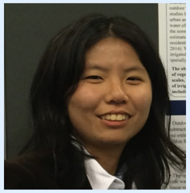

Employing the strengths of Generative AI supports the execution of time series analysis and forecasting

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Introduction

Effective energy management and climate change mitigation are increasingly critical in today's world. Time series analysis and forecasting play vital roles in understanding and predicting patterns in energy consumption, greenhouse gas emissions, and extreme weather events. These forecasts enable utility companies, policymakers, and businesses to make informed decisions, optimize resources, and develop strategies to combat climate change.

Traditional forecasting methods face challenges such as data noise, missing values, anomalies, and limited predictive performance. Recent advancements in artificial intelligence and machine learning, particularly Generative AI models, offer promising solutions. These models can generate synthetic data, smooth out noise, and provide robust predictions, enhancing the accuracy and reliability of forecasts.

In this study, we will explore different Generative AI model workflows, such as TimeGPT, llmtime, and AutoGluon–TimeSeries. We will compare their performance with traditional statistical and deep learning models, and demonstrate their efficacy through a case study on energy consumption forecasting. By showcasing these advanced techniques, our goal is to equip developers and scientists with the tools to leverage Generative AI in their own time series-related use cases. Ultimately, this will improve our ability to predict and manage future risks in energy consumption, greenhouse gas emissions, and extreme events, advancing the development of time series analysis and forecasting.

Data and Method

This study goal is to compare Generative AI models with traditional benchmarks by evaluating their accuracy, robustness, and computational efficiency in predicting time series data using error metrics like MAE, RMSE, and MAPE. Practical applications will be demonstrated through case studies on energy consumption, specifically utilizing the PJM Hourly Energy Consumption Data from 1998-2018 (20 years) [d]. This data, provided by PJM Interconnection LLC, covers hourly power consumption measurements in megawatts (MW) across multiple states in the Eastern U.S. This approach aims to advance time series analysis, enhance predictive power, and support sustainable and resilient decision-making.

In this study, we applied the following methods to better understand the power of generative AI-based time series forecasting models, comparing them with statistical and deep learning approaches. These methods offer tools for forecasting time series data, each with unique strengths tailored to different aspects of time series challenges.

ARIMA (AutoRegressive Integrated Moving Average)
ARIMA is a popular statistical method for time series forecasting, combining AutoRegressive (AR), Integrated (I), and Moving Average (MA) components. The AR component regresses the variable on its past values, the I component makes the data stationary by differencing, and the MA component models the error terms as a linear combination of past errors. ARIMA is effective for short-term forecasting and can handle trends and seasonality with appropriate parameterization.

xLSTM (Extended Long Short-Term Memory)
xLSTM, or Extended Long Short-Term Memory, is an advanced version of the LSTM neural network architecture, ideal for time series forecasting and sequence prediction. LSTM networks, a type of Recurrent Neural Network (RNN), can learn long-term dependencies using memory cells and gating mechanisms. The "extended" part of xLSTM often includes enhancements like additional layers, attention mechanisms, or integration with other deep learning architectures, making it powerful for large datasets and complex patterns.

TimeGPT [a]
TimeGPT is a Transformer-based time series model designed to handle diverse time series data without the need for retraining. It uses self-attention mechanisms and an encoder-decoder structure to forecast future data points based on historical values. TimeGPT can process data with different frequencies and characteristics, making it robust against noise, outliers, and missing data. It has been trained on a vast dataset of over 100 billion data points from various domains, enabling it to perform zero-shot inference and generate accurate predictions for unseen time series

llmtime [b]
The llmtime model leverages the capabilities of language models for time series forecasting. It uses a transformer-based architecture to capture the sequential dependencies in time series data, allowing for improved handling of long-term dependencies and trends. The model can be fine-tuned on specific datasets, making it adaptable to various domains and types of time series.

AutoGluon–TimeSeries [c]
AutoGluon–TimeSeries is part of the AutoGluon toolkit that automates machine learning workflows for time series forecasting. It simplifies the model training process by automatically selecting and tuning models. AutoGluon–TimeSeries can handle diverse datasets with minimal user intervention, making it accessible for both novices and experts. It supports various forecasting models, including statistical methods, machine learning models, and deep learning approaches, providing a comprehensive solution for time series analysis.

Results

In this study, we evaluated traditional, deep learning, and Generative AI-based time series models on the hourly energy consumption dataset. We used the trained models to forecast the next 30 days of hourly energy consumption. The results of the accuracy metrics used to evaluate the performance of the time series forecasting models are presented in Table 1. Overall, we found that xLSTM outperformed other models in Table 1, with lower MAE, RMSE, and MAPE values. Among Generative AI-based time series models, AutoGluon-TimeSeries performed better than the other two models, with lower MAE and RMSE values, and the second-lowest MAPE value. The model selected by AutoGluon-TimeSeries in this study is a weighted ensemble of 'DeepAR' (0.06), 'DirectTabular' (0.26), and 'TemporalFusionTransformer' (0.68).

Table 1. The results of the accuracy metrics for the models performed in this study.

	ARIMA	xLSTM	TimeGPT	llmtime	AutoGluon-timeseries
MAE	9760.65	240.16	10156.69	15309.53	6447.66
RMSE	11177.01	345.29	12265.35	18526.09	7623.08
MAPE	30.11	0.00065	29.94	0.439	17.05

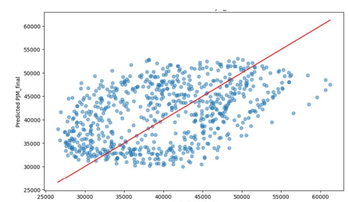

Figure 1. The actual vs. predicted results from the autogluon-time series model

In Figure 1, we noticed a certain level of deviation from the actual vs. predicted values from the AutoGluon time series model. Although the Generative AI-based model (i.e., TimeGPT) is powerful and can compute the forecasting results in less than 15 minutes, the accuracy metrics indicate that it performs even worse than the traditional ARIMA model. Furthermore, the forecasting of hourly energy consumption over the next 30 days from xLSTM and the AutoGluon time series is shown in Figure 2. Here we understand that a complicated AI ensemble model may not produce better results than the extended LSTM model. Thus, an ensembled model, which collects the strength of model performance based on generative AI, still needs to improve its capability at hourly timestamp forecasting.

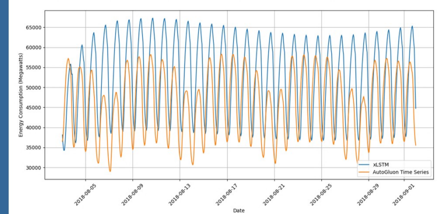

Figure 2. The hourly forecasting results from the xLSTM and auto-gluon model for next 30 days based on 20 years historical datase.

Conclusion

Time series forecasting predicts future values from past data, optimizing resources and mitigating risks in finance, climate science, and energy management. This study shows that xLSTM and an ensemble model from autogluon-time series excel in forecasting hourly energy consumption. These results highlight still the need for a foundational time series model. However, simpler, cost-effective models that still perform well are often more practical and ideal for real-world applications due to their ease of use and lower resource requirements.

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[d] Data Source: PJM Hourly Energy Consumption Data from Kaggle website (access 06/14/2024)