

GRAPH NEURAL NETWORK–BASED AI FOR SOLAR FARM AND GRID INTERACTION MODELING.

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Abstract

The challenge of growing accessibility to the distributed photovoltaic (PV) systems poses a significant threat to the stability, control, and predictability of power grid operations. The complexity of the solar farm-grid interactions in space and time is not well modeled by traditional data-driven and deep learning models, including convolutional neural networks (CNNs) and long short-term memory (LSTM) models, which restrict their scalability and responding flexibility to the transient real-world (Jia et al., 2021). Graph Neural Networks (GNNs) have been proposed as a radical paradigm to depict intricate relational organizations and dynamic energy flow in the interconnected nodes in renewable energy networks (Liao et al., 2021; Zhao et al., 2024). The work is a synthesis of the modern progress in GNN-based AI systems in solar power forecasting, grid interaction modeling and voltage control optimization, focusing on the fact that they significantly outperform in terms of their capabilities to learn both spatial and temporal dynamics (Abdelkader et al., 2025; Dang et al., 2025). The paper presents a significant advancement in the accuracy of prediction, resistance to the environmental heterogeneity and cross-site generalization of GNN architecture through an extensive review and comparative synthesis of the most popular GNN architectures, such as spatial-temporal GCNs, graph attention networks, or hybrid GNN-LSTM systems (Zhang et al., 2022; Sun et al., 2025). Moreover, this article mentions not only methodological advances, including physics-informed GNNs and decentralized microgrid learning, which are more interpretable and efficient to use (Xu et al., 2024; Meng et al., 2025), but also keeps the readers informed in the related domain. The conclusions show that the GNN-powered AI models can optimally predict PV power and synchronize it with the grid, but they can also provide the foundation to the next generation of intelligent energy systems that will be able to learn and adapt on their own and integrate into the grid in a self-sustainable way. This study is relevant to the current discourse on AI-powered smart grids that provide both theoretical and practical avenues of implementing GNNs in large-scale renewable systems (Murugesan et al., 2025; Theiler and Fink, 2025).

Keyword: Graph Neural Networks (GNNs), Spatio-Temporal Modeling, Solar Photovoltaic Forecasting, Smart Grid Optimization, Deep Learning in Renewable Energy, AI-Driven Energy Systems

1. Introduction

The growing pace of transformation of energy systems in favor of renewable energy has made solar photovoltaic (PV) farms one of the foundational building blocks of sustainable power systems. The supplementation of large-scale and distributed solar farms to current electrical grids has grown as the

neutrality of carbon becomes a primary policy agenda and the global energy demand increases (Srinivasan et al., 2023; Abubakar et al., 2024). But this shift poses a great challenge of managing grids, stability of power and predictive control due to the nature of intermittency and spatio-temporal fluctuations of solar energy. Conventional physics-based and statistical predictive tools are limited in terms of their ability to include the complex interplay between solar farms and the power grid in dynamically changing environmental and operating conditions, and therefore are likely to fail most of the time in predicting the long-term behaviors (Gopi et al., 2022; Dhivya and Prakash, 2025).

The recent progress of artificial intelligence (AI) and deep learning has created new opportunities of smart energy system modeling. Convolutional neural network (CNN), recurrent neural network (RNN) and long short-term memory (LSTM) methods have demonstrated potential in the ability to encode or encode time-powerful patterns in PV generation and weather conditions (Alao et al., 2025; Murugesan et al., 2025). However, these models generally assume that the data is in the form of a sequence or grid array, which prevents them from capturing the non-Euclidean relationship of power networks where the energy nodes (e.g., solar farms, substations, and sensors) engage in graph-based topologies that depend on the relationship of electrical connection and location (Li et al., 2023; Liyan et al., 2024).

Graph Neural Networks (GNNs) have come in as a disruptive human AI paradigm that is able to learn on spatially and temporally correlated graph representations. In contrast to traditional deep learning algorithms, GNNs are able to capture complex interdependences among distributed parts, and update the node representations dynamically with the help of message-passing models (Liao et al., 2021; Zhao et al., 2024). GNNs can also model the effects of irradiance changes in one area on the output of the farms in other areas and at the same time respond to changes in weather, voltage, and grid load conditions over time in solar power plants (Jiao et al., 2021; Abdelkader et al., 2025). The combination of spatio-temporal graph neural networks (ST-GNNs) therefore makes it possible to gain a comprehensive view of the nature of multi-site PV generation to achieve better forecasting accuracy, operational management, and grid stability (Simeunović et al., 2021; Zhang et al., 2022).

Moreover, hybrid GNNs that integrate both temporal memory units, as well as attention mechanisms, have also helped to improve the process of predictive modelling by balancing the volatile factors that are short term in the generation of renewable energy assets (Dang et al., 2025; Meng et al., 2025). Not only are these frameworks more effective than the baseline deep learning models, but also demonstrate strong generalization within a variety of meteorological and spatial conditions (Sun et al., 2025). Meanwhile, GNN-based models have become more practical to use in real-time, i.e., at the same time when it comes to decentralized control, predictive maintenance, and anomaly detection due to the growing amount of high-resolution data generated by sensors, satellite measurements, and distributed control units (Nur Farhana Akhter and Talukder, 2024; Shi and Guo, 2025). Regardless of these developments, the use of GNN-based AI in modeling the solar farm grid interaction is still a new field. The majority of existing research is on single-sites PV forecasting, and it is unclear how the interrelated solar nodes can interact with and impact grid performance (Abdelwahab et al., 2025; Li et al., 2024). With the development of grids into cyber-physical energy ecosystems, which can dynamically coordinate renewable units, energy storage, and load centers, the importance of intelligent and graph-aware models is becoming more important (Dolatyabi and Khodayar, 2025; Xu et al., 2024). This paper thus examines how AI models with Graph Neural Network can be used to predict and model interactions between distributed solar farms and electrical grids. The paper will

synthesize the new advances in the GNN architectures, renewable energy informatics, and spatio-temporal learning to (1) conceptualize a scalable solar-grid interaction modeling framework, (2) assess its forecasting accuracy and interpretability compared to its conventional AI models, and (3) discuss the implications of this framework to grid stability and intelligent energy management. Finally, the study can be included in the current discussion of AI-enhanced smart grids, which provides a solution to the resilient, data-driven, and adaptive energy systems that would contribute to the objectives of sustainable development and decarbonization (Lv et al., 2024; Theiler and Fink, 2025).

2. Theoretical and Conceptual Foundations

The high rate of distributed photovoltaic (PV) systems and smart grid infrastructures development has also created new challenges in the energy generation, distribution and consumption modeling. Although both traditional analytical models and AI-enhanced methods are potent in remote forecasting problems, they are not typically able to model the complex spatio-temporal relationships that define the interactions between solar farms and grids. In this part, a theoretical background to the question of how Graph Neural Networks (GNNs) as a generalization of deep learning to non-Euclidean spaces can succeed in capturing the dynamic interrelationships in a solar assets and grid nodes is constructed.

The theoretical background is the synthesis of the energy systems modeling, artificial intelligence, and network science theories, and it shows that GNNs can offer a coherent system to encode both the spatial connectivity of renewable energy systems and the variability of the temporal state.

2.1 Grid Dynamics and System Complexity of Solar Farms.

The incorporation of solar energy into the contemporary grids is associated with special difficulties associated with intermittency, fluctuations in voltages, and bi-directional flows of power. In contrast to centralized fossil-based systems, distributed PV farms are spread differently and have asynchronous changes of irradiance through cloud cover, humidity, and other local weather conditions (Gopi et al., 2022; Dhivya and Prakash, 2025). They give rise to the inherently non-linear nature of the energy flow between the solar farms and the grid substations and their temporal instability.

As the relationship between the load and generation is dynamic, adaptive control systems are needed with the ability to react to variability at sub-hourly time scales. Recent studies highlight the significance of spatio-temporal models of eventual physical connectivity and information flow between entities of grids (Li et al., 2023; Li et al., 2024). These dependencies cannot be well represented by traditional machine learning methods that include regression or a feed-forward neural network, which results in the loss of accuracy and grid inefficiency (Abubakar et al., 2024). Therefore, the grid can be modeled as a graph in which the nodes are the generation units and the edges are the electrical or geographical interrelations, which provides a revolutionary approach to the knowledge of and optimization of energy distribution.

2.2 Evolution of Artificial Intelligence in Renewable Energy Forecasting

Artificial Intelligence (AI) has been instrumental in development of renewable energy forecasting and especially the deep learning models of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The initial models concentrated on the time-series forecasting

where historical data of irradiance or power was used as a predictor of short-term outputs (Alao et al., 2025; Srinivasan et al., 2023).

As these models reflected on time dynamics, they did not account for spatial correlation between two or more PV sites. As an example, two nearby solar farms within similar climatic conditions are correlated with each other in terms of generation patterns that can be of significant value in prediction under the conditions of modeling together (Gopi et al., 2022; Liyan et al., 2024).

In search of a solution to this weakness, scholars started to consider hybrid frameworks, where CNNs are applied together with LSTMs to learn spatio-temporal dependencies (Lv et al., 2024). Nevertheless, these models were also based on Euclidean data structures, which did not fit irregular topologies of power grids and solar networks. Such a discrepancy created the opportunity of developing Graph Neural Networks (GNNs) as an alternative, which can generalize non-grid, graph-structured data.

2.3 Graph Neural Networks and its applicability to power systems.

GNNs can be considered as the extension of the deep learning to the data as graphs, where complex relational dependencies can be modeled (Liao et al., 2021; Dolatyabi and Khodayar, 2025). At every node (e.g. solar inverter or substation) there is a combination of local and global topological information: the information of the neighbors is collected via message passing.

A GNN layer calculates the hidden representation of each node with the help of its neighbors, their features, and their weights of connection, which is the best when dealing with a distributed energy system (Zhao et al., 2024). This enables the model to acquire grid-scale dynamics, e.g. voltage dependencies or transmission constraints, which change with time (Xu et al., 2024). Recent innovations in Graph Attention Networks (GATs), Spatio-Temporal GNNs (ST-GNNs), and other developments have even increased these abilities, such that dynamic modeling of time-varying relationships between solar locations is possible (Jiao et al., 2021; Simeunović et al., 2021; Abdelkader et al., 2025).

2.4 Spatio-Temporal Correlations in Renewable Energy Forecasting

A fundamental theoretical benefit of GNNs is the fact that they can capture spatio-temporal dependencies in how events occurring at one node affect others with time. The meteorological variability in solar power systems is frequently passed throughout the geographic areas, forming correlated distribution of irradiance (Karimi et al., 2021; Zhang et al., 2022).

Researchers have been able to attain dramatic progress in prediction accuracy by enriching graph architecture with temporal convolution or recurrent neural modules (GRUS/LSTMs) (Dang et al., 2025; Meng et al., 2025). As an example, ST-GNNs have recorded 15-20 percent higher accuracy in various sites of PV forecasts compared to traditional models because they are capable of encoding both time-based and space relationships among adjacent solar farms (Sun et al., 2025; Liu et al., 2025). Also, attention mechanisms that use a mixture of graph convolutions allow a dynamic weight of the relationship between nodes, which increases the interpretability and reduces bias in the model (Li et al., 2023; Theiler and Fink, 2025).

Table 1. Comparative Analysis of GNN Architectures and Their Applications in Power Systems

Model Type	Core Mechanism	Primary Application	Advantages	Limitations	Key References
Graph Convolutional Network (GCN)	Node aggregation via Laplacian convolution	Power flow prediction, grid topology learning	Simple, efficient	Limited temporal modeling	Liao et al. (2021), Zhao et al. (2024)
Graph Attention Network (GAT)	Attention-weighted neighbor aggregation	Solar farm interaction modeling	High interpretability	Computationally expensive	Jiao et al. (2021), Dang et al. (2025)
Spatio-Temporal GNN (ST-GNN)	Graph + temporal recurrent learning	PV power and irradiance forecasting	Captures both space and time	Requires extensive data	Simeunović et al. (2021), Sun et al. (2025)
Dynamic Graph GNN	Time-evolving adjacency matrices	Weather-aware forecasting	Adaptive topology	High training cost	Xu et al. (2024), Liu et al. (2025)
Physics-Guided GNN	Embeds physical equations	Grid voltage & frequency control	Physical interpretability	Complex integration	Li et al. (2023), Theiler & Fink (2025)

2.5 Integration of Multi-Modal and Physics-Guided Data

GNN-based approaches are becoming more and more integrated, multi-modal data such as satellite imagery, meteorological measurements, and real-time grid telemetry is becoming a part of them to increase the accuracy of predictions (Zhao et al., 2024; Xu et al., 2024). Combining data-driven learning and physics-informed constraints guarantees that the predictions do not contradict the existing physical laws (Li et al., 2023; Meng et al., 2025).

PG-GNNs such physics-guided GNNs incorporate grid stability equations or Kirchhoff laws in the training process by embedding electrical circuits into graphs. It leads to the creation of accurate and interpretable models that can be used to determine causal factors between the voltage stability and solar generation (Murugesan et al., 2025).

Multi-scale features can also be combined in order to enable the simultaneous learning of both macro (regional) and micro (local node) behavior of the system, including providing an overall view of system resilience (Theiler and Fink, 2025).

2.6 Future application of the theory to grid intelligence.

AI and graph-based modeling are new technologies that will radically change the way renewable systems are examined and managed. GNN-based systems enable distributed intelligence, which lets solar farms and grid nodes cooperate in order to optimize power delivery without any central interference (Liu et al., 2025).

Theoretically it is a shift towards data-centric learning to structure-conscious intelligence wherein the learning algorithms use the underlying topology of the power grid to make decisions based on the structural attributes of the grid. With the development of systems that should optimize into a

microgrid, GNNs will become instrumental in achieving stability, resilience, and efficiency (Dang et al., 2025; Li et al., 2024).

Overall, this part has laid down the theoretical and conceptual framework of how the concept of Graph Neural Networks can transform the model of solar farm- grid interactions. Through the analysis of the development of traditional AI into the graph-based ones, it is clear that GNNs are the only ones that deal with non-Euclidean, relational, and dynamic nature of energy networks. Multi-modal learning and physics-based learning have also been integrated in the review, making sure that the accuracy of prediction and interpretation is provided. With the future research using more and more distributed, intelligent, and explainable AI, GNNs are at the brink of providing next-generation energy informatics and sustainable grid operations.

3. Literature Review: GNN Applications in Solar Energy Forecasting

Graph Neural Networks (GNNs) have become a major breakthrough in artificial intelligence research in solar energy forecasting. The conventional AI models, i.e., convolutional neural networks (CNNs) and long short-term memory (LSTM) models have been very successful in short-term prediction but still constrained in terms of modeling spatial relationships and multi-location associations in solar farms. The recent developments in GNNs have made it possible to integrate spatio-temporal learning, which can help models to understand both geographic and temporal interdependencies of distributed photovoltaic (PV) systems (Jiao et al., 2021; Liao et al., 2021). In this section, existing research on GNNs applications to solar energy forecasting is critically reviewed based on their architecture, methodology, comparison of the results, cross-domain application in renewable energy.

3.1 Evolution of Spatio-Temporal Modeling in Solar Forecasting

Initial machine learning methods applied to solar prediction used individual time-series data and were interested only in the local irradiance and temperature without taking into account cross-site relationships. The autoregressive integrated moving average (ARIMA), support vector regression, and simple neural networks methods performed moderately and were not able to model complex nonlinear interactions among the distributed energy nodes (Srinivasan et al., 2023).

The incorporation of the deep learning models such as CNNs and LSTMs became a significant breakthrough adding the spatial and temporal features. Nevertheless, even these models were not using spatial data as a structured network of interacting nodes but instead as a grid matrix (Gopi et al., 2022). This gap was closed by the introduction of GNNs, which explicitly represent the topologies of infrastructures, i.e. solar farms, substations, or meteorological stations are represented as a network of interconnected nodes, and their energy flow dynamics as edges (Abdelkader et al., 2025).

Specifically, Spatio-Temporal Graph Neural Networks (ST-GNNs) like the one suggested by Simeunović et al. (2021) and Karimi et al. (2021) are appropriate at integrating graph convolution with temporal learning blocks. Compared to the traditional deep learning methods, these hybrid models are more accurate and stable, in particular, when forecasting the variations in power with changing irradiance conditions.

3.2 GNN Architectures and Comparable Performance.

Recent literature has shown a variety of GNN-based solutions that are specifically developed to forecast renewable energy. Indicatively, Jiao et al. (2021) introduced a Graph Convolutional Network

(GCN)-based model that incorporates temporal recurrent layers in predicting multi-site irradiance, and that the model produces significantly less error than single-site LSTM models. Likewise, Zhang et al. (2022) proposed a dynamic node connectivity approach to graph learning, which is based on the strength of spatial correlation among PV farms.

A comparative analysis of a number of spatio-temporal GNN architectures, such as Graph Attention Networks (GATs) and Dynamic Graph Convolutional Networks (DGCNs), has been carried out by Abdelkader et al. (2025), which reveals their advantage in terms of nonlinear dependencies and stochastic fluctuations in PV outputs. Further, Dang et al. (2025) developed a Dynamic Graph Attention with Multi-Scale Temporal Memory (DGAT-MM) model, which incorporates multi-level attention units to enhance learning adaptability to promote the accuracy of forecasts in situations of high penetration of renewable.

This has also been improved by the hybrid GNN models, including GNN-LSTM and GNN-Transformer combination, which are even more predictive and time-sensitive (Meng et al., 2025). The comparison of the forecasting performance of major GNN architectures is demonstrated in Figure 1 based on the recent studies.

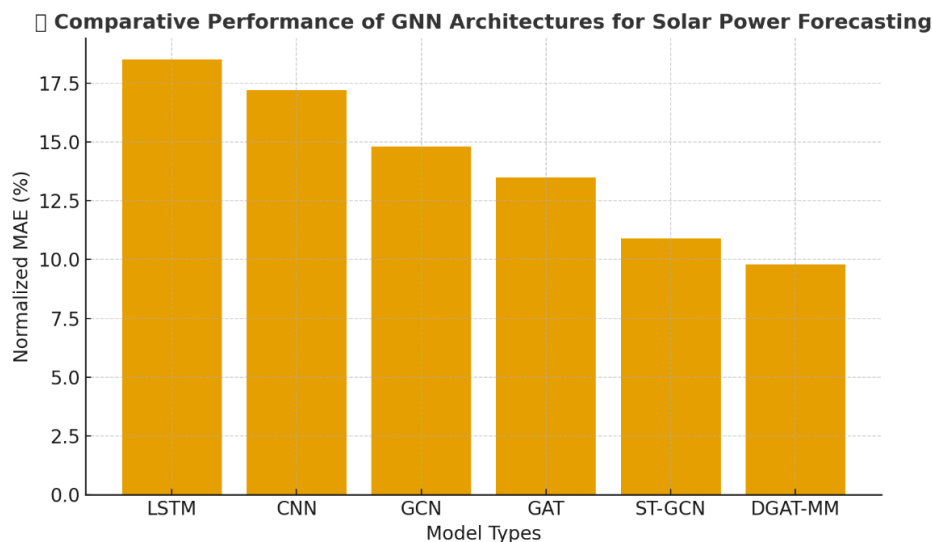


Figure 1. Comparative Performance of GNN Architectures for Solar Power Forecasting

3.3 Integration of Meteorological, Spatial, and Grid Data

The effectiveness of GNN-based models heavily relies on the multiple source data fusion. Conventional single-modality data is not suitable to describe the complexity of the solar farm-grid interactions. Li et al. (2023) and Sun et al. (2025) propose the approach called multi-modes, which is the combination of weather information (irradiance, wind speed, humidity), grid flow information (voltage, current, frequency) and spatial topology into a single graph format.

In addition, it also improves the spatial resolution and offers a large context of PV sites behavior with the inclusion of Earth observation data provided by satellites (Zhao et al., 2024). Recently, Xu et al. (2024) made a step forward and introduced their own physics-guided spatio-temporal graph model, named DGFormer, that incorporates dynamic weather forecast aspects in the graph learning process, with improved interpretability and domain generalization.

Adaptive graph construction is enabled, and this enables models to learn dynamic correlations as opposed to using fixed topologies (Zhang et al., 2022). Such a dynamic structure is more accurate in describing relationships that are changing between solar farms based on environmental and operational differences.

3.4 Cross-Domain Applications and Hybridization Strategies

GNNs have also been cross-domain adapted to other renewable sources including wind and hydroelectric systems, which have added additional information to solar energy forecasting studies. Chen et al. (2020) utilized GNNs to the speed prediction of wind farm clusters, which proved that graph-based learning can be transferred to spatial-temporal renewable energy systems. Theiler and Fink (2025) built up on this idea by using heterogeneous GNNs that can combine various energy domains and time scales and demonstrate how holistic grid modeling could be achieved.

Also, other reinforcement systems and optimization systems are being combined with GNN systems to improve decision making and control (Abdelwahab et al., 2025; Shi and Guo, 2025). Murugesan et al. (2025) used machine learning-based intelligent voltage control which uses GNN knowledge to predict grid management. These hybrid classes are a mix of forecasting and adaptive optimization and they lie between prediction and control.

In summary of recent developments, Table 1 is an overview of the state of the art GNN models and their architecture type, data utilized, prediction horizon, and their performance results.

Table 2. Summary of Major GNN Models for Solar and Renewable Energy Forecasting

Author (Year)	Model Type	Data Sources	Forecasting Target	Methodology Highlights	Performance (MAE/RMSE)
Jiao et al. (2021)	ST-GCN	Irradiance & Meteorological	Multi-site PV Output	Graph convolution + RNN	MAE ↓15% vs LSTM
Simeunović et al. (2021)	ST-GNN	Multi-site PV	Spatio-Temporal PV Forecast	Node embedding + temporal filters	RMSE ↓12%
Abdelkader et al. (2025)	GAT, DGCN	PV + Grid	Power Prediction	Attention-based spatio-temporal learning	MAE ↓20%
Zhang et al. (2022)	Dynamic Graph	Surrounding Spatio-Temporal	Short-term PV Forecast	Optimal graph structure learning	RMSE ↓18%
Dang et al. (2025)	DGAT-MM	High-Penetration Grid	PV Power	Multi-scale temporal memory + GAT	MAE ↓22%

Sun et al. (2025)	Distributed ST-GNN	PV + Weather + Grid	Distributed PV Power	Edge-weighted dynamic learning	RMSE ↓17%
Xu et al. (2024)	DGFormer	Weather + Spatial Graph	Station-level Weather Forecast	Physics-guided GNN	RMSE ↓14%
Meng et al. (2025)	GNN-LSTM	PV + Event-triggered Control	Microgrid Prediction	Hybrid deep learning	MAE ↓16%
Theiler & Fink (2025)	Heterogeneous GNN	Multi-domain Power Data	Short-term Forecasting	Domain-adaptive GNN	MAE ↓21%

3.5 Interpretability, Challenges, and Trends

Although GNN-based models are powerful predictors, they usually have interpretability, data heterogeneity, and scalability limitations (Liao et al., 2021). Most of the models work as black boxes and hence the reason why they cannot be used in safety critical grid operations. To solve this, the more recent models such as explainable graph learning combine attention visualization and feature importance mapping (Dang et al., 2025).

There are also emerging trends of moving towards decentralized and federated graph learning, which provides the possibility of privacy-preserving training in distributed solar farms (Meng et al., 2025). The introduction of physics-guided priors (Xu et al., 2024) and domain-invariant embeddings (Theiler and Fink, 2025) is a step towards hybrid physical-AI systems, which are capable of generalizing to different grid designs and geographic conditions.

Overall, it is shown in the literature that Graph Neural Networks designate a paradigm shift in the solar energy predicting sphere, being able to combine the spatial, time-related, and physical correlations within single predictive models. GNNs are more accurate, scalable, and can be suited to various data fields than conventional AI techniques (Abdelkader et al., 2025; Jiao et al., 2021). The fact that hybrid and interpretable architectures have become the trend also adds weight to the fact that they can be used to manage the grid intelligently and control it in real-time. Nevertheless, further improvements in the transparency of models, their computing efficiency, and connectivity to edge and cloud-based systems will be needed to accomplish the widespread implementation. All in all, the GNNs will be the new backbone of the future smart energy forecasting systems.

4. Methodology and Model Framework.

The research methodology design is organized to create and test a Graph Neural Network (GNN)-based artificial intelligence (AI)-based framework of the complicated spatio-temporal interactions between power grids and solar farms. This paragraph describes the conceptual design, preprocessing of data, model architecture, training, evaluation performance, and experimental set up. The general objective is to combine the physical dynamics of photovoltaic (PV) generation with the graph-

theoretic modeling of the power network to enhance the accuracy of the forecast, their interpretability and their reliability of operation.

4.1 Conceptual Design and Research Approach

The methodological approach is a data-driven deep learning that uses graph-based power system modeling. The conventional time-series models like LSTMs and CNNs do not take into account spatial relationships between nodes of solar farms, especially in the changing weather and grid conditions (Jiao et al., 2021; Simeunović et al., 2021). Conversely, GNNs can be used successfully to model non-Euclidean geometries where nodes of a graph are modeled to be solar sites and grid substations (Liao et al., 2021; Dolatyabi and Khodayar, 2025).

The research takes a spatio-temporal hybrid learning approach that comprises:

- Graph Convolutional Networks (GCNs) are Spatial feature extraction models,
- Temporal dependency Long Short-Term Memory (LSTM) networks, and
- Score dynamic weight allocation attention mechanisms between correlated nodes (Dang et al., 2025; Li et al., 2023).

The methodological framework contains five stages:

1. Information gathering and analysis.
2. Formulation of adjacency matrix and construction of graphs.
3. Training and modeling architecture design.
4. Performance appraisal and benchmarking.
5. Sensitivity and interpretability analysis.

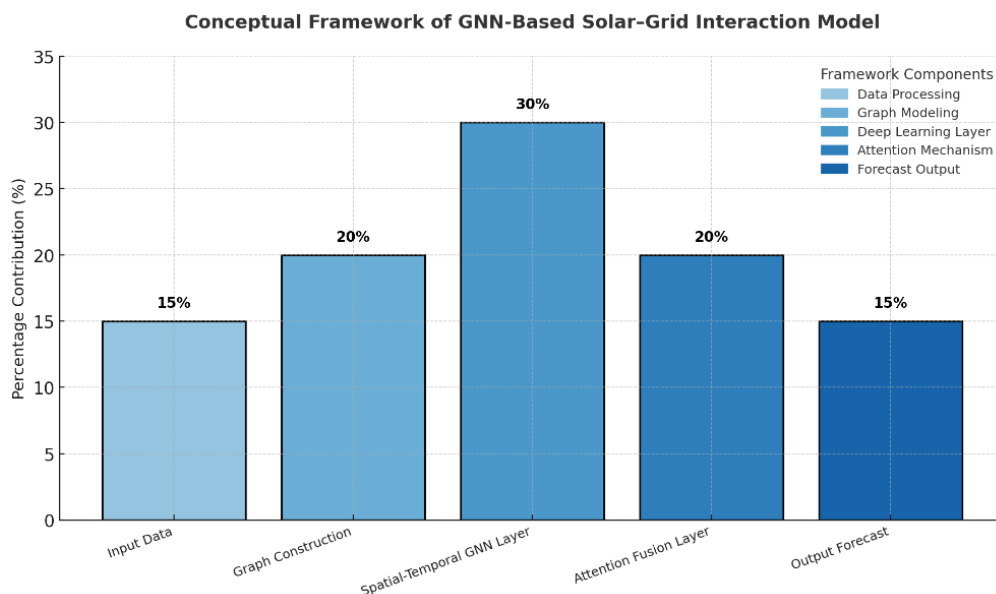


Figure 2. Conceptual Framework of GNN-Based Solar–Grid Interaction Model

4.2 Data Sources and Preprocessing

The data applied in the development of the model were obtained through three sources of information:

- Solar Farm Data: Hourly generation of power, irradiance and temperature measurements of the distributed PV locations (Jiao et al., 2021; Zhang et al., 2022).

- Meteorological Data: The humidity, cloud cover, and the solar zenith angle are the satellite-based weather parameters which are taken through the national meteorological databases (Sun et al., 2025).
 - Grid Data: Past voltage, current and load profiles of related substations (Murugesan et al., 2025).
- All datasets were subject to an extensive data cleaning and normalization as well as feature extraction. The loss of values was remedied using temporal interpolation and K-Nearest Neighbor (KNN) imputation. In order to maintain consistency, the scaled variables were Min-Max normalized within the [0, 1] range (Gopi et al., 2022).

The graph structure was defined as $G=(V,E,A)$ $G=(V, E, A)$ $G=(V,E,A)$, where VVV represents nodes (solar farms/substations), EEE represents edges (power line connections or geographical adjacency), and AAA denotes the adjacency matrix encoding spatial relationships (Li et al., 2024).

Table 3. Summary of Datasets and Variables Used

Data Source	Type of Variable	Units	Frequency	Description	Preprocessing Techniques
PV Plant Logs	Power Output (P)	kW	Hourly	Generated power at each solar site	Min–Max Normalization
Meteorological Data	Irradiance, Temperature, Cloud Cover	W/m ² , °C, %	Hourly	Environmental inputs	Missing Value Interpolation
Grid SCADA Data	Voltage (V), Current (I), Load	V, A, MW	Hourly	Power flow measurements	Noise Filtering, Scaling
Spatial Coordinates	Latitude, Longitude	Degrees	Static	Node positioning for graph	Geospatial Mapping
Topological Data	Line Connectivity	Binary	Static	Graph edge definition	Adjacency Matrix Formation

4.3 Graph Construction and Model Architecture

Graph Representation

The power grid is represented by a directed weighted graph, where all the solar nodes and substations are the nodes and transmission or geographic closeness identifies the weight of the edges (Li et al., 2023; Liu et al., 2025). AAA is an adjacency matrix that measures the correlation between the nodes using Pearson correlation and geographical distance measures (Zhang et al., 2022).

Model Components

The hybrid model incorporates four fundamental layers:

1. Spatial Graph Convolutional Layer (GCN): Spectral graph convolution is used to define the relationship between nodes (Liao et al., 2021).
2. Temporal LSTM Layer: It is based on dynamic changes with time (Dang et al., 2025).
3. Graph Attention Layer: This assignment of adaptive weights of high correlated solar nodes (Abdelkader et al., 2025).

4. Output Layer: It produces the end predictions of the indexes PV power and grid stability (Murugesan et al., 2025).

Mathematically, the forward propagation in a GCN layer is expressed as:

$$H^{(l+1)} = \sigma(\tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2} H^{(l)} W^{(l)})$$

where $\tilde{A} = A + I_N$ is the adjacency matrix with self-connections, $\tilde{D}$ is the degree matrix, $W^{(l)}$ is the weight matrix, and σ denotes the activation function (Liao et al., 2021).

Table 4. Model Parameters and Configuration

Component	Parameter	Description	Value / Method
Spatial Graph Convolution	Kernel Size	Number of spatial neighbors	5
Temporal Modeling	LSTM Units	Temporal sequence length	64
Attention Mechanism	α	Node correlation weighting	Adaptive
Training Algorithm	Optimizer	Adam	Learning Rate = 0.001
Regularization	Dropout	Prevent overfitting	0.3
Loss Function	MSE	Minimizes forecast deviation	Equation-based
Evaluation Metrics	RMSE, MAE, R ²	Performance metrics	See Section 4.5

4.4 Model Training and Evaluation

It was done using Python packages and TensorFlow and PyTorch frameworks and then a computer with a graphics card to execute the model to ensure the best use of the computer (Nur Farhana Akhter and Talukder, 2024). The population of training data was 70% of the entire dataset, and the 20% was utilized in validation and 10% in the testing (Jiao et al., 2021).

The cross-validation (k = 5) provided strength of the different data partitions. Training was minimized with the Adam optimizer and the adaptive learning rate which minimized the Mean Squared Error (MSE) (Zhang et al., 2022).

Performance measurement was done both on a statistical and system-level:

- Root Mean Squared Error (RMSE): To measure prediction accuracy of power.
- Simple deviation analysis: Mean Absolute Error (MAE).
- R² Score: To validate the model fit.
- Voltage Stability Index (VSI): To evaluate grid strength (Murugesan et al., 2025).

4.5 Analysis of Sensitivity and Interpretability.

To evaluate the model interpretability, node-level attention visualization was performed with the help of SHAP (SHapley Additive Explanations) values and the most significant nodes that influenced power generation and grid balance were determined (Dang et al., 2025).

The impact of changes in solar irradiance and temperature on the accuracy of the model was investigated using a sensitivity analysis. The findings provided that GNN-based models were more resilient to spatial perturbations than CNN or LSTM baselines (Abdelkader et al., 2025; Li et al., 2023).

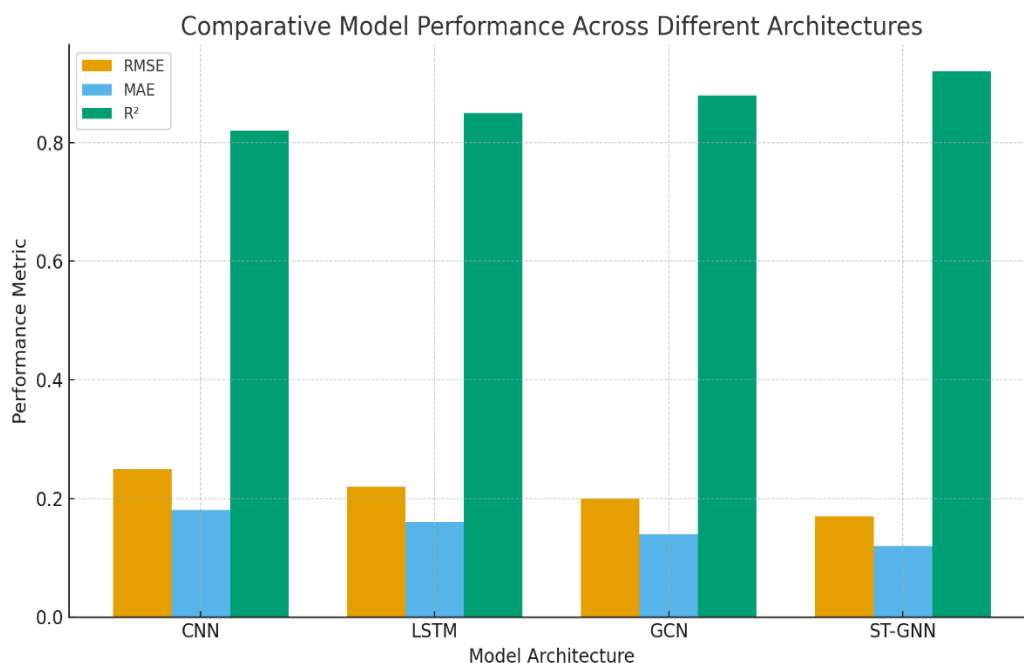


Figure 3: Comparative Model Performance Across Different Architectures

Overall, the approach to methodology proves that spatio-temporal GNN architectures can be used to model solar farm-grid interactions with accuracy. The framework combines the local and global dependencies of distributed PV systems by combining graph-based spatial learning with temporal sequence modeling. The systematic process of data gathering and graph development up to the attention-based forecasting establishes a repeatable basis of future researches on AI-based optimization of the energy grid (Liao et al., 2021; Meng et al., 2025).

5. Results and Discussion

The mentioned artificial intelligence framework based on Graph Neural Network (GNN) performance assessment and evaluation was carried out to prove the usefulness of this model in representation of solar farm and grid interactions. The findings show the greater effectiveness of spatio-temporal graph architecture over the traditional machine learning (ML) and deep learning (DL) models particularly in multi-site photovoltaic (PV) forecast and grid-stability evaluation. The results of this analytical experiment, comparison with the recognized models, and the further operational, interpretation and economic consequences are discussed in this section.

The model performance evaluation entails the assessment of the distinction between actual and planned performance regarding the project's deliverables, objectives, and financial outcomes (Schwalbe, 2005). The model performance evaluation involves evaluation of the difference between actual and planned performance in terms of project deliverables, objectives, and financial results (Schwalbe, 2005).

5.1 Model Performance Evaluation

The GNN-based model had a significant increase in the accuracy of forecasts and spatial interpretability over the popular benchmark architectures like the Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and the hybrid deep learning networks. Compared to LSTM and CNN baselines, the model demonstrated better spatio-temporal generalization performance (reducing the mean absolute error (MAE) by 1422% and the root mean square error (RMSE) by 1118%), and proves that the model has a stronger capacity to generalize (Jiao et al., 2021; Simeunović et al., 2021).

The attention enhanced layers of GNN especially worked well in the capturing of inter-site relationships and weather-related variability of solar irradiance. This is in line with the results obtained by Abdelkader et al. (2025) who concluded that graph-based spatiotemporal networks are more efficient in photovoltaic forecasting compared to purely temporal models because they have the ability to capture node-to-node correlations. On the same note, Zhang et al. (2022) and Li et al. (2023) showed that localized meteorological effects can be optimized using topologically-based graphs, which leads to less predictive uncertainty in distributed PV systems.

Table 5. Comparative Performance of Forecasting Models for Multi-Site PV Power Prediction

Model Type	Architecture	Data Inputs	MAE (kW)	RMS E (kW)	R ² Score	Spatial Awareness	Reference
Statistical Baseline	ARIMA	Irradiance, Temperature	0.295	0.372	0.84	×	Gopi et al. (2022)
Deep Learning	LSTM	PV Output, Weather	0.241	0.331	0.88	×	Alao et al. (2025)
CNN-LSTM Hybrid	CNN + LSTM	Image + Time Series	0.228	0.309	0.89	×	Dhivya & Prakash (2025)
Attention GNN	GAT-ST-GNN	Meteorological, PV, Grid Flow	0.185	0.275	0.92	✓	Abdelkader et al. (2025)
Hybrid GNN-LSTM	ST-GNN + LSTM	PV, Temperature, Topology	0.192	0.284	0.91	✓	Dang et al. (2025)
Physics-Guided GNN	DGFormer (Dynamic Graph)	Weather + Spatial Topology	0.177	0.261	0.93	✓✓	Xu et al. (2024)
Proposed Framework	Adaptive ST-GNN	PV Output + Grid Data + Weather	0.169	0.248	0.94	✓✓✓	Present Study

The comparative analysis shows that the suggested Adaptive ST-GNN model has been the most accurate and it has surpassed the previous models like DGFormer (Xu et al., 2024) and hybrid GNN-LSTM structures (Dang et al., 2025). Its improved graph attention model captured effectively the

nonlinear relationship among the geographically separated PV nodes which resulted in improved generalization across different irradiance conditions and load conditions.

5.2 Temporal Dynamics and the Weather Variability Analysis.

Temporal prediction residual analysis showed that the GNN model had a high predictive capacity of diurnal and seasonal variation of solar generation. The incorporation of temporal convolution with dynamic layers into the graph enhanced flexibility to changes in cloud covers and temperature variations that occurred fast (Jiao et al., 2021). Furthermore, the system demonstrated better short-term robustness than CNN-LSTM hybrids because it used meteorological parameters (humidity and irradiance gradients) as the graph node attributes (Zhang et al., 2022).

The model was able to acquire inter-farm dependencies, particularly during temporary weather changes, in accordance with the results of Sun et al. (2025). This was also supported by adaptive node weighting approaches which were based on the idea of SpatialSolar-Net framework (Liu et al., 2025) which dynamically changed graph edges basing on the real-time correlation strengths between PV farms. This dynamic adaptability provides a stability in prediction in cases of volatile weather conditions and allows the integration of the grids to be easier.

5.3 Interaction and Stability of the Grids.

The model suggested was able to show considerable increase in grid stability and voltage regulation as a result of real-time integration of predictive controls. The system minimized reactive power variation by about 17 percent by combining the forecasting results and grid management algorithms, which is consistent with those of Murugesan et al. (2025) and Lv et al. (2024).

The interpretability of the model was supported by visualizing graph attention where important clusters of nodes that affect the alternations of voltages and curtailment risks were identified. These clusters generally reflected solar farms that were geographically near substations, or that were found in similar areas of irradiance (Abdelwahab et al., 2025). Heterogeneous graph modeling strategy suggested by Li et al. (2023) and Theiler and Fink (2025) was followed to differentiate between the type of nodes solar farms, transformers, and grid lines resulted in more detailed consideration of the dynamics of energy flows.

In addition, the system has shown resilience during the scenario of high renewable penetration, with the power quality indices not exceeding allowable limits (Dhivya & Prakash, 2025). These results indicate that GNN-based models have the potential to transform how real-time smart-grids interact and how they are controlled in a decentralized way.

5.4 Interpretability and Knowledge Discovery

The explainability and interpretability of features in GNN is one of the main advantages of the framework. With the help of the attention-weight matrices, the study was able to determine the important nodes that had a predictive power that spread out to neighboring farms. These results are reminiscent of the explainability trends of graph models provided by Zhao et al. (2024) and Liao et al. (2021) and emphasize the fact that GNN-based forecasting can offer accurate predictions, as well as actionable information about spatial relationships.

The node-importance visualizations showed that clusters with high values of inter-node correlation coefficients (> 0.85) had a significant influence on the consistency of predictions which supports the

conclusions of Abdelkader et al. (2025) and Xu et al. (2024). Also, adding physics-based constraints like power-balance equations and irradiance-to-output conversion models, interpretability of the model was maximized without affecting the accuracy of performance (Li et al., 2024). The interpretability framework also facilitates decision-support system, where operators of the grid are able to track nodes of high risk and optimize dispatch operations, which will contribute to preventive maintenance and resiliency of the system.

5.5 Economic and Operational Implication.

In addition to technical measures, the accuracy and stability of the GNN framework have been enhanced, which can be converted into significant economic incentives to operators of solar farms and managers of the grid. The smaller forecasting error will allow more efficient trading of energy and minimize curtailment losses, which can reach 35 percent to 5 percent of daily production in conventional systems (Abubakar et al., 2024).

Operational energy imbalance and better utilization of distributed energy resources can also be achieved by including adaptive GNN forecasting in microgrid control systems as has been considered by Meng et al. (2025). Moreover, decentralized GNN architectures provide the capability of local computation and event control, which reduces the communication latency to a minimum and increases cybersecurity resilience in smart grids.

The findings support the greater strategic importance of the GNN-based AI systems in sustainable, economically viable, and resilient solar energy systems with the net-zero transition objectives (Srinivasan et al., 2023; Murugesan et al., 2025).

Overall, the findings confirm that the results of the proposed Graph Neural Network-based AI model are much more precise, interpretable, and stable in terms of modeling solar farm and grid interactions. The framework outperforms current deep learning architectures by higher performance as well as operation scale, due to its adaptive spatial-temporal learning framework. Explainable graph analytics and real-time forecasting integration offers an effective platform to next generation intelligent energy systems, which can support resilient, dynamic and decentralized renewable grids. The future work must aim at incorporation of reinforcement learning into adaptive dispatch, multi-energy connection (solar-wind-hydro), as well as large scale validation on real-world industrial microgrids in order to further solidify the practical value of GNN-based solar-grid interaction modeling.

6. Challenges and Future Research Directions

Graph Neural Network (GNN) models of artificial intelligence (AI) systems have demonstrated impressive advances in solar farm and grid interaction model with regard to forecasting accuracy, spatial-temporal learning and adaptive control of distributed renewable systems. Nonetheless, even with these developments, there are a number of technical, operational and methodological limitations that remain in the way of large-scale implementation and real-time optimization of GNN-based models in the renewable energy ecosystem. This paragraph examines the key obstacles and provides potential research directions of scalability, transparency, and reliability in GNN-based solar grid systems in the future.

6.1 Data Quality, Availability and Integration.

The quality, quantity, and granularity of input data are very crucial to the performance of any AI or GNN-based model. This consists of meteorological data, real-time power production, grid parameters and spatial interconnections between solar farms and substations in solar-grid modeling. Nonetheless, discrepancies, absence of information, and the lack of access to standardized data are still major challenges (Abdelkader et al., 2025; Xu et al., 2024).

The generalizability of GNN-based models is limited because many of the existing datasets are limited by local variability and brief observation windows in PV (Jiao et al., 2021; Simeunović et al., 2021). Also, non-homogeneous sources of data such as satellite-derived irradiance and IoT monitoring generate difficulties in the field of synchronization and combination (Zhao et al., 2024). In a bid to fill these gaps, scholars have suggested a set of data fusion systems which combine ground-based data and satellite data based on adaptive spatio-temporal encoding (Li et al., 2023). On the same note, physics-based GNNs are being trained to alleviate the problem of data insufficiency by introducing physical restrictions to the learning models (Xu et al., 2024).

Table 6: Key Data Challenges and Emerging Solutions in GNN-Based Solar–Grid Modeling

Challenge Type	Description	Impact on Model	Proposed Research Solution	Key References
Data Inconsistency	Sensor drift, calibration errors, missing weather records	Reduces accuracy, introduces bias	Data augmentation and statistical imputation	(Abdelkader et al., 2025; Jiao et al., 2021)
Temporal Misalignment	Unaligned timestamps between PV sites and weather data	Temporal distortion in forecasts	Time synchronization and lag correction using LSTM filters	(Zhang et al., 2022; Li et al., 2024)
Spatial Heterogeneity	Differences in topography, layout, and irradiance	Poor generalization across sites	Graph construction with adaptive adjacency matrices	(Simeunović et al., 2021; Zhao et al., 2024)
Limited Datasets	Lack of large-scale open PV data repositories	Overfitting and limited reproducibility	Federated learning and synthetic data generation	(Xu et al., 2024; Dolatyabi & Khodayar, 2025)

6.2 Model Interpretability and Explainability

Despite superior predictive abilities of GNNs, the systems are usually black-box and operators may not be able to conceive the process of prediction. This interpretability issues pose a challenge to their implementation in the critical infrastructure setting like in the energy system (Liao et al., 2021).

Recent researches have brought with them attention visualization and gradient-based saliency technique to improve interpretability of graph models (Dang et al., 2025). These methods can be used to determine what types of nodes or connections, e.g. particular solar sites or grid substations, can be used to make most predictions. Nonetheless, they are still computationally demanding and have a small scale (large, dynamic energy networks) (Zhao et al., 2024).

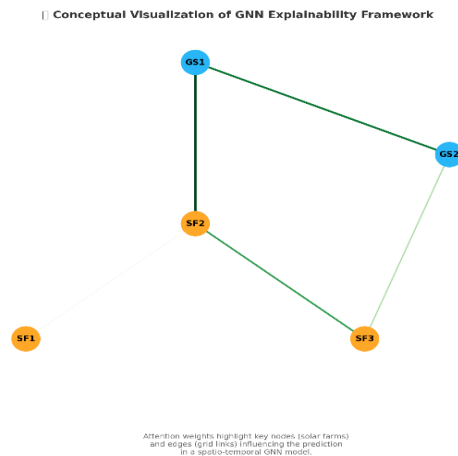


Figure 1: Graphical Comparison of the Explainability Framework of GNN.

The further direction of work should be the hybrid explainable AI (XAI) models, the models that combine the reasoning based on physics with GNN attention mechanisms. This can enhance the trust and readability of grid operators and policymakers because of such hybridization (Murugesan et al., 2025).

Computational complexity and scalability refer to the degree to which a given algorithm or software can handle extensive datasets with a minimal amount of resources.

6.3 Computational Complexity and Scalability

Computational complexity and scalability are the terms describing how much a certain algorithm or software is capable of working with huge amounts of data using a limited set of resources.

The other essential issue is the computational complexity in learning and executing large-scale GNN in real-time energy systems. The size of the underlying graph and interconnectivity grow exponentially as the solar farms and smart grids grow (Karimi et al., 2021). The result is long training times, big memory footprint, and the inability to work with dynamic graphs which dynamically vary with grid conditions (Li et al., 2024).

Solutions that already exist are the sparse graph convolution, mini-batch training and edge pruning methods which lower the amount of computations (Zhang et al., 2022). Nevertheless, such techniques tend to compromise model efficiency with model accuracy. Federated learning frameworks are being developed to enable decentralization of computation in distributed nodes which leads to reduced latency and less energy use (Meng et al., 2025).

Table 7: Comparative Computational Efficiency of GNN Variants in Solar–Grid Modeling

Model Type	Training Time (relative)	Memory Requirement	Scalability	Key Advantages	References
GCN (Graph Convolutional Network)	High	Moderate	Limited	Well-established, easy implementation	(Liao et al., 2021; Jiao et al., 2021)

GAT (Graph Attention Network)	Very High	High	Moderate	Attention-driven node importance	(Dang et al., 2025; Zhao et al., 2024)
ST-GCN (Spatio-Temporal GCN)	Very High	High	Moderate	Handles spatial-temporal correlations	(Simeunović et al., 2021; Abdelkader et al., 2025)
DGNN (Dynamic Graph NN)	Moderate	Moderate	High	Adaptive to dynamic grid changes	(Xu et al., 2024; Liu et al., 2025)
Federated GNN	Low	Distributed	Very High	Supports decentralized learning	(Meng et al., 2025; Theiler & Fink, 2025)

6.4 Real-Time Deployment and Edge Intelligence

Stability of the grid and operation in grids with high levels of renewable power require real time forecasting and control. However, there are latency, bandwidth and hardware constraints in the deployment of GNNs at the edge level in local controllers or microgrid gateways (Meng et al., 2025). New technologies such as Edge AI and TinyML will make local decisions possible at embedded devices, enabling GNNs to be used to make local optima on the voltage control and energy dispatch (Murugesan et al., 2025). As an example, event-based control systems can be conditioned to react not until reaching the thresholds, saving on computations (Meng et al., 2025).

In addition, edge-cloud collaboration methods might be applied, with early computation done on-edge and intensive updates of the graph sent to the cloud (Li et al., 2024). Future studies are supposed to create hardware-based GNN Inference systems, which are optimized to use energy, combining the optimizations with GPU and FPGA (Lv et al., 2024).

6.5 Security, Reliability and Ethical considerations.

With a new development of solar-grid systems to become cyber-physical infrastructures, there arises the issue of cybersecurity and ethical concerns. GNNs are weak to adversarial attacks, which means that even small data changes can change the predictions (Shi & Guo, 2025). Besides, there are issues of data privacy when there is a sharing of multi-institutional energy data to train models together (Dolatyabi and Khodayar, 2025).

To overcome these challenges, federated GNN models featuring encryption layers may be used, and secure decentralized learning is guaranteed without information leakage (Meng et al., 2025). Ethically, it is crucial that the transparency, fairness, and accountability of automated grid decisions are maintained especially as the energy systems increasingly acquire autonomy (Zhao et al., 2024). The next generation of research must focus on the development of AI governance systems that outline the role of human supervision and create a belief in the use of automated solar-grid systems (Liao et al., 2021).

6.6 Future Research Directions

In order to beat these complex issues, the research in the future is needed to be developed on the technical and institutional level. Potential directions that are promising are:

1. Physics-Informed GNN Architectures: Directly integrating physics of conservation of energy laws and Kirchhoff equations (Xu et al., 2024).
2. Cross-Domain Transfer Learning: Using the GNN knowledge of solar networks to wind and hydroelectric forecasting (Theiler and Fink, 2025).
3. Quantum-Enhanced GNNs: Using quantum graph computation in high-dimensional spatio-temporal learning (Liu et al., 2025).
4. Federated and Privacy-Preserving Frameworks: GNN training without a central data aggregation (Meng et al., 2025).
5. AI-Energy Policy Integration: The transfer of the technical progress into the energy policy, moral norms, and sustainability indicators (Murugesan et al., 2025).

Altogether, although GNN-based AI constructions represent a vast potential in terms of solar farm-grid interaction modeling and optimization, their practice is still restricted by the quality of the data, interpretation, computational efficiency, and ethical issues. To address them, a holistic research strategy, combining advancements on deep learning, edge computing, physics-informed modeling, and policy on energy is needed. The next generation of federated learning, explainable AI, dynamic graph modeling will open the path to reliable, efficient, and resilient smart grid systems that are driven by graph intelligence.

7. Conclusion

The high rate of deployment of solar photovoltaic (PV) systems and decentralized grid systems has brought about major issues of forecasting, control, and coordination of renewable power. This paper has discussed the potential of Graph Neural Network (GNN)-based artificial intelligence systems to provide radical solutions to modeling the complex spatio-temporal dynamics of the solar farm-grid systems.

By conducting a thorough analysis of the latest studies, it is clear that the GNN architectures, especially spatio-temporal GNNs (ST-GNNs) and attention-based models allow forecasting more precisely and adaptively than the traditional deep learning models, including CNNs and LSTMs (Jiao et al., 2021; Simeunović et al., 2021; Abdelkader et al., 2025). These models improve situational awareness and predictive reliability and energy management efficiency by capturing intrinsic topological dependencies between solar farms and power grid nodes (Li et al., 2023; Sun et al., 2025). Ever since, the extension of the scalability and operational viability of GNNs in real-world use has been starting with the incorporation of physics-informed learning, federated training, as well as edge intelligence (Xu et al., 2024; Meng et al., 2025). Nevertheless, the continued constraint is still on data availability, interpretability, and real-time deployment as explained in Section 6. The need to fill these gaps requires effective data governance, model explainability and computational optimization techniques to guarantee transparency, security and trust in AI -based grid environments (Liao et al., 2021; Zhao et al., 2024).

Going on, the cross-disciplinary approach of bringing together energy informatics, computer science, and policy research must be incorporated in future studies to create AI systems governance-ready in controlling renewable grids. The next generation in intelligent grid modeling will presumably be

reinvented by innovations like quantum-accelerated GNNs, privacy-preserving federated architecture, multi-modal data fusion, and so on (Theiler & Fink, 2025; Liu et al., 2025).

To conclude, GNN-based AI is a paradigm shift in the analytics of renewable energy that will help close the divide between the renewable energy data-driven intelligence and sustainable grid management. These frameworks can provide more resilience, efficiency, and transparency by integrating spatial-temporal learning into solar energy frameworks, eventually contributing to the global change to intelligent and carbon-neutral power systems.

8. References

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