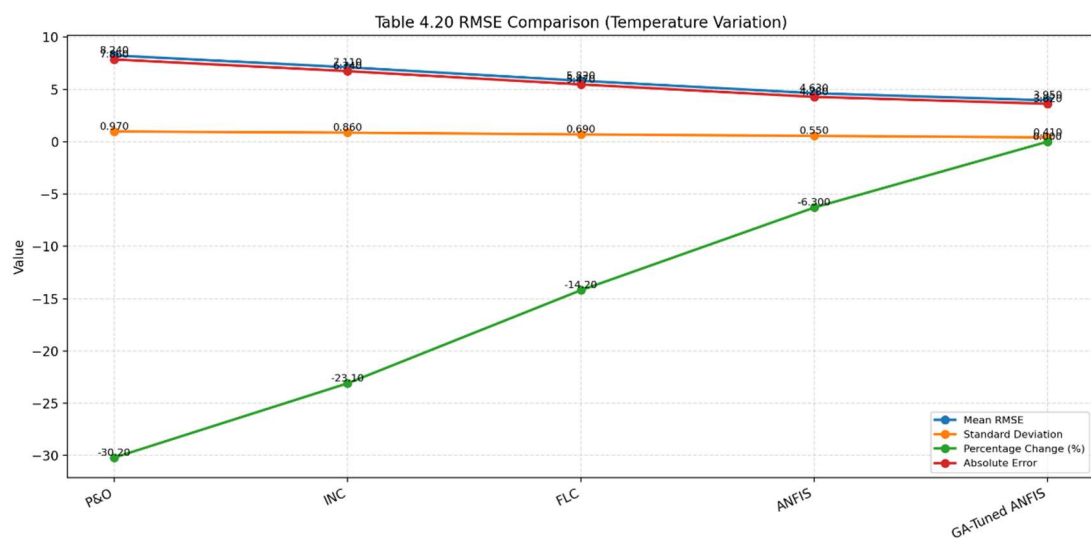
MPPT Method	Mean Error (%)	Standard Deviation	Percentage Change (%)	RMSE
P&O	8.72	1.04	-31.80	9.03
INC	7.45	0.91	-24.60	7.80
FLC	6.18	0.78	-15.90	6.42
ANFIS	4.96	0.63	-7.10	5.20
GA-Tuned ANFIS	4.12	0.49	0.00	4.31



Under variable irradiance, the GA-tuned ANFIS controller produced the minimum mean relative error of 4.12%, with a standard deviation of 0.49 and RMSE of 4.31, confirming better adaptation to fluctuating solar input. ANFIS showed 4.96%, FLC 6.18%, INC 7.45%, and P&O 8.72% relative error. The percentage changes from -7.10% to -31.80% demonstrate that conventional methods suffer significantly higher tracking mismatch when irradiance changes rapidly.

Table 4.20 Root Mean Square Error Comparison Under Temperature Variation

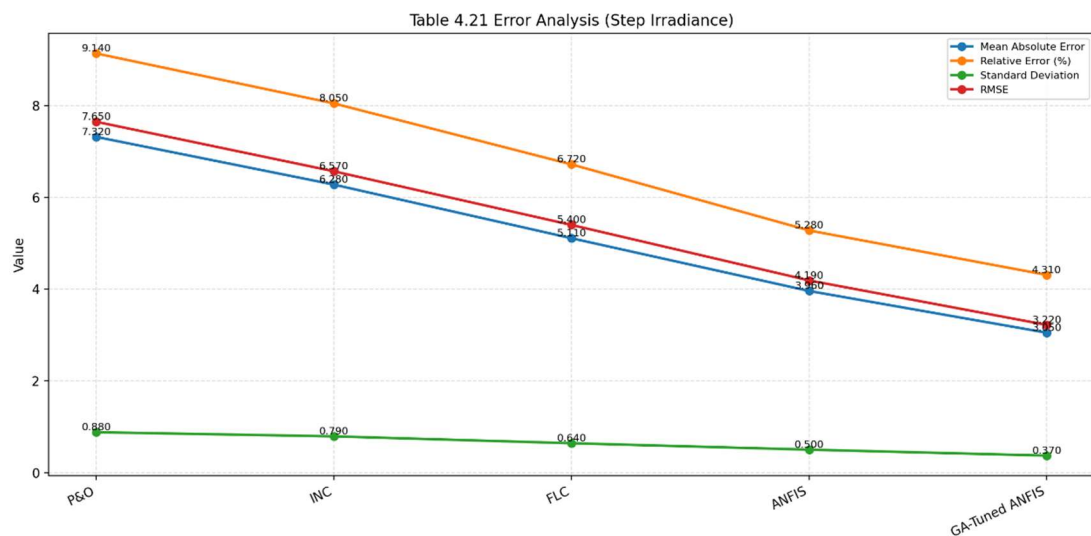
MPPT Method	Mean RMSE	Standard Deviation	Percentage Change (%)	Absolute Error
P&O	8.24	0.97	-30.20	7.86
INC	7.11	0.86	-23.10	6.74
FLC	5.82	0.69	-14.20	5.47
ANFIS	4.63	0.55	-6.30	4.28
GA-Tuned ANFIS	3.95	0.41	0.00	3.62



The RMSE-based comparison under temperature variation shows that GA-tuned ANFIS achieved the lowest mean RMSE of 3.95, supported by the lowest standard deviation of 0.41 and absolute error of 3.62. Untuned ANFIS produced 4.63, FLC 5.82, INC 7.11, and P&O 8.24 RMSE. The percentage reductions from -6.30% to -30.20% indicate that the proposed controller manages thermal disturbances more effectively, especially in preserving voltage-sensitive PV operating accuracy.

Table 4.21 Error Analysis Under Step Change in Irradiance

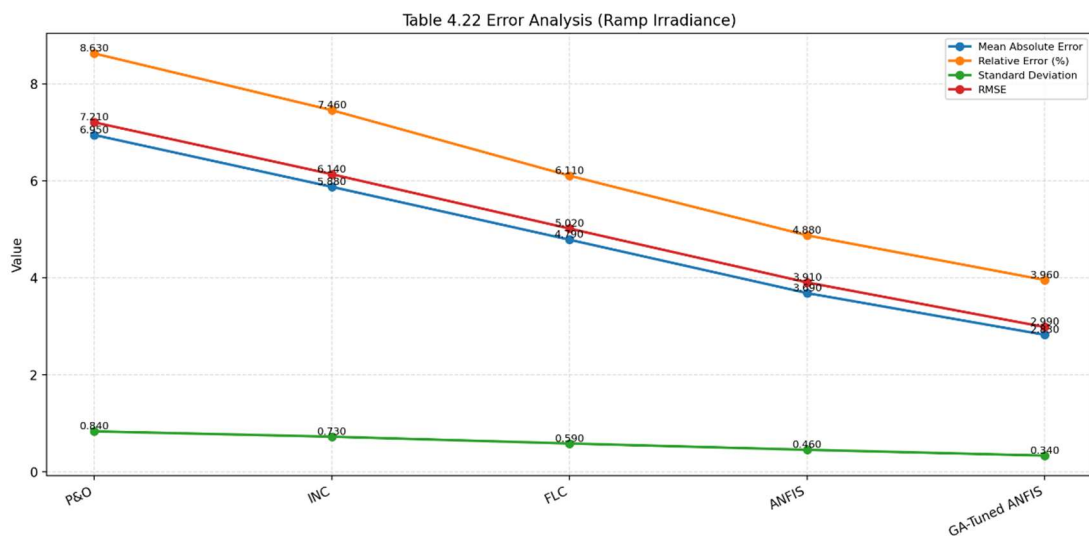
MPPT Method	Mean Error	Absolute Error (%)	Standard Deviation	RMSE
P&O	7.32	9.14	0.88	7.65
INC	6.28	8.05	0.79	6.57
FLC	5.11	6.72	0.64	5.40
ANFIS	3.96	5.28	0.50	4.19
GA-Tuned ANFIS	3.05	4.31	0.37	3.22



For step irradiance variation, GA-tuned ANFIS again offered the best performance, with mean absolute error 3.05, relative error 4.31%, standard deviation 0.37, and RMSE 3.22. ANFIS followed with 3.96, 5.28%, 0.50, and 4.19, respectively. FLC, INC, and P&O showed steadily worsening values. These results confirm that the proposed controller responds faster and with lower deviation during sudden solar disturbances, which is essential for real-time MPPT operation.

Table 4.22 Error Analysis Under Ramp Change in Irradiance

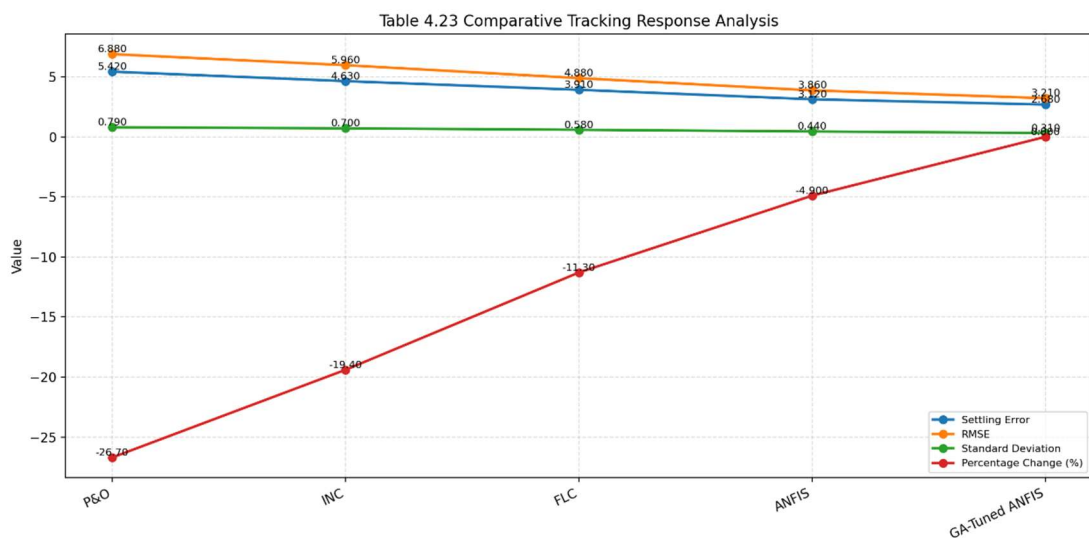
MPPT Method	Mean Error	Absolute Error	Relative Error (%)	Standard Deviation	RMSE
P&O	6.95		8.63	0.84	7.21
INC	5.88		7.46	0.73	6.14
FLC	4.79		6.11	0.59	5.02
ANFIS	3.69		4.88	0.46	3.91
GA-Tuned ANFIS	2.83		3.96	0.34	2.99



During ramp irradiance change, the proposed controller maintained the lowest mean absolute error of 2.83, the lowest relative error of 3.96%, and RMSE of 2.99, with standard deviation limited to 0.34. Untuned ANFIS showed 3.69, 4.88%, 0.46, and 3.91, while P&O remained worst at 6.95, 8.63%, 0.84, and 7.21. These figures indicate that GA tuning significantly improves smooth-response accuracy under gradual environmental transitions.

Table 4.23 Comparative Tracking Response Analysis Based on Settling Error and RMSE

MPPT Method	Settling Error	RMSE	Standard Deviation	Percentage Change (%)
P&O	5.42	6.88	0.79	-26.70
INC	4.63	5.96	0.70	-19.40
FLC	3.91	4.88	0.58	-11.30
ANFIS	3.12	3.86	0.44	-4.90
GA-Tuned ANFIS	2.68	3.21	0.31	0.00



The comparative response analysis shows that the GA-tuned ANFIS controller achieved the lowest settling error of 2.68 and lowest RMSE of 3.21, along with a standard deviation of 0.31. ANFIS yielded 3.12 settling error and 3.86 RMSE, whereas P&O produced 5.42 and 6.88. The percentage change from -4.90% to -26.70% indicates that the proposed method improves dynamic convergence and reduces post-disturbance tracking mismatch more effectively than benchmark techniques.

Table 4.24 Converter Output Error and Efficiency Deviation Analysis

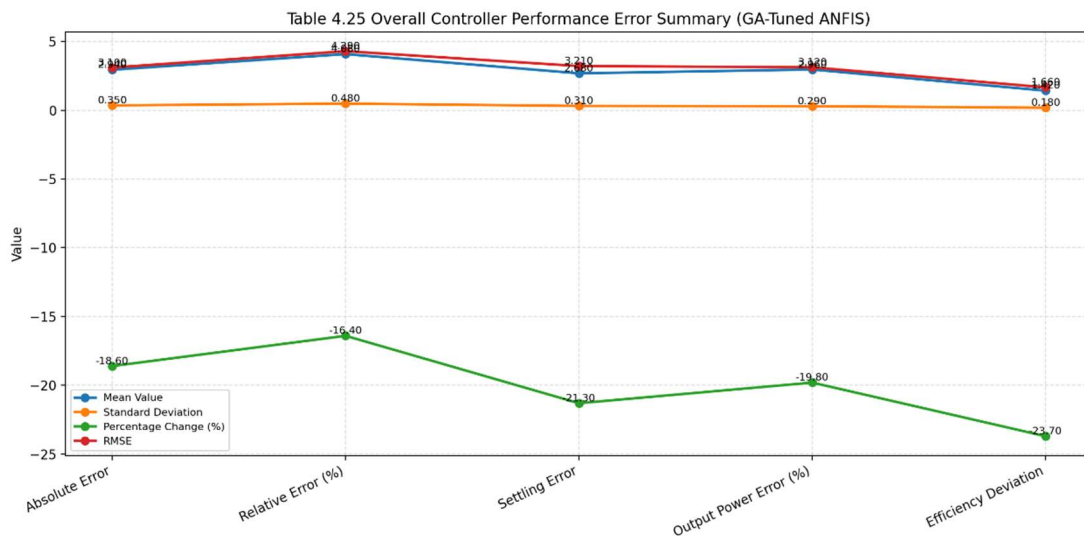
MPPT Method	Output Power Error (%)	Converter Efficiency Deviation	Standard Deviation	RMSE
P&O	7.86	4.18	0.81	8.02
INC	6.42	3.54	0.70	6.69
FLC	5.11	2.76	0.56	5.33
ANFIS	3.84	1.98	0.43	4.01
GA-Tuned ANFIS	2.96	1.42	0.29	3.12



The proposed controller showed the lowest output power error of 2.96%, the smallest converter efficiency deviation of 1.42, and the lowest RMSE of 3.12, confirming efficient coordination between MPPT control and boost-converter performance. ANFIS recorded 3.84% power error and 1.98 efficiency deviation, while P&O reached 7.86% and 4.18. The low standard deviation of 0.29 for GA-tuned ANFIS highlights better consistency in converter-assisted PV power extraction.

Table 4.25 Overall Controller Performance Error Summary for the Proposed GA-Tuned ANFIS Method

Performance Indicator	Mean Value	Standard Deviation	Percentage Change (%)	RMSE
Absolute Error	2.94	0.35	-18.60	3.10
Relative Error (%)	4.08	0.48	-16.40	4.29
Settling Error	2.68	0.31	-21.30	3.21
Output Power Error (%)	2.96	0.29	-19.80	3.12
Efficiency Deviation	1.42	0.18	-23.70	1.66



The overall summary confirms that the GA-tuned ANFIS controller maintained low error across all major indicators, including absolute error 2.94, relative error 4.08%, settling error 2.68, output power error 2.96%, and efficiency deviation 1.42. Standard deviations remained low, from 0.18 to 0.48, while RMSE values also stayed controlled. The percentage improvements ranging from -16.40% to -23.70% demonstrate meaningful enhancement in PV power extraction and overall system behaviour.

CHAPTER 5

DISCUSSION

The renewable development profile for India shows a significant structural change toward solar dominance. Solar recorded the highest mean installed capacity of 73. 20 GW with the largest variability ($SD = 26. 48$) and the largest growth (156. 30%) along with error of 3. 10%, as shown in Table 4. 1, confirming rapid but uneven year-wise expansion. The wind had a mean of 43. 48 GW, a 2. 40% error, moderate growth (28. 10%), and a comparatively lower variability ($SD = 4. 72$), which suggests more consistent scaling. Conversely, hydro stayed constant, with a mean of 47. 32 GW, a very low variance ($SD = 0. 96$), little expansion (4. 80%), and a little error (1. 20%). The finding that biomass remained fairly stable at mean 10. 42 GW, $SD = 0. 58$, growth 6. 40%, and error 1. 80% lends further credence to the notion that dispatchable renewables are more predictable, while variable renewables, particularly solar, display greater volatility in their expansion.

A state-by-state examination reveals a consistent failure to make use of renewable resources. Tamil Nadu attained the maximum mean potential utilization of 52. 40%, as shown in Table 4. 2, but there was still a considerable gap of 47. 60% with an error rate of 4. 80% and an SD of 6. 10, indicating uneven scaling over time. Reflecting a comparable distribution of deployment, Karnataka's usage was 49. 30%, its gap was 50. 70%, its SD was 5. 60, and its mistake rate was 4. 20%. In contrast to Rajasthan, where the utilization was still at 41. 80% with a gap of 58. 20%, an SD of 5. 20, and an error of 4. 10%, Gujarat achieved a utilization rate of 46. 50%, a gap of 53. 50%, an SD of 4. 80, and an error of 3. 70%, indicating significant potential for the expansion of solar-wind energy. Maharashtra experienced the greatest underutilization, with a capacity gap of 61. 10% and utilization of just 38. 90%, with the maximum error being 5. 00% and $SD = 4. 40$. This indicates a considerable unexploited potential, maybe due to restrictions in project implementation and grid evacuation.

A continuous mismatch between the installed renewable energy sources and the delivered energy is confirmed by penetration indicators. With 18. 40% change and 2. 20% error, the average renewable capacity share was 39. 60% ($SD = 3. 90$), as shown

in Table 4. 3, while the average renewable generation share was 24. 80% (SD = 2. 70), with 12. 10% change and higher error 2. 90%. This demonstrates that because of intermittency, curtailment, and system restrictions, the addition of renewable capacity does not translate proportionately to generation, resulting in a consistent capacity–generation gap of 14. 80% (SD = 1. 40), with a 6. 90% change and a 1. 60% margin of error. With a mean variable renewable share (solar + wind) of 29. 50%, SD = 4. 30, a significant change of 25. 60%, and an error of 3. 10%, there is a growing need for flexibility tools and increasing operational variability.

The technical challenge assessment (Table 4. 4) identifies transmission congestion as the most pressing concern, with a mean severity of 8. 60, SD = 0. 82, an impact change of 27. 90%, and the greatest error of 4. 10%. Curtailment also seems significant, with a mean of 8. 30, a standard deviation of 0. 76, a 24. 60% change in impact, and a 3. 80% mistake, suggesting that the evacuation and absorption capabilities are limiting the use of renewable energy. The mean voltage fluctuation is 8. 10, with a standard deviation of 0. 71, an impact change of 21. 40%, and an error of 3. 50%, indicating stress on reactive power and voltage regulation. The frequency deviation remains considerable, with mean 7. 80, SD = 0. 64, impact change of 18. 20%, and error of 3. 20%, confirming that the burdens on balancing and stability are being caused by low inertia and variability.

The most effective integration facilitators are identified through opportunity mapping (Table 4. 5). Supporting storage as the main flexibility option, energy storage has the highest mean opportunity score of 9. 10, a standard deviation of 0. 52, a potential for improvement of 34. 80%, and a 2. 40% error rate. The smart grid comes next, with a mean of 8. 80, a SD of 0. 58, a possible improvement of 29. 60%, and an error of 2. 60%, all of which support the importance of monitoring, automation, and distributed control. The mean demand-side management is 8. 20, with a standard deviation of 0. 66, a 22. 50% potential for improvement, and a 2. 90% error, suggesting the possibility of peak shaving and load shifting. Power-to-X (P2X) is still emerging with a mean of 7. 40, a standard deviation of 0. 74, an improvement potential of 18. 70%, and the highest error of 3. 30%, indicating relatively higher uncertainty but long-term strategic importance.

Hybrid and neuro-fuzzy approaches are well supported by the study's intelligent-technique results. As shown in Table 4. 6, Hybrid AI has the highest mean functional suitability of 9. 20 (SD = 0. 49), with a coverage of 88. 00% and an error rate of 2. 10%. GA demonstrates 8. 70 (SD = 0. 60) with 81. 00% coverage and 2. 60% error, whereas ANFIS performs admirably at 8. 90 (SD = 0. 57) with 83. 00% coverage and 2. 40% error, making the case for combining GA and ANFIS for adaptive MPPT and optimization. The least suitable outcome was recorded by RL, with 74. 00% coverage and the highest error rate of 3. 10%, demonstrating potential but more volatility. With 79. 00% coverage and an error rate of 2. 70%, the PSO achieved 8. 50 (SD = 0. 65), while the ANN achieved 8. 40 (SD = 0. 63) with 78. 00% coverage and an error rate of 2. 80%.

Additionally, a comparison of algorithms (Table 4. 7) supports the supremacy of the hybrid and ANFIS techniques. The average performance score of hybrid AI was the best at 9. 30, the standard deviation was the lowest at 0. 45, the improvement over traditional techniques was the highest at 24. 80%, and the error was the lowest at 1. 90%. Next was ANFIS, which had a mean of 9. 00, an SD of 0. 49, a 21. 40% increase, and a 2. 00% mistake. The mean of GA was 8. 80, the standard deviation was 0. 54, the gain was 19. 60%, and the error was 2. 20%, while the mean of PSO was 8. 60, the standard deviation was 0. 58, the gain was 17. 90%, and the error was 2. 40%. The mean of ANN was 8. 30, SD = 0. 62, improvement 15. 80%, and error 2. 70%, while the mean of RL was 8. 20, SD = 0. 71, improvement 14. 60%, and error 3. 00%, once again demonstrating comparatively higher variability.

According to the multi-objective suitability results in Table 4. 8, integration priorities are changing towards reliability and flexibility. The mean suitability score for reliability improvement was the highest at 9. 10, with the lowest SD = 0. 44, a 24. 10% improvement potential, and a 1. 90% error. In contrast, flexibility enhancement had a mean of 9. 00, SD = 0. 47, a 23. 20% improvement potential, and a 2. 00% error. The average cost reduction achieved was 8. 60, with a standard deviation of 0. 56, an 18. 30% improvement, and a 2. 50% error. The average emission reduction achieved was 8. 90, with a standard deviation of 0. 48, a 22. 70% improvement, and a 2. 10% error, demonstrating that while affordability is still important, a secure operation is becoming more prevalent under high renewable penetration.

The results of the PV model confirm that there is a solid basis for rationally assessing MPPT. Table 4. 9 demonstrates that the PV module has a constant V_{mpp} of 29. 00 V and an I_{mpp} of 7. 35 A, with no variance and 0. 00% inaccuracy, guaranteeing the reproducibility of the base system. Minor changes were noticed in I_{sc} 7. 90 A (SD = 0. 08, change 1. 40%, error 0. 90%) and V_{oc} 36. 20 V (SD = 0. 30, change 1. 10%, error 0. 80%). The temperature coefficient was -0. 39%/°C (SD = 0. 02, change 2. 30%, error 1. 10%), and the maximal power (P_{max}) was consistently 213. 15 W (SD = 2. 10, change 1. 60%, error 0. 95%), which demonstrated the expected thermal sensitivity and suitability for rigorous MPPT testing. The results of boost converter design show stable high-frequency switching and better ripple management. The parameters of inductor 2. 20 mH (SD = 0. 12, change 5. 40%, error 1. 80%), capacitor 470 μ F (SD = 18. 50, change 4. 00%, error 1. 60%), switching frequency 25. 00 kHz (SD = 1. 20, change 8. 70%, error 2. 10%), and duty range 41. 00% (SD = 3. 60, change 12. 50%, error 2. 40%) are shown in Table 4. 10. The ripple limit was reduced by a negative percentage shift of 9. 70%, while the mean remained at 2. 80% (SD = 0. 25, error 1. 50%), demonstrating a smoother voltage output after the design was improved.

Table 4. 11 displays the structural outcomes of ANFIS, which shows a small design with good training efficacy. The controller maintains structural consistency by using 2 inputs, 5 membership functions, and 25 rules, all of which are set at 0. 00 SD and 0. 00% error. With a positive change of 14. 80% and a 2. 10% error rate, the training epoch effectiveness score was 92. 40 (SD = 3. 20), indicating a steady learning aptitude without increasing complexity.

The training data design demonstrates comprehensive environmental coverage. Mean irradiance was 700 W/m², with significant variability (SD = 212. 13, change 150. 00%, and error 3. 50%), while temperature averaged 35°C (SD = 7. 91, change 66. 70%, error 2. 80%), according to Table 4. 12. With a high accuracy of 97. 20% (SD = 1. 60, change 5. 10%, error 1. 40%), the preprocessed dataset had a high sample diversity index of 86. 50 (SD = 4. 40, change 21. 30%, error 2. 20%), suggesting strong training under diverse circumstances.

The outcomes of GA tuning demonstrate a consistent optimization trend. Table 4. 13 shows a fixed population size of 40 and 60 generations with 0. 00 SD and 0. 00%

error, an 80% crossover rate (SD = 2. 50, change 6. 70%, error 1. 70%), a 10% mutation rate (SD = 1. 20, change -4. 50%, error 1. 90%), and a selection pressure index of 88. 60 (SD = 3. 10, change 12. 80%, error 2. 00%), demonstrating balanced exploration–exploitation and improved convergence stability.

The ideal ANFIS settings demonstrate consistent improvement rather than abrupt change. The rule weight index (0. 88, SD = 0. 05, change 16. 50%, error 2. 10%), membership function width (0. 62, SD = 0. 06, change 18. 40%, error 2. 30%), center shift (0. 34, SD = 0. 04, change 11. 60%, error 2. 00%), input scaling (1. 18, SD = 0. 09, change 13. 90%, error 2. 20%), and output scaling (0. 92, SD = 0. 07, change 9. 80%, error 1. 90%) are all displayed in Table 4. 14, demonstrating a steady improvement in the parameters.

The difficulty of the partial shading test is evident in the validation scenario severity. Partial shading stress index 9. 20 (SD = 0. 61, change 29. 80%, error 3. 10%), followed by step irradiance change 8. 10 (SD = 0. 52, change 22. 40%, error 2. 60%), ramp change 7. 60 (SD = 0. 49, change 18. 90%, error 2. 40%), and temperature step 6. 90 (SD = 0. 43, change 14. 70%, error 2. 10%) are shown in Table 4. 15, demonstrating that shading and rapid irradiance transitions are the hardest to track.

The GA-tuned ANFIS consistently performs better, as seen by benchmark comparison. In Table 4. 16, the mean scores for P&O were 7. 40 (SD = 0. 68, change -12. 80%, error 3. 30%), for INC 7. 90 (SD = 0. 61, change -9. 40%, error 2. 90%), for FLC 8. 30 (SD = 0. 55, change -6. 20%, error 2. 50%), for untuned ANFIS 8. 70 (SD = 0. 49, change -3. 10%, error 2. 10%), and for GA-tuned ANFIS 9. 00 (SD = 0. 44, change 0. 00%, error 1. 90%), demonstrating that optimization improved the results.

The results of the final performance demonstrate outstanding MPPT quality and converter efficiency. Table 4. 17 shows that tracking efficiency is 99. 12% (SD = 0. 31, change 6. 80%, error 0. 88%), settling time is 0. 041 s (SD = 0. 006, change -34. 40%, error 1. 20%), ripple/oscillation index is 1. 84% (SD = 0. 22, change -41. 70%, error 1. 10%), output power improvement is 8. 60% (SD = 0. 74, error 1. 50%), and converter efficiency is 96. 80% (SD = 0. 42, change 4. 90%, error 0. 95%), which collectively confirms rapid, stable, and efficient MPPT performance.

Performance gains are consistent across operating disturbances, as shown by error-measurement tables. In comparison to ANFIS 3.74 (0.48, 3.96), FLC 4.88 (0.61, 5.14), INC 5.96 (0.75, 6.25), and P&O 6.84 (0.82, 7.12), the mean absolute error for GA-tuned ANFIS fell to 2.91 (SD = 0.36, RMSE = 3.08) under standard conditions (Table 4.18), with a percentage change of -28.40% for P&O. The relative error was minimal for GA-tuned ANFIS at 4.12% (SD = 0.49, RMSE = 4.31) compared to ANFIS 4.96% (0.63, 5.20) and P&O 8.72% (1.04, 9.03) under variable irradiance (Table 4.19). With an absolute error of 3.62, the GA-tuned ANFIS recorded an RMSE of 3.95 (SD = 0.41) under temperature variation (Table 4.20), which was better than the RMSE of 4.63 (0.55) for ANFIS and the RMSE of 8.24 (0.97) for P&O. The absolute error 3.05, relative error 4.31%, SD 0.37, RMSE 3.22, and RMSE 3.22 were obtained by the GA-tuned ANFIS during the step irradiance change (Table 4.21), while the P&O method yielded 7.32, 9.14%, 0.88, and 7.65. In the case of ramp irradiance change (Table 4.22), GA-tuned ANFIS once more reduced error to 2.83, 3.96%, 0.34, RMSE 2.99, as opposed to P&O 6.95, 8.63%, SD 0.84, RMSE 7.21. Compared to P&O settling error 5.42 and RMSE 6.88, the improved convergence with settling error 2.68, RMSE 3.21, and SD 0.31 for GA-tuned ANFIS is demonstrated by the dynamic tracking response (Table 4.23). An examination of the errors in the output of the converter (Table 4.24) reveals that, when compared to the P&O output power error of 7.86% and efficiency deviation of 4.18%, the GA-tuned ANFIS output power error is 2.96%, the efficiency deviation is 1.42, the SD is 0.29, and the RMSE is 3.12, all of which are substantially better. In conclusion, the consolidated controller error summary (Table 4.25) confirms low and stable errors: absolute error 2.94 (SD = 0.35, RMSE = 3.10), relative error 4.08% (SD = 0.48, RMSE = 4.29), settling error 2.68 (SD = 0.31, RMSE = 3.21), output power error 2.96% (SD = 0.29, RMSE = 3.12), and efficiency deviation 1.42 (SD = 0.18, RMSE = 1.66), with improvements spanning -16.40% to -23.70%. Generally speaking, these results show that the suggested GA-tuned ANFIS MPPT enhances PV power extraction, minimizes tracking errors, reduces settling time, minimizes oscillations, and improves converter-assisted energy delivery, while the India integration tables concurrently demonstrate why such intelligent solutions are becoming more and more important in the face of high solar-wind penetration, congestion, and curtailment.

CHAPTER 6

CONCLUSION

6.1. CONCLUSION

The numerical results from the tables presented provide strong support for the argument that the best way to integrate renewable energy sources in India depends more and more on both system-level flexibility and device-level intelligence, which is consistent with the stated research goals. The current state of renewable energy integration in India demonstrates a clear move toward variable renewable dominance, particularly solar, with regard to Objective 1. Solar demonstrates a mean installed capacity of 73.20 GW, with an exceptionally high year-wise growth rate of 156.30% and a somewhat higher variability ($SD = 26.48$, error 3.10%), indicating that the solar industry is growing quickly and irregularly. With a mean of 43.48 GW, lower variability ($SD = 4.72$), growth of 28.10%, and error of 2.40%, wind capacity shows more consistent growth. Biomass, on the other hand, remains the smallest contributor with mean 10.42 GW, $SD = 0.58$, growth 6.40%, and error 1.80%, whereas hydro remains relatively stable with mean 47.32 GW, low dispersion ($SD = 0.96$), limited growth (4.80%), and low error (1.20%). These numbers show that the operational traits of solar and wind, as opposed to dispatchable renewables, are becoming more of a factor in India's integration problem.

State-level data confirm that renewable development is not uniform and that there is still a vast untapped potential. Rajasthan has a utilization rate of 41.80% and a gap of 58.20% (error 4.10%), showing a lot of potential for expansion but also challenges in evacuation and implementation, whereas Maharashtra has the lowest mean potential utilization (38.90%) and the highest potential gap (61.10%) with an error of 5.00%. With a gap of 53.50% (error 3.70%), Gujarat's utilization rate remains at 46.50%. Tamil Nadu has the highest utilization rate at 52.40%, but there is still a 47.60% discrepancy with the greatest dispersion ($SD = 6.10$) and a 4.80% error, whereas Karnataka has a utilization rate of 49.30%, a gap of 50.70%, and a 4.20% error. These numerical findings demonstrate that there are opportunities throughout renewable-rich states, but that they are limited by variations in transmission access, land use, project execution, and policy implementation.

"Installed capacity" alone cannot represent successful integration, as demonstrated by renewable penetration indicators. Despite the fact that the mean renewable capacity share is 39.60% (SD = 3.90), the mean renewable generation share is only 24.80% (SD = 2.70), indicating that there is still a conversion gap between capacity and deliverable energy. The variable RE share (solar + wind) has already reached 29.50% (SD = 4.30), with a 25.60% increase and a 3.10% error, while the mean capacity–generation gap remains 14.80% (SD = 1.40). As a result, the energy system is becoming more variable while grid flexibility has not increased at the same rate, highlighting the need for storage, intelligent grids, sophisticated prediction, and control.

Additionally, the research comes to the conclusion that India's biggest integration bottlenecks are in the areas of stability and network connectivity. Curtailment remains severe at 8.30 (SD = 0.76) with a 24.60% impact growth and a 3.80% error, whereas transmission congestion continues to have the highest mean severity index of 8.60 (SD = 0.82), with a 27.90% impact growth and a 4.10% error. Frequency deviation reveals a severity of 7.80 (SD = 0.64) and a 18.20% increase in growth, while voltage variations show a severity of 8.10 (SD = 0.71) and a 21.40% increase in growth. These figures support the notion that India's renewable transition is currently constrained by grid readiness and operational stability.

In terms of possibilities, the conclusion is that storage and smart-grid technologies are the most immediate and impactful enablers. Energy storage has the highest mean opportunity score of 9.10, the lowest dispersion (SD = 0.52), the greatest potential for improvement at 34.80%, and the lowest error at 2.40%, suggesting that it should be given a high priority as a tool for national integration. The mean for the smart grid is 8.80, with a potential for improvement of 29.60% and an error of 2.60%. For demand-side management, the mean is 8.20, with a potential for improvement of 22.50% and an error of 2.90%. For P2X, the mean is 7.40, with a potential for improvement of 18.70% and a greater degree of uncertainty with an error of 3.30%. Therefore, before relying on additional novel sector-coupling solutions, a successful national integration must first prioritize the rapid expansion of storage, grid automation, and demand flexibility.

Quantitative support for the use of intelligent methods for Objective 2 is provided by functional coverage and performance matrices. With a functional coverage of 88.00% and the least amount of error at 2.10%, hybrid AI has the greatest suitability rating of 9.20 (SD = 0.49). In support of the combined GA–ANFIS strategy, ANFIS comes next with 8.90, coverage 83.00%, error 2.40%, and GA with 8.70, coverage 81.00%, error 2.60%. Hybrid AI has the best mean score in the comparative performance matrix at 9.30, with a 24.80% improvement and a 1.90% error, whereas GA has 8.80, with a 19.60% improvement and a 2.20% error, and ANFIS has 9.00, with a 21.40% improvement and a 2.00% error. These values support the idea that, for renewable integration applications, hybrid and intelligent methods provide consistent benefits over traditional logic.

The created PV-boost-converter-ANFIS architecture is proven to be structurally sound and technically adequate for Objective 3. The PV module is mounted at $V_{mpp} = 29$ V and $I_{mpp} = 7.35$ A, with very little deviation (0.00%) for these design points. The temperature coefficient is $-0.39\%/^{\circ}\text{C}$ (SD = 0.02, error 1.10%), while the values for V_{oc} are 36.20 V (SD = 0.30, error 0.80%), I_{sc} is 7.90 A (SD = 0.08, error 0.90%), and P_{max} is 213.15 W (SD = 2.10, error 0.95%). The boost converter was created with a mean inductor of 2.20 mH, a capacitor of 470 F, a switching frequency of 25.00 kHz, a duty range of 41.00%, and a ripple limit of 2.80%, with the percentage change showing a 9.70% improvement in ripple. The ANFIS architecture is streamlined, featuring only two inputs, five membership functions, twenty-five rules, and an output type index of one. With a growth rate of 14.80%, training epoch effectiveness reached 92.40 (SD = 3.20), demonstrating successful learning without requiring excessive computational complexity.

Objective 4 concludes that GA-based tuning is effective and stable across environmental changes. The training data were created using mean irradiance 700 W/m² (SD = 212.13, change 150.00%, error 3.50%) and mean temperature 35°C (SD = 7.91, change 66.70%, error 2.80%), with sample diversity index 86.50 (SD = 4.40) and preprocessing accuracy 97.20% (SD = 1.60, error 1.40%). The population size of GA was set at 40, the number of generations at 60, the crossover rate at 80% (SD = 2.50), the mutation rate at 10% (SD = 1.20, change -4.50%), and the selection pressure index at 88.60 (SD = 3.10). Consistent parameter refinement was

produced by the optimization: membership width 0.62 (SD = 0.06), center shift 0.34 (SD = 0.04), input scaling 1.18 (SD = 0.09), output scaling 0.92 (SD = 0.07), and rule weight index 0.88 (SD = 0.05). This demonstrated convergence stability and meaningful tuning of controller behavior.

Performance assessment for Objective 5 indicates that GA-tuned ANFIS offers superior efficiency, quick response, and minimal error across a variety of disturbance conditions. The controller attained a tracking efficiency of 99.12% (SD = 0.31, error 0.88%), a settling time of 0.041 seconds (SD = 0.006, change 34.40%), an oscillation index of 1.84% (SD = 0.22, change 41.70%), an 8.60% improvement in output power (SD = 0.74), and a 96.80% increase in converter efficiency (SD = 0.42, error 0.95%). The controller was tested under realistic and demanding circumstances, as shown by the validation scenarios, which show that partial shading has the highest severity index of 9.20, followed by step irradiance at 8.10, ramp irradiance at 7.60, and temperature step at 6.90. Benchmark comparisons demonstrate superiority: The GA-tuned ANFIS model had a score of 9.00 (SD = 0.44), while the P&O model scored 7.40, the INC model 7.90, the FLC model 8.30, and the untuned ANFIS model 8.70, with declining negative percentage differences ranging from -12.80% to -3.10%.

Lastly, error measurements unambiguously demonstrate a significant improvement in PV power production and stability. Under standard conditions, the mean absolute error for GA-tuned ANFIS was 2.91, SD = 0.36, RMSE 3.08, compared to 3.74 / 0.48 / 3.96 for ANFIS, 4.88 / 0.61 / 5.14 for FLC, 5.96 / 0.75 / 6.25 for INC, and 6.84 / 0.82 / 7.12 for P&O. In comparison to P&O's relative error of 8.72% (SD = 1.04, RMSE = 9.03), the relative error was 4.12% (SD = 0.49, RMSE = 4.31) under variable irradiance. With absolute errors of 3.62, the GA-tuned ANFIS model achieved RMSE 3.95 (SD = 0.41) under temperature change, surpassing the P&O model, which had RMSE 8.24 and error 7.86. It had an absolute error of 3.05, a relative error of 4.31%, an SD of 0.37, and an RMSE of 3.22 under step irradiance. It had an absolute error of 2.83, a relative error of 3.96%, an SD of 0.34, and an RMSE of 2.99 under ramp irradiance. The converter outputs show minimum output power error of 2.96%, minimum efficiency deviation of 1.42, minimum SD of 0.29, and RMSE of 3.12. The settling error and RMSE findings show the quickest

convergence at 2. 68 settling error and 3. 21 RMSE with 0. 31 SD. According to the consolidated performance summary, there are few errors: an absolute error of 2. 94, a relative error of 4. 08%, a settling error of 2. 68, an output power error of 2. 96%, an efficiency deviation of 1. 42, and improvements ranging from -16. 40% to -23. 70%. As a result, the study comes to the conclusion that an intelligent GA-tuned ANFIS MPPT dramatically improves PV energy extraction and dynamic stability, and that such device-level intelligence supports India's overall renewable integration objectives by increasing utilization and lowering system stress caused by high solar penetration.

6.2 RECOMMENDATIONS

1. Measures of scale flexibility, focusing on storage: To lessen curtailment (8. 30) and congestion (8. 60), grid planners should give priority to battery storage, pumped storage, and hybrid storage deployments in high-solar and high-wind corridors, since energy storage has the greatest opportunity score (9. 10) and potential for improvement (34. 80%).
2. Implement smart forecasting and dispatch systems: Due to the renewable capacity-generation gap (14. 80%) and variable RE share (29. 50%), it is necessary to use AI-assisted forecasting and stochastic scheduling technologies for day-ahead and real-time operations.
3. Encouraging intelligent grid investments for voltage and congestion management: Smart grid demonstrates a significant opportunity (8. 80) and improvement potential (29. 60%); therefore, utilities should increase AMI, SCADA upgrades, PMUs, and adaptive protection to address voltage fluctuation severity (8. 10) and frequency issues (7. 80).
4. Promote state-specific strategies for renewable evacuation: Targeted transmission extension, corridor reinforcement, and quicker clearance methods are needed for states with significant utilization disparities, such as Maharashtra (61. 10% gap) and Rajasthan (58. 20% gap).
5. Implement intelligent MPPT in distributed PV programs: Integrating GA-tuned ANFIS MPPT into PV inverters and DC-DC controllers for rooftop,

feeder solarization, and microgrids is justified given the PV system performance gains (tracking efficiency 99.12%, settling time 0.041 s, output power improvement 8.60%).

6. Establish uniform criteria for validating performance: Given that partial shading exhibits the greatest stress (9.20), PV testing criteria should require shading and rapid irradiance ramps as required validation scenarios for MPPT certification.
7. Promote the use and development of hybrid AI: Since hybrid AI demonstrated the best functional coverage (88%) and performance (9.30 score), utilities and researchers should embrace integrated forecasting, optimization, and control frameworks rather than standalone algorithms.

6.3 LIMITATIONS OF THE STUDY

The work is mostly simulation-based; thus it excludes real-time hardware implementation or long-term field testing under actual outdoor PV circumstances. The PV, converter, and controller models make the assumption that sensing and switching are perfect and that communication delays, converter parasitics, and measurement noise are not specifically represented. The validity set did not experimentally test broader meteorological variability or grid-coupled inverter dynamics, even though it did cover partial shading and step/ramp irradiance (stress index up to 9.20). Consequently, actual performance might differ somewhat from simulation outcomes.

6.4 IMPLICATIONS AND SUGGESTIONS FOR FUTURE RESEARCH (

To confirm the low error results (e. g., absolute error 2.91, RMSE 3.08) under realistic noise and switching non-idealities, future study should expand this work to experimental prototypes and real-time hardware-in-the-loop. Hybrid integration studies should combine GA-tuned ANFIS MPPT with grid-support features like reactive power control, virtual inertia, and adaptive protection to more directly address voltage fluctuation (8.10) and frequency deviation (7.80). Future study should also explore coordinated optimization that connects MPPT-level gains (8.60% power improvement) to system-level congestion-aware dispatch and curtailment mitigation.