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Literature Review on Solar Power Prediction Using Bi-LSTM Classifier Considering Different Uncertainty Models

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Abstract

Accurate solar power prediction is critical for the efficient operation and integration of photovoltaic (PV) systems into modern power grids. The inherent uncertainty in weather conditions and sensor data presents major challenges for forecasting accuracy. While recent advances in deep learning, particularly using LSTM and its variants, have significantly improved performance, these models often ignore uncertainty in input data. This literature review critically analyzes state-of-the-art techniques for solar power forecasting, highlighting the role of metaheuristic optimization, hybrid neural models, and deep learning algorithms. Special attention is given to recent studies utilizing Bi-LSTM networks and the incorporation (or lack thereof) of uncertainty models. The review identifies key limitations in current approaches and underscores the need for a framework that explicitly integrates uncertainty distributions with Bi-LSTM for enhanced prediction accuracy.

1. Introduction

The rapid growth of renewable energy systems, especially solar PV installations, demands accurate short-term and long-term forecasting of solar power output. However, fluctuations in solar irradiance, weather variability, and sensor imperfections introduce nonlinearities and uncertainties that traditional models struggle to handle.

Deep learning approaches, particularly LSTM and Bi-LSTM, offer promising capabilities in modeling temporal dependencies and nonlinear relationships. However, most deep learning models assume deterministic input and do not account for real-world uncertainties such as measurement noise, system disturbances, and environmental variability. Recent research shows increasing interest in integrating metaheuristic optimization, hybrid neural architectures, and uncertainty quantification to improve the reliability and accuracy of predictions.

2. Review of Existing Methods

2.1 Optimization-Based Neural Forecasting

Several models integrate neural networks with metaheuristic algorithms for parameter tuning:

- **EMA-DNN (Sulaiman and Mustaffa, 2024)**: Combines Evolutionary Mating Algorithm with DNN to optimize weights. Strong global search capability, but is computationally intensive and slow to converge.
- **GRNN-GWO (Tu et al., 2022)**: Employs Grey Wolf Optimization with General Regression Neural Network. Offers fast convergence but may suffer from premature convergence.
- **MFFNN-MVO (Talaat et al., 2022)**: Uses Multiverse Optimization to tune Feedforward Neural Networks. Good flexibility and multimodal problem-solving ability, but convergence is slow and expensive.

2.2 Hybrid Deep Learning Models

Advanced architectures integrate multiple neural components for improved performance:

- **Bayesian Optimization with Attention-Dilated LSTM (Molu et al., 2024)**: Enhances accuracy by tuning hyperparameters and filtering noise. Highly accurate but computationally expensive.
- **CNN-LSTM (Lim et al., 2022)**: Combines CNN for feature extraction and LSTM for temporal prediction. High prediction accuracy but results in complex and large models.
- **JAYA-SMC+ANN (Jlidi et al., 2023)**: Integrates control optimization with ANN for prediction and maximum power point tracking. Cost-effective but prone to local optima.

2.3 Uncertainty-Aware and Sequential Models

Limited research explicitly incorporates uncertainty modeling:

- **GVSAO-Bi-LSTM (Wu et al., 2024)**: Uses a Snow Ablation Optimization algorithm to improve Bi-LSTM performance. Considers some optimization issues, but lacks detailed modeling of uncertainty distributions and suffers from premature convergence.
- **LSTM-Based Forecasting (Dhaked et al., 2023)**: Uses LSTM and BPNN to predict PV output based on weather features. While good at capturing temporal patterns, LSTM models risk overfitting in fluctuating conditions.

3. Summary of Literature

The following **Table 1** summarizes key features, advantages, and drawbacks of reviewed approaches:

Author	Model	Uncertainty Considered	Key Advantages	Limitations
[1] Sulaiman & Mustaffa (2024)	EMA + DNN	Yes	Strong search capability	Slow convergence
[2] Tu et al. (2022)	GRNN + GWO	Yes	Fast convergence	Premature convergence
[3] Talaat et al. (2022)	MFFNN + MVO	No	Flexible and simple	Computationally expensive
[4] Molu et al. (2024)	BO + Attention-LSTM	No	High accuracy	High complexity
[5] Jlidi et al. (2023)	JAYA-SMC + ANN	Yes	Real-world applicability	Risk of local optima
[6] Lim et al. (2022)	CNN + LSTM	Yes	Accurate and robust	Complex architecture
[7] Dhaked et al. (2023)	LSTM	No	Sequential modeling	Overfitting risk
[8] Wu et al. (2024)	GVSAO + Bi-LSTM	No	Low cost	Low accuracy, premature convergence

4. Identified Research Gaps

From the literature, the following key research gaps are identified:

- **Lack of Multi-Uncertainty Modeling**: Most models consider only noise or weather variability but not a comprehensive set of uncertainty distributions.
- **Limited Use of Bi-LSTM**: While Bi-LSTM models are powerful for capturing bidirectional temporal dependencies, their application in uncertainty-aware forecasting is limited.
- **Overfitting and Poor Generalization**: Existing deep learning models often suffer from overfitting due to lack of uncertainty handling.
- **Complex and Costly Architectures**: Highly accurate models often require significant computational resources, which limit their real-time usability.

5. Proposed Direction

To address these limitations, a **Bi-LSTM forecasting model integrated with five distinct uncertainty models** (Poisson, Bernoulli, Weibull, Exponential, Multinomial) is proposed. This combination aims to:

- **Model real-world variabilities more accurately**
- **Reduce overfitting and improve generalization**

- **Enhance forecast accuracy under uncertain conditions**
- **Maintain computational feasibility for real-time systems**

6. Conclusion

This review highlights the evolution of solar power forecasting techniques with a focus on deep learning and optimization. While various hybrid models have demonstrated success, the explicit integration of diverse uncertainty models with Bi-LSTM is still underexplored. The proposed direction aims to bridge this gap and enhance the robustness of PV power prediction systems in real-world, uncertain environments.

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