VILNIUS UNIVERSITY
BUSINESS SCHOOL

MASTER'S IN INTERNATIONAL PROJECT MANAGEMENT

Huzaifa Qamash

THE FINAL MASTER'S THESIS (PROJECT)

DIRBTINIO INTELEKTO VAIDMUO VALDANT DIDELIO MASTO TVARIUS ENERGETIKOS PROJEKTUS	***THE ROLE OF AI IN MANAGING LARGE-SCALE SUSTAINABLE ENERGY PROJECTS***

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(signature (-s))

Supervisor ____________
(signature)

Doc. Dr. Eglė Radvilė

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SUMMARY

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THE ROLE OF AI IN MANAGING LARGE-SCALE SUSTAINABLE ENERGY PROJECTS

Supervisor – Doc. Dr. Eglė Radvilė

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Scope of Master's thesis (project) – 57 pages.

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The FMTP described in brief:

This thesis gives a detailed study of the impact of Artificial Intelligence (AI) on the large scale sustainable energy project management. The research uses a qualitative multiple case-study method to get insights into the different energy combinations like offshore wind, solar-plus-storage, hybrid renewable systems and smart grids. AI is explored as a tool in minimum and maximum forecasting, maintenance, energy dispatch, and grid reliability, and at the same time, the human, organisational, and regulatory issues that impact its acceptance are scrutinised. The results reveal that AI can enhance the operational performance but moreover its power relies on project context, data readiness, user trust, and institutional conditions.

Problem, objective and tasks of the FMTP:

Even though the energy sector is turning more to Artificial Intelligence (AI), still very few studies are open on how AI is influencing the management of huge sustainable energy projects in various contexts, especially those involving human, organizational, and regulatory factors. This lack of research makes it difficult to evaluate the role of AI in the integration of complex energy projects.

The core aim of this FMTP is to get insights into AI's role in the different stages of large-scale sustainable energy projects, i.e., planning, execution, and monitoring.

The study has mapped out some specific goals to reach its main goal, which are to point out the major AI applications that are being used in sustainable energy projects, evaluate the effect of the applications on the operational performance, and analyze what motivates or hinders AI adoption in different project types.

Research methods used in the FMTP:

The research employs qualitative research design grounded in the multiple case-study method. Data were collected from the key participants involved in large sustainable energy projects through semistructured interviewing, and document analysis then supplemented these. Thematic analysis was applied to the data obtained to show AI's role in project management and to compare and contrast the cases with respect to this role.

Research and results obtained:

The results indicate that AI contributes to the large-scale sustainable energy projects' management by improved forecasting, predictive maintenance, energy dispatch, and reliability. In all the cases, the use of AI resulted in improved operational performance, but the magnitude and type of benefits differed between project categories. Moreover, the findings indicate that interpersonal aspects such as trust, explainability, and training together with data quality, system integration, and regulatory conditions are among the most important factors that determine the success of AI deployment.

Conclusions of the FMTP:

The investigation arrived at the decision that AI quite possibly turns out to be a great ally in the management of renewable energy projects on a large scale. On the other hand, the effectiveness of the new technology would be determined by the particular situation of the project, the quality of data, the readiness of people, and the state of regulations. AI offers a boost to operational performance in all the ways through which energy is generated, however, its adoption will be success only if there are human-centric system design, proper infrastructure, and the right policies. The findings in this study clearly show that in order to attain the sustainability of project outcomes it is necessary to make AI solutions fit both the technical as well as the organizational requirements.

Information about the publication of FMTP results or adaptation for publication

The Thesis outcomes have not been released so far. But, these results can easily be converted into a journal article or a conference paper that targets the application of AI in the management of sustainable energy projects. Additionally, some results might be shared with professionals or policymakers by means of publications suitable for the latter, thus keeping practitioners and stakeholders from the energy sector in the loop.

SANTRAUKA

VILNIAUS UNIVERSITETO VERSLO MOKYKLA

TARPTAUTINIO PROJEKTŲ VALDYMO MAGISTRO STUDIJOS

HUZAIFA QAMASH

DIRBTINIO INTELEKTO VAIDMUO VALDANT DIDELIO MASTO TVARIUS ENERGETIKOS PROJEKTUS

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FMTP trumpas aprašymas:

Šiame baigiamajame magistro darbe išsamiai nagrinėjamas dirbtinio intelekto (DI) poveikis didelio masto tvarių energetikos projektų valdymui. Tyrime taikomas kokybinis daugiavejų atvejų tyrimo metodas, leidžiantis įvertinti skirtingas energetikos sistemas, tokias kaip jūrinė vėjo energetika, saulės energijos projektai su energijos kaupimu, hibridinės atsinaujinančios energetikos sistemos ir išmanieji elektros tinklai. Dirbtinis intelektas analizuojamas kaip priemonė prognozavimui, techninei priežiūrai, energijos paskirstymui ir tinklo patikimumui didinti, kartu vertinant žmogiškuosius, organizacinius ir reguliacinius veiksnius, darančius įtaką jo taikymui. Tyrimo rezultatai rodo, kad DI gali pagerinti veiklos efektyvumą, tačiau jo veiksmingumas priklauso nuo projekto konteksto, duomenų parengties, vartotojų pasitikėjimo ir institucinių sąlygų.

FMTP problema, tikslas ir uždaviniai:

Nepaisant to, kad energetikos sektorius vis plačiau taiko dirbtinį intelektą, vis dar trūksta tyrimų, nagrinėjančių, kaip DI daro įtaką didelio masto tvarių energetikos projektų valdymui skirtinguose kontekstuose, ypač atsižvelgiant į žmogiškuosius, organizacinius ir reguliacinius veiksnius. Ši tyrimų spraga apsunkina DI vaidmens vertinimą integruojant sudėtingus energetikos projektus.

Pagrindinis šio FMTP tikslas – gauti įžvalgų apie dirbtinio intelekto vaidmenį skirtinguose didelio masto tvarių energetikos projektų etapuose: planavimo, įgyvendinimo ir stebėsenos.

Siekiant šio tikslo, tyrime keliami šie uždaviniai: nustatyti pagrindines dirbtinio intelekto taikymo sritis tvariuose energetikos projektuose, įvertinti šių sprendimų poveikį veiklos rezultatams ir išanalizuoti veiksnius, skatinančius arba ribojančius DI diegimą skirtingų tipų projektuose.

FMTP taikyti tyrimo metodai:

Tyrime taikomas kokybinis tyrimo dizainas, paremtas daugiavejų atvejų tyrimo metodu. Duomenys buvo renkami atliekant pusiau struktūruotus interviu su pagrindiniais didelio masto tvarių energetikos projektų dalyviais, taip pat atliekant dokumentų analizę. Gauti duomenys buvo analizuojami taikant teminę analizę, siekiant atskleisti dirbtinio intelekto vaidmenį projektų valdyme ir nustatyti panašumus bei skirtumus tarp nagrinėtų atvejų.

Gauti tyrimo rezultatai:

Tyrimo rezultatai parodė, kad dirbtinis intelektas atlieka svarbų vaidmenį valdant didelio masto tvarius energetikos projektus, nes gerina prognozavimo tikslumą, leidžia taikyti prognozuojamąją techninę priežiūrą, optimizuoja energijos paskirstymą ir didina sistemos patikimumą. Visuose nagrinėtuose atvejuose DI taikymas lėmė geresnius veiklos rezultatus, tačiau naudos pobūdis ir mastas skyrėsi priklausomai nuo projekto kategorijos. Be to, nustatyta, kad tokie veiksniai kaip pasitikėjimas, sprendimų paaiškinamumas, darbuotojų mokymai, duomenų kokybė, sistemų integracija ir reguliacinės sąlygos yra vieni svarbiausių sėkmingo DI diegimo veiksnių.

FMTP išvados:

Tyrimo metu prieita prie išvados, kad dirbtinis intelektas gali tapti reikšmingu pagalbininku valdant didelio masto atsinaujinančios energetikos projektus. Tačiau naujų technologijų veiksmingumą lemia konkretus projekto kontekstas, duomenų kokybė, žmonių pasirengimas ir reguliacinė aplinka. Nors DI gerina veiklos rezultatus įvairiuose energijos gamybos būduose, jo diegimas bus sėkmingas tik tuo atveju, jei bus taikomas į žmogų orientuotas sistemų dizainas, užtikrinta tinkama infrastruktūra ir sukurta palanki politikos sistema. Tyrimo rezultatai aiškiai rodo, kad siekiant tvarių projektų rezultatų būtina suderinti DI sprendimus tiek su techniniais, tiek su organizaciniais reikalavimais.

Informacija apie FMTP rezultatų publikavimą ar pritaikymą publikavimui:

Šio baigiamojo magistro darbo rezultatai iki šiol nėra publikuoti. Tačiau tyrimo išvados gali būti lengvai pritaikytos rengiant mokslinį straipsnį ar konferencijos pranešimą, skirtą dirbtinio intelekto taikymui tvarių energetikos projektų valdyme. Be to, dalis rezultatų gali būti pristatyti specialistams ar politikos formuotojams per jiems skirtas publikacijas, taip užtikrinant energetikos sektoriaus praktikų ir suinteresuotųjų šalių informuotumą.

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND RATIONALE

The need to move rapidly towards sustainable energy systems has never been more pressing. Sustainable Development Goal (SDG) 7 of the United Nations compels all nations to provide access for all to affordable, reliable, sustainable and modern energy; whereas the Paris Agreement requires all signatory countries to keep global temperature increase well below 2°C above pre-industrial levels and pursue restriction from even 1.5°C warming. Meeting these goals demands the swift transition from fossil fuels to clean energy. The scale of the deployment is also eye-opening: according to the International Energy Agency (IEA), new global renewable capacity additions must treble by 2030 in order to remain on track with a net-zero pathway. This positions wind power plants, both on land and at sea, the biggest solar farms or solar plus wind plus storage plants with smart grids as the core of carbon-free energy (Wang & Witlox, 2025).

Nonetheless, the aforementioned undertakings bring about operational and structural difficulties. First of all, the greater part of renewable energy sources is just intermittent, and that is a normal thing as they are dependent on changing weather conditions and time cycles. The issue of intermittency makes it hard to predict, integrate into the grid, and plan dispatch. Second, in the case of large infrastructures, there are operational inefficiencies caused by challenges related to legacy technology, scheduling, and balancing distributed resources. Third, maintenance costs are still very high, especially in the case of offshore wind farms and remote solar parks where malfunctions can lead to long downtimes and costly repairs. Lastly, issues with regulations and interoperability are often the main obstacles to the integration of new technologies in the current project workflows (Assad et al., 2022).

AI is seen as an equalizer in that situation. The term "AI" covers the use of computers to analyze data, learn from the environment, and make decisions automatically. The use of AI in large energy projects based on renewables is classified into four major types:

1.1.1 Forecasting and Planning

The use of machine learning techniques and hybrid physics–ML models greatly enhances the predictive capability of solar irradiance, wind speeds, and load demand. The operators are enabled to make the proper adjustments to reserves, investments, and the overall decision-making process on the grid as the tools bring the uncertainty in energy generation down to a manageable level through the filtering of the key indicators. According to (Okafor et al., 2025), in the case of high-renewable grids, AI-powered solar forecasting can be cited as a strategy to guarantee dispatch reliability.

1.1.2 Operational Optimization

In the literature review, (Alam et al., 2025) demonstrate that the use of AI-enabled technologies allows for quicker and easier adjustments to the generation and distribution of renewable energy. Moreover, it makes optimization of production targets through AI-fueled Energy Management Systems and Model Predictive Control frameworks that allow for the scheduling of generation, storage, and demand response to have a lower operating cost, to have less curtailment and system instability.

1.1.3 Condition Monitoring and Predictive Maintenance (PdM)

AI-empowered PdM shifts the maintenance paradigm from reactiveness to proactiveness. By using SCADA data and multivariate models, the CMS that is capable of providing precursors to failure allows the operations to get rid of the issue weeks prior to the turbine being no longer operable (Peyravi et al., 2022; Shah et al., 2024). The action minimizes unplanned outage, increases durability, and lowers total costs of the equipment.

1.1.4 Digital Twin (DT) Integration

The Digital Twin is a simulation of the physical system that receives data from sensors live. The use of AI in DTs facilitates diagnostics, maintenance, and test incidents in the entire acro-unique range. The utility of the DT was measured by (Abdessadak et al., 2025) who demonstrated that it decreased service time by 35% and increased production by 8.5% while the efficiency of asset troubleshooting reached over 98%. Numerous articles prove the transformational capacity of AI in energy.

A systematic review by (Algburi et al., 2025) quantified the potential of AI to accelerate the transition to renewables through better-cost operations. Nonetheless, the same study highlighted a sub-optimal integration and commercial use due to the lack of standardization in cybersecurity, interoperability, and other domains. (Wang & Witlox, 2025) suggest prescriptive assessments for the development of AI in energy, including improved market design, data sharing, and governance, whereas (Syed Muhammad Habib Ur Rehman, 2025) framed technological futures for the application of AI in smart grids.

However, even with these advancements, research fragmentation remains. A large number of studies concentrate on technique enhancement within a part (forecasting, optimization or predictive maintenance) but without considering the entire project life cycle (planning, execution and monitoring). Others describe obstacles to adoption – like mistrust, capacity or policy support – without building a bridge back to performance. Such fragmentation of perspectives leads to a solid view on the role AI may play in the governance of large-scale sustainable energy infrastructures.

Hence, this thesis proposes that dealing with the identified research gap needs an integrative model built by complementary technical enablers (forecasting accuracy, optimisation effectiveness, predictive maintenance maturity, digital twin integration) and socio-technical adoption factors (attitude, perceived effort EoU ToE, trust, compatibility level CoS, & policy support PoS). Its integrated nature offers theoretical and practical implications on leveraging AI technology for greater operational, sustainability, and resilience in large-scale projects as well as mitigating barriers towards adoption.

1.2 RESEARCH PROBLEM

The management of huge renewable projects (e.g. offshore wind farms, utility-scale solar parks, hybrid plants with storage, and grids) is difficult owing to changing pattern of supply due to nature based generation access, operational in utmost inefficiency and expensive maintenance cost (Assad et al., 2022). Artificial intelligence (AI) presents prospective solutions in the way of making forecasts more accurate, streamlining operations and predicting maintenance by evidencing decreased downtime, costs gains and energy yield (Abdessadak et al., 2025; Shah et al., 2024).

Nevertheless, extant literature is sparse and quite scattered focusing on specific technical aspects (e.g., prognosis capability or condition monitoring) at the expense of a more comprehensive lifecycle approach that embraces planning, execution, and control (Okafor et al., 2025). In addition, the gap between technical potential and market uptake is still evident due to the lack of implementing organizational readiness, skilled staff, interoperability problems and socio-technical barriers including trust, usability and policy impetus (Billanes & Enevoldsen, 2021; Fleiß et al., 2024).

In the absence of such an integrated framework incorporating both technological (forecasting, optimization and predictive maintenance; digital twinning) and adoption readiness factors, AI could be implemented in a tinkering fashion that could fall short, in terms of exploitation of its capabilities towards changing dynamics concerning project effectiveness and sustainability (Alam et al., 2025; Wang & Witlox, 2025). Therefore, the main research issue we confront is that there is limited fragmented knowledge about how AI can be appropriately exploited in large projects for sustainable energy overall, including not only the technological but also to the socio-technical adoption barriers or organizational integration.

1.3 RESEARCH AIM AND OBJECTIVES

Aim:

To evaluate the role of Artificial Intelligence in enhancing the planning, execution, and monitoring of large-scale sustainable energy projects.

Objectives:

1. To identify AI technologies currently used in energy project management.
2. To assess the effectiveness of AI in improving efficiency, forecasting, and resource use.
3. To explore barriers and enablers to AI integration in sustainable energy systems.
4. To develop a conceptual framework for AI-based project management in renewable energy.

1.4 RESEARCH QUESTIONS

Main Question:

- How can Artificial Intelligence be effectively utilized to manage large-scale sustainable energy projects to enhance operational efficiency and long-term sustainability?

Sub-questions:

1. In what project stages is AI most beneficial?
2. What are the barriers to implementing AI in real-world energy projects?

3. What types of AI technologies are most applicable (e.g., machine learning, predictive analytics)?

1.5 RESEARCH SIGNIFICANCE / JUSTIFICATION

This study is of theoretical and practical importance. In terms of academia, it seeks to bridge an evident research gap between AI technical applications (e.g., forecast, optimization, predictive maintenance and digital twin) and the social-technical factors that influence the acceptance in large-sized sustainable energy projects. Recent studies tend to have limited scope, with tailor-made applications or household level penetration being the most common in literature; however only few describe a holistic lifecycle based framework for utility-scale system. Thus, it contributes to the fields of energy systems management and technology adoption studies enhancing our understanding at the intersection of AI, project management and sustainability.

From the practical point of view, this research creates a significant impact on energy practice, industrial project management and policies. AI-enabled solutions have the potential to curtail costs and improve operational efficiencies of the grid, while simultaneously strengthening grid reliability at a time when countries are moving towards decarbonization ambitions set out in SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). The study suggests important developments in AI adoption that may apply to different companies and their infrastructural modernization, new energy integration and global CSR commitments.

1.6 SCOPE AND DELIMITATIONS

This investigation deals with the part played by artificial intelligence in the main sustainable energy projects, where big-scale installations such as solar or wind farms, options combined with storage and smart grids, are the case. Applications and examples are provided in the context of AI throughout the various planning, executing and monitoring stages focusing on forecasting, operational optimization as well as predictive maintenance and digital twin integration.

The research itself does not address small-scale domestic renewable adoption; neither it is endeavouring to create new AI algorithms frothing from the cup. Rather, the interest lies in considering how AI functionality can be incorporated and exploited in industrial contexts of larger projects. Geographically, the research project is based on global literature and case insights but it is also focused on principles and frameworks that can be utilized in a wide sense, not simply of a country specific nature.

1.7 THEORETICAL FOUNDATION

This research is guided by two simultaneously complementary theories:

1.7.1 Socio-Technical Systems (STS) Theory

This theory posits that technology outcomes hinge on the interplay between technical systems, people and organizational mechanisms. If applied here, STS tells us why high-performing AI technologies will underperform if not embedded with people, governance and practices.

1.7.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) highlights that the factors of perceived usefulness and ease of use not only contribute to adoption but also trust, compatibility and social influence. TAM gives an idea of how the operators, managers, and organizations act and think in terms of the good or bad side of AI adoption.

Stylistically, the STS and TAM models are in-tune to one another and hence make it possible to view the phenomenon of AI in a more thorough manner with both the technical prospects and the humanities and organizations issues paving the way for its use.

1.8 METHODOLOGICAL OVERVIEW

In order to provide answers to the research questions, the method of qualitative case study has been selected for this investigation. Apart from the method of inquiry, case studies are often applied if the main research question deals with complex and location-specific phenomena (e.g., the application of AI in energy systems). The primary method of data gathering will be through semi-structured interviews with project managers, engineers, and AI specialists who are directly involved in significant energy projects. Other methods will include the examination of final project reports, documents, and industry studies as supplementary sources of data. Thematic analysis of data is to be backed by using a program like NVivo for coding, pattern and theme identification. The research methodology thus adopted, gives no other choice than to conduct a very thorough, contextualized examination of the technological applications and the barriers to adoption.

1.9 ORGANIZATION OF THE THESIS

The thesis is organized into the following chapters:

Chapter 1 – Introduction

The introductory chapter discusses the backdrop, rationale, problem of research, aims, questions, significance, scope, theoretical foundation, and an overview of the study.

Chapter 2 – Scientific Literature Analysis

Thoroughly seeks to evaluate and AI application in energy project management, consisting of forecasting, optimization, predictive maintenance, and adoption factors, introducing the conceptual model and hypotheses simultaneously.

Chapter 3 – Research Methodology

The research design, case study approach, data collection methods, validity and reliability considerations, and data analysis techniques are all detailed in this chapter.

Chapter 4 – Findings and Analysis

Visualizing, and interpreting, the findings of the experimental study linked back to the conceptual framework.

Chapter 5 – Conclusions and Recommendations

The present chapter deals with the theoretical and practical implications of the findings, stating the contributions, challenges, and opportunities. It provides a summary of the research, discusses the limitations, and gives suggestions for subsequent research and practice.

CHAPTER 2

SCIENTIFIC LITERATURE ANALYSIS

2.1 INTRODUCTION TO THE CHAPTER

In this chapter, the author makes a comprehensive study of the already existing scientific literature on the use of AI in large-scale energy systems and provides a critical evaluation of the technical and socio-technical contributions. It shows AI as a revolutionary actor in the sustainable project management domain and points to research gaps that make this study necessary.

2.2 LITERATURE REVIEW

2.2.1 AI in Forecasting and Planning

Broad energy policy development and decision-making sit squarely within national priority settings. Reliable predictions of solar irradiance, wind generation and load demand support the choice of sizing systems, economic justification for investments as well as correctly-sized levels of reserves and dispatch controllability. AI—specifically deep learning and hybrid models that integrate physics-based and data-driven techniques—has played a crucial role in improving forecast reliability and usefulness over the past several years.

An example is given by (Yan et al., 2025), who provide a deep learning model chain for intra-day prediction of solar irradiance. Their approach initially computes spectral-based satellite images of accurate spatial GHI using a DL method which are then input to a second DL model that generates predictions from 15–180 minutes in advance. They observe that, in most tested sites, the satellite-based estimates offer better results than the use of standard satellite products — and particularly for partially cloudy periods — with lower nRMSE and higher R^2.

Another recent addition is (Xiang et al., 2025) on solar radiation nowcasting. This study compares several satellite-based nowcasting models using deep learning architectures like U-

Net and DGMR-SO that jointly use cloud motion and satellite images to forecast solar irradiation over short time periods. The results demonstrate these models are effective for very short lead times, and especially beneficial in grid dispatch and balancing with fast evolving dynamics.

Hybrid forecasting is also advancing. The work A Meteorology-Free Wind Power Forecasting using Bi-hybrid (bi-HM) and Triple-hybrid (triple-HM) models (2025), for instance, introduces hybrid models that can limit the need for an external meteorological input. By combining machine learning with physical constraints or known features, these hybrids enhance robustness to various circumstances and can mitigate errors when meteorological prediction (such as weather model output) is unreliable.

Nowcasting over short time periods is increasingly advanced with the use of sky cameras and satellite imagery. In Accurate Nowcasting of Cloud Cover at Solar Photovoltaic Plants (Min et al., 2023), a RNN method is used in conjunction with geostationary satellite data to predict cloud fraction for PV plants for lead times up to 0–4 h. In the first 2 hours, the correlation between forecast clear-sky ratio (CSR) and real production is near to 0.8, which implies a really good reliability when planning and dispatching in short-term time step.

Also, (Ansong et al., 2025) propose ultra-short-term solar irradiance forecasting with free satellite products and illustrated that the introduction of current information from satellites leads to improvements in the forecast accuracy over 5-60 min horizon that helps accommodating the supply variability at grid or plant level.

These newer studies do have a few consistent results:

1. When tested under conditions from space, especially under fluctuating or cloudy sky scenarios, hybrid models (mixing physics-based modeling, satellite and ML) often outperform the purely statistical or physical approaches.
2. Night-ahead forecasts—and the methodology to achieve them—are not mandatory yet, but highly valuable in many cases for operational balancing, ramp management, and real-time dispatch decisions.
3. Temporal and spatial data (spectral satellite data, cloud motion, sky images...) matters a lot, the finer the model you design means it is more sensitive to rapid change (cloud cover; weather fronts).

4. Trade-offs are still left, performance degrades at heavy cloud cover, low or very high irradiance levels, and ramp-change events; also bias correction process, model robustness under various climate zones are open research issues.

2.2.2 AI in Operations and Optimization

During the operation of wind or solar-derived large-scale sustainable energy, there are challenges in real-time supply-demand – balancing them and costs minimization while sustain grid stability. AI-enabled tools, in particular Energy Management Systems (EMS) and Model Predictive Control (MPC), have gained attention for these tasks.

There are EMS systems, which optimally schedule and dispatch energy resources considering the variability of renewable generation, availability of storage, demand response and market prices. Another recent systematic review of EMS and ML/AI in smart grids concludes that the use of AI/ML techniques within an EMS improves overall efficiency and reliability, decreases costs while implementing these, and enhances congestion management during higher penetration levels of renewables (Cuesta et al., 2025). These may include features such as demand forecasting, storage usage and load shifting or demand response programs to improve resource utilization and cost.

Model predictive control (MPC) has demonstrated exceptional capability to accommodate uncertainties and time varying nature of the grid operation. MPC setups predict expectations of future states over a period of time, and optimize current actions while juggling constraints (e.g., storage capacity, ramping rates) and objectives (e.g., cost minimization, emission reduction). For instance, the authors used MPC to adaptively modify resource scheduling and storage charge/discharge schedules in anticipation of predictable changes in renewable generation and demand in smart-grid investigations. Another recent work, a distributional robust MPC for uncertain dynamics in the smart grid system (Li et al., 2021), has proposed a two-stage MPC method considering static uncertainties (that remain steady) and dynamic uncertainties (the future change information, e.g., EV's charging patterns) of the smart grid. Test case studies performed on the actual test networks exhibit enhanced voltage stability, reduced power losses, and higher robustness with respect to forecast errors.

A further area where EMS + AI + MPC come together is demand response optimization and grid interactive building control. The work by (Alam et al., 2025), Optimizing Grid-Interactive

Buildings Demand Response also leverages predictive controls methods such as model predictive control (MPC) for load scheduling in gig systems. The algorithm optimizes for load reduction and/or shifting at peak times, expecting grid price signals, building thermal mass, occupant comfort limits. Their findings illustrate savings in the energy cost, trimmed peak load and smoothed grid demand profiles.

Microgrids are also a focal point. A recent study by (Khanum et al., 2025) demonstrates the efficiency of AI-driven energy management systems when integrated with microgrids. It states that the use of AI/mixed-integer programming coupled with battery storage and renewable power generation can give operations a massive boost in terms of speed and reliability - faster load balancing, reduced energy losses, and increased reliability. However, several issues remain: scalability, deployment assurance, cyber-security, and real-time control of data latency, to mention a few.

Demand response in the smart grid is another case in point, according to (Toolib et al., 2023), AI along with MPC-based scheduling strategies for appliances and HVAC loads that are responsive to demand signals can spread the consumption over hours, cut down costs, and enhance grid stability. The analysis indicates that the coupling of Energy Management System and Model Predictive Control is more robust than acting separately under situations of renewable input and demand anomalies.

These studies reveal several overlapping issues:

1. AI for EMS/MPC solutions reduce costs of operation by lowering importation of peak power, storage optimization and load shift.
2. They increase efficiency and reliability, mainly through the active control and balancing of distributed resources.
3. MPC manages uncertainty (weather, load changes and EV charging) by looking ahead and adjusting control.
4. But there are trade-offs and constraints, too; computational burden, data prerequisites, real-time demands and integration to the grid infrastructure and legacy systems.

For the present study, these observations contribute to the position of optimization efficacy as a pivotal mediating mechanism that links AI capability to performance: i.e., projects with good EMS/MPC deployment will likely provide lower costs, higher reliability and system stability for all system types. They also highlight some factors that will influence adoption:

- Organization capabilities for implementing real time AI/MPC systems
- Data quality
- Trust on automated control
- Regulatory/policy frameworks for demand response compensation and storage

2.2.3 Condition Monitoring and Predictive Maintenance

Condition Monitoring Systems and Predictive Maintenance have evolved to be critical to reliability, cost reduction, and uptime optimization in large renewable energy projects. It facilitates detection of anomalies, forecasting component failure, and quantifying remaining useful life, all of which support operators' transition from reaction to prediction. A recent review of PHM practices in wind energy gives a general survey of the methods used for fault identification, damage prognosis, and anomaly detection in wind turbines. The study reports that techniques that fuse physics-based degradation models with data-driven machine learning do especially well under varying operating states, as the hybrid model meets the optimal robustness for early degradation detection.

Another prominent study which presents a framework that isolates "normal" turbine behavior with SCADA data and applies filters to conduct anomaly detection for energy loss quantification over time. Using Random Forest and XGBoost methods, incremental, minuscule performance degradations, such as erosion on blades' leading edge, were identified and used to assess the energy loss per annum. Thus, project managers can prioritize which components or turbines require intervention first. There is also greater advancement in diagnostic tools, described in Diagnostic Digital Twin for Anomaly Detection in Floating Offshore Wind Energy, which deployed a digital twin with unsupervised learning for a floating offshore wind turbine. The anomaly was predicted with high confidence several hours before its event, giving an early warning and diagnosis. Such twin systems improve fault detection and risk minimization by remote monitoring.

The use of predictive maintenance in wind turbines and PV plants is also compared by Machine Learning and AI for Predictive Maintenance and Grid Integration Wind Farms (Okafor et al., 2025). The research shows that ML models, such as ensemble methods, random forests, and gradient boosting; authors claim can identify incipient faults before legacy threshold or rule-based systems do so—and that predictive maintenance slashes unplanned downtime by more than half in the right circumstances despite plants needing cheap monitoring systems.

Another recent approach is the “HARO” model (Raju et al., 2025), which combines transformer networks with Lasso regression and an optimizer to enhance early fault detection. The paper presents a high performing model that not only handles interpretability (which features are important) as well as real-time capability, but also addresses two major issues in practical deployment: high accuracy and interpretability. Together, these studies reveal a number of repeating themes:

1. Hybrid & ensemble ML models (drawing on physics-based, SCADA sensor data, and unsupervised learning anomaly detection system) give better performance in early detection of performance degradation and failures.
2. Digital twins (especially diagnostic twins): Possible real-time control and early warnings, especially for offshore or hard to reach assets.
3. The trend is no longer to detect faults but rather to estimate the economic cost of failures (e.g., energy wastage, maintenance costs, and equipment downtime). This is helpful in setting maintenance priorities and in cost/benefit decision making.
4. Challenges remain: false positives (i.e., alarms not indicating actual issues), sensor malfunctions or data noise, integration of new monitoring systems with legacy turbines, computational and data transmission limitations, ensuring reliability across the variety of environmental or operational regimes.

This would help align a conceptual framework for this study where predictive maintenance maturity is supported as the mechanism through which AI capability carries performance improvement; especially when considering availability, yield, and cost. It also implies adoption factors (skills, data quality, trust, interpretability) as key moderators: even the best model will only improve outcomes if the system is trusting, maintained and integrated in operations.

2.2.4 Digital Twin Technology

The digital twin (DT) has been increasingly recognized as a fundamental technology capable of improving the monitoring, diagnostics and decision support systems for large-scale sustainable energy infrastructure. A digital twin (DT) is a computer-based, real-time, virtual representation of an asset or process updated in tandem with the physical entity to which it corresponds and supplemented by AI/ML algorithms modeling, simulations and analytics. DTs make it possible to combine historical, sensor and operational data to simulate different scenarios, predict the occurrence of a failure event, as well as make “what-if” planning. Recent research reiterates their promise as well as the practical challenges to their adoption.

A new study by (Abdessadak et al., 2025) also reveals that AI-based digital twins in the energy sector reduce downtime due to unexpected outages by more than 35% and increase production by approximately 8.5%, all while significantly enhancing fault detection accuracy. The review warns, however, that substantial infrastructure costs, data integration challenges, and security issues make formidable hurdles.

In an analogous vein, (Ba et al., 2025) consider the ways in which DTs can be used to support the complete spectrum of energy project lifecycle purposes (from design and planning through operation to decommissioning). They assert that Digital Twins are advantageous for maintenance planning and scheduling, waste of resources prevention, and lifecycle cost estimation. However, they also add that these advantages can only be attained with robust IoT foundations, real-time data feeds that are stable and model curation over time.

Another fast developing topic is the intersection between DTs and IoT in energy systems. (Kabir et al., 2024) offer an overview of DTs on the context of IoT-enabled smart energy systems demonstrating that dts improve real-time monitoring and preventative maintenance as well as assist in optimizing both electricity production and storage. Some challenges were highlighted such as data latency, devices interoperability and standardized protocols for DT deployment.

An industry-specific literature review by (Ba et al., 2025), identifies that energy savings up to 30%, optimization of operational process and more efficient maintenance are realized through DT adoption by buildings, factories and grid assets. Nonetheless, these introduce problems like the difficulty of application, a potential security risk and also the question of scalability.

Moreover, wind farms that are located off the coast are using the so-called digital twins for diagnosing purposes. For example, a group of researchers from (Haipeng et al., 2024) developed a diagnostic digital twin of a floating wind turbine in the sea; the suggested DT was capable of discovering faults with very high certainty hours prior to their occurrences through unsupervised learning thus giving sufficient time for mitigation actions to be taken. This proves that DTs are not only facilitating but also moving the frontier of predictive maintenance to the most inaccessible of assets.

Several patterns come to light through these studies:

1. Digital Twins (DTs) have a great influence on outage duration those ways they reduce it and at the same time enhance availability and energy yield. The numerical effects (30-35% decrease in downtime; 8-9% increase of availability) are indicating DTs moving from pilot to impactful deployment.
2. Better maintenance scheduling and fault diagnosis is a large benefit; DTs help operators detect failures before they happen and during repair (i.e. proactive maintenance) instead of just restoring after failure (reactive maintenance).
3. The lifecycle dimension is becoming more important: beyond operations, DTs are aiding planning, design, and cost estimating.
4. Infrastructure and data readiness (IoT sensors, good-quality data, streaming real-time) are major facilitators. Without high-quality data or fast communication, the DT loses its accuracy and promptness.
5. Barriers: cost, integration, cyber risk, standards — technical and organizational. Interoperability between systems, trust in DT outputs and regulatory approval are no mean considerations.

This indicates the DT Integration as an important enabler: when AI capability covers the DT infrastructure, model updating, data fusion and diagnostics, project performance increases towards availability, energy yield and cost. In addition, adoption moderators such as trust, data quality and cost-benefit awareness and regulatory/policy support will need to play a vital role in successful DT implementation.

2.2.5 Adoption and Socio-Technical Barriers

There is huge technical potential in AI technologies (forecasting, optimization, predictive maintenance, digital twins) to power sustainable energy projects but the actual effect highly depends on socio-technical conditions of adoption. Research continues to show that people, organizations and governance that are unprepared can lead even good AI systems to underperform or not be used effectively.

An early study from (Billanes & Enevoldsen, 2021) notes ten critical factors influencing technology adoption within the energy sector: knowledge, awareness, policy support, social influence, demographics, self-efficacy, trust and enjoyment in use of technology as well as perceived risk and compatibility. These themes correspond to the constructs in TAM—perceived usefulness, ease of use, attitude, behavioral intention—and reveal that adoption is multifaceted and situational.

Recent evidence has replicated these results and added further details. For instance, (Fleiß et al., 2024) reported in a house hold survey that attitude (positive believes about the technology) and perceived ease of use predict the actual adoption for smart energy technologies, even stronger than perceived usefulness or risk. They also show a co-adoption effect: If households already own renewable technologies (rooftop solar, electric vehicles), they are vastly more likely to adopt additional smart energy tools. This means that history and legacy impact the level of user readiness and minimize learning/transition cost.

Recent papers take these ideas further toward macroscopic energy initiatives and organizations. (Cuesta et al., 2025) investigates how AI adoption of conditional and unconditional energies moderated institutional quality, measured by political stability as well regulation, financial access (investment capital– incentives and human capital). The authors find that financial incentives and policy schemes involving subsidies or tax credits substantially accelerate the use of AI tools in planning and operations in low-income economies.

Another related study on Advances and Challenges in Energy and Climate AI Infrastructure (Raju et al., 2025), suggests that the energy infrastructure also has to play catch-up with the demands of AI: usually unreliable data pipelines, IoT sensors, communications networks, cybersecurity preparedness and regulation are often weak links. Without these, fielded AI systems (EMS, MPC, DTs) suffer from latency and error or lack human trust because the decision-making of their implemented “black-box” algorithms cannot be challenged.

Another dimension that we will hear more about is “Trustworthy AI”. A recent landscape analysis of Europe (Pelekis et al., 2024) suggests a framework for the evaluation, so-called E-TAI, on energy systems that takes into consideration AI services in terms of performance and ethics; transparency; safety; compliance with GDPR and EU regulations and sectoral regulations governing bodies or agency (e.g., EU AI Act). Lack of explainability and regulation clarity made the respondents less likely to adopt AI systems, even though they offer technical advantages, stakeholders claimed.

These studies have reported the following important barriers for adopting GIS:

1. Organizations and their users want to trust and understand AI outputs; black box models are frequently rejected.
2. Subsidies, policy certainty, standards and regulatory support can drive roll-out; lack of regulation provides a disincentive.
3. Sensors, IoT (internet of things), real-time data, communications networks, and cyber security are crucial enablers.
4. Skills, training, cultural readiness, leader support for change, and work with existing systems and workflows count.
5. Old or disconnected current infrastructure may have these issues; using AI with old hardware and software is often a cause of complexity.

The above-mentioned results reinforce the importance of using other factors like attitude, perceived ease of use, trust, compatibility, human capital policy environment, and data/infrastructure readiness from the Adoption Theory as moderators. These factors can play a significant role in determining the extent to which AI capabilities can lead to performance improvements.

2.3 THEORETICAL FRAMEWORK

AI application in large sustainable energy projects is not just a technical issue. Instead, it needs an encompassing structure that includes technical and socio-organizational perspectives. Two theoretical perspectives are particularly pertinent: Socio-Technical Systems (STS) theory and the Technology Acceptance Model (TAM). These three frameworks together describe how the technical capabilities of AI are mediated and moderated by human, organisational and contextual factors.

2.3.1 Socio-Technical Systems (STS) Theory

Socio-Technical Systems (STS) theory originated in the field of organizational studies during the mid-20th Century by understanding that: "the ideal functioning ST system is one where it is possible to identify consistent relationships between technical and social aspects." This happens when: 'people work with applied technology under direct responsibility for improving their systems" (Haipeng et al., 2024). Instead of framing technology adoption and use as a merely engineering problem, STS emphasizes that technologies develop along with human and organizational systems. Applied to the renewable energy, this entails that whatever planning or optimisation tools and predictive components driven by AI one has in place will either support optimal decision-making only when organisations have adjusted their own workforce level and capacities, governance models, cultural readiness and policies to rely on these enhanced system outputs.

Recent research provides empirical support for the STS view. (Abdessadak et al., 2025) observe that digital twins can lower downtime by 35% and boost production by 8.5%, but hardly take off in practice because of obstacles such as systems integration problems or organizational unreadiness. Similarly, (Khanum et al., 2025) point out that AI driven EMS in MG brings tangible benefits—better reliability, faster balancing and cost savings—but only with the help of skilled workforce, secured ICT as well as prevailing policies. The above instances illustrate that the influence of the technical applications even when they are at their best depends on social and organizational factors, such as training, trust, or policy frameworks.

One of the key dimensions of STS is the emphasis on interdependence. The flaws in one subsystem could overpower the virtues in the other: the lack of buy-In, poor or inappropriate training, and the social system's reluctance to change can diminish the benefits of good technical solutions; on the other hand, the poor infrastructure (i.e. bad sensors, unreliable data pipelines, and cyber vulnerabilities) can make even well-trained operators ineffective. This interdependence is especially critical for AI in renewable energy because the predictive maintenance or AI-optimized operation is not only based on the perfect algorithms but also on the high-quality information flow, real-time communication, and operator trust in automated suggestions.

However, even with its holistic view, the STS theory was said to be more descriptive than prescriptive. Some scholars argue that the theory explains what causes failures but gives no advice on the ways that organizations can consciously harmonize their social and technical systems (Kabir et al., 2024). In the context of energy projects, a significant difference is that

STS gives priority to governance and culture rather than specifying particular interventions like training, participatory design or organizational reform to increase alignment. Another critique is that STS might overlook power relations and institutional barriers. To illustrate, the non-adoption of AI may not solely be the result of insufficient training but could also be due to vested interests, regulatory gridlock, or different stakeholders receiving unequal benefits (Markus & Rowe, 2018).

Despite such shortcomings, STS still has the merit of presenting a MAP in which the tech is not the point but the problems concerning AI rollout can be viewed in the context of renewable energy systems. It shifts the discussion from “what is the accuracy of the AI prediction?” to “what are the social and organizational conditions under which predictions will be trusted, acted upon or incorporated into daily life activities?” Such a reframing is essential for large-scale projects that might otherwise be stalled by incompatible expectations among stakeholders regarding innovative technical solutions.

In conclusion, (this STS) theory acknowledges the importance of hesitations in AI technology adoption and integration within sustainable energy, as it is not a straightforward but rather a co-evolutionary path which necessitates continuous adaptation between the machine and the organization. Its recognition of the interdependence of the social and technical subsystems gives STS a powerful tool to understand obstacles like distrust, reluctance to change, or misalignment. Meanwhile, its limitations point to the need for a combination of models, like TAM, that offer a more detailed insight into user perception and adoption behavior alongside complementary models.

2.3.2 Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) was originally proposed by (Davis, 1989), which is one of the most influential theoretical models in theory about technology adoption. It is based on the assumption that individual reactions to an acceptance of a new technology are influenced by two main perceptions: perceived usefulness (PU) one’s belief that using a particular system will enhance his or her job performance and perceived ease of use (PEOU) one’s belief that using the system will be free from effort. PU and PEOU collectively affect the user attitude towards a technology, which consequently predicts behavioral intention and real use. Subsequently, TAM has been expanded to draw other concepts into the model such as trust, compatibility, facilitating conditions and social influence which render it more applicable to explaining technology use in complex or high-stakes adoption (Davis, 1989; Venkatesh & Davis, 2000).

When applied to the energy sector, TAM can serve as a useful framework for explaining why technically powerful AI applications—including forecasting systems, predictive maintenance algorithms or digital twins—may not be deployed by operators and organizations. (Billanes & Enevoldsen, 2021) reported ten salient adoption factors for RET such as knowledge, policy support, trust, social influence and compatibility. These elements correspond to TAM's extended constructs, and demonstrate that adoption is not based solely on technical performance. Similarly, (Fleiß et al., 2024) found that attitude and ease of use were better predictors of adoption than estimated usefulness even for household energy technologies. Significantly, they show that owning complementary technologies (such as electric vehicles, rooftop solar) dramatically increases the probability of adopting more AI-driven energy devices/equipment, suggesting that adoption is influenced by a larger lifestyle and system integration perspective.

But despite the fact that TAM has been highly regarded among researchers a few critical views argue that it is inappropriate for large sustainable energy projects. Firstly TAM has faced some critiques as being too individual-oriented, because it concentrates on personal perceptions, while overlooking organisational, institutional and cultural contexts (University of Michigan & Bagozzi, 2007). In the case of large pen renewable projects, actings cannot be considered as individual, but also it mixes with further organisations governance structures and regulatory bodies, consisting most of all in a forceful negotiation among the diverse collective stakeholders. Hence, PU and PEOU could be underestimating the complexity of adoption in a multi-actor context.

Second, it is argued that TAM is static and a-historical. That means there has no consideration for time and developments on how perceptions and intentions change over time as individuals mature (Venkatesh & Davis, 2000). For example, operators who initially lack confidence using AI to optimize their schedule may change after exposure to the decision support system (DSS) over time. In power projects with implementation horizons that stretch over the course of years, this dynamic feature is key.

Third, there are frequently trust, ethical and transparency issues that TAM may not fully cover or does not take due account of in the context of AI. (Pelekis et al., 2024), in suggesting a framework for "trustworthy AI" across the energy sector, are of the opinion that acceptability, has to do not only with usefulness and usability but also with whether or not AI systems explainable, secure and ethical compliant. In situations such as predictive maintenance or dispatch optimization, being non-transparent creates a questioning attitude even if your underlying technical precision is excellent.

However, the Technology Acceptance Model (TAM) is still useful when paired with other models even though it has been criticized. Its main advantage is that it can simply predict the future as a model with clear elements that can be applied and tested by collecting data (PU, PEOU, attitude, intention). In the case of clean energy projects, the Technology Acceptance Model (TAM) not only points out the psychological and behavioral sides of AI acceptance but also puts the researchers on notice that even though the algorithms work perfectly and are easy to use, they still will not be utilized if the users find them difficult to use or not aligned with their tasks, or if they do not have confidence in the algorithms.

To sum up, the TAM model suggests that technology adoption is not only a technical issue but a social-cognitive one and that it is greatly influenced by perceptions, attitudes, and the contextual factors involved. The method's underestimation of the role of individuals, its inability to reflect and incorporate temporal dynamics in the study of trust and in institutional contexts, and its poor treatment of these aspects mean that it should not be used in isolation, and wider models like STS should be applied alongside it. Combined, they provide a much fuller picture: STS deals with systemic interactivity, while TAM focuses on how human perception can facilitate or crash-response in here and now. This bifocal perspective enhances the conceptual basis for studying the adoption of AI in large scale sustainable energy projects.

2.3.3 Integrating STS and TAM

Jointly, STS and TAM provide a holistic conceptualization for this study. Although STS correlates the systemic interaction between technology institutions, actors and processes while TAM focuses on micro-level behavioural reasons for why some individuals attitudes perceptions and social context lead to adoption. For industrial AI solutions, this integration means that AI technologies (forecasting, optimization, predictive maintenance, digital twins etc.) unlocked at mega energy projects scale result in enhanced operational efficiency when and only when supported by adoption factors like trust; carrying out simple tasks just as well as the previous solution; compatibility with adjacent services or work structures; policy framework.

Accordingly, this theoretical basis supports the conceptual model postulated in this thesis in which AI capability is conveyed as impacting on project performance via operational mechanisms and the role of socio- technical factors moderating the strength and/or realization of these effects.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 INTRODUCTION

This chapter explains the research strategy and methods used to answer the research questions and the research objectives. It justifies the choice of a qualitative multiple case study approach, describes participant selection, data-collection instruments (semi-structured interviews and document review), data analysis procedures (thematic coding), and outlines measures taken for validity, reliability (trustworthiness), and ethics.

3.2 RESEARCH PHILOSOPHY AND APPROACH

This study adopts a pragmatic-constructivist stance: it recognises that knowledge about how AI is used in large-scale sustainable energy projects is constructed through participants' experiences while also aiming to generate actionable insights for practitioners and policy makers. A qualitative approach is appropriate because the research questions focus on understanding complex, context-dependent phenomena (how AI is used across planning, execution and monitoring; the socio-technical barriers and enablers), not on estimating population parameters.

3.3 RESEARCH DESIGN — MULTIPLE CASE STUDY

A multiple case-study design (Yin, 2018) is used to provide in-depth, contextually-rich understanding and to permit cross-case comparison. Cases are large-scale sustainable energy projects (a utility-scale solar park, an offshore wind farm, a hybrid wind–solar–storage project, and a transmission-level smart-grid rollout) where AI tools (forecasting, EMS/MPC, PdM, digital twins) have been trialed or adopted. The multiple-case design increases external analytical validity by allowing patterns that are robust across different techno-organisational contexts to emerge.

3.4 CASE SELECTION CRITERIA AND SAMPLING STRATEGY

Cases are purposively selected based on the following inclusion criteria: (1) project size (utility-scale or above), (2) demonstrable use or pilot of at least one AI capability (forecasting, optimization, PdM, or digital twin), (3) availability of key informants (project managers, operations leads, data/AI engineers), and (4) access to project documents (reports, technical specs). Within each case, purposive and snowball sampling identify participants with relevant roles: project owners, O&M leads, AI/ML engineers, control-room operators, and relevant policy/regulatory stakeholders. The target is 6–10 interviewees per case (24–40 interviews total), sufficient for thematic saturation in qualitative case research.

3.5 DATA COLLECTION METHODS

3.5.1 Semi-Structured Interviews

Primary data are semi-structured interviews of approximately 45–75 minutes. An interview guide is developed to probe each research objective and the questions. The questions merge the use of descriptive prompts (for instance, “Describe the daily operations where forecasting tools are applied”) with the probing evaluative question (“What advantages have you seen? What obstacles were there to the comprehensive use?”) and comparison cases across projects.

***Sample interview topics**:*

The tools that were utilized along with their respective functions, the deployment stage (planning, execution, or monitoring), the impacts that were noted on forecasting accuracy, dispatch, maintenance schedules, downtime, energy yield, and organizational readiness and training; trust and explainability; data/infrastructure obstacles; policy and regulatory engagements; perceived risks and economic effects.

3.5.2 Document Review

Secondary data consist of project reports, O&M logs, PdM summaries, digital twin documentation, procurement and governance documents, and public filings. These documents triangulate interview claims, provide objective metrics where available (downtime, mean time to repair, forecast error metrics), and inform the case descriptions.

3.6 INSTRUMENT DEVELOPMENT AND PILOT

Interview guides and document-review templates are pilot-tested with 2–3 industry experts outside the selected cases to ensure clarity, relevance, and coverage of conceptual constructs. The pilot leads to refinement (shortening prompts, clarifying technical terms, ordering questions to build rapport).

3.7 DATA MANAGEMENT AND SECURITY

The qualitative data that were taken for this study were handled in a way that was secure, systematic and ethical. The main purpose was to protect the confidentiality of the data, preserve its integrity and comply with the research ethics standards. The interviews were transcribed word for word and then all the transcripts were anonymised by taking out the names of the individuals and the organisations, and any information that was sensitive in terms of business. In every case, the participant got a unique code (e.g., P1–P40) thereby guaranteeing anonymity during the analysis and reporting. Moreover, project names and locations were disguised and referred to by case labels (Case A, Case B, etc.). Notes in hard copy, when necessary, were kept in secured storage.

3.8 DATA ANALYSIS STRATEGY

3.8.1 Thematic Analysis

The qualitative data from semi-structured interviews and document review were subjected to reflexive thematic analysis which was the method used in this study. The analysis was done according to (Clark et al., 2023) framework, which offers a systematic yet flexible approach for spotting, analyzing, and interpreting qualitative data meaning through patterns. The method was selected on the basis that it is the most appropriate for analysing the users' experiences and perceptions of artificial intelligence within the intricate contexts of organizations and technology.

The analysis was data familiarisation whereby all the interview recordings were transcribed and then read numerous times together with the relevant project documents. This was an opportunity for the researcher to get very much involved with the data and to have a general view of the different points of view of the participants. The first analytical thoughts and observations were recorded in reflexive memos to aid the subsequent reading and to be aware of the researcher's role in the process of analysis.

The researchers performed the initial coding after they got familiar with the data. A hybrid strategy combining deduction and induction was used. The deductive codes were constructed from the study's conceptual framework and theoretical bases which included AI capabilities, trust, ease of use, data readiness, and regulatory context. In contrast, the inductive codes were extracted directly from the data thereby enabling the unintended matters such as organizational resistance, vendor dependency, and informal practices to be captured freely.

In the next step, the codes were analyzed and sorted into probable themes by identifying recurrent patterns and connections among the interviews and cases. The related codes were unified into broader thematic categories, which expressed the shared meanings like human trust in AI systems, readiness of data and infrastructure, and organizational and regulatory factors.

The themes were then subjected to an iterative process where they were reviewed and refined repeatedly. For each theme, internal coherence was evaluated to ensure that the data belonging to it formed a significant pattern and external distinction was confirmed to ensure that the themes were clearly separated from one another. Themes that were too broad in scope were either refined or split up, and overlapping themes were merged when that seemed appropriate. This provided analytical clarity and hence the credibility of the findings was further strengthened.

Once the peoples' preferences were analyzed, the main theme areas were unambiguously named and their significance to the research questions laid plain through explicit talk. Each main theme, therefore, had an analytical narrative formed to show how it contributed to the understanding of the role of artificial intelligence in the management of sustainable energy projects on a large scale. The writers were mindful of the requirement for a right proportion between explanatory detail and interpretative profundity.

Finally, the themes were analyzed in the light of the research questions and also in relation to the theoretical framework of the study with Socio-Technical Systems theory and the Technology Acceptance Model being the main ones. A comparison of the different cases (i.e., projects) was made to point out both similarities and differences with regard to the types of projects and their contexts. The use of selected interview quotations and documentary evidence to illustrate the key themes was done in a manner that ensured transparency and supported analytic claims.

3.9 VALIDITY, RELIABILITY AND TRUSTWORTHINESS

For the qualitative findings to be regarded as trustworthy, the application of the already existing criteria of credibility, transferability, dependability, and confirmability was inevitable. Through triangulation, the most significant credibility was achieved by integrating data from semi-structured interviews and document reviews. This approach of involving different sources allowed the findings to be corroborated and at the same time it mitigated the risk of being dependent on only one viewpoint. Furthermore, member checking was part of the process whereby findings and thematic summaries were shared with selected participants for them to indicate whether the interpretations are accurate or whether there is a need for clarification or correction.

It was the thick description method that gave the transferability and in this case, transferability was supported by the development of detailed and context-rich case narratives. These descriptions are giving enough contextual information for the readers to decide whether the findings can be used in other settings or not. Confirmability and dependability were addressed through reflexivity in which the researcher kept reflexive memos during the entire research process documenting assumptions, analytical decisions, and potential biases. This reflexive practice has increased transparency and has also helped in ensuring the findings were not just based on the researcher's personal perspectives but actually backed up by the data.

3.10 ETHICAL CONSIDERATIONS

Informed consent is obtained from all participants; they are told purpose, voluntary nature, right to withdraw, and measures for confidentiality. Sensitive information (commercially confidential metrics) is handled per non-disclosure agreements and anonymised in reporting.

3.11 LIMITATIONS OF THE METHODOLOGY

The qualitative multiple-case design limits statistical generalisability, though analytic generalisability is pursued through theory-building (linking to STS and TAM). Access constraints and potential response bias (participants may present favourable accounts) are acknowledged; triangulation and member checking are used to mitigate these risks.

3.12 SUMMARY

This chapter has discussed the research methodology adopted in the study, which was the qualitative multiple case-study design to scrutinize the application of artificial intelligence in big sustainable energy projects. It described the research philosophy, case selection and sampling strategy, data-collection methods, and thematic analysis approach, as well as procedures for data management, ethics, and trustworthiness. The methodology offers a robust basis for understanding AI adoption and performance in various project contexts. Empirical findings from the research are to be presented in the next chapter.

CHAPTER 4

FINDINGS AND ANALYSIS

4.1 INTRODUCTION

The study's qualitative results from multiple case studies are presented in this chapter. It uses interview and document data to investigate the application of artificial intelligence in large-scale sustainable energy projects and how its influence on operational performance is determined by a combination of technical, organizational, and contextual factors. The chapter discusses four project contexts—offshore wind, solar with battery storage, hybrid wind-solar, and smart grids—and then features a cross-case analysis that identifies the commonalities and differences in patterns among the cases.

4.2 CASE PROFILES

This segment gives short descriptions of the four cases that are included in the research in order to set the findings' context. Each of the cases stands for a distinct form of large-scale sustainable energy project where artificial intelligence tools have been either deployed or tested. The descriptions highlight the main features of all the projects, such as the type of project, size, AI uses, and working environment. By voicing these profiles, it is possible to locate the empirical results and facilitate comparison between the cases in the next parts.

4.2.1 Case A – Offshore Floating Wind Far

4.2.1.1 Background

Case A represents a magnificent offshore floating wind farm situated far away from the coast, which includes 120 wind turbines with a total capacity of about 450 MW. The operation with floating turbines is more technically demanding than with fixed-bottom offshore wind farms due to the use of dynamic mooring systems, higher structural movement, and increased sensitivity to weather and sea conditions. The activities are being carried out in a far-off oceanic zone where bad weather, unavailability of boats and safety rules limit access to the turbines. Due to the project being financially unviable with high capital and operational costs, the unplanned downtimes and emergency repairs will heavily influence the overall project economy. The maintenance operations require specialized vessels, highly-trained offshore personnel and precise weather forecasting coordination, which means operational planning is a key element in performance.

In the absence of AI tools, Case A maintenance was mostly reactive. The detection of faults depended on alarm thresholds and regular inspections, which very often culminated in the very late identification of component degraded state. The need for emergency vessel deployments was a very common practice, leading to very high logistics costs and exposing the offshore crews to more safety risks. Decision-making was also difficult given the short-term weather visibility. Sometimes, the maintenance trips were either completely cancelled or just aborted due to the sudden changes in offshore conditions, this causing a waste of mobilization efforts and repair delays. Turbines data was collected but it was available in a fragmented way which made the data their effective use for predictive analysis really limited.

Operational decisions in Case A are taken collaboratively by the control-room crew, maintenance planners, offshore operations managers, and external service providers. Before the introduction of AI, decisions relied on the experience of individuals and the manual interpretation of alarms and reports to a great extent. Communication delays between the onshore and offshore teams made coordination more complicated, especially during fault events. Thus, the objective of the AI tools was not to take over human decision-making but rather to assist the planners and operators with earlier warnings, better situational awareness, and improved scheduling capabilities.

The implementation of AI in Case A was mainly influenced by the prohibitive expenses related to offshore maintenance and the safety concerns attached to reactive repairs. Predictive maintenance and weather nowcasting were recognized by project management as potential techniques to lower the number of emergency interventions and enhance maintenance efficiency. The digital twin pilot was launched to investigate the possibility of long-term diagnostic and planning capabilities, especially for the case of complicated floating structures that are hard to inspect physically.

4.2.1.2 AI Tools Implemented

In order to solve the operational difficulties, the project employed different artificial intelligence–based tools. Among them were predictive maintenance (PdM) system based on SCADA and sensor data of turbines, a test digital twin model for certain turbines, and short-term weather nowcasting models that were meant to help in planning offshore maintenance and scheduling of vessels. The integration of these tools into the current workflows was done step by step and they were mainly used as decision-making aids rather than being completely automated solutions.

4.2.1.3 Findings from Interviews

Interview data support the claim that predictive maintenance had a profound impact on the maintenance procedures in the project. Without the AI, the maintenance staff was almost exclusively dependent on alarm systems and reactive measures. The words of the project manager were:

“Previously we went into action only when alarms signaled, but with the predictive model we get warnings several weeks ahead which dramatically altered our offshore maintenance scheduling.”

The statement shows a significant shift in the maintenance practices from being reactive to proactive. The project team was able to schedule their interventions beforehand to the early warnings, which in turn reduced the number of emergency responses and allowed for better coordination of offshore logistics. Predictive maintenance is found to have changed the decision-making routines instead of just being an additional monitoring tool.

Even with these advantages, the initial adoption of technology was met with doubt by the staff that was going to use it. One of the supervisors for operations and maintenance commented:

"In the very beginning it was quite difficult to trust the alerts because none of us had any idea about the causes of them. The people were really cautious when it came to taking action based on something that they couldn’t explain."

This reaction points out the importance of trust and openness in the process of AI adoption. The situation of receiving alerts that couldn't be explained led to uncertainty and resistance, which was especially true in the offshore oil drilling environment where the wrong decisions could have dire consequences. What has been concluded is that technical accuracy is not enough for user acceptance if the users are not able to grasp the rationale behind the AI recommendations.

Initially, trust was not at high level, but it grew as the transparency of the system increased. The users of the system expressed that the explanation of the sensors and parameters that led to the alerts made their trust in the system greatly increased. A control-room operator said:

"It was much easier to trust when the system started to show which sensor triggered the alert. Instead of a warning, you could see the logic."

The above statement highlights the fact that explainability was the main factor for user acceptance. The system was able to work well with the people's existing knowledge and decision-making process by making the AI outputs interpretable. This result indicates that explainable AI is an important feature for the integration of AI into the operations of today’s companies.

The digital twin was considered a very useful diagnostic and educational tool. A data engineer told about using it to create unnatural conditions and juxtaposing them with the real behavior of the turbine:

"The digital twin made it possible to play with various fault patterns. In one case, it was detected that there was an odd force in a mooring line weeks before the problem occurred."

The assertion reveals that the digital twin acted as a means of learning and risk mitigation rather than a control system operating entirely on automation. Even during the pilot stage, the digital twin was involved in the early detection of faults and the making of maintenance decisions, especially in offshore areas where it is hard and costly to carry out inspections physically.

Also, short-term weather nowcasting was pointed out as an important operational help. A control-room operator said:

“Offshore the weather changes rapidly. The nowcasting is helping us get rid of sending ships out when the situation is about to worsen. Just that saves time and money.”

The reaction of the operator reveals that nowcasting was helpful in terms of both safety and cost efficiency through better short-term operational planning. The capacity to foresee rapid weather changes not only but also reduced the number of vessels moved around and the risk of operation being unsafe. Thus, this showed that the AI tools are practically valuable in terms of operational efficiency and that the performance metrics are not only technical.

4.2.1.4 Observed Performance Outcomes

Around 27 percent of unplanned downtime was cut, 22 percent of the repair time was shrunk and emergency vessel trips were down by almost a third as the participants stated that there were visible operational improvements after AI tools were introduced. Enhanced fault detection accuracy allowed maintenance planning and offshore logistics to be coordinated better which in turn helped the operations to be both safer and more economical.

4.2.1.5 Critical Analysis

The results from Case A are very much in line with the literature on AI-supported prognosis of maintenance in offshore wind energy. Machine-learning-based predictive maintenance systems have been shown to allow component degradation notifications at an early stage and to minimize the use of reactive maintenance strategies, thus cutting down on both the number of hours the plant is not running and maintenance costs (Markus & Rowe, 2018; Shah et al., 2024). The use of predictive analytics in Case A thus supports these conclusions by illustrating the way such technology can reshape offshore maintenance scheduling.

Using a digital twin, although only for a pilot project, is a sign of the direction that is being taken in the management of offshore winds. According to (Abdessadak et al., 2025), digital twins bring about better early fault diagnosis as well as operational planning readiness through the integration of various data streams into one virtual representation of the physical asset. Case A thus serves as a concrete example that the digital twin can be quite beneficial in offering valuable insights even prior to its full-scale implementation, with respect to the floating turbines which are subjected to dynamic loading and complex structural behavior.

The results of weather nowcasting in Case A are consistent with the conclusions of recent works pointing out the importance of AI-assisted short-term forecasting for offshore operations. Two studies, one by (Min et al., 2023) and the other by (Cuesta et al., 2025), have established that the adoption of AI-dependent nowcasting models positively impacts the precision of short-term wind and weather forecasts, greatly decreasing the number of maintenance trips made for that reason and, at the same time, contributing to the safety of the entire operation. The control-room operators' experiences in Case A have been a direct reflection of these advantages, thus acknowledging the relevance of such models for the daily operations.

There are several difficulties that are attendant upon these advantages which are also reflected in Case A and discussed in the literature. Data interoperability issues arising from the presence of mixed turbine manufacturers are still a primary obstacle to the widespread adoption of AI. (Ba et al., 2025; Syed Muhammad Habib Ur Rehman, 2025) pointed out that lack of uniformity in the data architecture and the application of vendor-specific protocols adds to the difficulty of integration, which is the case here. Moreover, limited communication bandwidth offshore was another significant factor that slowed down the real-time data transmission and this is in line with previous studies that have pointed out infrastructure limitations in remote energy systems.

It was the human factors that presented themselves as the main determinant of AI success. The first distrust of AI alerts emphasizes the necessity of explainability and transparency, which are the main characteristics of the Technology Acceptance Model. According to (Pelekis et al., 2024), the AI systems used in safety-critical areas must always provide outputs that are easy to understand if they want to have the acceptance of users. In the case of A, it is shown that nothing but trust can be built if the users do not have any knowledge of how and for what reason AI systems are leading up to the recommendations they have generated.

Training, simple dashboards, and strong vendor support were pinpointed as the main facilitators. These results are in agreement with a study by (Fleiß et al., 2024) that proved the factors of technology acceptance in the industrial environment were mainly ease of use and user training. Therefore, Case A backs up the socio-technical viewpoint that the successful adoption of AI is determined by the harmony between the technical systems, human capabilities, and organizational processes.

4.2.1.6 Case Summary

In Case A, it was shown that AI could play a major role in creating better operations in offshore wind energy projects, which is done by cutting downtime down, bettering maintenance planning, and making logistics more economical. Also, the case points out that overall the above-mentioned advantages will only be realised if the corresponding conditions such as good data integration, proper IT infrastructures, transparent AI, and trust of the users are met. Through an empirical study linking to previously done research, the Case A strongly reiterated the viewpoint that the use of AI in offshore energy systems is both a technical and socio-organizational process thus careful consideration to human, technology and context factors is required.

4.2.2 Case B – Solar Farm with Battery Storage

4.2.2.1 Background

Case B refers to a solar power plant of utility scale with a maximum capacity of 300 MW and a 200 MWh battery energy storage system. The project is involved in various electricity markets, including day-ahead and intraday trading, where the revenue largely depends on precise generation forecasting and optimal battery dispatch. Unlike offshore projects, the solar plant in Case B benefits from physical constraints that are not so strict but nevertheless, it still has to deal with significant commercial and market risks. The battery storage system brought about the need for new operational methods with close cooperation between forecasting systems, market prices, and dispatch decisions. A slight inaccuracy in forecasting can result in a poor charging or discharging decision which will, in turn, impact the revenue directly.

The standard models that were used before the AI deployment to predict solar output were unable to capture the quick movement of clouds. This led to a situation where the curtailment levels were higher and the operation of batteries was very careful. The decisions about the battery dispatch were often made by following fixed rules instead of using predictive optimization which restricted the project's potential to take advantage of price volatility. Moreover, the data quality problems that were caused by the older inverters and sensors decreased the trust in the automated decision-support systems. The operators often had to intervene manually which in turn diminished the efficiency of battery utilization.

In Case B, battery dispatch decisions are still made by control-room operators, who coordinate their actions with market analysts and grid operators. The operators had to rely mostly on their judgment and manual scenario analyses before implementing AI. AI tools were meant to support the human being in the decision-making process by providing short-term forecasts and optimisation suggestions instead of taking over control completely.

In Case B, the main reason for the adoption of AI was financial. The project management realized that battery revenue and curtailment could be improved through forecasting and optimisation, thus making these the main levers. Government incentives for energy storage helped to a great extent in the high-risk AI tools investment that was financially risk-less and thus supported quicker deployment.

4.2.2.2 AI Tools Implemented

The project executed an array of AI-based tools composed of hybrid solar nowcasting models, an Energy Management System (EMS) incorporating Model Predictive Control (MPC), and AI-based electricity market price forecasting. The hybrid solar nowcasting model merges sky-camera data with satellite imagery. These tools were aimed at enhancing short-term production predictions, maximizing battery dispatch logic, and aiding market bidding tactics.

4.2.2.3 Findings from Interviews

The interviewees reported, without fail, that the accurate short-term forecasting was the reason for both the battery working more efficiently and the company's revenue increase. The project manager mentioned,

"The battery dispatch was so much better after we started using the new forecasting system. We made around 9 percent more revenue because we were able to foresee the best moments for charging and discharging."

This report points out that improvements in short-term forecasting had an immediate impact on battery dispatch decision making. The project team was able to charge and dispatch the battery at the right times by the use of wind and solar generation and market conditions. Thus, forecasting accuracy is viewed as a strategic factor rather than a mere technical improvement. The ability to predict charging and discharging windows with the least market risks was an attraction for the project to participate in the market and also led to revenue optimization. The discovery implies that AI-based forecasting systems are of great importance in the synchronization of physical system performance with commercial objectives leading to the linking of operational intelligence to financial outcomes.

Nevertheless, the quality of the data posed a serious technical concern. To that, a data engineer replied:

“Old solar inverters produced very noisy data, and that was the reason for the model’s confusion. Therefore, we had to perform data cleansing and filtering of errors first before AI could work effectively.”

This answer points out the lack of data as a major reason why AI was not able to continue. Poor and incompatible data from old machines were the causes of the low performance of the forecasting models, and this was one of the reasons that the sophistication of the algorithms could not be relied on without good input data. The necessity of complete data cleansing contributed to the time and resource commitment before the advantages were realized. This finding is a validation that the hidden costs of data engineering and infrastructure upgrade often accompany AI adoption, and that the transition from old technologies can be a barrier to the implementation of sophisticated digital systems. It further indicates that firms with contemporary sensor infrastructure can enjoy the advantages of AI much faster than those relying on outdated equipment.

The acceptance and the control by the operator were the other major topic. An operator from the control room had the following to say:

“I appreciate the fact that the MPC system gives recommendations, one of its good points. We are free to explore all the different possibilities and then select one. We feel secure because the final decision is still ours.”

The comment implies that human supervision is still required in those situations where the decision-making process entails both financial and reliability risks for the system. By the very nature of the MPC system being advisory, the operators were able to scrutinize the AI recommendations without giving up their decision-making power. The encouraged flow of people being involved in the process, the "human-in-the-loop" approach reduced the risk perceived and supported learning, thus allowing operators to develop trust over time through being repeatedly exposed to accurate recommendations. The study implies that staged automation, where AI at the very beginning of the process supports rather than replaces human judgment, facilitates acceptance and lessens resistance. Moreover, it points out that operator confidence is determined not solely by the accuracy of the system but also by the amount of control they have over the decision-making process.

Adoption decisions were also influenced by policy and regulatory support. One of the regulators participating in the project remarked:

"We provided incentives for storage projects. This made the company consider the use of AI tools that are cutting-edge earlier."

This statement reflects how regulatory incentives played an important part in influencing the decisions of organisations. Financial and policy support made it possible to consider the adoption of advanced AI and storage technologies as a less risky option and thus earlier deployment became economically viable. The data point to the fact that policy actions could be the catalysts for technological innovation by making the investment gains more attractive. Besides, it implies that the adoption of AI in the power sector is not merely an issue of technology's performance but largely a matter of the accompanying regulatory and market situations. Thus, supportive measures can spur the transition from trial runs to full-scale AI adoption in power plants.

4.2.2.4 Observed Performance Outcomes

After the introduction of AI, the participants noted a number of performance enhancements. The accuracy of solar forecasting in the short term went up by more or less 18 percent, energy curtailment was cut by roughly 14 percent, and the income from battery participation went up by nearly 9 percent. The major factors behind these improvements were the ability to anticipate cloud movements better, accurate dispatch planning, and the synchronization of forecasting and optimization systems.

4.2.2.5 Critical Analysis

The results obtained from Case B are almost the same as the results obtained in previous studies that showed that short-term solar nowcasting is a very important factor in making solar-plus-storage systems' operational decisions. That is the very reason why the studies (Haipeng et al., 2024) claim that hybrid nowcasting models which use local data sources, such as sky cameras, along with satellite images, provide the highest performance over single-source forecasting methods and where lead time is short. The improvements here are critically needed in the management of rapid cloud movements whose influence on photovoltaic output is direct and drastic. In this context, Case B takes the opportunity to confirm the theory by demonstrating that enhanced forecasting accuracy translated into real-time operational benefits in the form of less animal energy curtailment and more efficient battery storage usage. Hence, it could be inferred that forecasting accuracy is no longer a mere technical improvement, but rather a major enabler of the new energy management paradigms that are more flexible and responsive, and that, consequently, the technical improvement has opened the door to the new energy management strategies that are more flexible and responsive.

The installation of a Model Predictive Control-based Energy Management System in Case B agrees with earlier research that predictive optimisation increases battery dispatch efficiency and revenue capture under generation uncertainties. (Ansong et al., 2025) showed that MPC frameworks are ideal for variable renewable input energy systems as they predict future states and change control actions in line with that. The increase in the battery-related revenue reported in Case B is a clear indication that if one improves the accuracy of forecast and couples it with an optimisation algorithm, he or she will reap an economic benefit. This scenario is a perfect example of the interdependence between forecasting and control: accurate forecasts are useless unless they are embedded in decision-support systems that are capable of translating information into optimal operational actions.

Simultaneously, Case B underlines one of the main difficulties the literature has pointed out about the unpreparedness of data. On one hand, the data quality problems linked to the older solar inverters do indeed match the concerns which were raised by (Algburi et al., 2025), who pointed out data preprocessing, sensor noise, and equipment heterogeneity as the main, but often overlooked, costs of AI integration in the power sector. The vast data cleansing requirement in Case B implies that the advantages of AI are dependent on the quality of the underlying infrastructure. The work done here is definitely an important add-on to the literature since it claims that the industries using technology that is no longer contemporary will not only have longer implementation times but also face IoT and AI costs initially higher than those which might impede the technology's actualization or even limit the benefits of AI technologies. Thus, considering technical readiness only as algorithm selection is limited; rather, it is better to see it as a system-wide condition comprising hardware, communication infrastructure, and data governance.

Human factors which are emerged in Case B totally align with the principles of the Technology Acceptance Model. The operators' preference for an advisory system rather than an automated control was similar to the findings of (Fleiß et al., 2024), who identified usability and trust as the most important factors for technology acceptance in the workplace. The operators were allowed to assess and pioneer the application of MPC suggestions, which subsequently led to the reduction of perceived risk and the facilitation of slow learning. This approach indicates that the acceptance of AI tools is related not just to the performance gains, but also to the manner in which the tools get integrated within the workflow. Therefore, Case B proves that human-oriented system design is a major determinant in the integration of AI tools into everyday work or their being out of use.

In the light of Case B, the impact of regulatory incentives has been considered not only a supportive but also a powerful argument for the authors of the article (Bryła et al., 2022) who pointed out that the presence of such progressive regulatory policies is a major driver for the early adoption of both AI and energy storage technology. In such a case, the financial incentives played a role in minimizing the risk of investment and making it possible to execute the deployment of cutting-edge AI systems sooner than the original schedule. The result indicates that the process of implementation of AI is determined not only by the availability of proper technology but also by the existing market practices and policies. Case B indicates that when regulation is in favor, companies are more inclined to gradually scale up their operations from pilot testing to full implementation. On the other hand, in the absence of such support, the same AI applications could still be confined to a research stage, even though they possess the potential for industrial adoption.

4.2.2.6 Case Summary

In Case B, artificial intelligence is evidenced to be a great contributor to both operational efficiency and financial performance in case of solar power plants with battery storage. Improved forecasting accuracy caused cutting down on curtailment and this led to more profitable battery dispatch, while optimizing based on Model Predictive Control (MPC) was a good support of effective decision-making under uncertainty. However, the case revealed that data quality, human control, and policy incentives are the major factors influencing the adoption of AI. In general, Case B indicates that the greatest value of AI comes when the technology is capable, and trust by humans as well as support from the regulators are all in sync.

4.2.3 Case C – Hybrid Wind–Solar Plant

4.2.3.1 Background

Case C is a hybrid renewable energy project that consists of wind, solar, and battery storage with a total installed capacity of 250 MW, 150 MW, and storage, respectively. The hybrid setup was to output stability and better management of the grid, but it, nevertheless, involved considerable operational complexity. The project operates with machines produced by different manufacturers, and these manufacturers have different data formats and communication methods. Hybrid plants demand synchronized forecasting and maintenance for diverse technologies, which in turn makes their management more difficult compared to single-source projects.

Prior to the implementation of AI, wind and solar assets were dealt with individually in forecasting which very often resulted in inconsistent planning. Maintenance scheduling was likewise done separately and limited the prioritization of interventions according to system-wide risk. As a consequence, false alarms were frequent which made the operators less trusting of the automated monitoring tools. Data not being standardized made it quite hard to formulate integrated analytical models and thus, engineers had to intervene manually at a significant level.

The decision-making process concerning Case C is characterized by a strong teamwork of forecasting departments, maintenance workers, and planners. Before the utilization of AI, the various teams had to meet frequently to share updates and data sharing was still done manually, which, of course, made the coordination hard. The introduction of AI tools was meant to enhance the company's integration and at the same time give a better overall picture of the performance of the system.

Complexity was the main reason for the adoption of AI in Case C. The project leaders looked for solutions that would not only bring together various data flows but also cut the uncertainty in forecasting considerably and select the maintenance interventions according to the risk of the whole system instead of the alarms from individual assets.

4.2.3.2 AI Tools Implemented

The project executed ensemble forecasting models for wind and solar generation, a pilot predictive maintenance system on some wind turbines, and initial steps for a future digital twin. The ensemble forecasting strategy integrated several models that resulted in stronger outcomes and less uncertainty, on the other hand, predictive maintenance was early detection of part deterioration. When the study was conducted, the digital twin was still not completely operational and only on a planning stage.

4.2.3.3 Findings from Interviews

The participants of the interview expressed that the biggest improvement in AI adoption was in forecasting, this was the benefit which was the most visible. The project manager remarked;

"The improvement in forecasting was the most evident. Our planning became more precise and we cut down on last-minute changes."

One can deduce from this that the reliability of the forecast has been greatly improved, which positively affected operational planning both in the short-term and day-ahead for the whole hybrid energy system. The reduction in last-minute schedule changes is an indication of the greater trust being placed in the production estimates, which enabled the operators to be more certain in the commitments made to the plans for generation and storage. In a hybrid wind-solar plant, where the uncertainty from several weather-dependent sources could worsen the planning complexity, the improved forecasting made it possible to cut down on the number of reactive adjustments and emergency interventions. This discovery illustrates that ensemble forecasting contributed to operational stability by smoothing the interaction between wind, solar, and storage assets, thus making the entire system more predictable and lowering the operational stress.

Predictive maintenance has also brought considerable operational benefits. The maintenance manager expressed his/her view:

“The predictive maintenance tool warned us about the rising temperature of the turbine bearings. The part change carried out beforehand prevented an expensive failure.”

That reactions demonstrate the ability of AI to prevent the failures of maintenance tools in the upkeeping of the parts with their first detection, which done normally would not trigger the alert of some conventional systems. Not only did the maintenance cost get reduced but also the whole production area that could have been affected by the long wait for the bearing repair was saved due to the timely intervention against bearing failure. In the case of multiple assets, the outage of one part could cause bad operation of the entire system. The research shows that even predictive maintenance systems at the pilot scale can be very productive and supporting AI in its role of risk mitigator and lifespan extender for the asset by preventing low-frequency but high-impact failures thus making it easier to get an ROI.

The data scientists and engineers have said, “the model's reliability improvement is the most important aspect.” One of the data engineers mentioned:

“The model was improved with physics-based knowledge. The aftermath was the reduction of false alarms and the increase of alerting technicians' trust.”

The statement represents the combination of knowledge and data-driven models in the engineering field that not only enhanced the technical performance but also earned the users' acceptance. At the beginning, the high false-alarm rates shattered the confidence and created doubts among the maintenance personnel. Physics-based constraints were the reason for the model's gaining interpretability and matching the technicians' understanding of turbine behaviour better. Consequently, this not only led to a decrease in unneeded alerts but also strengthened the faith of the staff in the system. The inference made indicates that the mixed physics–AI methods are particularly excellent in operating complexes of engineering where only the statistical models might struggle to differentiate between normal operational variations and real fault cases.both technical performance and user acceptability.

One of the issues that were always pointed out was interoperability. The lead engineer shared his thoughts saying:

"Each turbine manufacturer has a different data format and that we couldn’t do AI properly until everything is directly going through each aspect and is then harmonized."

Such a statement points to not only the difficulties in practice but also the organization of AI's deployment in the energy systems that have different manufacturers. The urgent need for large-scale data harmonisation made the implementation longer and it took a lot of effort in technical coordination between the teams. This issue restricted the rate of AI tools' operationalization in spite of the advantages they could provide. The discovery means that putting together systems and having common data formats turned out to be the major factors for AI's success while the parameters of readiness of organisations and alignment of their technical capabilities were as important as the algorithm design. In the case of hybrid plants, where various technologies have to work together industrially, the issue of interoperability may greatly influence the pace and extent of AI adoption.

4.2.3.4 Observed Performance Outcomes

According to the participants, there were observable enhancements after the implementation of AI. The error in day-ahead forecasting was roughly reduced by 12 percent, while the number of false maintenance alarms dropped by about 40 percent, and one major turbine breakdown was prevented, which saved a lot of money. The reasons for these achievements were stronger forecasting, more accurately tuned predictive maintenance models, and improved engineering supervision.

4.2.3.5 Critical Analysis

The Case C-forecasts improvement closely connects to previous research that has established that the ensemble methods are far superior to the single model ones in renewable energy forecasting. In the work of (Lauro et al., 2015), it was concluded that uncertainty in forecasting can be mitigated through capturing a wider range of possible outcomes by the use of ensemble forecasting, this being especially important in hybrid systems that have multiple weather drivers influencing them. By showing better planning accuracy in a multi-source energy setting the Case C is supporting these researches.

The predictive maintenance results go along with previous studies that pointed out that AI-aided abnormality detection could catch up to the whole process using SCADA and sensor data (Okafor et al., 2025; Shah et al., 2024). But the Case C literature goes a step further and draws attention to the issue of false alarms that come with the early deployment of the technology. The company has completely absorbed and successfully utilized the basic knowledge of the research that innovative studies claim hybrid physics-ML models to be more interpretable and trustworthy than purely data-driven ones (Okafor et al., 2025; Raju et al., 2025). This indicates that the merger of engineering knowledge with the machine learning abilities is particularly a requirement in diverse industrial systems.

The interoperability problems experienced in Case C have solidified the concerns already raised by (Ba et al., 2025; Kabir et al., 2024), who have identified the diversity of vendors and the use of different data formats not being standardized as the main barriers to the adoption of AI in the power sector. Case C serves as a testament that these issues can still post a challenge to the utilisation of AI even if they are technically very efficient. This outcome supports the idea that the initial investment in data standards and system integration is going to be an absolute necessity when the AI deployments in hybrid plants are being planned.

On top of that, Case C had a lot to tell but still comes with restrictions. The digital twin had not yet reached its full functionality, and therefore, the project's overall capacity for running real-time simulations and making predictive diagnostics was severely impaired. In addition, the project placed a great deal of reliance on the strong engineering team's knowledge and skills to calibrate and shape AI models. This brings up concerns about the scalability problem, as less-funded projects might struggle to yield the same results. Moreover, hybrid systems are still very complicated to model because of the nonlinearities among the wind, solar, and storage assets, and even more so during extreme weather events.

4.2.3.6 Case Summary

Artificial Intelligence, as shown in Case C, is able to improve forecasting precision, minimize maintenance-related risk, and avoid the non-use of hybrid wind-solar energy systems that cost a lot. On the other hand, the case also demonstrates that all these advantages are reliant on good data integration, model calibration, and access to skilled engineers. In connection with previous studies and the empirical data, Case C presents both the possibilities and the real difficulties of using AI in the intricate and diverse renewable energy projects. This study gives further support to the opinion that AI success is determined not just by sophisticated algorithms but also by the strong foundations in both organization and technology.

4.2.4 Case D – Smart Grid with Microgrids

4.2.4.1 Background

In Case D, a regional utility is operating and controlling a number of interconnected microgrids in both the city and countryside. The main goals of the project were grid stability improvement, peak power demand reduction, outage management and distributed energy resources integration increased. Enhanced integration of distributed energy resources was one of the main goals of the project. Almost all power generation projects focus on the generation side while smart grid systems operate under very regulated and safety-critical conditions, where reliability, transparency, and cybersecurity are the main priorities. These conditions open the way to a more in-depth understanding of the adoption and usage of AI tools in D Case scenario due to the strict and limited regulatory and operational framework.

The peak load management prior to AI application was based on rule-based demand response and manual coordination of microgrids. Outage management was done after the fact, and the possibility of scenario simulation was very limited. Communication restrictions in rural areas made real-time optimization even less efficient.

The decision regarding grid control is in the hands of the operators in the control room who work in tandem with the planners, regulators, and cybersecurity experts. Automation is progressively implemented, with thorough testing and approval taking place beforehand. Consequently, AI technologies were first used in the guidance mode.

The driving force behind the use of AI in Case D was the intention to make the system more reliable and resilient but at the same time to keep safety as a priority. Digital twins were utilized for scenario testing, while control based on MPC optimization was used for managing peaks. Interaction with the regulators was a key factor in determining the strategies for deployment.

4.2.4.2 AI Tools Implemented

The project incorporated an AI-assisted Energy Management System (EMS) based on Model Predictive Control (MPC) for the coordination of microgrid operations, a digital twin's pilot to imitate outage scenarios and restoration strategies, and an AI-based demand response management to control peak loads. The use of these tools was done slowly, whereby the need for human supervision and adherence to regulations was given top priority throughout.

4.2.4.3 Findings from Interviews

The interviewees mentioned that the use of MPC-based optimisation was one of the most important factors in the interlinked microgrids' management of peak demand. The project manager made the following remark:

"MPC was the instrument through which we were able to cut peak loads in the high-demand periods. If it weren't for that, our electricity purchase costs would have gone up."

It can be inferred from this quote that the predictive optimisation process facilitated a change from reactive load balancing to proactive demand management. The MPC system, by predicting future demand patterns, making power generation availability and network constraints known, and so on, prescribed coordinated operation of distributed energy resources that were more efficient, including storage and demand response assets. The much-needed ability to shave peak loads, in turn, reduced the resort to expensive electricity purchases from the wholesale market and also eased the burden on network infrastructure during peak times. The result indicates that the application of AI-based optimisation has not only helped to reduce the cost but also to strengthen the system's ability to withstand shocks by improving the grid's capacity to cope with demand variation.

In this case, the regulatory oversight emerged as the principal feature of AI use. The representative of the regulation among the parties concerned expressed:

"It was essential for us to have the company demonstrate their automated decisions with logs and clear explanations. Safety should always come first."

The quote points out the necessity of governance, transparency, and accountability in the sector of AI which is imposed by government regulations, particularly in the case of energy systems. The regulatory obligation for clear and comprehensive audit trails and explainable decision-making reduced the speed of automation but at the same time made it possible for AI-related actions to be challenged and warranted. The result indicates that in environments where safety is a prime consideration, the technical performance of AI systems is not the only factor that can lead to their automation. On the contrary, AI systems should always be designed such that regulatory requirements for traceability and oversight are patiently waiting. Thus in such environments, the tendency of adoption pathways is to choose controlled experiments and slowly increasing automation rather than fast deployment.

The pilot of the digital twin was regarded as an essential means for verification and an important learning tool. One of the data engineers said:

"The digital twin was useful in our testing of outage scenarios. The real behaviour coincided with our simulation during the storm, and thus, we trusted it more."

This quote indicates that the digital twin was a verification tool and not a completely autonomous control solution. By accurately mimicking the system's behaviour during the actual outages, both the model and the assumptions about the system were made more reliable. This capability of validation provided ground for operators and engineers to practice their reactions to very rare but high-impact events without stopping the live operations. The result indicates that digital twins can be very influential in reducing the differences between simulation and real-world usage, especially in areas where system malfunctions can cause great social and economic losses.

Additionally, the aspect of human acceptance of AI tools was a constant topic throughout the interviews. A control-room operator shared his perspective:

“Initially we want the AI to be in the advisory mode. After proving its performance, we will let it perform more automated steps.”

The above comment illustrates a conservative, trust-building method to the use of automation, which is typical in the conduct of high-stakes operations. By first employing AI tools as advisors, the operators retained their decision-making power and at the same time were slowly assessing the system's reliability and accuracy. This gradual adoption process resulted in a reduction of the perceived risk and allowed for learning through experience, rather than compelling immediate reliance on automation. The conclusion points to the fact that human-in-the-loop strategies are crucial for the development of trust and acceptance, especially in the field of energy where mistakes can affect not only the customers but also the critical services.

4.2.4.4 Observed Performance Outcomes

Participants shared that there were many operational improvements after the AI implementation. The peak load shaving improved almost 6 percent, the customer outage complaints dropped approximately 9 percent, and the outage restoration planning was quicker and better coordinated. These effects were ascribed to the use of predictive optimisation, the digital twin for scenario planning, and increased communication among microgrids.

4.2.4.5 Critical Analysis

The scenario of Case D has been a good predictor of peak load reduction and is linked with the growing support of research that proves the use of Model Predictive Control (MPC)–based optimisation techniques in complex electricity networks for grid stability and demand management. (Sahut et al., 2022; Sun & Han, 2025) discussed that control prediction frameworks make it possible for the utilities to neglect and overlook the future system states like demand and network limitations, thus acting on the control changes in a proactive manner than a reactive one. Case D provides proof of this over and above by accruing with the peak shaving achieved under actual working conditions being measurable and noticeable. The case also indicates that reducing the peak load only slightly can, in fact, generate quite a large cost saving and do the grid reliability; this is particularly true when such reductions are summed up across several microgrids. In summary, the research contribution to the literature is done through demonstrating the different performance levels of MPC not just in trials or simulations but also in the real-time operational environment with the incurring constraints imposed by regulations and infrastructures.

In Case D, the deployment of a digital twin for outage simulation provides supporting evidence for the findings of (Abdessadak et al., 2025; Ansong et al., 2025) who have emphasized the role of digital twins in terms of planning, diagnostics, and risk assessment in the context of complex grid assets. However, Case D goes further in the argument by showing that digital twins are not only tools for building trust or optimizing but can actually do both at once. During storm events, the digital twin was able to perfectly mimic the real outage behavior thus not only confirming the model assumptions but also the understanding of the system which resulted in the engineers' and operators' increased confidence. This result strengthens the research status by indicating the social and organizational dimension of digital twins in making AI's acceptance easier, especially in critical safety environments where full automation has not yet been achieved.

The regulatory constraints apparent in Case D have once more brought the worries of (Pelekis et al., 2024), who pointed out that the explainability, auditability, and cybersecurity aspects of AI-powered energy systems will be more and more significant, to the fore. While the regulations on one hand delayed the automation process, on the other hand they assured safety, transparency, and accountability of the systems. Case D symbolizes a serious conflict in smart grid development: the war between rapid technological progress and regulatory confidence. The dilemma is most strongly seen in public utilities where a failure could lead to a lot of trouble for both the society and the economy. The findings of the research indicate that the incorporation of AI in smart grids is not only a matter of technological readiness but also of the ability of AI systems to satisfy governance and compliance requirements.

The human factors identified in Case D closely resemble the Technology Acceptance Model principles. Operators' choice of the advisory system rather than the fully automated system is in line with the results of (Billanes & Enevoldsen, 2021; Fleiß et al., 2024), who stated that trust, perceived ease of use, and perceived risk are very decisive factors for the adoption of technology in high-risk operational settings. Case D reveals that gradual automation—where AI systems are initially supporting decision-making rather than taking it over—can help in acceptance without endangering safety. This staged adoption process gave operators the chance to gain confidence by means of experience, which made human-centred system design even more crucial in the context of critical infrastructure.

The limitations of structures and infrastructures, which reduced the performance of AI, were still pointed out by Case D despite the good results. The slow data input process due to the low data transmission capacity in the rural areas had a negative effect on the responsiveness of the optimization algorithms. Moreover, the very high-level cybersecurity measures that had been established increased the time for deployment and made the operation more complicated. These issues have been interpreted in the context of the socio-technical perspectives which argue that AI's effectiveness depends not only on the algorithms but also on the supporting infrastructure and institutional frameworks. Consequently, Case D suggests that the massive AI adoption in smart grids will involve the investment in communication networks, cybersecurity, regulatory alignment, and workforce capability plus technological innovation.

4.2.4.6 Case Summary

In Case D, it has been shown that the use of artificial intelligence can not only make the stability of the grid better but also decrease the peak demand and outage management to smart grids. On the other hand, the results indicate that the government requirements, limitations of the infrastructure, and public trust have a great impact on the speed and extent of AI usage. Considering the empirical evidence along with the scholarly works, Case D points out that the successful application of AI in power grids is determined by the extent to which the companies are able to balance technological innovation with safety, transparency, and organizational readiness.

4.3 CROSS-CASE SYNTHESIS

All the four cases present the same finding that artificial intelligence was a factor in large-scale sustainable energy projects with improved operational performance, however, the specific nature and extent of these improvements differed from one case to another. AI assisted in making the forecasts more accurate, maintenance more planned, dispatch of energy more optimised, and the grid more reliable. The performance improvements were present in all the cases, but the ways of achieving them varied according to the type of project and the conditions in the operating area.

There was a common feature throughout the cases that pointed out the human factors as the most important factors in determining the AI efficacy. The trust in AI outputs, the user friendliness of decision-support systems, and the right training were recognized as the main facilitators for the successful implementation. In all the cases, AI tools generated more value when the users had comprehension of the way the recommendations were made and when they exercised some control over the decisions. In areas where the organizational culture was not supportive of AI, e.g., low explainability and user involvement, the adoption was slower and benefits were delayed. This cross-case evidence shows that technical capability alone is not sufficient; human acceptance is the deciding factor in realizing AI potential.

All cases also shared the problem of data quality and system integration. In addition to this, mixed-vendor hardware, outdated systems, different data formats, and insufficient communication channels reduced the efficiency of AI and escalated the effort for its implementation. The problems were so serious that they not only forced the projects to take longer to deploy but also to spend a lot of money on data cleaning and system harmonisation. It is evident from all these discussions that the primary factors hindering the widespread adoption of AI in the energy industry are the data and the interoperability issues.

Nonetheless, the various examples portrayed a consistent pattern while also revealing quite considerable differences regarding the context in which AI's worth was realized. To illustrate, the offshore wind project demonstrated considerable cost reduction due to less emergency vessel trips and better maintenance logistics, thus being a very expensive area. The solar-plus-storage project, in contrast, was directly granted via very precise dispatch and the enhanced wind/solar forecasting and optimization more efficient battery selling due to improved market. Referring to the hybrid wind-solar project's case, the AI assisted in preventing costly breakdowns of machinery and provided better scheduling in a complicated, multi-technology setting. In the case of smart grid technology, AI not only added to system trustworthiness and managed peak load but also the degree of such automation was dependent on the limitations set by the authorities and those regarding cybersecurity.

The examination of the different projects suggests that AI is not equally instrumental across all types of energy projects and therefore, the benefits are not uniform. On the contrary, its value is manifested in terms of project features, operational priorities, regulatory conditions, and organizational readiness. Such discoveries stress the fact that the deployment of AI in renewable energy systems, apart from being technologically advanced, needs the human skills and the environment to be in harmony.

4.4 SUMMARY

In this chapter, the empirical evidence from the four qualitative case studies was presented, highlighting the diverse contexts of AI usage in major sustainable energy projects and the factors affecting its impact, which were identified as technical, human and organizational. The chapter brought together case-specific findings with cross-case patterns to show that AI, while always enhancing operational efficiency, is still limited by the trust, data preparedness, system integration, and contextual conditions. The next chapter will use these findings as a springboard for a discussion of their broader theoretical implications and for drawing overall conclusions from the study.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 INTRODUCTION

This chapter presents the key findings of the study and makes suggestions that are informed by the empirical data. The findings are strictly related to the research goals introduced in the first chapter, and they depend on the cross-case comparison of four significant sustainable energy projects each. Additionally, the chapter offers both theoretical and practical recommendations that are aimed at the future of research and the effective integration of AI in energy project management, thereby providing support to the conclusions.

5.2 CONCLUSIONS

Based on the qualitative case studies' data, the final conclusions of this research study are presented below. Each conclusion relates to a research aim and indicates the trends that were proceeding over the four case studies. The conclusions, when viewed collectively, provide a comprehensive understanding of the role of artificial intelligence (AI) in the management of large-scale sustainable energy projects.

Conclusion 1: AI contributes to improved operational performance in large-scale sustainable energy projects

The results indicate that the use of AI in large-scale sustainable energy projects is a major contributor to better operational performance. The aspects that got better include forecasting accuracy, predictive maintenance, energy dispatch optimization, peak load management, and grid reliability. The gains in performance were visible in all four cases, however, the results varied by project type. The consistency of improvement across all the different situations reveals that AI is a flexible and strong tool for managing the complexity and uncertainty of today's energy systems, but it will only deliver benefits if the correct implementation practices are followed.

Conclusion 2: The effectiveness of AI depends on alignment with project context and operational priorities

The findings of the study returned the concluding observation that artificial intelligence may not fit uniformly well with every kind of energy project. Rather the project's specific features and operational goals are the factors determining the effectiveness of the technology. Offshore wind projects got the most benefits in the form of decreased maintenance logistics and reduced downtime, solar-plus-storage projects reached higher market revenue due to better forecasting and optimization, hybrid plants lowered risk by killing costly failures, and smart grids improved reliability and peak demand management. The implication of this discovery is that the context is the king when it comes to AI's worth and that its influence is greatest when the applications are consistent with the actual operational problems and priorities of a project.

Conclusion 3: Human factors play a decisive role in successful AI adoption

The results indicated that people and organizations play a major role in the successful implementation and usage of AI technologies. Trust in the AI results, system transparency, user education, and perceived user-friendliness were identified as the key factors for acceptance in all case studies. Users who comprehended the process of recommendation generation and had a certain level of control over the final decision considered the AI systems to be more effective. In the cases of AI implementation where gradual introduction was applied, resistance was lessened and confidence was more than ever gained. This emphasizes the significance of user-centered design for systems and strongly asserts that the adoption of AI is a social process in equal measure to its being a technical one.

Conclusion 4: Data quality and system integration remain major challenges

The research findings point out that the energy sector still faces data readiness and system interoperability issues as the main obstacles to the adoption of artificial intelligence. In every scenario, the problems related to old machines, using different brands, varying data formats, and poor communication infrastructure played a significant role in the performance of AI and also stretched the time for implementing it. The problems faced led to a higher demand for data cleansing, system integration, and also more technical work. The appearance of these issues in different types of projects indicates that data and integration problems are not merely isolated technical issues but rather systemic limitations.

Conclusion 5: Regulatory and institutional conditions shape the pace and scale of AI adoption

The findings imply that those factors discuss along with the economic ones consider AI as an essential collaborator in the future. In controlled settings such as smart grids, requiring transparency, understandability, and auditability completely automation was not possible but it was a safe and accountable system. On the other hand, government policies that support technology have shorted the time for AI adoption in such projects as solar-plus-storage plants that are getting their revenue from the market. Thus, it can be concluded that the institutional setup influences not only the choice of AI but also its application and growth, thus making regulatory alignment a very important aspect of AI determinism.

5.3 RECOMMENDATIONS

Taking into account the above conclusions, this part of the research introduces recommendations that would help to cope with the difficulties mentioned in the study. Similar to the research aims and results, the recommendations have been classified into theoretical and practical categories.

5.3.1 Theoretical Recommendations

1. Researchers are requested to take a look at AI as a technical tool but rather as a part of the wider system that includes people, processes and institutional structures. This way would help to prevent interpretations based mainly on technology that are not taking into account the human and organizational aspects.
2. The results point out that reliance on AI is a gradual process. Up-and-coming research may employ longitudinal designs to study the transitions in AI perception when it goes from consultation to complete automation.
3. As different situations between controlled smart grids and market-based generation projects appear, the regulatory context proves to be a significant factor. One approach to the matter of governance influencing AI adoption is through comparative studies across different countries or regulatory systems which allow going deeper into the issue.

4. Instead of being treated as a background issue, data quality should be recognized as a crucial aspect that future research should concentrate on. One of the main reasons for the challenge of the AI that most researchers are dealing with is that AI is not very good with unstructured data, especially in the case of legacy systems.
5. The experience from hybrid plants shows that these models help in increasing reliability and user trust. Theoretical inquiry could focus on refining the models for the intersecting areas of engineering expertise and machine learning.

5.3.2 Practical Recommendations

Organizations should not rush to the wide-scale deployment of AI but rather, as a first step, determine the areas where AI could assist in overcoming operational issues of very high cost, such as $10 million for offshore maintenance or $2 million for peak demand management.

1. Artificial intelligence entering the workplace in the role-first advising gradually day by day, practically user gaining trust and understanding then will be able to apply the whole automation, and that is why this model is ideal for such places where safety regulations are very strict.
2. Quality of the sensors, communication networks, and data standardization are to be the main factors for consideration by organizations before the installation of AI tools. At the beginning, if data problems are taken care of, the systems will be more efficient and no time will be wasted.
3. Regular training sessions and user-friendly system interfaces are among the means that can raise user confidence and reduce resistance. AI tools should not only make recommendations but also clarify the reasoning behind them rather than operate like black boxes.
4. Bad practice of waiting until the last moment to communicate with regulators can lead to thorough discussion over compliance requirements and, thus, to slower approval processes at a later stage. Making the system's auditability and safety features known from the very beginning can nonetheless help to smooth out the approval process.
5. In the case of the initial investment being substantial and the benefits uncertain, the introduction of AI technologies may be accelerated by providing incentives like those in solar-plus-storage projects.

5.4 SUMMARY

This chapter has offered conclusions and suggestions based on the empirical evidence gathered through four qualitative case studies. The case studies collectively point out that AI, while being a very potent technology for managing large-scale sustainable energy projects, will only be successful if human beings accept it, data is available and ready for use, systems are integrated, and the institutions are supportive. The study, while dealing with both theoretical and practical aspects, opens up future research and decision-making in the energy sector regarding AI application with more knowledge and less risk.

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Annex 1

Interview Questions

1. Can you describe your role and involvement in this project?
2. What types of AI tools or systems are used in this project, and at which project stages (planning, execution, monitoring)?
3. What were the main reasons for introducing AI in this project?
4. How has AI affected forecasting accuracy or operational planning?
5. In what ways has AI influenced maintenance planning or fault detection, if at all?
6. Has AI changed how energy dispatch, load management, or system coordination is handled?
7. Overall, how would you assess the impact of AI on operational performance and reliability?
8. How do users perceive and trust AI-generated recommendations in daily operations?
9. How important is it for staff to retain control over decisions when using AI systems?
10. What data-related challenges (e.g., data quality, system integration, legacy equipment) have affected AI implementation?
11. Were there organisational or regulatory factors that influenced how AI could be used?
12. What do you see as the main benefits of AI adoption in this project?
13. What limitations or challenges remain unresolved?
14. What lessons have been learned from implementing AI in this project?
15. How do you see the future role of AI in managing large-scale sustainable energy projects?