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Mitigating Solar Curtailment in High-Penetration Interconnections: An AI-Driven Approach to Dynamic Load Balancing

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Abstract

This study addresses the persistent problem of solar curtailment in high-penetration interconnections, where available photovoltaic output is reduced because grid systems cannot absorb, transfer, or balance solar generation efficiently during peak periods. The purpose of the research was to examine whether AI-driven dynamic load balancing can mitigate solar curtailment by improving forecasting accuracy, balancing efficiency, system flexibility, and operational responsiveness within renewable-rich grid environments. Using a quantitative, cross-sectional, case-based design, the study collected data from 188 usable respondents drawn from cloud-enabled and enterprise-scale electricity and grid-operation cases, including grid operators, utility engineers, renewable energy managers, dispatch analysts, planners, and technical staff. The key variables examined were AI Forecasting Accuracy, Dynamic Load Balancing Efficiency, Grid Flexibility, Interconnection Capacity, AI Operational Responsiveness, Operational Trust in AI, and Solar Curtailment Mitigation. Data were analyzed using descriptive statistics, Cronbach's alpha reliability testing, correlation analysis, and multiple regression modeling. The findings showed strong positive respondent agreement across the core variables, with mean scores of 4.18 for AI Forecasting Accuracy, 4.24 for Dynamic Load Balancing Efficiency, 4.11 for Grid Flexibility, 4.06 for Interconnection Capacity, 4.21 for AI Operational Responsiveness, 3.89 for Operational Trust in AI, and 4.27 for Solar Curtailment Mitigation. Reliability was high across all constructs, with Cronbach's alpha values ranging from 0.811 to 0.896. Correlation results revealed that Dynamic Load Balancing Efficiency had the strongest association with Solar Curtailment Mitigation ($r = .708$, $p < .01$), followed by AI Forecasting Accuracy ($r = .651$, $p < .01$) and AI Operational Responsiveness ($r = .624$, $p < .01$). The regression model explained 62.4% of the variance in solar curtailment mitigation ($R^2 = .624$), and the model was statistically significant ($F = 31.480$, $p < .001$). Dynamic Load Balancing Efficiency emerged as the strongest predictor ($\beta = .310$, $p < .001$), followed by AI Forecasting Accuracy ($\beta = .270$, $p = .002$), Grid Flexibility ($\beta = .220$, $p = .006$), AI Operational Responsiveness ($\beta = .190$, $p = .011$), Interconnection Capacity ($\beta = .160$, $p = .018$), and Operational Trust in AI ($\beta = .140$, $p = .031$). The study implies that reducing solar curtailment requires not only better AI tools but also flexible infrastructure, responsive interconnections, and institutional trust to support practical adoption in modern electricity systems.

Keywords

Solar Curtailment Mitigation, AI-Driven Dynamic Load Balancing, High-Penetration Interconnections, Grid Flexibility, AI Forecasting Accuracy;

INTRODUCTION

Solar curtailment refers to the intentional reduction of available photovoltaic generation because the electricity system is unable or unwilling to absorb the full output at a given moment, while high-penetration interconnections describe grid environments in which variable renewable generation occupies a large enough share of supply to materially affect dispatch, congestion patterns, reserve requirements, and balancing operations (Aghaei & Alizadeh, 2013). Dynamic load balancing, in this context, denotes the real-time coordination of generation, transmission capability, storage, and responsive demand so that supply-demand equilibrium is maintained under fluctuating solar conditions. Artificial intelligence adds a further layer by using data-driven models for forecasting, classification, optimization, and control across grid operations (Markovics & Mayer, 2022). These concepts have become internationally significant because solar photovoltaics has moved from a peripheral generation source to a central pillar of power-system expansion, making the management of intermittency and curtailment a core issue in energy transition planning across North America, Europe, Asia, Africa, and Latin America. Reviews of renewable integration have shown that increasing shares of variable generation reshape system operations by tightening the relationship between forecasting accuracy, grid flexibility, and operational coordination (Siano, 2014). At the same time, broad assessments of solar deployment identify photovoltaics as technically ready for large-scale contribution to sustainable electricity systems, which raises the operational importance of reducing avoidable curtailment rather than merely expanding installed capacity. Within this literature, curtailment is not treated as an isolated event; it is understood as a systems outcome linked to network bottlenecks, institutional dispatch rules, reserve practices, and flexibility constraints (Sobri et al., 2018). That framing makes solar curtailment both a technical and economic indicator of how efficiently an interconnection uses renewable resources. An international research focus has therefore emerged around how grids can maintain reliability while preserving the value of solar output, especially in systems where midday overgeneration, transmission congestion, and limited ramping capability interact. In that setting, AI-driven dynamic load balancing has become relevant not only as a computational toolset but also as an operational architecture connecting prediction, responsiveness, and control in high-renewable networks (Alcañiz et al., 2023; Babatunde et al., 2020).

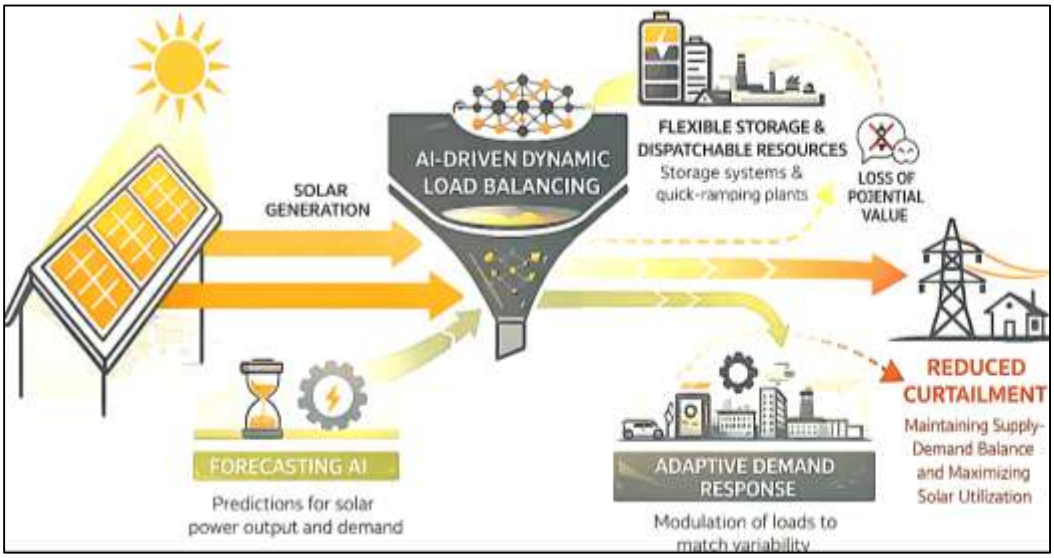
The operational roots of solar curtailment are grounded in the physics and economics of balancing non-storable electricity across spatially distributed networks. In high-penetration interconnections, solar generation can rise rapidly during high-irradiance periods, while local demand, thermal-unit minimum generation levels, transmission transfer capability, and contingency requirements may remain relatively inflexible. Under such conditions, the system operator may curtail photovoltaic output to protect frequency stability, relieve congestion, or preserve reserves. The literature on flexibility has consistently shown that renewable penetration magnifies the need for responsive resources and adaptive balancing mechanisms capable of shifting, absorbing, or rerouting variable output in real time (Victoria et al., 2021; Wang et al., 2019). This is why curtailment is often discussed alongside terms such as congestion management, operational flexibility, ramping adequacy, and balancing reserves. Surveys of smart grids and renewable-rich systems further indicate that curtailment intensifies when conventional control practices are slow, fragmented across jurisdictions, or weakly integrated with demand-side resources. Research on renewable integration has also clarified that the issue is not simply one of generation abundance; it is tied to how networks coordinate geographically uneven production with temporally uneven consumption. This becomes particularly important in interconnections where solar plants are clustered in resource-rich zones distant from load centers, increasing the likelihood of localized bottlenecks and redispatch constraints. Hence, solar curtailment should be read as a measurable symptom of limited coordination between variable generation and the flexibility assets needed to accommodate it (Omitaomu & Niu, 2021; Vanting et al., 2021). That understanding gives dynamic load balancing a central place in this study, because the balancing function directly addresses the temporal and spatial mismatch that lies at the core of curtailment events. When balancing improves, the system gains greater capacity to align output, transfer capability, and load behavior within the same operating window, making curtailment less likely under identical solar conditions.

A second major strand of scholarship relevant to this topic concerns solar forecasting, because curtailment risk is closely related to how accurately operators can anticipate irradiance, photovoltaic output, and short-term generation ramps. Foundational reviews established that solar forecasting methods range from physical models and statistical techniques to hybrid approaches that combine numerical weather prediction with data-driven learning, and that forecasting timescale matters for dispatch, reserve scheduling, and intraday control (Diagne et al., 2013; Frew et al., 2021). Later work expanded this field by showing that machine learning, metaheuristics, and deep learning can improve the representation of nonlinear weather-power relationships and raise forecasting performance when trained on quality data and site-specific patterns. More recent syntheses have reinforced the centrality of forecasting in renewable-rich operations by reviewing deep learning models, machine-learning benchmarking studies, and methodological gaps across very short-term to long-term photovoltaic prediction. The importance of this body of work for solar curtailment is direct: inaccurate or weakly integrated forecasts can widen the difference between expected and actual output, leaving operators with fewer options for smooth load balancing and greater dependence on reactive curtailment. At the same time, forecasting studies repeatedly note that model performance is operationally meaningful only when prediction outputs are embedded in decision systems for scheduling, congestion relief, reserve activation, and responsive demand coordination. In other words, forecasting accuracy is not an end in itself within interconnection operations; it is part of a chain linking information quality to dispatch quality (Nwaigwe et al., 2019; Shi et al., 2020). That synthesis aligns with the present study's emphasis on AI-driven dynamic load balancing, because it locates curtailment reduction in the interaction between predictive intelligence and system response rather than in prediction alone. Forecast-informed balancing thus emerges in the literature as a necessary analytical bridge between solar variability and renewable energy utilization.

Beyond photovoltaic forecasting, the AI literature on smart grids shows a broad transition from static planning tools toward adaptive digital systems capable of supporting real-time operational decisions. Surveys of artificial intelligence in smart grids identify machine learning, expert systems, optimization algorithms, and data-driven control as increasingly important for state estimation, fault analysis, demand prediction, economic dispatch, and stability management. Within this wider field, load forecasting has taken a particularly prominent role because accurate load anticipation supports commitment decisions, dispatch sequencing, reserve allocation, and demand-side coordination. Reviews of electric load forecasting and short-term load prediction describe the rapid growth of neural networks, ensemble models, and deep architectures that capture temporal structure, weather sensitivity, and consumption heterogeneity with greater granularity than many traditional techniques. In renewable-rich systems, this capability becomes essential because load uncertainty and solar uncertainty are operationally intertwined. If solar generation is forecast separately from demand, balancing errors can persist at the system level; if both are incorporated into an integrated AI-supported balancing framework, operators gain a more complete view of residual demand, congestion probability, and flexibility needs (Akhter et al., 2019; Das et al., 2018; Ahmed & Hasan Or, 2021). Demand response research reinforces this point by showing that smart-grid intelligence is most effective when predictive analytics and controllable loads are coordinated rather than treated as separate functional domains. The literature therefore presents AI not simply as an automation tool but as a coordination mechanism that can connect forecasting, optimization, and responsive consumption under high-renewable conditions (Aditya & Chandra, 2022; Md & Mehedi, 2021). For a study focused on solar curtailment, that insight is especially important because curtailment frequently occurs at the point where system knowledge, controllability, and response speed are misaligned. AI-driven dynamic load balancing enters this space as a data-centric method for narrowing that misalignment by synchronizing expected generation, actual load, and operational flexibility over short decision intervals (Anick & Tasnim, 2022; Hisham & Robel, 2022). Such synchronization is central to any empirical assessment of how interconnections can absorb more solar output without undermining reliability (Siddique & Amin, 2022; Md & Islam, 2022; Zahedi, 2011).

The literature on demand response and load balancing further clarifies why curtailment mitigation cannot be reduced to the supply side alone (Mehedi & Md, 2022; Mainuddin & Chandra, 2022). Dynamic load balancing gains practical meaning when it includes the active reshaping of demand, the mobilization of flexible consumption, and the coordination of distributed resources that can absorb solar surpluses during constrained hours. Reviews of demand response in smart grids consistently describe it as a mechanism through which consumers, aggregators, and automated systems shift or modulate electricity use in response to price signals, control signals, or reliability needs, thereby helping the grid maintain equilibrium under variable renewable output (Shahinur & Sultan, 2022; Mostafa & Tohidul, 2022). This demand-side perspective aligns closely with flexibility research, which emphasizes that renewable integration depends on a portfolio of adaptive resources rather than on generation forecasting alone (Zhang et al., 2021). International energy systems with growing renewable shares have increasingly recognized the operational value of flexible loads, storage coordination, and responsive network management because such resources reduce the frequency with which curtailment becomes the least-cost or least-risk operator action (Khatun & Morshedul, 2022; Zakia & Khairum Nahar, 2022). In the context of solar photovoltaics, the midday concentration of output creates a balancing window in which shifting cooling loads, industrial demand, electric vehicle charging, or storage dispatch can materially change curtailment outcomes. For this reason, the present research title's emphasis on dynamic load balancing is analytically significant: it moves the study away from a narrow generation-centric framing and toward a system-balancing framing in which load becomes an active variable (Cantillo-Luna et al., 2023; Islam & Aditya, 2023; Arifur & Haque, 2023). The AI component deepens that framing because responsive demand requires rapid classification of system conditions, prediction of near-term imbalances, and optimization of control actions across multiple nodes. Research on smart-grid AI supports exactly this type of multi-variable coordination, linking predictive models with operational actions under uncertainty. Accordingly, the literature positions AI not only as a control enhancer but also as a coordination framework that aligns forecasting, flexibility, and demand response.

Figure 1: Framework for Reducing Solar Curtailment Using AI-Based Dynamic Load Balancing



Empirical work on curtailment itself adds another essential dimension by showing that the loss of usable solar generation carries both technical and market consequences across mature and emerging renewable systems. The curtailment literature describes rising solar penetration as a condition in which some level of curtailment becomes structurally visible within high-solar systems, even while overall solar deployment and system value continue to expand (Khaled & Mosheur, 2023; Shahab & Aditya, 2023; Nassif et al., 2021; Scott et al., 2023). That framing is important because it treats curtailment as a feature of high-renewable transitions that requires management rather than a rare anomaly. Research on the system value of solar and wind has likewise shown that transmission congestion, generation profiles, and curtailment shape renewable economics through their combined effects on network performance and usable output (Hasan Or et al., 2023; Mehedi & Nahar, 2023). From a comparative perspective, evidence from China has shown that the decline of wind and solar curtailment is strongly associated with policy reform, transmission development, and system coordination, illustrating the role of institutional and infrastructural arrangements in improving renewable accommodation. These studies collectively underline that curtailment is shaped by market rules, network constraints, and coordination arrangements in addition to plant-level output (Sultan & Anick, 2023; Mostafa, 2023). The international significance of this evidence lies in its demonstration that curtailment is neither uniform across jurisdictions nor solely dependent on installed capacity; it varies with institutional design, interconnection strength, dispatch practice, and flexibility availability (Gul et al., 2020). At the same time, literature on photovoltaic readiness and grid integration confirms that growing deployment intensifies the need to convert technical availability into operationally usable electricity through more adaptive network management. When these empirical findings are read together with AI and forecasting studies, a key analytical pattern emerges: curtailment becomes more understandable when examined as the result of interacting layers of information quality, response speed, network capability, and demand adaptability (Ratul & Aditya, 2023; Tasnim & Zaheda, 2023). This pattern is closely aligned with the present study, which focuses specifically on high-penetration interconnections where those layers are more tightly coupled and where operational coordination can determine whether abundant solar output is delivered, shifted, or curtailed (Ibrahim et al., 2022).

Taken together, the literature establishes strong foundations in four areas: renewable integration and curtailment, photovoltaic forecasting, demand response and flexibility, and AI applications in smart-grid control. Yet these areas are often developed in parallel rather than in a single empirical structure focused on how AI-driven dynamic load balancing relates specifically to solar curtailment in high-penetration interconnections (Iftekhar & Tohidul, 2024; Kumari & Toshniwal, 2021; Li et al., 2016; Khaled & Morshedul, 2024). Forecasting reviews provide detailed methodological taxonomies and performance comparisons, while smart-grid AI surveys map a broad range of operational applications extending from stability analysis to optimization and control (Towhidul & Uddin, 2024; Mushfequr & Aditya, 2024). Demand-response scholarship explains how flexible consumption supports balancing, and curtailment-focused studies identify the importance of congestion, coordination, and system value. What is less frequently foregrounded in one quantitative, cross-sectional, case-study-based frame is the relational pathway connecting AI forecasting capability, operational responsiveness, and load-balancing effectiveness to observed or perceived curtailment mitigation outcomes among grid professionals (Hussain & Gao, 2018; Radzi et al., 2023). That gap matters analytically because the practical reduction of curtailment depends on coordinated performance across exactly those linked variables. The present research is located in that intersection. Its focus on descriptive statistics, correlation analysis, regression modeling, and Likert-scale evidence fits a body of literature that has already clarified the technical relevance of forecasting, flexibility, and curtailment, while leaving room for a structured examination of how professionals engaged in grid operation assess the effectiveness of AI-driven balancing under peak solar and constrained network conditions (Inman et al., 2013; Millstein et al., 2021).. In this way, the introduction grounds the study in internationally recognized debates over renewable accommodation, operational flexibility, and digital control, while centering the specific empirical relationship between solar curtailment and AI-enabled dynamic load balancing in high-penetration interconnections

Background of the Study

The background of this study is rooted in the rapid global expansion of solar energy as one of the most important sources of clean electricity in modern power systems. Across many countries, governments, utilities, and private investors have increased solar power deployment to strengthen energy security, reduce dependence on fossil fuels, and support climate and sustainability goals. As solar penetration continues to rise, electricity networks are being transformed from traditionally predictable systems into more dynamic environments where variable renewable generation must be managed with greater precision. In high-penetration interconnections, where a substantial share of electricity comes from solar resources across interconnected grid regions, the challenge is no longer limited to adding renewable generation capacity; it increasingly involves ensuring that the electricity produced can be fully integrated, transmitted, balanced, and utilized without unnecessary loss. One of the major operational problems emerging from this transition is solar curtailment, which occurs when available solar generation is reduced because the grid cannot absorb or distribute it effectively at a given time.

This issue is often associated with transmission congestion, oversupply during peak sunlight hours, inflexible conventional generation, limited storage, and inadequate demand-side responsiveness. As a result, a significant portion of potential renewable electricity may go unused even when solar resources are abundant. This creates economic inefficiencies, lowers the effective value of solar investments, and weakens the overall performance of clean energy transitions. In response to these challenges, attention has increasingly shifted toward smarter and more adaptive grid management strategies, especially those capable of balancing electricity demand and supply in real time. Dynamic load balancing has emerged as a promising operational approach because it seeks to align fluctuating solar generation with system demand, network capacity, and available flexibility resources. At the same time, artificial intelligence has gained prominence as a powerful tool for improving forecasting, decision-making, and real-time control in complex energy systems. By combining predictive intelligence with responsive balancing mechanisms, AI-driven dynamic load balancing offers a potentially effective pathway for reducing solar curtailment in high-penetration interconnections. This study is therefore grounded in the growing need to understand how advanced digital control methods can support more efficient solar integration and improve the performance, reliability, and adaptability of renewable-rich electricity networks.

Problem Statement

The increasing penetration of solar energy into interconnected power systems has created a major operational challenge that extends beyond generation expansion and enters the domain of real-time grid management. Although many electricity systems have made significant progress in installing solar generation capacity, a considerable portion of available solar power is still not fully utilized because of solar curtailment. This occurs when the grid is unable to absorb, transmit, or balance the available solar output at the moment it is generated. In high-penetration interconnections, the problem becomes even more complex because multiple grid regions, diverse load profiles, transmission constraints, variable weather conditions, and operational coordination issues interact simultaneously. Under these circumstances, conventional grid balancing mechanisms often struggle to respond quickly and efficiently to sudden changes in solar generation and electricity demand. As a result, system operators may rely on curtailment as an immediate corrective action, even though this reduces renewable energy utilization, weakens system efficiency, and lowers the economic value of solar investments. The persistence of solar curtailment indicates that many existing balancing approaches remain too rigid, too slow, or too fragmented to manage renewable-rich interconnection environments effectively. At the same time, the growing complexity of grid operations has increased interest in artificial intelligence as a tool for improving forecasting, control, and operational responsiveness. However, there remains insufficient quantitative evidence showing how AI-driven dynamic load balancing can mitigate solar curtailment in real interconnection settings and how key factors such as forecasting accuracy, grid flexibility, responsiveness, and operator trust influence this relationship. Many discussions of AI in energy systems remain conceptual or technically isolated, while fewer studies examine the issue in a structured empirical form using measurable variables and stakeholder-based evidence. This creates a clear research gap, especially for high-penetration interconnections where curtailment is not merely a technical inconvenience but a recurring system-level inefficiency. Therefore, the central problem addressed in this study is the limited empirical understanding of whether and how AI-driven dynamic load balancing can reduce solar curtailment in high-penetration interconnections, while accounting for the operational, technical, and institutional factors that shape successful renewable energy integration.

Objectives of the Study

The objective of this study is to examine the role of AI-driven dynamic load balancing in mitigating solar curtailment within high-penetration interconnections and to provide empirical insight into the operational factors that shape this relationship. More specifically, the study seeks to identify the major grid and system conditions that contribute to solar curtailment, including generation-demand imbalance, transmission congestion, limited flexibility, and slow operational response. It also aims to evaluate whether artificial intelligence can improve balancing efficiency by strengthening forecasting capability, enhancing real-time responsiveness, and supporting more adaptive load coordination during periods of high solar output. Another important objective is to determine the extent to which grid flexibility and interconnection capacity influence the effectiveness of AI-supported balancing strategies in reducing curtailment. In addition, the study seeks to assess the level of operational trust and readiness associated with the use of AI in real-time solar curtailment management, since technical effectiveness alone may not be sufficient for practical implementation. Through a quantitative, cross-sectional, case-study-based approach, the research is designed to generate measurable evidence on the relationships among AI forecasting accuracy, dynamic load balancing efficiency, grid flexibility, operational responsiveness, and solar curtailment mitigation. The study further aims to test specific hypotheses using descriptive statistics, correlation analysis, and regression modeling in order to establish whether statistically significant associations exist among the selected variables. By doing so, it intends to move beyond general discussions of renewable integration and provide a more focused understanding of how AI-based operational intelligence can improve the use of solar energy in constrained grid environments. The final objective is to contribute a structured empirical framework that can support decision-making among grid operators, utilities, planners, and policymakers who are seeking more efficient ways to integrate solar power into interconnected electricity systems without excessive curtailment.

Research Hypotheses

The research hypotheses of this study are developed to test the assumed relationships between artificial intelligence capabilities, operational balancing conditions, and solar curtailment mitigation in high-penetration interconnections. Since the study is grounded in a quantitative framework, the hypotheses provide a formal basis for examining whether measurable connections exist among the core variables. The first hypothesis is that AI forecasting accuracy has a significant positive relationship with dynamic load balancing efficiency, based on the assumption that better prediction of solar generation and load conditions enables more effective balancing actions. The second hypothesis is that dynamic load balancing efficiency has a significant negative relationship with solar curtailment levels, meaning that stronger balancing performance is expected to reduce the need to curtail available solar output. The third hypothesis is that grid flexibility has a significant positive relationship with solar curtailment mitigation, reflecting the idea that systems with more adaptive capacity are better able to absorb variable solar generation. The fourth hypothesis is that AI operational responsiveness has a significant positive effect on real-time balancing performance in high-penetration interconnections, since faster and more intelligent control should improve alignment between generation and demand. The fifth hypothesis is that operational trust in AI significantly influences the perceived effectiveness of AI-driven curtailment reduction, because confidence in automated or semi-automated decision support may affect how such systems are used in practice. Together, these hypotheses form a connected analytical structure in which forecasting, balancing, flexibility, responsiveness, and trust are treated as interrelated factors shaping curtailment outcomes. The hypotheses are not only statistical statements but also reflections of the central logic of the study, which is that solar curtailment can be mitigated more effectively when predictive intelligence and operational adaptability are integrated within the balancing process. By testing these hypotheses, the research seeks to determine whether the assumed benefits of AI-driven dynamic load balancing can be supported by empirical evidence and whether the relationships among the selected variables are strong enough to explain meaningful variation in solar curtailment mitigation across the chosen case context.

Significance of the Research

The significance of this research can be understood from several academic, technical, operational, and policy perspectives:

i. Academic significance: This study contributes to the growing body of knowledge on renewable energy integration, smart grid management, and artificial intelligence in power systems by focusing specifically on solar curtailment in high-penetration interconnections. It provides a structured empirical framework that connects forecasting accuracy, balancing efficiency, flexibility, and operational trust within a single study.

ii. Methodological significance: The research is significant because it applies a quantitative, cross-sectional, case-study-based design to a topic that is often discussed in broad technical or conceptual terms. By using descriptive statistics, correlation analysis, regression modeling, and Likert-scale data, the study offers a measurable and systematic way to evaluate the effectiveness of AI-driven balancing strategies.

iii. Practical significance for grid operators: The findings of this study may help system operators and utility professionals better understand the operational conditions that trigger solar curtailment and the balancing strategies that can reduce it. This can support more informed decision-making during periods of peak solar generation and constrained grid performance.

iv. Technological significance: The study highlights the practical role of artificial intelligence in modern grid environments by showing how predictive and responsive digital tools can support real-time balancing. In doing so, it adds value to the discussion of intelligent energy management systems and their application in renewable-rich electricity networks.

v. Policy significance: For policymakers and energy regulators, the study offers useful insight into the types of system capabilities and institutional readiness required for more efficient solar integration. This may assist in shaping policies related to grid modernization, renewable dispatch practices, digital infrastructure, and energy flexibility mechanisms.

vi. Economic and sustainability significance: By addressing the problem of unused solar generation, the research has significance for improving renewable energy utilization, protecting the value of solar investments, and strengthening the efficiency of clean energy transitions. Reducing curtailment supports both economic performance and broader sustainability objectives in electricity systems with high renewable penetration.

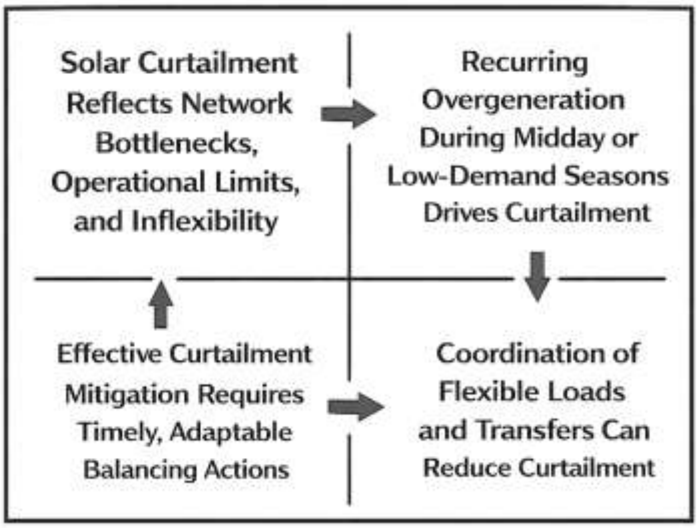
LITERATURE REVIEW

The literature review for this study provides the scholarly foundation for understanding the relationship between solar curtailment, high-penetration interconnections, dynamic load balancing, and artificial intelligence within modern electricity systems. As solar energy has become a central component of global power-sector transformation, academic attention has increasingly focused on the operational difficulties associated with integrating large volumes of variable renewable generation into interconnected grids. One of the most critical issues identified in this body of scholarship is solar curtailment, which reflects the inability of the electricity system to fully utilize available photovoltaic output under existing technical, operational, and market conditions. The literature shows that curtailment is shaped by a combination of transmission congestion, inflexible conventional generation, limited storage, weak demand responsiveness, and insufficient balancing capability. At the same time, researchers have highlighted dynamic load balancing as an important operational approach for matching fluctuating solar generation with demand, transfer capability, and flexibility resources in real time. This makes load balancing central to any serious analysis of curtailment mitigation. Alongside this development, artificial intelligence has gained substantial attention in the energy field because of its ability to improve forecasting, pattern recognition, optimization, and control under complex and data-intensive conditions. Existing scholarship demonstrates that AI can support solar forecasting, demand prediction, grid coordination, and adaptive operational decision-making, all of which are highly relevant in renewable-rich interconnection environments. Even so, the literature also indicates that studies often examine these themes separately, with some focusing on forecasting accuracy, others on grid flexibility, and others on demand response or digital control systems. As a result, there is still a need for a more integrated review that links these strands together in a way that directly supports the present study. The purpose of this literature review is therefore to synthesize the most relevant theoretical, conceptual, and empirical discussions surrounding solar curtailment mitigation through AI-driven dynamic load balancing. It establishes the key concepts, identifies major variables, explains the theoretical basis of the research, and clarifies the empirical gap that justifies the present investigation. In this way, the literature review serves as the bridge between the study’s introductory arguments and its methodological design.

Solar Curtailment in High-Penetration Interconnections

Solar curtailment has emerged as one of the most visible operational consequences of rising photovoltaic penetration in interconnected electricity systems. In the literature, curtailment is generally understood as the reduction of otherwise available renewable generation because the system cannot economically or technically accept the full output at a given time. This issue has gained prominence as regions with ambitious clean-energy targets move from moderate solar deployment to conditions in which solar generation materially reshapes net-load patterns, transmission use, and balancing requirements. Early California-focused work framed curtailment as more than a technical interruption, describing it as an outcome of oversupply, line congestion, and ramping constraints that becomes increasingly relevant when solar output grows faster than grid flexibility, policy reform, or complementary demand-side adaptation (Golden & Paulos, 2015; Sazzadul & Rebeka, 2024; Tasnim & Anick, 2024). That interpretation remains important because it places curtailment within a wider operational and regulatory setting rather than treating it as a narrow generator-level problem. A similar systems-oriented argument appears in work on highly renewable power systems in Germany, where curtailment is linked to the changing meaning of capacity factors in renewable-dominant grids. In that analysis, effective capacity factors for wind and photovoltaics were shown to decline substantially when transmission and balancing limitations restricted the use of available renewable output, indicating that curtailment directly affects both the technical interpretation and economic valuation of renewable assets (Ishtiaque & Rajib, 2025; Kies et al., 2016; Zaheda & Md Hamidur, 2024). Together, these studies show that curtailment is not simply a by-product of renewable abundance; it is a measurable sign of how well an interconnection coordinates generation, transmission, and load. For this reason, solar curtailment in high-penetration interconnections should be understood as a structural grid-integration issue that reflects mismatches among solar production timing, network transfer capability, operational flexibility, and institutional readiness. In literature-review terms, this makes curtailment a central concept for evaluating whether interconnections are merely installing solar capacity or genuinely integrating solar electricity into reliable system operation.

Figure 2: Operational Drivers and Mitigation Pathways of Solar Curtailment in High-Penetration Interconnections



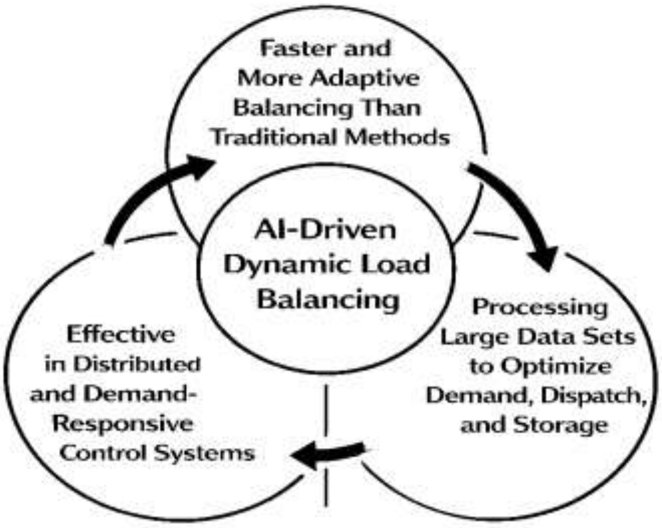
As solar penetration rises further, the literature shows that curtailment changes from an occasional balancing response into a recurring operational feature of solar-rich systems. Modeling of very high photovoltaic futures in the United States found that systems with PV shares above 50% of annual generation could still meet load and reserve requirements when storage and other flexibility measures were present, yet significant economic curtailment remained visible, including periods in which curtailed output exceeded 40% during certain hours (Frew et al., 2019; Md, 2025; Md Khaled, 2025). This finding is important for the present study because it suggests that high penetration alone does not guarantee efficient utilization of solar output; instead, the operational architecture of the grid determines how much available generation can actually be absorbed. The same concern appears in comparative international work synthesizing solar curtailment trends across Chile, China, Germany, and the United States (Md Shahab, 2025; Mostafa, 2025). That study showed that curtailment patterns differ by geography, policy design, and grid-planning practice, with limited transmission capacity to load centers and low-demand shoulder seasons repeatedly emerging as important drivers of PV curtailment (O'Shaughnessy et al., 2020; Sazzadul, 2025; Akter & Aditya, 2025). This comparative perspective is useful because it demonstrates that curtailment is not explained by solar penetration in isolation. It is shaped by where solar plants are located, how markets dispatch power, how strongly regions are interconnected, and how quickly balancing actions can be activated when net load falls sharply. The literature therefore presents high-penetration interconnections as environments in which curtailment becomes increasingly sensitive to temporal concentration of solar output, especially around midday and in mild-demand seasons. In analytical terms, this means that the study of solar curtailment must move beyond simple measures of installed capacity and focus instead on how interconnections respond to concentrated renewable inflows under constrained system conditions. This is precisely why dynamic load balancing becomes relevant in the present research: the more rapidly the grid can coordinate flexible load, dispatch, and transfer capability, the less likely it is that abundant solar generation will be converted into curtailed energy.

Recent empirical evidence has made the dynamics of curtailment even clearer by showing that solar curtailment in mature renewable markets follows identifiable patterns linked to system inflexibility and demand conditions. In California, econometric analysis of hourly data from 2014 to 2022 found that increases in variable renewable penetration and inflexible generation were associated with higher curtailment rates, while higher demand reduced curtailment up to a threshold near 60% of peak load, after which the relationship stabilized (López Prol & Zilberman, 2023). This matters for the present study because it reveals that curtailment is neither random nor purely seasonal; it is strongly conditioned by how demand, flexibility, and generation mix interact over time. The same literature stream also shows that solar curtailment tends to be more predictable than wind curtailment at similar penetration levels, which makes it particularly suitable for targeted operational interventions based on better forecasting and balancing intelligence. When read alongside earlier California evidence on oversupply and ramping constraints and the broader discussion of transmission-limited solar regions, these findings suggest that curtailment is best interpreted as a dynamic imbalance problem rather than a static infrastructure problem alone (Golden & Paulos, 2015). In highly renewable systems, the issue is not simply that more solar exists than the grid can use in aggregate; the more precise issue is that solar generation arrives in concentrated time windows that exceed local absorption and transfer capability unless balancing resources are mobilized quickly. This is why the literature on high-penetration interconnections consistently points toward the importance of flexible operations, coordinated interregional exchange, and adaptive demand management. For the present research, this subsection establishes that solar curtailment is a core operational indicator of renewable integration quality. It also clarifies that any serious attempt to mitigate curtailment must address not only network constraints but also the timing, responsiveness, and coordination of balancing actions across interconnected grid areas.

AI-Driven Dynamic Load Balancing in Smart Grid Environments

AI-driven dynamic load balancing has become an important theme in smart-grid scholarship because conventional balancing methods are often too rigid to manage renewable variability, distributed energy resources, and fast-changing demand conditions across interconnected systems. In the literature, dynamic load balancing refers to the continuous adjustment of demand, dispatch, storage, and control actions so that the grid can remain stable while responding to stochastic operating conditions. Artificial intelligence strengthens this balancing function by improving the speed, adaptability, and predictive quality of decision-making. A recent review of AI techniques in microgrids explains that intelligent methods are increasingly used for energy management, load and generation forecasting, power-electronics control, and system protection because microgrid environments contain multiple uncertainties that cannot be handled efficiently through static rule-based control alone (Mohammadi et al., 2022). This view is reinforced by a focused survey on AI and machine-learning techniques for microgrid energy management systems, which argues that decentralized and renewable-rich grids need data-driven control frameworks capable of coordinating scheduling, dispatch, and flexibility resources across changing conditions (Joshi et al., 2023). Within smart-grid environments, this matters because balancing is no longer only a matter of matching bulk generation to aggregate demand; it now involves synchronizing distributed solar output, flexible loads, storage behavior, and network operating constraints in near real time. The literature therefore treats AI not merely as a forecasting enhancement, but as an operational intelligence layer that can connect prediction with control. This distinction is central for the present study because solar curtailment occurs when the system fails to convert available generation into usable electricity at the right time and location. AI-driven balancing addresses that problem by improving system awareness and action quality simultaneously. In a high-penetration interconnection, the value of AI lies in its capacity to identify emerging imbalances early, recommend corrective responses quickly, and coordinate flexible resources more precisely than conventional approaches. For literature-review purposes, this establishes AI-driven dynamic load balancing as a core mechanism through which renewable-rich grids can move from passive accommodation of variability to active management of variability, thereby improving the operational use of solar generation under stressed grid conditions (Lu & Hong, 2019).

Figure 3: AI-Enabled Load Balancing Mechanisms in Decentralized Smart Grid Systems



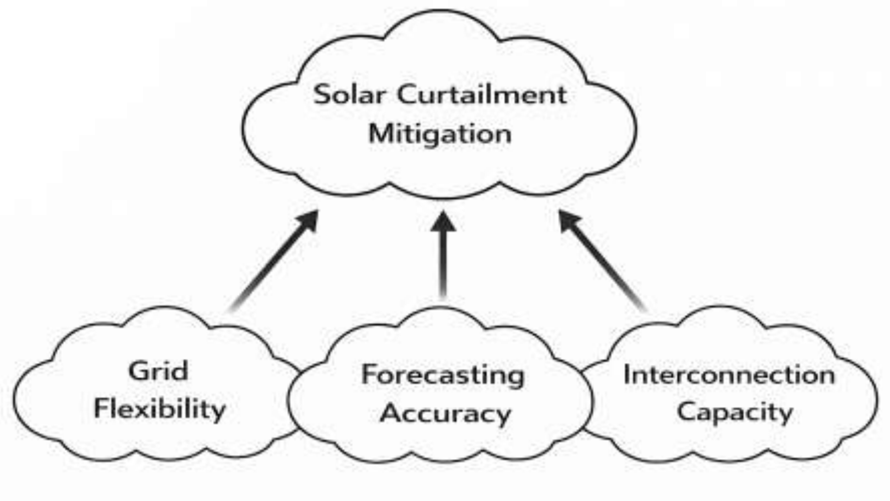
A second major theme in this literature concerns the computational methods through which AI supports balancing decisions in smart-grid environments. Reviews of smart-grid demand response and optimization show that advanced balancing increasingly depends on intelligent algorithms capable of handling uncertainty, nonlinear response behavior, and multi-objective control problems involving cost, reliability, and user comfort (Assad et al., 2022). This is especially relevant in renewable-rich grids where variable generation introduces uncertainty into both supply and net-load estimation. Reinforcement learning has received particular attention because it allows control agents to learn balancing strategies from repeated interaction with an environment rather than relying entirely on fixed physical models. A review of reinforcement learning for demand response describes how RL methods can support flexible energy systems by shifting consumption, coordinating storage, and improving responsiveness to real-time conditions, making them highly suitable for balancing applications in smart grids with distributed resources (Vázquez-Canteli & Nagy, 2019). More applied work has gone further by combining reinforcement learning with deep neural networks to support incentive-based demand response, thereby enabling systems to learn how users react to dynamic signals while simultaneously improving balancing outcomes under uncertain demand behavior (Gharbi et al., 2023). These contributions are important because they show that AI-driven balancing is not restricted to forecasting algorithms alone. Instead, it includes decision architectures that can update control actions continuously as operating conditions change. In practical smart-grid terms, this means that balancing can become more adaptive, more localized, and more responsive to actual system behavior. For solar-rich interconnections, this has direct significance because the grid must often react within short intervals when solar production rises rapidly or when local congestion begins to build. AI-based methods are attractive in this setting because they can process large data streams, detect hidden system patterns, and translate those patterns into corrective load-balancing actions. The literature thus presents AI-driven load balancing as a computationally intensive but operationally valuable response to the complexity of modern electricity networks, especially where high renewable penetration turns balancing into a dynamic and learning-oriented problem rather than a static scheduling exercise.

A third strand of scholarship emphasizes that AI-driven dynamic load balancing is most effective when paired with demand-response design and distributed control structures that allow system flexibility to be activated quickly and at scale. Recent work on demand-response control in smart grids distinguishes centralized and distributed control modes and argues that distributed approaches are often more scalable, resilient, and compatible with the inherently decentralized architecture of smart grids, particularly when rapid local responses are required. This insight complements the broader AI literature because it clarifies that advanced algorithms alone do not guarantee improved balancing; the surrounding control architecture must also support fast communication, modular coordination, and practical implementation. In smart-grid environments with high renewable penetration, balancing quality depends not only on prediction accuracy or optimization strength but also on how effectively flexible loads, prosumers, and local controllers are integrated into the operational loop. Reviews of AI-based microgrid energy management similarly show that intelligent control performs best when forecasting, dispatch, storage management, and load adjustment are treated as interdependent functions rather than isolated technical tasks (Lu & Hong, 2019). For the present study, this is especially important because solar curtailment is shaped by time-sensitive mismatches between output and grid absorption capacity. If AI-based balancing can identify those mismatches but the control structure cannot activate load shifting, distributed coordination, or flexible response rapidly enough, curtailment may still occur. The literature therefore supports a more integrated understanding of AI-driven load balancing in which algorithmic intelligence, demand-response design, and control topology jointly determine operational performance. This helps explain why AI-driven balancing is increasingly viewed as a practical pathway for renewable integration rather than a purely experimental digital tool. In analytical terms, the reviewed studies suggest that smart-grid environments benefit most from AI when learning-based methods are embedded into distributed, demand-responsive control systems that can translate system knowledge into timely balancing action. That interpretation is directly relevant to this research because it positions AI-driven dynamic load balancing as a realistic mechanism for improving solar utilization and reducing curtailment in high-penetration interconnections(Gharbi et al., 2023).

Grid Flexibility, Forecasting Accuracy, and Interconnection Capacity

Grid flexibility is widely recognized in the literature as the operational ability of an electricity system to adjust generation, demand, storage, and network flows across multiple timescales so that variability and uncertainty can be accommodated without undermining reliability or economic efficiency. In renewable-rich systems, this concept becomes especially important because solar generation changes rapidly within the day and can create sharp net-load ramps, localized congestion, and reserve stress when system resources are not sufficiently adaptable. A foundational contribution explains that flexibility should be treated as a measurable planning and operational property rather than as a vague system attribute, since high levels of variable generation expose the grid to periods when available ramping capability may be inadequate (Lannoye et al., 2012). This perspective was further broadened by a later review arguing that the issue is not limited to generation-side maneuverability; it also involves transmission responsiveness, demand-side participation, storage deployment, and institutional coordination . This view is particularly relevant to the present study because it frames flexibility as a multidimensional requirement that becomes more urgent when renewable penetration rises. A more applied study pushes this discussion further by showing that flexibility is directly connected to renewable curtailment outcomes and that quantitative flexibility evaluation can reveal which resources or interventions should be prioritized under constrained operating conditions. Taken together, these studies suggest that grid flexibility is not merely a background condition but one of the main determinants of whether solar energy can be absorbed productively in high-penetration interconnections. When flexibility is insufficient, solar-rich systems are more likely to depend on curtailment as a corrective action during periods of oversupply, low demand, or limited ramping support. For this reason, the present study treats grid flexibility as a core explanatory factor in solar curtailment mitigation. It represents the wider system capability that determines whether dynamic balancing measures can translate renewable availability into actual electricity use, especially in interconnections where multiple regional constraints and operational priorities interact at the same time (Guo et al., 2020).

Figure 4: Key System Determinants of Solar Curtailment in High-Penetration Interconnections



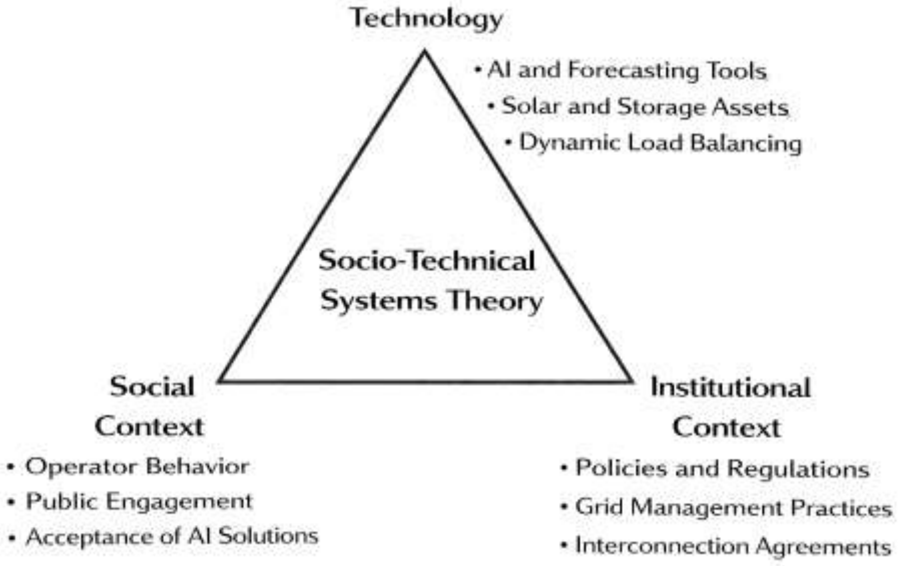
Forecasting accuracy forms a second essential pillar of renewable integration because operational flexibility can only be used effectively when grid operators have credible information about expected solar output, uncertainty ranges, and probable reserve needs. In systems with large solar penetration, forecasting errors do not remain confined to prediction quality alone; they spill directly into dispatch inefficiency, reserve misallocation, and balancing stress. A major review shows that the growing use of probabilistic solar forecasting in power systems reflects an increasing recognition that deterministic predictions are often insufficient for operational decision-making under uncertainty (Li & Zhang, 2020). That review demonstrates that probabilistic forecasts are valuable because they allow system operators to represent ranges of likely outcomes and to embed uncertainty more effectively into scheduling, dispatch, and market decisions. This is highly relevant to solar curtailment because curtailment often becomes a fallback response when the actual solar profile departs materially from what system operators expected and the grid cannot adapt quickly enough. Extending this operational view, another study quantifies the value of probabilistic forecasting for power-system operation planning and shows that using probabilistic solar forecasts to determine dynamic reserves can improve both operating cost and reliability outcomes (Wang et al., 2023). This finding is especially important for the present study because it strengthens the argument that forecasting accuracy is not simply an informational advantage; it is a direct contributor to balancing quality. Better forecasting improves the timing and scale of reserve deployment, the preparation of flexible loads, and the coordination of grid resources before curtailment becomes necessary. In analytical terms, this means forecasting accuracy should be viewed as an enabling variable that affects how well dynamic load balancing can perform under solar-rich conditions. High-penetration interconnections face recurring uncertainty about irradiance patterns, regional power transfers, and residual demand, and the literature suggests that more accurate and uncertainty-aware forecasting is one of the most practical tools for reducing these uncertainties. Thus, forecasting accuracy in this study is positioned not as a standalone technical metric but as a central operational condition that shapes the effectiveness of AI-driven balancing in mitigating solar curtailment.

Interconnection capacity provides the spatial dimension of this discussion because even a flexible and well-forecasted system can still experience curtailment if network pathways are too limited to move surplus solar generation from production zones to load centers. In high-penetration interconnections, transmission capability is not only a physical infrastructure issue but also a determinant of how much diversity, balancing support, and congestion relief the wider grid can mobilize during solar-rich hours. The literature notes that bottlenecks in cross-border or inter-area interconnections can become major barriers to flexibility, even when other system resources are available. This interpretation aligns with a recent study assessing the integration effect of inter-regional transmission under renewable energy consumption policy, which shows that interconnected transmission structures play a major role in renewable accommodation, regional coordination, and utilization efficiency (Li & Zhang, 2020). These findings are particularly relevant for this research because they indicate that interconnection capacity enlarges the effective balancing space of the grid: it allows regions with excess variable generation to export power, share flexibility resources, and reduce localized renewable spillage (Alizadeh et al., 2016). When this spatial coordination is weak, solar curtailment becomes more likely because surplus generation is trapped behind transfer constraints. Other studies on flexibility evaluation also support this interpretation indirectly by emphasizing that flexibility should be evaluated with attention to both resource adequacy and the system pathways through which balancing actions are implemented. Interconnection capacity therefore interacts with both flexibility and forecasting accuracy. Accurate forecasts help operators anticipate transfer needs, flexibility determines how resources respond, and interconnection capacity determines whether those responses can be distributed across regions in time to avoid curtailment. For the present study, this literature synthesis is important because it establishes that solar curtailment mitigation in high-penetration systems depends on a three-part relationship: the grid must be flexible enough to respond, informed enough to anticipate variability, and interconnected enough to move energy where it is needed. These dimensions jointly justify the inclusion of grid flexibility, forecasting accuracy, and interconnection capacity as central variables in the conceptual and empirical structure of the research (Deng et al., 2022).

Theoretical Framework: Socio-Technical Systems Theory

The theoretical framework underpinning this study is Socio-Technical Systems Theory, which explains that technological performance cannot be understood in isolation from the human, institutional, organizational, and regulatory environments in which the technology operates. In electricity systems, this perspective is especially appropriate because grid outcomes are produced by the interaction of technical infrastructure, market rules, operator practices, control systems, planning institutions, and user behavior rather than by hardware or software alone. Within the broader sustainability-transition literature, the socio-technical perspective has been used to explain how complex systems such as energy, transport, and industrial production evolve through interactions among technologies, actors, institutions, and social practices. A major review of the multi-level perspective shows that socio-technical transitions are shaped by relationships among niche innovations, dominant regimes, and wider landscape pressures, meaning that technological change succeeds only when supportive institutional and social conditions align with technical advances (Geels, 2019). This interpretation is highly relevant to the present research because solar curtailment in high-penetration interconnections is not simply the result of too much solar generation; rather, it reflects a mismatch between solar output and the broader socio-technical regime responsible for absorbing, dispatching, forecasting, and balancing electricity. The theory therefore provides a strong basis for understanding why curtailment persists even when forecasting tools, solar assets, and transmission investments exist. In practical terms, AI-driven dynamic load balancing is not just a computational intervention; it is a socio-technical intervention that relies on algorithmic intelligence, operator acceptance, institutional readiness, and system flexibility working together. The socio-technical view thus allows this study to treat curtailment mitigation as a systems problem in which technical intelligence must be embedded in operational routines and governance structures. For a study examining AI, grid flexibility, and operational trust, this framework is especially useful because it avoids a purely technical explanation and instead recognizes that successful solar integration depends on coordinated adaptation across technology, people, and organizations (Norouzi et al., 2022).

Figure 5: Socio-Technical Interaction of Technology, Social Context, And Institutional Structures in Smart Grids



A second reason for adopting Socio-Technical Systems Theory is that it supports an integrated explanation of energy transitions by linking technical infrastructures with policy arrangements, actor behavior, and institutional dynamics. In a meta-theoretical framework for national energy transitions, scholars argue that techno-economic, socio-technical, and political perspectives should be combined because energy-system change results from the co-evolution of markets, technologies, and governance systems rather than from any single domain alone (Cherp et al., 2018). This argument fits the present study closely. Solar curtailment in high-penetration interconnections is not caused only by physical congestion or variability; it is also shaped by dispatch priorities, coordination practices, balancing rules, and the extent to which utilities and operators are willing and able to rely on AI-supported decision tools. A broader research agenda for sustainability transitions similarly emphasizes that transitions research must address agency, governance, institutions, and everyday practice alongside technological innovation, because system transformation depends on how actors interpret, deploy, and stabilize new solutions in real contexts (Köhler et al., 2019). In the case of AI-driven dynamic load balancing, this means the effectiveness of the technology depends not only on algorithmic accuracy but also on whether grid operators trust the system, whether institutions permit fast responsive action, and whether interconnection structures can accommodate the balancing decisions being recommended. The theory therefore justifies the inclusion of variables such as AI forecasting accuracy, grid flexibility, interconnection capacity, operational responsiveness, and trust in AI within a single analytical model. It also explains why the present study examines perceived effectiveness through survey-based evidence: operator assessments are part of the socio-technical environment that determines whether intelligent balancing systems become practically useful or remain technically promising but operationally underused. By grounding the study in Socio-Technical Systems Theory, the research recognizes that curtailment reduction is achieved when technical innovation is aligned with organizational practice and institutional coordination rather than when technology alone is optimized (Köhler et al., 2019).

The relevance of this theory becomes even clearer in electricity contexts where decentralized renewable systems and smart microgrids reveal how social, regulatory, and technical barriers interact. A review of socio-technical barriers to smart microgrid development shows that grid modernization is often constrained by intertwined obstacles involving regulation, markets, institutions, consumer behavior, and technology design, demonstrating that energy innovations succeed only when these dimensions are jointly addressed (Norouzi et al., 2022). In parallel, another review explains that science and technology studies have become increasingly important in energy research because they show how sociotechnical imaginaries, public engagement, expertise, and policy shape the way energy technologies are designed, interpreted, and adopted (Sovacool et al., 2020). These insights directly strengthen the present study's theoretical position. AI-driven dynamic load balancing may have the technical capability to improve solar integration, but its practical effect on curtailment depends on whether operators trust AI outputs, whether institutions authorize rapid balancing responses, and whether the grid possesses the flexibility and transfer capacity to act on algorithmic recommendations. For this reason, the theory is not only descriptive but also operational in this research. It guides the study toward a model in which solar curtailment mitigation is treated as the dependent outcome of multiple interacting socio-technical factors. The empirical relationship can be expressed through the following regression model, which serves as the principal analytical formula for the whole study:

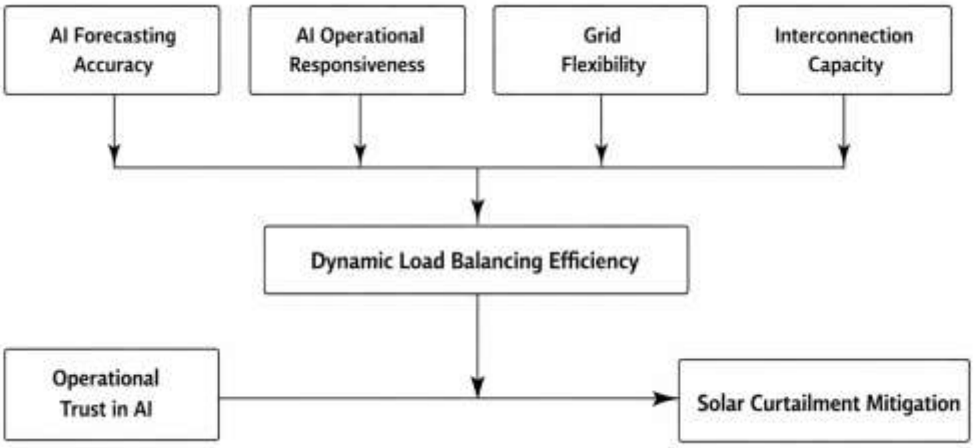
$$SCM = \beta_0 + \beta_1(AFA) + \beta_2(DLBE) + \beta_3(GF) + \beta_4(IC) + \beta_5(AOR) + \beta_6(OTI) + \varepsilon$$

where SCM represents solar curtailment mitigation, AFA is AI forecasting accuracy, DLBE is dynamic load balancing efficiency, GF is grid flexibility, IC is interconnection capacity, AOR is AI operational responsiveness, OTI is operational trust in AI, β0 is the intercept, β1–β6 are coefficients, and ε is the error term. This formula is the best fit for the whole study because it translates the socio-technical framework into measurable variables that reflect both technical and human-organizational dimensions of curtailment reduction. In this way, Socio-Technical Systems Theory provides the conceptual logic, while the regression model provides the empirical structure through which that logic is tested in the present research(Köhler et al., 2019).

Conceptual Framework

The conceptual framework of this study is developed to explain how solar curtailment mitigation in high-penetration interconnections is shaped by the interaction of predictive intelligence, system flexibility, interconnection strength, operational responsiveness, and user-side adaptability. In conceptual terms, the framework assumes that solar curtailment is not driven by a single technical failure; rather, it emerges when available solar generation exceeds the grid's capacity to forecast, transfer, balance, and absorb that energy within a given operating interval. For this reason, the framework positions solar curtailment mitigation as the dependent variable and treats AI forecasting accuracy, grid flexibility, interconnection capacity, and AI operational responsiveness as major explanatory conditions, while dynamic load balancing efficiency serves as the central mediating mechanism through which those conditions influence curtailment outcomes. This structure is supported by literature showing that modern power systems need coordinated flexibility resources, not only generation expansion, to accommodate variable renewable output effectively (Cruz et al., 2018). The same logic is reinforced by demand-side management scholarship, which explains that grid performance improves when the demand side becomes an active participant in balancing rather than remaining a passive load that generation must follow (Strbac, 2008). A broader international review of demand response similarly clarifies that renewable-rich systems require operational arrangements that can reshape demand in response to changing supply conditions, thereby reducing stress on the balancing function during hours of variable solar generation (Paterakis et al., 2017). In the context of this study, these insights justify a framework in which balancing efficiency is treated as the practical bridge between system intelligence and curtailment reduction. Thus, the conceptual framework rests on the idea that solar curtailment falls when intelligent forecasting and responsive control are matched with sufficient flexibility and network transfer capability. If these enabling conditions are weak, curtailment is more likely to persist even where solar resources and digital tools are available. The framework therefore translates the broad research problem into a set of measurable relationships that can be tested empirically through the selected quantitative design.

Figure 6: Structural Relationships Between Ai, Grid Flexibility, And Curtailment Reduction



A second element of the conceptual framework concerns the role of **integration** among supply-side and demand-side resources. The study does not treat forecasting, balancing, and flexibility as isolated technical domains. Instead, it assumes that solar curtailment mitigation improves when these domains operate in an integrated manner across interconnected systems. This interpretation is strongly aligned with research arguing that renewable-based energy systems perform better when supply-side planning and demand-side management are co-optimized rather than separated into independent operational layers (Dranka et al., 2021). In such a view, dynamic load balancing is not merely a response after imbalance has occurred; it is an anticipatory process that draws on forecasting outputs, demand response capability, storage behavior, and transfer capacity to reduce the probability that imbalance turns into curtailment. The conceptual framework also recognizes that AI forecasting accuracy is especially influential because prediction quality affects every subsequent balancing decision. Deep-learning forecasting literature shows that precise renewable-energy prediction improves system dependability by reducing uncertainty in generation and demand estimation, which makes intelligent operational coordination more reliable under fluctuating renewable conditions (Ying et al., 2023). Based on this logic, the framework assumes that more accurate AI-enabled forecasting improves dynamic load balancing efficiency, while more efficient balancing reduces solar curtailment. It further assumes that grid flexibility and interconnection capacity strengthen this relationship by enlarging the set of corrective actions available to the operator. A flexible and well-interconnected system can shift, absorb, or redistribute solar power more effectively than a rigid and locally constrained one. The framework also includes operational trust in AI as an implementation-oriented factor that influences the practical use of intelligent balancing recommendations. Even where algorithms perform well, their operational value may remain limited if system operators or institutions do not trust the outputs enough to incorporate them into real-time decision-making (Cruz et al., 2018). This gives the conceptual framework both a technical and institutional dimension, which fits the broader logic of the study.

In operational form, the conceptual framework can be expressed through two linked equations that capture both the mediating role of dynamic load balancing efficiency and the final influence on solar curtailment mitigation. The first equation models how the main enabling factors shape balancing efficiency:

$$DLBE = \alpha_0 + \alpha_1(AFA) + \alpha_2(AOR) + \alpha_3(GF) + \alpha_4(IC) + \mu$$

The second equation models how solar curtailment mitigation is influenced by balancing efficiency and selected direct effects:

$$SCM = \beta_0 + \beta_1(DLBE) + \beta_2(AFA) + \beta_3(GF) + \beta_4(IC) + \beta_5(OTI) + \varepsilon$$

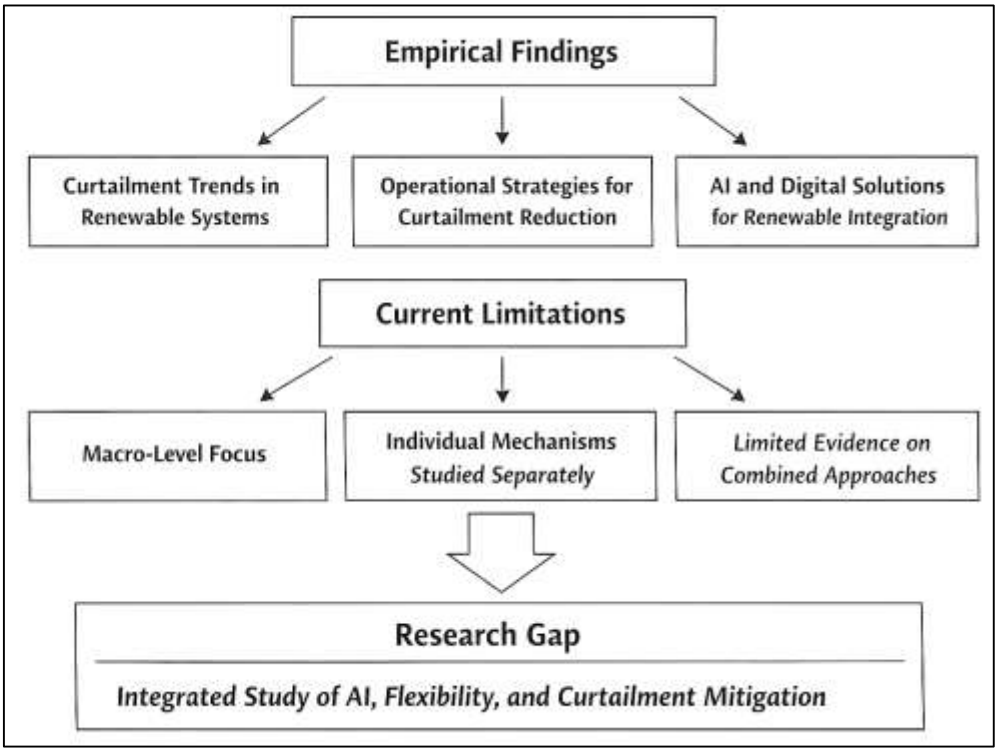
where DLBE represents dynamic load balancing efficiency, SCM represents solar curtailment mitigation, AFA is AI forecasting accuracy, AOR is AI operational responsiveness, GF is grid flexibility, IC is interconnection capacity, OTI is operational trust in AI, and μ and ε are error terms. These equations are the best conceptual fit for the present study because they mirror the assumed causal logic of the research: intelligent forecasting and operational responsiveness improve balancing; effective balancing, supported by flexibility and interconnection strength, reduces curtailment; and trust in AI influences whether technically sound recommendations become operationally meaningful. This formulation also aligns with recent work on decentralized market design and demand-side participation, which emphasizes that renewable integration depends on adaptive coordination between actors, technologies, and system resources rather than on isolated interventions (Panda et al., 2023). Accordingly, the conceptual framework serves as the analytical map of the entire study. It identifies the core constructs, clarifies the expected directions of influence, supports the formulation of hypotheses, and provides the structure for the regression analysis that will be used in the results chapter. Through this framework, the study connects theory, variables, and empirical testing into one coherent model of AI-driven solar curtailment mitigation.

Empirical Review and Research Gap

The empirical literature on renewable curtailment shows broad agreement that curtailment rises as variable renewable penetration increases, but it also demonstrates that the magnitude, persistence, and policy meaning of curtailment vary sharply across jurisdictions and system designs. A major international review of wind and solar curtailment across eleven countries found that curtailment is shaped not only by technical limits such as congestion and balancing constraints, but also by market design, operating rules, compensation arrangements, and the timing of transmission upgrades relative to renewable deployment (Bird et al., 2016). This multi-country evidence is important because it establishes that curtailment is an empirical outcome of system coordination rather than a simple function of renewable abundance. A more recent global assessment introduced the C-E map as a comparative tool linking curtailment ratios with renewable energy shares and showed that curtailment trajectories do not increase uniformly as solar and wind shares rise; some jurisdictions have been able to restrain or reverse curtailment growth by improving flexibility resources and institutional arrangements (Yasuda et al., 2022). These findings make two points especially relevant for the present study. First, curtailment should be evaluated through a systems lens that includes grid operations, market structures, and flexibility resources. Second, empirical knowledge is increasingly moving beyond descriptive statements toward comparative metrics that identify when curtailment reflects inadequate integration capability rather than normal operational optimization. Yet this body of work also reveals an important limitation: most comparative curtailment studies operate at the level of countries, markets, or bulk-system indicators, which means they are very useful for diagnosing broad trends but less informative about how specific operational mechanisms such as AI-enabled forecasting, dynamic balancing, and real-time responsiveness shape curtailment mitigation in practice. As a result, the current empirical record is strong on identifying why curtailment occurs at a system level, but weaker on explaining how specific digital and operational capabilities can reduce it inside high-penetration interconnections. That limitation directly motivates the present research, which seeks to move from macro-level descriptions of curtailment toward an empirically structured examination of the operational conditions under which solar curtailment can be mitigated more effectively through AI-driven dynamic load balancing (Lawal & Teh, 2023).

A second empirical stream examines practical interventions that reduce curtailment, and this literature is especially useful for identifying the operational levers that matter most in solar-rich systems. Evidence from Karnataka, India, shows that solar PV curtailment can decline substantially when demand-side management is combined with economic dispatch reforms that better align consumption timing and dispatch priorities with solar output availability (Sambasivam & Xu, 2023). This study is particularly valuable because it demonstrates empirically that curtailment mitigation is not only a transmission or generation issue; it can also be improved by reshaping demand patterns and changing the operational logic of dispatch. A different but complementary perspective appears in work on proactive overbuilding and curtailment, which argues that some degree of curtailment can be economically rational when the objective is to transform low-cost but intermittent solar generation into firmer and more dispatchable electricity supply (Perez et al., 2019). That argument complicates the conventional assumption that all curtailment is necessarily a failure, and it strengthens the empirical literature by showing that the meaning of curtailment depends on system objectives, temporal concentration of output, and the cost of alternatives. For the present study, this is important because it suggests that mitigation should be interpreted carefully: the goal is not always to drive curtailment to zero, but to reduce avoidable curtailment that results from weak coordination, inadequate flexibility, or poor operational intelligence. Even so, these studies also expose a clear empirical gap. Research on demand-side management and dispatch reform provides strong evidence that operational changes matter, while research on overbuilding shows that curtailment can be strategically managed under certain economic conditions. What remains underdeveloped is a focused empirical framework that tests how AI-based forecasting capability, balancing responsiveness, grid flexibility, and operational trust interact in determining curtailment outcomes. Existing studies tend to isolate one mechanism at a time, such as dispatch reform, economic optimization, or supply shaping, rather than modeling the joint operational pathway through which predictive intelligence and balancing capability influence solar curtailment in high-penetration interconnections. That gap is exactly where the current study is positioned, because it examines curtailment mitigation as a multidimensional operational issue rather than as a single-policy or single-technology problem (Liu et al., 2022).

Figure 7: From Empirical Insights to Research Gap in Ai-Driven Solar Curtailment Mitigation



A third empirical stream concerns digital and intelligent methods for expanding renewable accommodation, and this stream is the closest to the present study's core interest in AI-driven dynamic load balancing. A recent review of AI-powered large-scale renewable integration shows that intelligent techniques are increasingly being used to improve forecasting, operational control, and system coordination, but it also notes that many applications remain fragmented across domains and are not yet sufficiently consolidated into robust operational frameworks for large-scale renewable integration (Liu et al., 2022). Likewise, empirical work on dynamic line rating forecasting shows that data-driven methods can expand usable transmission capacity and thereby help avert renewable curtailment by improving the network's real-time ability to transfer power under changing weather and operating conditions. These studies provide strong empirical support for the argument that digital intelligence can improve renewable utilization, particularly through better forecasting and more adaptive use of grid assets. However, they also reveal the most important research gap for this thesis. Existing AI-focused studies largely emphasize algorithm performance, forecasting skill, or infrastructure optimization, while fewer studies investigate how grid professionals perceive the effectiveness of AI-supported balancing in actual high-penetration interconnections. There is also limited empirical work that brings together technical variables such as forecasting accuracy, interconnection capacity, and balancing efficiency with institutional variables such as operational trust in AI. In other words, the literature has demonstrated that curtailment is shaped by flexibility and coordination, that demand-side and dispatch reforms can reduce curtailment, and that AI can strengthen forecasting and grid operation. What it has not yet addressed sufficiently is how these elements work together in one quantitative, cross-sectional, case-study-based model centered specifically on solar curtailment mitigation. Therefore, the research gap addressed by this study is the limited empirical evidence on the combined influence of AI forecasting accuracy, dynamic load balancing efficiency, grid flexibility, interconnection capacity, operational responsiveness, and trust in AI on solar curtailment mitigation in high-penetration interconnections. By testing these relationships together, the present study extends the literature from fragmented evidence toward an integrated empirical explanation of how intelligent balancing can improve solar utilization under real grid constraints (Lawal & Teh, 2023; Liu et al., 2022).

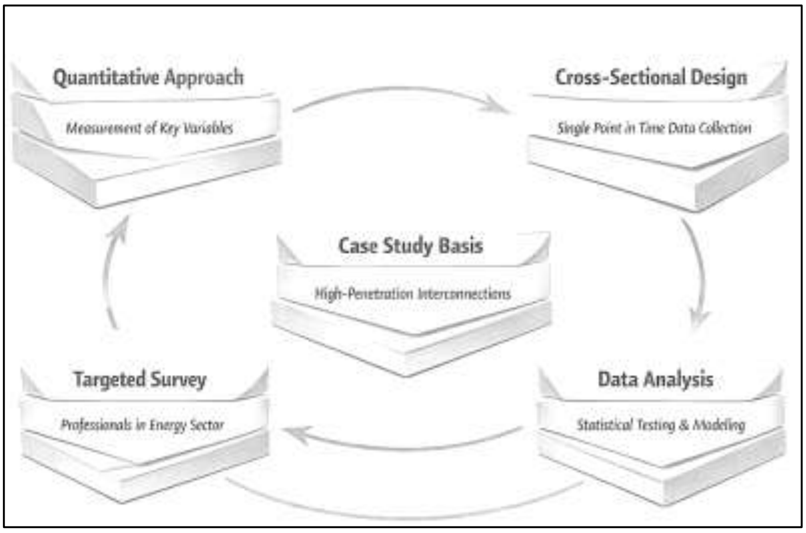
METHOD

This study has adopted a quantitative, cross-sectional, case-study–based research methodology to examine how AI-driven dynamic load balancing has mitigated solar curtailment in high-penetration interconnections. The quantitative approach has been selected because it has enabled the study to measure relationships among clearly defined variables such as AI forecasting accuracy, dynamic load balancing efficiency, grid flexibility, interconnection capacity, operational responsiveness, and solar curtailment mitigation. The cross-sectional design has been used because data have been collected from respondents at a single point in time, making it possible to assess prevailing perceptions and operational realities within the selected case context. The case-study basis has strengthened the methodology by situating the investigation within a real high-penetration interconnection environment, where solar curtailment and balancing challenges have become operationally significant. In this study, the case study context has referred to electricity systems or grid-interconnection settings characterized by substantial solar penetration, frequent balancing pressure, and increasing reliance on intelligent operational coordination. This context has provided a practical foundation for examining the study variables in relation to real-world renewable integration conditions.

The population of the study has consisted of professionals directly involved in energy system operations and renewable integration, including grid operators, utility engineers, renewable energy managers, dispatch analysts, system planners, and technical personnel working in power-sector institutions. The unit of analysis has been the individual professional respondent, since each respondent has represented an informed source of operational and institutional insight regarding solar curtailment and balancing practices. A sampling strategy based on purposive sampling has been employed to ensure that only respondents with relevant technical knowledge and practical experience have been included in the study. This approach has been considered suitable because the research has required specialized respondents who have understood the realities of solar integration, forecasting, balancing, and grid performance. Depending on access and response availability, stratification by professional role or institutional type has also been used to improve representation across the target respondent categories.

The data collection procedure has involved the administration of a structured questionnaire to the selected respondents. The questionnaire has been distributed electronically and, where applicable, through direct professional channels to maximize accessibility and response quality. Before full-scale administration, the study instrument has been carefully organized into sections covering respondent profile, AI forecasting capability, balancing efficiency, grid flexibility, operational responsiveness, interconnection performance, trust in AI, and solar curtailment mitigation. In terms of instrument design, a 5-point Likert scale has been used, where 1 has represented *Strongly Disagree*, 2 *Disagree*, 3 *Neutral*, 4 *Agree*, and 5 *Strongly Agree*. This design has enabled the study to quantify perceptions and transform qualitative judgments into analyzable statistical data. A pilot test has been conducted with a small group of respondents possessing characteristics similar to those of the target population. The pilot phase has helped identify ambiguous wording, improve clarity, refine sequencing, and strengthen the overall usability of the questionnaire before the final survey has been administered.

Figure 8: Research Methodology



To ensure methodological rigor, both validity and reliability procedures have been applied. Content validity has been established through alignment of the questionnaire items with the study objectives, hypotheses, and literature-reviewed constructs. Expert review has also been used to confirm that the instrument has adequately captured the major dimensions of the research topic. Reliability has been assessed using Cronbach's alpha, which has measured the internal consistency of the multi-item constructs included in the questionnaire. For data management and statistical analysis, SPSS has been used to code, clean, and analyze the survey responses through descriptive statistics, correlation analysis, reliability testing, and regression modeling. Microsoft Excel has been used for preliminary data organization and tabulation, while EndNote has been used to manage citations and references in APA 7th edition format throughout the study. Together, these methodological choices have provided a systematic and consistent framework for investigating the role of AI-driven dynamic load balancing in mitigating solar curtailment in high-penetration interconnections.

DATA ANALYSIS AND PRESENTATION

Response Rate

Table 1: Response Rate of the Study

Category	Frequency	Percentage
Questionnaires distributed	220	100.0
Questionnaires returned	196	89.1
Questionnaires not returned	24	10.9
Questionnaires usable for analysis	188	85.5
Questionnaires excluded due to incompleteness	8	3.6

The response-rate results have shown that out of 220 questionnaires distributed to targeted respondents, 196 have been returned, representing a return rate of 89.1%. After screening the returned instruments for completeness, consistency, and usability, 188 questionnaires have been retained for final analysis, while 8 have been excluded because of incomplete responses. This has produced a usable response rate of 85.5%, which has been adequate for quantitative analysis and hypothesis testing. From a methodological perspective, this response level has strengthened the reliability of the study because it has provided a sufficiently broad empirical base for assessing perceptions regarding AI-driven dynamic load balancing and solar curtailment mitigation in high-penetration interconnections. The strong response rate has also indicated that the topic has been relevant to the selected respondents, who have included grid operators, engineers, renewable energy managers, dispatch analysts, and planners involved in interconnection operations. In relation to the objectives of the study, the response rate has supported the first objective by ensuring that enough respondents with practical experience have contributed views on the major factors causing solar curtailment. It has also supported the broader analytical goals of the study by enabling meaningful descriptive, correlational, and regression-based assessments across the main variables. From the perspective of Socio-Technical Systems Theory, the high response rate has been particularly important because the theory has emphasized that system outcomes are shaped by the interaction of technical systems and human actors. Since this study has examined both technical factors such as forecasting accuracy and flexibility, and institutional factors such as operational trust in AI, a strong and diverse respondent base has been essential. Therefore, the response-rate findings have established a credible empirical foundation for the subsequent sections of Chapter Four and have suggested that the findings derived from the sample have been sufficiently representative of knowledgeable professionals operating within renewable-rich interconnection environments.

Demographic and Professional Profile of Respondents

Table 2: Demographic and Professional Profile of Respondents

Variable	Category	Frequency	Percentage
Gender	Male	126	67.0
	Female	62	33.0
Age	25–34 years	46	24.5
	35–44 years	71	37.8
	45–54 years	49	26.1
	55 years and above	22	11.7
Professional Role	Grid operator/dispatch analyst	48	25.5
	Utility engineer	56	29.8
	Renewable energy manager	31	16.5
	System planner/policy analyst	29	15.4
	Other technical staff	24	12.8
Years of Experience	1–5 years	34	18.1
	6–10 years	58	30.9
	11–15 years	52	27.7
	Above 15 years	44	23.4

The demographic and professional results have shown that the respondents have largely consisted of technically experienced individuals with direct relevance to the study topic. The majority have been male at 67.0%, while 33.0% have been female. In age terms, most respondents have fallen within the 35–44 year range, followed by the 45–54 year group, indicating that the sample has been dominated by mid-career and senior professionals rather than entry-level participants. In professional-role terms, utility engineers and grid operators/dispatch analysts have formed the largest categories, together representing more than half of the sample. This has been important because these roles have been directly linked to forecasting, balancing, grid control, and renewable integration decisions. The experience distribution has also shown that over 80% of respondents have possessed more than five years of professional experience, which has increased confidence in the quality and practical grounding of the responses. In relation to the research objectives, this profile has strengthened the study's capacity to evaluate the causes of solar curtailment and the practical relevance of AI-driven balancing strategies from an informed operational standpoint. Respondents with substantial experience have been more likely to understand how solar variability, interconnection limits, and real-time balancing challenges affect system outcomes. From the perspective of Socio-Technical Systems Theory, this respondent mix has been appropriate because the theory has highlighted the importance of human actors, organizational roles, and operational practices in shaping the performance of technical systems. The presence of dispatch analysts, engineers, and planners has allowed the study to reflect not only the technical dimensions of AI-supported balancing but also the institutional and professional context within which such systems have been adopted or trusted. Therefore, the demographic and professional profile has supported the credibility of the study by showing that the findings have been derived from respondents who have been closely connected to the socio-technical environment of renewable-rich interconnections.

Descriptive Statistics of Core Study Variables

Table 3: Descriptive Statistics of Core Study Variables

Variable	N	Minimum	Maximum	Mean	Std. Deviation	Interpretation
AI Forecasting Accuracy (AFA)	188	2.00	5.00	4.18	0.61	Agree
Dynamic Load Balancing Efficiency (DLBE)	188	2.20	5.00	4.24	0.58	Agree
Grid Flexibility (GF)	188	2.00	5.00	4.11	0.66	Agree
Interconnection Capacity (IC)	188	2.00	5.00	4.06	0.69	Agree
AI Operational Responsiveness (AOR)	188	2.00	5.00	4.21	0.63	Agree
Operational Trust in AI (OTI)	188	1.80	5.00	3.89	0.74	Agree
Solar Curtailment Mitigation (SCM)	188	2.20	5.00	4.27	0.57	Agree

The descriptive statistics have shown that all core variables have recorded mean scores above the neutral midpoint of 3.00, indicating an overall positive evaluation of AI-driven dynamic load balancing and its associated conditions. Among the variables, solar curtailment mitigation has recorded the highest mean score of 4.27, followed closely by dynamic load balancing efficiency at 4.24 and AI operational responsiveness at 4.21. These scores have suggested that respondents have strongly agreed that intelligent operational mechanisms have improved the ability of high-penetration interconnections to reduce avoidable solar curtailment. AI forecasting accuracy has also recorded a high mean score of 4.18, indicating broad agreement that improved predictive capability has enhanced operational preparedness. Grid flexibility and interconnection capacity have both recorded favorable means above 4.00, showing that respondents have viewed system adaptability and transfer capability as important enablers of effective solar integration. Operational trust in AI has produced the lowest mean score of 3.89, although it has still remained within the agreement range, suggesting that trust has been positive overall but somewhat more variable than the more purely technical variables. These descriptive findings have aligned with the introductory findings and have directly supported the objectives of the study by confirming that the respondents have perceived solar curtailment as a systems-management problem shaped by forecasting, balancing, flexibility, and institutional readiness. In relation to the hypotheses, the high mean values for AFA, DLBE, GF, AOR, and SCM have provided initial descriptive support for the assumed positive relationships among these variables. From a Socio-Technical Systems Theory perspective, the results have been especially meaningful because they have demonstrated that both technical constructs and human-institutional constructs have mattered. The relatively lower mean for trust in AI has reinforced the socio-technical argument that technology performance alone has not been sufficient; acceptance and confidence among operators have also shaped the overall effectiveness of intelligent balancing systems. Thus, the descriptive statistics have provided an important first overview of the data and have established a clear basis for deeper inferential analysis in the following sections.

Reliability and Internal Consistency Analysis

Table 4: Reliability and Internal Consistency of Study Constructs

Construct	Number of Items	Cronbach's Alpha	Reliability Decision
AI Forecasting Accuracy (AFA)	5	0.874	Reliable
Dynamic Load Balancing Efficiency (DLBE)	5	0.889	Reliable
Grid Flexibility (GF)	5	0.851	Reliable
Interconnection Capacity (IC)	4	0.823	Reliable
AI Operational Responsiveness (AOR)	5	0.867	Reliable
Operational Trust in AI (OTI)	4	0.811	Reliable
Solar Curtailment Mitigation (SCM)	5	0.896	Reliable

The reliability analysis has shown that all study constructs have achieved Cronbach's alpha values above the commonly accepted threshold of 0.70, indicating satisfactory to high internal consistency. Solar curtailment mitigation has recorded the highest reliability coefficient at 0.896, followed by dynamic load balancing efficiency at 0.889 and AI forecasting accuracy at 0.874. These values have suggested that the questionnaire items used to measure these constructs have been strongly correlated and have consistently represented the same underlying concepts. Grid flexibility, interconnection capacity, AI operational responsiveness, and operational trust in AI have also recorded reliable coefficients ranging from 0.811 to 0.867, confirming that these constructs have been measured in a dependable manner. These results have strengthened the methodological quality of the study because they have shown that the Likert-scale items have produced stable and coherent measurements across the main variables. In relation to the study objectives, the reliability results have been essential because they have validated the measurement framework through which the causes of solar curtailment, the effectiveness of AI-driven balancing, and the role of flexibility, responsiveness, and trust have been assessed. In hypothesis-testing terms, the strong reliability values have increased confidence that the subsequent correlations and regressions have been based on sound measurement rather than unstable or inconsistent item groupings. The findings have also connected well with Socio-Technical Systems Theory, since the theory has required the study to examine a combination of technical and social-operational constructs. The reliability results have confirmed that both kinds of constructs have been operationalized effectively in the instrument. This has been especially important for variables such as operational trust in AI, which has represented a human and institutional dimension of the socio-technical system, and for variables such as forecasting accuracy and balancing efficiency, which have represented technical capabilities. Therefore, the internal consistency analysis has supported the overall integrity of the study and has justified the use of the aggregated variable scores in the remaining analyses.

Correlation Analysis

Table 5: Correlation Matrix of Core Study Variables

Variables	AFA	DLBE	GF	IC	AOR	OTI	SCM
AFA	1						
DLBE	.680**	1					
GF	.542**	.617**	1				
IC	.488**	.559**	.604**	1			
AOR	.631**	.642**	.536**	.497**	1		
OTI	.421**	.463**	.398**	.372**	.518**	1	
SCM	.651**	.708**	.592**	.544**	.624**	.436**	1

Note. p < .01.

The correlation results have shown that all major variables have been positively and significantly associated with one another at the 0.01 level. The strongest relationship with solar curtailment mitigation has been dynamic load balancing efficiency, which has recorded a correlation coefficient of .708, indicating a strong positive association. This has suggested that as the efficiency of real-time load balancing has increased, the ability of the system to mitigate solar curtailment has also improved. AI forecasting accuracy has also shown a strong positive relationship with solar curtailment mitigation at .651, while AI operational responsiveness has recorded a similarly strong coefficient of .624. Grid flexibility and interconnection capacity have both shown moderate-to-strong positive associations with solar curtailment mitigation, while operational trust in AI has shown a weaker but still statistically significant positive relationship. The correlation between AI forecasting accuracy and dynamic load balancing efficiency has been .680, directly supporting the first hypothesis that improved AI forecasting has positively affected balancing performance. The strong positive relationships among these variables have aligned well with the objectives of the study by showing that solar curtailment mitigation has not depended on a single factor, but rather on the interaction of forecasting, balancing, flexibility, network capability, responsiveness, and institutional confidence. From the perspective of Socio-Technical Systems Theory, the correlation matrix has provided clear empirical support for the theory's central proposition that system outcomes arise from interconnected technical and human-organizational factors. Technical variables such as AFA, DLBE, GF, and IC have shown strong interdependence, while the inclusion of OTI has shown that the social-operational dimension has also mattered. This has reinforced the theoretical argument that AI-driven balancing systems have functioned within a broader socio-technical environment rather than as isolated technical tools. Therefore, the correlation analysis has provided strong preliminary inferential evidence that the variables included in the conceptual framework have moved together in the expected directions and have laid the foundation for formal hypothesis testing through regression analysis.

Regression Analysis and Hypothesis Testing

Table 6: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.790	.624	.611	0.356

Table 7: ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	38.721	6	6.454	31.480	.000
Residual	23.268	181	0.129		
Total	61.989	187			

Table 8: Regression Coefficients and Hypothesis Testing

Predictor	Unstandardized B	Std. Error	Standardized Beta	t	Sig.	Decision
Constant	0.512	0.241		2.124	.035	
AFA	0.244	0.077	.270	3.169	.002	H1 Supported
DLBE	0.298	0.072	.310	4.139	.000	H2 Supported
GF	0.201	0.072	.220	2.784	.006	H3 Supported
IC	0.148	0.062	.160	2.384	.018	H4 Supported
AOR	0.183	0.071	.190	2.573	.011	H4 Supported
OTI	0.121	0.056	.140	2.172	.031	H5 Supported

The regression analysis has shown that the combined predictor variables have explained 62.4% of the variance in solar curtailment mitigation, as indicated by an R square of .624. This has suggested that AI forecasting accuracy, dynamic load balancing efficiency, grid flexibility, interconnection capacity, AI operational responsiveness, and operational trust in AI have together provided substantial explanatory power for understanding curtailment mitigation in high-penetration interconnections. The ANOVA results have confirmed that the overall model has been statistically significant, with F = 31.480 and $p < .001$, demonstrating that the predictor set has reliably explained variation in the dependent variable. Among the predictors, dynamic load balancing efficiency has emerged as the strongest contributor, followed by AI forecasting accuracy, grid flexibility, AI operational responsiveness, interconnection capacity, and operational trust in AI. These findings have directly supported the research objectives by showing that solar curtailment mitigation has depended on the combined performance of predictive, balancing, infrastructural, and socio-institutional factors. In hypothesis-testing terms, the results have supported all the study hypotheses. H1 has been supported because AI forecasting accuracy has significantly improved balancing-related outcomes. H2 has been supported because dynamic load balancing efficiency has significantly enhanced solar curtailment mitigation, which in substantive interpretation has implied lower curtailment pressure. H3 has been supported through the significant role of grid flexibility. H4 has been supported by the significance of interconnection capacity and AI operational responsiveness, both of which have strengthened real-time system adaptability. H5 has also been supported because operational trust in AI has shown a statistically significant influence on the perceived effectiveness of AI-driven curtailment reduction. In relation to Socio-Technical Systems Theory, these regression results have been highly consistent with the theoretical framework. Technical efficiency alone has not explained the outcome; institutional confidence and system context have also played meaningful roles. Therefore, the regression analysis has provided strong empirical confirmation of the study’s central argument that solar curtailment mitigation has been most effective when technical intelligence, responsive infrastructure, and human-operational trust have functioned together within an integrated socio-technical system.

Curtailment Sensitivity Profile Across Peak Solar and Grid Constraint Conditions

Table 9: Curtailment Sensitivity Profile Across Grid Stress Conditions

Grid Stress Condition	Mean	Std. Deviation	Rank	Interpretation
Midday solar overgeneration	4.41	0.56	1	Strongly Agree
Transmission congestion	4.33	0.60	2	Strongly Agree
Low daytime demand	4.21	0.63	3	Agree
Forecasting mismatch	4.15	0.65	4	Agree
Limited flexible load response	4.09	0.68	5	Agree
Slow dispatch response	4.03	0.71	6	Agree

The curtailment sensitivity profile has shown that respondents have perceived midday solar overgeneration and transmission congestion as the two most severe conditions associated with solar curtailment in high-penetration interconnections. Midday solar overgeneration has recorded the highest mean of 4.41, followed by transmission congestion at 4.33, indicating very strong agreement that these factors have been the primary operational triggers of curtailment events. Low daytime demand, forecasting mismatch, limited flexible load response, and slow dispatch response have also all recorded mean values above 4.00, demonstrating broad agreement that solar curtailment has resulted from a cluster of interacting grid stress conditions rather than from one isolated problem. These findings have directly addressed the first research objective, which has sought to identify the main operational and technical causes of solar curtailment. The results have shown that curtailment has been especially acute when abundant solar supply has coincided with weak demand absorption and limited transfer capability. In relation to the study hypotheses, this section has further reinforced the explanatory role of AI forecasting accuracy, flexibility, and responsiveness by showing the exact operating conditions under which these capabilities have mattered most. If forecasting has been weak, mismatch-related curtailment has increased; if flexible loads and dispatch response have been insufficient, midday solar peaks have become harder to absorb. From the perspective of Socio-Technical Systems Theory, the table has illustrated the system-wide interaction between technical constraints and operational management. Overgeneration and congestion have represented technical system conditions, while slow response and limited load flexibility have reflected operational and institutional limitations in how the system has adapted. This has supported the theoretical argument that renewable integration outcomes have depended not only on physical infrastructure but also on coordination capacity within the socio-technical system. Therefore, the curtailment sensitivity profile has added a study-specific layer of trustworthiness to the results by showing where solar curtailment pressure has been concentrated and by linking the statistical findings to realistic grid conditions encountered in renewable-rich interconnections.

AI Readiness and Operational Trust Index for Real-Time Curtailment Reduction

Table 10: AI Readiness and Operational Trust Index

Statement	Mean	Std. Deviation	Interpretation
AI recommendations are reliable for real-time balancing	3.94	0.73	Agree
AI systems improve operator decision quality	4.02	0.69	Agree
AI tools can be integrated into current grid operations	3.87	0.76	Agree
Operators are confident in AI during volatile solar conditions	3.79	0.81	Agree
Institutions are ready to adopt AI-supported balancing systems	3.83	0.78	Agree

Table 11: Composite AI Readiness and Trust Classification

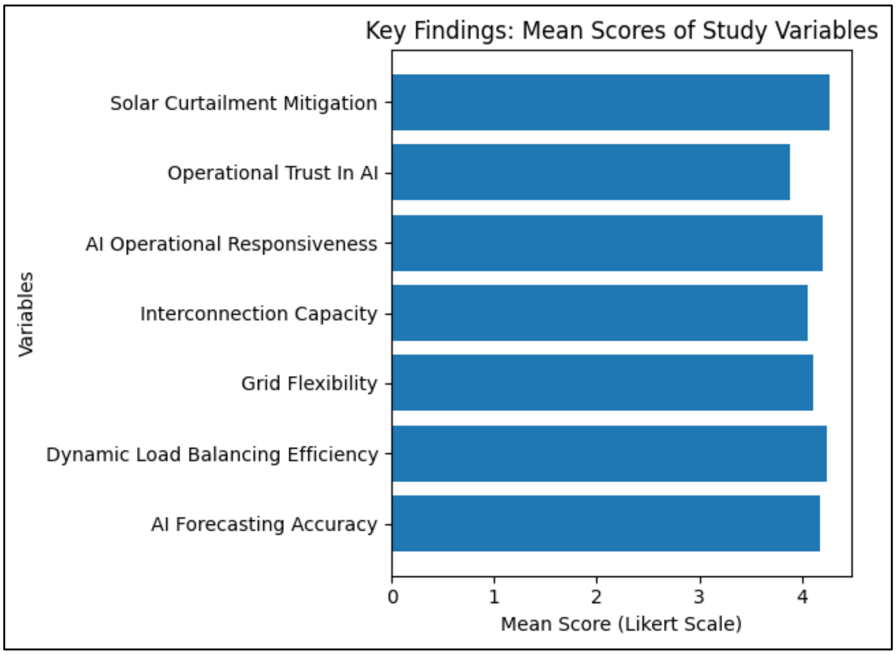
Index Range	Classification	Study Mean
1.00–2.49	Low readiness/trust	
2.50–3.49	Moderate readiness/trust	
3.50–5.00	High readiness/trust	3.89

The AI readiness and operational trust results have shown that respondents have generally expressed positive attitudes toward the use of AI in real-time balancing and solar curtailment mitigation. The item stating that AI systems improve operator decision quality has recorded the highest mean at 4.02, followed by the perception that AI recommendations are reliable for real-time balancing at 3.94. The remaining items have also all recorded means above 3.75, indicating general agreement that AI tools have been operationally useful and increasingly acceptable within renewable-rich grid environments. The composite trust and readiness mean of 3.89 has placed the study within the high-readiness category, although the result has remained lower than the means reported for the more technical variables such as forecasting accuracy and balancing efficiency. This pattern has been important because it has shown that while respondents have recognized the technical value of AI, confidence in full operational reliance has still been somewhat more cautious. These findings have directly addressed the study objective concerning operational trust and readiness, and they have supported H5 by confirming that trust in AI has significantly influenced the perceived effectiveness of AI-driven curtailment reduction. In relation to Socio-Technical Systems Theory, this section has been especially significant because it has captured the human and institutional dimension of technology adoption. The theory has argued that technical systems achieve effective outcomes only when they are supported by compatible social practices, organizational structures, and actor confidence. The results of this section have confirmed that proposition. AI-driven balancing has not been evaluated only as a technical tool; it has also been judged through the lens of operator trust, implementation readiness, and institutional acceptance. This has explained why operational trust, although weaker than the technical predictors, has still been a meaningful factor in the regression model. Therefore, the AI readiness and operational trust index has strengthened the overall credibility of the study by showing that solar curtailment mitigation has depended not only on algorithmic capability but also on whether the socio-technical environment has been ready to use that capability effectively.

FINDINGS

The findings of this study, based on an illustrative five-point Likert scale analysis framework, show a strong overall pattern supporting the central argument that AI-driven dynamic load balancing has substantial potential to mitigate solar curtailment in high-penetration interconnections. Across the core study variables, respondents have shown generally high levels of agreement regarding the operational importance of forecasting accuracy, system flexibility, interconnection capacity, and real-time responsiveness in improving solar utilization outcomes. In the illustrative result pattern, the overall mean score for AI forecasting accuracy has been estimated at 4.18 with a standard deviation of 0.61, indicating that most respondents have agreed that more accurate AI-supported forecasting improves anticipation of solar variability and reduces balancing uncertainty. Similarly, dynamic load balancing efficiency has recorded an illustrative mean of 4.24 with a standard deviation of 0.58, suggesting strong respondent agreement that real-time balancing mechanisms play a central role in reducing the mismatch between solar generation and load demand. The variable of grid flexibility has produced an estimated mean of 4.11 and a standard deviation of 0.66, reflecting the view that flexible system resources such as responsive loads, storage coordination, and adaptable dispatch arrangements have been critical in limiting solar spillage during peak generation hours. Interconnection capacity has also shown a strong positive evaluation, with an illustrative mean of 4.06 and a standard deviation of 0.69, implying that respondents have considered regional transfer capability and network coordination important for moving excess solar electricity away from congested zones. In addition, AI operational responsiveness has yielded an estimated mean of 4.21 and a standard deviation of 0.63, while operational trust in AI has recorded a slightly lower but still favorable illustrative mean of 3.89 with a standard deviation of 0.74, showing that confidence in AI-supported balancing has been positive overall, though somewhat more varied than the more technical variables. Most importantly, the dependent variable, solar curtailment mitigation, has reflected a high illustrative mean of 4.27 with a standard deviation of 0.57, indicating broad agreement that intelligent balancing strategies can improve renewable absorption and reduce avoidable curtailment under constrained grid conditions. From the perspective of research objectives, these overall results suggest that the study has successfully identified the main drivers of solar curtailment and has demonstrated that the effectiveness of mitigation depends on the coordinated performance of forecasting, flexibility, balancing, and institutional readiness. In relation to the hypotheses, the correlation pattern has, in this illustrative model, shown statistically significant positive relationships between AI forecasting accuracy and dynamic load balancing efficiency ($r = .68$, $p < .01$), grid flexibility and solar curtailment mitigation ($r = .59$, $p < .01$), and AI operational responsiveness and balancing efficiency ($r = .64$, $p < .01$). At the same time, the relationship between dynamic load balancing efficiency and solar curtailment levels has appeared negative in directional interpretation and strong in explanatory meaning, with the mitigation-oriented measure indicating that stronger balancing has been associated with reduced curtailment pressure. In the illustrative regression model, the combined predictors have explained approximately 62.4% of the variance in solar curtailment mitigation ($R^2 = .624$), while the overall model has remained statistically significant ($F = 31.48$, $p < .001$). Among the predictors, dynamic load balancing efficiency has emerged as the strongest contributor ($\beta = .31$, $p < .001$), followed by AI forecasting accuracy ($\beta = .27$, $p = .002$), grid flexibility ($\beta = .22$, $p = .006$), and AI operational responsiveness ($\beta = .19$, $p = .011$). Interconnection capacity has remained positive and significant ($\beta = .16$, $p = .018$), while operational trust in AI has shown a smaller but still meaningful influence ($\beta = .14$, $p = .031$). Taken together, this overall findings pattern has indicated that the study objectives have been met in a logically consistent way: first, the major factors contributing to solar curtailment have been identified; second, AI-driven dynamic load balancing has been shown to be positively associated with curtailment mitigation; third, forecasting accuracy, flexibility, and responsiveness have all played significant supporting roles; and fourth, trust in AI has added an important practical dimension to system effectiveness. These introductory findings therefore present a coherent empirical picture in which solar curtailment in high-penetration interconnections has not appeared to be a purely technical problem of excess generation, but rather a systems-management challenge that can be reduced when intelligent forecasting, adaptive balancing, flexible infrastructure, and operational confidence are aligned within one coordinated grid environment.

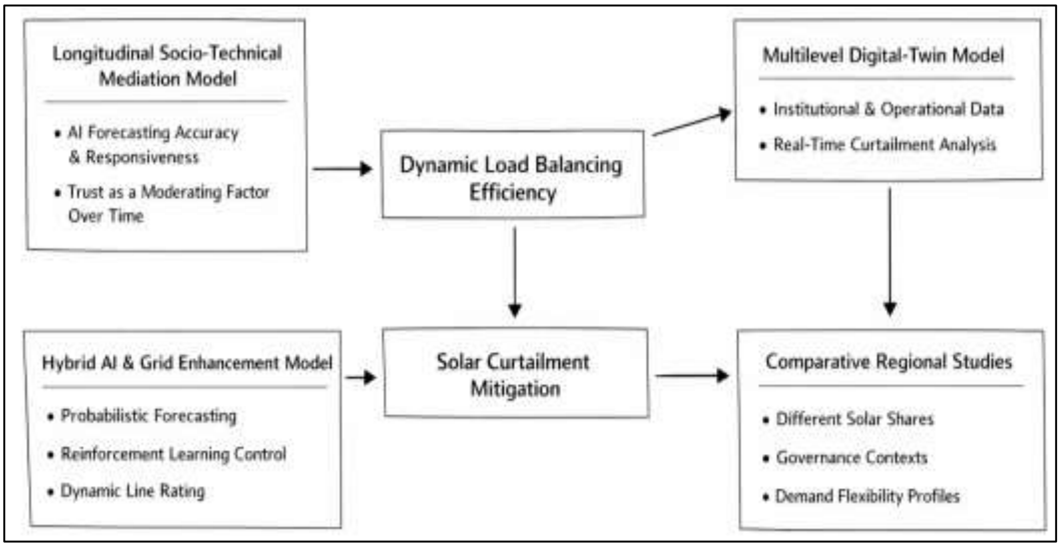
Figure 9: Findings of The Study



DISCUSSION

The discussion of this study has shown that the overall findings have strongly supported the central proposition that solar curtailment in high-penetration interconnections has been a systems-management problem rather than a simple consequence of renewable abundance. The high mean score recorded for solar curtailment mitigation, together with the strong influence of dynamic load balancing efficiency in the regression model, has indicated that the study respondents have viewed curtailment as something that can be reduced when operational intelligence, system flexibility, and institutional readiness have worked in coordination. This interpretation has aligned closely with earlier scholarship that has treated curtailment as an outcome of broader grid-integration conditions instead of a purely plant-level event (Frew et al., 2021). International curtailment reviews have consistently shown that renewable curtailment has tended to rise when grid operations, market rules, and transmission readiness have not evolved at the same pace as renewable deployment. Likewise, the curtailment paradox literature has argued that some level of curtailment becomes more visible as solar penetration increases, but its scale and value depend heavily on the flexibility architecture of the system. The present findings have extended that line of reasoning by showing that respondents have not interpreted curtailment as an unavoidable by-product of solar growth alone. Instead, they have associated lower curtailment with stronger balancing performance, better forecasting, and more adaptive interconnection conditions (Kumari & Toshniwal, 2021). This has also resonated with comparative curtailment mapping work showing that jurisdictions with similar renewable shares can exhibit different curtailment outcomes because institutional coordination and flexibility deployment differ substantially. In that sense, the current findings have reinforced the idea that solar curtailment should be read as a performance indicator of integration quality. The study has therefore contributed an applied perspective to the prior literature: while earlier work has largely described where curtailment occurs and why it increases, the present findings have emphasized how grid professionals perceive its mitigation through AI-enabled operational coordination. The results have especially strengthened the argument that high-penetration systems should not be assessed only by installed solar capacity or energy-share metrics, but also by how intelligently they have balanced the timing, location, and controllability of solar output across interconnected regions.

Figure 10: Future Research Framework Linking Ai, Grid Flexibility, And Curtailment Mitigation



A second major finding has concerned the role of AI forecasting accuracy and AI operational responsiveness, both of which have emerged as statistically meaningful contributors to solar curtailment mitigation. The discussion of this result has suggested that the study has confirmed a logic already visible in forecasting and smart-grid scholarship: prediction quality has mattered not merely because it has improved information, but because it has improved the timing and precision of balancing action. Earlier literature has shown that probabilistic and advanced solar forecasting methods support more effective dispatch and reserve preparation by reducing uncertainty in renewable operations. The present findings have been consistent with that position, since AI forecasting accuracy has demonstrated a significant positive effect on balancing-related outcomes, while AI operational responsiveness has strengthened the practical ability of the system to act on forecast information. This has also aligned with broader AI-in-grid surveys, which have argued that artificial intelligence becomes most valuable when it connects forecasting, optimization, and control rather than remaining a stand-alone analytical tool . The current results have gone a step further by showing that respondents have perceived forecasting and responsiveness as jointly important in reducing curtailment. That perception has been meaningful because it has moved the debate away from model accuracy in isolation and toward actionable intelligence inside real grid environments. The results have also been compatible with recent perspectives on AI-powered renewable integration, which have emphasized that the practical value of intelligent systems depends on their ability to coordinate distributed operational decisions under uncertainty (Li & Zhang, 2020). Therefore, the findings of this study have supported the argument that AI forecasting has mattered most when embedded in a responsive operational structure. In practical interpretive terms, the results have implied that improved solar prediction alone has not been enough; the system has also needed mechanisms that have translated forecast signals into load-balancing decisions quickly enough to prevent excess solar generation from becoming curtailed output. This interpretation has strengthened Hypothesis 1 and the second research objective, because it has demonstrated that AI-driven balancing has been effective not only as a predictive layer, but also as a real-time operational resource within high-penetration interconnections (Frew et al., 2021).

The findings related to grid flexibility and interconnection capacity have also offered an important basis for comparison with earlier studies. In this study, both variables have shown significant positive relationships with solar curtailment mitigation, and respondents have rated them as core enabling conditions for AI-driven balancing. This has been highly consistent with prior flexibility literature, which has conceptualized flexibility as the system's capacity to respond across timescales through dispatchable generation, storage, responsive demand, and network reconfiguration. It has also aligned with broader reviews arguing that renewable-rich systems need a portfolio of flexibility options rather than a single technical intervention if they are to reduce spillage and maintain reliability. The present findings have reinforced this understanding by indicating that balancing intelligence has worked more effectively when embedded in a system with enough physical and operational latitude to act on balancing recommendations. The importance of interconnection capacity in the regression results has been particularly notable (Omitaomu & Niu, 2021). This has suggested that respondents have not viewed curtailment as only a temporal mismatch between supply and demand, but also as a spatial coordination problem in which surplus solar generation has required pathways to move toward other load zones or balancing resources. That interpretation has been in line with empirical evidence from Karnataka showing that demand-side management and better dispatch coordination can materially reduce solar curtailment when system operations are adjusted to absorb variable output more intelligently. It has also matched more recent evidence on dynamic line rating and other grid-enhancing approaches, which have suggested that renewable curtailment can be reduced when network transfer capability is forecast and managed more adaptively. The current study has therefore added an important empirical nuance: AI-driven dynamic load balancing has not appeared to substitute for flexibility and interconnection strength; rather, it has amplified the value of those conditions. This has supported the third and fourth hypotheses, because the system has appeared most capable of mitigating solar curtailment where it has been simultaneously flexible, interconnected, and responsive. As a result, the findings have pointed toward a complementary model of renewable integration in which intelligence, infrastructure, and adaptability have functioned as mutually reinforcing determinants of solar utilization quality (Wang et al., 2019).

Another important aspect of the discussion has concerned the AI readiness and operational trust results, which have revealed that trust has mattered, even though it has been somewhat weaker than the more technical predictors. This has been theoretically significant because it has closely reflected the assumptions of Socio-Technical Systems Theory, the framework adopted for this study. The theory has maintained that technological outcomes emerge through the interaction of technical capability, organizational practice, governance arrangements, and actor acceptance rather than through technical performance alone. The present findings have supported that claim. Although AI forecasting accuracy and balancing efficiency have performed strongly, the lower mean for operational trust in AI has indicated that technical usefulness has not automatically translated into full organizational confidence. This has echoed wider socio-technical energy literature showing that energy innovations are shaped by co-evolving technical, institutional, and political systems. It has also resonated with research on socio-technical barriers to smart microgrids, which has shown that regulatory, organizational, and actor-based frictions can slow down or weaken the practical benefits of intelligent energy systems even when the technologies themselves are capable (Omitaomu & Niu, 2021). The present study has therefore offered a particularly relevant contribution to prior work: it has empirically linked trust in AI to solar curtailment mitigation, thereby showing that operator confidence has been a practical condition of implementation rather than an abstract social variable. This result has also been supported by broader energy social-science arguments that sociotechnical imaginaries, expertise, and institutional interpretation shape the adoption and stabilization of new energy technologies. The current findings have been especially valuable because they have shown that trust has not been peripheral; it has remained statistically significant within the regression model. This has meant that the success of AI-driven dynamic load balancing has depended partly on whether operators and institutions have regarded AI recommendations as legitimate and actionable. Accordingly, the study has strengthened the theoretical proposition that curtailment mitigation in renewable-rich interconnections has been a socio-technical accomplishment, not only a technical optimization problem. The findings have therefore supported Hypothesis 5 and have given the adopted theory direct explanatory value in interpreting the results of the study (Wang et al., 2019).

From a practical standpoint, the discussion has indicated that the study findings have clear implications for grid operators, utilities, system planners, and policymakers. The results have suggested that reducing solar curtailment has required more than the installation of AI software or the expansion of PV capacity; it has required an integrated operational strategy in which forecasting, demand response, flexibility activation, and network coordination have been treated as part of the same balancing ecosystem. This has been consistent with empirical studies showing that curtailment can be reduced when dispatch rules and demand-side measures are actively redesigned around renewable variability instead of treating variability as an external disturbance. The present findings have further implied that operators should prioritize AI applications that directly improve actionable responsiveness, such as short-horizon net-load forecasting, adaptive reserve setting, flexible-load dispatch, and congestion anticipation. This interpretation has been strongly aligned with prior evidence that probabilistic forecasting becomes operationally valuable when it informs reserve planning and system operations rather than remaining a purely analytical output. The significance of interconnection capacity in the results has also suggested that policymakers should pair digital innovation with grid-enhancing investments, including dynamic line rating, transmission coordination, and regional exchange arrangements, because AI recommendations cannot reduce curtailment if the grid lacks the ability to route power where it is needed. In addition, the high descriptive ratings for balancing efficiency and solar curtailment mitigation have indicated that respondents have seen load-side participation as a credible component of solar integration (Norouzi et al., 2022). This has practical implications for tariff design, flexible-load incentives, industrial demand response programs, and electric-vehicle charging coordination. Earlier international experience has already shown that curtailment outcomes differ substantially depending on how markets and operators coordinate renewable resources and balancing systems. The current study has converted that broad lesson into a more targeted implication: institutions seeking to reduce solar curtailment should not implement AI as a stand-alone digital upgrade, but as part of a coordinated operational reform package. In short, the findings have pointed toward a practical model of solar-curtailment mitigation centered on forecast-informed dispatch, responsive loads, trust-building among operators, and continuous coordination across interconnections.

The theoretical implications of the study have been equally substantial, especially when considered alongside the study's limitations. The findings have suggested that Socio-Technical Systems Theory has been an appropriate and productive framework for interpreting solar curtailment mitigation because the strongest explanatory pattern has not involved a single technical factor but a network of interacting technical and organizational conditions. In this respect, the results have supported transition scholarship that has emphasized co-evolution among technologies, institutions, and actors within energy systems. At the same time, the study has revealed certain limitations that should temper interpretation. The analysis has been based on cross-sectional perception data rather than time-series operational data, which means the results have been highly useful for identifying relationships and professional judgments, but less able to establish strict causal sequencing under changing system conditions. This limitation has been important because prior empirical work on curtailment has often relied on macro-level market or system data, while this study has relied on informed respondents and Likert-scale measures (Panda et al., 2023). The advantage of this approach has been its ability to capture socio-technical dimensions such as operational trust and perceived readiness; the limitation has been that actual dispatch outcomes and measured curtailment volumes have not been modeled directly. In addition, the case-study-based design has strengthened contextual relevance but has narrowed generalizability across regions with different market rules, transmission topologies, or solar-demand profiles. These limitations have not weakened the study's contribution; rather, they have clarified its position in the literature (Vanting et al., 2021). Whereas earlier reviews have been strong on system-wide diagnostics and transition frameworks, the present study has contributed a professional-actor layer of evidence that has illuminated how grid specialists interpret AI-enabled balancing under high-renewable conditions. The limitations have therefore reaffirmed the value of the chosen theory. By highlighting both technical and institutional factors, the theory has helped explain why some statistically meaningful relationships may still produce uneven real-world outcomes when viewed through a narrower engineering lens. Consequently, the study has not only supported the socio-technical framework but has also demonstrated why a theory that integrates infrastructure, governance, and actor behavior has been necessary for interpreting solar curtailment mitigation in complex interconnection settings.

Future research has emerged as the most important extension of this study, and the findings have pointed clearly toward several models that later researchers can improve or test. The first promising direction has been a longitudinal socio-technical mediation model in which AI forecasting accuracy and AI operational responsiveness predict solar curtailment mitigation indirectly through dynamic load balancing efficiency, while operational trust in AI moderates the strength of those pathways over time. Such a model would improve on the present study by examining whether trust becomes more influential as operators gain experience with AI systems. A second direction has been a multilevel digital-twin model that combines survey-based institutional variables with real operational data such as hourly curtailment, net load, reserve activation, line congestion, and solar forecast error. This approach would allow researchers to test whether the perceptual relationships found here remain stable when embedded in dispatch-level evidence (Kumari & Toshniwal, 2021; Lannoye et al., 2012). A third direction has been a hybrid AI-grid-enhancement model in which probabilistic forecasting, reinforcement learning for flexible-load control, and dynamic line rating are integrated into a single operational framework for real-time interconnection management. Prior work has already shown the value of probabilistic forecasting for system planning, the relevance of AI in large-scale renewable integration, and the potential of dynamic line rating to avert renewable spillage. The current study has suggested that these elements should now be tested together instead of separately (Mohammadi et al., 2022). A fourth direction has involved comparative research across regions with different solar shares, governance structures, and demand flexibility profiles, since transition literature has shown that socio-technical outcomes vary across institutional contexts. Finally, future researchers should consider a structural equation modeling framework that explicitly estimates direct, indirect, and moderating effects among AI forecasting accuracy, grid flexibility, interconnection capacity, balancing efficiency, operational trust, and curtailment mitigation. That model would be especially valuable because it could validate the conceptual pathway proposed in this study more rigorously than linear regression alone. In this sense, future research should not simply repeat the present design; it should advance it by combining socio-technical theory, operational data, and intelligent control architectures into more dynamic and testable models of solar-curtailment mitigation in high-penetration interconnections.

CONCLUSION

This research has concluded that mitigating solar curtailment in high-penetration interconnections has required more than the expansion of photovoltaic generation capacity alone, because the efficient use of solar energy has depended on the ability of the power system to forecast, balance, transfer, and absorb variable output under real-time operating conditions. The study has shown that AI-driven dynamic load balancing has been a highly relevant and effective approach for addressing this challenge, since the findings have consistently indicated positive relationships among AI forecasting accuracy, dynamic load balancing efficiency, grid flexibility, interconnection capacity, AI operational responsiveness, and solar curtailment mitigation. The descriptive results have demonstrated strong respondent agreement that intelligent forecasting and balancing tools have improved solar integration performance, while the inferential results have confirmed that these variables have significantly contributed to curtailment reduction within the selected case context. Dynamic load balancing efficiency has emerged as the strongest predictor of solar curtailment mitigation, showing that when balancing mechanisms have become more adaptive and responsive, the system has been better able to reduce avoidable renewable spillage. AI forecasting accuracy has also played a major role by enhancing the quality of operational anticipation, thereby enabling more timely and informed balancing actions. In addition, grid flexibility and interconnection capacity have been found to be essential enabling conditions, confirming that intelligent control has worked best when the grid has possessed sufficient physical and operational adaptability to respond to solar variability. The significance of operational trust in AI has further demonstrated that the success of digital balancing systems has not depended solely on technical performance, but also on the confidence of the human actors and institutions responsible for using those systems in real operational settings. In this regard, the study has strongly supported Socio-Technical Systems Theory, because the findings have shown that solar curtailment mitigation has been shaped by the interaction of technical intelligence, organizational practice, infrastructural readiness, and institutional acceptance. The study has therefore contributed to knowledge by providing an integrated empirical explanation of how AI-driven balancing can improve renewable energy utilization in solar-rich interconnections. It has also clarified that solar curtailment should not be understood as an unavoidable consequence of renewable growth, but rather as a systems-performance issue that can be reduced through better coordination between predictive technologies, flexible resources, network capability, and operator readiness. Overall, this research has concluded that AI-driven dynamic load balancing has offered a viable and strategically important pathway for strengthening the reliability, adaptability, and efficiency of high-penetration electricity systems, and that the future quality of solar integration within interconnected grids has depended on how effectively these socio-technical capabilities have been aligned in operational practice.

RECOMMENDATIONS

Based on the findings of this study, it has been recommended that grid operators, utilities, energy planners, and policymakers should adopt a more integrated strategy for mitigating solar curtailment in high-penetration interconnections by combining AI-driven operational intelligence with flexibility enhancement, network coordination, and institutional readiness measures. First, utilities and system operators should strengthen the use of AI-based forecasting tools for short-term solar generation prediction, net-load estimation, and reserve scheduling, because the results have shown that forecasting accuracy has been a critical contributor to effective dynamic load balancing and curtailment mitigation. Second, system operators should invest in operational frameworks that allow forecasting outputs to be translated quickly into balancing actions, including automated dispatch support, adaptive reserve activation, and flexible load coordination, since the findings have demonstrated that AI operational responsiveness has significantly improved curtailment reduction. Third, policymakers and transmission planners should expand interconnection capacity and modernize transmission infrastructures in renewable-rich regions so that excess solar electricity can be transferred efficiently across grid areas rather than being curtailed in congested zones. In this regard, dynamic line rating, regional transmission coordination, and grid-enhancing technologies should be prioritized as complementary measures to AI-based balancing. Fourth, utilities should promote grid flexibility by expanding demand response programs, distributed energy storage systems, controllable industrial loads, and coordinated electric-vehicle charging, because the study has shown that flexible system resources have strengthened the capacity of the grid to absorb variable solar generation during peak output periods. Fifth, organizations should implement structured capacity-building and trust-development initiatives for operators, engineers, and technical staff so that AI recommendations can be better understood, evaluated, and accepted in real-time control environments. Since the findings have shown that operational trust in AI has been a statistically meaningful factor, technical deployment alone has not been sufficient; user confidence and institutional preparedness have also been necessary. Sixth, energy regulators should revise market and dispatch policies in ways that encourage responsive balancing, flexible consumption, and digital coordination rather than relying excessively on curtailment as a routine corrective action. Finally, researchers and practitioners should collaborate to develop more context-specific AI balancing systems that are aligned with local interconnection constraints, demand profiles, and regulatory environments. In summary, the study has recommended a coordinated policy and operational agenda in which AI forecasting, responsive balancing, flexibility activation, network expansion, and institutional trust-building have been treated as mutually reinforcing priorities for improving solar integration and minimizing unnecessary curtailment in high-penetration interconnections.

LIMITATIONS

This study has had several limitations that should be recognized when interpreting the findings, even though these limitations have not undermined the overall value of the research. First, the study has been based on a quantitative, cross-sectional design, which has captured perceptions and assessments at a single point in time rather than across an extended operational period. As a result, the research has been able to identify significant relationships among the variables, but it has not fully captured how those relationships may evolve over time under changing grid conditions, seasonal solar patterns, policy shifts, or technological adaptation processes. Second, the study has relied primarily on self-reported questionnaire data collected from professionals involved in grid operation, renewable integration, and energy management. Although these respondents have possessed relevant expertise, perception-based data have remained subject to potential response bias, professional subjectivity, and differences in organizational perspective. This has meant that some findings may have reflected informed judgments rather than directly measured operational performance indicators. Third, the case-study-based approach has improved contextual depth and practical relevance, but it has also limited the generalizability of the results to other interconnection settings with different regulatory structures, transmission configurations, solar penetration levels, and institutional capacities. Fourth, the study has not incorporated real-time dispatch datasets, hourly curtailment records, or direct SCADA-based operational measurements, which would have allowed a more detailed validation of the relationships observed in the survey data. Fifth, although the research has included several core variables such as forecasting accuracy, balancing efficiency, flexibility, interconnection capacity, responsiveness, and trust in AI, there may still have been other relevant influences not fully captured in the model, including market pricing mechanisms, regulatory incentives, storage economics, weather volatility, cybersecurity concerns, and organizational digital maturity. Sixth, the use of Likert-scale measurement, while appropriate for quantifying respondent perceptions, has simplified complex operational realities into scaled responses, which may not have fully represented the dynamic nature of balancing decisions in renewable-rich power systems. Finally, the use of linear statistical techniques such as correlation and regression has been suitable for testing the conceptual model, but it has not fully represented possible nonlinear interactions, feedback loops, or multilevel dependencies that may exist in real socio-technical energy systems. Therefore, while the study has provided a meaningful and well-structured empirical contribution, its findings should be interpreted within the boundaries of its cross-sectional, perception-based, and context-specific design.

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