European Journal of Energy Research
Vol 5 | Issue 6 | November 2025
ISSN 2736-5506

RESEARCH ARTICLE

Predictive Maintenance and Digital Twins for Greener Power Generation: Case Studies from China, Germany, Norway, and The Netherlands

Agil Mammadov[1,*] and Yaroslav Danilov[2]

ABSTRACT

Predictive maintenance (PdM), supported by artificial intelligence (AI) and digital twin methods, is gaining attention as a practical and cost-efficient way to manage power generation assets. In the renewable energy sector, where performance, stability, and cost control are central concerns, PdM enables operators to anticipate equipment faults, schedule interventions more effectively, and reduce unplanned downtime. This paper reviews how such approaches are being applied in four different national contexts: China, Germany, Norway, and the Netherlands, and considers their contribution to cleaner and more reliable energy systems. The discussion highlights several patterns that emerge across these countries. In China, the rapid expansion of wind and solar capacity has driven the use of PdM to improve fault detection and optimize turbine and panel performance. Germany demonstrates how PdM can be integrated into broader energy transition policies, using digital twins and AI to balance fluctuating renewable output with grid demands. Norway shows the value of predictive tools in extending the life and efficiency of hydropower equipment, while the Netherlands illustrates the benefits of PdM in offshore wind projects, where remote monitoring and early fault recognition are critical. Evidence from these cases points to three consistent outcomes: improved uptime of renewable assets, measurable reductions in maintenance costs, and smoother integration of intermittent power sources through more advanced grid management. Taken together, these findings suggest that PdM is not only a set of technical tools but also a strategic component in building sustainable, resilient, and economically viable energy systems. Its wider adoption may help accelerate the transition toward low-carbon power on a global scale.

Keywords: Digital twins, predictive maintenance, power generation, smart grids.

Submitted: September 12, 2025
Published: November 23, 2025

10.24018/ejenergy.2025.5.6.179

[1] *MGIMO University, Moscow, Russia.*
[2] *MCS School, Moscow, Russia.*

****Corresponding Author:***
e-mail: agilmsu@gmail.com

1. INTRODUCTION

With the recent introduction of the Internet of Things (IoT) and rapid development of artificial intelligence (AI) technologies, the maintenance field has undergone significant transformation. Traditionally, only two forms of maintenance are available: reactive and Preventive Maintenance (PM). Reactive maintenance is performed only after component failure, which limits operational efficiency and increases safety and repair costs. Preventive maintenance schedules inspections and repairs at fixed intervals to avoid failures but can cause excessive maintenance and operational disruptions.

Recently, Predictive Maintenance (PdM) was introduced as an innovative approach. Maintenance is applied only when analytical models predict failure or degradation based on data gathered from the IoT, analyzed via Big Data techniques, and computed with powerful hardware. This approach reduces costs, enhances safety, and extends machinery lifespan by performing only the necessary maintenance [1].

The increasing human population is driving higher electricity demand, making sustainable and effective energy systems crucial. Renewable sources such as photovoltaics, wind turbines, and hydropower are variable and decentralized, requiring the agile management of distributed

Copyright: © 2025 Mammadov and Danilov. This work is under a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.

microgrids. AI algorithms analyze historical weather, wind, and solar data, thereby enhancing the effectiveness of renewable systems. AI-powered smart grids react to real-time disturbances to balance demand and supply, thereby increasing grid stability and energy yield while prolonging machinery life [2], [3].

Traditional preventive maintenance has drawbacks in terms of renewable energy because of the downtime during maintenance. The PdM, combined with machine learning, machine vision, smart sensors, and digital twin technology, has emerged as the optimal solution. Digital twins represent virtual copies of physical systems with varying functional levels from standalone to autonomous, enabling forecasting, diagnostics, prescriptive recommendations, and closed-loop control. PdM shifts maintenance from time to condition-based, enhancing cost-efficiency and reliability.

2. WHY THIS MATTERS

Predictive maintenance in power generation addresses the key factors of clean energy transition, namely: climate impact, grid stability, and economic efficiency. AI-based PdMs avoid unplanned outages and inefficient equipment use, thereby lowering fuel consumption and emissions. Maintaining agility in renewable-dependent grids is essential for a supply-demand balance without reliance on fossil fuels. Economically, extended asset lifespans and optimized maintenance schedules generate significant annual savings. These benefits accelerate the delivery of reliable, affordable, and sustainable electricity toward net-zero goals.

3. LITERATURE REVIEW

The concept of predictive maintenance (PdM) has evolved through several technological generations, from reactive and preventive strategies to condition-based and predictive approaches powered by data analytics. Foundational reviews such as Zhu *et al*. [1] established PdM as a key outcome of the convergence of the Internet of Things (IoT), Big Data, and machine learning, emphasizing its role in reducing maintenance costs and extending asset life.

In the energy sector, research has increasingly examined how PdM supports renewable generation systems, where variability, decentralization, and weather dependency complicate operations. Hamdan *et al*. [3] reviewed artificial intelligence (AI) applications in renewable energy, identifying PdM and energy optimization as the most mature and impactful use cases. Their study highlighted the role of sensor data, machine learning algorithms, and digital platforms in detecting anomalies and predicting equipment degradation.

Digital twins—virtual models of physical assets—have expanded PdM's predictive potential. Stadtmann *et al*. [4] surveyed emerging digital twin applications in wind energy, classifying five maturity levels from basic monitoring to autonomous control. The authors emphasized that combining SCADA data, computational fluid dynamics, and AI enables proactive fault detection and improved turbine efficiency. Similar findings by Bossert *et al*. [5] show that multi-level digital twin architectures can simulate turbine behavior under real-time weather conditions, thus bridging the gap between design and operation.

Industrial and corporate studies provide complementary insights. Siemens and NVIDIA demonstrated that physics-informed digital twins can reduce corrosion-related downtime in combined-cycle plants by up to 10%, while Fraunhofer's DeepTrack project [6] applied PdM to solar arrays using adaptive algorithms to adjust panel orientation dynamically. These examples confirm PdM's relevance across diverse renewable assets.

From a systems perspective, international organizations such as the International Energy Agency (IEA) [7]–[9] identify PdM and digital twins as enabling technologies for grid flexibility and decarbonization. IEA country reviews of Germany, Norway, and the Netherlands note that predictive analytics enhance reliability, reduce maintenance costs, and support the integration of variable renewables.

However, existing research remains fragmented. Most studies focus on single technologies, sectors, or national contexts, lacking a comparative synthesis that evaluates PdM's adaptability across differing energy systems. Furthermore, few analyses explicitly connect PdM's operational impacts with macro-level sustainability goals. This study addresses these gaps by comparing experiences in four contrasting energy systems—China, Germany, Norway, and the Netherlands—drawing cross-country lessons on how AI-driven PdM and digital twins contribute to greener, more reliable power generation.

4. METHODOLOGY

This study reviews specialized technical studies and corporate reports to draw conclusions on the impact of PdM and AI analytics. It compiles data from governmental and corporate sources and examines the current PdM achievements and statistics across selected countries. A cross-country comparison contrasts the experiences of industry leaders in identifying challenges and lessons learned.

Tables I–V summarize the methodology employed in this study. Table I outlines the general academic, corporate, and technical sources used to establish the analytical framework. Tables II–V present country-specific case studies, detailing for each source its type, analytical method, and relevance to the research objectives. Together, these tables provide the foundation for the cross-country comparison of predictive maintenance (PdM) and digital-twin applications in the power generation sector:

5. COUNTRY CASE STUDIES

5.1. China

China operates the largest number of coal-fired power plants, but also leads to renewable generation, accounting for 38% of the country's power from low-carbon sources such as hydro, wind, and solar power. Electricity demand is rapidly growing owing to electrification and AI-driven

TABLE I: General Sources and Analytical Methods Used in the Study

Source	Type of source	Method of analysis	Relevance to research
A Survey of Predictive Maintenance: Systems, Purposes, and Approaches	Academic preprint	Literature review of PdM and IoT integration	Foundational theoretical basis for predictive vs. preventive maintenance.
IJSRA 2024	Peer-reviewed article	Critical reading, synthesis of AI & Big Data in grids	Shows how AI improves grid stability and CO_2 reduction.
Siemens AI overview	Corporate site	General review	Provides general industry framing for AI in energy.
Stadtmann F *et al*. *Digital Twins in Wind Energy: Emerging Technologies and Industry-Informed Future Directions*. IEEE Access. 2023.	Academic review	Literature synthesis of digital twin applications in wind energy, including classification of maturity levels, survey of AI/ML techniques, and case study references from industry	Supports predictive maintenance framework by detailing current digital twin technologies in wind farms (sensor fusion, SCADA integration, AI for anomaly detection). Provides a maturity scale useful for cross-country comparison of implementations.

TABLE II: China: Sources and Case Study Methods for Predictive Maintenance in Power Generation

Source	Type of source	Method of analysis	Relevance to research
CREA 2025 China coal power report	NGO/Think tank	Data/statistical analysis	Provides baseline on fossil-heavy energy mix, urgency of renewables.
Ember—China country data	NGO database	Data mining	Tracks share of renewables and growth trends.
China Power company page	Corporate website	Contextual review	Provides company-level energy operations context.
Wuqiangxi hydropower	Corporate report	Case study extraction	Example of predictive maintenance in a hydro plant.
Jinweizhou hydropower	Industry database	Technical profile analysis	Gives capacity and operational data for Chinese hydro PdM.
Hydropower.org case study	NGO/Industry case study	Case review	Documents AI + PdM applications in hydropower globally (China included).
Bentley case—POWERCHINA 80 MW solar	Corporate case	Document analysis	Shows digital twin use in solar farm planning.
Longyuan Power wind PdM	Corporate release	Case-specific analysis	Example of an AI-based wind turbine PdM project (200+ turbines).

TABLE III: Germany: Sources and Case Study Methods for Predictive Maintenance in Power Generation

Source	Type of source	Method of analysis	Relevance to research
IEA Germany 2025	IEA country report	Policy/system analysis	Frame Germany's renewable strategy and maintenance needs.
BASE nuclear phase-out	Government page	Policy context	Context for Germany's energy transition away from nuclear.
IEA France country profile	IEA country report	Comparative analysis	Contextualizes German reliance on French nuclear imports.
BMWi 2024—Germany & France grid flexibility	Government press release	Policy context	Shows regional interconnection and flexibility agreements.
CEIC—Germany electricity imports	Database	Data analysis	Quantifies German dependence on imports.
Fraunhofer DeepTrack	Research project	Review of technical design	Example of digital twin + deep learning in solar plants.
Siemens/NVIDIA case	Corporate blog	Technology impact analysis	Digital twin PdM in power plants (combined cycle).
Schluchseewerk Flyer (Siemens)	Corporate flyer	Case-specific review	PdM in German pumped-storage hydropower with vibration monitoring.

facilities, necessitating reliable grid infrastructure. Considering the nuances of renewable sources of electricity, such as dependence on external factors and the need for regular maintenance, the integration of AI with its outstanding predictive and analytical capabilities into the working processes is an obvious choice for the Chinese energy system [10]–[12].

Examples of PdM application in China include:

1. *Wuqiangxi and Jinweizhou Hydropower Plants*: Since 2020, these plants have employed a Smart Remote O&M system utilizing AI tools, machine vision, sound recognition, and sensors for predictive maintenance. Benefits include 10% maintenance cost savings, a 0.5% increase in available generation time, and 0.3% more power output [13]–[15].
2. *POWERCHINA Hubei Electric Engineering PV Station*: An 80 MW solar plant that used Bentley's

TABLE IV: THE NETHERLANDS: SOURCES AND CASE STUDY METHODS FOR PREDICTIVE MAINTENANCE IN POWER GENERATION

Source	Type of source	Method of analysis	Relevance to research
IEA Netherlands electricity page	IEA database	Statistical analysis	Provides an electricity mix and policy targets.
IEA Netherlands 2024 country report	IEA report	Policy/system review	Comprehensive review of the Dutch grid and renewables.
TenneT website	TSO/corporate site	News analysis	Provides operational updates and real-world PdM examples.
RAP—Transparent Grids toolkit	NGO toolkit	Policy + governance analysis	Explains the importance of grid transparency and AI tools.
em-power.eu—digital twin grids	Industry news	Technology review	Case overview of digital twin applications in grids.
Van Dinter et al. 2023, PHM	Peer-reviewed research paper	Methodological case review	Provides a detailed case study of PdM for Dutch cable joints.

TABLE V: NORWAY: SOURCES AND CASE STUDY METHODS FOR PREDICTIVE MAINTENANCE IN POWER GENERATION

Source	Type	Method of analysis	Relevance to research
IEA Norway country page	Government report	Statistical and policy analysis	Provides an energy mix overview and strategic priorities for Norway's energy transition.
IEA Norway 2022 Energy Policy Review	Country review	Policy & system evaluation	Contextualizes national energy strategy and infrastructure challenges.
Business Insider article on Elvia's digital twin	Media report	Case study summarization	Offers insights into AI-enhanced grid resilience and digital twin deployment.
Disruptive Technologies article on Elvia sensors	Industry article	Technology implementation analysis	Highlights IoT-based PdM solutions applied in Norway's distribution network.
Digital Twin for Wind Energy: Latest updates from the NorthWind project	Academic preprint	Conceptual frameworks & technical methods	Supplies digital twin maturity model (0–5) and methods applicable to wind energy.
NorthWind research portal (WP4)	Research center page	Research overview	Delivers strategic direction on predictive maintenance and digital twin innovation in Norway's energy sector.

digital twin technology during construction to optimize panel placement, minimize shading (<2%), and save 20 working days [16].

3. *Longyuan Power Wind Turbines*: AI-based PdM monitors over 200 turbines continuously for performance and malfunction diagnosis, thereby enabling a shift from preventive to predictive maintenance [17].

5.2. Germany

Germany targets net zero by 2045 and phases out nuclear power by 2023. It imports electricity from France, which relies heavily on nuclear (64.3%). Owing to reduced natural gas availability, the demand for renewables is increasing, requiring AI deployment for grid stability [7], [18]–[21].

PdM examples in Germany:

1. *Fraunhofer DeepTrack*: Digital twins and data-driven algorithms used in the Merdingen solar pilot plant adjust panels dynamically based on weather conditions to maximize output. The project aims to reduce upgrade costs for widespread adoption [6].
2. *Siemens Energy & NVIDIA*: Physics-infused digital twins simulate real-time steam and water flows in combined-cycle power plants and predict corrosion to reduce planned shutdowns. A 10% reduction in downtime can save $1.7 billion industry-wide [22], [23].

5.3. The Netherlands

Electricity generation in 2023 is 37.9% natural gas, 24% wind, and 16.5% solar PV. The Dutch government plans to expand nuclear capacity and address grid congestion through a "National Grid Congestion Action Programme" focused on grid extensions, smart solutions, and improved grid insight [8], [24]–[26].

PdM initiatives include:

1. *Alliander and Siemens* introduced Gridscale X software, combining digital twins and AI analytics to boost grid efficiency by 30%, optimize energy distribution, and manage congestion [27], [28].
2. *Alliander and Wageningen University*: Digital twin framework for model-based systems engineering monitors medium-voltage cable joint degradation in real-time, reducing outages and increasing asset lifespans [29].

5.4. Norway

Norway's electricity system is among the world's cleanest, with 95.6% renewables (89.1% hydropower and 9% wind). Despite fossil fuel exports, domestic electrification is increasing, with some high-energy sectors still being fossil-dependent [9], [30].

Examples include:

1. *Elvia Smart Grids*: Collaboration with Siemens and Disruptive Technologies builds a digital twin of a low-voltage network (Gridscale X LV Insights), real-time asset monitoring, and wireless temperature

sensors. This shifts maintenance from reactive to predictive, preventing outages [31], [32].

2. *NorthWind Project*: Develops digital twins for wind turbines with a maturity model (0–5) and hierarchical asset information models conforming to ISO 81346, and uses reduced-order and fluid dynamics models for simulations. Real-time visualizations and wind farm layout optimization improve the predictive maintenance and operational efficiency [4], [5].

6. Cross-Country Comparison

AI-driven predictive maintenance (PdM) and digital twin technologies improve renewable integration, grid stability, and cost efficiency across different national contexts. The case studies demonstrate that although China, Germany, the Netherlands, and Norway operate under distinct energy mixes and policy frameworks, similar advantages are consistently achieved. In China, PdM supports the rapid scaling of renewables along with a dominant coal sector. Germany uses digital twins to stabilize the grid during the phase-out of nuclear power. The Netherlands applies PdM to ease grid congestion and manage high shares of wind and solar power, whereas Norway employs it to enhance the reliability of its largely hydro-based system.

Despite these differences, common benefits stand out, such as higher uptime, reduced maintenance costs, and smoother integration of variable renewables. These results confirm that PdM is not limited to a single type of energy system but can be adapted to diverse conditions. The shared outcomes strengthen the case for wider adoption, showing that predictive approaches not only optimize operations but also accelerate progress toward global clean energy goals.

7. Conclusions

This study examined how predictive maintenance supported by artificial intelligence and digital twin technologies is changing asset management in power generation. Shifting from scheduled or reactive maintenance to condition-based strategies makes it possible to improve reliability, reduce costs, and extend the useful life of equipment. These gains are closely tied to the wider goals of efficiency and sustainability that underpin today's energy transition.

Case studies from China, Germany, the Netherlands, and Norway show that even in very different energy systems, common results appear reduced downtime, more stable integration of renewables, and stronger grid resilience. This suggests that predictive maintenance is not limited to specific technologies or policy settings but can be applied broadly across diverse national contexts.

At the same time, barriers remain. High initial costs, the need to train personnel, and the lack of shared standards for digital twins all limit wider use. In addition, the effective application of predictive maintenance depends on access to high-quality operational and failure data, which are often scarce in power-generation assets designed for long service lives. Data collected from different sensors and control systems can also vary in format and resolution, complicating model training and integration. Developing accurate digital-twin models requires significant computational resources and specialised expertise, which may not be available to all operators. Organisational resistance and difficulties in embedding predictive insights into established maintenance workflows further restrict progress. Addressing these technical and institutional challenges will be necessary if predictive maintenance is to move from isolated projects to industry-wide practice [33].

Overall, the evidence indicates that predictive maintenance is more than a technical improvement. It should be seen as a strategic instrument for building cleaner, more reliable, and more cost-effective power systems. The lessons from early adopters provide a useful starting point, while future research and cooperation will determine how far and how quickly these approaches can spread.

Conflicts of Interest

The authors have no conflicts of interest to declare.

Abbreviations

AI	Artificial Intelligence
BMWi	Bundesministerium für Wirtschaft und Energie (Federal Ministry for Economic Affairs and Energy, Germany)
CO_2	Carbon Dioxide
IEA	International Energy Agency
IoT	Internet of Things
ISO	International Organization for Standardization
MW	Megawatt
NGO	Non-Governmental Organization
O&M	Operation and Maintenance
PdM	Predictive Maintenance
PHM	Prognostics and Health Management
PM	Preventive Maintenance
PV	Photovoltaic
SCADA	Supervisory Control and Data Acquisition
TSO	Transmission System Operator

References

[1] Zhu T, Ran Y, Zhou X, Wen Y. A survey on Intelligent Predictive Maintenance (IPDM) in the era of fully connected intelligence. *IEEE Commun Surv Tutor*. 2025;1:1–1. doi: 10.1109/comst.2025.3567802.

[2] Montasham J. Review article-renewable energies. *Energy Proc*. 2015;75:1234–40. doi: 10.1016/j.egypro.2015.07.774.

[3] Hamdan A, Ibekwe KI, Ilojianya VI, Sonko S, Etukudoh EA. AI in renewable energy: a review of predictive maintenance and energy optimization. *Int J Sci Res Appl (IJSRA)*. 2024;11(1):3–4. doi: 10.30574/ijsra.2024.11.1.0112.

[4] Stadtmann F, Rasheed A, Kvamsdal T, Johannessen K, San O, Kolle K, *et al.* Digital Twins in Wind Energy: emerging Technologies and Industry-Informed Future Directions. *IEEE Xplore*. 2023;11:110762–95. doi: 10.1109/ACCESS.2023.3321320.

[5] Rasheed A, Stadtmann F, Fonn E, Tabib M, Tsiolakis V, Panjwani B, *et al.* Digital Twin for Wind Energy: latest updates from the NorthWind project. arXiv preprint. 2024;1:3–6. doi: 10.48550/arXiv.2403.14646.

[6] Fraunhofer ISE. *DeepTrack Solar Project*. Fraunhofer Institute for Solar Energy Systems; 2024. Available from: https://www.ise.fraunhofer.de.

[7] IEA. *Germany Energy Report 2025*. International Energy Agency; 2025. Available from: https://www.iea.org.

[8] IEA. *Netherlands Electricity Profile*. International Energy Agency; 2023. Available from: https://www.iea.org.

[9] IEA. *Norway Energy Policy Review*. International Energy Agency; 2022. Available from: https://www.iea.org.

[10] CREA. *China Coal Power Report 2025*. Centre for Research on Energy and Clean Air; 2025. Available from: https://energyandcleanair.org.

[11] Ember. *China Country Data*. Ember Climate; 2024. Available from: https://ember-climate.org.

[12] China Power Company. *Energy Operations*. 2024. Available from: https://www.chinapower.com.

[13] Chemtecone. *Wuqiangxi Hydropower*. 2024. Available from: https://www.chemtecone.com.

[14] Power-Technology. *Jinweizhou Hydro Plant Profile*. 2024. Available from: https://www.power-technology.com.

[15] Hydropowerorg. *AI in Hydropower: Case Study*. International Hydropower Association; 2023. Available from: https://www.hydropower.org.

[16] Bentley Systems. *POWERCHINA 80 MW Solar Digital Twin*. Bentley Case Studies; 2022. Available from: https://www.bentley.com.

[17] CEIC. *Longyuan Power Wind Turbine Predictive Maintenance*. CEIC Data; 2022. Available from: https://www.ceicdata.com.

[18] Federal Government of Germany. *Nuclear Phase-Out Policy*. 2023. Available from: https://www.bundesregierung.de.

[19] IEA. *France Country Profile*. International Energy Agency; 2024. Available from: https://www.iea.org.

[20] BMWi. *Press Release: Germany & France Grid Flexibility*. German Federal Ministry for Economic Affairs and Energy; 2024. Available from: https://www.bmwi.de.

[21] CEIC. *Germany Electricity Imports*. CEIC Data; 2024. Available from: https://www.ceicdata.com.

[22] NVIDIA. *Siemens Digital Twin for Energy Systems*. NVIDIA Blog; 2023. Available from: https://blogs.nvidia.com.

[23] Siemens Energy. *Predictive Maintenance in Hydropower*. 2021. Available from: https://www.siemens-energy.com/global/en/home/products-services/product-offerings/omnivise-digital-solutions/predictive-solutions.html.

[24] IEA. *Netherlands Country Report 2024*. International Energy Agency; 2024. Available from: https://www.iea.org.

[25] TenneT. *Corporate Updates on Grid Operations*. TenneT; 2024. Available from: https://www.tennet.eu.

[26] RAP. *Transparent Grids Toolkit*. Regulatory Assistance Project; 2023. Available from: https://www.raponline.org.

[27] em-powereu. *Digital Twins in Power Grids*. 2024. Available from: https://www.em-power.eu.

[28] Siemens. *AI Solutions for Energy Systems*. Siemens Corporate Publications; 2024.

[29] Van Dinter R, Ekmekci G, Rieken S, Tekinerdogan B, Catal C. Architecting a digital twin-based predictive maintenance system for modelling cable joint degradation. *Prognostics Health Management (PHM)*. 2023;4(1):1–5. doi: 10.36001/phmap.2023.v4i1.3753.

[30] IEA. *Norway Energy Profile*. International Energy Agency; 2023. Available from: https://www.iea.org.

[31] Business Insider. *Elvia Digital Twin Case Study*. 2024. Available from: https://www.businessinsider.com.

[32] Disruptive Technologies. *Smart Sensors for Grid Applications*. 2024. Available from: https://www.disruptive-technologies.com.

[33] NorthWind Research Centre. *NorthWind Project Portal*. 2024. Available from: https://northwindresearch.no.