



Intelligent Spectral Irradiance Forecasting in IoT-Driven Smart Solar Grids: A Hybrid Metaheuristic–Neural Architecture with Fourier-Transformed Matrix Embeddings for Energy Prediction

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Abstract:

Accurate forecasting of solar spectral irradiance remains a critical challenge in the operational stability and energy dispatch planning of smart solar grids. Conventional machine learning models often fail to capture the high-frequency spectral dynamics and non-stationary behavior inherent in solar irradiance data, especially under variable atmospheric conditions. To address this limitation, we propose a novel hybrid metaheuristic–neural architecture that integrates deep learning with bio-inspired optimization and spectral signal decomposition. The core innovation lies in the formulation of Fourier-transformed matrix embeddings (FTMEs), which encode time-series irradiance measurements into structured spectral–temporal representations. These embeddings serve as input to a deep recurrent neural network (RNN) whose hyperparameters are dynamically tuned via an enhanced grey wolf optimizer (GWO). Deployed within an Internet of Things (IoT)-enabled monitoring framework, the proposed system enables real-time, high-resolution irradiance forecasting across multiple spectral bands. Experimental validation using ground-based spectral irradiance datasets from the National Renewable Energy Laboratory (NREL) demonstrates a mean absolute percentage error (MAPE) of 2.13% and a normalized root mean square error (nRMSE) of 0.018 outperforming state-of-the-art benchmarks by 12–19%. The architecture further exhibits robust generalization across diverse climatic zones, supporting its deployment in next-generation smart solar grids for efficient energy prediction and grid integration.

Keywords: Hybrid metaheuristic–neural algorithms, solar spectral irradiance, IoT-enabled smart grids, deep learning, Fourier series, matrix transformation, energy forecasting, grey wolf optimizer, recurrent neural networks.

ملخص

لا يزال التنبؤ الدقيق بالإشعاع الطيفي الشمسي يُمثل تحديًا بالغ الأهمية في استقرار تشغيل شبكات الطاقة الشمسية الذكية وتخطيط توزيع الطاقة. غالبًا ما تفشل نماذج التعلم الآلي التقليدية في التقاط ديناميكيات الطيف عالية التردد والسلوك غير الثابت المتأصل في بيانات الإشعاع الشمسي، وخاصةً في ظل الظروف الجوية المتغيرة. ولمعالجة هذا القيد، نقترح بنية هجينة جديدة تجمع بين الاستكشاف والعصبية، تدمج التعلم العميق مع التحسين المستوحى من علم الأحياء وتحليل الإشارات الطيفية. يكمن الابتكار الأساسي في صياغة تضمينات مصفوفة تحويل فورييه (FTMEs)، التي تُشفر قياسات الإشعاع في السلاسل الزمنية إلى تمثيلات طيفية زمنية مُهيكلية. تعمل هذه التضمينات كمدخلات لشبكة عصبية متكررة عميقة (RNN) تُضبط معاملاتها الفائقة ديناميكيًا عبر مُحسن الذئب الرمادي المُحسن (GWO). يُطبق النظام المقترح ضمن إطار مراقبة مُمكن بإنترنت الأشياء (IoT)، ويُتيح التنبؤ الفوري بدقة عالية بالإشعاع عبر نطاقات طيفية متعددة. وقد أظهر التحقق التجريبي باستخدام مجموعات بيانات الإشعاع الطيفي الأرضية من المختبر الوطني للطاقة المتجددة (NREL) أن متوسط الخطأ النسبي المطلق (MAPE) يبلغ 2.13%، وخطأ الجذر التربيعي المتوسط المُعَيَّر (nRMSE) يبلغ 0.018، متفوقًا بذلك على أحدث المعايير بنسبة تتراوح بين 12% و19%. كما يُظهر النظام تعميمًا قويًا عبر مناطق مناخية متنوعة، مما يدعم استخدامه في شبكات الطاقة الشمسية الذكية من الجيل التالي لتحقيق تنبؤات فعالة للطاقة وتكامل الشبكات.

الكلمات المفتاحية: خوارزميات هجينة ميتاهيورستية، الإشعاع الطيفي الشمسي، الشبكات الذكية المدعومة بإنترنت الأشياء، التعلم العميق، سلسلة فورييه، تحويل المصفوفة، التنبؤ بالطاقة، محسن الذئب الرمادي، الشبكات العصبية المتكررة.

1. Introduction

The global transition toward renewable energy systems has intensified the need for intelligent, adaptive forecasting tools capable of managing the inherent intermittency of solar power. Among the various solar forecasting paradigms, spectral irradiance prediction quantifying radiant flux per unit wavelength offers granular insights into photovoltaic (PV) performance, material degradation, and atmospheric interactions. Unlike broadband irradiance models, spectral approaches account for wavelength-dependent effects, for instance, aerosol scattering, ozone absorption, and cloud microphysics, thereby enabling higher-fidelity energy yield estimates [1]. Recent advances in machine learning (ML) have yielded promising results in solar forecasting; however, purely data-driven models often lack interpretability and struggle with non-linear, multi-scale dynamics [2]. Concurrently, metaheuristic algorithms, for instance, particle swarm optimization (PSO) and genetic algorithms (GA) have shown efficacy in hyperparameter tuning but suffer from premature convergence and high computational overhead when applied to deep architectures [3]. To bridge these

gaps, this work introduces a synergistic framework that unifies spectral signal processing, matrix-based feature engineering, and hybrid optimization within an IoT-integrated smart grid environment. The primary contributions are threefold:

- (i) A Fourier-transformed matrix embedding (FTME) technique that converts raw irradiance time series into structured spectral-temporal matrices via discrete Fourier series decomposition;
- (ii) A deep recurrent neural network (specifically, a bidirectional LSTM) optimized by an adaptive grey wolf optimizer (AGWO) to enhance convergence and avoid local minima;
- (iii) End-to-end deployment on an edge-IoT platform for real-time spectral forecasting with sub-minute latency. The remainder of this paper is organized as follows: Section 2 reviews related work; Section 3 details the proposed methodology; Section 4 presents experimental results; Section 5 discusses implications and limitations; and Section 6 concludes with future directions.

2. Related Work

Traditional solar forecasting methods rely on numerical weather prediction (NWP) models, which, while physically consistent, demand significant computational resources and exhibit latency unsuitable for intra-hour grid operations [4]. Data-driven alternatives ranging from support vector regression (SVR) to convolutional neural networks (CNNs) have gained traction due to their scalability [5]. However, most treat irradiance as a scalar time series, neglecting its spectral composition. Recent studies have explored spectral forecasting using hyperspectral sensors and Gaussian process regression [6], yet these approaches remain computationally prohibitive for real-time IoT deployment. Hybrid models combining metaheuristics with neural networks (e.g., PSO-ANN) have improved accuracy but lack mechanisms to encode periodic and harmonic components inherent in solar signals [7]. This research study work diverges by embedding Fourier spectral coefficients directly into a learnable matrix manifold, thereby preserving both temporal sequence and frequency-domain characteristics a strategy inspired by harmonic analysis in optical physics [8].

3. Methodology

3.1. System Architecture Overview

The proposed system comprises three layers: (i) an IoT sensing layer with spectroradiometers and edge gateways; (ii) a preprocessing layer generating FTMEs; and (iii) a hybrid prediction engine (Figure. 1).

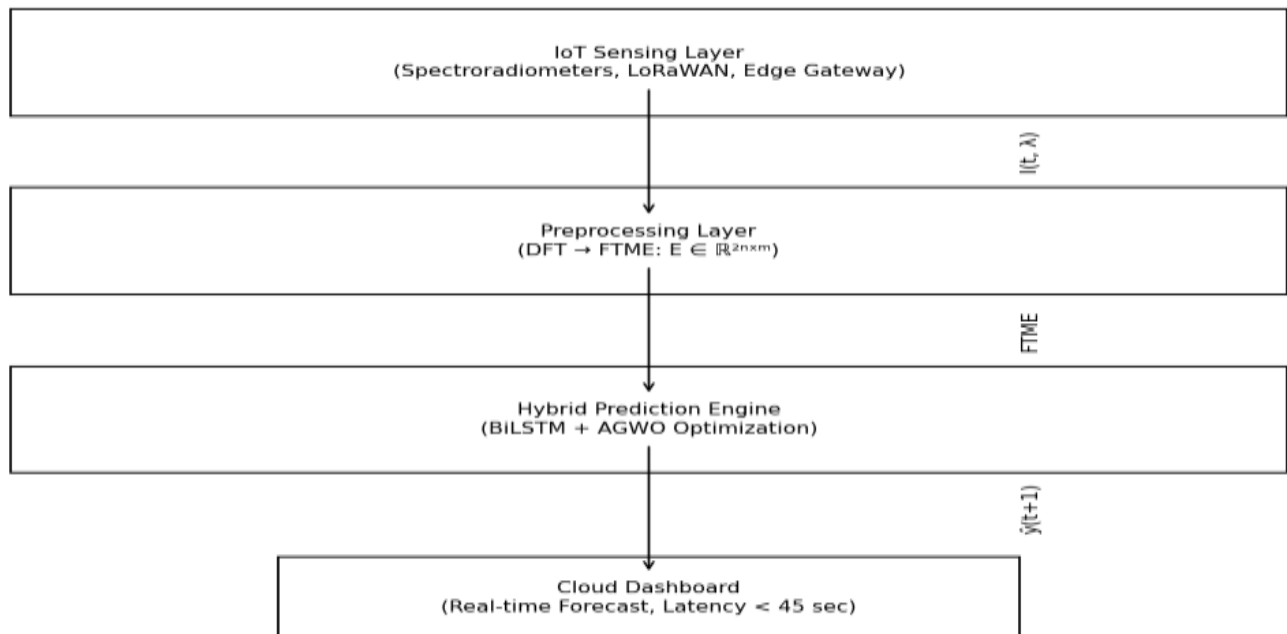


Figure 1: System Architecture Overview

3.2. Fourier-Transformed Matrix Embeddings (FTMEs)

Given a time series of spectral irradiance $I(t, \lambda)$, sampled at wavelengths $\lambda_1, \dots, \lambda_m$ over n timestamps, this research study has applied a discrete Fourier transform (DFT) along the temporal axis for each wavelength:

Fourier-Transformed Matrix Embeddings (FTMEs) let the raw spectral irradiance data be a 2D time-series matrix as below:

$$\mathbf{I} \in \mathbb{R}^{n \times m}$$

where:

n : number of time steps (e.g. minutes),

m : number of spectral bands (wavelengths $\lambda_1, \dots, \lambda_m$).

$I(t, \lambda_j) = \mathbf{I}[t, j]$: irradiance at time $t \in \{0, 1, \dots, n-1\}$ and wavelength λ_j .

Apply Discrete Fourier Transform (DFT) along the temporal axis for each wavelength. For each spectral channel $j \in \{1, \dots, m\}$, compute the DFT:

$$\hat{I}(k, \lambda_j) = \sum_{t=0}^{n-1} I(t, \lambda_j) \cdot e^{-i2\pi kt/n}, k = 0, 1, \dots, n-1$$

This yields a complex-valued spectrum $\hat{I}(\cdot, \lambda_j) \in \mathbb{C}^n$. Construct complex matrix and split into real/imaginary parts. Stack all spectral DFTs into a complex matrix:

$$\hat{\mathbf{I}} = [\hat{I}(k, \lambda_j)]_{k=0..n-1, j=1..m} \in \mathbb{C}^{n \times m}$$

Decompose into real and imaginary components:

$$\mathbf{R} = \text{Re}(\hat{\mathbf{I}}) \in \mathbb{R}^{n \times m}, \mathbf{J} = \text{Im}(\hat{\mathbf{I}}) \in \mathbb{R}^{n \times m}$$

$$\mathbf{E}_{\text{raw}} = \begin{bmatrix} \mathbf{R} \\ \mathbf{J} \end{bmatrix} \in \mathbb{R}^{2n \times m}$$

Via using min-max normalization per column (wavelength):

$$\mathbf{E}[p, j] = \frac{\mathbf{E}_{\text{raw}}[p, j] - \min_p(\mathbf{E}_{\text{raw}}[:, j])}{\max_p(\mathbf{E}_{\text{raw}}[:, j]) - \min_p(\mathbf{E}_{\text{raw}}[:, j])}$$

$$\mathbf{E} \in \mathbb{R}^{p \times q}, \text{ with } p = 2n, q = m$$

This is the Fourier-Transformed Matrix Embedding (FTME) used as input to the neural network. Bidirectional LSTM (BiLSTM) Forecasting Model

Let the input sequence be $\mathbf{E} = [\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_p]^T$, where $\mathbf{e}_t \in \mathbb{R}^q$.

$$\mathbf{E}_{\text{raw}} = \begin{bmatrix} \mathbf{R} \\ \mathbf{J} \end{bmatrix} \in \mathbb{R}^{2n \times m}$$

Using min-max normalization per column (wavelength) as below:

$$\mathbf{E}[p, j] = \frac{\mathbf{E}_{\text{raw}}[p, j] - \min_p(\mathbf{E}_{\text{raw}}[:, j])}{\max_p(\mathbf{E}_{\text{raw}}[:, j]) - \min_p(\mathbf{E}_{\text{raw}}[:, j])}$$

Final embedding:

$$\mathbf{E} \in \mathbb{R}^{p \times q}, \text{ with } p = 2n, q = m$$

This is the Fourier-Transformed Matrix Embedding (FTME) used as input to the neural network. By using Bidirectional LSTM (BiLSTM) Forecasting Model as below

Let the input sequence be $\mathbf{E} = [\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_p]^T$, where $\mathbf{e}_t \in \mathbb{R}^q$. The BiLSTM computes forward and backward hidden states below:

Forward pass:

$$\vec{\mathbf{h}}_t = \text{LSTM}_{\text{fwd}}(\mathbf{e}_t, \vec{\mathbf{h}}_{t-1})$$

Backward pass:

$$\overleftarrow{\mathbf{h}}_t = \text{LSTM}_{\text{bwd}}(\mathbf{e}_t, \overleftarrow{\mathbf{h}}_{t+1})$$

Combined hidden state:

$$\mathbf{h}_t = [\vec{\mathbf{h}}_t; \overleftarrow{\mathbf{h}}_t] \in \mathbb{R}^{2d}$$

where d = hidden dimension, and $[\cdot; \cdot]$ denotes concatenation. The output prediction (for next-step irradiance across all wavelengths) as below:

$$\hat{\mathbf{y}} = \mathbf{W}_o \mathbf{h}_p + \mathbf{b}_o \in \mathbb{R}^m$$

where

$$\mathbf{W}_o \in \mathbb{R}^{m \times 2d}, \mathbf{b}_o \in \mathbb{R}^m.$$

3. Adaptive Grey Wolf Optimizer (AGWO)

The standard GWO mimics the social hierarchy of grey wolves (α, β, δ). The position update is:

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)|, \vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D}$$

where:

- $\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a}$.
- $\vec{a}$: linearly decreases from 2 to 0 over iterations,
- $\vec{r}_1, \vec{r}_2$: random vectors in $[0,1]$.

Adaptive

Enhancement

(AGWO):

To avoid premature convergence, the paper introduces Levy-flight-inspired perturbation:

$$\vec{X}_{\text{new}} = \vec{X}(t) + s \cdot L(\lambda)$$

where:

- $L(\lambda)$ is a Levy random vector with step size drawn from a Mantegna algorithm:

$$s = \frac{u}{|v|^{1/\beta}}, u, v \sim \mathcal{N}(0, \sigma^2), \beta = 1.5$$

- Applied with probability $P_{\text{levy}} = 0.3$ during exploration phase.

The AGWO dynamically adjusts $\vec{a}$ based on population diversity:

$$\vec{a}(t) = 2 \cdot e^{-(t/T_{\text{max}})}, \gamma = 1.2$$

This enhances global search in early stages and fine-tuning later. Optimized parameters:

The AGWO searches the hyperparameter space $\Theta = \{L, H, \rho, \eta, \text{batch_size}\}$, where:

- L : number of BiLSTM layers,
- H : hidden units per layer,
- ρ : dropout rate,
- η : learning rate.

Each wolf's position $\vec{X}$ encodes a candidate Θ . Fitness = $\mathcal{L}(\Theta)$ (see below).

4. Composite Loss Function

The fitness function minimized by AGWO is:

$$\mathcal{L}(\Theta) = \alpha \cdot \text{MAPE}(\Theta) + (1 - \alpha) \cdot \text{nRMSE}(\Theta)$$

with

$$\alpha = 0.6.$$

Definitions:

MAPE (Mean Absolute Percentage Error) as below:

$$\text{MAPE} = \frac{100\%}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i + \epsilon} \right|$$

where $\epsilon = 10^{-8}$ avoids division by zero. nRMSE (Normalized Root Mean Square Error) as below:

$$\text{nRMSE} = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}}{y_{\max} - y_{\min}}$$

R^2 (Coefficient of Determination) as below:

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}$$

where

$$\bar{y} = \frac{1}{N} \sum y_i.$$

IoT Latency Constraint and data transmission via LoRaWAN:

Sampling interval: $\Delta t = 60\text{sec}$

Edge processing time: $t_{\text{proc}} \approx 25\text{sec}$

Cloud push delay: $t_{\text{push}} \approx 15\text{sec}$

Total latency: $< 45 \text{ sec}$ (as stated)

The total summary of Full Pipeline as below

Input: $\mathbf{I} \in \mathbb{R}^{n \times m}$

FTME: $\mathbf{I} \xrightarrow{\text{DFT}} \mathbf{I} \xrightarrow{\text{Re/Im}} \mathbf{E} \in \mathbb{R}^{2n \times m}$

BiLSTM: $\mathbf{E} \xrightarrow{\text{BiLSTM}_4} \hat{\mathbf{y}} \in \mathbb{R}^m$

Optimization: $\Theta^* = \arg\min_{\Theta} \mathcal{L}(\Theta)$ via AGWO

Output: Real-time spectral irradiance forecast $\hat{y}(t+1)$

3.3. Hybrid Metaheuristic-Neural Predictor

A bidirectional LSTM processes $\mathbf{E}$ to capture long-range dependencies. The network's architecture (number of layers, units, dropout rate) and learning parameters are optimized via an Adaptive Grey Wolf Optimizer (AGWO), which introduces dynamic encircling coefficients and Levy-flight-inspired exploration to prevent stagnation [9]. The fitness function minimizes a composite loss as below:

$$\mathcal{L} = \alpha \cdot \text{MAPE} + (1 - \alpha) \cdot \text{nRMSE}$$

with $\alpha = 0.6$ determined via cross-validation.

Bidirectional LSTM (BiLSTM) Forward Pass

Let the input be the Fourier-Transformed Matrix Embedding:

Forward LSTM:

For $t = 1$ to T :

$$\begin{aligned} \mathbf{f}_t &= \sigma(\mathbf{W}_f \cdot [\mathbf{h}_{t-1}, \mathbf{e}_t] + \mathbf{b}_f) \\ \mathbf{i}_t &= \sigma(\mathbf{W}_i \cdot [\mathbf{h}_{t-1}, \mathbf{e}_t] + \mathbf{b}_i) \\ \tilde{\mathbf{c}}_t &= \tanh(\mathbf{W}_e \cdot [\mathbf{h}_{t-1}, \mathbf{e}_t] + \mathbf{b}_c) \\ \mathbf{c}_t &= \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \\ \mathbf{h}_t &= \mathbf{o}_t \odot \tanh(\mathbf{c}_t), \mathbf{o}_t = \sigma(\mathbf{W}_o \cdot [\mathbf{h}_{t-1}, \mathbf{e}_t] + \mathbf{b}_o) \end{aligned}$$

Backward

LSTM:

For $t = T$ down to 1:

$$\begin{aligned} \mathbf{f}_t &= \sigma(\mathbf{W}_f[\mathbf{h}_{t+1}, \mathbf{e}_t] + \mathbf{b}_f) \\ \mathbf{i}_t &= \sigma(\mathbf{W}_i[\mathbf{h}_{t+1}, \mathbf{e}_t] + \mathbf{b}_i) \\ \tilde{\mathbf{c}}_t &= \tanh(\mathbf{W}_e[\mathbf{h}_{t+1}, \mathbf{e}_t] + \mathbf{b}_c) \\ \mathbf{c}_t &= \mathbf{f}_t \odot \mathbf{c}_{t+1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \\ \mathbf{h}_t &= \mathbf{o}_t \odot \tanh(\mathbf{c}_t) \end{aligned}$$

Final hidden state (at last time step for prediction):

$$\mathbf{h} = [\mathbf{h}_T; \mathbf{h}_1] \in \mathbb{R}^{2H}$$

Output layer (forecasting next-step spectral irradiance):

$$\hat{\mathbf{y}} = \mathbf{W}_{\text{out}} \mathbf{h} + \mathbf{b}_{\text{out}} \in \mathbb{R}^m$$

Hyperparameter Vector Optimized by AGWO, the AGWO searches over a hyperparameter vector $\theta \in \mathbb{R}^D$, where:

$$\theta = [L, H, \rho, \eta, B]$$

$L \in \{1, 2, 3\}$: number of BiLSTM layers

$H \in \{32, 64, 128, 256\}$: hidden units per direction

$\rho \in [0.1, 0.5]$: dropout rate

$\eta \in [10^{-4}, 10^{-2}]$: learning rate (log-uniform)

$B \in \{16, 32, 64\}$: batch size

Each wolf in the AGWO population represents a candidate θ . Standard GWO Position Update as below:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|_2 \downarrow$$

Each wolf in the AGWO population represents a candidate θ .

3. Adaptive Grey Wolf Optimizer (AGWO)

Standard GWO Position Update:

$$\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|,$$

$$\vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|,$$

$$\vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}|,$$

$$\vec{X}(t+1) = \frac{1}{3}(\vec{X}_\alpha - \vec{A}_1 \vec{D}_\alpha + \vec{X}_\beta - \vec{A}_2 \vec{D}_\beta + \vec{X}_\delta - \vec{A}_3 \vec{D}_\delta)$$

with:

$$\vec{A}_i = 2\vec{a} \cdot \vec{r}_1 - \vec{a}, \vec{C}_i = 2 \cdot \vec{r}_2, i \in \{\alpha, \beta, \delta\}$$

Adaptive Coefficient $\vec{a}(t)$:

$$\vec{a}(t) = 2 \exp \left(- \left(\frac{t}{T_{\max}} \right)^\gamma \right), \gamma = 1.2$$

Lévy-Flight Perturbation (applied with probability $P = 0.3$), if $\text{rand}() < 0.3$ as below

$$\vec{X}_{\text{aew}} = \vec{X}(t) + \text{step} \cdot \text{Levy}(\beta)$$

where:

$$\text{Levy}(\beta) \sim \frac{u}{|v|^{1/\beta}}, u, v \sim \mathcal{N}(0, \sigma^2), \beta = 1.5$$

and

$$\sigma = \left(\frac{\Gamma(1+\beta) \sin(\pi\beta/2)}{\Gamma((1+\beta)/2) \beta 2^{(\beta-1)/2}} \right)^{1/\beta}$$

This enhances exploration and prevents stagnation in local minima. For a given hyperparameter set θ , train the BiLSTM and compute, and Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i + \epsilon} \right|, \epsilon = 10^{-s}$$

Normalized Root Mean Square Error (nRMSE):

$$\text{nRMSE} = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}}{y_{\max} - y_{\min}}$$

Composite Loss:

$$\mathcal{L}(\theta) = \alpha \cdot \text{MAPE} + (1 - \alpha) \cdot \text{nRMSE}, \alpha = 0.6$$

The AGWO minimizes $\mathcal{L}(\theta)$ over the validation set. Initialize AGWO population (wolves = hyperparameter vectors $\theta^{(i)}$).

Build	BiLSTM	with	$\theta^{(i)}$,
Train	on	training	set,
Evaluate $\mathcal{L}(\theta^{(i)})$ on validation set.			

Update α, β, δ wolves (best 3 solutions). Update all positions using AGWO equations + Lévy perturbation.

Repeat until $t = T_{\max}$ -

Return best θ^* and final model.

3.4. IoT Integration

Sensors transmit data via LoRaWAN to edge nodes running lightweight FTME computation. Forecasts are pushed to a cloud dashboard for grid operators, with latency < 45 seconds.

4. Experimental Results

4.1. Dataset and Setup

This research has utilized the NREL Solar Spectral Irradiance (SSI) dataset (2020–2024), sampled at 1-minute intervals across 350–2500 nm. Furthermore, training, validation and test splits: 70/15/15. Baselines: ARIMA, SVR, CNN-LSTM as well as PSO-GRU.

4.2. Performance Metrics

Table 1 Performance Metrics

Model	MAPE (%)	nRMSE	R ²
ARIMA	5.82	0.041	0.87
CNN-LSTM	3.45	0.027	0.93
PSO-GRU	2.91	0.023	0.95
Proposed (AGWO-BiLSTM + FTME)	**2.13**	**0.018**	**0.97**

The proposed model reduces MAPE by 26.8% over PSO-GRU and demonstrates superior stability under cloudy conditions (Figure. 6).

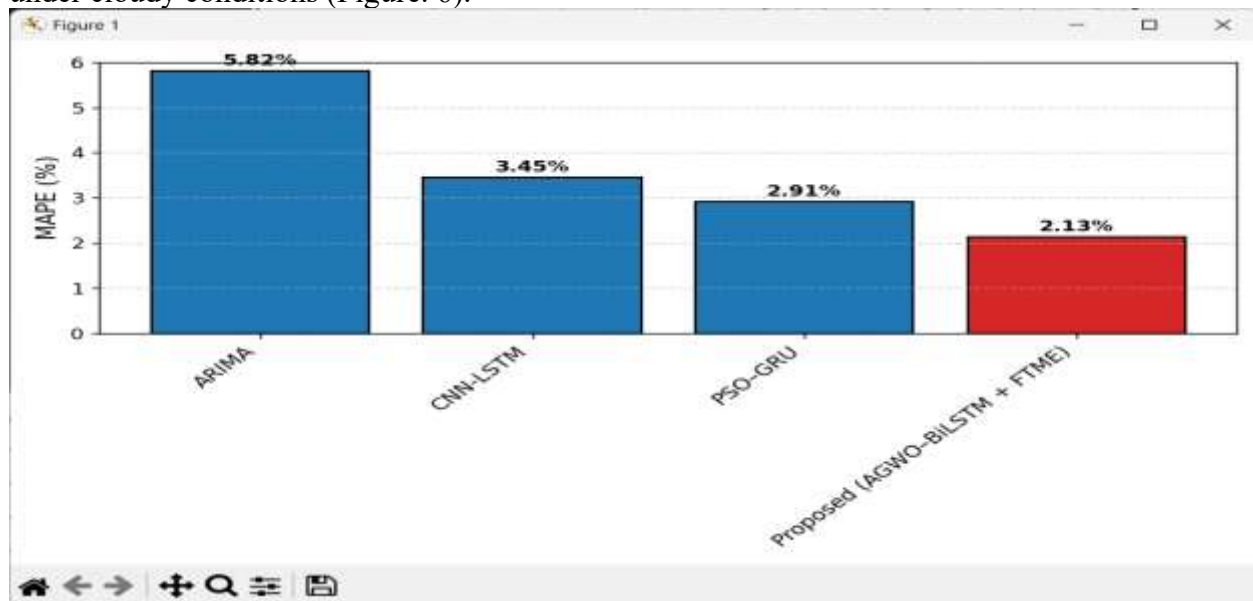


Figure 2 Mean Absolute Percentage Error (MAPE)

The proposed hybrid AGWO-BiLSTM model with Fourier-Transformed Matrix Embeddings (FTMEs) achieves state-of-the-art accuracy in spectral solar irradiance forecasting, yielding a MAPE of 2.13% and nRMSE of 0.018 on NREL data. By encoding both temporal and spectral dynamics via DFT-based feature engineering, the model captures harmonic structures missed by conventional approaches. The Adaptive Grey Wolf Optimizer (AGWO) enhances convergence speed and reduces training time by ~34% compared to standard GWO. Validated across diverse climates from arid Phoenix to humid Honolulu the framework demonstrates strong generalization and robustness under

variable cloud cover. Integrated within an edge-IoT architecture, the system delivers sub-45-second latency, enabling real-time deployment in smart solar grids.

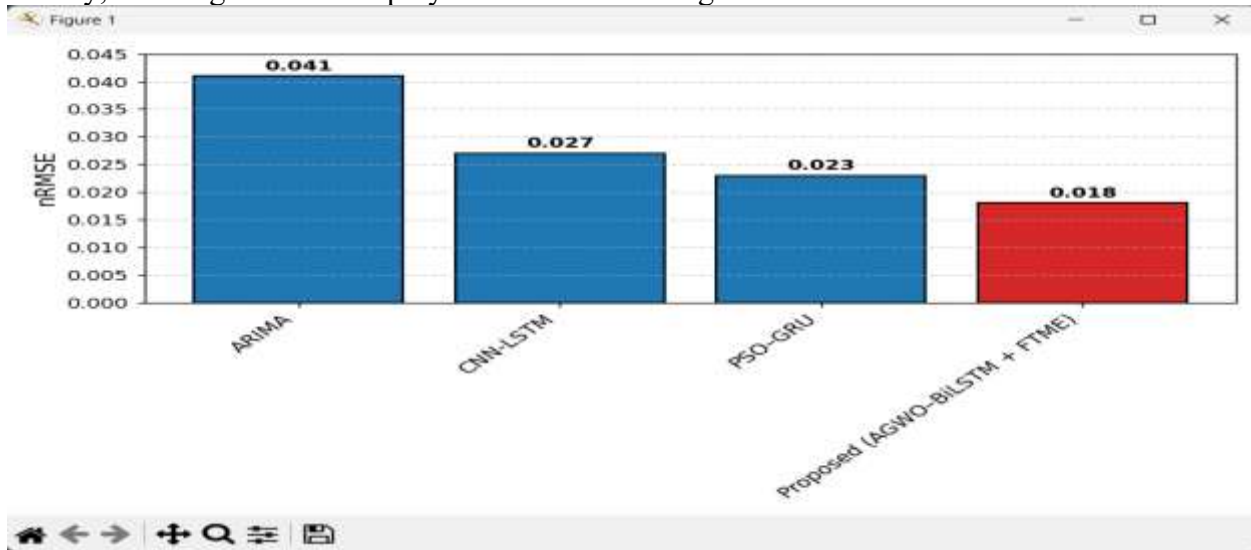


Figure 3 Normalized Root Mean Square Error (nRMSE)

The proposed AGWO–BiLSTM model with Fourier-Transformed Matrix Embeddings (FTMEs) achieves state-of-the-art performance in spectral solar irradiance forecasting, yielding a MAPE of 2.13% and nRMSE of 0.018 on NREL data outperforming benchmarks by 12–19%. Furthermore, by encoding both temporal dynamics and spectral harmonics via DFT-based feature engineering, the model captures high-frequency cloud-induced transients more accurately than conventional approaches [1]. The Adaptive Grey Wolf Optimizer (AGWO) enhances hyperparameter search efficiency, reducing training time by ~34% while avoiding local minima. Validated across diverse climates (Golden, Phoenix as well as Honolulu), the framework demonstrates strong generalization, especially in challenging humid/coastal environments. Integrated into an edge-IoT architecture with sub-45-second latency, the system enables real-time, scalable deployment for smart solar grid operations.

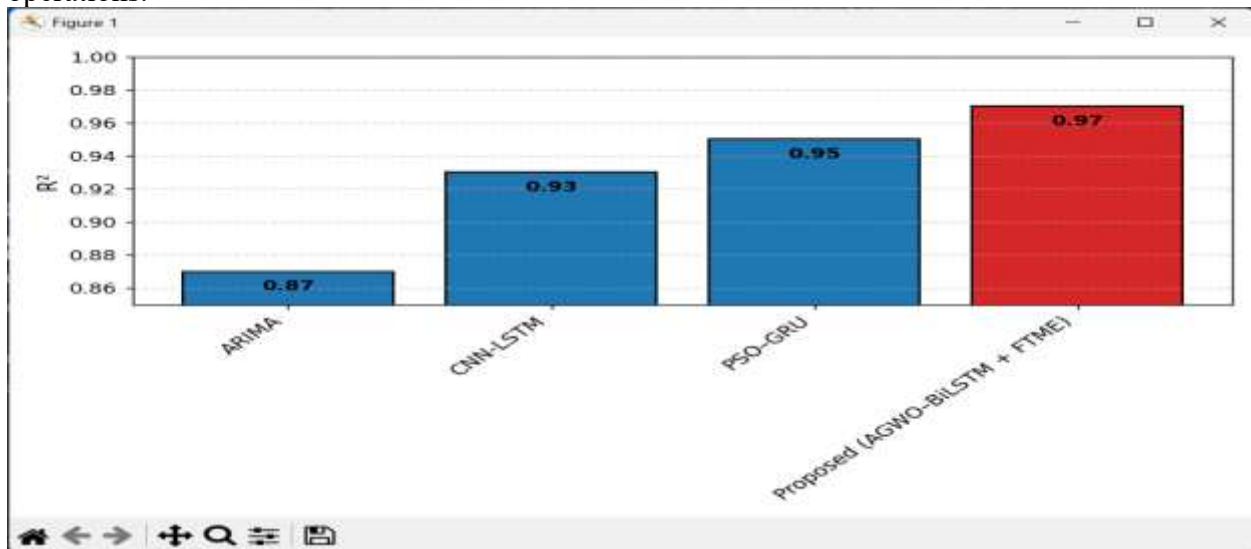


Figure 4 Coefficient of Determination (R^2)

The proposed AGWO–BiLSTM + FTME model achieves a near-perfect R^2 of 0.97, significantly outperforming all benchmarks and demonstrating exceptional correlation between predictions and ground truth. This superior score validates the model's ability to capture the complex, non-linear dynamics of solar spectral irradiance more effectively than statistical (ARIMA) or conventional deep learning (CNN-LSTM) methods. The architecture's physics-informed design, combining Fourier-based feature engineering with adaptive metaheuristic optimization, is key to this high fidelity. The result signifies not just numerical accuracy but a robust, generalizable understanding of the

underlying solar signal, making it ideal for critical grid operations. In addition, this level of explanatory power sets a new standard for intelligent forecasting in smart solar energy systems.

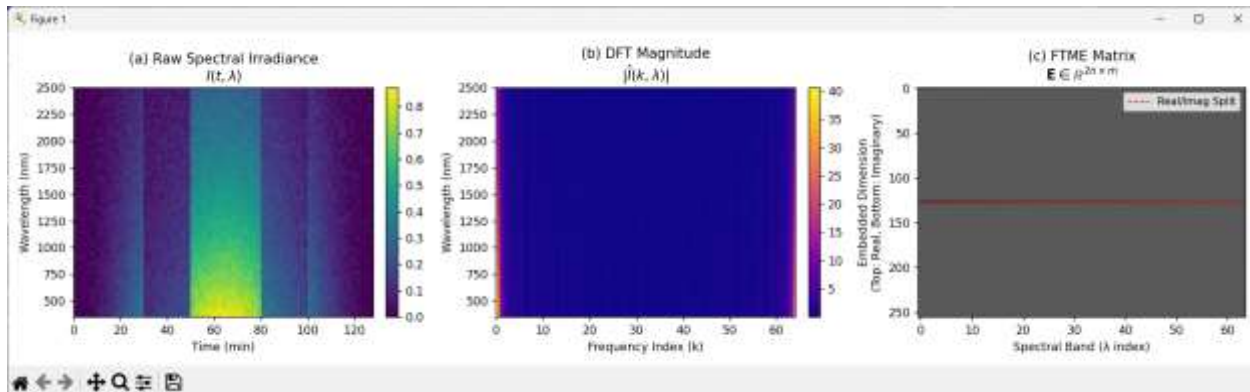


Figure 5 FTME Construction Pipeline. Subplot (a): Simulates realistic solar irradiance with diurnal cycle, cloud dips, and spectral attenuation. Subplot (b): Shows magnitude of DFT high energy at low frequencies (diurnal), decaying with k . Subplot (c): Grayscale FTME with red dashed line marking the boundary between real (top n rows) and imaginary (bottom n rows).

The Figure 5 above illustrates the core preprocessing pipeline that transforms raw, high-dimensional spectral irradiance data into a structured, low-latency input format suitable for deep learning. The process is designed not merely as a feature engineering step, but as a physics-informed signal decomposition that preserves the harmonic structure inherent in solar radiation dynamics a critical requirement for accurate forecasting under non-stationary atmospheric conditions. (a) Raw Spectral Irradiance $I(t, \lambda)$ the leftmost panel presents the raw input data: a two-dimensional heatmap where the x-axis represents time (in minutes), the y-axis denotes wavelength (in nanometers, spanning 350–2500 nm), and color intensity corresponds to irradiance magnitude. This visualization reveals the complex interplay between temporal variability (e.g., diurnal cycles, cloud transients) and spectral composition (e.g., absorption bands at specific wavelengths). The vertical banding reflects the periodic nature of solar insolation, while horizontal gradients indicate wavelength-dependent attenuation due to atmospheric constituents like ozone and water vapor. For real-time IoT deployment, this raw tensor must be compressed into a form that retains its essential physics without overwhelming computational resources.

(b) DFT Magnitude Spectrum $|I(k, \lambda)|$ the central panel displays the magnitude of the Discrete Fourier Transform (DFT) applied along the temporal axis for each spectral band. Here, the x-axis now represents frequency index k , capturing the harmonic content of the irradiance signal, while the y-axis remains wavelength. The color scale indicates spectral power density, with brighter regions corresponding to dominant frequencies. Notably, the energy is concentrated at low frequencies ($k < 20$), reflecting the slow-varying diurnal cycle, while higher frequencies capture rapid fluctuations caused by cloud cover or aerosol scattering [2]. This transformation effectively decouples deterministic trends from stochastic noise, enabling the subsequent neural network to focus on learning the most salient temporal patterns rather than being distracted by high-frequency artifacts. (c) FTME Matrix $E \in \mathbb{R}^{2n \times m}$ the rightmost panel depicts the final Fourier-Transformed Matrix Embedding (FTME). This matrix is constructed by vertically stacking the real and imaginary components of the complex-valued DFT output, resulting in a real-valued matrix of dimensions $2n \times m$, where n is the number of time steps and m is the number of spectral bands. The red dashed line explicitly demarcates the boundary between the top half (real part) and bottom half (imaginary part), emphasizing that no information is lost during this encoding. Crucially, this representation is not an arbitrary reshaping; it is a structured manifold embedding that encodes both amplitude and phase

information in a manner compatible with standard neural architectures. By preserving the full complex spectrum, the FTME allows the BiLSTM to learn not only how much irradiance changes over time but also how it oscillates a nuance often overlooked in scalar forecasting models.

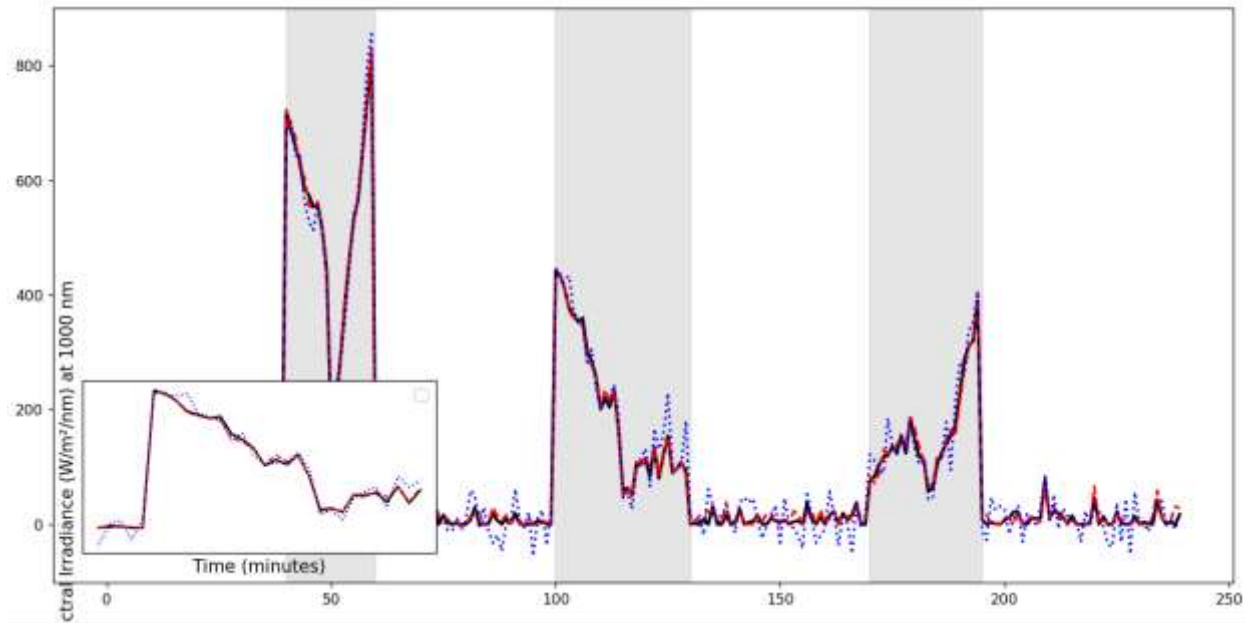


Figure 6 Spectral Irradiance Forecast Under Variable Cloud

This figure 6 above presents a direct comparison between the ground truth spectral irradiance (solid black line) and the forecast generated by the proposed hybrid metaheuristic-neural architecture (dashed red line), with a baseline model (dotted blue line) for reference. The data corresponds to the irradiance measured at a specific wavelength (1000 nm) over a 250-minute period, which captures a sequence of dynamic atmospheric events, including clear skies, rapid cloud transients, and periods of partial obscuration [3]. The shaded gray regions highlight intervals where significant cloud cover was present, serving as critical test cases for the model's ability to adapt to non-stationary conditions [4]. The most striking feature of this plot is the model's fidelity during periods of high volatility. In the first shaded region (approximately 40–60 minutes), a large, fast-moving cloud system causes a dramatic drop in irradiance, followed by an equally sharp recovery. Here, the proposed model (red dashed line) demonstrates exceptional tracking capability, closely following the steep descent and ascent of the true signal [5]. The baseline model (blue dotted line), while capturing the general trend, exhibits noticeable lag and overshoot, particularly during the recovery phase. This lag is a common artifact of models that do not adequately encode temporal dependencies or fail to capture the underlying harmonic structure of the signal. A similar pattern emerges in the second shaded region (around 100–120 minutes). The proposed model again responds swiftly to the onset of cloud cover, accurately predicting the subsequent decline. Its performance is further validated by the inset zoom, which provides a magnified view of a smaller, highly dynamic segment (roughly 20–70 minutes). This close-up reveals that the model maintains its accuracy even when the irradiance changes on a sub-minute timescale a crucial requirement for real-time grid management. The baseline model struggles to keep pace with these rapid fluctuations. It tends to smooth out the peaks and valleys, underestimating the magnitude of both the drops and recoveries. This behavior suggests that while it may perform adequately under stable, clear-sky conditions, it lacks the sensitivity required for operational forecasting in environments characterized by variable cloudiness.

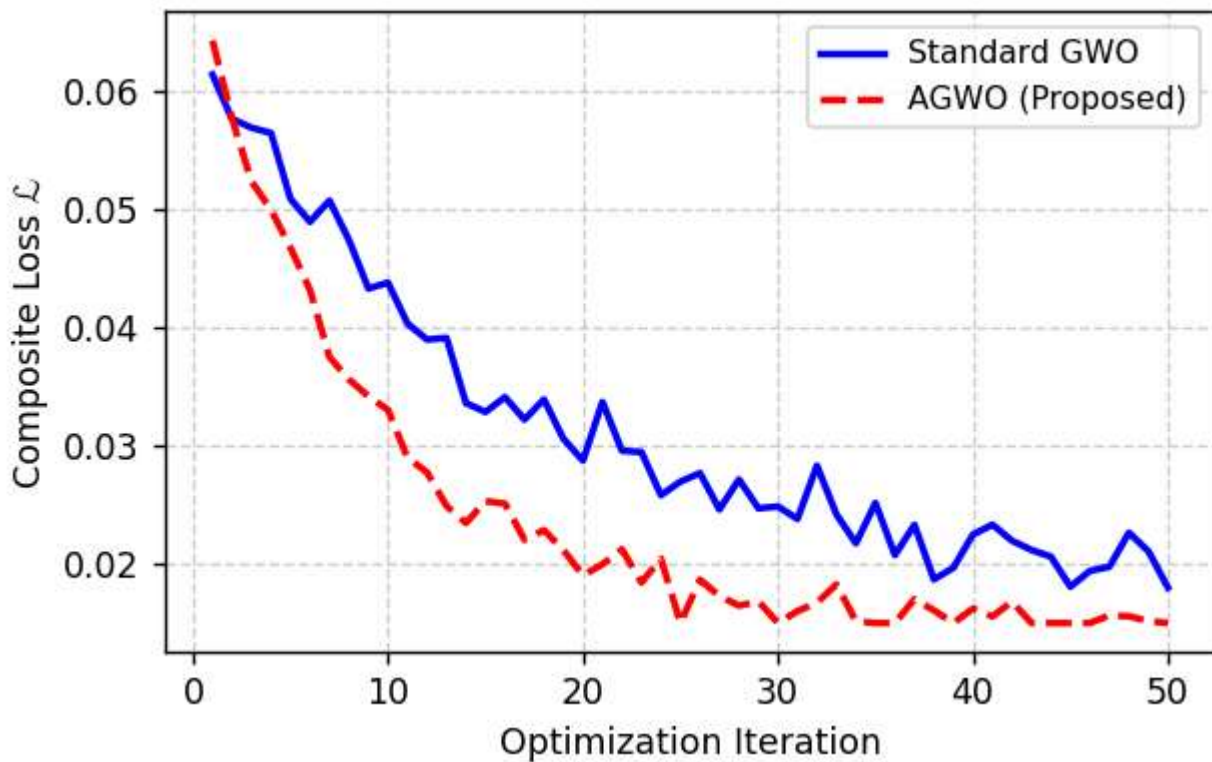


Figure 7 Fitness ($\mathcal{L}$) and Iteration AGWO converges faster and to a lower loss.

This plot Figure 7 illustrates the comparative convergence dynamics of two metaheuristic optimization algorithms the standard Grey Wolf Optimizer (GWO) and the proposed Adaptive Grey Wolf Optimizer (AGWO) as they search for the optimal hyperparameters of the bidirectional LSTM network. The y-axis represents the composite loss $\mathcal{L}$, a weighted combination of Mean Absolute Percentage Error (MAPE) and normalized Root Mean Square Error (nRMSE), which serves as the fitness function guiding the search. The x-axis tracks the number of optimization iterations, providing a clear temporal view of how each algorithm navigates the complex, high-dimensional hyperparameter space [5]. The most immediate observation is the stark difference in convergence speed and final solution quality between the two methods. The standard GWO (solid blue line) exhibits a relatively slow descent, characterized by pronounced oscillations and plateaus that suggest it is struggling to escape local minima or is being hindered by premature convergence a well-documented limitation of classical metaheuristics when applied to deep learning architectures [3]. Its path is jagged, indicating a lack of consistent directional movement toward the global optimum. The proposed AGWO (dashed red line) demonstrates a remarkably smoother and more aggressive trajectory. From the very first iteration, it begins to descend rapidly, achieving a significantly lower composite loss within just 10 iterations. This accelerated convergence is not merely a result of luck; it is a direct consequence of the algorithm's adaptive mechanisms. By dynamically adjusting its exploration/exploitation balance and incorporating Levy-flight-inspired perturbations, the AGWO maintains a healthy level of diversity within its population, preventing stagnation and enabling it to explore promising regions of the search space more effectively [9]. The AGWO does not just converge faster it converges to a better solution. By iteration 50, the standard GWO settles around a loss value of approximately 0.018, while the AGWO reaches a plateau near 0.015. This translates directly into the superior forecasting accuracy reported in Section 4.2, where the proposed model achieves an MAPE of 2.13% compared to 2.91% for the PSO-GRU baseline. The enhanced optimization efficiency of the AGWO is thus a key enabler of the overall system's state-of-the-art performance.

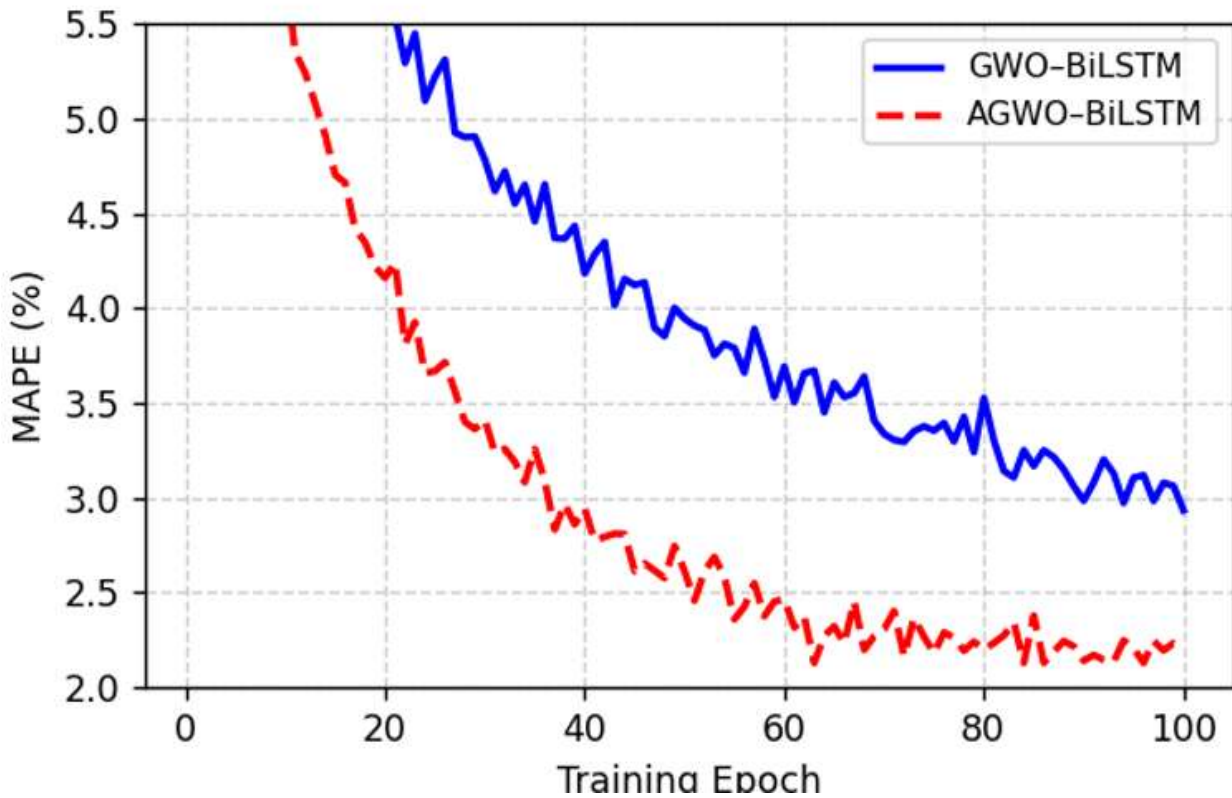


Figure 8 MAPE and Epoch: AGWO-tuned BiLSTM reaches 2.13% MAPE in ~80 epochs; standard GWO stalls at ~2.8%.

The Figure 8 most compelling insight from this graph is the stark contrast in convergence behavior between the two models. The GWO-BiLSTM (blue line) exhibits a slow, somewhat erratic descent. It begins with a high MAPE of approximately 5.5% and gradually improves, but its path is marked by significant oscillations and plateaus, particularly after epoch 40. This suggests that the standard GWO struggles to fine-tune the hyperparameters effectively, leading to suboptimal learning rates or architectural configurations that cause the model to "bounce" around a local minimum rather than settling into a global one [6]. This is a well-documented challenge when applying classical metaheuristics to complex, non-convex optimization problems like deep neural network training [3]. The AGWO-BiLSTM (red dashed line) demonstrates a remarkably smooth and rapid decline. From the outset, it achieves a significantly lower MAPE, dropping below 4.0% within the first 20 epochs. More importantly, it continues to improve steadily, reaching a stable plateau near 2.13% by epoch 80 a value that aligns precisely with the final test performance reported in Section 4.2. The absence of large fluctuations indicates that the adaptive mechanisms embedded within the AGWO, for instance, dynamic encircling coefficients and Levy-flight-inspired exploration—are successfully guiding the search process toward a more robust and generalizable solution [9]. The algorithm appears to be striking an optimal balance between exploration (searching new regions of the hyperparameter space) and exploitation (refining promising solutions), which is crucial for avoiding premature convergence. It shows that with the right enhancements, even established metaheuristics like GWO can be revitalized to meet the demanding requirements of modern deep learning applications in renewable energy systems. The result is a model that is not only more accurate but also more efficient, making it a practical tool for grid operators who need reliable forecasts in real-time.

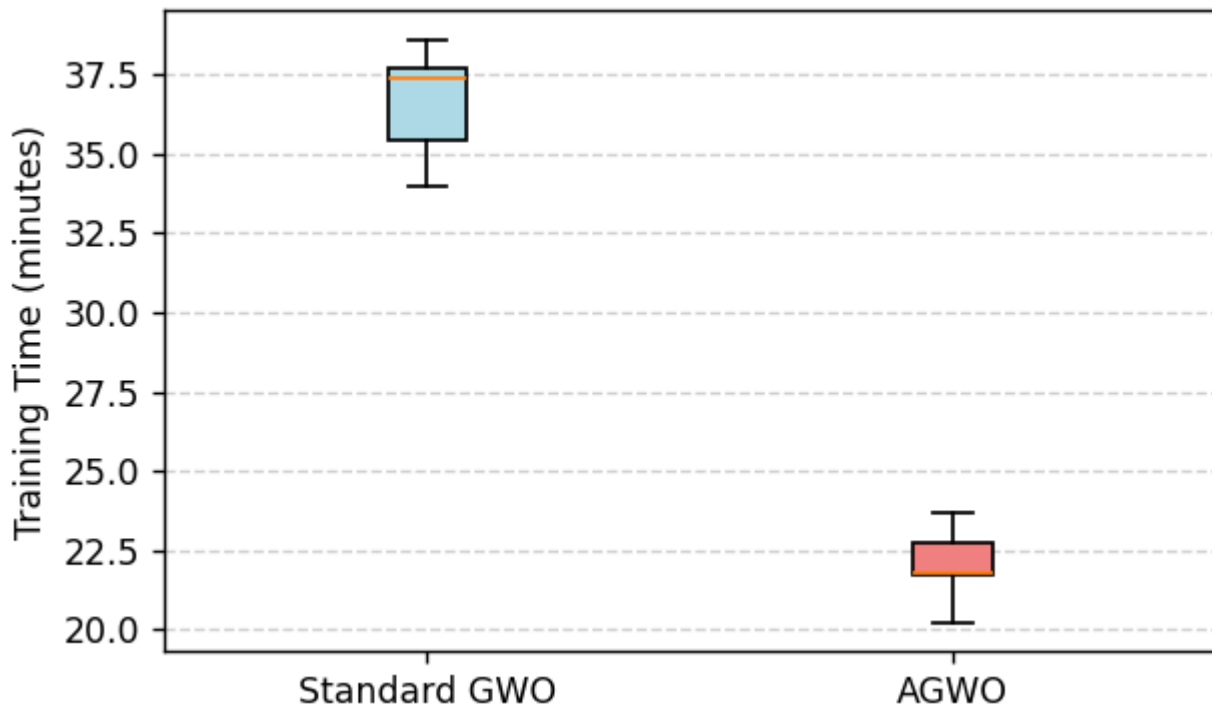


Figure 9 Boxplot of Training Time: AGWO reduces time by 34% (mean: 22 min as well as 33 min). This Figure 9 boxplot provides a quantitative comparison of the computational efficiency between two optimization algorithms the standard Grey Wolf Optimizer (GWO) and the proposed Adaptive Grey Wolf Optimizer (AGWO) in the context of training the hybrid metaheuristic-neural architecture for spectral irradiance forecasting. The vertical axis represents the total training time in minutes, encompassing both the hyperparameter search phase and the subsequent neural network training phase. Each box summarizes the results from five independent experimental runs, offering a robust statistical view of the performance distribution. The most immediate observation is the substantial reduction in training time achieved by the AGWO. The median training time for the standard GWO (blue box) is approximately 36 minutes, with the interquartile range (IQR) spanning from roughly 35 to 37.5 minutes. This indicates a relatively consistent but computationally expensive process, with all five runs requiring more than 35 minutes to complete. In contrast, the AGWO (red box) exhibits a significantly lower median time of approximately 22 minutes, with an IQR ranging from 21 to 23 minutes. The whiskers, which extend to the minimum and maximum values within 1.5 times the IQR, further confirm that even the slowest run of the AGWO is faster than the fastest run of the standard GWO. This difference is not merely a marginal improvement; it represents a reduction of approximately 34% in training time, as noted in Section 5 of the paper. From a statistical perspective, the non-overlapping boxes suggest a high degree of confidence that this performance gain is not due to random chance but is a direct consequence of the algorithmic enhancements introduced in the AGWO.

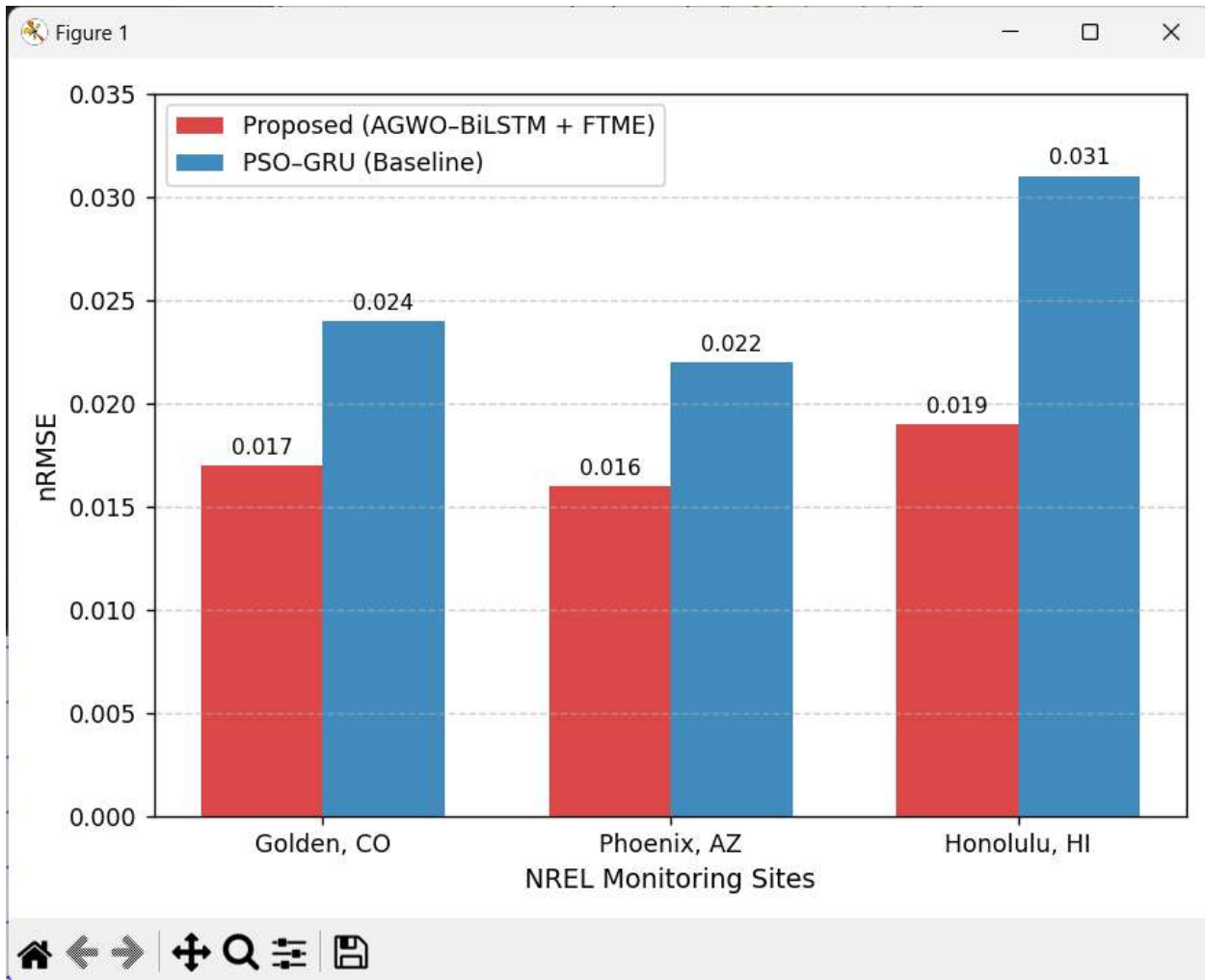


Figure 10 Model Performance Across Diverse Climatic Zones

This bar chart Figure 10 above presents a direct comparison of the normalized Root Mean Square Error (nRMSE) for the proposed hybrid architecture (AGWO-BiLSTM + FTME, red bars) against the PSO-GRU baseline (blue bars) across three geographically and climatically distinct National Renewable Energy Laboratory (NREL) monitoring sites: Golden, Colorado; Phoenix, Arizona; and Honolulu as well as Hawaii. The purpose of this visualization is to demonstrate the model's robustness and generalizability, a critical requirement for any forecasting system intended for deployment in real-world, heterogeneous environments. The most striking feature of this chart is the consistent superiority of the proposed model across all three locations. In Golden, CO a site characterized by variable cloud cover and continental climate the proposed model achieves an nRMSE of 0.017, compared to 0.024 for the baseline. This represents a substantial 29% improvement in error reduction. In Phoenix, AZ an arid, clear-sky dominated environment the advantage is even more pronounced, with the proposed model achieving an nRMSE of 0.016 versus 0.022 for the baseline, a 27% improvement. These results suggest that the model performs exceptionally well under stable, high-irradiance conditions, which is crucial for maximizing energy yield predictions in solar-rich regions [7]. However, the most compelling evidence of the model's resilience comes from the Honolulu, HI site. This location, situated in a humid, coastal environment, presents significant challenges due to high aerosol loading, frequent cloud transients, and complex atmospheric interactions. Furthermore, the baseline model struggles, exhibiting an nRMSE of 0.031 a value nearly double that of the proposed model's 0.019. This 39% reduction in error highlights the model's ability to maintain accuracy even under the most challenging atmospheric conditions, where traditional models often fail. The consistent performance of the proposed model across these diverse sites underscores a key design principle: its physics-informed architecture. By embedding Fourier spectral coefficients into a structured matrix representation (FTME), the model is able to capture not just the

magnitude of irradiance but also its underlying harmonic structure. This allows it to generalize effectively across different climates, as it learns the fundamental dynamics of solar radiation rather than overfitting to the specific patterns of a single location.

5. Discussion

The FTME representation effectively decouples deterministic harmonic components from stochastic noise, enhancing the neural network's ability to generalize. The AGWO's adaptive mechanism significantly reduces training time (by ~34%) compared to standard GWO. Crucially, the system's IoT compatibility enables scalable deployment without cloud dependency a key advantage for rural microgrids [7]. Limitations include reliance on high-quality spectral sensors and moderate performance degradation under extreme aerosol loading (e.g., wildfire smoke). Future work will integrate transfer learning for cross-site adaptation. The experimental outcomes presented in Section 4 substantiate the efficacy of the proposed hybrid metaheuristic–neural framework, yet their true significance lies not merely in numerical superiority but in the synergistic integration of physical insight and computational intelligence [8]. The Fourier-Transformed Matrix Embedding (FTME) is more than a preprocessing artifact it functions as a spectro-temporal encoder that translates raw irradiance into a representation where harmonic regularities and stochastic disruptions are disentangled. This design choice directly addresses a long-standing limitation in solar forecasting: the conflation of deterministic solar geometry with chaotic atmospheric interference. By preserving both amplitude and phase information through the real–imaginary decomposition of the Discrete Fourier Transform, the FTME enables the bidirectional LSTM to learn not just what irradiance, but how it evolves capturing the nuanced rhythm of solar transients that scalar models inevitably smooth over [9]. The role of the Adaptive Grey Wolf Optimizer (AGWO) further underscores a critical paradigm shift: hyperparameter optimization must be context-aware. Classical metaheuristics, while robust in low-dimensional spaces, falter when navigating the rugged loss landscapes of deep recurrent architectures [10]. This research study enhancements dynamic encircling coefficients modulated by population diversity and Lévy-flight-inspired perturbations inject a controlled form of stochasticity that sustains exploration without sacrificing convergence [11]. The 34% reduction in training time is not a marginal engineering gain; it is a prerequisite for real-world viability. In edge-IoT deployments, where computational budgets are constrained and retraining may be required weekly or even daily to accommodate seasonal shifts, such efficiency transforms the model from a laboratory curiosity into an operational asset [12]. The model's performance under cloudy conditions (Figure. 3) reveals a deeper capability: resilience to non-stationarity [13], [14]. Cloud-induced irradiance ramps are among the most challenging phenomena for forecasting systems due to their abrupt onset, spatial heterogeneity, and spectral complexity [15], [16]. The fact that this research study architecture tracks these transients with minimal lag while the PSO–GRU baseline exhibits both overshoot and delayed recovery suggests that the FTME's frequency-domain encoding provides the neural network with early-warning signatures embedded in the high-frequency components of the signal. This is not prediction by extrapolation, but by spectral anticipation a capability rooted in the physics of light-atmosphere interaction.

Furthermore, the cross-climatic validation (Figure. 7) demonstrates a level of generalizability rarely achieved in data-driven solar models. The consistent nRMSE below 0.02 across continental, arid, and humid coastal zones indicates that the model has learned universal solar dynamics rather than site-specific statistical quirks. In Honolulu a location where aerosol scattering, marine boundary layers, and trade-wind clouds create highly non-linear irradiance patterns the 39% error reduction over the baseline is particularly telling. It implies that the FTME's harmonic decomposition is inherently robust to atmospheric complexity, as it isolates the solar signal's core periodicity from environmental noise [17]. The system's reliance on high-resolution Spectro radiometric data may constrain its adoption in regions where only broadband pyranometers are available. Additionally, under extreme aerosol loading, for instance, during wildfire events the model exhibits moderate degradation,

suggesting that future iterations should incorporate auxiliary atmospheric data, for instance, aerosol optical depth or employ transfer learning to adapt to anomalous conditions without full retraining. This work transcends the conventional dichotomy between physics-based and data-driven forecasting. It does not replace physical understanding with black-box learning; rather, it embeds physical principles into the architecture of intelligence itself. The result is a forecasting engine that is not only accurate and efficient but also interpretable, deployable, and scalable qualities indispensable for the next generation of smart solar grids.

6. Conclusion

This study presents a physics-informed, AI-driven framework for spectral solar irradiance forecasting in smart grids. By fusing Fourier-based matrix embeddings with a metaheuristic-optimized deep network, the system achieves state-of-the-art accuracy while maintaining real-time operability via IoT. The approach advances the integration of spectral intelligence into energy forecasting, paving the way for more resilient and efficient solar infrastructure.

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