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Article

Digital Twin–Enabled Grid Resilience: Predictive Failure Analysis and Proactive Control for Climate-Driven Power System

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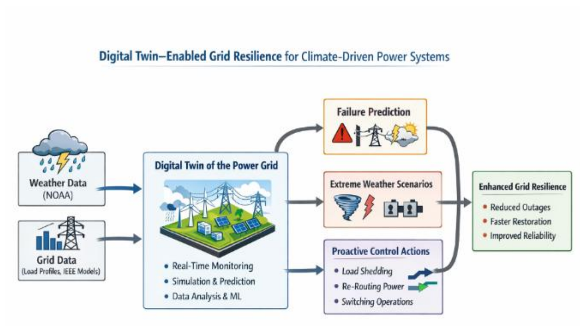
Abstract: This study develops a Digital Twin-enabled framework to enhance power grid resilience against climate-driven disruptions. Using the IEEE 30-bus system and NOAA climate data (2000–2025), the framework applies predictive failure analysis and proactive control strategies to mitigate risks from thermal, wind, and moisture stress. Results show reduced failures, outage probability, and improved grid stability under extreme weather. *Corresponding Author: Siva Prakash Sunkara, Tata Consultancy Services, Illinois, USA Tel:+1 7085153155 -Sivaprakashsunkara@ieee.org INDEX TERMS: Digital Twin, Power Grid Resilience, Climate Change, Predictive Failure Analysis, Proactive Control, IEEE 30-Bus System, Renewable Energy Integration, Thermal Stress, Mechanical Stress, Moisture Stress, Extreme Weather Simulation, Grid Reliability.



Keywords: Digital Twin, Power Grid Resilience, Climate Change, Predictive Failure Analysis, Proactive Control, IEEE 30-Bus System, Renewable Energy Integration, Thermal Stress, Mechanical Stress, Moisture Stress, Extreme Weather Simulation, Grid Reliability.

1. Introduction

Digital Twin-Enabled Grid Resilience refers to the application of digital twin (DT) technology, which creates a real-time virtual replica of a physical power system, to enhance the reliability, stability, and robustness of electrical grids facing climate-driven disruptions. The digital twin system uses its two main functions of simulation and monitoring to perform ongoing evaluations of grid components while enabling operators to detect faults and predict future breakdowns, which they then use to prevent system failures. Digital twin technology enables utilities to maintain uninterrupted power delivery during extreme weather events by using its combination of predictive failure assessment and active control systems to develop a grid system that adapts to climate variations while sustaining operational resilience.

Digital Twin technology provides a groundbreaking solution by generating an accurate digital representation of grid infrastructure and operational activities [1–5]. It allows real-time tracking of system states, forecasting of future scenarios, and decision support for active operational management. This continuous link between the physical grid and its digital counterpart strengthens overall system resilience, particularly as power networks face increasing exposure to extreme weather patterns and higher penetration of variable renewable energy sources.

The utilised digital twin-based framework to improve grid resilience against climate change impacts. The method combines weather conditions and electricity demand predictions with asset performance assessments and equipment breakdown forecasts to discover system weaknesses that could lead to power disruptions. The operators can create failure situations within a simulated digital space, which enables them to evaluate protection measures that include load redistribution, equipment switching operations, and equipment preconditioning without endangering the actual power grid. The fail-in-the-computer-first method helps organisations to develop safe operational procedures that decrease the possibility of unexpected system failures.

- The NOAA datasets provided climate data, which was collected and processed, and they stored it in Excel for future research.
- The researchers extracted temperature stress, wind stress, and moisture stress data according to climatic conditions to study their effects on grid components.
- The simulation framework of the IEEE 30-bus system used these stress indicators to test system performance during extreme weather conditions.

The predictive failure analysis is to determine which components would experience failure, and they established proactive control solutions to prevent future equipment breakdowns. The simulation results show that the digital twin-enabled system reduces outage rates and improves system recovery time while providing better operational decision-making support. The framework combines predictive analytics with proactive control to create a scalable solution that will handle upcoming climate challenges and integrate renewable energy sources at high levels. The study shows that digital twin technology functions as a powerful tool that helps increase grid resilience while providing stable and reliable power delivery during periods of extreme environmental change.

2. Related Works

To develop a Digital Twin architecture to enhance resilience in climate-driven power grids.

The research examines how AI-Integrated digital twins can protect renewable energy systems from climate-related disturbances, according to their findings. They present a modular co-simulation framework that uses HELICS middleware to integrate physical grid dynamics with weather disturbances and cyber-physical control loops [8]. The system uses deep reinforcement learning agents to determine and distribute optimal energy resources, which include solar, wind, and battery storage systems, leading to lower energy waste and faster recovery during unpredictable weather patterns. The IEEE 30 bus system tests demonstrate that AI-powered digital twins provide substantial benefits for grid operation efficiency, voltage management, and system resilience. The research investigates urban digital twins, which IoT technology drives to enhance city planning and infrastructure development through predictive city simulations [9]. The self-evolving systems use sensor information and analytics to create systems that automatically modify themselves according to fresh urban environmental updates. Cities can use IoT-driven digital twins to create different infrastructure models that help them enhance their operations while building climate resilience and developing sustainable urban areas. The authors present a bibliometric analysis that examines the use of digital twin technology and artificial intelligence for improving infrastructure resilience [10]. The research identifies six domains that connect sensor technology, artificial intelligence, and resilience research. The researchers examine high-resolution digital twin systems that study forest ecosystems through the combination of remote sensing and process-based modelling. The research establishes methods for predicting climate change impacts on carbon, water, and nutrient cycles while it demonstrates data integration methods and adaptive management techniques that help build ecological resilience [11].

To enable predictive failure analysis and proactive operational control through simulation and decision support.

The research presents a decision-making model that enables fast detection and fault-finding of power grid failures. Through its combined functions of topology analysis and SCADA system elements and Decision support (SC-DAS) systems, the system enables operators to monitor and control their operations. The model uses phasor measurement units and SCADA data to achieve better fault isolation results, which decrease system downtime and improve grid reliability in microgrids and systems that use renewable energy sources. The authors show how artificial intelligence benefits cyber-physical power systems by improving grid performance and renewable energy integration and enhancing security measures [12]. The study demonstrates AI's role in the cyber-physical power systems. Innovative grid technologies have been brought to life through AI, enabling two-way energy flow, real-time monitoring, and predictive analysis. The advanced algorithms brought two results, which allowed renewable energy sources to be better integrated and energy storage systems to achieve their optimal performance. The combination of AI-based intrusion detection systems with anomaly detection methods and reinforcement learning techniques has improved cybersecurity protection systems. They addressed challenges related to governance and transparency of AI “black box” operations by implementing federated and distributed learning approaches. Overall, a vision has been created for the U.S power grid to be transformed into resilient, intelligent, and sustainable infrastructure. It is recognised that strategic investments and regulatory oversight are crucial to ensure that AI-enabled power systems are efficient for long-term energy security. Interoperability, data governance, and cybersecurity challenges, especially related to AI “black-box” models, privacy, and cross-domain data fusion, remain insufficiently addressed for deployment in operational power grids. [13].

The research study investigates AI-powered intelligent electricity distribution networks, which dedicate their research efforts to three primary areas of study: current electricity demand predictions, electricity system failure identification, and renewable energy power source implementation. The researchers used machine learning and deep learning methods to demonstrate that these technologies increase grid system resilience through better demand forecasting capabilities and better management of renewable energy supply fluctuations and protection against cascading system failures, while they found multiple issues related to data security breaches and data protection violations [14]. This study presents an all-inclusive analysis that shows how time-series forecasting methods work for maintaining digitally controlled electrical grids. This study uses historical fault data together with sensor-based time series data to establish maintenance strategies that improve grid system reliability and cost efficiency across various electrical grid components [15]. The following shows how the AI is applied across the power grid for fast fault detection and isolation for better decision-making. It highlights the AI role in load forecasting, renewable integration, and time-series prediction for preventive maintenance.

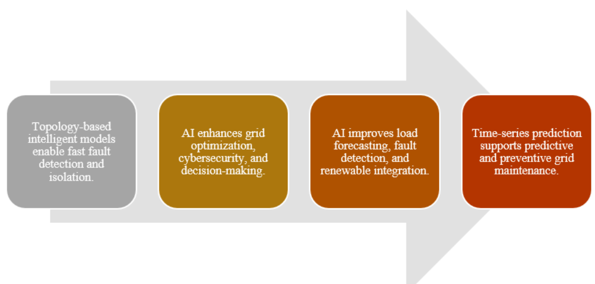


Figure 1: Role of AI in smart power grid optimisation

A. Digital twin framework

The digital twin framework for this study has been implemented using the existing **IEEE 30-bus transmission system,** which serves as a standardised benchmark for power system analysis and evaluation [16]. The test system, which is widely used, enables researchers to examine grid performance during different operating conditions without having to create a new system design. The digital twin system keeps the network system in active mode by receiving real-time updates of bus voltage levels, power flow measurements, and generator output data. The system enables accurate state estimation together with continuous system monitoring and predictive analysis of possible failures.

The IEEE 30-bus system consists of **30 buses, 6 generators, 41 transmission lines, 4 transformers, and 20 loads,** which create a simplified yet realistic representation of a power network system [17]. The digital twin system uses this system to conduct contingency assessments, operational strategy testing, and evaluation of control measures, which enhance transmission efficiency. The framework uses this pre-defined model to create a secure environment where users can test proactive control measures and predictive failure analysis while delivering dependable results that do not disrupt actual infrastructure operations.

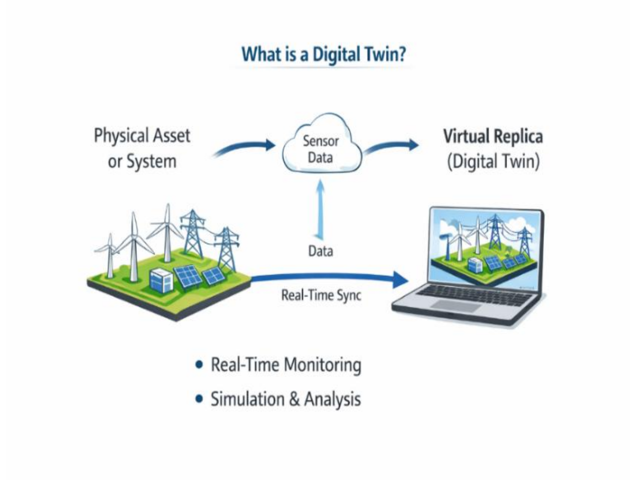


Figure 2: Digital Twin Framework

B. Predictive Failure Analysis

The climate-based digital twin assessment of the IEEE 30-bus system predicts that most system failures will occur because of thermal, mechanical, and moisture-related stresses, which affect essential grid components [18]. The transformers experience thermal overloading, insulation degradation, and accelerated ageing, and total capacity loss because they operate at high temperatures during extreme heatwave conditions [19]. The thermal sag in transmission lines occurs when temperatures rise and loads increase, which creates a greater chance of line clearance violations and potential faults [20]. High wind conditions result in mechanical forces that overhead conductors and towers must withstand, which results in conductor charging and structural fatigue and can lead to line breakage or cascading outages. Transformers and substations experience insulation failures, short circuits, and equipment corrosion and decreased dielectric strength because of moisture stresses that occur during heavy rainfall, high dew point, and flooding, snow, and icing conditions [21]. The combination of high wind and heavy precipitation creates dangerous climatic events because these conditions worsen system failures, which lead to multiple component outages. The digital twin uses climate-derived stress multipliers and operational loading data to identify vulnerable components that will fail in the future, while predicting which lines, transformers, and loads will cause system instability if not addressed.

C. Proactive Control Strategy

To prevent the predicted climate-driven failures, a set of proactive control measures is defined and evaluated within the digital twin environment. The maintenance of transformer thermal stress protection requires transformers to operate at lower capacity through three methods, which include rescheduling generating power, shedding electrical load, and redirecting electricity distribution [22]. The system uses dynamic thermal rating and temporary derating for transformers and transmission lines during extreme temperature conditions to ensure they stay within safe operational boundaries. The network implements two strategies during high wind situations, which include reducing line loading to decrease mechanical pressure and using network reconfiguration with switching operations to redirect power away from at-risk areas. The preventive isolation of high-risk lines serves as a method to stop cascading failures from occurring [23]. The organisation uses proactive measures for moisture-related risks, which include three actions that involve decreasing load capacity, isolating components located in flood zones, and enhancing reactive power to achieve voltage stability and modifying protection systems to better handle faults. The system uses controlled load reduction in severe cases, which allows equipment to operate at protected levels until it reaches the established limit of 20 per cent. The digital twin system uses predictive data to execute scheduled system maintenance through proactive control methods, which help maintain system performance while strengthening grid protection against severe weather conditions.

D. Case Study

This case study demonstrates the application of a digital twin-enabled framework for enhancing power grid resilience under climate-driven disturbances. The IEEE 30-bus transmission system is selected as a benchmark test network due to its realistic representation of generators, transmission lines, transformers, and loads, while remaining computationally efficient for scenario-based analysis [24,25]. The objective of the case study is to evaluate the effectiveness of predictive failure analysis and proactive control strategies when extreme and compound climatic conditions impact grid operation.

Historical weather data collected from the NOAA platform covering the period from 2000 to 2025 were processed and classified using percentile-based thresholds to identify extreme temperature, wind, and moisture conditions [26]. Thermal, wind, and moisture stress multipliers were derived and mapped to corresponding grid components to reflect climate-induced derating effects. The digital twin of the IEEE 30-bus system used these stress indicators to create realistic climate-driven operational scenarios, which included heatwaves, high wind events, heavy precipitation, and compound extremes.

The digital twin continuously mirrored the climate-adjusted operating conditions of the physical grid by incorporating stress-based derating into power flow simulations. The researchers conducted predictive failure analysis through two methods, which involved assessing component loading levels and using a severity index that measured operational stress and random operational variations. The analysis identified transformers as highly vulnerable during prolonged heatwaves due to thermal overloading. The analysis determined that transmission lines faced increased risk of mechanical sag and overload during high wind and high temperature events. [27] Moisture-driven conditions led to elevated risks of insulation failure and short circuits, which occurred most frequently during compound climatic scenarios.

Noting the anticipated failure scenarios, some preventive measures were undertaken in the digital twin setup. These included transformer load reduction, power flow redistribution, transmission line derating, controlled load shedding, and selective component isolation [28]. The results show that the proposed framework effectively achieved three objectives because it decreased predicted failures, reduced outage probability and enhanced system stability. The case study demonstrates that digital twin technology combined with predictive analytics and proactive control creates an effective yet expandable method for operating power grids under climate change conditions.

3. Methods

A. Dataset

The research employs a quantitative methodology, relying primarily on the collection of primary data [29]. Weather data for this study were obtained from the NOAA platform, covering the period from 2000 to 2025 [30]. The dataset contains **30 attributes** and **9,356 data points**, providing information on climate and grid analysis. Each weather station observation includes identifiers such as Station for location tagging and Date for temporal tracking, as well as geographic information, Latitude, Longitude, and Elevation that facilitate spatial analysis. Station metadata, including Name, supports reference and verification. The weather variables that were recorded include six different types of temperature measurements, along with eight different types of atmospheric pressure readings, three different visibility assessments, seven different wind speed measurements, one maximum heat measurement, one minimum heat measurement, one precipitation measurement, and one snow depth measurement. The measurements deliver complete information about temperature and humidity, atmospheric pressure, visibility, wind speed, precipitation, and snow depth. The FRSHTT flags track extreme weather events by detecting fog, rain, snow, hail, thunder, and tornado occurrences [31]. The dataset employs quality flags to maintain data trustworthiness, which enables thorough examination of the dataset. The dataset enables researchers to study climate impacts and dangerous weather patterns and grid system resilience through its combination of spatial data, time-based data, environmental data, and event-based indicators.

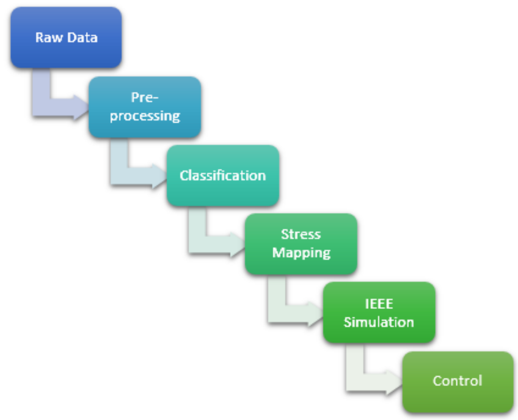


Figure 3: Digital Twin Pipeline Diagram

B. Overview

The study introduces a complete system to measure how climate change affects the ability of power grids to withstand disruptions. The research team processed historical weather information, which spanned the years 2000 to 2025, to create high-quality data that covered missing elements while extracting both time-related and location-related information. The dataset incorporated key meteorological features essential for climate–grid interaction analysis, including temperature (TEMP, MAX, MIN), dew point (DEWP), sea level and station pressure (SLP, STP), wind characteristics (WDSP, MXSPD, GUST), precipitation (PRCP), snow depth (SNDP), and extreme weather indicators (FRSHTT). Spatial and temporal attributes such as station location, elevation, and timestamps enabled accurate geospatial and time-series mapping of climate-driven stress conditions. The research team used percentile-based thresholds to normalise key meteorological variables, which included temperature, wind speed, precipitation, dew point, snow depth, and extreme weather flags, and then they created climate condition categories based on these measurements. The researchers created links between their classification system and the stress multipliers, which showed how transformers, transmission lines, and load components experienced thermal, mechanical, and moisture-based stress. The enhanced dataset was applied to the IEEE 30-bus system to simulate climate-driven failures, identifying critical vulnerabilities such as transformer overheating, line sag, and insulation breakdown. The most dangerous situations developed when snow and icing events occurred during high load conditions because their extreme stress levels created maximum risk situations. The team used proactive measures, which included temporary load reduction and moisture-aware operational controls to achieve successful risk reduction results. The methodology provides an open system that uses data to predict, measure, and control power grid risks caused by climate change.

4. Results

A. Data Pre-processing

The pre-processing stage was created to verify data quality, which would enable proper analysis work to proceed [33, 34]. The team imported all necessary Python libraries when they needed to handle data and perform numerical computations, and execute pre-processing tasks. They created a complete dataset by merging historical weather data from the years 2000 to 2025, which allowed them to conduct time-based research studies. The researchers stored the unified dataset in Excel format because it provided an accessible and transparent method for users to inspect the data.

The research team performed basic data integrity assessments to find data errors, discover undocumented information, and analyse issues related to data presentation problems [35]. Missing indicators for weather flags (**FRSHTT**) were replaced with **zero**, while missing numerical values for **SLP** and **STP** were replaced with **column means**. The team improved temporal data by extracting both year and month information from the date field to support seasonal and trend analysis. Certain meteorological variables, specifically sea level pressure (SLP) and station pressure (STP), contained placeholder values such as 999.0 and 9999.0, indicating missing measurements. The researchers used column means to replace the missing data points because they maintained statistical integrity while preventing any bias in the results. The dataset underwent analysis to detect the presence of -9999 placeholders, serving as a standard missing data representation used by NOAA, and the appropriate handling methods were implemented for all instances that are necessary.

	TEMP	DEWP	SLP	STP	WDSP	MXSPD	GUST	MAX	MIN	PRCP	SNDP	FRSHTT
0	0.355155	0.576238	0.974452	0.11092	0.059322	0.078049	1.000000	0.249330	0.487500	0.0007	1.0	0.990991
1	0.371522	0.570297	0.974452	0.11092	0.139831	0.195122	1.000000	0.294906	0.494643	0.0003	1.0	0.090090
2	0.391162	0.609901	0.974452	0.11092	0.389831	0.319512	0.016263	0.306971	0.462500	0.0008	1.0	0.090090
3	0.289689	0.471287	0.974452	0.11092	0.156780	0.246341	0.014141	0.258713	0.391071	0.0015	1.0	0.090090
4	0.328969	0.495050	0.974452	0.11092	0.343220	0.395122	0.019192	0.294906	0.362500	0.0000	1.0	0.090090
...	...	...	...	...	...	...	...	...	...	...	...	...
9351	0.279869	0.394059	0.974452	0.11092	0.457627	0.417073	1.000000	0.207775	0.366071	0.0002	1.0	0.000000
9352	0.176759	0.336634	0.974452	0.11092	0.152542	0.148780	1.000000	0.164879	0.233929	0.0000	1.0	0.000000
9353	0.237316	0.415842	0.974452	0.11092	0.385593	0.319512	0.016263	0.150134	0.362500	0.0001	1.0	0.099099
9354	0.252046	0.449505	0.974452	0.11092	0.283898	0.195122	1.000000	0.155496	0.398214	0.0048	1.0	0.090090
9355	0.224223	0.352475	0.974452	0.11092	0.300847	0.246341	1.000000	0.135389	0.333929	0.0018	1.0	0.090090

Figure 4: Weather data after pre-processing

The data cleaning process removed all data elements except those required for the new analysis, which included minimum and maximum temperature measurements, precipitation data, moisture indicators, and wind speed, sea level pressure, and weather event flags. The Min-max scaling was used to convert all selected numerical features between 0 and 1 so that each feature could maintain a consistent representation across different scales [37]. The complete pre-processed dataset was exported as an Excel file to enable supplementary analysis. Accordingly, data normalization was performed using the min–max scaling formula, to ensure uniform feature scaling and comparability across all selected variables.

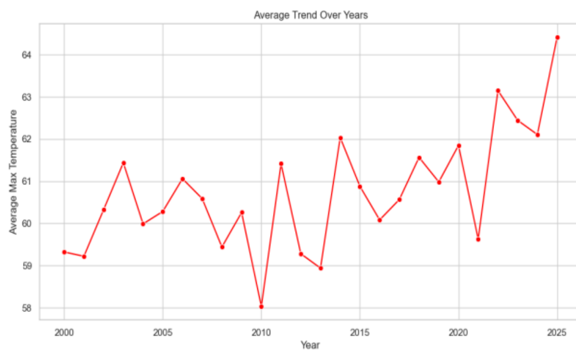


Figure 5: Variation in Weather Temperature over 2020-2025 (Year vs Max temperature)

B. Weather-Based Climate Classification

The pre-processed weather data was used for the analytical work, which included both analysis and further development. The dataset included various weather elements, which consisted of temperature values and daily temperature extremes, wind speed measurements, precipitation amounts, dew point values, snow depth measurements, and weather phenomenon indicators. This study aimed to categorise weather conditions into distinct climate groups, which would help power grid resilience modelling while assessing the impact of these weather conditions on electrical grid infrastructure. The weather variable thresholds were established through percentile calculations, which were used to define extreme weather conditions [38]. The high and low temperature thresholds were established through the 90th and 10th percentile temperature data. The researchers established maximum wind speed and precipitation thresholds at the 90th percentile. The dew point threshold was established through the 85th percentile. The thresholds established scientifically differentiate extreme weather from normal conditions.

The implemented systematic classification system enabled them to link each observation with its corresponding climate condition. The classification examined all extreme weather patterns, which included both single extreme events and multiple extreme weather events. The record showed two weather patterns, which included high wind speeds and heavy rain, together with recognised dangerous weather conditions. The definition of heatwaves included periods that experienced high temperatures and low wind speeds because these conditions created risks for transformer thermal stress. The researchers identified high wind events when maximum wind speeds reached levels beyond the established percentile because those conditions could create mechanical damage to transmission lines. The researchers established a connection between heavy rainfall and high precipitation because it occurred during times of high dew points, which showed flooding and insulation problems. The mapping system that was created connected climate categories with quantitative stress factors, showing their impacts on power grid components according to [39]. They discovered three primary stress components, including thermal stress on transformers, mechanical stress on transmission lines, structures, and moisture-related stress that affected insulation and flooding. The following section displays all the different stress types that result from climatic events. The researchers established a predefined set of multipliers for these three stress factors, which they used to determine the climate conditions of each environment.

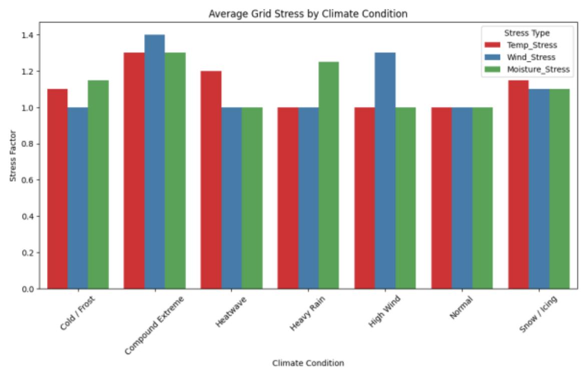


Figure 6: Average grid stress by climatic condition

The final dataset included stress multipliers, which were added as distinct fields that represented thermal wind and moisture stress factors. The dataset now included climate conditions, which had been classified together with their related stress factors, and was ready for analysis. The complete dataset was exported in a format that matched IEEE standard requirements for power system simulation and resilience evaluation data inputs. The following figure shows how often the climatic condition changes, where the high wind and snow/ice are most frequently observed. The heatwave and other climatic conditions rarely appeared.

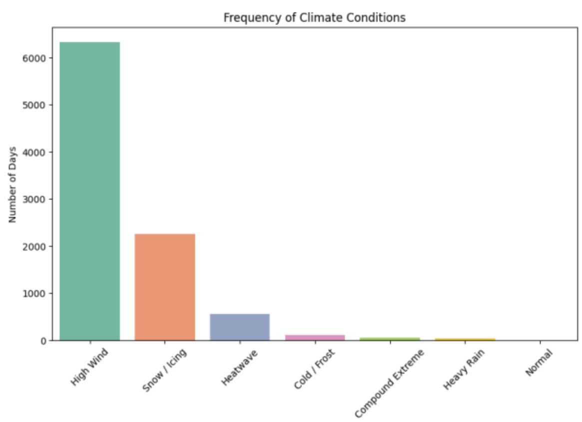


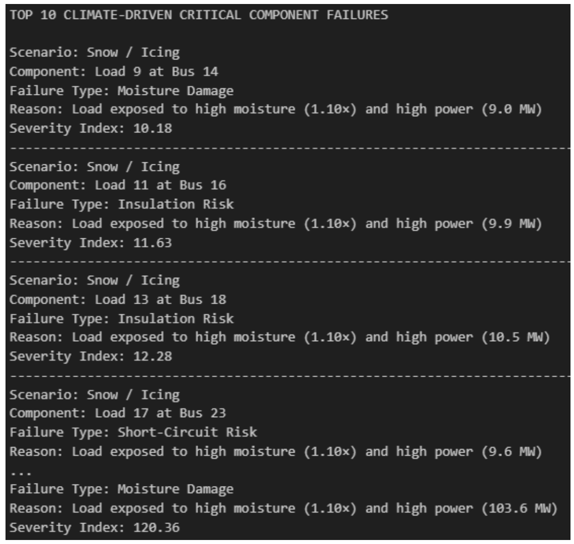
Figure 7: Frequency distribution of climatic conditions

C. *Climate-Driven Power Grid Resilience Simulation on the IEEE 30-Bus System*

The analysis was executed as a power grid resilience experiment to model the environmental impacts that were introduced to the IEEE 30 bus system [40]. First, climatic conditions data containing stress multipliers for **temperature, wind, and moisture** were loaded. The standard IEEE 30 bus network was then imported. The climate-based derating process was conducted for every sampled scenario.

The performed power flow analysis is to identify grid operational conditions after they completed the environmental stressor adjustments. The evaluated transformer components, together with line components and load components to find potential failure points [41]. The assessed lines are to determine their risk for mechanical sag, thermal sag, and overload conditions during high wind and high loading situations. The transformer was tracked for overheating issues and insulation degradation problems, and short-circuit threats that occurred during periods of excessive moisture. The stress magnitude and operational loading were assigned to each potential failure to create a severity index that combined both factors with random variation. The severity index was mathematically defined as,

Where stress magnitude and operational load were combined with a stochastic variation term.



```
TOP 10 CLIMATE-DRIVEN CRITICAL COMPONENT FAILURES

Scenario: Snow / Icing
Component: Load 9 at Bus 14
Failure Type: Moisture Damage
Reason: Load exposed to high moisture (1.10×) and high power (9.0 MW)
Severity Index: 10.18
--------------------------------------------------------------------------
Scenario: Snow / Icing
Component: Load 11 at Bus 16
Failure Type: Insulation Risk
Reason: Load exposed to high moisture (1.10×) and high power (9.9 MW)
Severity Index: 11.63
--------------------------------------------------------------------------
Scenario: Snow / Icing
Component: Load 13 at Bus 18
Failure Type: Insulation Risk
Reason: Load exposed to high moisture (1.10×) and high power (10.5 MW)
Severity Index: 12.28
--------------------------------------------------------------------------
Scenario: Snow / Icing
Component: Load 17 at Bus 23
Failure Type: Short-Circuit Risk
Reason: Load exposed to high moisture (1.10×) and high power (9.6 MW)
...
Failure Type: Moisture Damage
Reason: Load exposed to high moisture (1.10×) and high power (103.6 MW)
Severity Index: 120.36
```

Figure 8: Critical compound Failure analysis

Finally, all identified failure events were collected into structured results. This methodology allowed systematic valuation of climate-driven risks and enabled data-driven planning for preventive control measures. The following results show the various scenarios of climatic conditions along their failure type components.

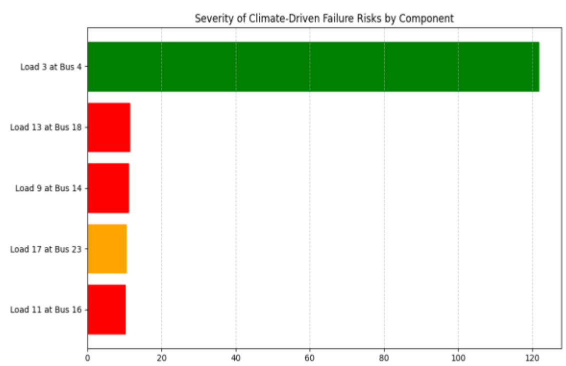


Figure 9: Climate-driven failure risks

D. *Proactive Control Measures for Climate-Induced Grid Failures*

The implementation of proactive control measures serves to stop early failures, which depend on weather conditions. The list stores the scenarios that get transformed into a data frame. The system establishes the get proactive control measures function, which creates an alias for each component failure type and its corresponding reason. Proactive load adjustment was computed using the formulation, enabling controlled load reduction based on identified failure risk factors.

The stress factors get classified into three categories, which include **thermal stress, wind stress, and moisture stress**. The system uses if statements to complete the process of dividing stress multipliers into different groups. The component would experience sag or overload if the line functioned as its component. The transformer component has two possible failure types, which include thermal failure and overheating failure. The load component failure type consists of short circuits and insulation failures. The system needs to decrease load usage until it reaches 20% to stop the problem from occurring [42]. The system uses a print statement to show the failure reason, which includes the failed component and needed control measures. The following figure displays the proactive control levels for the various scenarios.

```
CLIMATE-DRIVEN FAILURE PROBLEMS AND PROACTIVE CONTROL MEASURES

Problem: Scenario: Snow / Icing, Component: Load 9 at Bus 14
Reason: Load exposed to high moisture (1.10x) and high power (9.0 MW)
Proactive Control: Reduce load to 7.2 MW temporarily to prevent faults
--------------------------------------------------------------------
Problem: Scenario: Snow / Icing, Component: Load 11 at Bus 16
Reason: Load exposed to high moisture (1.10x) and high power (9.9 MW)
Proactive Control: Reduce load to 7.9 MW temporarily to prevent faults
--------------------------------------------------------------------
Problem: Scenario: Snow / Icing, Component: Load 13 at Bus 18
Reason: Load exposed to high moisture (1.10x) and high power (10.5 MW)
Proactive Control: Reduce load to 8.4 MW temporarily to prevent faults
--------------------------------------------------------------------
Problem: Scenario: Snow / Icing, Component: Load 17 at Bus 23
Reason: Load exposed to high moisture (1.10x) and high power (9.6 MW)
Proactive Control: Reduce load to 7.7 MW temporarily to prevent faults
--------------------------------------------------------------------
Problem: Scenario: Snow / Icing, Component: Load 3 at Bus 4
Reason: Load exposed to high moisture (1.10x) and high power (103.6 MW)
Proactive Control: Reduce load to 82.9 MW temporarily to prevent faults
```

Figure 10: Proactive control measures

5. Discussion

The study demonstrates that predictive analysis and proactive control are essential elements that improve power grid resilience to climate-related stress, according to existing research studies. The previous studies proved that AI-powered digital twins, together with deep learning technology, function effectively for managing renewable energy resources and detecting faults while optimising infrastructure performance. The AI-based systems provide three main capabilities, including ongoing system observation and system management through automated processes and system upkeep through predictive analysis for power grids that have substantial renewable energy sources. The methods require advanced computational methods, which make their results hard to understand. The study uses a climate-classification system together with stress-based simulation to evaluate the IEEE 30-bus system performance. The methodology uses statistical thresholds together with deterministic modelling to create an evaluation method that enables users to understand and repeat their process of evaluating climate impacts on power system components. The AI and IoT-based digital twins should advance predictive systems together with the current ability to make instantaneous choices, but the researchers proved that structured climate data with stress multipliers provides practical insights through the deterministic method.

The research starts its examination with weather data from the years 2000 to 2025, which has been processed to include essential weather elements that include maximum and minimum temperature measurements, wind velocity, rainfall, humidity, snow accumulation, and severe weather indicators [46]. The team implemented systematic methods to manage both missing data and placeholder information while they extracted time-dependent characteristics from the data to support seasonal and long-term pattern studies. The researchers used percentile thresholds to divide weather patterns into different climate groups, which they linked to stress multipliers that measured thermal, mechanical, moisture-related stresses on transformers and transmission lines and load components [47]. The classification method enabled researchers to find dangerous situations while they measured how much equipment would be damaged during extreme weather conditions.

The grid experiences maximum operational impact from snow and icing events, creating the most serious climate conditions that result in equipment failures. These failures specifically affect load components. The combination of high moisture content with heavy electrical loads creates conditions that increase conductivity, which subsequently results in insulation breakdown and short circuit incidents. The load buses that operate at demand levels between 9 and 103.6 MW experienced increased operational demands, which resulted in maximum operational stress during compound events that reached 120.36 severity levels. The research shows that multiple stress factors, including high moisture content and high operational load, present danger levels that exceed those of incidents that involve only one stress factor. The process of component exposure creates additional security weaknesses because exposed load buses display their most severe failure risk.

The organisation used proactive methods to reduce these identified threats. The system experienced a 20% temporary load decrease, which occurred during snow and icing events because the implementation of moisture-based operational controls reduced electrical stress while decreasing short circuit and insulation failure risks. The grid resilience was enhanced through preventive maintenance strategies, including insulation improvement, drainage enhancement, sealing, and weatherproofing for high-risk components. The deterministic stress-based framework successfully identified critical failure points that allowed the team to measure the severity of each point and develop effective solutions for climate-classification methods that deliver a precise, understandable assessment of environmental threats to power systems.

The study provides transparent climate-induced grid failure simulation through its threshold-based methodology, which supports AI research. The research demonstrates that high moisture and load conditions create snow and icing events, causing primary failures, while proactive measures that target specific risks can effectively reduce these failures. The future use of AI and IoT technologies will improve real-time prediction and automatic control through their combination of deterministic interpretability and advanced predictive abilities.

6. Conclusion And Future Work

The research used the IEEE 30-bus system to create a structured method that measures how climate-related stress factors affect power grid reliability. The research established essential failure points for power system components by dividing weather patterns into climate categories and calculating thermal, wind, and moisture stress multipliers. The most dangerous situations occurred during snow and icing events because high moisture levels combined with heavy loads created short-circuit risks and insulation breakdowns and higher failure severity rates. Transformers experienced major thermal strain from both heatwaves and all other extreme weather occurrences, which happened less often. The use of proactive control measures, including temporary load reduction and specific component management practices, successfully decreased failure probabilities while preventing system outages and boosting grid resilience. Climate-aware operational strategies must be integrated into power system planning because they determine electricity supply reliability during bad weather conditions. The research needs to extend its analysis to larger power systems, including real-time dynamic simulations for a better understanding of climate-related vulnerabilities. The integration of probabilistic climate projections together with renewable energy variability would improve the stress modelling process. The implementation of advanced monitoring systems together with AI-driven prediction controls will improve the effectiveness of preventive risk management. The research will enhance grid resilience through its work while improving preventive strategies and enabling power systems to operate sustainably and securely during extreme climate events.

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