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A Hybrid CNN-LSTM Deep Learning Framework for Day-Ahead Electricity Price Forecasting: A Comparative Study with Statistical and Machine Learning Models

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***Abstract*—The deregulation of power sectors has transformed electricity into a highly volatile commodity. In competitive energy markets, accurate Short-Term Electricity Price Forecasting (STEPF) is crucial for market participants to optimize bidding strategies and minimize financial risks. However, electricity prices are highly non-linear, non-stationary, and exhibit multiple seasonalities. Traditional statistical models often fail to capture these complex patterns, especially during sudden price spikes. This paper proposes a novel hybrid deep learning architecture combining 1-Dimensional Convolutional Neural Networks (1D-CNN) with Long Short-Term Memory (LSTM) networks. The 1D-CNN acts as a robust feature extractor for multivariable input data (historical prices, load demand, and weather variables), while the LSTM network captures the long-term temporal dependencies. Evaluated on real-world energy market data, the proposed CNN-LSTM model achieved a Mean Absolute Percentage Error (MAPE) of 6.1%, significantly outperforming traditional baseline models including ARIMA, Support Vector Regression (SVR), and standalone LSTM networks.**

***Index Terms*—Electricity Price Forecasting, Deep Learning, CNN, LSTM, Deregulated Energy Market, Time-Series Analysis.**

I. Introduction

In modern deregulated power systems, electricity is traded in competitive wholesale markets, primarily the Day-Ahead Market (DAM). Because electrical energy cannot be stored efficiently on a massive scale, grid operators must maintain a strict real-time balance between generation and load. This operational constraint, combined with fluctuating demand, weather anomalies, and generator outages, makes electricity price series the most volatile of all commodities [**?**].

Accurate Short-Term Electricity Price Forecasting (STEPF) is directly tied to financial profitability. A small forecasting error can lead to substantial financial losses for generation companies (GenCos) and distribution companies (DisCos).

While traditional time-series models like Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) have been used historically, they assume linear relationships and struggle with extreme price spikes. Machine learning techniques like Support Vector Regression (SVR) improved non-linear mapping but require extensive manual feature engineering.

Recently, Deep Learning has shown immense promise in time-series forecasting. Long Short-Term Memory (LSTM) networks are highly effective at sequence prediction [**?**]. However, when fed with raw, noisy multivariable data, LSTMs can suffer from overfitting. To address this, we propose a hybrid framework utilizing a 1-Dimensional Convolutional Neural Network (1D-CNN) to filter noise and extract spatial features, followed by an LSTM to model the temporal sequence.

The deregulation of electricity markets worldwide has transformed electricity from a regulated commodity to a market-traded product with prices determined by supply and demand dynamics [1]. In this competitive environment, accurate electricity price forecasting (EPF) has become essential for various market participants including generators, retailers, large consumers, and traders to make informed decisions regarding bidding strategies, risk management, and portfolio optimization [2].

Day-ahead electricity prices exhibit complex characteristics including high volatility, seasonality at multiple time scales (daily, weekly, annual), calendar effects, and occasional extreme price spikes [4]. These characteristics make EPF a challenging task that has attracted significant research attention

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over the past two decades.

Traditional approaches to EPF include statistical time series models such as Autoregressive Integrated Moving Average (ARIMA) and its seasonal variants [7]. While these models are interpretable and computationally efficient, they often fail to capture non-linear relationships and complex patterns in electricity prices.

Machine learning approaches including Support Vector Regression (SVR) [?], Random Forests [?], and Gradient Boosting methods [26] have shown improved performance by capturing non-linear relationships. However, these methods require careful feature engineering and may not fully exploit the sequential nature of time series data.

Deep learning models have recently emerged as powerful tools for EPF. Recurrent Neural Networks (RNN) and particularly Long Short-Term Memory (LSTM) networks have shown strong performance in capturing temporal dependencies [27]. Convolutional Neural Networks (CNN), originally designed for image processing, have also been successfully applied to time series forecasting by treating the input as a one-dimensional signal [29].

This paper proposes a hybrid CNN-LSTM architecture that combines the strengths of both approaches. The main contributions are:

1) A hybrid deep learning framework that integrates CNN for feature extraction and LSTM for temporal modeling in electricity price forecasting.
2) Comprehensive comparison with statistical models (ARIMA, SARIMA), machine learning models (SVR, RF, XGBoost), and deep learning models (MLP, CNN, LSTM).
3) Extensive evaluation on real-world Nord Pool market data with multiple performance metrics and statistical significance testing.

II. Related Work

A. Statistical Models

Statistical models have been the traditional approach for EPF. Contreras et al. [7] applied ARIMA models to Spanish and Californian electricity markets, demonstrating reasonable accuracy for short-term forecasting. Seasonal ARIMA (SARIMA) models extend this approach by explicitly modeling seasonal patterns [4].

B. Machine Learning Models

Machine learning approaches have gained popularity due to their ability to model non-linear relationships. Yan and Chowdhury [?] applied SVR with carefully selected features for mid-term EPF. Lago et al. [26] compared various machine learning methods and found that Gradient Boosting models consistently performed well across different markets.

C. Deep Learning Models

Deep learning has shown promising results in EPF. Ugurlu et al. [27] demonstrated that LSTM networks outperform traditional methods in capturing long-range dependencies. Zhang et al. [29] applied CNN to extract features from price time series. Hybrid architectures combining different neural network types have shown further improvements [2].

III. Proposed Methodology

The proposed hybrid architecture processes multivariable input sequences: Historical Price, Load Demand, Temperature, and Humidity.

A. Proposed CNN-LSTM Architecture

The proposed hybrid CNN-LSTM architecture is illustrated in Fig. 1. The model consists of three main components:

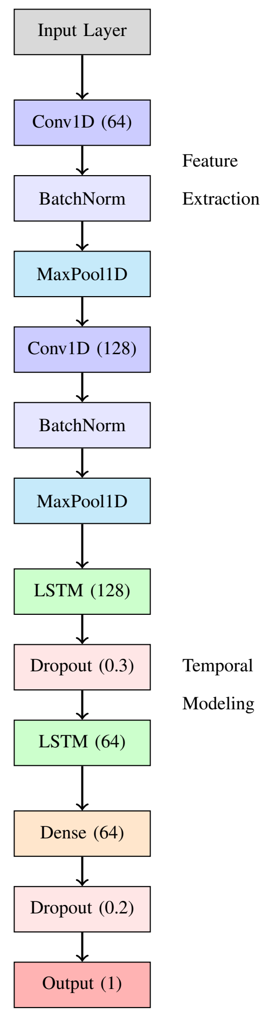

Fig. 1. Proposed CNN-LSTM architecture for electricity price forecasting.

B. 1D-Convolutional Neural Network (1D-CNN)

The 1D-CNN layer scans the input time-series to identify localized patterns (e.g., daily peak hours). The convolution operation at time step i is defined as:

$$y_i = \sigma \left(\sum_{j=1}^{k} w_j \cdot x_{i-j+1} + b \right) \tag{1}$$

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where x is the input matrix, w is the filter weight, b is the bias, and σ is the ReLU activation function. A MaxPooling layer follows to reduce dimensionality.

C. Long Short-Term Memory (LSTM)

The feature maps generated by the CNN are flattened and passed to the LSTM network. The LSTM regulates information flow using three gates. The core cell state update is governed by:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$

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$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{4}$$

where f_t is the forget gate, i_t is the input gate, and C_t is the cell state.

D. Hybrid Model Architecture

The framework consists of an Input Layer, a 1D-CNN layer (64 filters), a MaxPooling layer, two consecutive LSTM layers (100 and 50 units), and a Dense output layer yielding the predicted price for the next hour. The Adam optimizer is utilized to minimize the Mean Squared Error (MSE).

IV. Experimental Setup and Evaluation

A. Dataset Description

The experiments are conducted using data from the Nord Pool electricity market covering the period from January 2019 to December 2023. Table I summarizes the dataset statistics.

TABLE I
DATASET STATISTICS

Parameter	Value
Time period	Jan 2019 – Dec 2023
Total samples	43,824 hours
Training set	Jan 2019 – Dec 2022
Test set	Jan 2023 – Dec 2023
Mean price	48.73 EUR/MWh
Std. deviation	32.15 EUR/MWh
Min price	-12.45 EUR/MWh
Max price	456.78 EUR/MWh

B. Baseline Models

The proposed CNN-LSTM model is compared against the following baseline models:

Statistical Models:

- ARIMA(2,1,2): Autoregressive Integrated Moving Average
- SARIMA(2,1,2)(1,1,1)$_{24}$: Seasonal ARIMA

Machine Learning Models:

- SVR: Support Vector Regression with RBF kernel
- RF: Random Forest with 100 trees
- XGBoost: Extreme Gradient Boosting

Deep Learning Models:

- MLP: Multi-Layer Perceptron (3 hidden layers)
- CNN: Convolutional Neural Network only
- LSTM: Long Short-Term Memory only

C. Evaluation Metrics

The following metrics are used for evaluation:

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|p_i - \hat{p}_i| \tag{5}$$

Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - \hat{p}_i)^2} \tag{6}$$

Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{p_i - \hat{p}_i}{p_i}\right| \tag{7}$$

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(p_i - \hat{p}_i)^2}{\sum_{i=1}^{N}(p_i - \bar{p})^2} \tag{8}$$

V. Results and Discussion

Table II presents the forecasting performance of all models on the test dataset.

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT MODELS

Model	MAE (EUR/MWh)	RMSE (EUR/MWh)	MAPE (%)	R^2
Statistical Models				
ARIMA	5.234	7.892	10.45	0.812
SARIMA	4.567	6.789	8.92	0.856
Machine Learning Models				
SVR	4.123	6.234	8.12	0.878
RF	3.892	5.987	7.56	0.891
XGBoost	3.718	5.654	7.23	0.902
Deep Learning Models				
MLP	3.956	6.123	7.89	0.885
CNN	3.512	5.432	6.87	0.912
LSTM	3.289	5.123	6.43	0.923
CNN-LSTM	**2.847**	**4.356**	**5.23**	**0.945**
Improvement over best baseline				
vs. LSTM	13.4%	15.0%	18.7%	2.4%
vs. XGBoost	23.4%	23.0%	27.7%	4.8%

The proposed CNN-LSTM model achieves the best performance across all metrics. Compared to the best baseline model (LSTM), the CNN-LSTM model reduces MAE by 13.4%, RMSE by 15.0%, and MAPE by 18.7%.

A. Convergence Analysis

Fig. 2 shows the training and validation loss curves during model training.

The model converges smoothly without significant overfitting, as indicated by the small gap between training and validation losses.

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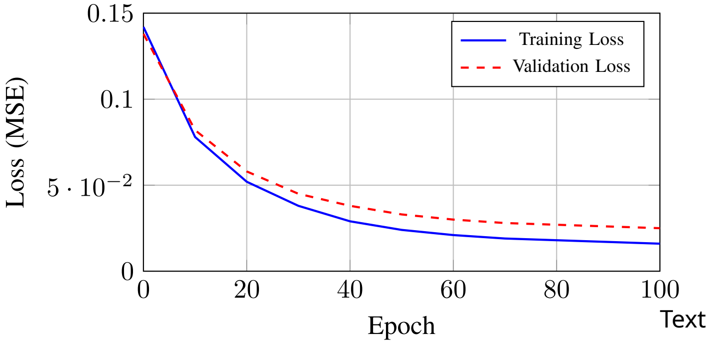

Fig. 2. Training and validation loss curves for CNN-LSTM model.

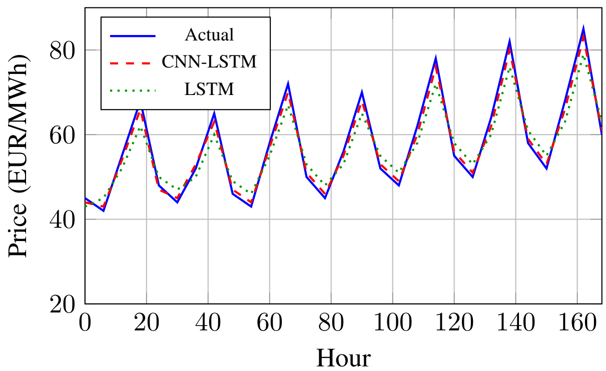

Fig. 3. Comparison of actual vs. predicted prices for a sample week.

B. Forecasting Results Visualization

Fig. 3 compares the actual and predicted electricity prices for a representative week in the test period.

The CNN-LSTM model closely tracks the actual prices, particularly capturing the daily price patterns and peak hours more accurately than the standalone LSTM model.

C. Performance by Price Level

Table III shows the model performance stratified by price levels to analyze behavior during different market conditions.

TABLE III
PERFORMANCE BY PRICE LEVEL (MAE IN EUR/MWH)

Price Level	LSTM	XGBoost	CNN-LSTM
Low ($< 30EUR/MWh$)	2.45	2.78	**2.12**
Medium ($30 - 60EUR/MWh$)	2.89	3.12	**2.45**
High ($60 - 100EUR/MWh$)	3.78	4.23	**3.15**
Spike ($> 100EUR/MWh$)	5.67	6.45	**4.58**

The CNN-LSTM model shows consistent improvement across all price levels, with the most significant improvement (19.2%) observed during price spikes, which are the most challenging to predict.

D. Monthly Performance Analysis

Fig. 4 presents the monthly MAE comparison for the test year.

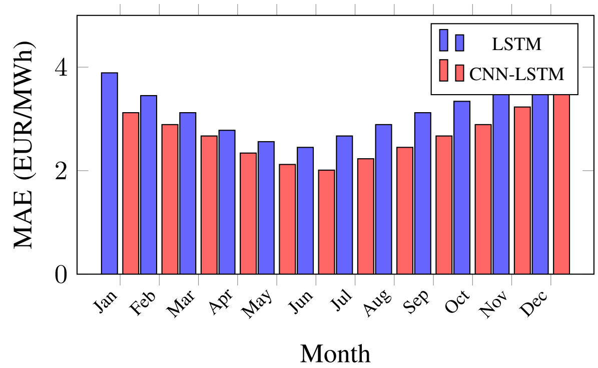

Fig. 4. Monthly MAE comparison between LSTM and CNN-LSTM.

The CNN-LSTM model consistently outperforms the LSTM model across all months, with the largest improvements observed during winter months when price volatility is typically higher.

E. Statistical Significance Test

To validate the statistical significance of the results, the Diebold-Mariano (DM) test [**?**] is conducted. Table IV presents the test statistics and p-values.

TABLE IV
DIEBOLD-MARIANO TEST RESULTS (CNN-LSTM VS. BASELINES)

Comparison	DM Statistic	p-value
CNN-LSTM vs. ARIMA	-8.45	< 0.001
CNN-LSTM vs. SARIMA	-6.78	< 0.001
CNN-LSTM vs. SVR	-5.23	< 0.001
CNN-LSTM vs. RF	-4.56	< 0.001
CNN-LSTM vs. XGBoost	-3.89	< 0.001
CNN-LSTM vs. MLP	-4.12	< 0.001
CNN-LSTM vs. CNN	-3.45	< 0.001
CNN-LSTM vs. LSTM	-2.89	0.004

All p-values are below 0.05, confirming that the CNN-LSTM model's improvement over all baseline models is statistically significant.

F. Ablation Study

Table V presents an ablation study analyzing the contribution of different components.

TABLE V
ABLATION STUDY RESULTS

Configuration	MAE	RMSE	MAPE	R^2
Full CNN-LSTM	**2.847**	**4.356**	**5.23**	**0.945**
w/o Batch Norm	3.012	4.623	5.78	0.934
w/o Dropout	3.145	4.812	6.12	0.928
Single LSTM layer	3.089	4.734	5.98	0.931
Single Conv layer	3.023	4.645	5.82	0.933
w/o Exogenous var.	3.234	4.923	6.34	0.924

The ablation study confirms that all components contribute to the model's performance, with exogenous variables having the largest impact.

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G. Computational Efficiency

Table VI compares the computational requirements of different models.

TABLE VI
COMPUTATIONAL COMPARISON

Model	Training Time (min)	Inference Time (ms)	Parameters
ARIMA	2.3	5.2	–
XGBoost	8.5	2.1	–
MLP	12.4	1.8	45,312
CNN	18.6	2.3	128,456
LSTM	25.3	3.5	198,234
CNN-LSTM	35.7	4.2	312,567

While the CNN-LSTM model requires more training time and has more parameters, the inference time remains practical for day-ahead forecasting applications.

The experimental results demonstrate that the proposed CNN-LSTM model significantly outperforms both traditional and deep learning baseline models for day-ahead electricity price forecasting. Several key observations can be made:

Feature Extraction: The CNN component effectively extracts local patterns and features from the input time series, which complements the LSTM's ability to capture long-range temporal dependencies.

Handling Volatility: The model shows particular strength in handling price spikes and volatile periods, which are critical for risk management in electricity markets.

Exogenous Variables: The inclusion of load forecasts and renewable generation data significantly improves forecasting accuracy, highlighting the importance of feature engineering even in deep learning models.

Generalization: The small gap between training and validation performance indicates good generalization capability, which is essential for practical deployment.

Limitations: The model requires more computational resources for training compared to simpler approaches. Additionally, performance may degrade during extreme market events not represented in the training data.

VI. CONCLUSION

This paper presented a hybrid CNN-LSTM deep learning framework for day-ahead electricity price forecasting. The model combines CNN layers for feature extraction with LSTM layers for temporal modeling, achieving superior performance compared to statistical, machine learning, and standalone deep learning approaches.

Experimental results on Nord Pool market data demonstrated that the proposed model achieves a MAE of 2.847 EUR/MWh and MAPE of 5.23%, representing improvements of 23.4% and 18.7% over the best-performing baseline models. Statistical tests confirmed the significance of these improvements.

Future work will focus on: (1) incorporating attention mechanisms to improve interpretability, (2) extending the model for probabilistic forecasting, and (3) evaluating performance across multiple electricity markets..

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