



Transformer-Based Deep Learning Framework for Renewable Integrated Power Demand Prediction in Smart Grids Forecasting for Smart Grids

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Abstract. Currently, the custom of renewable energy to moderate the effects of global warming and its impact on the environment has become increasing day to day. Several nation-states currently have a majority of photovoltaics in use, which suggests that these renewable energy sources can be calculated with significant effect. Short-term power-demand forecasting is essential for renewable integrated smart grids, where the stochastic nature of solar resources complicates real-time balancing. In previous work, Challenges have been faced in accurate load demand predictions for specific solar renewable energy sources, The load demand in smart grids is partially dynamic, requiring estimates or adaptation to real-time operational shifts. This analysis propose a hybrid deep learning approach that integrates Temporal Fusion Transformers (TFT) with Dilated Temporal Convolutional Networks (TCNs) to accurately forecast solar renewable integrated energy needs in smart grids, managing the factors that standard forecasting measures. TCN can extract multi-scale temporal patterns from past power demand (e.g., from historical loads) and renewable energy information. TCNs can be trained both short-term and long-range dependencies and detected patterns were passed through a Temporal Fusion Transformer (TFT), which fuses static and time-varying inputs using attention mechanisms, gating layers, and variable range procedures into a single model. The TFT also displayed point forecasts and probabilistic forecasts featuring quantiles, allowing the smart grids manage to make more accurate estimates RMSE of 1.53 and MAPE of 2.12%. The experimental results validate that the proposed approach enhances load demand efficiency through an experiment conducted in MATLAB.

Keywords: Temporal Fusion Transformers (TFT), Dilated Temporal Convolutional Networks (TCNs), Solar, Load demand, Demand Prediction

1 Introduction

The distribution of electricity to each user is carried out through the traditional electrical grid, which enables electricity to be transported from generation to specific load demand. If the commercial use of electricity has a limited load demand, the distribution

of electricity will be evaluated using demand forecasting. In this case, the electricity-generating sources and the transmission lines are all part of the physical electricity structure that delivers the electricity to the end user. Factors that affect small term demand forecasting can take a significant impact, such as sudden climate variations or the Chaos Theory and the butterfly effect. Conversely, the quality of short-term demand forecasting enables to participate effectively in the electricity market [15].

The issues in medium-term request forecasting display a grade of persistence as seasonal weather changes. The factors that affect long-term demand forecasting can be assumed to have a relatively long-time frame, considering multiple forecast periods [1]. Electricity is poised to take an even greater dominance as the primary energy vector for industry, homes, and transportation. Therefore, forecasting electricity demand becomes increasingly valuable, as this influences several operational and commercial processes. The analysis of electricity demand is often referred to as load when Distribution Generation (DG) electricity is involved [14]. An outline for the emergence of machine learning approaches, based in particular on ANNs, which are well-suited to manage recorded data, with the major challenge of non-linearities, multiple types of input features, and the choice of training and test sets [2].

Load forecasting (LF) has gathered significant consideration, which is usually required in various applications to amalgamate the performance of SG. Very Short-Term Load Forecasting (VSTLF) is a forecasting procedure that is applied a short time in development, where the smart grid values are guided to the operative for usage later in almost real-time. Short-Term Load Forecasting (STLF) is a method that affects the reliability and power consumption of the energy system, which in turn is influenced by the accuracy and reliability of the method. Long-term Load Forecasting (LTLF) is a method essential to energy utilities and planners due to advancements in smart grids, future investments, and planning distribution [3]. A smart grid is a transmission approach that connects energy sources suppliers to the electricity grid, while enhancing protection.

Smart grids allow the two-way movement of electrical source of data, including smart meters, smart electrical devices. This can negatively impact the implementation of model fitting, and the predictive outcomes, in terms of misclassification error, may be over-calibrated. As the smart grid produces a large amount of data, it can be frequently improved over time, and there is room for implementing new predictive models [4]. The power is generated based on load demand calculated on demand forecasting, which involves combining statements, logic operators, mathematical functions, and other elements.

A different case of predicts variables by observing the output that results from applying the rules to the input data. This means that with a rule-based prediction model, the prediction is more transparent and easier to interpret. Overfitting or underfitting

occurs when a statistical model is overly complicated, or if it is too simple, it either overfits (fitting to the noise) or underfits (not capturing the relevant information). Data quality refers to whether the prediction is accurate or not, and it depends on the quality and relevance of the data input. Error occurs in data or insufficient data will certainly compromise the model's performance [5]. The advancement of electronic devices, along with renewable energy, is revolutionizing the electrical grid. Solar energy sources can be applied as a major and sustainable energy source, typically in conjunction with several electronic devices using power electronics.

Smart Grid have wide applications and have positively enhanced with different energy sources; however, issues associated with integrative applications need to be addressed to ensure the dependability and stability of the electrical grid. Smart electronics devices, including converters, generators, and inverters, can be effectively integrated when incorporating renewable energy sources into an electrical grid system. The collected data will undergo multiple processing steps before being analysed and converted into a model [6]. The energy management system of the Smart Grid data is analysed to gain a demand load of the functionalities and uses of each method based on EMS. Smart grids are defined as electricity grids that intelligently include Information and Communication Technology (ICT) from generation points to customers, for instance.

The centralized structure of an EMS can be interpreted as a control structure that consists of a single controller, which features a powerful computing system and a secure, devoted network for monitoring energy use. The controller can be a collector or utility that compiles the energy consumption patterns of their loads/consumers, as well as the energy generation from their generation sources, etc. The controller can then run optimization programs using that information to achieve their evaluated output, thereby ensuring overall better operational performance [7].

2 Previous Research Work

By integrating enormous production points as the sole energy source at several sites, SGs are used for energy transmission and distribution. SGs are one-way electrical connectivity systems. In addition to data analytics, energy providers improve SG optimization and increase client engagement. In particular, RES promotes the use of predictive analytics and big data. They differ from weighted means in that they take into account how the weights relate to the size of the inputs, rather than their particular values [8]. The gathering and combining data from several sources to enhance tasks involving categorization, forecasting, recognition, and decision-making is detailed as multimodal information fusion.

A random forest-based characteristic selection methodology to find essential input characteristics for load forecasting. Super short-term load forecasting predicts the electric load of power customers on an hourly or less than hourly basis. Short-term load

forecasting predicts the daily electric load of customers, medium-term load forecasting predicts the electric load of customers on a weekly basis, and long-term load forecasting predicts the electric load of customers on a monthly and beyond basis. Short-term load forecasting has more practical request rate than the load forecasting research focused on other time scales [9].

An effective data-driven load forecasting model that uses advanced deep learning techniques to accurately estimate the power grid's generation of RERs as well as real-time load demand. An adaptive control technique that maintains system frequency stability while skilfully handling the power supply's inherent nonlinearities and uncertainties. load forecasting model and adaptive controller performance utilizing Real-Time Data and In-Depth Hardware In-Loop (HIL) analysis. To investigate mistakes are altered in response to different noise levels or data manipulations, a thorough error analysis has also been carried out [10].

To schedule energy sources and manage energy transactions between the system and the utility grid under circumstances of surplus or shortage power, energy management systems utilize ANN-predicted day-ahead load demand. Two interoperable areas are connected to create the cluster, and each area is connected to two microgrids. Energy transactions between the two interconnected regions in the cluster and microgrid are designed to operate in both isolated and grid-connected modes, and each area is connected to a local MG controller, load demand forecaster, and Real Time Data (RTD) monitoring [11].

Strong time-aware validation processes are also included in evaluation to generate the models' dependability. By addressing typical problems such as overfitting and data leakage, these techniques ensure that the act reported is accurate. The OPS, current electrical load demand, and distributed PV systems related to the TX-OPS contain the port microgrid, as outlined in this examine. Ship attributes, including size, engine power, and back of energy management, are used to forecast additional demand for port microgrids, especially those in island locations with shore power connections [12].

Load shifting involves moving loads from peak to off-peak times without altering the way energy is applied. First, the load needs of a low-efficiency appliance usage-based scenario, without Demand Side Management (DSM), were used to assess these six setups using LF and CC techniques. Later, utilizing the load needs, the optimal outline derived from the scenario based on the utilization of low-efficiency purposes was further assessed using LF and CC techniques. The average energy consumption by encouraging energy use during off-peak hours. Customers may be encouraged to load and charge during off-peak hours to achieve. For instance, clients can store thermal energy and utilize it to maintain a warm room throughout the day during off-peak hours [13].

This work leverages multiple network resources to enhance the system's capacity to accommodate uncertainty securely. This skill is frequently referred to as operational flexibility. The second strategy is to employ suitable risk management techniques, in conjunction with a Constrained Optimal Power Flow (OPF) model and Conditional Value-at-Risk (CVaR). Due to the need to collect, store, and interpret vast amounts of data, data availability may be a practical difficulty. The model structure does not need to be significantly altered to incorporate N-1 security limitations into the suggested formula [14].

Examines the worldwide trends and developments in energy demand forecasting techniques by doing a thorough assessment and analysis of demand-side forecasting, energy demand, and battery management. An integrated management strategy of the power sector is therefore crucial for the sustainable development of any country. The forecasting methodologies are classified into statistical and advanced models, and the output results show that hybrid models are ideal due to their sustained accuracy and enhanced flexibility. In contrast, ML/AI-based models are applied more frequently in electricity demand forecasting than statistical models [15].

3 Materials and Methods

This work explains the research methodology for power demand prediction, energy prediction, and focusing on the dataset's collected in renewable energy source. The selection of each procedure evaluated over a typical input is thorough, concluding with model validation evaluating forecast and Electric power generated from cases of Solar Energy renewable energy source sources.

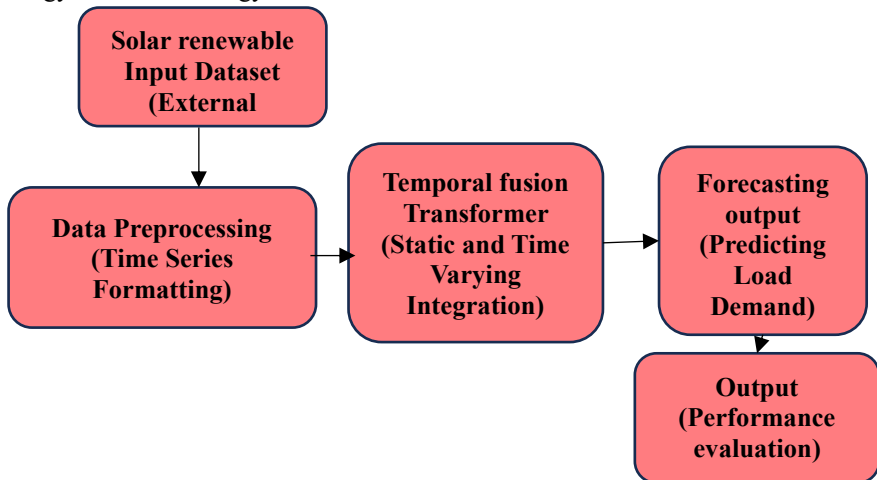


Fig 1. Proposed Block diagram of Demand Forecasting

In Fig.1, the block diagram illustrates a load demand forecasting classification using a Temporal Fusion Transformer (TFT), where the input data consists of customer information and external factors, as well as solar renewable energy parameters. The input data undergoes preprocessing, a crucial step that involves formatting the time series for model resolution. After this, the cleaned data is fed into the Temporal Fusion Transformer model, which incorporates both static variable quantities and varying features. A forecasting output is generated, whereby the model predicts future load demand based on the inputs, and the forecasted output is then evaluated appropriate metrics. As emphasized in the flow, it is essential to have well-structured data, robust modelling, and evaluation for accurate demand forecasting and represents a complete pipeline for time-series load forecasting.

3.1 Demand Forecasting in Smart Grid

In smart grids, predicting power demand plays a vital role in utilizing real-time data created by smart electrical devices. This real-time data is processed using specific patterns with different load demands in energy consumption. Each type of demand prediction applies to optimize their energy supply and better enable and integrate renewable sources, such as solar and wind, as well as establish various load management approaches. This improves the grid, in addition to improving carbon emissions, and creates a different parameter for each type. Different approaches have been employed to predict demand in smart grids. The TFT and TCNs approaches rely on past load data and integrate other relevant contextual data such as weather conditions, time of the day, and approximate seasonal demands. Among these model types, the deep learning approach can capture complex, nonlinear relationships and dependencies over time, while still producing accurate predictions of demand based on past usage patterns.

Fig.2 describes the demand forecasting working procedure, and Energy Consumption is a real-time working approach for users that is constantly restructured.

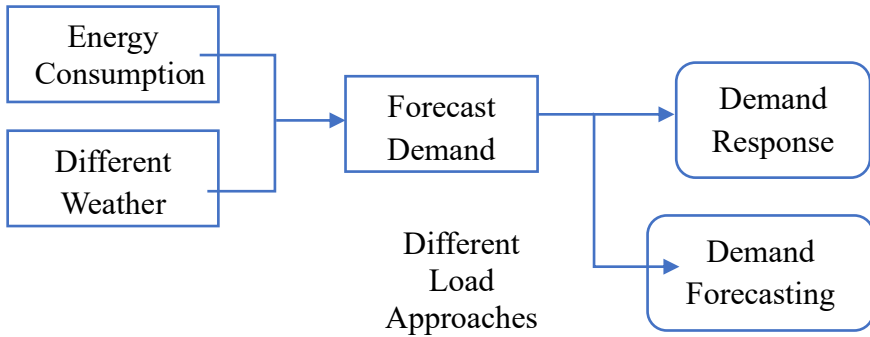


Fig. 2. Demand Forecasting in Smart Grid

$$N = \frac{N - N_{min}}{N_{max} - N_{min}} \quad \dots \quad (1)$$

In equation (1) calculated demand and supply prediction models to hybrid models that utilize both physical datasets of specific durations to predict future states of demand. Each time, hourly parameters are monitored to ensure accurate power demand predictions for smart grids and sustainable energy systems.

3.2 Temporal Fusion Transformers (TFT) with Dilated Temporal Convolutional Networks (TCNs)

TFTs are evaluated using a time-series forecasting approach, which employs a specific mechanism to weight relevant features over time and produce interpretable predictions flexibly. The value of TFTs in renewable integrated power demand prediction is mainly due to their capacity to incorporate multiple inputs (such as weather and calendar data along with past demand), address complicated temporal dependencies across multiple time horizons and to provide reliability that allows energy demand and determine power demand at different points in time. TCNs improve upon time-series models by providing a wide receptive field through dilated convolution. TCNs utilize convolutional layers instead of recurrent ones, which enables TCNs to train faster and exhibit slightly more stable long-term dependencies when modelling classifications. Combined with TFT, TCNs can capture both short-term and long-term patterns in power demand data, especially when variations from renewable sources (e.g., solar) output to be both non-linear and unbalanced. In Fig.3, renewable integrated system applications, power demand is influenced by numerous uncertain factors, including solar radiation, wind speed, and temperature, all of which vary in time, space, or both. TFT using TCN offers a unique solution as it combines the capability of transformers in emphasizing significant time steps and features with the capability of TCNs to learn order dependencies of sequences. Together, they enable the prediction model to learn about

sudden changes in power generation and consumption, as well as seasonal patterns in renewable energy generation and consumption.

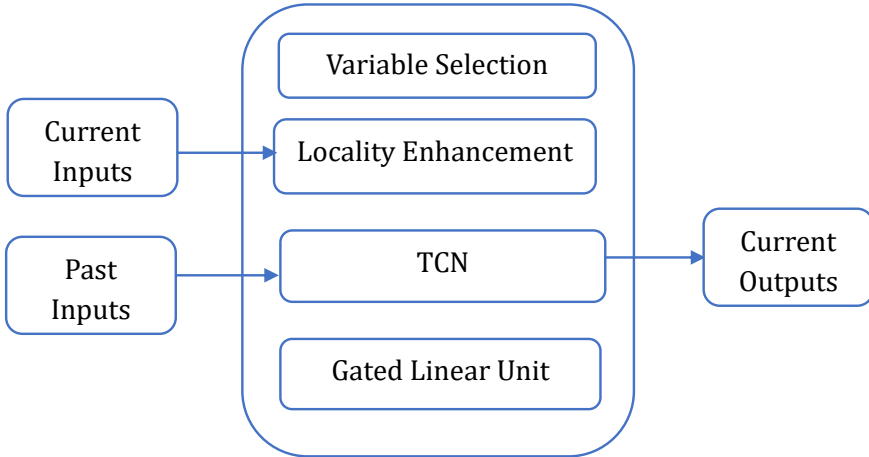


Fig. 3. Working architecture TFT and TCNs

Applying a TFT with TCNs transformer for improve forecast accuracy and increases robustness, critical to the power grid's stability and optimal energy dispatch. For example, in the case of bad weather condition days or unexpected drops in wind levels, the forecast model can quickly adapt its predictions influenced by what was learned regarding patterns, other recent time-step features representing current conditions and time steps with more uncertainty. The forecast model and integrated support tools for monitoring and controlling energy sources when combined will reinforce the reliable integration of renewable energy into the power grid reducing reliance on fossil fuels and carbon emissions. The integration of Temporal Fusion Transformers and Dilated TCNs offers a best-in class solution for power demand forecasting in integrated renewable systems. It capitalizes on the virtues of both models' attention-based feature extraction and effective temporal pattern detection to make precise, explainable, and scalable predictions. This is particularly crucial for contemporary smart grids where dynamic demand response and real-time forecasting are indispensable to sustainable energy management.

Smart grids are upgraded electrical grids utilize digital technology to improve monitoring, control, and optimization of power flow from generation to consumption. Smart grids allow utility companies to communicate in real-time with energy consumers, enabling better efficiency and reliability beyond that of traditional grids. This is possible because smart grids will include automated smart meters with sensors and data analytics to respond rapidly to changes in energy consumption. Making energy systems more resilient, power demands at the level of the end user is the most

fundamental need for efficient operation and planning in this space. Power demand prediction, also referred to as load forecasting, entails forecasting much electricity consumers will need at a point in time in the future. Load forecasting can either be short-term (minutes to days), medium-term (weeks to months), or long-term (years). Accurate load forecasting helps utilities balance loads with supply, avoid energy lacks, and minimize operational costs. Forecasting is important for scheduling the operations of power generation plants, ensuring stability in the grid, and planning new capital infrastructure. Lack of accurate and timely load forecasts can result in wasted energy, unnecessary expenses and possibly even blackouts.

4 Result and Discussion

This performance analysis was conducted using the MATLAB simulation environment and calculated evaluation metrics to measure from solar renewable source and predictive capabilities. It estimated and verified the overall performance and calculated with four different cases with value standard output, using specific data and results were normalized using the mean value of the measurements in the test dataset

4.1 Case 1: Solar Irradiance Forecasting

Depending on the range of prediction criteria employed, solar power forecasting techniques are divided into univariate and multivariate categories. Multi-input characteristics that impact solar energy production, such as solar irradiance, cloudiness, clearness indices, temperature, wind speed, and relative humidity, are characteristically used in multivariate procedures to assess solar power. Conversely, univariate methods rely just on the time series values of solar power, either past or present. In table 1 sample of datasets is particular collected specific hours, day and week. Each output is then calculated by combining the output of the same models with the test data set. Several base learners or based models are designed using the ensemble approach and sampling data set will be supplied for each model's training.

Table 1. Data Set Provides the forecaster function hour month function actual one day solar irradiance.

Day in Hours	24 Hours
Day in Seven	1.7
Four in weeks	1-4
Photovoltaic Irradiance of current day during an hour	W/m^2

The energy efficiency management system for photovoltaic integrated greenhouses is divided into three sectors: the supply side, which includes the photovoltaic system, energy storage structure, and External Power Grid (EPG); the demand side, which consists of various electrical equipment; and the energy efficiency monitoring and dispatching system (server). The demand side forecasting gathers factors such as solar, energy storage, electrical parameters, and monitors the dispatching of the internal power grid

4.2 Case 2: Load Forecast Evaluation Over Time

This section shows a time-wise comparison among actual and predicted power load over a 24-hour day. The Fig.4 and Table 2 show the effectiveness of the prediction at each interval.

Table 2. Validation of Load Forecasts Over Time

Hour	Actual Load (kWh)	Predicted Load (kWh)
0	120	118
4	135	133
8	150	148
12	145	147
16	160	159
20	155	154

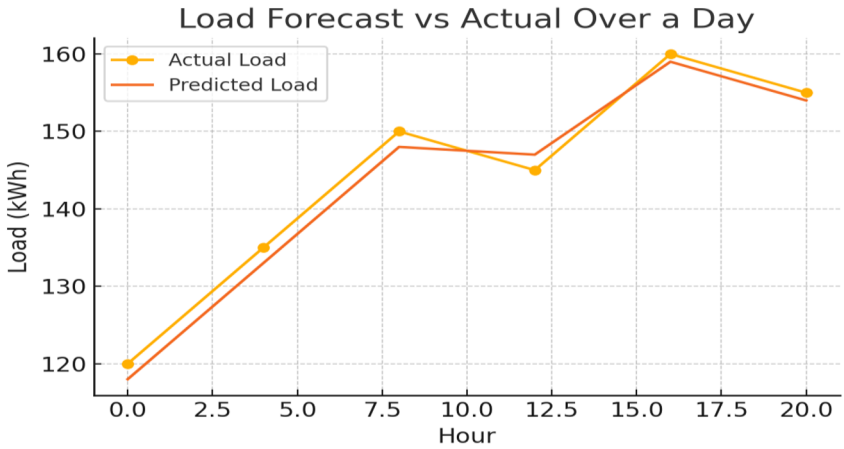


Fig. 4. Actual and Predicted Load Comparison During the Day

4.3 Case 3: Solar Irradiance Forecasting Evaluation

Predicting solar irradiance is essential for predicting the generation of renewable energy and weekly comparison of actual and expected sun irradiance is shown the Fig 5 and Table 3.

Table 3. Assessment of Solar Irradiance Forecasting

Day	Actual Irradiance (W/M ²)	Predicted Irradiance (W/M ²)
Mon	450	448
Tue	460	462
Wed	470	469
Thu	440	442
Fri	455	457

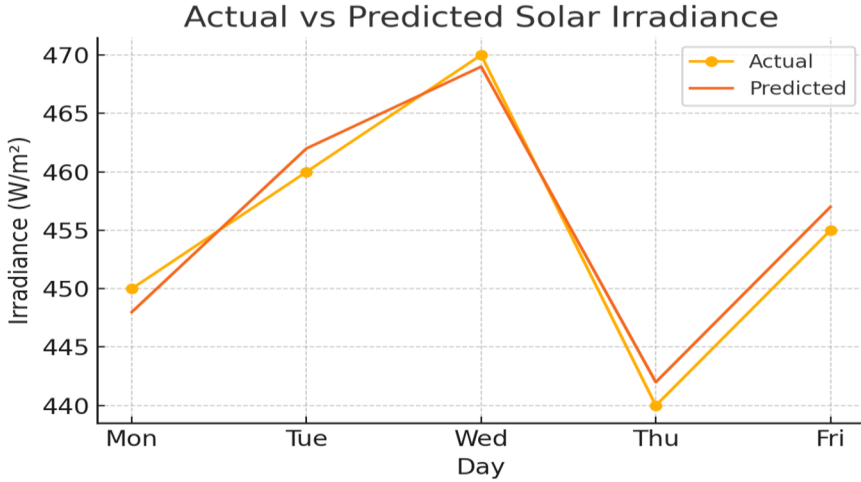


Fig. 5. Solar Irradiance Actual and Predicted Irradiance

4.4 Case 4: Forecasting with Two different type

The hybrid TFT with TCN calculates a forecasting accuracy for solar renewable integrated power demand prediction in smart grids. The results show that the combined TCN+TFT models outperformed the state-of-the-art approach, TCNs, and TFTs, individually. The input values are applied for prediction evaluation. Furthermore, these metrics are provided by Metrics, which capture both short-term and long-term temporal dependence and models the stochastic nature of solar-based power generation. As shown in Table 4 below, the combined TCN+TFT model yielded the lowest Mean Absolute Error (MAE) of 0.94, the lowest Root Mean Squared Error (RMSE) of 1.53, and the lowest Mean Absolute Percentage Error (MAPE) of 2.12%.

Table 4. Performance Evaluation Metrics

MODEL	MAE	RMSE	MAPE (%)
TCN	1.34	2.18	3.45
TFT	1.12	1.89	2.87
TCN+TFT	0.94	1.53	2.12

Table 5. Performance Metrics of Two different dataset applied

Month	Technique	Data Set 1 (Solar Type 1)	Data Set 1 (Solar Type 2)
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		MAE	RMSE	MAPE	MAE	RMSE	MAPE
March	TFT	0.124	0.284	7.18	0.191	0.319	9.58
	TCNs	0.29	0.365	5.62	0.217	0.426	4.95
April	TFT	0.205	0.42	4.03	0.29	0.234	4.69
	TCNs	0.21	0.338	7.61	0.137	0.5	6.69
May	TFT	0.168	0.207	6.86	0.227	0.381	7.62
	TCNs	0.204	0.419	7.98	0.147	0.437	6.01
June	TFT	0.141	0.377	6.0	0.143	0.479	5.76
	TCNs	0.158	0.374	6.5	0.29	0.314	5.38
July	TFT	0.261	0.402	3.64	0.177	0.492	5.35
	TCNs	0.14	0.368	4.49	0.166	0.487	6.25

In Table 5 and Fig 6-8, two solar types: Type 1 (rooftop installations) and Type 2 (utility-scale systems), and Solar Type 2 (Dataset Small-scale Utility-scale / Industrial), with a three-factor calculation based on four months of data analysis for two different factors: TFT and TCN. The MAE and RMSE values are relevant for assessing the model's accuracy, as they are directly related to prediction errors. Each data type is analysed these measures, indicating that TCN's temporal feature extraction and TFT's integration device complement each other, resulting in a more robust and interpretable model, which is suitable for specific models adaptable to real-time data analysis of indeterminate renewable energy variability. The combination of TCN and TFT enhances accuracy while also improving grid stability, enhancing dispatch, and reducing errors in smart grids.



Fig. 6. MAE comparison analysis.

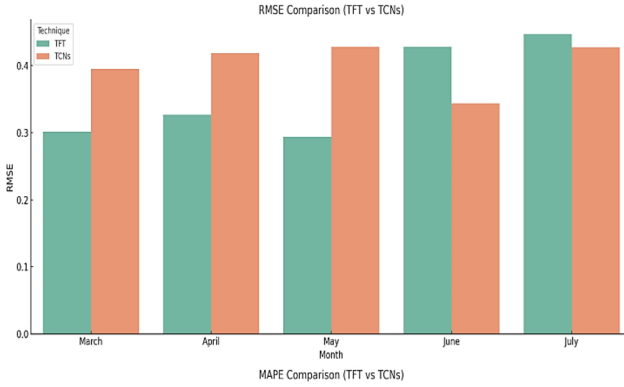


Fig. 7. RSME evaluation analysis

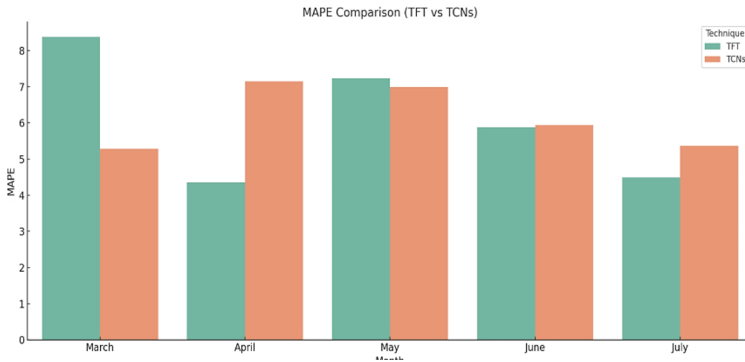


Fig. 8. MAPE estimation analysis

5 Conclusion

Energy issues are a key concern for the sustainability of our current electrical demand. This demand forecasting is based on the integration of renewable sources and the development of new energy distribution systems, which aim to meet consumer demands. The TFT and TCNs are analysed, and solar generation is classified based on weeks, errors, and throughput through a power management system, considering and using levels. Minimizing grid power loss or improving grid management aids is usually These values can discontinue loading as required, without notifying the customer, thus minimizing the potential for power system instability and overloading. In case 1 output RMSE of 1.53 and MAPE of 2.12%, In case 3 two different types of data set applied and outperforming the standalone models for power demand forecasting. The results specify that the hybrid model achieved a better overall ability to capture both short- and long-term dependencies of dynamic energy data due to the inherent non-stationarity of

the data. The lower RMSE provides evidence of the model's increased accuracy in predicting smart grid demand integrated with solar energy in an uncertain environment

6 Future Scope

In future work, the advanced hybrid transformation, which has been developed with different renewable energy sources and devices such as smart grids, has the potential to improve estimates under dynamic conditions. Edge computing, combined with federated learning, may also offer privacy-protective and low-latency predictions. Furthermore, various approaches could be applied, such as integrating adaptive learning methods to enable the model to take self-action in response to behavioural and/or seasonal oscillations. It is key to focus on regional forecasting, as these outcomes in significantly lower uncertainties due to spatial smoothing effects.

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