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Original Article

Deep Learning Driven Short Term Solar Radiation Forecasting System Using Temporal Attention Gated Convolutional Network Model

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Abstract *- Forecasting solar irradiance is very important for improving the effectiveness and dependability of solar energy systems. Predicting short-term changes in solar irradiance is crucial for different uses, such as managing energy, integrating with power grids, and planning operations. In this area, the suggested framework gives a new method by merging complex machine learning models with Temporal Attention Gated Convolutional Network or TAGC-Net design and Generative Adversarial Network (GAN). The proposed work integrates TAGC-Net to catch time dynamics with GAN's expertise in modeling difficult data distributions, giving a joint improvement that boosts forecasting accuracy and trustworthiness. In this regard, TAGC-Net is generally applied to model temporal dynamics and patterns of sequential solar irradiance data to ensure enhancement in various ways, including improved short-term forecast accuracy regarding its time-dependent feature. Besides, in this context, GAN is used for modeling sophisticated data distributions and generating realistic synthetic data, which would make the training more effective, hence enhancing robustness in general, especially when a few data points or noisy data are available. All these models would contribute to enhancing the accuracy and dependability of forecasting solar irradiance for better power administration and grid integration. The framework has a particular focus on this novel combination, which adds to the progress of solar irradiance prediction. It offers great potential for advancements in using renewable energy and making grids more stable. Analysis of the projected architecture reveals its superiority in predicting solar irradiance levels in different ways, owing to an MAE of 0.28 and RMSE of 0.35. Finally, as a result of comparative analysis with existing models like RNN, GRU, LSTM, and so on, the model excelled in all metrics, such as low errors and high* R^2*. Overall, it is seen that the combined model always works better than other methods, which confirms its ability to give dependable and accurate short-term forecasts.*

Keywords *- Solar radiation, Short term forecasting, Deep Learning, Renewable Energy Sources, Photovoltaic systems and prediction.*

1. Introduction

rising significance of renewable energy, especially solar power, has increased the requirement for precise and dependable solar radiation prediction systems [1, 2]. Estimating solar radiation is crucial in managing energy effectively, keeping the grid stable and maximizing the output of solar energy systems. Nonetheless, forecasting sunlight is difficult because its variation is natural and it depends on different atmospheric and environmental elements. Usual methods for predicting solar radiation, such as statistical and physical models, are not very accurate in catching the intricate non-linear patterns [3, 4]. The main challenge of using solar energy to generate electricity is that the voltage generated by it is rarely steady and usually varies with time. They are attributed to the various concerns arising from characteristics of solar radiation, temperature, and atmospheric conditions that impact on Photovoltaic (PV) systems' performance and efficiency. This is because the intensity of the sunlight is not fixed bearing in mind it alters due to weather, cloud or even the composition of the atmosphere, which determines the abilities of a PV system to generate power. This causes a variation of the amount of astral energy reaching the PV panels, which causes voltage instability since there is a constant change in the energy received. Such fluctuations can cause difficulties in maintaining the uninterrupted power supply [5-7]. Adding renewable resources to electrical grids presents several other challenges due to the source's intrinsically variable and intermittent character, such as solar radiation or wind. Compared to conventional power plants [8, 9], which can be ramped up or dialed back according to demand, renewable energy sources are based on natural phenomena that vary in time. While most countries try to increase the proportion of renewables in their energy mix to ensure a low-carbon economy and sustainability, this brings up the need for even more urgent management of such intermittent sources.

In this respect, several precise prediction models of solar radiation will help conquer the variability of this energy source and other renewable resources. Precise forecasting of solar radiation helps grid operators anticipate changes in solar power generation and adjust accordingly other controllable sources of electricity [10]. A better forecast allows stability in the grid, assists largely in ensuring reliability of supply to the consumers, and brings about a lot of efficiency in the overall energy system [11]. Machine learning overcomes this limitation by automatically discovering patterns and relationships in the data to create models that can classify, regress, cluster, and more [12]. Therefore, the applications of machine learning are very wide-ranging across multiple domains.

Machine learning models [13, 14] learn directly from historical data, finding patterns that may not be immediately evident or, in any case, be hard and sometimes impossible to express in some simple algorithmic form. This constitutes the reason machine learning models are phenomenally effective in big and complex data domains where traditional methods would serve to no avail. Consider, for instance, pattern recognition or, for that matter, any classification task: machine learning models, during the processing of large volumes of data, can identify trends or classify items much more effectively than human analysts would do, or, for that matter, any conventional algorithms.

Data mining models analyze enormous volumes of data to extract significant information, hidden patterns, or anomalies within the datasets. Further, machine learning models are useful for developing forecasts, mainly in the renewable energy sector, where forecasted production has to be determined by ever-changing environmental conditions [15]. Further, the preprocessing and preparation of data involved in developing accurate forecasts can also be effectively done with the aid of ML models. These models will clean and transform the raw data to such an extent that it improves the exactness and dependability of the forecast.

1.1. Problem Statement and Motivation

Solar energy is considered an accessible renewable resource; thus, it arguably plays a significant role in the fight against the depletion of fossil fuels as well as combating the effects of climate change [16]. Nevertheless, solar power's variable and unpredictable nature makes it difficult to incorporate into power grids. Conventional statistical methods are inadequate in extrapolating temporal and spatial variability as observed in solar radiation data. They often use deterministic techniques or bare-bone statistical tools that cannot capture the complex dependence and non-linearities in the weather data. To maximize the utilization of solar power, stabilize the power grid, and effectively manage energy, it is imperative to build complex models to predict solar irradiance over short and long-term periods [17-19]. The rationale for the proposed work lies in the fact that there is a greater need to enhance the prediction of solar radiation due to the shift in focus towards green energy.

1.2. Objectives

- To develop a hybrid TAGC-Net and GAN architecture to work with large volumes of data and make accurate estimations.
- To support all levels of the electrical grid and related industries from day-ahead markets all the way to real-time energy management and backup.
- To deal with optimization of energy management, grid integration, and efficient operational functions in solar power systems.

The following sections of this paper are prepared: Section 2 investigates certain recent forecasting methodologies. Section 3 presents a clear and in-depth explanation of the proposed work, along with the flow and descriptions. Section 4 validates the performance and comparative results of the proposed work with findings. Finally, the overall summary, along with the outcomes and future scope, is presented in Section 5.

2. Related Works

It is important to note that forecasting helps in correct prediction and hence in increasing the production of energy, making the grid stable and efficiently managing resources. The literature review of this paper presents an account of the main approaches, how they have developed over the years, and the merits and demerits of each. In the past, the forecast of solar energy was mainly dependent on the physical model, which depended on meteorological data and atmospheric physics. These models rely on equations of the nature of the atmosphere influencing solar irradiation, including the formation of clouds, aerosols and water vapour. Another advantage of physical models is that they provide an accurate picture of the atmosphere influencing solar radiation. However, they often call for significant computing power and rely on a high level of accuracy of the input data [20]. Further, these models are deficient in predicting at high spatial-temporal accuracy, which could be essential for real-time grid control. However, this type of physical model still remains an important instrument for solar energy forecasting when it is used in combination with other technologies. Statistical models, which were the second approach in solar forecasting, use historical information to predict solar radiation based on the occurrence of patterns. In comparison to physical models, these models are comprehensible and less computational power is needed for their application. Nevertheless, it significantly relies upon the availability and quality of data from past occurrences. Therefore, statistical models are composed with other approaches to improve their evaluation results.

Lai et al [21] presented a novel method for identifying Global Horizontal Irradiance (GHI) with a deep learning-based hybrid model, specifically made and tested on 1-hour ahead predictions. The main methodology is to combine advanced machine learning methods to handle problems caused by the changeable nature and irregular appearance of solar energy. Zhou et al [22] gives a plan for guessing the amount of Photovoltaic (PV) energy created, suggesting applying a mixed deep learning method. The fresh model combined clustering methods, attention mechanisms, Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) with a wireless sensor network. Osorio et al [23] offer a complex data-based machine learning modeling framework that is built on a customized side of the Deep Operator system planning.

Irshad et al [24] introduced a new prediction model, known as Arithmetic Optimization with Hybrid Deep Learning (AOHDL-SRP), for an effective solar radiation prediction. The suggested framework uses the standard data preprocessing and prediction operations with hyperparameter tuning. By incorporating arithmetic optimization with a deep learning technique, the forecasting precision and reliability of the suggested framework are greatly improved. Neshat et al [25] developed a cross LSTM-RNN technique with covariance matrix adaptation evolution strategy. The integrated use of optimization and deep learning in the suggested framework could significantly enhance the overall prediction performance. Azizi et al [26] gives a new idea for predicting long-term future values of worldwide solar radiation and temperature, using deep learning methods. The model is not like old ones that forecast only one step ahead with a single output; it uses a time series framework combined with a multi-step multivariate output to predict various variables simultaneously across an extended forecasting period. The suggested model predicts more than one future value over a given time range instead of just one possible outcome. This method, with several steps, gives a fuller comprehension of upcoming patterns and differences in solar irradiance and temperature. This makes the predictions more useful for planning and making decisions. Duan et al [27] used a mix of chaotic Aquila optimization algorithm, WRF-Solar model, and deep Fully Convolutional Networks (FCNs). The method to optimize FCN model parameters is called the chaotic Aquila optimization algorithm. This technique, which takes inspiration from chaos theory, aids in fine-tuning and enhancing the prediction power of the FCN-based solar radiation prediction model.

Assaf et al [28] made a detailed study of different models that use deep learning for solar irradiance forecasting. The study included methods such as LSTM, GRU, RNN, CNN, GAN and AM, and other hybrid forms. This ensures that readers acquire an understanding of different techniques with their own benefits and weaknesses. Multiple studies look into combination deep learning models, applying many deep learning methods or mixing deep learning with old-style prediction techniques. These mixed ways often display enhanced forecast precision and strength compared to solitary models. Much progress has been made in forecasting solar irradiance using deep learning, but there are still some difficulties that persist. These include handling large and diverse data collections, comprehending the model's semantics, and managing computational intricacy. The deep learning techniques are more useful for enhancing the forecasting accuracy and prediction performance, since they help to make accurate decisions while predicting solar radiation.

Coupling physical, statistical, and machine learning methods into hybrid models has received increasing interest in the last few years. This technique helps to increase the skill in forecasting, particularly for strongly nonlinear and variable given contexts. This is where hybrid models become handy, especially when the quality and availability of data vary due to the integration of multiple sources and types of information.

Table 1 summarizes the limitations and descriptions of research works discussed in the literature.

Table 1. Summary of different research works discussed in the literature

Author / Work	Description / Approach	Limitations
Lai et al. [21]	Deep learning + time-series clustering for 1-hour ahead GHI prediction.	Limited to short-term forecasting.
Zhou et al. [22]	The hybrid model uses CNN, LSTM, attention mechanisms, and clustering.	Complexity in integrating multiple modules.

Osorio et al. [23]	Machine learning model using a modified Deep Operator Network.	Dependence on historical data.
Irshad et al. [24]	AOHDL-SRP model combining arithmetic optimisation and DL with hyperparameter tuning.	Generalizability to unseen data is unclear.
Neshat et al. [25]	The hybrid model uses LSTM-RNN with a Covariance Matrix Adaptation Evolution Strategy.	Computation-heavy.
Azizi et al. [26]	Multi-step multivariate DL architecture for lasting forecast.	May suffer from overfitting.
Duan et al. [27]	Combines chaotic Aquila optimization, WRF-Solar model, and deep FCNs.	Complex architecture.

2.1. Research Gap

Despite the progress in forecasting solar energy, a number of challenges remain. One key challenge arises with the fusion of a number of different data types and sources- satellite imaging, ground-based observations, and numerical weather predictions- which call for sophisticated data fusion techniques and models that are able to cope with heterogeneously sourced data. Besides that, a further complication lies in the intrinsic uncertainty of the weather forecast and variability in the solar radiation, which worsens the challenges to predictive accuracy. It is within the quest for new methodologies, including ensemble learning, transfer learning, and incorporating real-time data, that researchers are constantly in the process of devising better forecast reliability and robustness.

3. Materials and Methods

A detailed focus is given to the Temporal Attention Gated Convolutional Network (TAGC-Net) and Generative Adversarial Networks (GAN) model proposed in the study. Furthermore, it also considers complex patterns better than the other models and integrates effectively with the operations such as temporal convolutional, attention and the gated recurrent unit. Climates an enhanced solar radiation forecast. Second, estimating the low-frequency parts with GAN provides a novel and appealing feature to the structure. Because of this, they can identify and reproduce the basic behavior and long-term oscillation that is inherent in solar irradiance data that GAN is capable of recognizing. It improves one's ability to be precise and accurate in the forecasts made in the future. This combined model of TAGC-Net and GAN is a new advancement in different solar irradiance predictions. It could ultimately result in more detailed and more comprehensive predictions for various application options.

EMD breaks down data adaptively into Intrinsic Mode Functions (IMFs) and residuals. On the other hand, with EEMD, a decrease in mode mixing is noticed because it adds random noise from a white Gaussian distribution to the signal. However, this causes residual noise that causes errors while reconstructing. Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) addresses these problems by significantly reducing mode mixing, achieving near-zero reconstruction error and lowering computational costs. This method is highly efficient for various applications like analysing signals from satellites, recognizing speech, and predicting economic data. In this approach, white Gaussian noise is initially added to the original signal, and EMD is applied to every noise realization of that signal.

The first Intrinsic Mode Function (IMF) from each iteration is extracted and averaged to get a better first mode. It does so by adding noise-adapted residuals and applying EMD to each iteration's result, taking the average of all these iterations for the extraction of every subsequent IMF. This process continues until all IMFs are obtained from the decomposing process step by step; it ensures that every mode comes out as a result of previous decompositions' residual and helps reduce mode mixing while enhancing decomposition precision. The last step is about computing the complete residual after acquiring all IMFs, which holds the remaining tendency of the initial signal. This leftover part is normally smoother and is helpful in reducing the forecast errors, and it will provide for a better glimpse of the concealed trends. Thus, the process of decomposing the signal into distinct IMFs and one final piece helps CEEMDAN to examine different timescales and frequency sections included in a signal. This method demonstrates usefulness in analytic situations that involve nonlinear as well as non-stationary time series.

The novelty of the proposed model is that it will combine, for the first time, a Temporal Attention Gated Convolutional Network and a Generative Adversarial Network. These two strong architectures are integrated into this model, enabling it to learn both the intrinsic temporal dependencies in the solar irradiance data and heavy tail distributions of the underlying data. The attention mechanism of TAGC-Net allows the model to focus only on those salient time-varying features, enabling it to handle the sequential nature of solar irradiance data effectively and to enable an accurate short-term forecast. Temporal focus is an ability indispensable in forecasting solar radiation because it naturally varies depending on daily, seasonal, and weather-related factors. On the other hand, one of the big challenges in solar irradiance forecasting includes managing sparsity and noisiness in data that may not be available for high-quality training. This is where GAN's contribution plays its role. It is really good at generating realistic synthetic data that captures the real-world distribution of solar irradiance. The ability of GAN to augment this dataset with more and higher-quality samples helps the model generalize better on limited or noisy data. It merges the capability of handling temporal dynamics by TAGC-Net with the generation capabilities of GAN, hence forming a model that enhances forecasting accuracy and the predictive capability of the model towards solar irradiance under many conditions. This new hybrid approach guarantees more reliability.

3.1. Temporal Attention Gated Convolutional Network (TAGC-Net)

The short-term solar irradiance prediction framework formulated in this work consists of a preprocessing and decomposition process from CEEMDAN. This approach is used to extract IMFs and residuals from the irradiance data obtained from the surface of a body. It also effectively transforms the original data into various parts that, in one way or another, act as a measure of different frequency scales. The disadvantage of decomposition is used to understand frequent changes in the solar irradiance data set, referred to as high-frequency variation and low-frequency variation. After decomposition, the subsequences for the data are split into two parts, namely high-frequency and low-frequency. There are fast and short-lived variations in solar irradiance frequencies of these groups, and we subjected them to the Temporal Attention Gated Convolutional Network (TAGC-Net). TAGC-Net has been designed to handle the squiggly and dynamic nature caused by frequent data by incorporating temporal convolution networks and focus systems along with gated recurrent units. This enhances its ability to focus on time-critical attributes while at the same time dealing with longhorn connections at the network. Conversely, regions with low-frequency subsets are smoother and denote gradual fluctuations in irradiance data.

After the CEEMDAN decomposition, the data is segmented into two primary categories: global and three low-frequency noise components. With the help of temporal convolutional networks combined with attention mechanisms and gated recurrent units, TAGC-Net expands its capacity to pay attention to selected time-dependent features and address the dynamic character of high-frequency data.

On the other hand, the low-frequency sub-sequences, which indicate gradual changes in the irradiance level, are comparatively stable and possess a more deterministic characteristic. These components are processed separately, acknowledging that they are not as high frequency as the data normally dealt with. When it comes to the low-frequency analytics, simple modeling methods are usually incorporated, as such data sets are not characterized by significant fluctuations. However, it is important to manipulate these components in a way that enhances the accuracy of the gradual variation in the overall prediction model.

This is made possible by the detailed division of the data into high and low frequency components, which the TAGC-Net then processes for the high frequency component, and the other suitable methods for the low frequency component allow for adequate solar irradiance prediction. This methodology is beneficial for making accurate short-term predictions. Figure 6 elaborates these ideas, depicting how the framework deals with frequency components of irradiance data to improve the predictive capability.

These sections are generated using a Generative Adversarial Network, which works in sections. As a result, GANs are beneficial for modelling and predicting data distributions in data-related trends under the bottom and less fluctuating aspects of low-frequency components. It effectively combines TAGC-Net, whose strength lies in processing high-topology information with frequency, and GAN with low-topology details. This structure ensures the accuracy and thoroughness of predictions concerning different periods of time. The last part of the framework combines the prediction results from both models. This final aggregation gives a strong and unified forecast of solar irradiance, including changes happening right away as well as those that occur over longer periods. The combined method, explained through CEEMDAN's accurate breakdown and specialized prediction models, greatly improves the precision and trustworthiness of short-term predictions about solar energy's strength. The proposed TAGC-Net is given in Figure 1, and the flowchart of operation is given in Figure 2.

In this technique, the convolution layer operation is performed initially after collecting data, as mathematically represented below:

$$c_{\mathrm{i}} = \mathrm{Conv}(c_{\mathrm{i}}, \mathcal{W}_{\mathrm{x}}) + \mathscr{b}_c \tag{1}$$

Where, c_{i} indicates the input, $\mathcal{W}_{\mathrm{x}}$ denotes the kernel of convolution, and $\mathscr{b}_c$ is the bias term. Then, the temporal attention mechanism is implemented for estimating the attention score according to the following equation:

$$\mathcal{A}_{\mathrm{k}} = \tanh(\mathcal{W}_{\mathcal{A}} \hbar_{\mathrm{k}} + \mathscr{b}_{\mathcal{A}}) \tag{2}$$

Where, $\hbar_{\mathrm{k}}$ represents the feature vector, $\mathcal{W}_{\mathcal{A}}$ indicates the weight matrix of the attention module, and $\mathscr{b}_{\mathcal{A}}$ is the bias term. Moreover, the context vector is computed with the attention score based on the following equation:

$$\wp = \sum_{\mathrm{k}=1}^{\mathrm{K}} \mathcal{A}_{\mathrm{k}} \hbar_{\mathrm{k}} \tag{3}$$

Where $\wp$ denotes the context vector. As a consequence of this, the GRU layer operation is performed for effectively handling temporal dependencies, and its memory state output is determined as follows:

$$\hbar_{\mathrm{k}} = u_{\mathrm{k}} \hbar_{\mathrm{k}-1} + (1 - u_{\mathrm{k}}) \tilde{\hbar}_{\mathrm{k}} \tag{4}$$

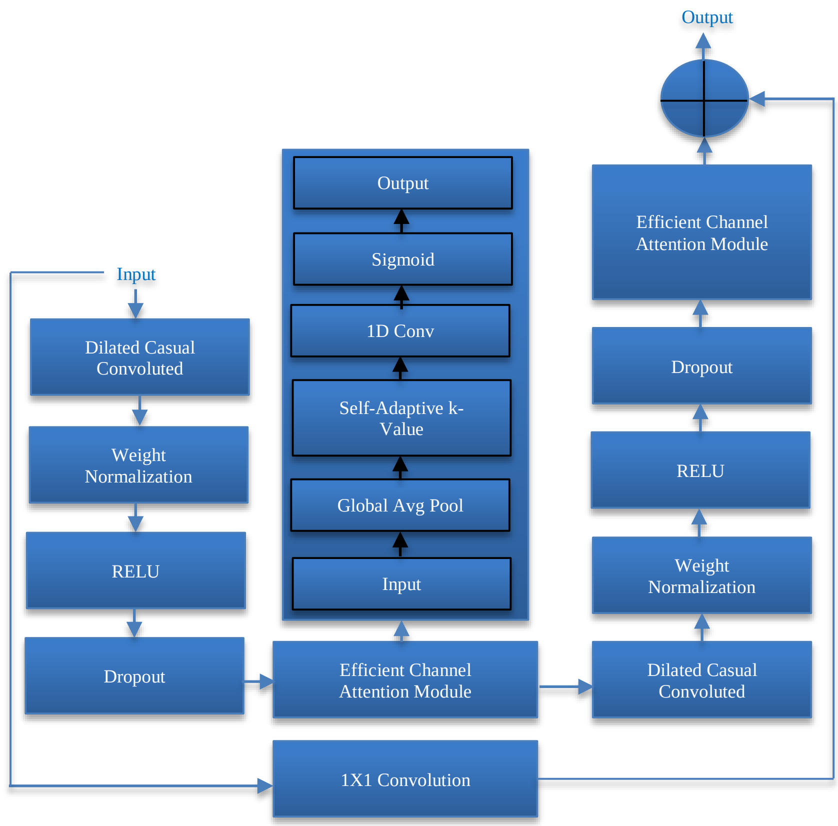

Fig. 1 Architecture of proposed TAGC-Net

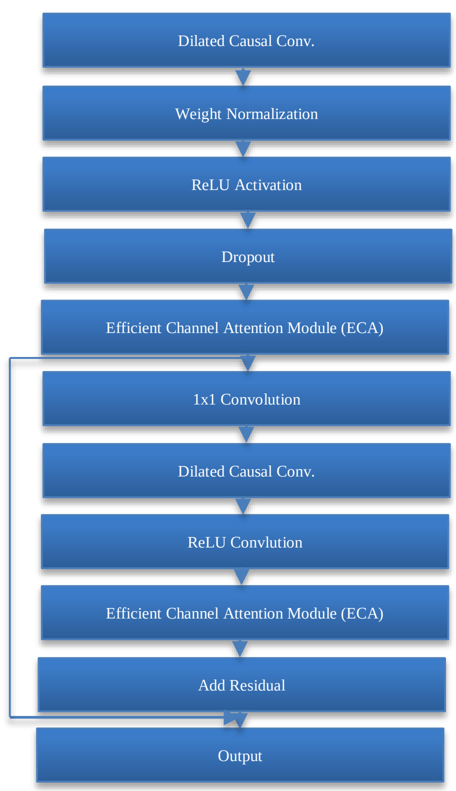

Fig. 2 Flowchart of proposed model

Where, u_k is the update gate information. The final output $\hat{O}_k$ of TAGC-Net is obtained with the use of a fully connected layer, as shown below:

$$\hat{O}_k = \text{Dense}(h_k, W_o) + b_o \quad (5)$$

Where, W_o and b_o are the output weight matrix and bias values. The mathematical expressions represented in the model directly enhance its predictive capability through well-defined key operations at each stage of the process. The first operation, the convolution layer, is represented by Equation (1), where the important features are extracted from the input data, spatial or local patterns, essential to the nature of solar irradiance. This is followed by the temporal attention mechanism; Equation (2) allows the model to attend to the most informative time-dependent feature by computing attention scores that drive the network to determine where it should put more influence between temporal elements in a dataset. The operation of the GRU layer, as defined by Equation (4), addresses temporal dependencies due to the maintenance of memory states; this allows the model to persist in memory certain important information from past steps in time and adjust its forecast at any given time, accordingly. Finally, the result is further refined using a fully connected layer according to Equation (5). The proposed method could enable much-enhanced grid stability and optimum energy storage since the forecasting of short-term solar irradiance is more accurate and reliable. As forecasting of energy generation through solar systems is better, it is relatively easy for grid operators to monitor the energy flow and prevent imbalance conditions, resulting in energy supply-demand mismatch. The algorithm applied to the Efficient Channel Attention Module is given below:

Algorithm: Efficient Channel Attention Module
Input: Time-series input data X with meteorological variables
Output: Predicted solar irradiance values
Step 1: Begin.
Step 2: Apply dilation, causal convolution and weight normalization;
Step 3: Apply ReLU activation and dropout.
Step 4: Apply Efficient Channel Attention Module (ECA);
Step 5: Apply 1x1 convolution;
Step 6: Repeat steps 2 to 6;
Step 7: Add residual connection from input F8=F7+X;
Step 8: Output;

3.2. Generative Adversarial Network

In the proposed work, low-frequency subsets are fed into a GAN for prediction, which is an innovative and special part. This utilizes the strength of GANs in representing intricate data distributions to predict the hidden trends and long-term changes in solar irradiance. Low-frequency subsets capture smoother alterations found within irradiance data, unlike high-frequency components that represent fast fluctuations and short-term dynamics. When these subsets are subjected to a GAN, the model can properly understand and imitate the complex designs existing in low-frequency parts. The generator network of the GAN learns to create fake data samples, ones that are similar to real low-frequency irradiance data. A discriminator network checks how genuine these made-up samples are. By using an adversarial training method, the GAN gets knowledge about the main structure and changeability of low-frequency data. This makes it give good predictions, which show longer-term patterns in solar irradiance. This new combination of GANs to predict low-frequency patterns improves the system's general forecasting ability, giving a complete comprehension of how solar irradiance changes over various time periods.

Relatively, in the proposed framework, the use of GAN, especially for predicting low-frequency subsets of solar irradiance data, is innovative and makes a big difference. Long-term trends and smoother oscillations in irradiance can be predicted with the help of this technique since GANs are efficient at modeling and understanding complex data distributions. Several subsets of the solar irradiance data have low frequency as opposed to the high frequency radiation schematics, and these show slow, less unsteady changes, which are used in understanding wider fluctuations in solar radiation. The above subsets show trends that are likely to extend for a long time, like changes resulting from seasonal changes and slow changes as a result of climatic change. In contrast to high-frequency data that are characterized by high frequency and short duration, low-frequency data present low-frequency data of irradiance variation with time.

The innovative use of GANs in this context involves two main components: It gives two networks: the generator and the discriminator. In the GAN structure, the generator's role is to generate low-frequency irradiance data samples similar to the real data samples. This process entails understanding the distribution of the data and structures that are difficult to explicate in the low-frequency data. In other words, the goal of the generator is to come up with data that consists of gradually varying patterns similar to what is observed in the real-world irradiance data. At the same time, the second network, the discriminator, compares the samples with real low-frequency data and synthetic data produced by the generator. It is in this process of repeated opponents' battle between the generator and the discriminator that the GAN develops better algorithms for producing realistic data. The generator optimizes its outputs to deceive the discriminator, giving accurate simulations of low-frequency data trends.

In this manner, the GAN becomes proficient in distinguishing and generating the subtle changes and possible long-term features inherent in the low-frequency subsets. It also increases the potential of this model to produce long-term patterns of the solar irradiance data with higher accuracy.

Many of these trends are captured and modeled well by the GAN, thus enhancing the overall forecasting capability of the model. It not only improves the short-term solar irradiance forecast, the most important variable affecting the generation of solar electricity, but also adds to the overall knowledge of how solar irradiance changes at different frequencies. Thus, this innovative approach proves more effective, making both sharp short-term changes and slow trends predictable, which makes the created system quite reliable and universal. The present work, therefore, poses an improvement over the application of GANs for low-frequency prediction in that the dynamics of the solar irradiance data are captured better and in more detail by this model.

4. Results and Discussion

The results part is for verifying that the suggested framework for solar irradiance forecasting is effective in many ways. In order to demonstrate the results of this model's effectiveness, special attention is paid to assessing how well it performs in terms of solar irradiance level by employing a number of measuring instruments and standard tools to answer the questions about how reliable and accurate it is. This will enable us to check if this model is flexible enough to work on other datasets other than the one we used in developing it. The set of data applied in the research of the present study has been obtained from the National Solar Radiation Database (NSRDB) [29, 30].

This dataset was pre-processed for the proposed model by cleansing and preparing it for the appropriate quality and relevance of inputs. It normally contains the hourly variables of the measured solar irradiance, like Global Horizontal Irradiance, Direct Normal Irradiance, Diffuse Horizontal Irradiance, temperature, wind speed, and other meteorological variables that can be useful in any solar energy forecast. First, missing or inconsistent values were identified, followed by interpolation or imputation using the median or mean of surrounding data points. It provides the level of different irradiances in Texas within a year. The numbers were collected at a measuring station, which, according to existing information, consists of 118. 31 degrees west longitude, and 33. 98 degrees north latitude. The experiment or validation is performed using the following software and hardware configurations mentioned in Table 2.

This specific site displays typical weather conditions; similar to the other locations within this region, there are four seasons and daily fluctuations in temperature. These climatic conditions have an impact on solar irradiance and are quite evident when comparing the different months of the year. In summer, the irradiance level tends to remain constant and produces a steady rate of solar energy input because the day is long and the weather is normally fine. However, it depicts variable values irradiated by factors such as short days, cloud cover, and different weather conditions in winter. In the collected data, it is possible to observe regular annual changes in irradiance and a considerable daily temperature variation. This shows the variation of the data, and therefore, it is useful in the study and development of models for research in solar irradiance forecasting.

Table 2. Hardware/Software Specifications

Programming environment	Python 3.10
Libraries	PyTorch 2.0 and TensorFlow 2.12
Training/Validation /Test split	70% / 15% / 15%
Batch size	64
Learning rate	0.001 (with Adam optimizer)
Epochs	100 (with early stopping if validation loss plateaued)
Loss function	Mean Squared Error (MSE)
Evaluation metrics	MAE, RMSE, MAPE, R² Score
Cross-validation	5-fold cross-validation

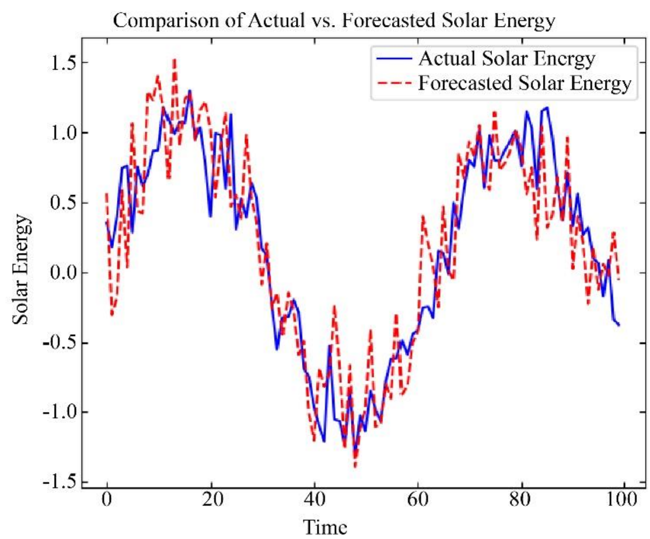

Fig. 3 Solar energy predicted output

Figure 3 presents the forecasted output of solar energy as a function of time. In this graph, the red dashed line represents predicted solar energy values generated by the forecasting model. This could be important in visualizing how the model forecasts solar energy from applications in grid management, energy storage, and optimization of solar power systems. Forecasted values are obtained using elaborate models that study historical data in order to predict future energy output. In this graph, the red dashed line represents the forecasted values of solar energy obtained from the forecasting model. This may be important for visualizing how the model forecasts solar energy from applications in grid management, energy storage, and optimization of solar power systems. Forecasted values are obtained from elaborate models that study historical data in order to predict future energy output.

Figure 4 gives a detailed comparison of the actual and forecasted solar energy outputs, including the confidence intervals with the model uncertainty. The graph depicts observed solar energy data, as shown in blue, and the forecasted values shown by the red dashed line. The confidence intervals are given by the area around the forecasted line in red, which is important in order to quantify the degree of certainty of the forecast. These intervals are defined statistically by considering various sources of error and variability in the data. The confidence intervals shown in this figure represent a range within which forecasted values can be expected to lie, given that a forecast, by definition, cannot be devoid of uncertainty. By visualizing these intervals, it is investigated how reliable the forecasted values are and how well the model accounts for uncertainty. Besides that, the graph also includes a rolling mean on the forecasted data represented by the green dashed line. Such a use of the rolling mean will smooth out short-term variations and underline the tendencies that may occur in the forecasted data. The rolling mean is computed over a specified window size. The specified window size balances responsiveness to recent changes against the stability of long-term trends. This provides a view of both immediate predictions and broader patterns in the data. Forecasted solar energy production was obtained using the model. The figure shows the various levels of irradiance that the system is to predict within a given timeframe. Schematically, this is how the said fluctuations of solar energy production could change with time, weather conditions, and seasons. This graph hence can show that such variations are well captured by the model with very high accuracy; thus, the model is quite suitable for practical applications in energy management. The proposed model attained an MAE and RMSE value of 0.28 and 0.35, which is graphically represented in Figure 4. To further validate the model, the error rates for each of the seasons, spring, summer, autumn and winter are depicted in Figures 5 to 8. The calculation of these error rates is based on four important performance measurements, such as MAE, RMSE, MAPE, and R2. MAE is a measure of the typical absolute deviation of the sum of the differences in some set of forecast values and corresponding actual values. MAPE provides an initial idea of how closely the model identifies actual values approximately- it shows how, on average, the numbers estimated actually deviate from the numbers observed. RMSE stands for root mean square error. Compared with sequentially processed LSTM and GRU, the proposed model possesses high accuracy. Apart from this, LSTM and GRU are subject to such issues as vanishing gradients, or they cannot work well on noisy and sparse data, while the GAN part enhances the robustness of the whole model due to its capability to generate highly realistic synthetic data for complementing a real-world training dataset.

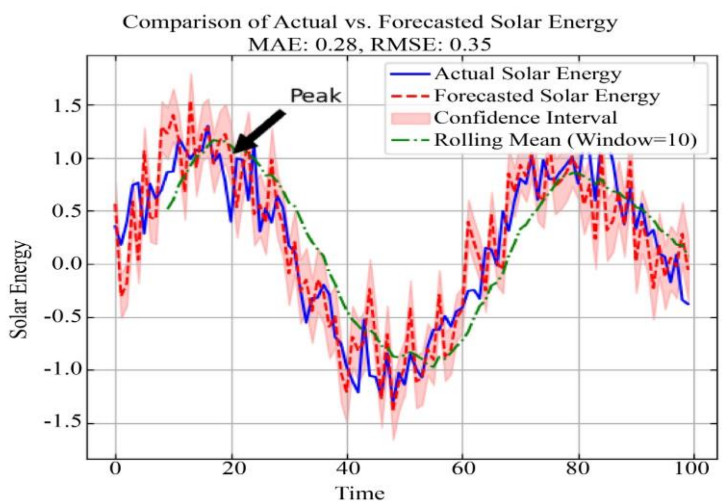

Fig. 4 Comparison with confidence intervals

The augmented data helps the model generalize to hitherto unseen conditions because the problems brought in by limited or noisy datasets are resolved. Besides, convolutional layers implemented in the architecture enable the TAGC-Net to capture the spatially relevant features necessary for understanding solar radiation patterns, a layer of depth noticeably missing in the models based on either LSTM or GRU. Therefore, the proposed model will be able to learn complex temporal dynamics and spatial features of solar irradiance supported by a much stronger architecture for better performance regarding high accuracy, low error, good generalization, and reliability compared to other traditional methods. At last, the R^2 score or the coefficient of determination shows a model's explanatory strength. Checking the error rates for various seasons, both in the models already present and those proposed, gives us an important understanding of how well each approach performs and its effectiveness. These visuals reveal the high forecasting accuracy of the suggested solar irradiance prediction framework. They make it easy to understand, helping with making decisions and improving the model for future use cases.

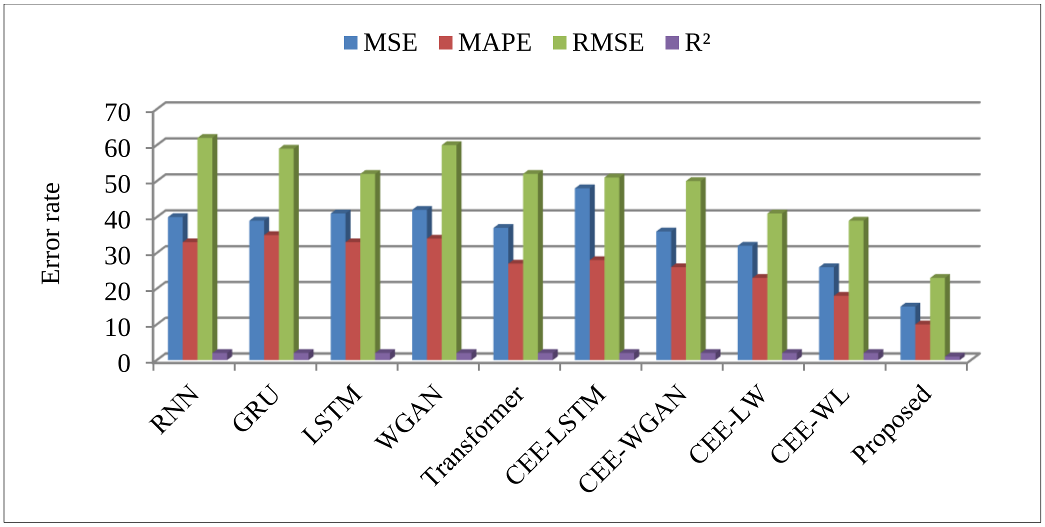

Fig. 5 Error rate for the spring season

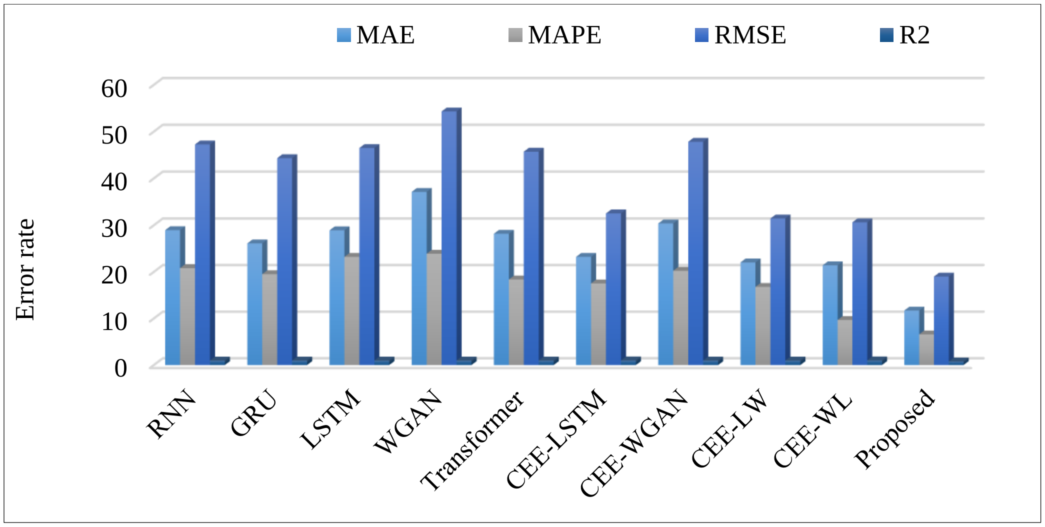

Fig. 6 Error rate for the summer season

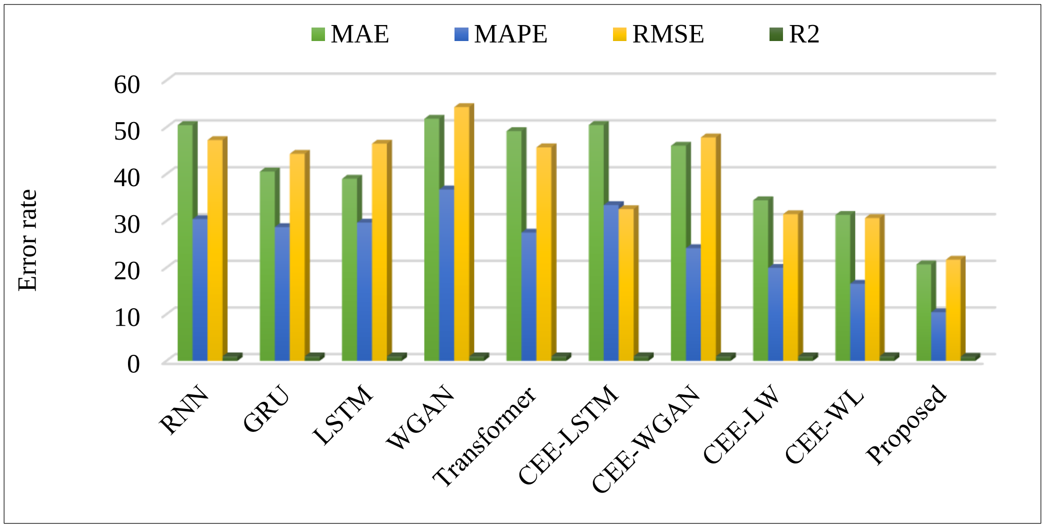

Fig. 7 Error rate for the autumn season

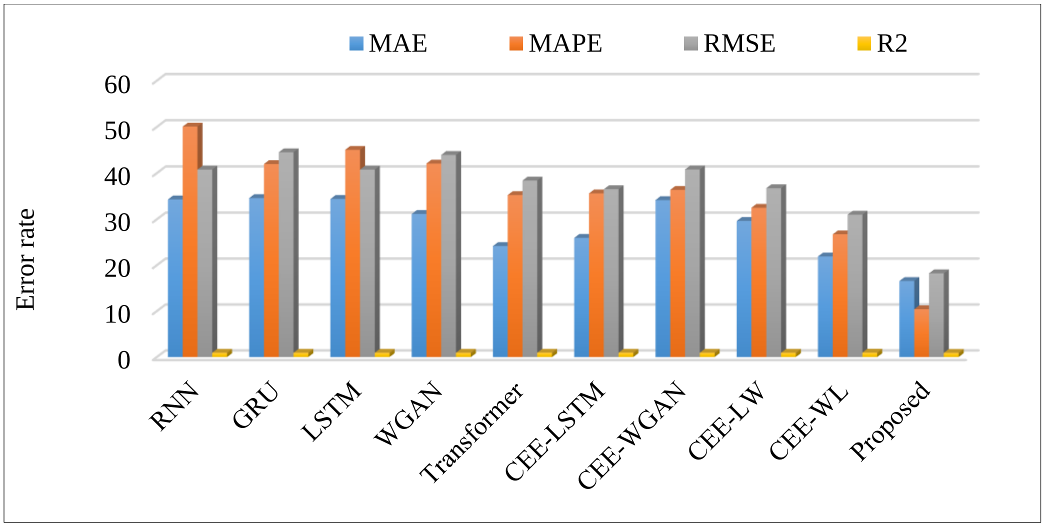

Fig. 8 Error rate for winter season

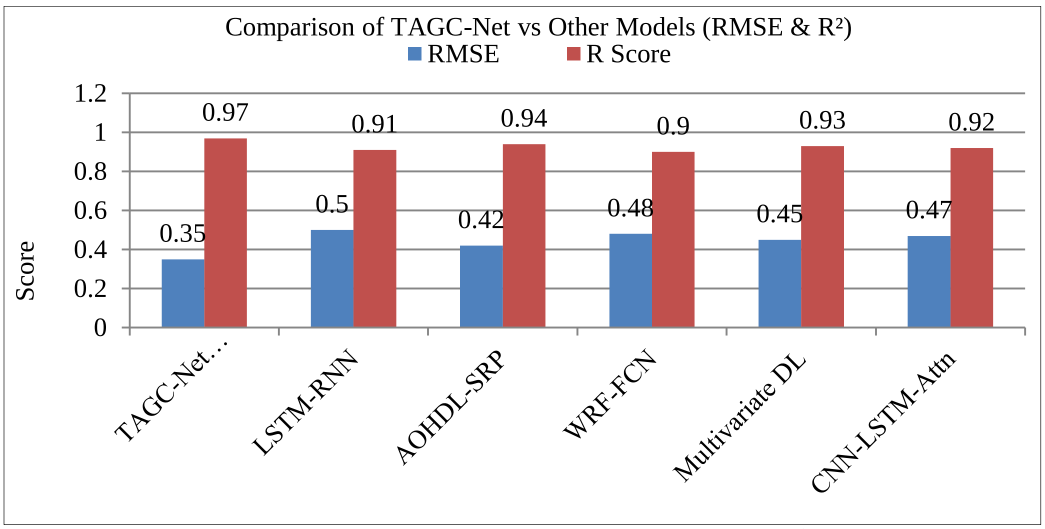

Fig. 9 Comparison of different models based on RMSE and R^2

Finally, a comparative analysis is performed with the proposed TAGC-Net and other models discussed in the literature, like LSTM-RNN, AOHDL-SRP, WRF-FCN, Multivariate DL, and CNN-LSTM-Attention, based on RMSE and R^2 factor. Upon interpretation n Figure 9, it can be seen that TAGC-Net clearly outperforms with the lowest RMSE (0.35) and a high R^2 value (0.97), indicating high prediction accuracy and reliability.

5. Conclusion

This paper developed a new TAGC-Net model integrated with a GAN to make better predictions about short-term solar irradiance. The combination of these new designs shows great accuracy and trustworthiness in forecasting short-term solar irradiance levels. The complete examination of the suggested model confirms its superiority to current methods, highlighting its possible role in changing how renewable energy and grids are used. With the increased need for sustainable energy solutions, this research helps improve efficiency and practicality in solar energy systems. It moves towards a more eco-friendly and lasting future. Analysis of the projected model reveals its superiority in predicting solar irradiance levels in different ways, owing to an MAE of 0.28 and RMSE of 0.35. Finally, as a result of comparative analysis with existing models like RNN, GRU, LSTM, and so on, the model excelled in all metrics, such as low errors and high R^2. This confirmation strengthens how well the novel method works and its possible influence on improving predictions of solar irradiance. Yet, the system still requires a large amount of high-quality data for the evaluation of the model. Additionally, high training, inference cost, and model interpretability are encountered, which are considered in future enhancements. Future work on this model could be done in many areas to further its performance and applicability. One such area is incorporating more advanced hybrid architectures, using proposed TAGC-Net and GAN with reinforcement learning for greater instantaneous managerial power, such as the ability to animatedly regulate the forecasting strategy based on current grid conditions or energy storage levels. This would involve further development of the dataset of previous environmental conditions, like atmospheric pressure, cloud wrap, and pollution, that may influence the solar irradiance received but are probably not reflected by this model. That would help give the model robustness for quite a few places and weather conditions.

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