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This Study Applies Artificial Intelligence To Optimize Solar Energy Systems In Pakistan, Improving Efficiency, Forecasting Accuracy, And Sustainable Power Generation.

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ABSTRACT

Pakistan is suffering from a major energy crisis due to its chronic 7,000 MW peak deficits and 18-20% losses in energy transmission, resulting in a heavy reliance on the imported fossil fuel based energy sources which account for 57% of the total installed capacity of 45 GW in 2025. The situation is worsening for the average household which faces high tariffs (PKR 80-100 / W installation) and net metering caps (1.0 MW per site) for the installation of solar energy systems, given there is an estimated solar potential of 5.3 kWh/m²/day, from latitudes of 24° to 37°N. This study developed an innovative hybrid artificial intelligent framework that addresses these issues by creating a specific data framework for the solar energy market in Pakistan; this data framework combined with the LSTM-GRU multi horizon forecasting methodology (MAE 2.6% /37%) has been created to forecast energy production from solar systems and provide energy management through Reinforcement Learning DQN (RL-DQN) while utilizing the Adaptive Particle Swarm MPPT (99.1% efficiency / AOD 1.2 solar soiling). This framework was validated at 10 different heterogeneous sites urban Karachi, industrial Lahore, desertic Quetta, and rural Dera Ismail Khan with over 2.5 years of 5-minute data (over 1.2 million discrete time steps). The framework has been validated and verified through extensive MATLAB and Simulink testing as well as OPAL RT hardware in the loop testing. The scenarios used for validation of the framework incorporated Pakistan specific elements / stressors including dust accumulation (85% on SR panel efficiency), monsoon shading (20 to40% occlusion), topography (SRTM contours) and NTDC curtailments mimicking the existing 7,000 MW energy gaps.The project will provide the following main impacts: LCOE decrease of 18.23% (latest costs of 7.80 PKR/kWh compared to the first year at 9.54 PKR)); Energy improvement by 12.65% (1248 kWh/kWp/year

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compared to a baseline of 1115 kWh/kWp/year); 65% reduction in curtailment (4.21% vs. 12.07%); Peak shaving of 61.99%. The deployment of Edge AI based on TensorFlow Lite which enables latency of 48ms and less than 500KB on Raspberry Pi Gateways provides the appropriate scalability for rural applications. Finally, the use of a Socio Technical Genetic Algorithm (Gini index of 0.324) provides a goal of 70% of the target market in Khyber Pakhtunkhwa/Balochistan will be provided to off grid customers.

Innovations encompass curated Pakistan datasets blending ERA5 reanalysis with localized soiling indices, attentionaugmented forecasting capturing aerosol optical depth patterns, and VPP orchestration simulating 100-node clusters for frequency regulation (22% inertia gain). The efficiency benefits accrued via the results prove critical to reaching NEPRA's solar target of 4,447 GWh (2025), as they will release USD 5 billion worth of fossil fuel imports, reduce 50 MtCO2/year from SDG7, and promote a renewable energy system at 30% by 2030. The analysis has important implications for developing AI-assisted practical measures such net metering reform with a focus on enhancing current VPP protocols and building throughout Pakistan's regions solar observatories to facilitate the rapid installation of more than 20 GW of rooftop based systems within a short period of time.

Keywords: Solar PV Optimization, AI Based Energy Management, LSTM-GRU Energy Forecasts, Adaptive PSO-MPPT Technology, Reinforcement Learning Based DQN Methodologies.

Chapter#1.Introduction:

Pakistan is facing a significant energy crisis with ongoing power outages, rising electricity prices, and a heavy dependence on imported fossil fuel, which will provide over 57% of its 2025 generation mix (1, 2). The country has an installed capacity of approximately 45 GW and has a peak demand supply shortfall of over 7000 MW and 18-20% transmission and distribution losses, out dated infrastructure and vulnerability to market prices of oil globally (2, 5, 6). Due to favourable geographic conditions from 24°50’ to 37°, with annual solar radiation averaging 5.3 kWh/m²/day, solar photovoltaic (PV) systems are a critical renewable energy option providing a theoretical capacity greater than 50,000 MW (11, 15). The National Electric Power Regulatory Authority (NEPRA) estimates that solar generation will reach 4,447 GWh in 2025 compared with 2,438 GWh in 2024, with 13 GW of anticipated rooftop solar imports, due to no duties on PV panels (1, 9).

Persistent Energy Challenges and Solar Imperatives

The journey to achieving solar power as the number one source of energy faces multiple barriers/things to overcome. Firstly, output instability (up to a 30% loss in efficiency) occurs due to the times of day there is sun in combination with various environmental conditions such as: clouds, dust accumulation on solar panels, rain and severe weather. Secondly, the grid will struggle to integrate all of the new solar generation as the electrical transmission system in Pakistan will have approximately 16-20% losses. Solar generation will create reverse flows (power flowing back to the grid) that will cause voltage variations (too low or too high) and cause the frequency

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to oscillate which will create the potential for solar produced power to be cut off and add to the frequency problems on the electrical grid. Thirdly, the cost of installing solar systems in Pakistan is exacerbated by limited access to financing for low income households since installation costs range from PKR.80-100 per watt and through the current net metering policy only can systems be installed that produce up to 1MW each, which discourages large scale installations. Lastly, many environmental factors cause solar panels to degrade more quickly, high aerosol optical depth from winter pollution and significant differences in microclimates between arid areas of Balochistan and humid locations such as Karachi, in addition to the shortage of skilled labor in Pakistan leads to substantial delays in getting solar panels installed and operational.

Despite these issues the Government program to increase renewable energy in Pakistan appears promising. The Alternative and Renewable Energy Policy of 2019 targets 30% of the electricity produced in Pakistan will come from renewable sources by 2030. A summary of the top initiatives of the government in support of the AREP is the 1000 MW Quaid-e-Azam Solar Park in Bahawalpur and the 600 MW Muzaffargarh solar projects. The rooftop solar has also grown rapidly and by mid 2025 is projected to represent 2.8 GW of the total installed solar capacity and will be installed in large numbers primarily in the provinces of Punjab and Sindh. The economic benefits of installing rooftop solar have produced reductions of 40-60% in the residential sector. Additionally, distributed generation has helped to reduce the number of outages in urban centers, but the system must operate more efficiently than conventional solar panels with efficiency ratings of 15-20% (years 2025-2026) to achieve the goal of 20 GW.Conventional optimization techniques fall short in harnessing this potential amid Pakistan's variable irradiance and grid frailties (11).

The Transformative Role of Artificial Intelligence

Artificial Intelligence (AI) is changing solar energy systems by offering ways to predict performance, control systems in real-time, and make smart decisions. Common Maximum Power Point Tracking methods, like Perturb and Observe (P&O) or Incremental Conductance (IncCond), are about 95-97% , but they struggle when there's shading or quick changes in sunlight. AI methods, such as Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), used Genetic Algorithms (GA), and neural networks, can raise this to around 99.1%, boosting energy production by roughly 7.5% in real situations. PSO, which takes inspiration from how birds flock together, is great at handling tricky power curves to quickly find the best possible power output, doing better than other methods by 5-10% when there's partial shading.

AI's influence also shows up in forecasting. For photovoltaic output, machine learning models, especially Long Short Term Memory (LSTM) networks, which are recurrent neural networks, can predict PV output with a Mean Absolute Error (MAE) of less than 5%. This is better than basic methods (MAE 10-15%) and physical models that depend on how clear the sky is. In Pakistan, LSTM systems at Quaid-e-Azam Solar Park, incorporating local weather data like humidity, wind speed and temperature have reached 92% for hourly predictions. Even better results come from combined setups: Convolutional Neural Networks (CNNs) take spatial irradiance patterns from

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satellite images and Recurrent Neural Networks (RNNs) handle time based changes. This helps inmapping rooftop potential as seen in Islamabad using Sentinel 2 data.
Beyond just tracking and predicting AI organizes whole system . Genetic Algorithms can automate how PV arrays are sized, how inverters are picked and how battery storage is set up lowering the Levelized Cost of Energy (LCOE) from PKR 12/kWh to PKR 8/kWh while satisfying load types and grid rules. Reinforcement Learning systems can change inverter settings on the fly avoiding overvoltages and cutbacks by predicting changes in demand and export rules. Predictive maintenance uses data from IoT sensors like voltage, current and temperature to spot problems early using Random Forests or Autoencoders. This cuts downtime by 25% by spotting issues like hot spots, microcracks or dirt. Edge based AI makes these good things more widely available doing calculations on low power microcontrollers that work well for off-grid microgrids.

Pakistan-Specific Applications, Achievements, and Gaps

Local innovations underscore AI's viability. A 2025 Beacon Energy pilot deployed Pigeon-Inspired Optimization (PIO) for MPPT across dusty Punjab sites, propelling efficiency from 95.2% to 99.1% and mitigating soiling losses (2, 13). Shams Power's AI platform for Lahore's commercial sector integrates weather APIs with LSTM, delivering 96% forecasting fidelity and optimizing self-consumption to 85% under net metering constraints (12). Premier Energy's RL-driven cleaning schedules in rooftop arrays salvaged 15% yield, adapting to pollen and industrial effluents (16). YouTube documented Final Year Projects (FYPs) from Pakistani universities exemplify grassroots momentum with real time PV load predictors fusing ARIMA and deep learning (17).
Notwithstanding these strides, critical lacunae impede scalability. Predominant models train on global datasets neglecting Pakistan's elevated aerosol optical depths (winter averages 0.8-1.2), topographic influences (e.g, northern highlands) and bimodal irradiance regimes (summer peaks vs. foggy winters) (4, 18). Data scarcity afflicts training: merely 20% of installations boast irradiance monitors with historical records fragmented across AEDB, NEPRA and private entities (6, 17). Computational exigencies overwhelm local hardware; cloud dependencies falter in bandwidth poor rural expanses (6). Regulatory voids persist no standards govern AI enhanced net metering, virtual power plants (VPPs) or demand response exacerbating investor reticence (9).
Hybrid paradigms offer redress: Adaptive PSO fused with deep reinforcement learning for edge deployment as piloted in hybrid microgrids (2, 8). Socio economic modeling via AI can prioritize low income adoption, simulating subsidies and pay as you go financing to bridge equity gaps (9)

Objectives, Methodology, and Novel Contributions

This research introduces a comprehensive AI system designed specifically for Pakistan's solar energy market. It consists of a combined LSTM Gated Recurrent Unit model to predict weather up to 24 hours ahead with a minimum of 3% error rate and an Adaptive PSO system to obtain maximum power from solar panels when they are affected by shading or dust. It will also incorporate Model Predictive Control and

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Reinforcement Learning to obtain the best way to dispatch batteries to the electrical grid (3, 14). The validation of the proposed system will use real-time weather data from 10 different locations (Karachi, Lahore, and Quetta) that have solar generation capabilities between 500 kW and 5 MW. Also, an Aerosol Robotic Network (AOD) will be used to estimate aerosols in the atmosphere, and elevation data will be obtained from the Shuttle Radar Topography mission (14).

Some of the key innovations that will be tested in this research are: (1) creation of localize datasets that contain data from ground-based solar sensors, ERA5 weather reanalysis, and localize soiling index; (2) use of Edge AI via the TensorFlow Lite platform that can perform inference (< 100 ms) on Raspberry Pi devices, allowing these devices to operate autonomously in rural areas; (3) development of multi objective genetic algorithms to optimize both LCOE and equity (i.e., those that have higher Gini coefficients) while balancing grid inertia; (4) synthesizing multiple VPPs to form 100 trunk clusters to provide ancillary services (i.e., frequency and voltage regulation) (12). Overall, achieving the above results will increase efficiency by 10-15%, decrease LCOE by 20% and reduce curtailments by 30%, leading to the same amount of penetration of renewable energy as SDG7 and Vision 2025 (9, 11).

In addition, comparing the results of the proposed system (i.e., LSTM + PSO + Rule-Based) to those of existing systems for the different scenarios assessed (cloudy, dirty, or peak load), this system demonstrated better performance. Specifically, the proposed system yielded 12% more energy than the existing systems, had 4.2% lower mean average error than the existing systems, and 18% lower relative to another LCOE than the existing systems. Eventually, ongoing studies will provide an assessment of how well different hardware devices participate in providing synergies (e.g., battery discharges) to the proposed system as well as the sensitivity of varying hyperparameters (e.g., 20% reduction in sun output) and extreme shocks (e.g., 20% reduction wind) during this process.

Broader Implications and Future Directions

This endeavor not only augments technical efficacy but catalyzes policy metamorphosis. AI derived insights advocate revised net metering tariffs incorporating forecast incentives, standardized VPP protocols and public datasets via national solar observatories (9). Scalability to 20 GW unlocks USD 5 billion in import substitutions curbing PKR 1.5 trillion annual fossil bills while abating 50 MtCO2/year (1, 15). Equitable dissemination targeting 70% off grid households advances energy justice with RL agents prioritizing underserved Khyber Pakhtunkhwa and Balochistan.

Future trajectories encompass federated learning for privacy preserving multi stakeholder data fusion, quantum inspired optimization for ultra large arrays and blockchain secured energy trading (3). Integration with wind hybrids and green hydrogen positions Pakistan as a regional renewables hub.

Methodology

This chapter delineates the systematic approach employed to realize AI based optimization of solar energy systems in Pakistan. There is a description of how the method comprises data collection and cleaning; hybrid AI model creation; creating

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simulation platforms; and completing thorough validation/testing in a reproducible and generalizable way (1, 2). An example of the process from first collecting raw data to establishing performance benchmarks can be seen in Figure 3.1.

Data Acquisition and Sources

Data collection spanned meteorological, PV performance, and grid operational parameters from 10 heterogeneous sites across Pakistan: urban (Karachi), industrial (Lahore), arid (Quetta), and rural (Dera Ismail Khan, Muzaffargarh) clusters, totaling 2.5 years (Jan 2023–Dec 2025) at 5-minute granularity (500 kW–5 MW scales) (12, 15). Data collected from multiple sources were consolidated to create a single, comprehensive dataset with ground-truth data taken from both the Pakistan Meteorological Department (PMD) as well as AERONET. This dataset contains pyranometer readings including GHI (Global Horizontal Irradiance) and DHI (Diffuse Horizontal Irradiance), ambient temperature, humidity, wind speed, and aerosol optical depth (AOD) collected at PMD stations, and AERONET nodes located in Lahore and Karachi; all totaling four PMD stations and eighteen AERONET nodes (4, 18).

Data collected from SCADA systems at the Quaid-e-Azam Solar Park and private PV installations, including PV DC/AC power, voltage/current, PV operating temperatures; supplemented the inputs from the PV system and were compiled to create a total of 1.2 million timestamps (9, 17).ERA5 reanalysis (ECMWF) furnished gap filled auxiliaries: cloud cover, pressure, topography via SRTM (90m resolution) (14). Grid data (load profiles, curtailment logs) sourced from National Transmission Dispatch Company (NTDC) archives with net metering exports from NEPRA (1, 10). Table 3.1 enumerates features: 28 inputs (e.g., GHI, T_mod, AOD) for forecasting; 12 states (P_pv, V_dc, I_sc) for MPPT/RL.

Feature Category	Key Variables	Source	Granularity
Meteorological	GHI, DHI, T_amb, Humidity, Wind	PMD/AERONET/ERA5	5-min
PV Performance	P_dc, P_ac, V_mp, I_mp, T_mod	SCADA/PMD	5-min
Environmental	AOD, Dust Index, Topography	AERONET/SRTM	Hourly
Grid/Load	Demand, Curtailment, Freq.	NTDC/NEPRA	15-min

Table 2.1: Dataset features and sources (1, 4, 9).

Data Preprocessing and Augmentation

To remove noise and fill in missing values (about 5-8% of total), preprocessing was performed on raw signals according to the following guidelines: First, Isolation Forests were employed to detect outliers in the data (i.e., sensor malfunctions such as GHI > 1.5 kW/m²). Second, any short missing segments (under 2 hr) were filled using KNN (k=5) and longer segments were filled using ERA5 data resulting in imputed data with significantly similar ($r>0.95$), timed correlations (14).

Third, domain specific indicators were created through feature engineering. These

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indicators included a clear sky index (K_t = GHI/ GHI_cs), a soiling ratio (SR = P_actual/ P_clean), and a temperature coefficient adjusted power (P_tcorr) (2, 18). Fourth, each site's data was normalized using a MinMaxScaler, which accounted for rolling windows (window=24 hrs, stride=1 hr) to split time-series into a training (70%), validation (15%), and test (15%) set with no leakage and in chronological order (4). Fifth, samples of partial shading (5% of total samples) were augmented in order to mitigate the effects of class imbalance in the training set using SMOTE and physics-informed perturbations (i.e., ± 20% GHI variance to mimic monsoon conditions) (3, 7). Finally, several stationarity tests (Augmented Dickey-Fuller test; $p<0.05$) were conducted to determine if the preprocessing steps were suitable for LSTM-GRU analysis, and cross-correlation matrices were generated to assist in selecting input variables (i.e., GHI lag-1 autocorrelation = 0.92) (5).

Hybrid AI Framework Development

This system combines an LSTM-GRU forecaster, Adaptive PSO-MPPT, and an RL-based energy management system (EMS) as detailed in references (2, 3). It's built using Python 3.10 with TensorFlow 2.15, PyTorch 2.1, and Stable Baselines3. Optuna was used to fine tune settings (100 attempts, TPE sampler).

Multi-Horizon PV Forecasting (LSTM–GRU)

A stacked LSTM–GRU setup predicts photovoltaic power (P_{pv}) for multiple time frames (h = 1\text{–}24) hours. The model uses an encoder decoder structure. A bidirectional LSTM encoder (128 units, 3 layers) spots time based patterns in the input and a GRU decoder (64 units, 2 layers) with added attention makes multi step predictions (14).

The input tensor is shaped like ((T, 28 \text{ features}, 24 \text{ timesteps})), and the output is structured as ((h, 1)). An attention component gives time based importance to hidden states, cutting down on long term prediction errors.The attention weights are computed as:

$$\alpha_t = \frac{\exp(e_{ht})}{\sum_{t'} \exp(e_{ht'})}$$

To make the model less sensitive to outliers, the loss function mixes Mean Absolute Error (MAE) and 20% Huber loss. The AdamW optimizer is used to train the model, with a learning rate of (1 \times 10^{-4}) and a weight decay of (1 \times 10^{-5}). Early stopping is used to avoid overtraining, with a patience of 15 epochs (4, 8).

To keep the model from being too complex, dropout (0.2) and L2 weight penalties are included. The training and validation performance is less than 2% different which means overfitting is being handled well (5).

Adaptive Particle Swarm Optimization MPPT

PSO tracks global MPP under partial shading/soiling, with adaptive inertia ω(t) = ω_max - (ω_max - ω_min)(gen/max_gen)^2 (2). Population: 50 particles; velocity update (Eq. 3.2):

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$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t)$$

Position clamps to [V_oc0.1, V_oc0.95]; fitness = P_pv(V_duty). Chaos map (logistic: x_{n+1}=4x_n(1-x_n)) initializes diversity; elitism retains top-5 (3, 7). Hybridization injects gradient hints from IncCond during stagnation (>5 iter no-improvement).

Reinforcement Learning Energy Management

Battery (50-200 kWh LiFePO4) and grid exports (12-action discrete: charge/discharge rates [-50,50],curtailment thresholds) based on a Deep Q-Network.

State s_t: [P_pv_forecast, SOC, P_load, grid price, curtailment risk]; reward r_t = η_eff P_util - λ_curtail P_cut + γ_soc_penalty (Eq. (3.3)). Double DQN + dueling heads; ε-greedy with decay of 5e-5; PER with α=0.6 and β=0.4. Trained for 1 million steps in Gym environment to simulate NTDC curtailments.

Figure 3.2 shows a multi-layer LSTM/GRU architecture with an attention mechanism.

Simulation and Experimental Setup

MATLAB / Simulink were utilized to model the performance of PV arrays (7 kW CS6X-55M Canadian Solar PV Modules, 300 modules each site) using Simulation and Experimental PSIM solver (1uS time step), incorporating soiling for their location (SR=0.85 Punjab, 0.92 Quetta), as well as shading profiles (building shading, 20-40% occluded) (2,18). Additionally, a hardware-in-the-loop (HIL) test using OPAL-RT was performed on the EMS using a dSPACE1006, with the dSPACE1006 interfacing with off-the-shelf SMA Sunny Tripower inverters. Lastly, TensorFlow Lite Micro was utilized to convert the proposed models with INT8 quantization (size < 500KB) and ran them on a Raspberry Pi 5 (ARM Cortex-A76, latency of 50mS) with the use of MQTT telemetry (12) to provide: (1) Baseline scenario (P&O MPPT and persistence forecast, Rule-based EMS); (2) Proposed scenario; and (3) Ablation scenarios (no-attention PSO, vanilla PSO, or no-PER DQN).

Performance Metrics and Validation

Forecasting tools needed: MAE, RMSE, nMAE (as % of mean P_pv), tracking efficiency (η_mppt), and convergence time for MPPT, and energy yield (E_yield kWh), LCOE (PKR/kWh), peak shave ratio for EMS. Statistical validity will be determined via 5-fold temporal CV (MAPE < 4%), Diebold-Mariano test ($p < .01$ for superiority), ANOVA for variance in scenarios ($F > 25$; $p < .0001$). Uncertainty quantified via bootstrapping (10,000 resamples with 95% CI) and sensitivity via Sobol indices on hyperparameters (20% plus or minus variation in lr and AOD). Convergence plots (Figure 3.3) and radar charts benchmarked multi-metrics.

Ethical Considerations and Limitations

Data anonymization (GDPR compliant); no human subjects. Limitations: site-specificity (northern mountains underrepresented); assumes LiFePO4 (future: flow batteries). Computational footprint audited (0.5 GWh CO2-eq training, offset via solar) (9).

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Results

This chapter describes the results obtained through a validation process conducted with our proposed hybrid AI framework at 10 different heterogeneous sites across Pakistan, i.e., Karachi (urban), Lahore (industrial), Quetta (arid), Dera Ismail Khan and Muzaffargarh (rural) location. For this validation, we analyzed data over 30 months (Jan 2023 – Dec 2025) collected in five-minute increments using simulations in MATLAB/Simulink and through hardware-in-loop (HIL) testing using OPAL-RT for real world applications. The scenarios analyzed included both clear-sky (normal) and dusty (AOD=0.8-1.2) conditions; partial shading (20-40% blockages due to buildings/topography) and peak demand (with NTDC curtailments reflecting a deficit of 7000 MW). Results benchmark against baselines Perturb-and-Observe (P&O) MPPT, persistence forecasting, and rule-based energy management system (EMS)—demonstrating statistically significant superiority (5-fold temporal CV, Diebold-Mariano $p<0.01$, ANOVA $F>25$, $p<0.001$). Key metrics include MAE <3% for forecasting, 99.1% MPPT efficiency, 12% energy yield increase, and LCOE reduction to PKR 7.8/kWh.

Multi-Horizon PV Forecasting Results (LSTM-GRU)

The attention-based stacked LSTM-GRU forecasting model provided remarkably accurate forecasts over the 1 - 24 hour horizons. The average MAE was 2.6% (nMAE = 2.2% of the mean of the PV power), while the RMSE was 20 W/m² and the R^2 value was excellent at 0.96, which was a 37% improvement over using an LSTM-only (MAE = 4.1% and RMSE = 28 W/m²) and a 79% improvement over persistence method (MAE = 12.5% and RMSE = 45 W/m²). Results varied considerably by location and scenario; arid Quetta (irrigation of 5.4 kWh/m²/day) achieved a nMAE of 1.8% based on the consistency of GHI values during the entire forecast period while humid Karachi achieved a nMAE of 3.2% during monsoon rains (cloud cover >60%). During the winter months in Kingston (AOD = 1.2) the average MAE of the model predictions was 2.8% and the attention weights consistently favored the lag-1 GHI (autocorrelation of 0.92) and AOD independent variables as inputs to the predictive model.

Table 3.1: Multi-horizon forecasting metrics across sites (mean ± 95% CI, bootstrapped 10,000 resamples).

Horizon (h)	Proposed MAE (%)	LSTM MAE (%)	Persistence MAE (%)	RMSE (W/m²) Proposed
1	2.4 ± 0.1	3.8 ± 0.2	10.2 ± 0.5	18 ± 1
6	2.6 ± 0.1	4.2 ± 0.2	11.8 ± 0.6	20 ± 1
24	2.9 ± 0.2	4.5 ± 0.3	15.1 ± 0.8	22 ± 2
Average	2.6 ± 0.1	4.1 ± 0.2	12.5 ± 0.6	20 ± 1

In partial shading scenarios (e.g., Dera Ismail Khan topography), the model maintained MAE <3.1%, with 15% reduced drift versus no attention ablation. Figure 3.1 illustrates hourly forecasts versus actuals for Lahore (dusty day), highlighting precise capture of noon peaks (1.2 kW/m² GHI).

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Figure 3.1: LSTM-GRU forecasts vs. actual PV power (Lahore, AOD=1.1; self generated).

MPPT Tracking Efficiency Results (Adaptive PSO)

Adaptive PSO-MPPT achieved 99.1% average tracking efficiency (η_mppt) under dynamic conditions, with convergence in 12 iterations (<50 ms on Raspberry Pi 5). This yielded 7.5-14% energy harvest gains over P&O (95.2%) and vanilla PSO (97.8%). Site-specific results reflected local stressors: Quetta's low soiling (SR=0.92) hit 99.4% η_mppt (+14% yield); Punjab's dust (SR=0.85, Lahore) reached 99.0% (+10%); rural Dera Ismail Khan managed shading-induced multimodal curves at 98.7% (+11%). Hybrid IncCond hints resolved 92% stagnations, clamping duty cycles to [0.1-0.95 V_oc].

Table 3.2: Site-wise MPPT efficiency and yield gains (shading/soiling scenarios).

Site	η_mppt (%)	Convergence (iters)	Yield Gain vs. P&O (%)	SR/AOD
Quetta (arid)	99.4	10	14	0.92/0.6
Lahore (dusty)	99.0	13	10	0.85/1.2
Karachi (monsoon)	98.9	14	9	0.88/0.9
D.I. Khan (rural)	98.7	12	11	0.87/1.0
Average	99.1	12	11	0.88/0.9

Figure 3.2: Power-voltage (P-V) curves under 30% partial shading (Quetta; global MPP tracked by adaptive PSO).

Energy Management and System-Level Results (RL-DQN)

RL-DQN EMS optimized battery-grid dispatch, delivering 1,248 kWh/kWp/year energy yield (12% > baseline 1,115 kWh/kWp/year), LCOE of PKR 7.8/kWh (18% reduction from PKR 9.5/kWh), 4.2% curtailments (65% less than baseline 12.1%), and 62% peak shaving during 7,000 MW deficits. Battery SOC averaged 75% efficiency, with 12 discrete actions balancing P_pv_forecast, load, and curtail_risk. Edge deployment latency was 48 ms (TensorFlow Lite INT8, <500 KB model).

Table 3.3: System-level performance metrics (annual averages, 500 kW-5 MW scales).

Metric	Proposed	Baseline	Improvement (%)
E_yield (kWh/kWp/yr)	1,248 ± 25	1,115 ± 30	12
LCOE (PKR/kWh)	7.8 ± 0.2	9.5 ± 0.3	18
Curtailment Rate (%)	4.2 ± 0.5	12.1 ± 1.0	65
Peak Shave Ratio (%)	62 ± 2	38 ± 3	63
Self-Consumption (%)	85 ± 1	65 ± 2	31

VPP simulations (100 nodes) added 22% grid inertia for frequency regulation. Socio-technical GA yielded Gini coefficient 0.32, prioritizing low-income Khyber Pakhtunkhwa sites.

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Figure 3.3: Monthly energy yield comparison (avg. across sites).

Discussion

The data collected demonstrates conclusive proof of the hybrid artificial intelligence framework's ability to solve issues related to intermittent energy production from solar systems (due to dust storms/monsoon season), gridlosses (18-20% sizeable), and electronic curtailments as an advanced and scalable solution to reach Pakistan's goal of generating 20 GW's of renewable power by 2030. Achieving a 12% increase in energy output and cutting Levelized Cost of Energy by 18%, can be used to create annual savings from fossil fuel imports of 1.5 Trillion rupees ($9 Billion) and avoid 50 MtCO2 (carbon dioxide) from fossil fuel combustion each year is aligned with SDG #7 (Sustainable Development Goal No. 7) and the basis for Vision 2025.

Interpretation of Forecasting Superiority

The LSTM-GRU's MAE of 2.6% (37% below LSTM) stems from bidirectional encoding and attention, which weighted AERONET AOD (35% Sobol variance) and ERA5 topography, capturing Pakistan specific patterns like Lahore's winter fog (GHI drop 40%) and Quetta's stable peaks. This precision enabled RL-EMS to preempt 28% curtailments by adjusting export thresholds pre-NTDC peaks, far surpassing persistence models' 12.5% MAE that exacerbate load shedding. In Dera Ismail Khan, rural shading profiles benefited from SMOTE-augmented training, reducing forecast errors by 22% during topographic occlusions critical for off grid equity.

MPPT Resilience Under Local Stressors

Adaptive PSO's 99.1% η_mppt navigated multimodal P-V curves under SR=0.85 (Punjab dust), with chaos initialization and ω(t) decay ensuring 12-iteration convergence. This 7.5-14% yield uplift eclipses P&O's oscillations (95.2%), mirroring Beacon Energy's PIO pilot (95.2%→99.1%). Karachi monsoons tested transient response, where IncCond hybridization resolved 92% stagnations, boosting rooftop net metering (1 MW cap) viability amid 40-60% household bill cuts.

Holistic EMS Optimization and Economic Impact

RL-DQN's rewards ($r_t = \eta_{eff} P_{util} - \lambda_{curtail} P_{cut}$) stabilized SOC at 75%, slashing LCOE to PKR 7.8/kWh via optimal sizing (GA: 50-200 kWh LiFePO4). Peak shaving (62%) directly mitigates 7,000 MW deficits, with 85% self consumption under net metering doubling Shams Power's Lahore platform (85%). VPP inertia (22%) addresses grid frailties, while Gini 0.32 promotes equity for 70% off grid households in Balochistan/Khyber Pakhtunkhwa. Edge-AI (48 ms) democratizes rural deployment bypassing bandwidth issues.

Comparative Analysis and Ablations

Versus literature: Forecasting beats Quaid-e-Azam LSTM (MAE~5%, 92% accuracy); MPPT exceeds global PSO/GA (5-10%) under local AOD; EMS outperforms rule based (38% shave) and Premier Energy RL (15% yield). Ablations quantify synergies no attention raised MAE 1.8%; vanilla PSO cut η_mppt 2.1%; no-PER DQN spiked curtailments 14%. Sensitivity (Sobol): AOD (35%), lr (22%) dominate; framework

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robust to ±20% irradiance shocks (yield -8% vs. baseline -15%).

Figure 4.1: Radar chart of multi metric benchmarks (proposed vs. baselines; self generated).
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Figure 4.2: Ablation study convergence (E yield over 1M steps).

4.5 Limitations, Broader Implications and Future Directions

Limitations include northern highlands underrepresentation (topography bias), LiFePO4 focus (future flow batteries) and 0.5 GWh CO2-eq training (solar offset). Data scarcity (20% monitored sites) was mitigated via ERA5 but federated learning beckons.

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