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# FORECASTING OF SOLAR RADIATION FOR SOLAR SYSTEM UNDER DIFFERENT CLIMATIC CONDITION

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**Abstract-** Sun oriented energy is a perfect, plentiful, and sustainable power source. The utilization of photovoltaic boards to produce power from sun-based energy is turning out to be more well known. Since sunlight-based energy is discontinuous, the produced power is variable. This vulnerability could be decreased by using energy stockpiling frameworks and exact sunlight-based power determining. The objective of this proposal is to carry out a sun-oriented figure module as a component of an improved Energy Management System (EMS). Measurable techniques, sky imagers, satellite imaging, and mathematical climate forecast are among the strategies examined (NWP). To meet EMS necessities, counterfeit brain organizations (ANNs), a subset of factual strategies, were picked as a forecast strategy. For the EMS to work appropriately, exact anticipating in the momentary expectation skyline is required. The expectation skyline is how much time coming down the line for which an expectation is required. Additionally, the paragraph mentions the Temporal Convolutional Network (TCN) architecture, which uses temporal convolutions to process sequential data and has shown promise for time-series analysis tasks. Albeit every one of the techniques referenced above give OK execution, TCN engineering gives additional promising outcomes. To enhance the accuracy of solar radiation predictions, the possibility of dividing the dataset into sub-datasets based on radiant and overcast weather conditions and implementing a dedicated prediction module for each sub-dataset is being investigated. The outcomes show that bunching the dataset further develops expectation exactness for all models. Besides, recreation results on datasets from various geological areas with fluctuating environment conditions show that forecast exactness is higher in regions with additional steady climate and bright days.

**Keywords:** Climate, Machine Learning, Solar Energy Predictions, Solar Radiation.

## 1. INTRODUCTION

As per ongoing examination, in spite of the way that the sun-oriented energy area has seen the most improvement among environmentally friendly power sources, sun-based energy's commitment to drive age stays unassuming. Gerhard Knies and Franz Trieb have suggested that if by some stroke of good luck 0.5% of the planet's warm regions were covered with planetary groups, the entire planet's energy necessities could be provided, as the Earth gets multiple times more energy from the Sun than is consumed around the world [1].

Solar energy has been in use for around 2500 years, with the Greeks and Romans using it to orient their buildings to the south in order to maximize its use. However, this was largely only possible for the wealthy, as wood was the primary source of energy. In order to make the most of solar energy, it is important to be aware of the available solar radiation, as well as its requirements for a particular system. Climate plays a large role in this, yet it is not economically feasible to install instruments at each weather station to obtain this information. Thus, having a reliable model to predict solar radiation is invaluable [8].

Providing energy to sectors such as buildings which consume two thirds of the total energy is a major challenge. To meet the needs of these energy consuming sectors, existing systems alone are not enough. As such, renewable energy sources such as solar energy need to be used in order to meet the energy requirements. Solar energy is abundant and can be used to fulfill the energy needs of these sectors [13]. The future of renewable energy looks very promising, with solar radiation being a particularly attractive source for increased energy generation. In order to advance solar energy technologies, it is essential to develop accurate models and systems for predicting the amount of solar radiation available in a given area. This will enable the efficient deployment of solar energy infrastructure and ultimately increase the amount of clean energy available for use. To that objective, numerous insightful and reproduction techniques for further developing sun powered radiation figure models and frameworks have been created. As sun-oriented energy builds up forward movement, it is probably going to become one of the world's essential energy sources before very long. methods. It is believed that solar energy will be one of the major energy sources of the future [14].

Existing DL approaches for time series forecasting are classified as deterministic or probabilistic [1, 2]. Because of their irregular and complicated character, RE data carry varying degrees of uncertainty. Deterministic projections uncover less about vulnerability. Probabilistic determining uncovers more about the level of vulnerability in expectations. The essential objective of a probabilistic figure is to give a likelihood circulation over the anticipated outcomes [16]. There are two techniques for making a Probability Density Function estimate (PDF). The parametric methodology expects that the information has hidden factual conveyances, while the nonparametric methodology doesn't.[7] introduced a model for probabilistic forecasting based on CNN dubbed Probabilistic Forecasting with Temporal Convolutional Neural Network (DeepTCN).

To evaluate probability density, the proposed model can be used in both parametric and nonparametric approaches. Salinas et al. developed a deep learning-based approach called Probabilistic Forecasting with Auto backward Recurrent Networks, which utilizes a stacked residual block to learn intricate features from time series data utilizing both prior observations and external inputs. This strategy, referred to as DeepAR, is designed to generate precise probabilistic estimates. The procedure utilizes countless time series to prepare an autoregressive RNN model. The organization's result isn't forecast results, but instead the probabilistic capability's boundaries. Numerous new investigations have investigated DL procedures as a potential answer for the weaknesses of factual systems. Moreover, the LSTM RNN calculation is the most broadly utilized for determining sustainable power age. The blend models of the worldwide DL are one of the key examination regions for working on model execution [15, 17].

## 2. PROPOSED SYSTEM

In these days of global energy crisis, solar energy is emerging as a viable alternative to fossil fuels. Even if they are closer to the Equator or receive more sunlight, developing or underdeveloped countries cannot benefit as much from solar energy as developed countries. Solar energy panels are installed and adjusted according to the angle of direct normal irradiance to achieve efficiency. However, direct normal irradiance is measured using a pyrheliometer. The plans viable are LSTM, TCN, and LSTNet, in a specific order. TCN outperforms LSTM and LSTNet regarding forecast exactness and relationship, as indicated by reenactment information. During reproductions, two elective forecast skylines are utilized: 5 minutes and 24 hours. At the point when the figure exactness of these reenactments is looked at, obviously expanding the expectation skyline brings about a fall in forecast precision. It tends to be reasoned that estimating turns out to be more troublesome as the forecast skyline protracts.

### 2.1. Time Series Forecasting with Artificial Neural Networks (ANNs)

Time Series Forecasting is a crucial aspect of Artificial Intelligence, and solar power prediction is a specific application of this field. Time Series Forecasting is testing a result of presence of combination of present moment and long-haul rehashing designs. Repetitive brain organizations (RNN) are principally utilized in consecutive information handling. Advanced RNNs, such as Long Short-Term Memory (LSTM) [10] and Gated Recurrent Unit (GRU) [11], are highly successful variations of RNNs [12]. One approach to improve performance in time series forecasting is to use hybrid models that combine different variations of RNNs. For instance, the Long- and Short-term Time Series Network (LSTNet) architecture incorporates both convolutional and recurrent neural network properties. Short-term patterns are detected by the convolutional layer, whereas long-term patterns are detected by the recurrent layer.

In 2018, a new family of architectures was proposed for sequential tasks, the Temporal Convolutional Network (TCN). These models are based on Convolutional Neural Networks (CNNs), and use dilated causal convolutions and residual connections. Additionally, the Recurrent-Skip structure is capable of detecting patterns of very long-term reliance [15]. In this review, the LSTM engineering is utilized as a pattern against which elective models are looked at. The LSTNet model, a high-level half-breed design, is a decent decision for the sunlight-based estimate issue. Moreover, in light of the fact that TCN configuration beats standard repetitive organizations in various grouping displaying undertakings, utilizing TCN engineering on sun powered expectation challenge is engaging.

#### 2.1.1. Long Short-Term Memory (LSTM)

Because of the evaporating slope issue, preparing Intermittent Brain Organizations after some time is testing [16]. During backpropagation, the vanishing slope issue causes an outstanding reduction or ascend in the impact of a given contribution on the secret layer and result [17]. Due to the utilization of entryways, LSTM is fit for saving data over extensive stretches of time and doesn't experience the ill effects of the evaporating slope issue.

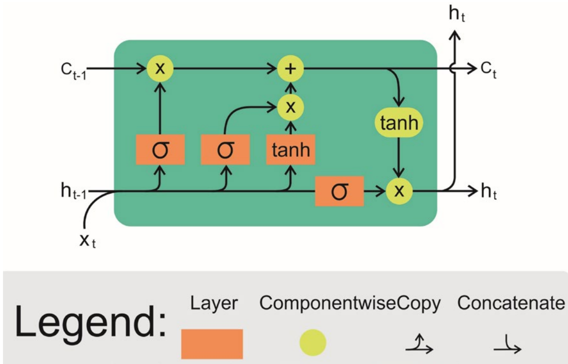


Figure 1. LSTM unit architecture [18]

A bunch of intermittently associated LSTM units, otherwise called memory blocks, include the LSTM engineering. Each LSTM unit has three entryways: an information door, a result entryway, and a neglect entryway. The information entryway manages what is put away in the memory block, while the result door controls the progression of data to the remainder of the organization [10]. At the point when memory contents become insignificant, the neglect door allows the LSTM unit to self-reset [20]. Figure 1 portrays a LSTM unit.

### 2.1.2. Long and Short-Term Time Series Network (LSTNet)

Lai et al., presented LSTNet, a solid half breed model, in 2017. Figure 2 portrays the LST-Net design. LSTNet is comprised of four parts: convolutional, repetitive, intermittent skip, and autoregressive. Every part is talked about and formed independently:

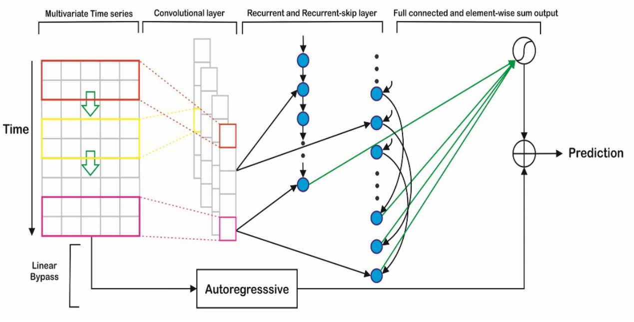


Figure 2. LSTNet architecture [13]

### 2.1.3. Temporal Convolutional Network (TCN)

TCNs are presented as a new alternative to other typical RNN models for time series forecasting. The backbone of this CNN is one-dimensional causal convolution, often dilated, with multiple layers constituting one block and many blocks the model Input and output sizes of such blocks are equal in size. This type of convolution helps capturing temporal features by looking at past values only and extracting the important relationships. We trained our models using Mean Squared Error (MSE) as loss function and the Adam optimizer.

Expanded causal convolutions with remaining associations are the fundamental parts of TCN plan. TCN utilizes a 1D completely associated convolutional network (FCN) with zero cushioning to accomplish a similar grouping length in information and result. Besides, to keep away from spillage from the future to the past, TCN utilizes causal convolutions. To achieve the desired output at a given time step, convolutions are performed on the input data at that step and previous time steps in the preceding layers.

The open field of causal convolutions extends straightly with network profundity. Widened convolutions are utilized in TCN design to free the issues from dealing with exercises that need a greater responsive field. The utilization of widened convolutions enjoys the benefit of permitting the open field to dramatically create. Enlargement is the expansion of fixed-sized strides between adjoining channel taps. TCN enlargement increments dramatically with network profundity. Thus, all data sources are moved by channels in the responsive field. Figure 3 portrays a TCN block which ($k_1$) $d$ is utilized to figure the successful history of each layer. The channel size is $K$, and the expansion factor is $d$. Therefore, channel size or potentially widening variable can be raised to improve responsive elements.

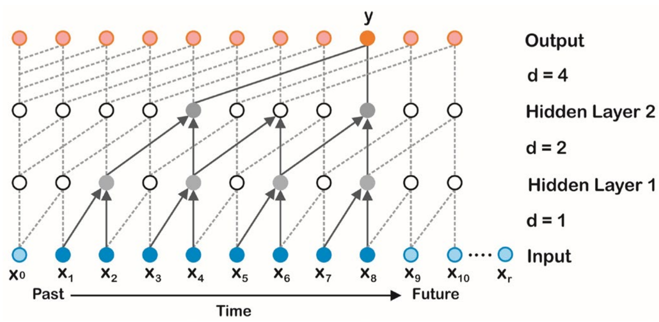


Figure 3. TCN architecture [14]

### 2.2. Forecasting of Solar Radiation

To manage the unconventionality in power values from one day to another, which has made expectation more troublesome, this approach utilizes two separate models, one for sunny days and the other for overcast days. To improve solar power prediction accuracy, the dataset is divided into two sub-datasets based on sunny and overcast weather conditions, and each sub-dataset is trained on a model specific to that type of weather. The model trained on the sunny day's dataset is then used to generate power predictions specifically for sunny days. The circumstance is additionally comparable on shady days. The days that are more like each other as far as created power are in this way bunched in a similar classification, and information fluctuation inside each set is diminished. This part examines the effect of information grouping on expectation precision. The initial step is to group the dataset. By taking the mean irradiance value for each day, the dataset can be sorted according to its connection with solar irradiance.

Clear sky models are commonly used to estimate this value, taking into account factors such as the area of the sky and weather patterns. PVLIB, a Python bundle, is utilized to figure clear sky irradiance [17]. PVLIBget clearsky () gets the area's scope, longitude, and rise level from ocean, clear sky irradiance models can be used to determine the period series of clear sky irradiance for a given period of time. These models are used to calculate the clear sky irradiance for a specific time frame, as well as for a predefined stretch of time. During this review, the ocean clear sky model was utilized to appraise clear sky irradiance.

## 3. RESULTS AND DISCUSSION

Power is expected by means of multivariate estimating in view of force and meteorological information. In univariate estimating, power is exclusively anticipated utilizing information from before timestamps. In univariate mode, the forecast skyline is set to 5 minutes and 24 hours. Since the example rate in univariate expectation is 5 minutes, both present moment and exceptionally transient skylines can be investigated. Conversely, the examining rate in multivariate forecast is 60 minutes, and the expectation skyline is set to 24 hours.

### 3.1. Dataset

After discussing the principles of radiation and its path from the Sun to Earth, we concentrate on the specifics of this study. The dataset includes numerous types of solar radiation as well as numerous meteorological units. Let us examine the units of measurement for these characteristics and the creation of the dataset. The dataset was received from the National Renewable Energy Laboratory of the US Department of Energy (NREL). The NREL tool NRSB Data Viewer enables users to choose and query geographical inputs like longitude and latitude, as well as data series including years, months, and frequency of data. The dataset was queried using the coordinates 41.09, 29.1, and data from the closest meteorological weather station.
The dataset consists of hourly data at starting 00:30, 01.01.2017 to 23:30, 31.12.2017, Latitude: 41.09, Longitude: 29.1, Beykoz, Istanbul and Turkey, respectively district, city and country name. There are 8760 rows and 23 columns in the raw data set. After passing it a data frame to 'df' variable, pandas data frame was used as a read function and the 'Unnamed: 23' variable created by pandas was discarded due to misinterpretation.

### 3.2. Data Pre-Processing

All rows having a DNI values of zero are eliminated since the purpose of this research is to forecast DNI levels. If the 0 values were not removed, the night and day values would be confused. As is well-known, there is no daylight at night. Keeping these values also reduces the reliability of the model. Then, a new date column was created by merging five existing date columns: Year, Month, Day, Hour, and Minute. The index of the date-time column is then set in order to generate meaningful visualisations. Also available is Clearsky DNI column, which is measured by the same sensor as DNI. Therefore, the decision was made to eliminate it due to its nearly one-to-one correlation with DNI. It could threaten the quality of our model. The Solar Zenith Angle and DHI values also have been eliminated from the GHI equation, as previously demonstrated. Otherwise, every element of the equation would be known, and there would be no need to predict results. The dataset now contains 3167 rows and 13 columns due to these modifications. In this dataset, there are no missing values. DNI is the target value, and the initial visual representation aims to convey a first impression to the reader.

A linear relationship between variables is known as correlation. It provides an overview of feature selection. The correlation coefficients range from -1 to 1. If there is positive correlation, it will be between 0 and 1, whereas if it is negative correlation, it will be between -1 and 0. A strong linear relationship exists when a variable is close to 1 or -1.

The heatmap below represents the correlation between all features in the entire dataset. The correlation between all features is displayed in Figures 5 and 6 depicts a correlation bar plot in which features are only compared to the target value DNI.

Table 1. Dataset features, their units, and meanings

| Dataset Features | | | |
|---|---|---|---|
| Numerical Values | | Categorical Values | |
| Features | Unit | Features | Meaning |
| DNI | w/m² | Cloud Type 0 | Clear |
| DHI | w/m² | Cloud Type 1 | Probably Clear |
| GHI | w/m² | Cloud Type 2 | Fog |
| Dew points | C (Celsius) | Cloud Type 3 | Water |
| Temperature | C (Celsius) | Cloud Type 4 | Super-Cooled Water |
| Pressure | mbar | Cloud Type 5 | Mixed |
| RelativeHumidity | (percentage) % | Cloud Type 6 | Opaque Ice |
| Precipitable Water | cm | Cloud Type 7 | Cirrus |
| Wind Direction | Degree ° | Cloud Type 8 | Overlapping |
| Wind Speed | m/s | Cloud Type 9 | Overshooting |
| Surface Albedo | ratio | Cloud Type 10 | Unknown |
| Clearsky DNI | w/m² | Cloud Type 11 | Dust |
| Clearsky GHI | w/m² | Cloud Type 12 | Smoke |
| Clearsky DHI | w/m² | Fill Flag 0 | N/A |
| Solar Zenith Angle | Degree ° | Fill Flag 1 | Missing Image |
| | | Fill Flag 2 | Low irradiance |
| | | Fill Flag 3 | Exceeds Clearsky |
| | | Fill Flag 4 | Missing Cloud Properties |
| | | Fill Flag 5 | Rayleigh Violation |

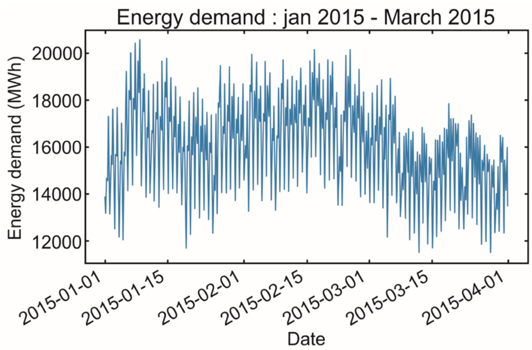


Figure 4. Target Value DNI Pattern

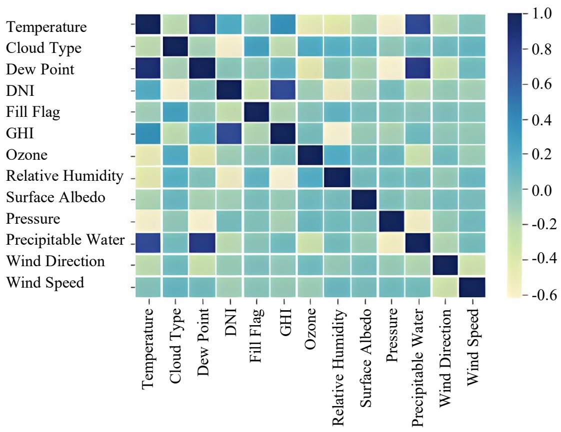


Figure 5. Correlation Heatmap

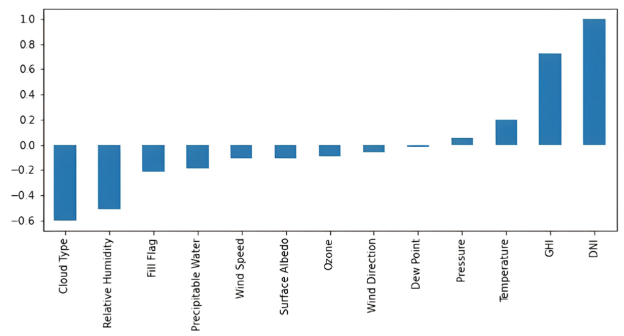


Figure 6. Correlation with Target Value DNI

### 3.3. LSTM

Different from standard LSTM models in which multiple LSTM layers, the LSTM model that was adapted is a primary consistent of one LSTM Layer of 50 neuron followed by 3 Dense layers. In addition, two separate input layers are used to separate between the temporal inputs which are the Energy consumption for each day of the 7 days input and the calendrical features used which are the day of the year, week of the year, and whether any of the dates we want to predict are Holidays. Therefore, one the temporal information will be fed to the LSTM layer. The model’s output layer has 7 neuron each associated to one weekday we wish to predict. The detailed proposed structure of the neural network is shown in Figure 7. The LSTM model proposed was trained and hyper tuned on the validation data. The model was trained for 300 epochs while using an early stopping monitor to prevent overfitting. A mean square error loss function was adapted to train the model. The final validation error reached by model was an MSE of 0.1482 while the average error over 10 run was 0.1466. To further evaluate the model the predicted value of the model on the validation data was plotted compared to the expected values for the first predicted day and the 7th predicted day. The obtained plots are shown in Figures 7 and 8.

### 3.4. LSTNet

A Long- and Short-term Time Series Network model basically utilizes time series data to forecast future trends. This model is divided into several parts which include: Autoregression, moving average, and integrated. Long- and Short-term Time Series Network, refers to a model that shows the next periodic value which is found through regressing over the past or previous values. Moving Average (Equation 2) indicates the forecast error as a linear combination of the past value errors. The Integrated step is the differencing of the raw untouched observations (in our case the energy load consumption) to make the time series stationary. This is essential since it can stabilize the mean of the time series which eliminates any trends and seasonality before performing any predictions. Simulation results using LSTNet architecture are illustrated in Figure 9.

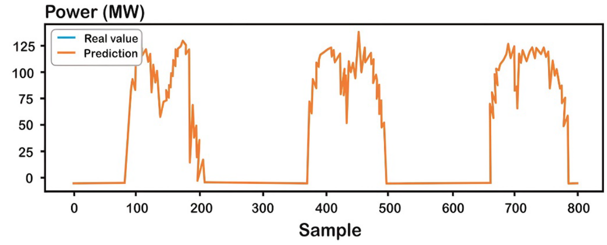


Figure 7. Power prediction using LSTM

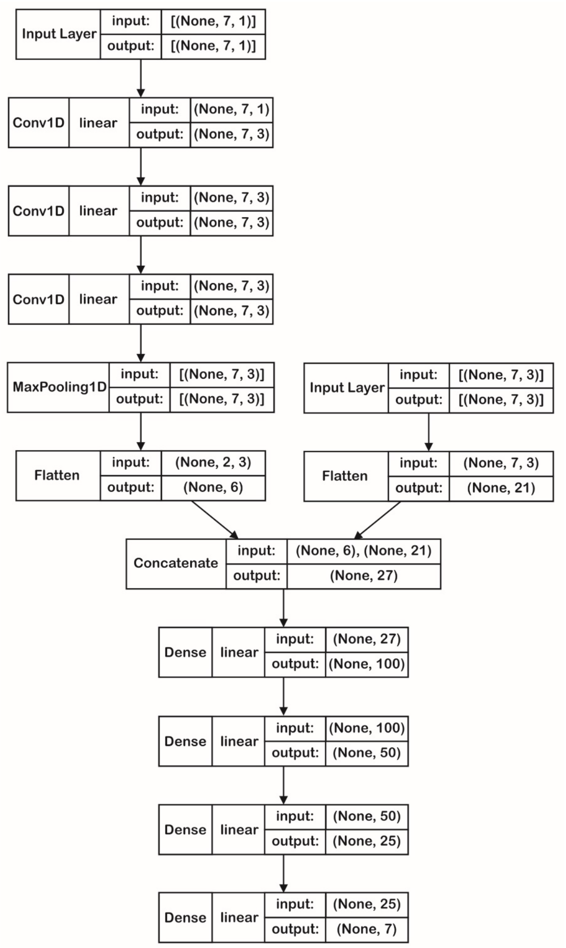


Figure 7. LSTM proposed structure

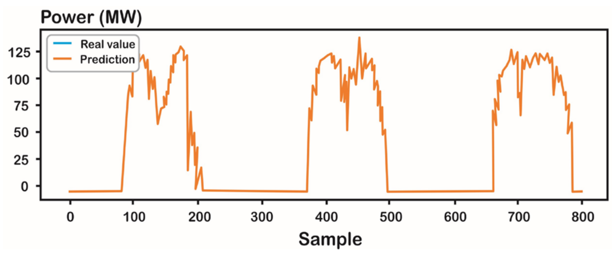


Figure 9. Power prediction using LSTNet

### 3.5. TCN

To better capture trends in forecasting, our model considers the time series data of power consumption, as well as static features relating to the calendrical characteristics of the days, like the day of the year, month, day of the week, day of the month, occurrence of holiday, the year and quartile of the year.

The model uses a TCN architecture that takes the time series data, 7 instances of power consumption, and the output is fed to an ANN block that also takes as input the rest of the static features. Figure 10 below illustrates our complete model. The TCN stack consists of 1 block with 3 convolutional layers: kernel size of 2, dilation of 5, 3 filters and with linear activation. We noticed that adding a max pooling layer of size 5 and strides of 4 steps improves the model. The output of the TCN block is concatenated with the static features input and fed into an ANN with 3 hidden layers of 100, 50, 25 neurons per layer, linear activation, and an output layer of 7 neurons.

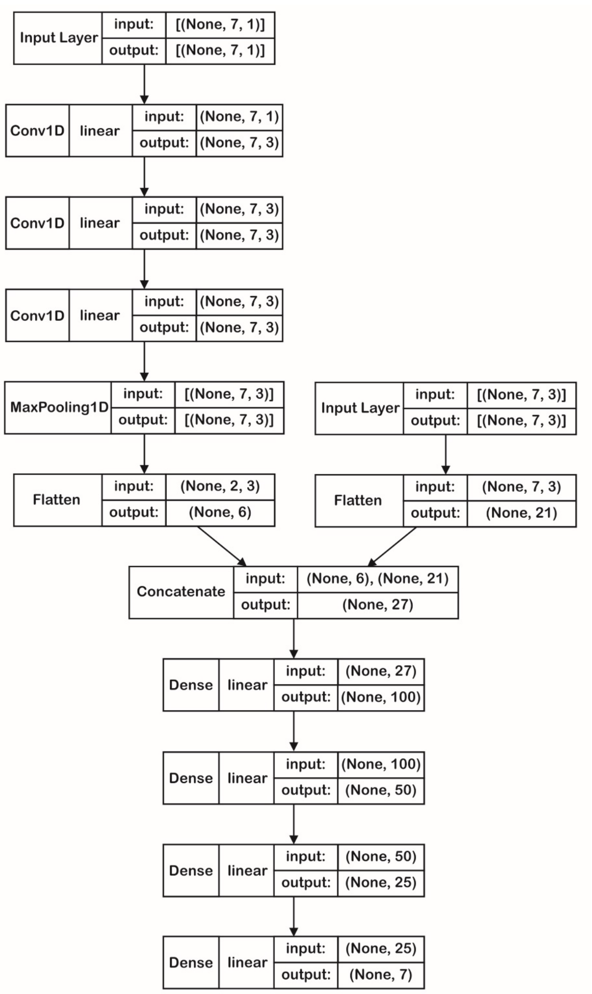


Figure 10. Detailed summary of the TCN-based model

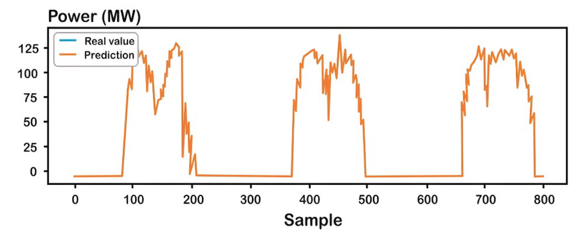


Figure 11. Power prediction using TCN

### 3.6. Comparison

When compared to univariate methods, multivariate approaches produce more accurate and correlated results. As expected, forecasting accuracy decreases with increasing prediction horizon, making it difficult to forecast for long horizons. The evaluation of the three models reveals, whereas LSTNet performs the best when the prediction horizon is set to 5 minutes. This is likely due to the architectural improvements made in the LSTNet model which makes it more efficient than the more straightforward LSTM model, resulting in a smaller RSE error. The three architectures discussed for time series prediction tasks are ARIMA, LSTNet, and TCN. ARIMA is relatively simple but can yield limited results. LSTNet, which uses both CNN and RNN networks, has shown good performance but has a high computational cost due to its complicated architecture. TCN, the newest of the three architectures and with a medium complexity level, appears to be the most promising in terms of achieving the best simulation results. This suggests that Convolutional Neural Networks could be a better choice than Recurrent Neural Networks for time series prediction tasks.

Table 2. Results summary of all methods

| Metric | LSTNet | LSTM | TCN |
|---|---|---|---|
| Mean absolute percentage error (MAPE) | 3.87 | 0.028 | 0.025857 |
| Mean absolute error (MAE) | 15326.65 | 13986.82 | 12751.4 |
| Mean squared error (MSE) | 451210321 | 348520660.6 | 316231388.5 |
| Minmax, Error | -1.1567 | 0.0277 | 0.025 |

The three models were all tested on a test set unseen by all models. The results for each model are demonstrated in the table of Table 2. The TCN model performed the best compared to the LSTM and LSTNet model by having the lowest MAPE of approximately 0.026. The LSTNet model preformed very poorly having a much higher MAPE error compared to the other two models. Moreover, the LSTM model performed slightly worse than the LSTM Model. Furthermore, comparing other performance metrics also yield the same result where TCN seem to be outperforming two other models.

## 4. CONCLUSIONS

Many time series forecasting problems use DL approaches, and the results are promising. To perform probabilistic forecasting, DL models can be combined with probability models. Because of its capacity to extract characteristics from provided data. The text you provided describes a solar forecasting module that is part of an Energy Management System (EMS). The module uses various techniques, including measurable techniques, sky imagers, satellite imaging, and mathematical climate forecast (NWP) to make accurate solar forecasts. Among the methods explored, artificial neural networks (ANNs) were chosen as a forecasting technique to meet EMS requirements. To make the EMS work properly, accurate predicting in the short-term prediction horizon is needed. Additionally, the paragraph mentions the Temporal Convolutional Network (TCN) architecture, which uses temporal convolutions to process sequential data and has shown promise for time-series analysis tasks. Although the methods mentioned above all provide good performance, the TCN architecture gives more promising results.

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