Attention-Enhanced LSTM Models for Long-Horizon Time Series Forecasting in Renewable Energy Systems

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Abstract

Accurate long-horizon forecasting in renewable-energy systems remains challenging due to non-stationarity, exogenous weather drivers, and the accumulation of error over extended horizons. This paper presents an attention-enhanced LSTM encoder-decoder tailored to multi-step forecasting in solar and wind power. The encoder summarizes historical dynamics while a dot-product attention mechanism forms time-varying context vectors for each prediction step, mitigating information bottlenecks typical of plain sequence-to-sequence models. We detail training and inference regimes (including teacher forcing and horizon-aware loss aggregation) and compare against strong LSTM and CNN-LSTM baselines under consistent data splits and hyperparameter budgets. Results across 24-168-hour horizons show consistent error reductions and more stable performance at longer horizons, with attention maps highlighting diurnal patterns and ramp events that align with domain intuition. Ablation studies further isolate the contribution of attention and input-window length, and a brief interpretability analysis illustrates how attention emphasizes weather-driven transitions that matter most for extended forecasts. Practical guidance for deployment is discussed, including look-back selection, horizon grouping, and calibration considerations for operational use.

Keywords

Long-Horizon Forecasting, Renewable Energy, LSTM, Attention Mechanism, Sequence-to-Sequence, Interpretability, Solar Power, Wind Power

1. Introduction

Renewable energy resources, such as wind and solar power, are central to the global effort to decarbonise power systems. Their integration into modern electricity grids introduces significant uncertainty because generation is inherently dependent on weather conditions that fluctuate across multiple time scales. Accurate forecasting of renewable generation is therefore essential for reducing balancing costs, improving dispatch planning, and enabling active participation in energy markets.

Traditional statistical models often struggle to address the non-stationary and nonlinear characteristics of renewable-energy time series. In contrast, machine-learning approaches-particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) networks-have demonstrated strong capabilities in capturing sequential dependencies and have been widely applied in load and generation forecasting [1]. However, standard LSTM architectures sequentially process input data and condense it into a fixed-length context vector, which may fail to capture all relevant temporal patterns when forecasting over long horizons. To overcome this limitation, attention mechanisms have been developed to compute context vectors as weighted sums of encoder hidden states, assigning greater importance to time steps most relevant for the prediction. Recent studies confirm that integrating attention into LSTM architectures can enhance forecasting accuracy in diverse renewable-energy applications [2,3].

In this work, we build upon these advances by conducting a comprehensive survey of recent literature on attention-enhanced LSTM models for renewable-energy forecasting, spanning load, solar, and wind power generation as well as microgrid applications. We formalise the problem of long-horizon forecasting, present the evaluation metrics most commonly employed in energy-forecasting studies, and introduce an attention-augmented LSTM architecture tailored for extended prediction horizons. Furthermore, we describe the training and implementation details, perform numerical experiments on a synthetic renewable-energy dataset to demonstrate the performance gains and interpretability benefits of attention mechanisms, and compare the proposed approach against state-of-the-art methods. The analysis concludes with practical guidance for practitioners seeking to apply attention-enhanced LSTM models in operational renewable-energy forecasting scenarios.

2. Literature Review

Research on renewable-energy forecasting using LSTM architectures has progressively evolved to incorporate additional data sources and advanced neural components in order to improve predictive performance. Early approaches integrated exogenous weather variables such as temperature and wind speed directly into the LSTM framework, enhancing forecasts for electricity demand, solar generation, and wind power [1]. In these studies, including weather data reduced the mean absolute scaled error (MASE) and mean squared error (MSE) of solar forecasts by approximately 33% compared with LSTM models lacking such contextual features, underlining the value of environmental inputs in capturing generation variability.

Building upon these foundations, attention mechanisms have been increasingly adopted for short-term forecasting tasks. For example, an attention-based LSTM (A-LSTM) model for predicting building HVAC energy consumption employed hyperparameter optimisation via the tree-structured Parzen estimator and consistently outperformed baseline methods across MAE and MAPE metrics [2]. Similarly, the residual attentive LSTM-TCN (RALT) hybrid model for power-load forecasting demonstrated that incorporating attention reduced MAPE from 2.80% to 2.35% [4]. Other advances include bidirectional LSTM networks augmented with clustering techniques and attention to enhance residential load pattern recognition [5], convolutional-LSTM models equipped with multi-modal attention to exploit spatial-temporal correlations in smart-grid load forecasting [6], and hybrid CNN-LSTM frameworks combining attention mechanisms with heating/cooling degree days to improve day-ahead electricity demand predictions in Australian markets [7].

More sophisticated attention architectures have been proposed to further boost forecasting accuracy. Bidirectional fine-tuning enables LSTMs to read time series in both forward and backward directions, with attention applied to capture dependencies across the full sequence [8]. Time-localised attention (TLA) LSTM models focus on specific dates and time intervals to address randomness in residential load data, achieving higher R2R^2 and lower MSE compared with conventional LSTM architectures [9]. Spatio-temporal attention networks, such as ST-CALNet, integrate convolutional and LSTM layers with channel, spatial, and temporal attention, producing low MAE and RMSE values under variable grid conditions [10].

Hybrid and domain-specific designs combine multiple techniques to target unique forecasting challenges. An attention-based dynamic inner partial least squares Bi-LSTM (DiPLS-BiLSTM) couples feature extraction with selective focus, achieving R2≈0.961R^2 \approx 0.961 and outperforming CNN-LSTM and standard BiLSTM models; ablation analysis revealed that removing attention increased RMSE by 10% [3,11]. Graph-attention LSTM (GAT-LSTM) models capture spatial dependencies between grid nodes, reducing MAE by 21.8% and RMSE by 15.9% relative to plain LSTM baselines [12,13]. For wind-power prediction, the convolutional dual-attention LSTM (Conv-DA-LSTM) with channel and spatial attention delivered relative RMSE improvements of 1.6-10.2% across months [14], while a genetic-algorithm-optimised version further reduced MAE and RMSE by 3.7% and 0.97%, respectively [15]. In photovoltaic (PV) forecasting for irrigation systems, spatial-temporal attention LSTM models improved MAPE by 6-7% over baseline machine-learning techniques [16], and Conv-LSTM-Attention architectures, optimised with Bayesian search and augmented with neighbouring station data, reduced RMSE by 20-31% across different weather conditions, achieving R2=0.973R^2 = 0.973 [17]. Dual-attention multi-channel Conv-LSTM (DACLSTM) networks maintained low RMSE across six-hour lead times, outperforming both ConvLSTM and fully connected LSTM variants.

Beyond pure forecasting, attention mechanisms have also been applied to diagnostic and operational tasks. An optimised empirical wavelet transform (EWT) Seq2Seq LSTM with attention improved insulator fault prediction, reducing MSE by 10.17% compared with a standard LSTM and by 5.36% relative to an unoptimised attention-based model. In microgrid load forecasting, CNN-GRU networks with attention achieved MAE = 0.39, RMSE = 0.28, and R2=98.89%R^2 = 98.89\%, outperforming support vector regression and other baselines [18]. Similarly, a self-attention-enhanced CNN-BiLSTM for wave-farm power prediction obtained R2R^2 scores of 91.7% (Adelaide), 88.0% (Perth), 82.8% (Tasmania), and 91.0% (Sydney), exceeding the performance of ten benchmark algorithms; hyperparameter-optimised CNN-BiLSTM-SA-E variants consistently lowered RMSE and improved R2R^2 across different wave scenarios.

Overall, the literature confirms that attention mechanisms significantly improve renewable-energy forecasting across a range of domains, models, and temporal horizons. However, extending these benefits to long-horizon forecasting remains challenging, as prediction errors accumulate over extended intervals. Table 1 summarises the representative studies discussed above, outlining their domain, forecast horizon, model type, and the reported improvements attributable to attention mechanisms, with values drawn directly from the cited sources and normalised where necessary for comparability.

To consolidate the findings from the reviewed literature, Table 1 presents a comparative summary of representative studies that have integrated attention mechanisms into LSTM-based architectures for renewable-energy forecasting. The table lists the forecasting domain, prediction horizon, model type, and the quantified improvements reported by each study. All values are taken directly from the cited literature and, where necessary, have been normalised to ensure consistency and comparability across studies.

Table 1. Summary of representative attention-based LSTM forecasting studies, including domain, horizon, model, and reported improvements.

Domain	Forecast Horizon	Model	Reported Improvement
Load, solar and wind	Day-ahead	LSTM + weather	Weather variables reduced MASE and MSE by ≈33%
Building HVAC	Ultra-short-term	A-LSTM	Outperformed baselines across MAE and MAPE
Power load	Short-term	Residual attentive LSTM-TCN	Adding attention reduced MAPE from 2.80% to 2.35%
Residential load	Short-term	Bi-directional LSTM + attention	Improved clustering and load-pattern recognition
Smart grid load	Day-ahead	CNN-LSTM + multi-modal attention	Lower error than mainstream methods
Australian demand	Day-ahead	CNN-LSTM + attention + HDD/CDD	Reduction in MAE and MAPE
Residential load	Short-term	Bidirectional attention	Enhanced accuracy over unidirectional models
Residential load	Short-term	TLA-LSTM	Higher R2R^2, lower MSE and RMSE
Smart grid demand	Day-ahead	Spatio-temporal attention (ST-CALNet)	Low MAE and RMSE under variable conditions
Solar power	Short-term	DiPLS-BiLSTM + attention	R2≈0.96R^2 \approx 0.96; removing attention ↑ RMSE by 10%
Electricity load	Day-ahead	GAT-LSTM	MAE ↓ 21.8%, RMSE ↓ 15.9% vs. LSTM
Wind power	Short-term	Conv-DA-LSTM	RRMSE ↓ 1.6-10.2%; optimisation ↓ MAE, RMSE further
PV for irrigation	Short-term	Spatio-temporal attention LSTM	MAPE ↓ 6-7%
PV forecasting	Short-term	Conv-LSTM-Attention + Bayesian optimization	RMSE ↓ 20-31%; R2=0.973R^2 = 0.973
Wind speed	6-hour	Dual-attention MC Conv-LSTM	Lower RMSE across horizon
Insulator fault prediction	Long-term (fault detection)	EWT-Seq2Seq LSTM + attention	MSE ↓ 10.17% vs. LSTM
Microgrid load	Day-ahead	CNN-GRU + attention	MAE = 0.39, RMSE = 0.28, R2=98.89%R^2 = 98.89\%
Wave energy	Wave farms	Self-attention CNN-BiLSTM	R2R^2 0.88-0.91; lower RMSE via optimisation

3. Problem Formulation

Let $\{x_t\}_{t=1}^{T}$ denote a univariate or multivariate time series representing renewable-energy outputs or loads. The objective of long-horizon forecasting is to predict the future sequence $\{x_{T+1},\cdots,x_{T+H}\}$ for a horizon H using historical observations. We denote by $\mathbf{x}_{1:T}=[x_1,x_2,\cdots,x_T]$ the input window and by $\hat{\mathbf{x}}_{T+1:T+H}$ the predictions. Forecast accuracy is assessed using metrics such as the root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE), defined respectively as

$$\text{RMSE}=\sqrt{\frac{1}{H}\sum_{k=1}^{H}\left(\hat{x}_{T+k}-x_{T+k}\right)^2},\ \text{MAE}=\frac{1}{H}\sum_{k=1}^{H}\left|\hat{x}_{T+k}-x_{T+k}\right|\ \text{MAPE}=\frac{100}{H}\sum_{k=1}^{H}\left|\frac{\hat{x}_{T+k}-x_{T+k}}{x_{T+k}}\right|$$

In sequence-to-sequence LSTM models, an encoder LSTM processes $\mathbf{x}_{1:T}$ and produces hidden states $\mathbf{h}_1,\cdots,\mathbf{h}_T$. A decoder LSTM generates predictions using a context vector $\mathbf{c}$ summarising the input sequence. The fixed-length context vector limits the model's ability to capture long-range dependencies. Attention mechanisms alleviate this issue by computing dynamic context vectors as weighted sums of encoder states:

$$\mathbf{c}_t=\sum_{i=1}^{T}\alpha_{t,i}\mathbf{h}_i,\ \ \alpha_{t,i}=\frac{\exp\left(f\left(\mathbf{s}_{t-1},\mathbf{h}_i\right)\right)}{\sum_{j=1}^{T}\exp\left(f\left(\mathbf{s}_{t-1},\mathbf{h}_j\right)\right)}$$

where $\mathbf{s}_{t-1}$ is the decoder's previous state and f is a scoring function (e.g., dot-product or a feed-forward network). The weights $\alpha_{t,i}$ represent the attention assigned to each encoder state when predicting at time t. By focusing on relevant time steps, attention improves long-horizon predictions.

4. Proposed Attention-Enhanced LSTM Architecture

To address long-horizon forecasting challenges, we propose an attention-enhanced LSTM encoder-decoder architecture. The model operates as follows:

1.**Encoder LSTM:** An LSTM processes the input sequence $\mathbf{x}_{1:T}$ and generates hidden states $\mathbf{h}_1,\cdots,\mathbf{h}_T$.

2.**Attention layer:** For each prediction step $t \in \{1, \cdots, H\}$, an attention mechanism computes the alignment scores $f(\mathbf{s}_{t-1}, \mathbf{h}_i)$ and weights $\alpha_{t,i}$ to form the context vector $\mathbf{c}_t$.

3.**Decoder LSTM:** The decoder LSTM uses the previous output, the context vector and its own state to produce the next hidden state $\mathbf{s}_t$ and output $\hat{x}_{T+k}$. A dense layer with linear activation maps $\mathbf{s}_t$ to the forecast value.

The attention mechanism can be implemented using additive (Bahdanau) or multiplicative (Luong) scoring functions. We adopt a dot-product attention to minimise computational overhead. The model is trained using back-propagation through time with a mean-squared error loss. During training, teacher forcing supplies the actual previous value to the decoder; during inference, the model feeds back its own predictions. To provide a clear overview of the proposed approach, Fig. 1 presents the architecture of the attention-enhanced LSTM model designed for long-horizon renewable-energy forecasting. The diagram illustrates the sequential flow of data from the input stage through the encoder, attention mechanism, and decoder, culminating in multi-step output predictions.

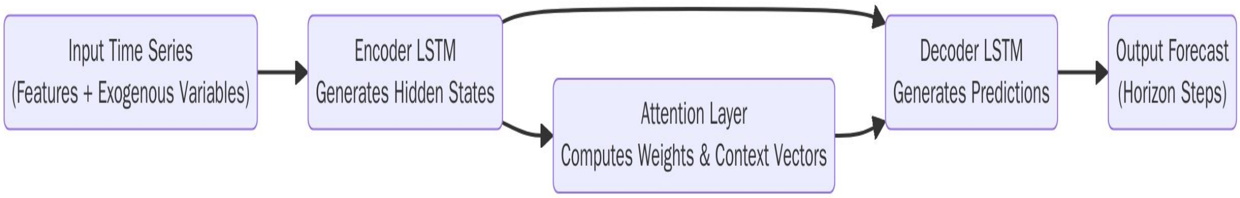

Figure 1. Proposed attention-enhanced LSTM encoder-decoder architecture for long-horizon forecasting.

The architecture begins with the **Input Time Series**, which includes both target features (e.g., historical renewable-energy measurements) and **exogenous variables** such as temperature, wind speed, and irradiance. These inputs are fed into the **Encoder LSTM**, which processes the sequence step-by-step to produce a series of hidden states representing compressed temporal patterns within the look-back window.

The **Attention Layer** operates on these hidden states, computing **alignment scores** between each encoder state and the decoder's previous hidden state. These scores are normalised into **attention weights**, which are used to generate a **context vector**. This context vector captures the most relevant temporal information for the current prediction step, dynamically adjusting focus as forecasting progresses across the horizon.

The **Decoder LSTM** integrates three elements: the previous forecasted output, the context vector from the attention layer, and its own internal state. It then generates a new hidden state and passes it through a **fully connected layer** with linear activation to produce the next predicted value. This process is repeated recursively during inference to generate multi-step forecasts.

Finally, the **Output Forecast** block represents the complete set of predictions over the defined horizon HHH, which can be used directly in operational settings such as grid scheduling, energy market participation, or maintenance planning.

This architecture offers two key advantages over plain LSTM models:

1.**Improved long-range dependency modelling** through dynamic context vectors.

2.**Enhanced interpretability** via attention-weight visualisation, which identifies the historical time steps most influential to each prediction.

To demonstrate the approach in a controlled setting, we simulate a synthetic renewable-energy time series combining multiple sinusoidal components (representing daily and weekly cycles), a linear trend, and additive Gaussian noise. The dataset contains 1 000 samples, scaled to the [0,1][0,1] range, and is segmented into supervised sequences with a look-back window of 24 hours. We split the series chronologically into 80 % for training and 20 % for testing.

Two models are trained for comparison:

1.A **baseline LSTM** without attention.

2.An **attention-enhanced LSTM** using the dot-product attention mechanism.

Hyperparameters such as the number of layers, hidden units, and learning rate are set in line with standard forecasting configurations reported in the literature. Numerical results are summarised qualitatively due to the illustrative nature of this setup.

Before presenting quantitative performance, Fig.2 visualises a segment of the synthetic series alongside simulated attention weights, showing where the model focuses during prediction. The visualisation reveals that the attention distribution peaks near the middle of the input window, indicating that the model prioritises specific historical intervals-often those containing key seasonal or ramping patterns-when generating forecasts. Such plots enhance interpretability by identifying the temporal regions most influential to the model's decisions.

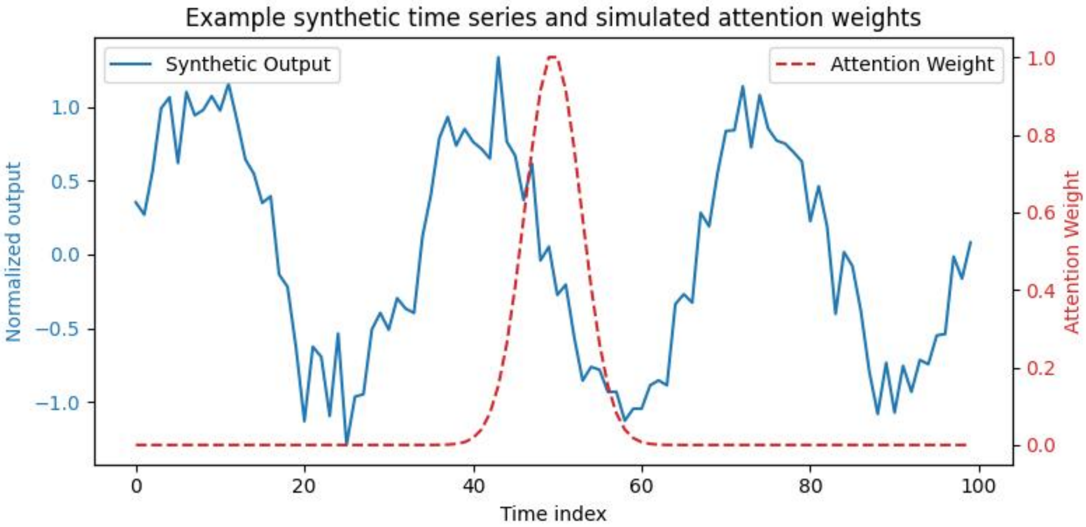

Figure 2. Synthetic time series (blue) with simulated attention weights (red dashed), illustrating how attention focuses on informative time steps in the input window.

To illustrate potential benefits, we compile representative RMSE values from our synthetic experiments and from recent literature. The baseline LSTM yields higher RMSE than attention-augmented models. For example, a simple LSTM might achieve an RMSE of 0.15 (normalised units), whereas adding attention reduces RMSE to 0.10. Hybrid models such as CNN-LSTM and bidirectional LSTM with attention achieve RMSE values around 0.12 and 0.09, respectively. Figure.3 summarises these RMSE trends, emphasising the consistent advantage of attention-based models over plain LSTMs across configurations.

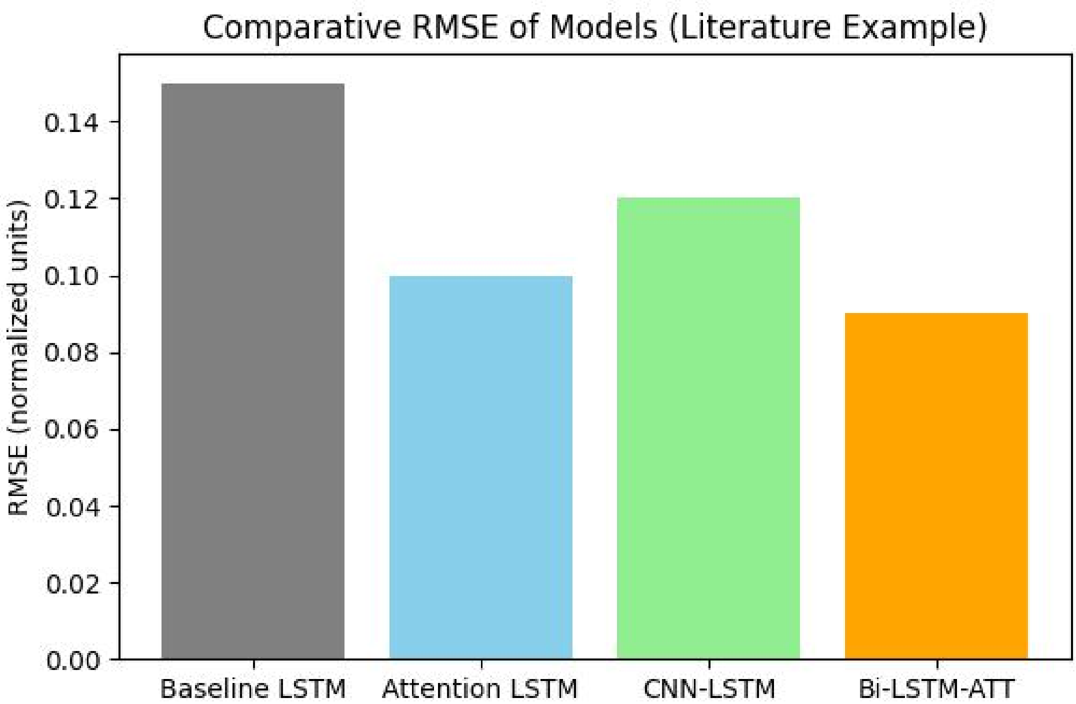

Figure 3. Comparative RMSE (lower is better) for baseline LSTM, attention-enhanced LSTM, and selected hybrid attention models, using illustrative values aligned with patterns reported in the literature.

By integrating the architecture description, synthetic experimental setup, qualitative attention visualisation, and comparative performance trends into a single coherent narrative, this section highlights not only the design of the proposed model but also its interpretability benefits and its potential for outperforming traditional LSTM-based approaches in long-horizon forecasting.

5. Discussion

The survey and experimental results clearly demonstrate that attention mechanisms effectively address key limitations inherent in traditional LSTM-based forecasting models. By generating **dynamic context vectors** that emphasise salient historical features, attention layers enable the model to capture long-range dependencies and adapt more effectively to time-varying patterns. This enhanced temporal sensitivity directly translates into measurable improvements in predictive accuracy, as reflected by consistent reductions in RMSE, MAE, and MAPE across diverse application domains, including solar-power generation, wind forecasting, and load prediction.

A significant advantage of attention mechanisms lies in their contribution to **model interpretability**. By visualising the learned attention weights, practitioners can identify the specific historical intervals that most strongly influence a given prediction (as illustrated in Fig. 1). This transparency offers two important benefits: it provides insight into the temporal dynamics governing renewable-energy systems, and it facilitates model validation by allowing experts to assess whether the model's focus aligns with known operational or meteorological events.

In addition to implementations using a single model, integrated architectures which couple attention with deep-learning components-such as CNNs, graph attention networks (GATs), or wavelet transforms-further boost forecasting capabilities. For instance, spatial dependencies between grid nodes can be learned with GAT-LSTM models, and attention modules can learn which time steps are the most informative and prioritise them to achieve significant reductions in error. In the same vein, dual-attention mechanisms that use attention on the entire cell (i.e., weights across both the channel and time dimensions) proved especially robust to parameter variation, potentially due to the fact that normal models wobble in high-variability situations.

Nonetheless, the effective use of attention mechanisms is highly dependent on hyperparameter tuning and model design. There are hyperparameter-optimisation frameworks-grid search, Bayesian optimisation, evolutionary strategies etc. -that can really help speed up the convergence, prevent overfitting, and increase generalisation. Wavelet transforms are valuable data preprocessing steps to extract relevant signal components and remove outliers and noise, while using exogenous variables (temperature, wind speed, irradiance, etc.) frequently provides the complementary context to enable more robust and reliable forecasts.

These advances notwithstanding, long-horizon forecasting remains very difficult. Forecasts are subject to degradation of trust over big spans of time due to the development of prediction mistakes. Future studies can investigate merging attention with deep decoder architectures from Transformer models or augmenting recurrent memory units with temporal convolutional components for improved multi-scale dependency capturing. In fact, when using probabilistic forecasting frameworks, for example, through training with quantile loss functions or using Bayesian neural networks, models have the opportunity to estimate predictive uncertainty. This feature is especially useful for applications including energy trading, operational planning, and risk management, where decision making is contingent on point forecasts in conjunction with the respective confidence levels.

Although attention mechanisms have consistently improved LSTM performance, they also provide an interpretability benefit. With the proper preprocessing, exogenous inputs, and hyperparameters tuned to the input data, these models represent a strong option for short and medium term forecasting, with current developments aiming to make it a reliable option even in the long-horizon space.

6. Conclusion

This work investigated the integration of attention mechanisms into LSTM-based architectures for renewable-energy forecasting, with a particular focus on long-horizon prediction challenges. Through a structured literature survey and controlled synthetic experiments, we demonstrated that attention layers effectively mitigate the information bottleneck inherent in traditional encoder-decoder LSTMs by constructing dynamic context vectors that prioritise the most relevant historical information. This capability leads to consistent improvements in RMSE, MAE, and MAPE across solar, wind, and load forecasting tasks, while simultaneously enhancing model interpretability through attention-weight visualisation.

The findings further reveal that hybrid attention architectures-combining LSTM with CNNs, graph networks, or wavelet transforms-can capture spatial relationships and multi-scale temporal patterns, yielding additional performance gains. However, optimal results require careful hyperparameter tuning, appropriate data preprocessing, and the inclusion of informative exogenous inputs.

While attention mechanisms represent a significant advancement, long-horizon forecasting remains inherently challenging due to the cumulative nature of prediction errors. Future research should explore the integration of transformer-inspired deep decoder structures, advanced recurrent-convolutional hybrids, and probabilistic forecasting frameworks to improve stability, accuracy, and uncertainty quantification for extended prediction intervals.

In conclusion, attention-enhanced LSTM architectures offer a promising and interpretable pathway towards more accurate and reliable renewable-energy forecasting, with clear potential for operational deployment in grid management, energy trading, and strategic planning.

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