TimeGPT vs LSTM-CNN for predicting PV panels energy production

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***Abstract*— In recent years, photovoltaic systems have raised significant interest among small households and industrial enterprises, due to their potential of producing cost-effective energy. Accurate predictions of both energy consumption and production are particularly important but the task of predicting solar energy generation is complicated due to its intermittent nature and the influence of meteorological changes. Therefore, a specialized machine learning (ML) model that can cope with these rapid changes is an important research direction. In this paper, two different approaches are discussed and analyzed, a hybrid deep learning model Long Short-Term Memory Convolutional Neural Network (LSTM-CNN) and a generative pre-trained transformer model TimeGPT. LSTM-CNN has proven to be great in capturing temporal and spatial features but only when the amount of historical data is large and sufficient. TimeGPT stands out for its capability of generating acceptable forecasts even with small input data. Our analysis shows that TimeGPT consistently delivers robust and generalizable predictions across all horizons in zero-shot settings, highlighting its potential as a scalable, low-maintenance solution for energy forecasting.**

Keywords—LSTM-CNN, TimeGPT, solar energy generation, transformer model, forecasting renewable energy.

I. Introduction

Climate change and global warming are two of the most serious problems facing the 21st century. To mitigate their impact on the Earth, the use of renewable energy is growing considerably. Global electricity demand increased by 4.3% in 2024 compared to the previous year, and consumption is expected to grow at its fastest pace between 2025 and 2027 [1]. This growth is fueled by increased industrial production, greater use of air conditioning, the automotive industry's shift towards electric vehicles, accelerating electrification and expanding data centers worldwide.

Photovoltaic (PV) systems have recently gained particular interest among small households and at the industrial level, increasing electricity generation [2]. Thanks to policies implemented by governments and international organizations, installing photovoltaic panels is becoming a popular choice among electricity consumers, helping to balance the amount of energy used with this sustainable energy source.

The transition to clean energy involves a significant increase in electricity demand and the large-scale introduction of variable renewable energy sources, such as solar power, which places greater demands on electricity grids. The balance between consumers and producers is essential for optimizing any smart grid. Consequently, accurately predicting energy production is as important as forecasting consumption and is essential for networks to function properly and for photovoltaic systems to be correctly integrated with smart buildings [3].

Currently, specialty literature is divided into three broad categories of methods proposed for the subject of electricity production forecasting [4]: physical methods, statistical methods, and methods based on machine learning (ML). The concept of physical methods consists of using physical models to build the relationship between photovoltaic energy production and other factors, such as numerical weather prediction data, sky images, and satellite images [5]. Statistical methods consist of applying statistical principles such as Bayesian model averaging (BMA), exponential smoothing, or autoregressive integrated moving average (ARIMA) to extract correlations and patterns of variation between historical data [4]. Both physical and statistical methods have the advantage of stable prediction. However, it is very difficult to establish a model of the two types that can cover the various forecast scenarios with high accuracy, as there are many hidden characteristics that are difficult for these algorithms to capture.

To address the shortcomings of physical and statistical methods, ML-based methods have been proposed and have gained significant attention over the past decade [6, 7]. Energy production forecasting models are powerful tools for optimizing energy management. Among the various models, Neural Networks [8] and Transformer-based models [7, 9] have become increasingly popular and have demonstrated their ability to accurately predict time-series data.

This paper focuses on highlighting the capabilities and limitations of two machine learning models in the context of accurately predicting energy generation in a photovoltaic panel field: Long Short-Term Memory Convolutional Neural Network (LSTM-CNN) [10] and TimeGPT-1 [11, 12].

LSTM models are not always the best choice in terms of accuracy but in combination with CNN, they form a robust and high-performance model that is not only less complex than LTCN (Liquid Time-Constant Networks) or Transformer but also has improved accuracy. The CNN model is used to obtain spatial characteristics, and the LSTM model is used to capture the dynamic characteristics of the photovoltaic panel field.

The TimeGPT-1 is part of the latest generation of technologies, a high-performance generative transformer, pre-trained and specialized in time-series data. Being trained on massive and diverse time series datasets from fields such as finance, transportation, banking, web traffic, weather, energy, healthcare, etc. [12], it claims to be able to accurately predict future numerical values with very little historical information for a given task. The model is compared with classical statistical methods such as ARIMA, LightGBM, or N-HiTS and tends to outperform them in certain scenarios but does not guarantee that it is always superior.

The rest of the paper is structured as follows: Section II presents the proposed bio-inspired approach; Section III discusses experimental results. The paper ends with conclusions.

II. BACKGROUND OF RESEARCH

The task of predicting the energy generated by photovoltaic panels is closely dependent on external, uncontrollable factors such as solar irradiance, various weather conditions, and rapid microclimate changes. In [4] the relationship between the input and the output of PV panels is explored. The predominant factor is the level of solar irradiance. Furthermore, another range of meteorological parameters are taken into consideration, including atmospheric temperature and relative humidity.

Positive correlations can be seen between power and solar radiation (Fig. 1.) and temperature (Fig. 2.) – as one variable increases, the other increases proportionally.

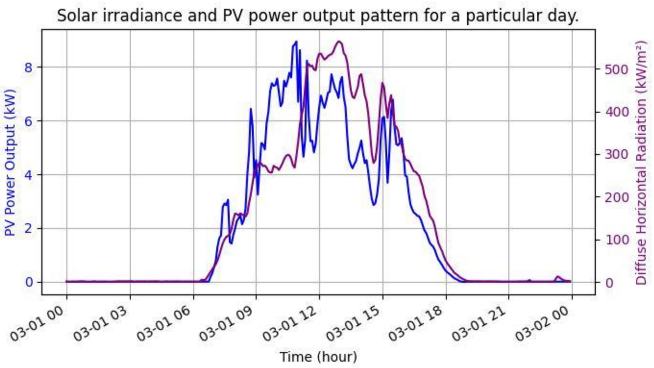

Fig. 1. Correlation between diffuse solar radiation and power output on a specific day

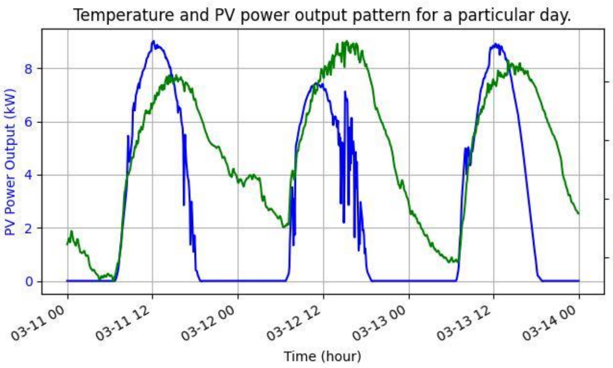

Fig. 2. Correlation between temperature and active power output over 3 days

Humidity and power are negatively correlated (Fig. 3.), the underlying reason for this phenomenon being the increased cloud coverage during precipitations that signifies lower irradiation.

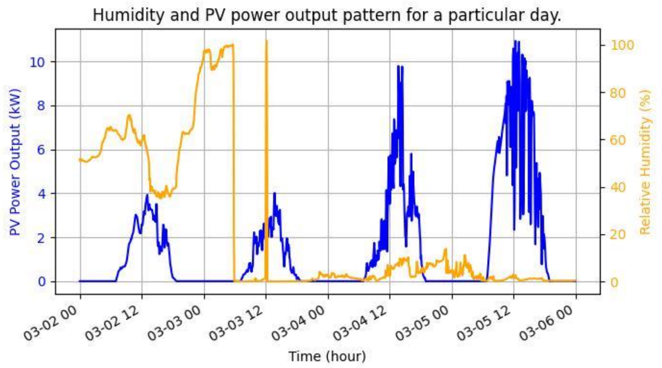

Fig. 3. Correlation between humidity and power output over 4 days

A. LSTM-CNN

To address the problem of non-linear solar and weather data, a hybrid deep learning architecture is proposed in [6]. The LSTM-CNN model is used to extract temporal features initially via LSTM layers, which are effective for capturing long-term dependencies in time series data. Spatial features are then learned via one-dimensional convolutional neural network (CNN) layers applied to the LSTM output. This sequential extraction approach (temporal-to-spatial) aligns with the inherent dynamics of PV data and eliminates the need for dimensional transformation (e.g., from 1D to 2D), thereby reducing preprocessing complexity and preserving data integrity.

Despite substantial advancements, traditional machine learning (ML) and deep learning models, including standalone LSTM and CNN, may lack robustness and adaptability, necessitating the development of more generalizable foundation models for reliable PV output prediction. [6]

B. TimeGPT

Recent advances in Generative Pre-trained Transformer (GPT) architectures have led to the creation of TimeGPT-1, a large-scale foundation model for time series forecasting. It has been trained using over 100 billion time series data points from various domains, including energy. TimeGPT-1 leverages the transformer architecture, which integrates multi-head self-attention, positional encoding, plus convolutional layers, allowing it to capture both long-range dependencies and local temporal patterns. Unlike traditional models which rely on domain-specific data sets for training, TimeGPT-1 is pre-trained on diverse time-series and can be fine-tuned with limited historical data. These characteristics are particularly advantageous in the context of newly installed PV systems.

However, TimeGPT-1 also presents notable limitations. While the model demonstrates the ability to generalize, its performance may decrease when the distribution of the target time-series diverges significantly from that of the training distribution. This is particularly relevant in site-specific patterns that are not well represented in the pre-training corpus.

III. METHOD

A. Data preparation

In the context of data-driven energy management, the reliability and precision of predictive models are fundamentally dependent on the quality of the input data. Forecasting models, particularly deep learning architectures, require structured, coherent, and noise-reduced datasets to accurately capture temporal and spatial patterns inherent in energy systems. However, raw energy data directly collected from photovoltaic panels, sensors or smart meters, is often plagued by inconsistencies such as missing values, numeric anomalies, or hardware limitations.

Neglecting data cleaning and pre-processing before feeding the data in a model for training purpose not only compromises the learning capacity of complex models but can also propagate errors throughout the forecasting pipeline, resulting in poor generalization and unreliable predictions.

Initially the dataset [13] contained over 1 million rows including timestamp at five minutes frequency, active energy, current phase, power output, wind speed and direction, weather temperature, relative humidity and daily rainfall, diffuse horizontal radiation, global tilted radiation and diffuse tilted radiation as described in Table I. This dataset was previously used in [10] to showcase the performance of LSTM-CNN over standalone LSTM and CNN, and hybrid CNN-LSTM.

Table I. Dataset analysis

Column name	Missing values (%)	Correlation with target column
Timestamp	0%	-
Active_Energy_Delivered_Received	<1%	-0.21
Current_Phase_Average	<1%	0.99
Active_Power	<1%	1.0
Wind_Speed	67%	0.24
Weather_Temperature_Celsius	<1%	0.41
Weather_Relative_Humidity	<1%	-0.39
Global_Horizontal_Radiation	<1%	0.86
Diffuse_Horizontal_Radiation	<1%	0.49
Wind_Direction	<1%	0.05
Weather_Daily_Rainfall	<1%	-0.03
Radiation_Global_Tilted	12%	0.88
Radiation_Diffuse_Tilted	8%	0.23

Subsequently, it was decided to eliminate columns with lots of missing values: Wind_Speed, Radiation_Global_Tilted, radiation_Diffuse_Tilted or with correlation index close to zero: Active_Energy_Delivered_Received, Diffuse_Horizontal_Radiation, Wind_Direction, Weather_Daily_Rainfall. Timestamp column is essential in forecasting time-series data, Active_Power was set as target column, Current_Phase_Average could not be classified as exogenous variable, so it is not particularly relevant to the prediction. Final dataset contains Timestamp, Active_Power, Weather_Temperature_Celsius, Weather_Relative_Humidity and Global_Horizontal_Radiation.

After significant consideration, to capture capabilities and limitations of both LSTM-CNN and TimeGPT-1 in not previously addressed contexts, two training scenarios were extracted as shown in Table II.

Table II. Training scenarios

Scenario	Time Frame
Case 1 – 1 month of data	2020-01-01 – 2020-01-31
Case 2 – 12 months of data	2020-03-01 – 2021-02-28

B. Importance of forecasting horizon selection

In energy systems the definition and selection of look-ahead times plays a pivotal role in determining the modelling approach, feature representation and application-specific requirements. Forecasting horizons are categorized in [14] into short-term (minute to hours), medium-term (days to weeks), and long-term (months to years), each category serving different operational and strategic objectives.

Energy forecasting across multiple temporal scales is essential for maintaining grid stability, optimizing energy trading and supporting efficient energy dispatch strategies in smart buildings. After carefully analyzing different approaches, three look-ahead times were selected:

- 24 hours look-ahead time – aligns with day-ahead operational planning. As noted in [14] real-time monitoring and responsive control systems in smart buildings and microgrids require reliable short-term forecasts to balance demand and supply dynamically.
- 72 hours look-ahead time – serves as a traditional window between short-term and mid-

term scheduling. This time frame is especially important for multi-grid coordination and contingency handling, as highlighted in [14].
- 5 days look-ahead time – targets long-term strategic horizon, facilitating energy procurement planning and load curtailment strategies under scenarios with greater variability and uncertainty [14].

C. *Models technical features*

The reference model LSTM-CNN was built as proposed in [10], following the layer structure presented in Table III:

Table III. Parameter settings of LSTM-CNN model

Model	Configuration		
LSTM-CNN	LSTM	Units1	Units1 = 64
		Units2	Units2 = 128
	CNN	Convolutional	Filters = 64, kernel size = 3, stride = 1
		Max-pooling	kernel size = 2; stride = 2
		Convolutional	Filters = 128, kernel size = 3, stride = 1
		Max-pooling	kernel size = 2; stride = 2
	Dropout	Dropout = 0.1	
	Fully connected	Neurons = 2048	
	Fully connected	Neurons = 1024	

The model was trained across 100 epochs in batches of 600 datapoints with patience of 15 epochs. After each epoch the best model was saved in a Keras [15] format file.

TimeGPT model is built on transformer architecture (see Fig. 4), originally introduced by Vaswani et al. [16] and later adapted for time-series tasks to model both short and long-range dependencies using self-attention mechanisms. The model comprises an encoder-decode structure, multi-head attention layer, residual connections, and positional encoding to retain sequence of information, while a final linear layer maps the output to the desired forecasting window.

Unlike traditional sequential models such as LSTM, which process input sequentially, transformers use parallel attention-based processing. This structure enables TimeGPT to effectively learn from large-scale, heterogenous data and forecast unseen series without re-parametrization – something called zero-shot inference. [11, 12]

D. *Forecasting and evaluation*

Given that TimeGPT-1 model does not require epoch training phase like LSTM-CNN and due to the dissimilarity of the input data, we decided to implement each model in a separate python program.

In this research, a zero-shot forecasting approach was employed for energy prediction using TimeGPT, without applying any fine-tuning. This decision was motivated by the model's robust generalization capabilities across diverse time-series tasks. By leveraging TimeGPT in a zero-shot setup, we could generate forecasts directly on unseen PV panels data. For evenness reasons, no additional fine-tuning steps were performed in LSTM-CNN model.

To rule out the possibility of a good result by chance, each forecasting session was ran three times and results were saved in .csv format containing timestamp, actual power value and predicted value. The forecasted PV data generated by both models is stored in a PostgreSQL database to ensure structured access and long-term persistence.

The evaluation step consists of comparing the results using a visualization tool. Grafana, a popular open-source analytics platform [17] is configured to connect to PostgreSQL database [18], then queries are constructed in Grafana interface to extract and plot the values over time.

Additionally, two metrics were computed for each case and horizon to compare the actual performance of the model, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

IV. RESULTS AND DISCUSSION

The findings of each prediction underscore the strengths of

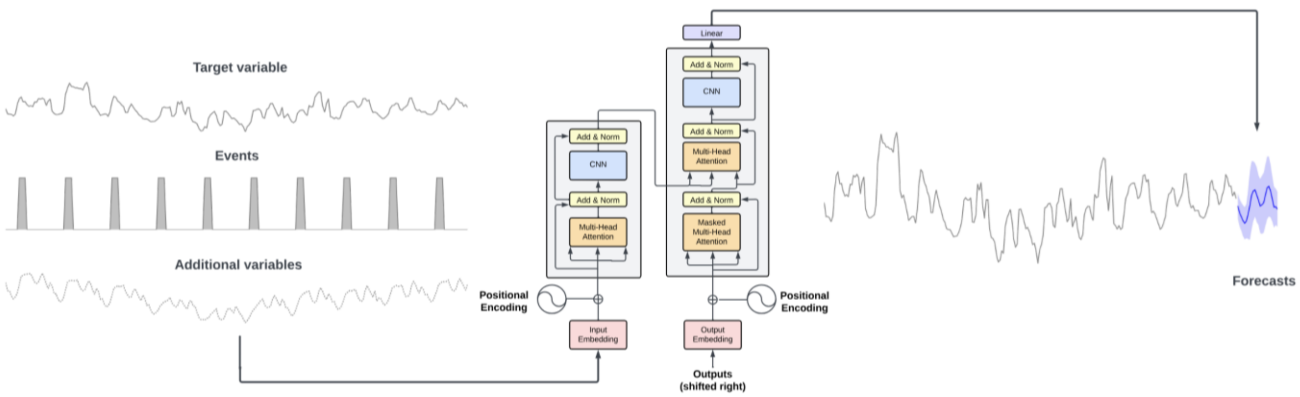

Fig. 4. TimeGPT-1 architecture [12]

each model. The employment of multiple and diverse test scenarios has facilitated the formulation of a clear and accurate conclusion regarding the capabilities and limitations of the TimeGPT-1 model in context of photovoltaic power output forecasting.

A. Case 1 – 1 month of data as training set

This specific case aims to reproduce scenarios where historical data is scarce or almost non-existent, such as newly installed PV plants. Table IV indicates better accuracy for TimeGPT in case of short and medium length horizons.

Table IV. Metric evaluation for Case 1

	24 h		72h		5d	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
TimeGPT	**0.99**	**0.50**	**2.39**	**1.23**	2.11	1.15
LSTM-CNN	1.66	1.02	2.91	1.90	**1.73**	**1.02**

Both TimeGPT-1 and LSTM-CNN track daily production curve reasonably well (Fig. 5.). LSTM-CNN's predictions are smoother and more conservative, slightly underestimating peaks and higher overall, while TimeGPT is better at capturing the steep ramp-up and ramp-down transitions of energy output throughout the day.

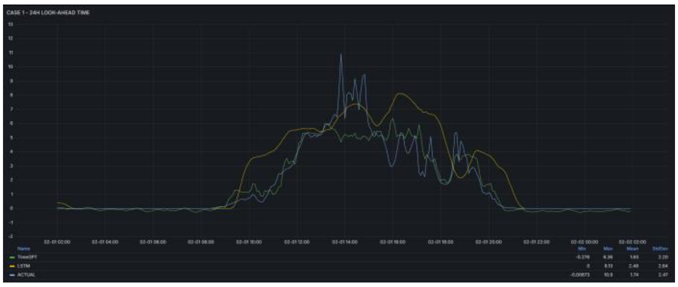

Fig. 5. Case 1 – 24 hours look-ahead time

TimeGPT tends to have more stable forecasts, remaining close to baseline in low-activity periods, but it is generally underestimating actual peaks reflecting less confidence in high-amplitude fluctuations (Fig. 6.). It struggles with short-term fluctuations and high-frequency variability, producing a flatter curve. It avoids exaggerated errors and has a more generalized approximation of the energy trend. Unfortunately, LSTM-CNN overfits to the general daily pattern (Fig. 6.),

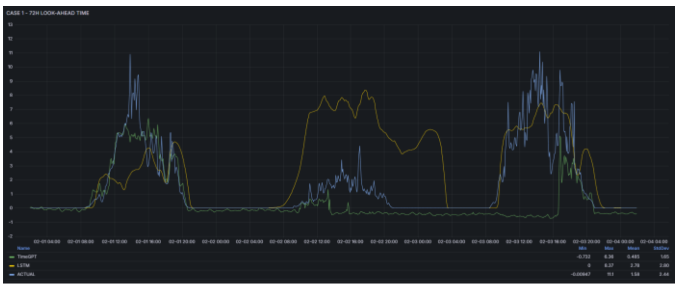

Fig. 6. Case1 – 72 hours look-ahead time

repeating nearly identical shapes even when the actual PV output fluctuates due to weather conditions, like higher cloud coverage and decreased irradiation.

TimeGPT demonstrates clear robustness over extended forecasting, maintaining low variance and consistently predicting overall daily trend (Fig. 7.). The model frequently underestimates peaks, probably because of the zero-shot approach. LSTM-CNN tends to perform better (Table IV) because of its pattern memorization. It continues to reproduce idealized solar curves even when data deviates significantly and lacks flexibility to adjust on unseen weather patterns – expected behavior when a model is trained on small time window then asked to generalize aver a longer period (Fig. 7.).

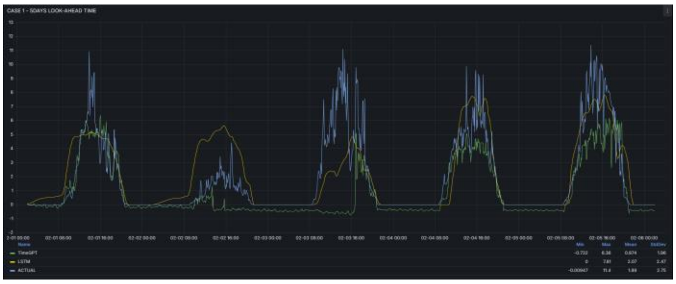

Fig. 7. Case 1 – 5 days look-ahead time

B. Case 2 – 12 months of data as traning set

Second case is almost an ideal representation because one year of data – 105120 datapoints – is enough for a model to learn hidden patterns and seasonality. Table V shows clear performance improvements can be seen for both models in this case.

Table V. Metric evaluation for Case 2

	24 h		72h		5d	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
TimeGPT	**0.27**	**0.17**	1.23	0.68	1.23	0.65
LSTM-CNN	0.78	0.50	**0.70**	**0.40**	**0.65**	**0.37**

For the short term case, models performed almost the same (Fig. 8.). Here metrics show the superiority of TimeGPT but LSTM-CNN does not fall short either.

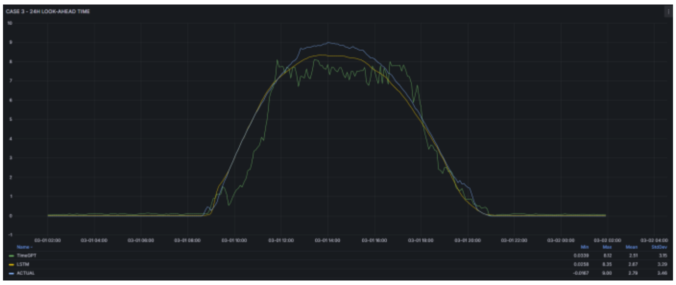

Fig. 8. Case 2 – 24 hours look-ahead time

TimeGPT's performance improved for medium-term predictions comparing to first case. It succeeds in capturing mid-day values and output variations (Fig. 9.). LSTM-CNN produces slightly smoother and symmetrical curves. However, the model now follows the shape of each solar cycle more accurately. Both models underpredict the mean and peak (Fig. 9.) but are much closer to actual values than in Case 1 (see Fig. 6.).

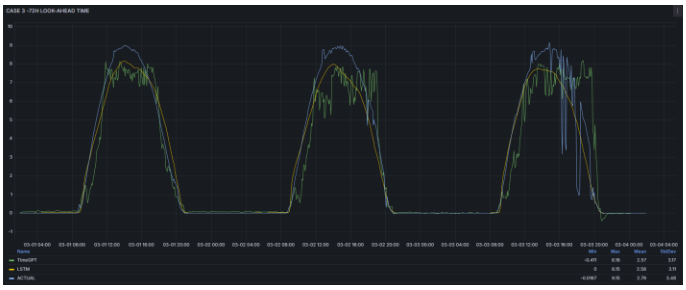

Fig. 9. Case 2 – 72 hours look-ahead time

TimeGPT forecasts are visibly more dynamic than in Case 1 for 5 days look ahead scenario. The model shows better responsiveness to fluctuations, even matching some subtle dips and short-term anomalies. It shows overall increased accuracy in daily cycles but still introduces minor noise in peaks due to attempting to mirror real data fluctuations. LSTM-CNN also improved when trained on a larger dataset and now tracks the daily solar cycle more closely. The predicted peaks closely match the actual output, and the model exhibits more flexible adaptation to small variations (Fig. 10.).

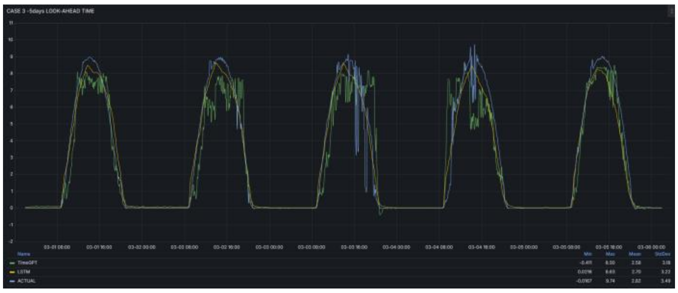

Fig. 10. Case 2 – 5 days look-ahead time

V. CONCLUSION

This paper provides analysis of the capabilities and limitations of the TimeGPT model in predicting electricity production from a PV field.

In contrast to the LSTM-CNN model, it exhibits superior generalization capabilities, even with limited data, augmented flexibility relative to conventional ML approaches, a considerable degree of adaptability to pattern and cycles of unseen data, and, notably, enhanced ease of use and integration due to its accessibility via API call.

Future investigation may entail the analysis of TimeGPT with fine-tuning enabled, different sampling frequencies for the data, longer horizons (months to year) and comparison with other specialized time-series models like Auto-TimeGPT [19], Liquid Time-constant Networks [20], FFBP or GRNN [21].

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