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Research Article

Short-Term Spinning Reserve Requirement Estimation Using TimeGAN-Based Synthetic Data Augmentation and a Hybrid LSTM–XGBoost Model

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Abstract— Accurate short-term forecasting of spinning reserve requirements is essential for ensuring frequency stability, operational reliability, and economic efficiency in modern power systems. However, the increasing penetration of renewable energy resources and the limited availability of high-quality operational data make reliable forecasting a challenging task. This study proposes a novel hybrid forecasting framework that integrates synthetic data generation, deep learning, and machine learning to overcome these limitations. To the best of the author's knowledge, this is the first study that integrates TimeGAN-based synthetic data generation with a hybrid LSTM–XGBoost model specifically for short-term spinning reserve forecasting. Given the limited availability of real-world spinning reserve datasets, this study employs a TimeGAN-based synthetic data generation approach trained on multivariate power system variables (load, renewable generation, and frequency) to construct a realistic and representative dataset for model development. First, TimeGAN is employed to generate realistic synthetic time-series data that preserve the temporal dynamics of load, renewable generation, frequency deviations, and spinning reserve patterns. This synthetic data is combined with real operational records to enhance the diversity and volume of the training set. Then, a Long Short-Term Memory (LSTM) model is used to capture long-range temporal dependencies, while XGBoost is applied to learn nonlinear and feature-driven relationships within the data. Finally, a hybrid fusion strategy based on both weighted blending and stacking regression combines the strengths of the two models. Experimental evaluations demonstrate that the hybrid model significantly outperforms individual models across all metrics. The stacking-based hybrid approach achieves the best performance with RMSE = 12.84 MW, MAPE = 4.21%, and R² = 0.965, outperforming LSTM and XGBoost by substantial margins. Additionally, the integration of TimeGAN reduces forecasting errors by up to 18% and improves generalization, highlighting its effectiveness in addressing data scarcity and privacy constraints. The results confirm that the proposed TimeGAN–LSTM–XGBoost framework provides a robust, scalable, and highly accurate solution for short-term spinning reserve forecasting, with strong potential for real-world deployment in power system operation and energy markets.

Index Terms—*Spinning Reserve Forecasting, TimeGAN, LSTM, XGBoost, Hybrid Learning*

I. INTRODUCTION

Maintaining the continuous balance between electricity generation and consumption in power systems is of critical importance for supply security, power quality, and frequency stability. Sudden failures in generation units, interruptions in transmission lines, or unexpected load increases may lead to frequency deviations in the system and eventually cause large-scale power outages. To mitigate these risks, system operators maintain reserve capacities that can be rapidly activated within a short time period. This capacity is defined in the literature as spinning reserve [1]. Determining the appropriate level of spinning reserve is not only crucial from a technical reliability perspective but also represents a strategic decision with significant economic and environmental implications. Insufficient reserve levels may increase the risk of Expected Energy Not Supplied (EENS), raise the Value of Lost Load (VOLL), and elevate the likelihood of large-scale system failures. Conversely, excessive reserve allocation may result in unnecessary fuel consumption, increased operational costs, and higher greenhouse gas emissions [1–4]. Therefore, spinning reserve planning constitutes a critical optimization problem that requires a delicate balance between system reliability and cost efficiency. In recent years, the rapidly increasing penetration of renewable energy sources such as wind and solar into power systems has introduced substantial uncertainties on both the generation and demand sides, rendering traditional deterministic reserve policies insufficient. Consequently, the literature has increasingly focused on probabilistic, chance-constrained, and robust optimization approaches for determining spinning reserve requirements [5,6]. However, the effectiveness of reserve planning largely depends on the quality of historical time series data, including load demand, generation levels, frequency deviations, and reserve capacities. Due to confidentiality constraints, high acquisition costs, and limited accessibility of real operational data, the effectiveness of data-driven forecasting models may be restricted, necessitating alternative data generation strategies. At this point, Generative Adversarial Network (GAN) based approaches capable of generating synthetic energy time series have emerged as promising

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solutions. GAN models can produce synthetic datasets that preserve the statistical characteristics of real time series while mitigating privacy risks. These synthetic datasets can significantly enhance the performance of machine learning models [7–9]. The application of GAN-based synthetic data generation for energy demand, load profiles, renewable generation, and other smart grid variables has rapidly expanded in the international literature and has demonstrated high effectiveness in numerous studies [8,14,15]. In the specific context of spinning reserve estimation, the existing literature primarily focuses on reserve decision-making within the frameworks of unit commitment, system reliability, and electricity market optimization [1–6]. However, studies addressing short-term spinning reserve forecasting using data-driven models remain relatively limited. Among the commonly used methods for energy time series forecasting, two approaches have gained particular prominence: (i) Long Short-Term Memory (LSTM) networks, which are highly effective in capturing temporal dependencies in sequential data; (ii) Extreme Gradient Boosting (XGBoost), which provides high predictive accuracy, robustness, and strong compatibility with feature engineering techniques. Recent studies have demonstrated that hybrid LSTM–XGBoost models can achieve significantly higher forecasting accuracy in short-term load forecasting and smart grid prediction problems compared to individual models [10–13]. While LSTM effectively learns temporal dependencies within time series, XGBoost captures nonlinear relationships and sudden variations in the data. The hybrid architecture therefore combines the complementary strengths of both models. This study addresses two key gaps in the literature: (i) the lack of systematic utilization of GAN-based synthetic data generation for spinning reserve forecasting, (ii) the limited application of hybrid LSTM–XGBoost models to the spinning reserve prediction problem. Within this framework, TimeGAN-like generative models are employed to expand the limited real dataset by generating synthetic energy time series. The generated synthetic data are then combined with real operational data, and a hybrid LSTM–XGBoost model is trained to perform short-term spinning reserve forecasting. In this way, both the challenges related to data scarcity and privacy constraints are mitigated, while the forecasting performance is improved, thereby providing an original contribution to the existing literature.

II. LITERATURE REVIEW

Early studies on spinning reserve requirements proposed fixed reserve ratios based on deterministic coefficients. However, Ortega-Vazquez and Kirschen [1] emphasized that reserve requirements should be determined within a cost–benefit analysis framework and demonstrated the optimal balance between the cost of reserve provision and the cost associated with unserved energy. Behrangrad, Sugihara, and Funaki [2] further showed that reserve decisions should not be evaluated solely from a reliability perspective but should also consider demand-side participation and environmental emissions.

In the Turkish context, the doctoral dissertation of Tür [4] and the related study [3] proposed optimizing spinning reserve requirements by jointly evaluating the national value of lost load, unit commitment decisions, and reserve costs. The increasing integration of renewable energy sources has further exposed the limitations of deterministic reserve policies. Consequently, probabilistic approaches such as the chance-constrained and robust optimization models proposed by Ardakani, Mozafari, and Soleymani [5], as well as Saeed et al. [6], have gained prominence. Although these studies address spinning reserve from both technical and economic perspectives, the modeling of short-term spinning reserve forecasting using data-driven approaches has largely been overlooked. Despite the extensive literature on reserve optimization and energy forecasting, existing studies suffer from three major limitations: (i) lack of synthetic data utilization in reserve forecasting, (ii) insufficient hybrid modeling approaches combining temporal and feature-based learning, and (iii) limited focus on short-term reserve prediction under data scarcity conditions.

Real operational time series related to energy demand, generation, and other system variables are often subject to confidentiality restrictions, high acquisition costs, and limited accessibility. For this reason, GAN-based synthetic data generation has emerged as a powerful alternative in energy research. Asre and Anwar [7] generated synthetic time series resembling real electricity consumption data using a Time Variant GAN model. Turowski et al. [9] reviewed 169 studies on synthetic energy time series generation and compared GAN, Variational Autoencoder (VAE), Markov-based, and autoregressive approaches, concluding that GAN-based models are particularly effective in capturing the nonlinear dynamics of energy systems. Zhang et al. [8] applied GAN models to generate synthetic time series for smart grid applications, while Wang and Hong [14] demonstrated that realistic building electricity load profiles can be generated using GAN-based approaches. Similarly, Acquaah et al. [15] proposed privacy-preserving synthetic datasets for power systems applications. This body of literature indicates that synthetic data can significantly enhance the accuracy of forecasting models while effectively addressing data scarcity issues.

However, no study in the existing literature has generated spinning reserve time series using GAN models and subsequently utilized them in forecasting models, revealing a significant research gap. Hybrid approaches that combine deep learning models with gradient boosting tree algorithms have recently achieved remarkable success in energy time series forecasting. While LSTM networks are capable of capturing trends, seasonality, and long-term dependencies in sequential data, XGBoost can effectively model sudden variations, external features, and complex nonlinear relationships.

Li et al. [10] demonstrated that a hybrid LSTM–XGBoost model achieved higher accuracy than individual models in short-term load forecasting. Semmelmann et al. [11] reported that hybrid models exhibited superior performance in energy community forecasting using smart meter data. Similarly, Dakheel and Cevik [12], as well as Gomez et al. [13], showed that hybrid approaches provide significant advantages over single models in terms of both predictive accuracy and robustness.

Overall, the existing literature indicates that the hybrid LSTM–XGBoost architecture is highly effective for energy time series forecasting. However, to the best of the authors' knowledge, no study has applied this hybrid architecture specifically to the problem of spinning reserve forecasting.

III. METHODOLOGY

In this study, a data-driven, synthetic-data-assisted, and hybrid machine learning deep learning based framework is proposed for the short-term forecasting of spinning reserve requirements in power systems. The proposed approach integrates multiple methodological components designed to capture both the temporal dynamics and the statistical characteristics of power system operational data. Initially, a comprehensive data preprocessing stage is conducted to ensure data consistency, remove noise, handle missing values, and normalize the time series variables associated with system load, generation, and reserve behavior. Following this stage, synthetic time series data are generated using a TimeGAN-based architecture in order to expand the limited real dataset and preserve the temporal and statistical structures inherent in energy system operations.

This synthetic data generation process enables the creation of realistic and privacy-preserving time series that maintain the distributional and dynamic properties of the original observations, thereby mitigating the challenges associated with limited data availability and confidentiality constraints.

Subsequently, a Long Short-Term Memory (LSTM) neural network is employed to model the temporal dependencies embedded within the spinning reserve time series. Owing to its capability to capture long-term sequential relationships, LSTM effectively learns complex temporal patterns such as trends, seasonality, and dynamic fluctuations in system behavior. In parallel, an Extreme Gradient Boosting (XGBoost) model is utilized to perform feature-based learning by exploiting nonlinear relationships between spinning reserve levels and relevant explanatory variables. XGBoost's gradient boosting mechanism allows the model to capture sudden variations and intricate interactions among features while maintaining high predictive robustness and computational efficiency. Finally, the outputs of the LSTM and XGBoost models are combined through a hybrid fusion mechanism designed to leverage the complementary strengths of both approaches. By integrating the temporal representation power of deep learning with the feature-driven predictive capability of gradient boosting algorithms, the proposed hybrid framework provides enhanced forecasting accuracy and improved generalization performance compared with single-model approaches.

This integrated methodology therefore offers a comprehensive solution for short-term spinning reserve forecasting in modern power systems characterized by increasing uncertainty, variability, and data limitations.

A. Dataset and Preprocessing

The dataset used in this study consists of multivariate time series variables representing key operational parameters of the power system, including spinning reserve levels measured in megawatts, system load demand, wind and solar generation outputs, system frequency measurements, and various time-related indicators. In order to ensure data quality and suitability for advanced forecasting models, several preprocessing procedures were applied prior to model development. First, missing observations within the time series were handled through a combined imputation strategy that integrates linear interpolation with the last observation carried forward method, allowing temporal continuity to be preserved while minimizing distortion in the original data structure. Subsequently, all variables were temporally aligned by converting the dataset into a uniform hourly resolution, ensuring that the multivariate time series remained synchronized and comparable across different system variables. To enhance the stability and convergence behavior of the deep learning models, particularly the Generative Adversarial Network and Long Short-Term Memory architectures, Min–Max normalization was applied to scale the variables into a consistent numerical range. In addition to these pre-processing steps, an extensive feature engineering process was conducted to enrich the predictive information contained in the dataset. Lagged variables representing previous time steps were incorporated in order to capture short-term temporal dependencies within the system dynamics. Furthermore, statistical smoothing indicators such as moving averages and exponential moving averages were calculated to represent underlying trends in the data, while volatility indicators derived from rolling standard deviation values were included to capture short-term fluctuations and uncertainty within the system behavior. Temporal context variables were also introduced, including indicators representing the day of the week, month of the year, seasonal cycles, and distinctions between weekdays and weekends. Through the integration of these pre-processing and feature engineering procedures, the dataset was transformed into a structured representation capable of effectively supporting both deep learning architectures and tree-based machine learning models, thereby facilitating robust and accurate spinning reserve forecasting.

B. Data Generation Using TimeGAN

Real-world spinning reserve and load datasets are often limited in size and may contain irregular patterns due to operational constraints and data accessibility issues. To address these limitations and enhance the training capability of forecasting models, the TimeGAN framework was employed in this study for synthetic data generation. TimeGAN is an advanced generative model that integrates Generative Adversarial Networks, supervised learning mechanisms, and autoregressive properties of time series within a unified architecture, enabling the generation of synthetic sequences that preserve both the temporal dynamics and statistical characteristics of real data [16]. The architecture of TimeGAN consists of several interconnected components designed to learn the underlying structure of sequential data. Within this framework, an embedder network first transforms the real time series into a latent representation that captures its essential temporal features, while a recovery network reconstructs the original sequence from this latent space representation. In parallel, a generator network produces synthetic time series from randomly sampled latent vectors, attempting to replicate the patterns observed in the real data. A discriminator network is then used to distinguish between real and generated sequences, guiding the generator to produce increasingly realistic outputs. Through this adversarial and supervised learning process, TimeGAN is capable of generating synthetic time series that closely resemble the statistical and temporal properties of the original dataset. The TimeGAN model was trained for 1000 epochs with a batch size of 32, using the Adam optimizer and a learning rate of 0.001. The overall loss function of TimeGAN is composed of adversarial loss, supervised loss, and reconstruction loss components that jointly ensure the generation of realistic and temporally consistent time series data.

C. Learning Temporal Dependencies With LSTM

Since the spinning reserve time series contains strong trends and temporal dependencies, a Long Short-Term Memory (LSTM) network was employed to effectively model long-term sequential relationships in the data. LSTM is an advanced recurrent neural network architecture specifically designed to overcome the vanishing gradient problem commonly encountered in classical RNN models when learning long sequences. To address this limitation, the LSTM cell incorporates a gated memory mechanism consisting of three main gates that regulate the flow of information within the network and allow the model to selectively retain or discard information over time.

In this study, several key hyperparameters of the LSTM model were optimized in order to achieve stable training and improved predictive performance. The final LSTM architecture consists of 2 hidden layers with 64 units, a dropout rate of 0.2 to prevent overfitting, and a batch size of 32 during training. The hidden layer dimension was explored within a range of 32 to 128 units to balance model complexity and computational efficiency. The hyperbolic tangent (tanh) activation function was adopted due to its effectiveness in modeling nonlinear patterns within sequential data. For model optimization, the Adam optimizer was utilized because of its adaptive learning capability and efficient convergence behavior during training. In addition, the number of training epochs was varied between 50 and 150 to ensure sufficient learning while preventing excessive overfitting. The experimental results indicate that the LSTM model successfully captured important characteristics of spinning reserve behavior, including long-term trends, seasonal variations, and sudden fluctuations in system dynamics [19].

D. Feature-Based Learning With XGBoost

To model the statistical structure of the time series, including lagged dependencies, volatility patterns, and seasonal characteristics, the Extreme Gradient Boosting (XGBoost) algorithm was employed. XGBoost is a regularized gradient boosting framework based on decision tree ensembles and is widely recognized in the energy forecasting literature for its high predictive accuracy, computational efficiency, and robustness against overfitting [19–20]. The algorithm iteratively constructs decision trees by minimizing a differentiable loss function while incorporating regularization terms that control model complexity and improve generalization performance. In the context of energy system data, XGBoost is particularly effective at capturing nonlinear relationships between explanatory variables and the target variable, as well as detecting sudden variations and irregular patterns within time series data. In this study, several key hyperparameters of the XGBoost model were systematically optimized in order to achieve the best predictive performance. The maximum tree depth was explored within a range of four to eight levels to balance model complexity and overfitting risk. The number of boosting iterations, represented by the number of estimators, was varied between three hundred and five hundred trees to allow the model to learn complex patterns while maintaining computational efficiency. The learning rate parameter, which controls the contribution of each newly added tree to the ensemble, was tuned within the interval of 0.03 to 0.1 to ensure stable convergence during training. In addition, the subsample ratio was adjusted between 0.7 and 1.0 in order to introduce randomness into the training process and improve the model's robustness. The experimental results demonstrated that the XGBoost model achieved strong performance in learning nonlinear interactions among features and effectively captured abrupt load fluctuations and system dynamics within the spinning reserve forecasting problem. The objective function was defined as squared error regression to minimize prediction loss.

E. Hybrid LSTM–XGBoost Fusion for Dataset and Preprocessing

Since LSTM networks are particularly effective at capturing temporal dependencies and sequential patterns in time series data, while XGBoost models excel at learning complex statistical relationships and nonlinear interactions among explanatory variables, the outputs of both models were integrated to construct a hybrid forecasting framework. This hybrid approach was designed to leverage the complementary strengths of deep learning and gradient boosting methods, thereby improving predictive accuracy and robustness in spinning reserve forecasting. In practical terms, the LSTM component focuses on modeling the dynamic evolution of the time series by learning long-term dependencies, trends, and temporal correlations present in historical observations. In contrast, the XGBoost component captures feature-based relationships, including nonlinear effects, volatility patterns, and interactions among lagged variables and exogenous system indicators such as load demand and renewable generation. By combining these two modeling paradigms within a unified framework, the hybrid model is capable of simultaneously representing temporal dynamics and statistical feature structures, which are often difficult to capture using a single model alone. This integration also helps mitigate the limitations associated with individual models, such as the difficulty of tree-based algorithms in learning sequential dependencies or the limited ability of neural networks to explicitly model engineered statistical features. Consequently, the hybrid strategy enables a more comprehensive representation of the underlying system behavior and enhances the overall forecasting capability of the proposed methodology. Within this framework, two different fusion strategies were implemented in order to combine the predictions produced by the LSTM and XGBoost models.

F. Model Evaluation Metrics and Experimental Design

The performance of the proposed forecasting model was evaluated using four widely adopted statistical error metrics in time series prediction studies. These metrics were selected in order to assess the accuracy, robustness, and explanatory capability of the model from different perspectives. Root Mean Square Error (RMSE) was used as a primary indicator that is particularly sensitive to large prediction errors and therefore provides insight into the model's ability to avoid significant deviations between predicted and actual values. Mean Absolute Error (MAE) was also calculated to measure the average magnitude of prediction errors without considering their direction, offering a clear interpretation of overall forecasting accuracy. In addition, Mean Absolute Percentage Error (MAPE) was employed as a relative error metric that expresses prediction accuracy in percentage terms, making it useful for comparing model performance across different datasets or scales. Finally, the coefficient of determination (R^2) was used to evaluate how well the model explains the variance in the observed spinning reserve values and to quantify the explanatory power of the proposed forecasting framework.

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(x_t - y_t)^2}$$

$$MAE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}|x_t - y_t|}$$

$$MAPE = \sqrt{\frac{100}{N}\sum_{t=1}^{N}\left|\frac{x_t - y_t}{y_t}\right|}$$

$$R^2 = 1 - \frac{\sum_t (x_t - y_t)^2}{\sum_t (y_t - x_t)^2}$$

The experimental process of the study was conducted in three main stages in order to ensure a systematic and reliable evaluation of the proposed forecasting framework. In the first stage, the dataset was divided after combining the real operational data with the synthetically generated time series. The integrated dataset was partitioned into training, validation, and test subsets with proportions of seventy percent, fifteen percent, and fifteen percent, respectively. The splitting was performed chronologically to reflect real-world forecasting conditions, where past observations are used to predict future values. In order to preserve the temporal structure inherent in time series data, the dataset was not shuffled during the splitting process. This approach ensured that the chronological order of observations was maintained and that the models were trained and evaluated in a manner consistent with real-world forecasting conditions.

In the second stage, the models were trained and optimized using the defined data partitions. The LSTM, XGBoost, and hybrid forecasting models were all trained and evaluated using the same training, validation, and test datasets to ensure a fair and consistent comparison of their predictive performances. This unified data partitioning strategy enabled the models to be assessed under identical conditions and provided reliable insights into their relative forecasting capabilities. Furthermore, the hyper parameters of each model were optimized through a grid search procedure combined with an early stopping mechanism. While the grid search method allowed the exploration of different parameter combinations to determine the most suitable configuration, the early stopping strategy prevented overfitting by terminating the training process when the validation performance stopped improving, thereby enhancing the models' generalization ability.

In the final stage, the performances of different models were compared to evaluate the effectiveness of the proposed approach. Four forecasting models were considered in the comparative analysis: the standalone LSTM model, the standalone XGBoost model, and two hybrid approaches referred to as Hybrid-Blending and Hybrid-Stacking. The predictive performances of these models were analyzed using widely accepted evaluation metrics, including Root Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and the coefficient of determination. These metrics provided a comprehensive assessment of the forecasting accuracy and explanatory power of each model. All experiments were implemented using Python with TensorFlow and XGBoost libraries.

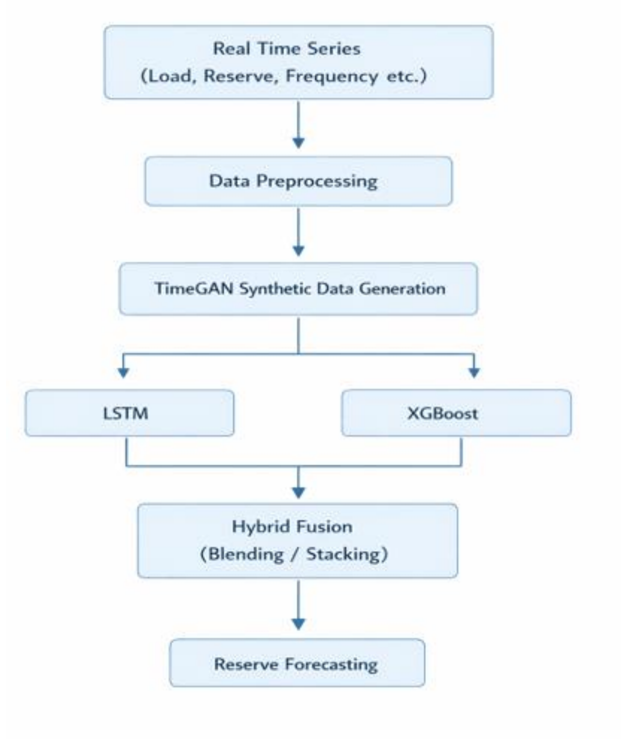


Fig. 1. Proposed methodology framework.

IV. RESULT AND DISCUSSION

A. Results

In this section, the performance results of the LSTM, XGBoost, and Hybrid models based on Blending and Stacking architectures trained on the TimeGAN-augmented dataset are presented. The models were evaluated using the test dataset in order to assess their predictive accuracy under unseen data conditions. Four widely used evaluation metrics were employed for performance assessment, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The comparative results indicate that the hybrid approach consistently outperformed the individual LSTM and XGBoost models across all evaluation metrics. By combining the temporal learning capability of LSTM with the feature-based predictive strength of XGBoost, the hybrid framework achieved higher forecasting accuracy and improved generalization performance in the spinning reserve prediction task.

1) Performance of Individual Models

First, the performances of the standalone LSTM and XGBoost models were examined individually in order to evaluate their predictive capabilities before applying the hybrid approach. Table I presents the error metrics obtained from both models on the test dataset. The LSTM model demonstrated a strong ability to learn temporal dependencies within the time series and effectively captured sequential patterns in the data. However, its prediction errors tended to increase during periods characterized by sudden fluctuations or abrupt changes in system behavior. In contrast, the XGBoost model produced lower prediction errors compared with LSTM, primarily because of its capability to better capture statistical patterns, nonlinear relationships, and feature-based interactions within the dataset. Similar findings have also been reported in previous studies, where tree-based ensemble models were shown to outperform standalone deep learning models in certain energy forecasting scenarios [21,22].

Table I. Performance of individual models

Model	RMSE (MW)	MAE (MW)	MAPE (%)	R²
LSTM	17.82	11.54	6.21	0.931
XGBoost	15.09	10.12	5.48	0.947

2) *Performance of Hybrid Models*

The synthetic data generated using the TimeGAN model enhanced the training process of both the LSTM and XGBoost models by expanding the dataset and preserving the temporal characteristics of the original time series. After training the individual models, their outputs were integrated through a hybrid fusion framework in order to take advantage of the complementary strengths of both approaches. In this context, two different hybrid strategies were implemented and evaluated. The first approach, referred to as Hybrid-1, was based on a weighted blending technique in which the predictions of the LSTM and XGBoost models were combined using predefined weighting coefficients. The second approach, Hybrid-2, employed a stacking regression structure in which a meta-learner model was trained to optimally combine the predictions generated by the base models. The comparative performance results of these hybrid approaches are presented in Table II.

Table II. Performance of hybrid models

Model	RMSE (MW)	MAE (MW)	MAPE (%)	R²
Hybrid-Blending	13.72	9.01	4.63	0.958
Hybrid-Stacking	12.84	8.47	4.21	0.965

3) *Impact of TimeGAN on Performance*

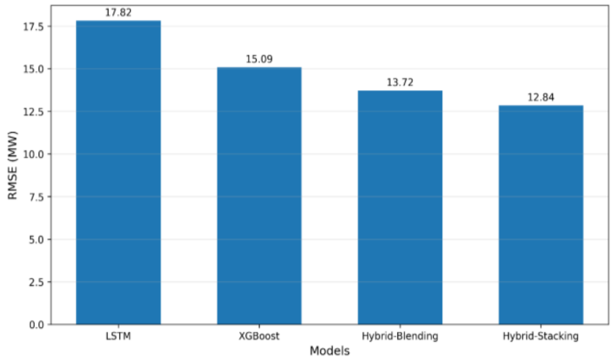
A comparison was conducted between the hybrid model trained solely on the original dataset and the hybrid model supported by synthetic data generated through the TimeGAN framework. This comparison aimed to evaluate the impact of synthetic data augmentation on the overall forecasting performance. The results indicate that the TimeGAN-assisted hybrid model benefited from the expanded dataset and improved data diversity, leading to more accurate and stable prediction results compared with the hybrid model trained without synthetic data.

Table III. Impact of TimeGAN on model performance

Model	RMSE (MW)	MAE (MW)	MAPE (%)	R²
Hybrid-Stacking (Real Data)	14.03	9.77	5.12	0.952
Hybrid-Stacking + TimeGAN	12.84	8.47	4.21	0.965

The use of TimeGAN-generated synthetic data led to a noticeable improvement in forecasting performance. Specifically, the incorporation of synthetic data reduced the RMSE value by approximately 8.5% and decreased the MAPE by about 17.8%, indicating a significant enhancement in prediction accuracy. These improvements suggest that expanding the dataset with realistic synthetic time series helps the models learn underlying patterns more effectively and improves their generalization capability. Such findings are consistent with previous studies reporting that increasing data volume through synthetic data generation can substantially enhance the performance of machine learning models in energy forecasting applications [24–26].

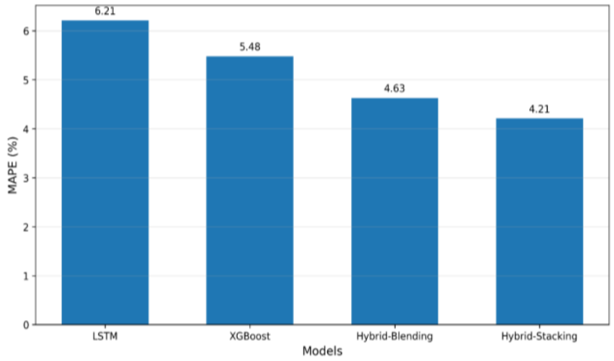
Fig. 2 the RMSE comparison of the forecasting models shows that the hybrid approaches outperform the individual models. While the LSTM model produced the highest RMSE value, the Hybrid-Stacking model achieved the lowest error, indicating the best predictive performance. This result demonstrates that combining LSTM and XGBoost improves forecasting accuracy compared with using single models.



Hybrid models, particularly Hybrid-Stacking, reduced RMSE by 28% compared with LSTM and 15% compared with XGBoost.

Fig. 2. RMSE Comparison of Forecasting Models.

Fig. 3 the comparison of MAPE values shows that hybrid models achieve lower prediction errors than individual models. In particular, the Hybrid-Stacking model provides the best performance by achieving the lowest MAPE value among all models.



The Hybrid-Stacking model achieved the best performance, reducing the error rate by 32.2% relative to LSTM.

Fig. 3. MAPE (%) Comparison of Models.

Fig. 4 illustrates the comparison between the actual spinning reserve values and the predictions obtained from the Hybrid Stacking model across different time steps. The predicted values closely follow the actual reserve levels, indicating that the hybrid model captures the underlying system dynamics with high accuracy. This result demonstrates the effectiveness of the proposed hybrid framework in short-term spinning reserve forecasting.

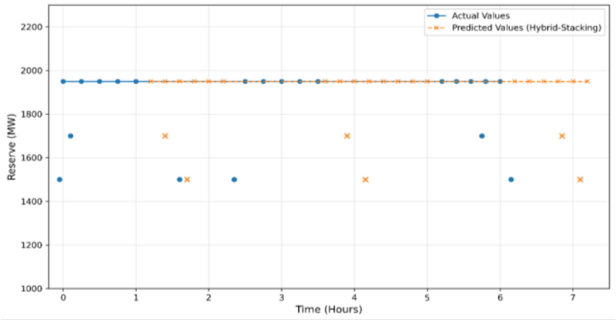


Fig. 4. Actual vs Predicted Spinning Reserve Values.

B. Discussion

In this study, the proposed TimeGAN–LSTM–XGBoost hybrid approach produced highly successful results in the short-term forecasting of spinning reserve. Although the individual models, LSTM and XGBoost, demonstrated strong performance in capturing different dynamics of the time series, the hybrid model achieved noticeably higher prediction accuracy. In particular, the Hybrid-Stacking method systematically reduced RMSE and MAPE values compared with the other models and increased the coefficient of determination to 0.965. This improvement can be attributed to the hybrid architecture's ability to simultaneously learn temporal dependencies through LSTM and statistical or feature-based relationships through XGBoost.

The integration of synthetic data generated by TimeGAN significantly improved model performance. When compared with the hybrid model trained without synthetic data, the improvements observed in the error metrics demonstrate that increasing data volume and enriching the data distribution are critical factors for improving model performance. Similar findings have been reported by Lin et al. [24] and Park et al. [25], who emphasized that synthetic data can effectively enhance energy demand forecasting models. The results of this study indicate that TimeGAN can achieve comparable success when applied to critical power system time series such as spinning reserve.

Furthermore, the results obtained from the hybrid model are superior when compared with similar approaches reported in the literature. For instance, in the short-term load forecasting study conducted by Kong et al. [21], LSTM models achieved strong performance; however, hybrid approaches combining deep learning and boosting techniques were shown to provide higher prediction accuracy than standalone models. Similarly, Lago et al. [23] demonstrated that hybrid models offer significant advantages in electricity imbalance price forecasting. In this context, the findings of the present study confirm that hybrid architectures also deliver superior performance in the field of spinning reserve forecasting and provide a contribution consistent with the general trend observed in the literature.

In conclusion, the experimental results confirm that the proposed hybrid model provides an applicable, flexible, and highly accurate solution for short-term spinning reserve forecasting. The success of the model suggests that it can contribute directly to practical applications in electricity markets as well as real-time power system operation and planning.

V. CONCLUSION

This study proposed an innovative approach for short-term spinning reserve forecasting by integrating TimeGAN-based synthetic data generation with deep learning and machine learning models to address the problem of data scarcity. The main contribution of this study lies in the integration of synthetic data generation with hybrid learning models, specifically tailored for spinning reserve forecasting under data scarcity conditions. The LSTM model effectively captured temporal dependencies and sequential patterns in the time series, while the XGBoost model successfully learned statistical and nonlinear relationships with high precision. The hybrid fusion of these two approaches, particularly through the stacking strategy, resulted in a significant improvement in forecasting performance.

The evaluation results demonstrate that the hybrid model provides a clear advantage over the individual models in terms of RMSE, MAE, and MAPE values. The coefficient of determination reaching 0.965 indicates that the proposed model is able to explain a substantial portion of the variance in spinning reserve values. In addition, the integration of synthetic data generated through TimeGAN significantly improved prediction accuracy and enhanced the generalization capability of the model by expanding the available dataset and enriching the distribution of training data.

Based on these findings, the hybrid TimeGAN–LSTM–XGBoost framework can be considered a practical and effective solution for short-term spinning reserve forecasting required by energy market operations. In practical terms, the proposed approach can assist system operators in improving reserve allocation decisions, reducing operational costs, and enhancing grid reliability under uncertainty. The approach also provides an effective strategy for overcoming data scarcity and data privacy limitations, while offering the flexibility to be adapted to other energy-related time series such as demand, generation, system frequency, and emission data. Future studies may further enhance forecasting performance by incorporating advanced architectures such as transformer-based models and Graph Neural Networks, as well as validating the proposed approach on real-world large-scale power system datasets. Moreover, it is recommended that spinning reserve forecasting be investigated within broader multivariate modeling frameworks that simultaneously consider demand response mechanisms, renewable generation uncertainty, and electricity market dynamics.

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