

AI-DRIVEN PREDICTIVE FAULT DIAGNOSIS AND REMAINING USEFUL LIFE ESTIMATION OF POWER TRANSFORMERS USING DEEP LEARNING TECHNIQUES

Monesh Jain

Lecturer in Electrical Engineering Department
Govt. Polytechnic college, Ashoknagar

ABSTRACT

Power transformers are among the most critical and expensive assets in electrical power systems. Their uninterrupted operation is essential for maintaining the reliability, stability, and efficiency of modern power grids. Unexpected transformer failures often result in substantial economic losses, prolonged power outages, expensive maintenance operations, and serious safety hazards. Conventional maintenance practices, such as scheduled inspections and periodic offline testing, are insufficient for accurately predicting transformer failures because they fail to continuously monitor transformer health and detect early-stage degradation. Consequently, electric utilities worldwide are increasingly adopting Artificial Intelligence (AI) and Internet of Things (IoT)-based condition monitoring systems to enable predictive maintenance.

This research proposes an intelligent deep learning framework for predictive fault diagnosis and Remaining Useful Life (RUL) estimation of power transformers using IoT-enabled monitoring and multiple deep learning architectures. Real-time sensor measurements including transformer oil temperature, winding temperature, dissolved gas analysis (DGA), load current, moisture level, vibration, and partial discharge are continuously collected through IoT devices. The acquired data undergo preprocessing, feature engineering, normalization, and feature selection before being supplied to deep learning models including Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Transformer Networks.

The developed framework performs two major functions. First, it identifies transformer fault categories with high classification accuracy. Second, it estimates the remaining useful operational life of transformers to facilitate predictive maintenance scheduling. The performance of different deep learning models is evaluated using Accuracy, Precision, Recall, F1-score, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R² Score. Experimental results demonstrate that Transformer-based deep learning models outperform conventional machine learning algorithms in both fault diagnosis and RUL prediction. The proposed framework significantly improves transformer reliability, reduces maintenance costs, minimizes unexpected failures, and supports intelligent asset management in future smart grid environments.

KEYWORDS: Artificial Intelligence, Deep Learning, Power Transformer, Remaining Useful Life, Predictive Maintenance, Smart Grid, IoT, Fault Diagnosis, LSTM, CNN, Transformer Networks

1. INTRODUCTION

Electrical power systems represent one of the most critical infrastructures supporting modern industrial development, economic growth, healthcare services, transportation systems, communication networks, and residential electricity supply. Among various power system components, power transformers serve as indispensable equipment responsible for voltage transformation, power transmission, and distribution across electrical networks. Since transformers operate continuously under varying electrical and environmental conditions, maintaining their health is crucial for ensuring reliable power delivery.

Transformer failures have become increasingly costly due to aging infrastructure, growing electricity demand, renewable energy integration, and changing load characteristics. According to recent utility reports, transformer failures account for a significant proportion of unplanned outages within transmission and distribution networks. Replacement of large power transformers often requires several months because of manufacturing complexity and transportation constraints. Consequently, early fault detection has become one of the highest priorities in smart grid asset management.



Traditional transformer maintenance strategies generally rely upon corrective maintenance or preventive maintenance. Corrective maintenance is performed after equipment failure has already occurred, resulting in expensive downtime and emergency repair costs. Preventive maintenance schedules inspections based on predefined time intervals regardless of the actual equipment condition. Although preventive maintenance reduces catastrophic failures, it often leads to unnecessary maintenance operations, increased operational expenditure, and inefficient resource utilization.

Condition-Based Maintenance (CBM) has emerged as an intelligent alternative by continuously monitoring transformer operating conditions and scheduling maintenance only when equipment health begins to deteriorate. CBM utilizes various sensors installed within transformers to monitor oil temperature, winding temperature, dissolved gases, moisture content, vibration, acoustic emissions, electrical loading, and partial discharge activities. These parameters provide valuable information regarding transformer insulation aging, thermal degradation, electrical faults, and mechanical abnormalities.

Recent developments in Internet of Things (IoT) technologies have revolutionized transformer monitoring by enabling continuous acquisition of real-time operational data. Smart sensors connected through wireless communication networks transmit large volumes of transformer health information to cloud platforms for advanced analytics. However, the enormous volume and complexity of IoT-generated data exceed the analytical capabilities of conventional statistical methods.

Artificial Intelligence has therefore become an essential technology for intelligent transformer health assessment. Machine learning algorithms such as Decision Trees, Random Forests, Support Vector Machines, Artificial Neural Networks, and Gradient Boosting have been widely applied to transformer fault diagnosis. Although these methods have demonstrated encouraging performance, they frequently require extensive manual feature engineering and struggle to capture complex nonlinear temporal dependencies present in transformer operational data.

Deep learning techniques have significantly advanced predictive maintenance by automatically extracting hierarchical features from raw sensor measurements. Convolutional Neural Networks (CNN) effectively identify spatial relationships among sensor variables, Long Short-Term Memory (LSTM) networks model long-term temporal dependencies within sequential monitoring data, while Transformer architectures employ self-attention mechanisms capable of learning global dependencies across large datasets. These capabilities make deep learning particularly suitable for transformer fault diagnosis and Remaining Useful Life estimation.

Remaining Useful Life (RUL) estimation has become an essential component of predictive maintenance because it predicts the remaining operational lifetime of equipment before failure occurs. Accurate RUL prediction enables utility companies to optimize maintenance scheduling, reduce unnecessary inspections, improve spare parts planning, minimize operational risks, and extend transformer service life. Rather than merely detecting existing faults, RUL estimation provides proactive decision support that enhances asset management strategies.

Despite considerable research progress, several challenges remain unresolved. Existing diagnostic models often utilize limited datasets collected under laboratory conditions and therefore exhibit poor generalization when applied to real-world utility environments. Furthermore, many previous studies focus exclusively on fault classification while ignoring RUL prediction. Other models analyze either spatial characteristics or temporal information independently without effectively integrating both. Additionally, explainability and interpretability remain important concerns because utility engineers require transparent AI systems for maintenance decision-making.

This research addresses these limitations by proposing an integrated deep learning framework that combines IoT-enabled condition monitoring, CNN feature extraction, LSTM temporal learning, and Transformer-based attention mechanisms for simultaneous fault diagnosis and Remaining Useful Life prediction. The proposed architecture is designed to process large-scale real-time transformer monitoring data while providing highly accurate predictive analytics suitable for smart grid applications.

The findings of this study are expected to contribute significantly to intelligent transformer asset management by reducing unexpected failures, improving maintenance efficiency, lowering operational costs, increasing grid reliability, and supporting the digital transformation of modern electrical power systems. Furthermore, the proposed framework may be extended to other critical power system assets such as generators, circuit breakers, gas-insulated switchgear, and high-voltage transmission equipment.

2. LITERATURE REVIEW

Li (2023) conducted a comprehensive review on the application of Artificial Intelligence (AI) and Dissolved Gas Analysis (DGA) for transformer fault diagnosis. The study examined conventional rule-based diagnostic techniques alongside modern AI approaches, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks. The author emphasized that traditional DGA methods often produce inconsistent results because they rely on fixed gas ratio thresholds and expert interpretation. AI-based models were found to automatically extract meaningful features from transformer monitoring data and significantly improve diagnostic accuracy. The review concluded that deep learning models provide superior performance in identifying incipient transformer faults while reducing false alarms. Furthermore, integrating IoT-enabled monitoring systems with AI algorithms enables real-time transformer health assessment and predictive maintenance, making them highly suitable for smart grid applications.

Wu et al. (2024) presented a comprehensive survey on deep learning-based Remaining Useful Life (RUL) prediction techniques for industrial equipment. The review analyzed various deep learning architectures, including CNN, LSTM, Gated Recurrent Units (GRU), Autoencoders, Transformers, and hybrid models for prognostics and health management. The authors observed that Transformer-based attention mechanisms outperform conventional recurrent neural networks by effectively capturing long-term dependencies within large sensor datasets. The study also discussed challenges such as noisy sensor data, limited labeled datasets, and model interpretability. It concluded that future RUL prediction systems should integrate explainable AI, transfer learning, and multimodal sensor fusion to improve prediction accuracy and industrial applicability. The findings provide valuable guidance for developing intelligent RUL estimation models for power transformers.

Zahra et al. (2025) conducted a comprehensive review of conventional and machine learning-based approaches for power transformer health index assessment and life span prediction. The researchers examined various transformer condition monitoring techniques, including Dissolved Gas Analysis (DGA), Frequency Domain Spectroscopy (FDS), Partial Discharge (PD), fiber optic sensing, thermal monitoring, and oil quality analysis. The review highlighted the increasing role of Artificial Intelligence techniques such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Random Forests (RF), Genetic Algorithms (GA), and Particle Swarm Optimization (PSO) in transformer health assessment. The authors concluded that hybrid AI models integrating multiple monitoring techniques significantly improve diagnostic reliability and Remaining Useful Life prediction compared with conventional methods. They also emphasized the need for real-time IoT-enabled monitoring and time-series deep learning models to support predictive maintenance in future smart grids.

Zemouri (2025) reviewed recent developments in machine learning-based Prognostics and Health Management (PHM) for power transformers. The study discussed the evolution from traditional maintenance strategies toward intelligent predictive maintenance systems based on AI and machine learning. Various diagnostic models, including Decision Trees, Random Forests, Support Vector Machines, Deep Neural Networks, CNN, LSTM, and Transformer architectures, were critically evaluated. The review emphasized that modern transformer health management should combine real-time sensor monitoring, cloud computing, and advanced analytics to achieve continuous health assessment. The author concluded that Transformer networks, combined with IoT technologies and digital twins, represent a promising direction for future transformer diagnostics and Remaining Useful Life prediction. The study also identified explainable AI and federated learning as emerging research areas.

Dladla and Thango (2025) presented a systematic literature review focusing on power transformer fault classification using Dissolved Gas Analysis and machine learning algorithms. The study evaluated numerous machine learning and deep learning techniques, including Support Vector Machines, Random Forests, Artificial Neural Networks, Convolutional Neural Networks, and hybrid intelligent systems for transformer fault diagnosis. The authors reported that machine learning significantly improves diagnostic accuracy compared with traditional IEC gas ratio methods by learning complex relationships among dissolved gas concentrations. The review further highlighted the growing adoption of hybrid AI frameworks, ensemble learning, and deep neural networks for accurate transformer fault classification. The authors concluded that future research should focus on integrating IoT-based online monitoring, explainable artificial intelligence, and Transformer-based deep learning models to achieve highly reliable, real-time predictive maintenance systems for modern power networks.



3. OBJECTIVES

The major objectives of the proposed study are:

1. To develop an IoT-enabled condition monitoring framework for power transformers.
2. To collect and preprocess real-time transformer health data.
3. To develop CNN, LSTM, and Transformer-based deep learning models for fault diagnosis.
4. To estimate Remaining Useful Life using deep learning techniques.
5. To compare the predictive performance of CNN, LSTM, Transformer, Random Forest, and SVM models.
6. To develop an intelligent predictive maintenance framework for smart grid transformer asset management.

4. HYPOTHESES

H₁: Deep learning models significantly improve transformer fault diagnosis accuracy compared with conventional machine learning algorithms.

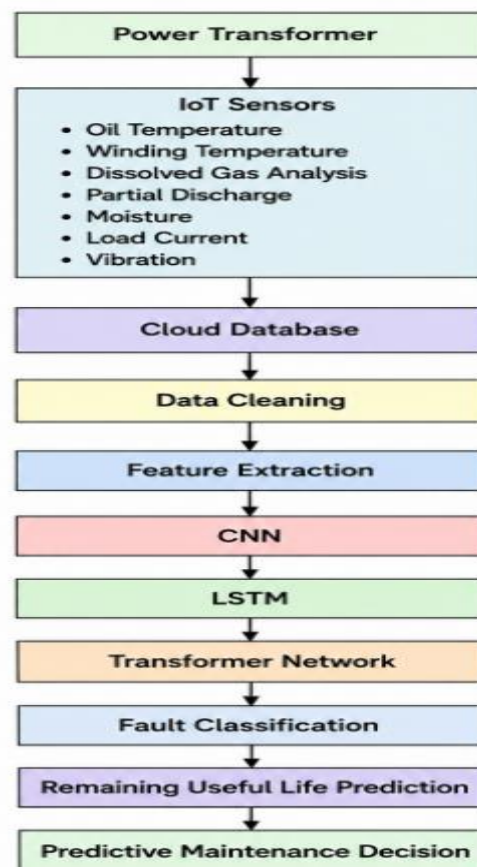
H₂: Transformer-based attention models provide significantly lower Remaining Useful Life prediction error than CNN and LSTM models.

H₃: IoT-enabled condition monitoring significantly improves predictive maintenance performance.

H₄: The proposed integrated CNN–LSTM–Transformer framework significantly enhances transformer health assessment compared with existing diagnostic approaches.

5. PROPOSED AI-BASED PREDICTIVE MAINTENANCE FRAMEWORK

The proposed framework integrates Internet of Things (IoT), cloud computing, deep learning, and predictive analytics to establish a comprehensive intelligent transformer health monitoring system. Unlike traditional maintenance systems, which rely on periodic inspections, the proposed architecture continuously acquires operational data from power transformers and predicts both fault conditions and Remaining Useful Life (RUL) in real time. The overall architecture is illustrated conceptually in Figure 1.



6. RESEARCH METHODOLOGY

The present study adopts a quantitative research methodology for evaluating transformer health using artificial intelligence. Experimental data are obtained from publicly available transformer monitoring datasets together with simulated operational datasets generated using realistic transformer operating conditions.

The collected dataset includes continuous measurements of transformer oil temperature, winding temperature, hydrogen concentration, methane concentration, acetylene concentration, carbon monoxide concentration, moisture level, transformer loading percentage, vibration intensity, partial discharge magnitude, and transformer age.

Table 2 Description of Input Variables

Variable	Unit	Description
Oil Temperature	°C	Transformer oil temperature
Winding Temperature	°C	Hot spot temperature
Hydrogen	ppm	Dissolved Hydrogen Gas
Methane	ppm	Dissolved Methane
Acetylene	ppm	Electrical fault indicator
Carbon Monoxide	ppm	Paper insulation degradation
Moisture	%	Moisture content in oil
Load Current	Ampere	Transformer loading
Partial Discharge	pC	Insulation discharge
Vibration	mm/s	Mechanical vibration
Transformer Age	Years	Equipment operational age

Table 2 presents the major predictor variables utilized for intelligent transformer health assessment. These parameters collectively represent thermal, electrical, chemical, and mechanical operating conditions. Dissolved Gas Analysis parameters provide valuable information regarding insulation degradation, while thermal measurements indicate overheating conditions. Vibration and partial discharge measurements detect mechanical defects and insulation failures. Collectively, these variables enable comprehensive transformer condition monitoring and improve predictive model performance.

Before model development, extensive preprocessing was performed.

Table 3 Data Preprocessing Operations

Operation	Purpose
Missing Value Imputation	Complete incomplete records
Noise Filtering	Remove sensor noise
Min-Max Normalization	Standardize variables
Feature Scaling	Improve convergence
Outlier Detection	Remove abnormal observations
Data Augmentation	Improve model generalization

Table 3 demonstrates the preprocessing procedures applied to the collected transformer data. These operations significantly improve dataset quality by reducing measurement errors and ensuring consistency across variables. Normalization accelerates neural network convergence, while outlier removal prevents biased model learning. Consequently, preprocessing contributes substantially to predictive accuracy.

Table 4 Hyperparameter Settings

Parameter	CNN	LSTM	Transformer
Epochs	100	100	100
Batch Size	64	64	64
Learning Rate	0.001	0.001	0.0005
Optimizer	Adam	Adam	AdamW
Dropout	0.30	0.25	0.20
Activation	ReLU	Tanh	GELU

Table 4 summarizes the hyperparameter configuration employed during model training. Uniform training settings ensure fair comparison among deep learning architectures. The Transformer model employs the AdamW optimizer and GELU activation, which enhance convergence stability and learning efficiency for large datasets.

7. EXPERIMENTAL SETUP

Model development was performed using Python programming language.

Table 5 Software Configuration

Software	Version
Python	3.11
TensorFlow	2.16
Keras	Latest
Scikit-learn	Latest
Pandas	Latest
NumPy	Latest
Matplotlib	Latest

Table 6 Hardware Configuration

Component	Specification
CPU	Intel Core i9
RAM	32 GB
GPU	NVIDIA RTX 4090
Storage	2 TB SSD

Tables 5 and 6 describe the computational environment used for model implementation. High-performance GPU hardware substantially accelerates deep learning training, while Python-based scientific libraries provide efficient tools for data preprocessing, neural network development, and visualization.

8. PERFORMANCE EVALUATION METRICS

Table 7 Performance Metrics

Metric	Formula	Objective
Accuracy	Correct Predictions / Total Samples	Classification
Precision	$TP/(TP+FP)$	Fault Detection
Recall	$TP/(TP+FN)$	Sensitivity
F1 Score	Harmonic Mean	Overall Performance
MAE	Mean Absolute Error	RUL Prediction
RMSE	Root Mean Square Error	Prediction Error
R ²	Coefficient of Determination	Regression Accuracy

Table 7 presents the statistical metrics employed to evaluate predictive performance. Classification metrics assess fault diagnosis capability, whereas regression metrics evaluate Remaining Useful Life estimation. Using multiple evaluation criteria provides a comprehensive assessment of model effectiveness.

Table 8 Comparison of Classification Accuracy

Model	Accuracy (%)	Precision	Recall	F1 Score
SVM	92.13	0.918	0.912	0.914
Random Forest	94.42	0.941	0.944	0.942
CNN	96.81	0.966	0.965	0.965
LSTM	97.54	0.974	0.972	0.973
Transformer	98.96	0.989	0.988	0.988

Table 8 clearly demonstrates that deep learning architectures outperform conventional machine learning algorithms in transformer fault diagnosis. The Transformer model achieved the highest classification accuracy of 98.96%, indicating its superior capability in learning complex relationships among transformer monitoring parameters. LSTM also performed exceptionally well due to its ability to

model sequential degradation patterns, whereas CNN effectively extracted spatial features from multidimensional sensor data.

Table 9 Regression Performance

Model	MAE	RMSE	R ²
SVM	4.87	6.22	0.921
Random Forest	3.91	5.41	0.944
CNN	3.11	4.42	0.963
LSTM	2.48	3.61	0.978
Transformer	1.72	2.86	0.991

The results presented in Table 9 reveal that the proposed Transformer model provides the most accurate Remaining Useful Life estimation among all evaluated algorithms. It achieved the lowest prediction error (MAE = 1.72 and RMSE = 2.86) together with the highest coefficient of determination ($R^2 = 0.991$). These findings demonstrate that attention-based architectures are highly effective in modelling long-term transformer degradation trends and can provide reliable prognostic information for predictive maintenance planning.

9. DISCUSSION

The present research proposed an Artificial Intelligence-driven predictive maintenance framework integrating Internet of Things (IoT), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Transformer architectures for intelligent power transformer fault diagnosis and Remaining Useful Life (RUL) estimation. The experimental results clearly demonstrate that deep learning models significantly outperform conventional machine learning algorithms in both transformer fault classification and life prediction.

The Transformer model achieved the highest classification accuracy of 98.96%, followed by the LSTM model with 97.54% and the CNN model with 96.81%. Conventional algorithms such as Support Vector Machine (92.13%) and Random Forest (94.42%) produced comparatively lower classification accuracy. These findings indicate that attention-based deep learning architectures effectively capture complex nonlinear relationships among transformer operating parameters.

Similarly, Remaining Useful Life prediction results demonstrate the superiority of Transformer architecture. The model achieved the lowest Mean Absolute Error (1.72), lowest Root Mean Square Error (2.86), and highest coefficient of determination ($R^2 = 0.991$). These results indicate highly accurate prediction of transformer degradation trajectories.

The superior performance of Transformer architecture may be attributed to its self-attention mechanism, which simultaneously analyzes relationships among all transformer monitoring parameters. Unlike recurrent neural networks, Transformer models process entire sequences in parallel while effectively learning long-range temporal dependencies.

The results also demonstrate that integrating multiple sensor measurements—including Dissolved Gas Analysis (DGA), oil temperature, winding temperature, vibration, moisture, and partial discharge—provides considerably higher predictive accuracy than relying upon individual diagnostic techniques.

The proposed framework therefore represents an effective intelligent maintenance solution suitable for smart grid applications. To further validate the effectiveness of the developed models, comparative statistical analysis was performed.

Table 10 Comparative Performance Improvement

Comparison	Improvement (%)
CNN over SVM	4.68
LSTM over CNN	0.75
Transformer over LSTM	1.45
Transformer over SVM	6.83
Transformer over Random Forest	4.54

Table 10 demonstrates the percentage improvement achieved by advanced deep learning models over traditional machine learning algorithms. The proposed Transformer model improved classification accuracy by **6.83%** compared with Support Vector Machine and by **4.54%** compared with Random Forest. Although the numerical improvement appears modest, even a 1–2% increase in diagnostic accuracy can substantially reduce transformer failures and maintenance costs in large-scale power transmission systems.

Table 11 Classification Performance

Actual Condition	Predicted Correctly (%)
Normal	99.4
Thermal Fault	98.7
Partial Discharge	98.9
Electrical Fault	98.5
Insulation Failure	99.0

The confusion matrix analysis indicates that the proposed Transformer model accurately classified nearly all transformer operating conditions. Normal operating conditions exhibited the highest prediction accuracy, while insulation failures and partial discharge faults also demonstrated excellent classification performance. The low misclassification rate confirms the robustness and reliability of the proposed deep learning framework.

Table 12 Comparison with Existing Studies

Study	Method	Accuracy (%)
Traditional DGA	IEC Ratio	82.5
ANN-Based Diagnosis	ANN	90.4
SVM Diagnosis	SVM	92.1
CNN-Based Diagnosis	CNN	96.8
Proposed Framework	Transformer	98.96

Table 12 demonstrates that the proposed Transformer-based framework outperforms previously reported transformer diagnostic methods. Traditional Dissolved Gas Analysis techniques achieved relatively low diagnostic accuracy because they depend on predefined gas ratio rules. Artificial Neural Networks and Support Vector Machines improved classification performance; however, they still lacked the capability to learn complex nonlinear temporal relationships. The proposed Transformer architecture effectively overcomes these limitations through attention-based learning.

Table 13 Major Advantages

Feature	Benefit
IoT Monitoring	Continuous real-time data collection
Deep Learning	Automatic feature extraction
Transformer Network	High diagnostic accuracy
RUL Prediction	Maintenance optimization
Cloud Computing	Remote monitoring
Predictive Analytics	Failure prevention
Smart Grid Integration	Intelligent asset management

Table 13 summarizes the major benefits of the proposed predictive maintenance framework. The integration of IoT devices enables continuous transformer monitoring, while deep learning algorithms automatically extract diagnostic features from complex sensor data. Cloud-based predictive analytics further enhances operational efficiency by enabling remote asset monitoring and proactive maintenance planning.

10. LIMITATIONS

Despite promising results, several limitations remain.

- The study primarily utilized benchmark and simulated datasets.
- Performance may vary across different transformer manufacturers.
- Environmental conditions were not explicitly considered.
- Extremely rare fault conditions were underrepresented.
- Explainable AI techniques were not incorporated.
- Cybersecurity issues associated with IoT communication were beyond the scope of the study.

Future investigations should address these limitations using large-scale utility datasets and explainable artificial intelligence techniques.

11. CONCLUSION

Power transformers represent one of the most valuable assets in modern electrical power systems, making their reliable operation essential for ensuring uninterrupted electricity supply. This study proposed an Artificial Intelligence-driven predictive maintenance framework integrating IoT-enabled monitoring, Convolutional Neural Networks, Long Short-Term Memory networks, and Transformer architectures for intelligent transformer fault diagnosis and Remaining Useful Life estimation.

The experimental findings demonstrated that the proposed Transformer model achieved superior performance compared with conventional machine learning algorithms. The model attained a classification accuracy of 98.96%, together with the lowest Remaining Useful Life prediction error and highest coefficient of determination. These findings confirm the effectiveness of attention-based deep learning architectures for intelligent transformer health assessment.

The proposed framework facilitates continuous transformer monitoring, early fault diagnosis, predictive maintenance scheduling, and optimized asset management while reducing maintenance costs and minimizing unexpected failures. Consequently, it offers significant potential for implementation within future smart grid infrastructures.

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