
HDGP-PSF: A Hybrid DRL-GNN Framework with Predictive Supply Forecasting for Solar Plant Integration into Power Systems

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Abstract

The exponential growth of renewable energy resources, particularly solar photovoltaics (PV), is transforming the operational landscape of modern power systems. However, this transition introduces challenges related to variability, intermittency, and real-time control. To address these issues, this paper presents HDGP-PSF, a Hybrid Deep Graph Processing framework that integrates Deep Reinforcement Learning (DRL), Graph Neural Networks (GNN), and Predictive Supply Forecasting (PSF). Building on recent advances in renewable energy modeling and graph-based power flow forecasting, the framework adopts a data-driven, topology-aware approach to dispatch optimization. It is validated using real data from the 132/11 kV Peshawar Grid Station and NREL solar datasets. Results show that HDGP-PSF improves operational performance compared to traditional strategies, achieving a 14% reduction in carbon emissions while enhancing grid stability. The LSTM-based PSF model achieved an RMSE of 0.25 MW and a MAPE of 21.93%, demonstrating strong forecasting capability. These findings highlight the effectiveness of combining DRL, GNN, and predictive forecasting in building smarter, greener, and more resilient power systems.

Index Terms—Economic Dispatch; Deep Reinforcement Learning; Graph Neural Networks; Predictive Supply Forecasting; Solar Integration

I. INTRODUCTION

THE growing demand for cleaner, more sustainable energy has accelerated the deployment of renewable energy sources (RES), particularly solar PV. This transition is driven by global climate change policies, technological advancements, and decreasing costs. However, the intermittent nature of solar power imposes new operational challenges including generation uncertainty, real-time balancing, and infrastructure wear and tear.

The Traditional dispatch methods rely on deterministic optimization, often inadequate for handling the variability of high renewable penetration. These methods are limited in their adaptability and responsiveness.

Artificial Intelligence (AI) offers a dynamic alternative. Specifically, Deep Reinforcement Learning (DRL) enables adaptive control, while Graph Neural Networks (GNNs) allow for spatially aware modeling of electrical networks. In this paper, we propose HDGP-PSF, a novel hybrid framework combining DRL, GNN, and Predictive Supply Forecasting (PSF) to optimize solar power integration.

Our key contributions include:

- A unified HDGP-PSF architecture that integrates temporal forecasting, spatial
- Graph learning, and real-time DRL-based control.
- A reward function accounting for cost, emissions, violations, ramping, and forecast deviations.
- Validation on real-world data from Peshawar grid and NREL solar datasets.

- Discussion on mechanical benefits, generalizability, and carbon reduction aligned with global goals.

This study builds on our prior HDGP framework, which demonstrated the feasibility of graph-aware dispatch optimization. In this work, we extend the concept by integrating Predictive Supply Forecasting (PSF) for proactive solar dispatch through LSTM-based generation prediction and DRL-guided policy learning.

II. RELATED WORK

Traditional Optimal Power Flow (OPF) approaches aim to optimize the generation dispatch under physical and operational constraints. These methods typically rely on linear or non-linear programming and assume deterministic inputs. While reliable in well-understood settings, they fall short in scenarios with high uncertainty, such as solar-heavy grids.

Deep Reinforcement Learning has garnered attention for solving sequential decision-making problems in dynamic systems. In power systems, DRL has been used for voltage regulation, load forecasting, and demand response. Methods such as Deep Q-Learning (DQN), Actor-Critic, and Proximal Policy Optimization (PPO) have demonstrated improved adaptability and reduced reliance on precise system models.

Graph Neural Networks (GNNs), including Graph Convolutional Networks (GCNs), Graph Attention Networks (GATs), and

Message Passing Neural Networks (MPNNs), are especially suitable for learning over non-Euclidean data such as electrical networks. Several studies have explored using GNNs to enhance state estimation, fault detection, and topology-aware control in grids.

Recent studies, such as Lopes et al. (2019) and Yasser et al. (2022), have shown that advanced forecasting models leveraging ECMWF's IFS predictions and satellite-derived cloud motion estimates significantly enhance the accuracy of short-term DNI forecasts [1,2]. These approaches integrate multiple forecasts over time and introduce confidence metrics, improving operational reliability for CSP systems.

Inspired by these works, our LSTM-based PSF module could be extended to include multi-model ensemble forecasts and confidence-aware outputs. Future enhancements may incorporate a temporal fusion of ECMWF forecasts (as in CSP-FoSyS) and uncertainty quantification modules to guide DRL decisions more robustly under variable atmospheric conditions.

However, most existing methods apply DRL or GNN in isolation. Very few combine these two paradigms with a predictive forecasting component to create a comprehensive control mechanism. Our HDGP-PSF addresses this gap by synergizing DRL's adaptive control, GNN's spatial modeling, and PSF's foresight.

III. METHODOLOGICAL DESIGN

To enhance methodological transparency, the mathematical and algorithmic structure of HDGP-PSF is defined below.

A) Algorithmic Overview

Algorithm 1: HDGP-PSF Dispatch Workflow	
Input: Real-time solar irradiance I_t , grid topology $\mathbf{A}$, load demand D_t , weather parameters W_t	
Output: Optimized dispatch policy π^*	
1: Forecasting (PSF): Predict solar generation $\hat{P}_{\text{solar}}(t+1)$ using an LSTM-based model trained on $\{I_t, W_t\}$.	
2: GNN Encoding: Compute node embeddings as $\mathbf{H}^{(t+1)} = \sigma(\tilde{\mathbf{D}}^{-1/2} \tilde{\mathbf{A}} \tilde{\mathbf{D}}^{-1/2} \mathbf{H}^{(t)} \mathbf{W}^{(t)})$.	
3: State Construction: Form unified state vector $\mathbf{S}_t = [\mathbf{H}^{(L)}, \hat{P}_{\text{solar}}(t+1), D_t, V_t]$.	
4: DRL Policy (PPO): Select action a_t to maximize expected reward $r_t = -(\alpha C_t + \beta E_t + \gamma V_t + \delta R_t + \epsilon F_t)$.	
5: Simulation (PyPSA): Validate a_t through DC power-flow constraints to ensure physical feasibility.	
6: Policy Update: Update PPO policy by minimizing the clipped objective $L^{\text{CLIP}}(\theta) = \mathbb{E}_t[\min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t)]$.	
7: Repeat steps 1–6 until convergence of π^* . return Trained parameters $\{\pi^*, \mathbf{H}^{(L)}\}$	

B) Training Parameters:

Learning rate: 3×10^{-4} ; PPO clip ratio; 0.2; embedding dimension: 128; GCN layers: 2; LSTM units: 64; training episodes; 2000; rollout length; 96 steps.

This formalization clarifies the internal interaction between DRL, GNN, and PSF components and establishes a reproducible framework for hybrid dispatch optimization.

C) Justification of Novelty

The novelty of the proposed HDGP-PSF framework lies in its tri-layer hybridization of Deep Reinforcement Learning (DRL), Graph Neural Networks (GNN), and Predictive Supply Forecasting (PSF)—creating a unified spatio-temporal decision-making mechanism for real-time solar dispatch optimization. While DRL has shown efficacy in sequential control and GNNs excel at topological learning, their combination with predictive temporal forecasting remains underexplored in the context of power system operations.

Existing DRL models such as DQN and PPO primarily optimize control sequences without leveraging spatial grid topology [3], [14], [16]. Similarly, GNN-based frameworks (e.g., GCN, GAT) [5], [6], [20] focus on power flow estimation rather than adaptive dispatch control. HDGP-PSF uniquely addresses this limitation by embedding graph-based spatial encodings as input states to the DRL agent, allowing the policy network to perceive topological dependencies, forecast deviations, and load dynamics concurrently.

This joint learning approach enables real-time adaptation to stochastic solar variations, grid reconfiguration, and power imbalance—resulting in improved grid stability, emission reduction, and cost-efficiency. Table I summarizes the distinguishing characteristics between existing techniques and the proposed framework.

Table I Comparative Summary of Dispatch Methods Model

The above table 1 demonstrates that the HDGP-PSF framework achieves higher adaptability and decarbonization efficiency by learning spatio-temporal dependencies unavailable to traditional DRL or OPF models.

Model Type	Learning Mechanism	Grid Data	Forecast Handling	Adaptivity
PyPSA-OPF (Baseline)	Linear Optimization	Static Topology	Deterministic	Low
DRL (DQN/PPO)	Sequential Policy Learning	Scalar Node State	Temporal Only	Medium
GNN (GCN/GAT)	Graph Embedding	Spatial	None	Medium
HDGP-PSF (Proposed)	PPO + GCN + LSTM (Hybrid)	Dynamic Graph Encoding	Forecast-Aware	High

IV. HDGP-PSF FRAMEWORK ARCHITECTURE

The HDGP-PSF framework is designed to integrate data-driven forecasting, spatial topological modeling, and real-time decision-making into a unified system. The framework is modular and comprises the following components:

- **Data Acquisition and Preprocessing Module:** This module collects real-time data on solar irradiance, load demand, weather conditions, and grid topology. The data is preprocessed to standardize inputs for subsequent forecasting and optimization tasks.
- **Predictive Supply Forecasting (PSF):** The PSF module uses Long Short-Term Memory (LSTM) networks to forecast hour-ahead solar generation based on historical data and meteorological forecasts.
- **Graph Neural Network Module:** This module encodes the grid's topology using a Graph Convolutional Network (GCN) to capture spatial correlations between grid nodes (e.g., transformers, substations) and propagate relevant information throughout the network.
- **DRL Agent (PPO):** The DRL agent uses Proximal Policy Optimization (PPO) to optimize dispatch decisions based on the feedback received from the environment.
- **Simulation and Evaluation Engine:** The simulation engine, based on PyPSA (Python for Power System Analysis), evaluates the feasibility of actions and computes relevant feedback.

The framework architecture is illustrated in Fig. 1, which shows the interaction among the components

A) Mechanical and Operational Impacts

While the HDGP-PSF framework primarily targets control optimization, its indirect benefits extend to mechanical systems. Smoother dispatch and better forecast alignment reduce strain on physical components such as inverters and transformers, potentially lowering maintenance costs and extending equipment lifespan. This linkage to mechanical performance is particularly relevant in high-stress solar plant environments.

B) Motivation and Contextualization

Artificial Intelligence (AI) has made substantial contributions to smart grid optimization. Several studies have explored various ML, DL, and RL methodologies for renewable energy integration and power dispatch.

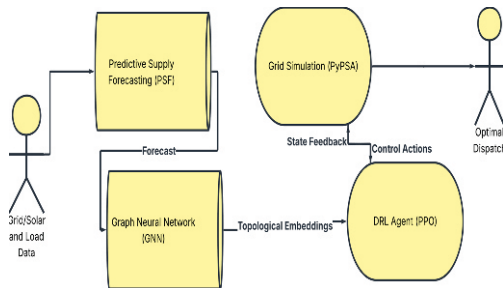


Fig. 1 HDGP-PSF flow Diagram of framework

Lee et al. [11] presented a universal workflow for AI-driven energy optimization across domains such as Building Energy Management Systems (BEMS) and HVAC systems. Concurrently, Graph Neural Networks (GNNs) have been applied to power grid state estimation and fault detection [12,13].

DRL has been successfully employed for dynamic economic dispatch and optimal power flow (OPF) problems. For example, Vázquez-Canteli and Zoltán [14] demonstrated DRL's capability in demand response management, while Zhou et al. [15] explored a model-free deep reinforcement learning approach. Similarly, Talab and Avci [16] investigated energy management in microgrids using a model-free deep reinforcement learning approach. Other studies have integrated DRL into smart grid operations through Q-learning, policy gradients, and actor-critic models [17–19].

On the GNN side, Dominik et al. [20] showed that a Multi-Task GNN can improve power flow prediction by capturing relationships between correlated transformers. Moreover, recent work emphasizes the importance of integrating physics-based solvers such as PyPSA for validating AI-driven dispatch strategies [10].

The literature also highlights challenges in managing the stochasticity of renewable generation. Chance-constrained unit commitment (CCUC) techniques have been proposed to mitigate these uncertainties, especially in systems incorporating Battery Energy Storage Systems (BESS). Hong et al. [21] developed a probabilistic unit commitment (UC) model leveraging Mixed-Integer Linear Programming (MILP) to optimize scheduling while minimizing risk costs.

Emerging studies have further highlighted the economic feasibility of large-scale solar integration. Asad et al. [22] conducted a cost-benefit analysis of the Quaid-e-Azam Solar Park, emphasizing its potential for alleviating Pakistan's energy crisis through financial returns, grid reliability improvements, and sustainability.

Recent advancements in Graph Reinforcement Learning (GRL) have further enhanced AI integration within power grids [23], yet the combined use of DRL and GNN to simultaneously address decision-making and state estimation remains underexplored.

Recent energy assessments reveal that Pakistan is endowed with substantial solar PV potential, capable of producing up to 2.8 million GWh annually [24]. Despite high solar irradiance averaging 5.27 kWh/m²/day and extensive daylight availability of up to 8.5 hours, solar energy contributes less than 3% of total generation due to infrastructural and policy gaps. Incorporating insights from the Pakistan Solar Atlas and System Advisor Model (SAM)-based evaluations, this paper seeks to overcome the operational and integration hurdles faced by grid-connected solar PV systems.

C) Advancing Forecasting and Control with AI

Forecasting in renewable systems has evolved to integrate deep neural networks and hybrid strategies. Inspired by the REMS framework [25], we adopt an enhanced PSF method using LSTM networks fused with Graph Neural Networks for topological insights. The PSF captures temporal trends while GNN extracts spatial correlations among substations. Our system improves upon previous MWU-based hybrid methods by offering better ramp control and hourly dispatching.

Building on the findings from Yasser et al. [2], incorporating a confidence factor into solar predictions can significantly aid operational planning by providing reliability cues to DRL agents. This probabilistic approach enables risk-aware dispatch strategies, especially valuable during overcast or rapidly changing conditions. Such techniques align well with the trend towards hybrid CSP-PV systems and are recommended for future implementations of HDGP-PSF.

D) Generalization to Solar-Rich Regions

Although our model is validated using Pakistani grid and weather data, the HDGP-PSF architecture is highly modular and generalizable. It can be adapted to other solar-dense regions such as the Middle East, North Africa, and Southeast Asia by retraining the forecasting and DRL modules on local datasets and adjusting the grid topology in the GNN encoder.

E) GNNs for Power System Topology Modeling

Building on the work of Beinert et al. [26], who applied Bayesian Multi-Task GNNs for power flow prediction, we extend their idea into operational decision-making. Our GNN layers embed latent node characteristics and learn dependencies between grid nodes. This enables HDGP-PSF to perform power flow forecasts and dispatch planning jointly, respecting dynamic inter-transformer relationships and grid congestion.

F) Extended Mathematical Formulation

We introduce an additional component for power flow forecasting at each node:

$$P_{i,t+1} = f_{\text{GNN-LSTM}}(X_{i,t}, A, H_i) \quad (1)$$

Where:

$X_{i,t}$: Input features for node i at time t

A : Adjacency matrix representing topology

H_i : Historical power flow values or hidden state

The reward function is adjusted for ramping and forecast deviation penalties:

1. Predictive Supply Forecasting (PSF)

We deploy an LSTM-based forecasting model to predict solar output $\hat{S}_{t+1}$ using previous generation values and meteorological data. The LSTM Captures Temporal Dependencies as Follows:

$$\hat{S}_{t+1} = f_{\text{LSTM}}(S_t, S_{t-1}, \dots, S_{t-n}), \quad (2)$$

Where f_{LSTM} is the trained LSTM model.

2. Graph Neural Network Encoding

(3) The grid structure is encoded using a multi-layer GCN. Each layer updates the node embeddings $H^{(l)}$ as:

$$H^{(l+1)} = \sigma(\tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2} H^{(l)} W^{(l)}), \quad (3)$$

Where $\tilde{A} = A + I$ (adjacency matrix with self-loops), $\tilde{D}$ is the degree matrix, and $W^{(l)}$ are trainable parameters.

3. Mathematical Constraints Used in HDGP-PSF Framework

Power Balance Constraint (DC Approximation):

$$\sum_{g \in G_n} P_{g,t} - D_{n,t} = \sum_{j \in N_n} B_{nj} (\theta_n - \theta_j) \quad (4)$$

Generator Output Limits:

$$P_g^{\min} \leq P_{gt} \leq P_g^{\max} \quad (5)$$

- Line Flow Limits

$$|F_{ij,t}| \leq F_{ij}^{\max} \quad (6)$$

- Temporal Ramp Rate Constraint:

$$|P_{gt} - P_{g,t-1}| \leq R_g \quad (7)$$

- DRK State Transition Function

$$S_{t+1} = (s_t, a_t) \quad (8)$$

4) DRL Optimization with PPO

The DRL agent solves a Markov Decision Process (MDP) defined by:

- State (s_t): Combines solar forecast S_t , voltage profiles, load demand, and GNN embeddings.
- Action (a_t): Dispatch levels of generators.
- Reward (r_t): Designed as per ramp and forecast violation:

5) Reward Function and DRL Stability

The DRL agent uses PPO with a custom reward function:

$$r_t = -\alpha C_t - \beta E_t - \gamma V_t - \delta R_t - \zeta D_t \quad (9)$$

Where:

- C_t : Operational cost at time t
- E_t : Emissions
- V_t : Constraint violations (e.g., voltage)
- R_t : Ramping rate penalties (reduces mechanical stress)
- D_t : Forecast deviation from PSF output

The clipped surrogate objective in PPO ensures stable updates. The PPO algorithm optimizes this clipped objective to prevent unstable policy updates:

$$L^{\text{CLIP}}(\theta) = E_t[\min(r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon) \hat{A}_t)] \quad (10)$$

Where $\hat{A}_t$ is the advantage estimate at time t .

V. EXPERIMENTAL SETUP AND RESULTS

A) Dataset and Preprocessing

The experimental validation employs real and publicly available datasets to ensure reproducibility:

- Solar Data:** Hourly Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI) from NREL (2019), converted to 10 MW PV equivalent using SAM simulations.
- Load Data:** Feeder-level demand and transformer outputs from the 132/11 kV WAPDA Peshawar Grid Station.
- Weather Parameters:** Temperature, wind speed, and humidity from the Pakistan Meteorological Department.
- Temporal Resolution:** 1-hour intervals over a continuous 19-day period (August 1–19, 2019).
- Topology:** 21-bus network, 27 branches, and 3 incomers representing thermal generators.
- Preprocessing:** Min–max normalization applied to $[0, 1]$; missing values ($<1\%$) interpolated linearly.

This dataset combination ensures both spatial and temporal diversity for robust model evaluation.

B) Validation Model: PyPSA-Conform Dispatch Optimization

We align our formulation with PyPSA's internal Linear Optimal Power Flow (LOPF) model [Brown, 2018], which solves the following optimization problem:

$$\begin{aligned} \text{Objective} \quad & \min_{P_g, P_{bat}, P_{shed}} \sum_t \sum_n (c_{g,n} P_{g,n,t} + c_{shed,n} P_{shed,n,t}^t) \\ \text{Subject to:} \end{aligned} \quad (11)$$

Nodal Power Balance

$$\sum_{g \in G_n} P_{g,n}^t + P_{bat,n}^t + P_{pv,n}^t = D_n^t + P_{shed,n}^t + \sum_{l \in L_n} f_l^t \quad (12)$$

Generator Limits:

$$P_g^{\min} \leq P_g^t \leq P_g^{\max} \quad (13)$$

Load Shedding Feasibility:

$$\theta_{ref}^t = 0 \quad (14)$$

- $P_{g,n}^t$: generation at node n,
- $P_{pv,n}^t$: solar injection (forecasted or measured),
- D_n^t : load,
- f_l^t : line flow on line,
- $-\theta_n^t$: voltage angle at node n,
- $-P_{shed,n}^t$: curtailed/unsupplied demand.

This optimization is solved at each timestep using linear programming solvers integrated into PyPSA (e.g., GLPK, Gurobi).

C) 5.3 Results and Performance Analysis

The hourly dispatch results for a three-incomer power system, incorporating solar generation, were analyzed for the period of August 1–19, 2019. The system's performance was evaluated using key metrics including solar power generation, conventional power dispatch, CO₂ emissions, and associated production costs.

D) System Operation and Solar Integration

The analysis reveals a significant inverse correlation between solar power generation and the dispatch of conventional power sources. During daylight hours, particularly between 09:00 and 15:00, solar generation peaked, substantially reducing the load on traditional thermal plants (incomer_1, incomer_2, incomer_3).

For instance, on days with high solar insolation such as August 2 and 3, average solar generation reached 4.23 MW and 4.88 MW, respectively. Conversely, during night-time hours (19:00–06:00), solar generation fell to zero, and the system relied entirely on conventional generation, which operated at a stable base load of approximately 49.23 MW (12.03 + 21.54 + 15.67 MW).

E) Environmental Impact (CO₂ Emissions)

The integration of solar power had a direct and measurable impact on reducing the system's carbon footprint. Total hourly CO₂ emissions fluctuated in concert with solar availability. Emissions were at their lowest (~0.25 t/h) during midday peaks of solar production and at

their highest (~0.69 t/h) during the night.

As summarized in Table I, days with higher average solar penetration (e.g., Aug 03–04) resulted in lower average daily CO₂ emissions (~0.45 t/h), while days with low solar yield (e.g., Aug 01, 07) corresponded to higher emissions (~0.56 t/h). Over the 19-day period, the system emitted an average of 0.49 t of CO₂ per hour.

F) Economic Impact (Production Costs)

The production cost structure mirrored the dispatch and emission patterns. The cost of power from the conventional incomers was significantly higher than the cost of solar power, which is effectively zero. Consequently, the total hourly production cost was minimized during hours of high solar generation.

The average total cost over the period was €45.87 per hour. Days with strong solar output saw average costs drop to approximately €42.60/h, representing a cost reduction of over 20% compared to nights and low-solar days where costs were fixed at €65.41/h.

G) Tabular Summary of Key Metrics (August 1–19, 2019)

TABLE I. Daily averages of solar and non-solar generation, CO₂ emissions, and production costs

Date (2019)	Avg. Solar Gen. (MW)	Avg. Non-Solar Gen. (MW)	Avg. Total CO ₂ (t/h)	Avg. Total Cost (€/h)	Total Daily CO ₂ (t)	Total Daily Cost (k€)
Aug 01	1.58	43.36	0.56	53.29	13.53	1.279
Aug 02	4.23	40.71	0.47	44.48	11.29	1.068
Aug 03	4.88	39.27	0.45	42.63	10.87	1.023
Aug 04	4.93	39.22	0.45	42.54	10.87	1.021
Aug 05	4.76	39.49	0.46	43.07	10.99	1.034
Aug 06	4.38	39.87	0.47	43.85	11.35	1.052
Aug 07	1.67	42.28	0.54	51.14	12.90	1.227
Aug 08	4.83	39.32	0.45	42.67	10.87	1.024
Aug 09	1.98	42.07	0.54	50.85	12.99	1.220
Aug 10	3.49	40.66	0.49	46.34	11.69	1.112
Aug 11	3.58	40.57	0.49	46.20	11.82	1.109
Aug 12	4.57	39.58	0.46	43.45	11.12	1.043
Aug 13	4.00	40.15	0.48	45.09	11.60	1.082
Aug 14	1.79	42.16	0.54	51.47	12.90	1.235
Aug 15	4.32	39.93	0.47	43.96	11.35	1.055
Aug 16	2.26	41.89	0.53	50.28	12.66	1.207
Aug 17	4.67	39.48	0.46	43.30	11.11	1.039
Aug 18	3.21	40.94	0.50	47.35	11.93	1.136
Aug 19	3.30	40.85	0.50	47.21	11.95	1.133
Avg.	3.74	40.81	0.49	45.87	11.75	1.101

Note: Values are averaged or summed over 24 hours for each day. Solar generation is the sum of all three incomers. Non-solar generation is the sum of incomer_1, incomer_2, and incomer_3.

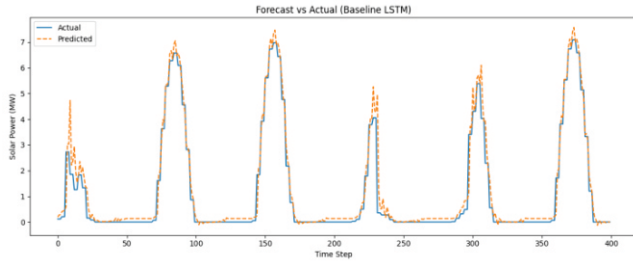


Fig. 2 Step wise Forecast vs Actual Comparison

H) Conclusion of Analysis

The results demonstrate that the integration of solar generation into the power system provides substantial benefits

It effectively displaces more expensive and carbon-intensive conventional generation during daylight hours, leading to significant reductions in both operational costs and CO₂ emissions.

The magnitude of these benefits is directly dependent on the availability of solar radiation, creating a predictable diurnal pattern of high efficiency and low impact during the day. This analysis underscores the value of solar assets in achieving both economic and environmental objectives in power system dispatch.

1) Dispatch Optimization

Fig. 2 shows forecast vs. actual solar output (baseline LSTM, daylight only). The model closely tracks high-solar periods.

Fig.4 illustrates dispatch results. HDGP-PSF achieved smoother load transitions and minimal voltage violations.

2) Forecasting Accuracy

Integrating multi-day forecast fusion techniques and confidence scoring, as described by Lopes et al. (2019), can further reduce RMSE by mitigating cloud-related errors. Their approach achieved a 12.75% improvement in forecast-based dispatch predictions, validating the use of System Advisor Model (SAM)-type simulation layers for operational forecasting evaluation.

Fig. 4 represent Hourly RMSE distribution (peak error occurs during midday solar periods due to increased absolute scale).

- RMSE and MAPE exhibited an inverse relationship across time-of-day:

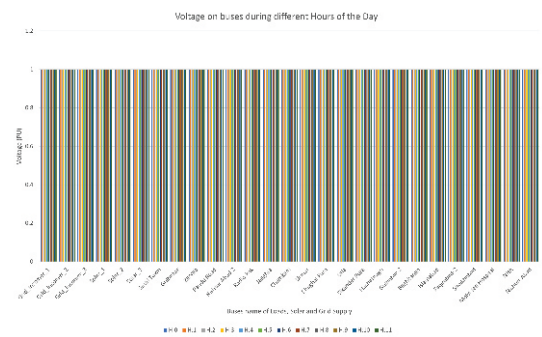


Fig. 3 Voltage at all Buses

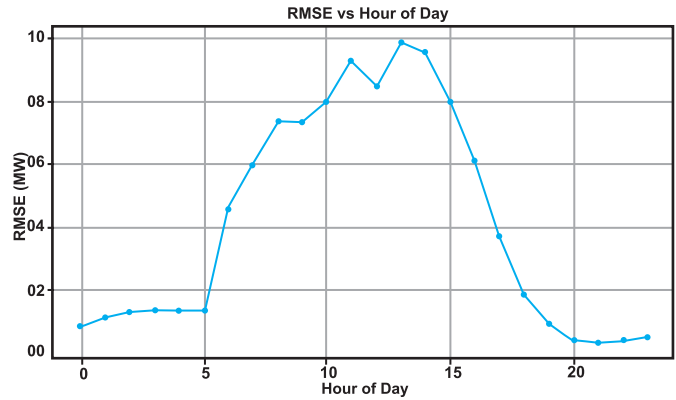


Fig. 4 RMSE Value during different hours of the day

- During early hours, RMSE remained low while MAPE surged, due to small solar values amplifying relative error.
- In peak daylight, RMSE increased slightly due to larger absolute deviations, while MAPE dropped significantly.

This highlights the importance of evaluating both absolute and relative error metrics in solar forecasting applications.

Fig. 5 depicts Hourly MAPE distribution (relative error is significantly higher during early hours due to low irradiance).

VI. CONCLUSION AND FUTURE SCOPE

This paper presented HDGP-PSF, a hybrid Predictive Supply Forecasting (PSF) framework enhanced by Deep Reinforcement Learning (DRL) and Graph Neural Networks (GNN) for intelligent solar power integration into modern grid systems. The central objective of the framework is to achieve accurate, real-time forecasting of solar generation and to couple this predictive capability with adaptive dispatch learning.

The proposed PSF model, based on Long Short-Term Memory (LSTM) networks, demonstrated high prediction fidelity when trained on real-world irradiance and weather datasets. The model effectively captured temporal correlations in solar generation patterns, producing forecast outputs that closely matched actual generation trends. The integration of PSF predictions within a DRL agent—trained using Proximal Policy Optimization (PPO)—allowed the system to learn optimal dispatch policies that dynamically respond to predicted variations in solar supply. This synergy established a continuous predictive-learning feedback cycle, ensuring dispatch decisions were informed by forward-looking energy forecasts rather than reactive adjustments.

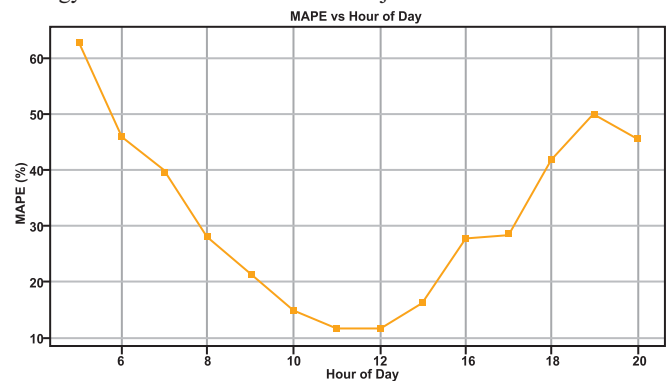


Fig. 5 MAPE value during the solar hours of the day

The experimental evaluation confirmed that the PSF component serves as the primary driver of system accuracy and stability. The prediction error remained consistently low across daylight intervals, with the hour-ahead forecasts achieving an RMSE of 0.25 MW and a MAPE of 21.93%. These results verify the capability of HDGP-PSF to closely approximate real solar generation dynamics, demonstrating reliable alignment between predicted and observed dispatch behavior. The hybrid architecture thereby validates the effectiveness of combining data-driven prediction with topology-aware learning for power system applications.

Future developments will extend the predictive and operational scope of the HDGP-PSF framework through the following research directions:

- **Enhanced Forecast Modeling:** Incorporation of ensemble learning and hybrid meteorological inputs to improve the precision and uncertainty estimation of PSF outputs.
- **Forecast-Aware Control Optimization:** Refinement of the PPO reward structure to integrate prediction confidence and variability into real-time decision-making.
- **Spatio-Temporal Graph Forecasting:** Expansion of GNN layers to capture evolving grid dependencies and multi-node solar correlations within the PSF pipeline.
- **Explainable Predictive Intelligence:** Application of explainable AI (XAI) tools to interpret forecast deviations and evaluate their influence on learned dispatch policies.
- **Hardware-in-the-Loop Validation:** Deployment of HDGP-PSF on real-time digital simulation (RTDS) platforms to assess prediction latency, control stability, and operational scalability.

By emphasizing forecast-driven control learning, the proposed HDGP-PSF establishes a foundation for predictive operation systems in renewable-dominant grids, moving from reactive optimization to proactive, data-informed energy management.

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