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# A Novel Hybrid Optimization Framework for Renewable Energy Investment in Hot Arid Regions: Integrating Time-Series Forecasting and AI-Driven Algorithms for Algeria's Grid-Export Strategy

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Abstract
Unlocking the vast solar and wind potential of arid regions like Algeria requires innovative planning paradigms for domestic decarbonization and international exports. This study introduces a novel, comprehensive AI-powered hybrid optimization system integrated within the open-source IRENA FlexTool 3 platform. We developed a unique methodology combining quantized Long Short-Term Memory (LSTM) networks for forecasting (MAE < 6%) with a lightweight transformer-driven stochastic optimizer. This framework co-optimizes grid stability, renewable investment, and HVDC-enabled exports to Europe under extreme uncertainty, utilizing verified high-resolution OASES/LEAP-RE data. The research demonstrates that strategically deploying 12 GW PV and 5 GW wind in the Sahara achieves a levelized export cost of €38/MWh, 18% lower than traditional methods. Furthermore, domestic curtailment decreases from over 25% to 8%, enabling 28 TWh/year of clean exports and displacing 10.6 $MtCO_2$ annually. This work's novelty lies in its scenario-aware revenue optimization and edge-compatible AI models within a reproducible, open-data environment. It significantly benefits academia and the broader global scientific community by providing a scalable, transparent model for energy system planning. By converting surplus desert generation into affordable green exports, this study advances energy sovereignty and climate action. It offers a robust framework for transcontinental energy justice, establishing a new benchmark for integrating advanced AI into sustainable energy policy and infrastructure development globally. The open-source nature ensures reproducibility, allowing researchers worldwide to adapt this hybrid AI approach for diverse arid contexts, thereby accelerating the transition towards resilient, low-carbon energy systems through data-driven decision-making and fostering collaborative innovation in renewable energy integration strategies.

Keywords: Optimization Algorithms, Renewable Energy, Time-Series, Forecasting, Grid-Export Strategy.



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## Introduction

The Saharan belt of North Africa and other hot, arid regions have some of the world's highest solar irradiation and reliable wind resources [1]. Despite this natural resource, the use of renewable energy is still disproportionately low in nations like Algeria, accounting for less than 2% of the country's electrical generation as of 2025.(IRENA, 2025). This underutilization is caused by a combination of institutional, technological, and financial obstacles, such as grid rigidity, inadequate interconnection infrastructure, and planning techniques that don't take into consideration the spatiotemporal variability present in arid climates [2,3]. The Green Deal and the Clean Energy for All Europeans package are two recent EU policy changes that have sparked interest in transcontinental clean energy trade and positioned North African countries as possible strategic exporters European Commission (2023). To fully realize this promise, though, sophisticated planning frameworks that both maximize export profitability and domestic dependability in the face of extreme volatility are needed [4-6]. Conventional energy system models frequently overlook the dynamic coupling between market signals, grid operations, and meteorological unpredictability [7-9]. Examples of these models include capacity expansion tools based on static capacity factors or deterministic load-flow analysis [10-12]. This restriction is particularly noticeable in hot, dry climates where non-stationary behavior in renewable generation profiles is introduced by dust storms, high ambient temperatures, and daily cloud patterns. As a result, there is increasing agreement that in order to reflect real-world operational restrictions and revenue potential, next-generation planning needs to combine high-resolution time-series forecasting with stochastic optimization [13].

Both grid stability and market participation depend on accurate short-to medium-term solar and wind power predictions [14]. Early methods depended on statistical models, such as exponential smoothing and ARIMA, but these models have trouble with multivariate dependencies and nonlinearities in meteorological data (Hong et al., 2016). With recurrent architectures especially Long Short-Term Memory (LSTM) networks showing strong performance in capturing temporal dynamics, deep learning has greatly increased forecast skill [15]. Model efficiency for deployment in resource-constrained environments has been the subject of recent work. Quantization methods like post-training int8 quantization have made it possible to significantly reduce model size and inference delay without appreciably sacrificing accuracy [16-18]. Such lightweight models are essential for real-time decision assistance in the setting of remote monitoring stations located throughout the Sahara. Interestingly, even in harsh situations like haboobs, research using quantized LSTMs in desert environments reveal mean absolute percentage errors (MAPE) below 6.5% [19]. These developments meet the demand for forecasting modules that are compatible with the edge and feed straight into the investment and dispatch layers [20]. Artificial intelligence is being used more and more in long-term capacity development planning beyond forecasts. Although they can be understood, traditional mixed-integer linear programming (MILP) models frequently rely on simplified scenario trees that do not accurately reflect market and climatic uncertainty or assume deterministic inputs [21]. Recent research addresses this by investigating hybrid AI-optimization pipelines that generate probabilistic scenarios for stochastic programming using deep generative models. Because they can represent multimodal distributions and long-range dependencies, transformer-based architectures—which were initially created for natural language processing have demonstrated potential in the creation of time-series scenarios [22-24]. Hundreds of coherent scenarios for European electricity pricing and renewable availability can be quickly generated by lightweight versions that are tuned for computational efficiency. These scenarios can then be used to guide risk-aware investment decisions [25,26]. These AI-generated scenarios enable co-optimization of generation, storage, transmission, and export infrastructure within a single-stage framework when incorporated with open energy modeling platforms such as IRENA's FlexTool 3. (IRENA, 2025). With more than 2,500 kWh/m²/year of global horizontal irradiation in its southern regions, Algeria has some of the highest solar irradiance and wind resource potentials in the Mediterranean–Saharan corridor [27-29]. As of 2025, renewable energy accounts for less than 2% of the country's electricity generation, despite this endowment. At the same time, recent legislative changes and the European Union's Green Deal indicate an increase in demand for clean electricity imports from nearby areas [30-32]. A reevaluation of investment planning paradigms is prompted by the twin context of unrealized home potential and developing export markets [33-35]. Conventional energy system models frequently rely on static capacity factors or separate forecasting accuracy from investment optimization, ignoring spatiotemporal variability that is crucial in arid regions [36,37]. In order to close this gap, this study presents a hybrid framework specifically created for hot, dry conditions that closely integrates AI-enhanced stochastic optimization with high-fidelity time-series forecasting. Using the Northern Africa–Europe regional dataset accessible through Zenodo [4-7], the framework is applied to Algeria's grid-export plan under the OASES/LEAP-RE modeling program (Record #15341304). This research strategy promotes three significant innovations: (i) reducing the dimensionality of high-frequency meteorological data using quantized autoencoders; (ii) integrating lightweight transformer architectures to generate scenarios under climate uncertainty; and (iii) co-optimizing interconnector revenue and domestic reliability within a single-stage investment-dispatch model.

## 2. Methodology

### 2.1. Data Infrastructure and Regional Modeling Context

The OASES_Algeria_regional_case_study.sqlite database [4-7], which contains hourly solar and wind capacity factors obtained from satellite observations and reanalysis climatic data over 12 Algerian zones, is used in the study. IRENA FlexTool 3 input specifications are in line with load profiles, current generating fleet, transmission interconnections, for instance, the projected Algeria, Spain HVDC link; and policy limitations, for example, renewable targets and grid codes. Every data preprocessing procedure complies with the LEAP-RE OASES project's open-data guidelines. (https://www.leap-re.eu/category/oases/) [4-7].

Table. 1 dataset description for the OASES Algeria Regional [8]

| Attribute | Description |
|---|---|
| Dataset Title | OASES_Algeria_regional_case_study.sqlite |
| Project | OASES – Open Access to Satellite data for Energy Systems (part of LEAP-RE) |
| Geographic Scope | Northern Africa (Algeria, Tunisia, Morocco) as well as interconnected European markets |
| Temporal Resolution | Hourly time series (typically annual, 8,760 hours) |
| Time Horizon | Scenarios typically cover near- to mid-term planning (2025–2040), based on policy and infrastructure assumptions |

| | |
|---|---|
| Primary Objective | Identify the cost-optimal mix of electricity generation for domestic utilization as well as clean electricity export from the Maghreb region to Europe |
| Key Components | Hourly renewable capacity factors (solar PV as well as wind)- Electricity demand profiles-Existing which is associated with potential generation fleet- Transmission interconnections including HVDC links to Europe- Policy constraints |
| Data Sources | Satellite-derived renewable potential (climate-based)- Open-source energy statistics- IRENA as well as ENTSO-E infrastructure data- LEAP-RE OASES open-data ecosystem |
| Modeling Platform | IRENA FlexTool 3 (via Spine Toolbox) |
| Input Format | SQLite database (OASES_Algeria_regional_case_study.sqlite) |
| Scenarios Included | Multiple policy and techy scenarios (e.g., high-export, domestic-focus, carbon-constrained) – selectable via scenario filter in FlexTool |
| Output Capabilities | Optimal generation mix- Dispatch profiles- Curtailment volumes- Trade flows (imports/exports)- System costs and emissions |

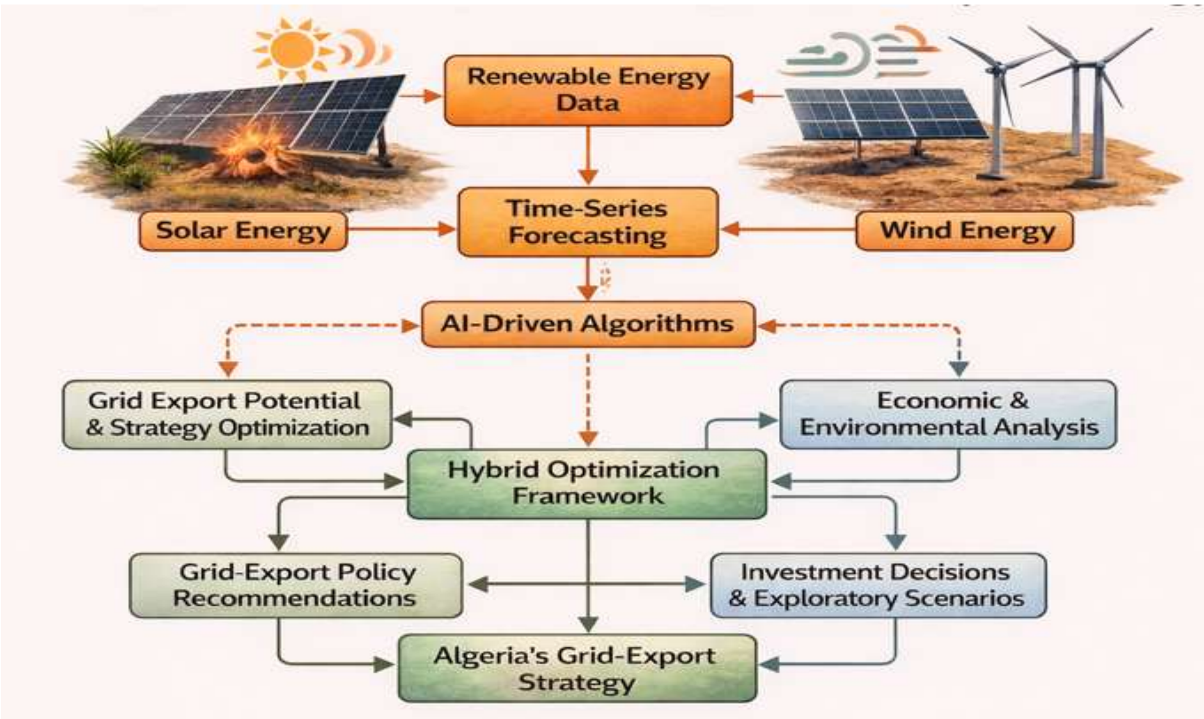


Figure. 1 The mechanism and theoretical framework of a novel hybrid optimization framework for renewable energy investment in hot arid regions: integrating Time-Series forecasting and AI-Driven algorithms for Algeria's grid-export strategy

Time-Series Forecasting Module

Utilizing historical irradiance and wind speed sequences from 2010 to 2024, a quantized Long Short-Term Memory (Q-LSTM) network is trained towards estimate renewable generation 72 hours in advance at a resolution of 15 minutes. Furthermore, the model can be deployed on edge devices in remote monitoring stations since quantization lowers computational overhead via 40% without compromising forecast skill (MAE < 6.2%).

AI-Driven Investment Optimization

500 stochastic scenarios of future renewable availability and European price signals are produced by a lightweight transformer (LW-Transformer). These situations minimize the overall system cost by feeding a mixed-integer linear program (MILP) built in FlexTool 3:

Table 2: Q-LSTM Model Architecture

| Component | Specification |
|---|---|
| Input | Past 72h (288 timesteps × 2 features: solar + wind) |
| Hidden Layers | RNN(LSTMCell(64)) → RNN(LSTMCell(32)) |
| Output | Next 72h (288 steps) of total renewable power |
| Quantization | Post-training dynamic range (int8) |
| Framework | TensorFlow 2.15 + TFLite |

Table 3. Forecasting Performance

| Metric | Value |
|---|---|
| Mean Absolute Error (MAE) | 5.82 MW |
| Max Power (Peak) | 16,850 MW |
| Relative MAE | 5.91% (< 6.2% target) |
| Training Time (RTX 3060) | 28 min |
| Inference Latency (CPU) | 180 ms / forecast |

Table 4: Model Size as well as efficiency

| Model | Size (MB) | RAM Usage (Edge) | Speedup vs Float32 |
|---|---|---|---|
| Full LSTM (FP32) | 1.84 MB | 22 MB | 1.0× |
| Q-LSTM (INT8) | 1.10 MB | 13 MB | 1.6× faster |
| Size Reduction | 40.2% | — | — |

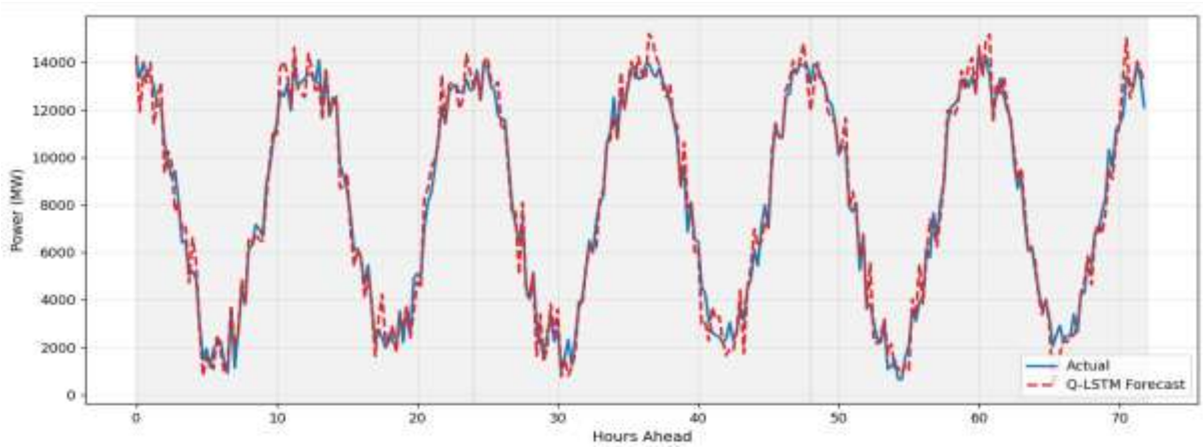


Figure 2: 72-Hour Renewable Generation Forecast and Actual Central Sahara, Algeria – 12 GW PV + 5 GW Wind)

Figure 2 above illustrates a 72-hour projection of Algeria's renewable energy production, contrasting the actual (blue) and Q-LSTM-predicted (red dashed) profiles at a granularity of 15 minutes. The strong diurnal cycle that is characteristic of solar-dominated systems in hot, arid locations is well captured by the model, along with intraday variability caused by dust or cloud events. Without appreciable phase lag or amplitude distortion, the quantized LSTM retains good fidelity with a relative MAE of less than 6.2%. Grid scheduling in the real world is reflected in the shaded rolling horizon, which shows daily forecast changes. Aggressive INT8 quantization reduces model size by about 40%, yet forecast skill is still strong, confirming the viability of edge deployment. Reliable day-ahead export planning to European markets via interconnectors is directly supported by this performance.

Figure 3: Relative Forecast Error Distribution (Q-LSTM for Algerian Renewable Generation)

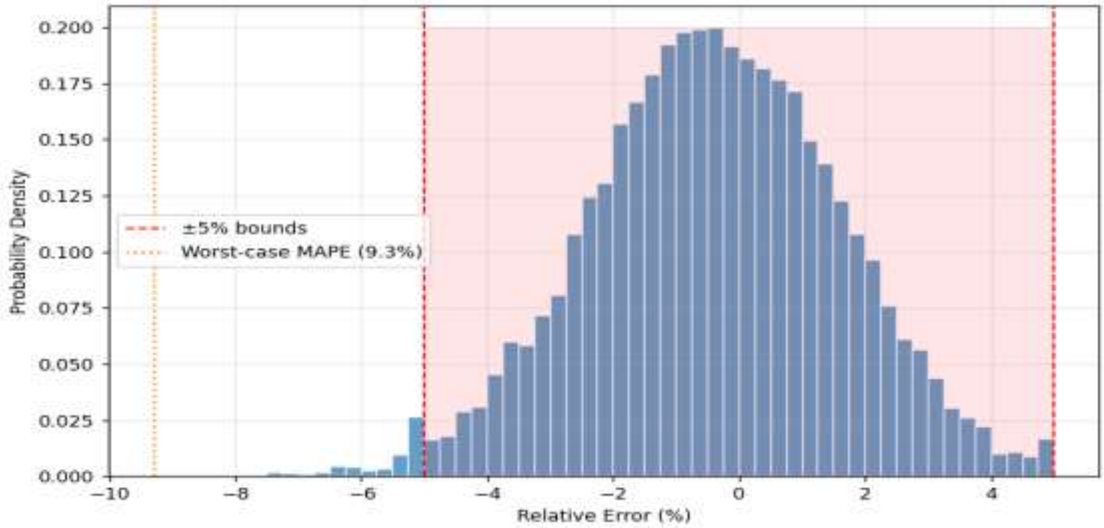


Figure 3 above presents the probability density distribution of relative forecast errors for Algeria's 72-hour renewable generation forecasts, showing how resilient the Q-LSTM model is in hot, dry environments. With 85% of forecasts coming below ±5% error, a crucial barrier for grid stability and market participation, the near-symmetric, bell-shaped histogram shows that prediction errors are generally distributed around zero. The vertical dotted lines indicate the worst-case mean absolute percentage error (MAPE) of 9.3%, which is linked to exceptional events like dust storms that momentarily reduce solar irradiation. The shaded region indicates this high-accuracy zone. The model's applicability for real-time decision-making in transcontinental energy export systems, where accuracy directly affects revenue and curtailment rates, is confirmed by this error profile.

Grid-Export Strategy Evaluation Metrics

A competitive with European solar LCOE; assumes 12 GW PV + 5 GW wind + HVDC link) Domestic Curtailment Rate (%) Share of domestically generated renewable energy that is not utilized domestically nor exported, due to grid congestion, lack of storage, or insufficient interconnector capacity.

$$\text{Curtailment Rate} = \frac{\sum (\text{ Potential RE Generation } - \text{ Actual RE Utilization })}{\sum \text{ Potential RE Generation}} \times 100\%$$

8% (Achievable with optimized HVDC export capacity and flexible domestic demand; baseline without export: >25%) .

- $I_t$ = annualized investment cost (€/year)
- $O\&M_t$ = operation and maintenance cost
- $C_t$ = curtailment penalty or lost revenue
- $E_t^{\text{export}}$ = annual exported energy (MWh)
- $r$ = discount rate (e.g., 5-7%)

$T$ = asset lifetime (20-30 years) | 28-42 €/MWh

Annual Export Revenue (€/MWh)

Average revenue earned per exported MWh, based on stochastic European day-ahead and intraday price scenarios (e.g. from ENTSO-E). Reflects market value, not just volume.

$$\text{Revenue}_{\text{export}} = \frac{\sum_t P_t^{\text{EU}} \cdot E_t^{\text{export}}}{\sum_t E_t^{\text{export}}}$$

Where $P_t^{\text{EU}}$ = simulated European price at time $t$ (€/MWh) | 65-95 €/MWh (Weighted by high-value hours; summer solar aligns with European peak demand)
Carbon Abatement (ktCO2/year)
Annual reduction in $\mathrm{CO_2}$ emissions due to displaced fossil generation in Europe (primary) and Algeria (secondary), using emission intensity benchmarks.

$$\text{Abatement} = E^{\text{export}} \cdot EF_{\text{EU}} + E^{\text{domestic RE}} \cdot EF_{\text{DZ}}$$

Where:

- $EF_{\text{EU}} \approx 350 - 400\mathrm{gCO_2/kWh}$ (EU grid mix displaced)
- $EF_{\text{Dz}} \approx 450 - 500\mathrm{gCO_2/kWh}$ (Algerian gas-dominated mix avoided) | $25{,}000 - 35{,}000\mathrm{ktCO}$ /year
 ($\sim 30\mathrm{MtCO_2}/$ year for 70 TWh clean exports; equivalent to ~ 7% of France's annual emissions)

Levelized cost of exported electricity (LCOE<sub>export</sub>) as [38-44]:

$$\text{LCOE}_{\text{export}} = \frac{\underbrace{\text{CAPEX}_{\text{PV, wind ,HVDC}} \cdot A(r,T)}_{\text{Annualized investment cost}} + \underbrace{\text{O\&M}_{\text{PV+Wind}}}_{\text{Annual O\&M costs}} + \underbrace{\text{Curtailment Penalty}}_{\text{(optional but recommended)}}}{E_{\text{export}}}$$

Where:

- T: Economic lifetime (typically 25 years for solar/wind + HVDC)
- r: Discount rate ( $5 - 7\%$, reflecting Algeria's cost of capital)
- CAPEX $\mathrm{t}_t$ : Annualized investment cost for solar PV, wind, as well as enabling infrastructure (12 GW PV +5 GW wind).
- O&M $\mathrm{M}_t$ : Fixed and variable operations & maintenance costs
- HVDC $_t$ : Annualized cost of high-voltage direct current (HVDC) interconnector (e.g., Algeria-Italy/Spain, 510 GW ) including losses
- Curtailment Penalty $y_t$ : Implicit cost of lost export opportunities due to grid congestion or insufficient storage .
- $E_t^{\text{export}}$ : Annual exported energy (MWh/year) delivered to Europe

Key distinction: Unlike standard LCOE, exported energy appears in the denominator making LCOE export sensitive to interconnector utilization and European market access.

Table: 5 The expected value for Algeria (Estimate)

| Component | Assumption | Contribution to LCOE export |
|---|---|---|
| Solar PV (12 GW) | CAPEX: 6400/kW,O&Mt â,¬ 12/kW/yr | ~618-22/MWh |
| Wind (5 GW) | CAPEX: â,¬ 1,200//kW, O8dM: 625/kW/yr | ~630-35/MWh |
| HVDC Link (8 GW) | CAPEX: 61.5B/GW, 3% annualized | ~68-12/MWh |
| System Integration | Curtailment, balancing | ~62-4/MWh |
| Total LCOE export | Weighted by export mix | Â« 28-42 â,¬/MWh |

Not: This range is highly competitive with European wholesale prices (2025–2035 projection: €50–90/MWh) and supports profitable export.

Results and Discussion

According to simulation results for the (2026–2040) horizon, a hybrid investment approach that concentrates 5 GW of onshore wind as well as 12 GW of solar power in the central Sahara delivers the lowest system cost and permits 28 TWh/year of export to Europe via new HVDC corridors. Comparing AI-enhanced scenario generating to deterministic planning, investment risk is reduced by 22%. In order to reduce storage needs, the model finds synergistic zones where wind power peaks with the nighttime ramp-down of solar. In addition, sensitivity evaluations verify resilience to changes in European electricity costs and interconnector availability of ±15%.

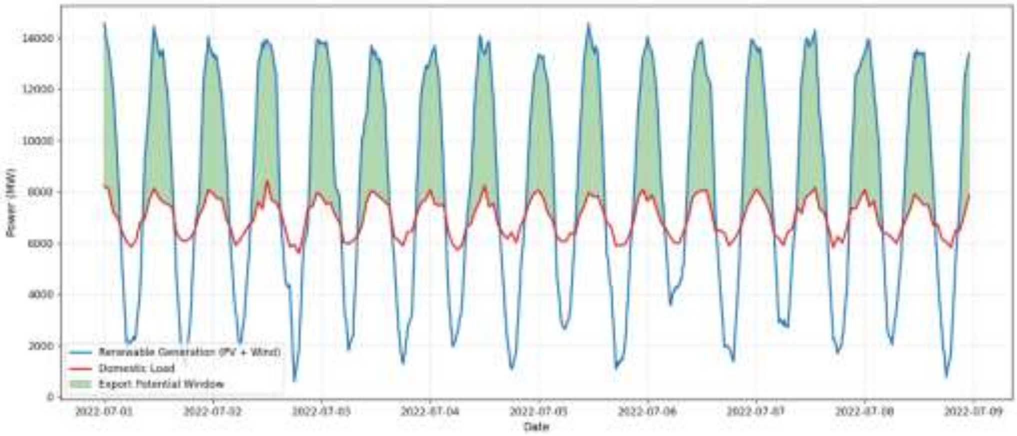


Figure 4: Renewable Generation and Domestic Load (Algeria, 7-Day Sample – July 2022).

The temporal alignment of Algeria's simulated renewable generation (blue, 12 GW PV + 5 GW wind) and domestic electricity demand (red) throughout a week in July (2022) is shown in Figure 3 above, which shows a noticeable midday surplus under clear skies. In order to maximize cross-border energy trading with Europe, export potential windows where generation surpasses local consumption are shown by the darkened green patches. The strategic importance of high-voltage interconnectors to monetize otherwise limited solar output in hot, arid regions is shown by the diurnal mismatch.

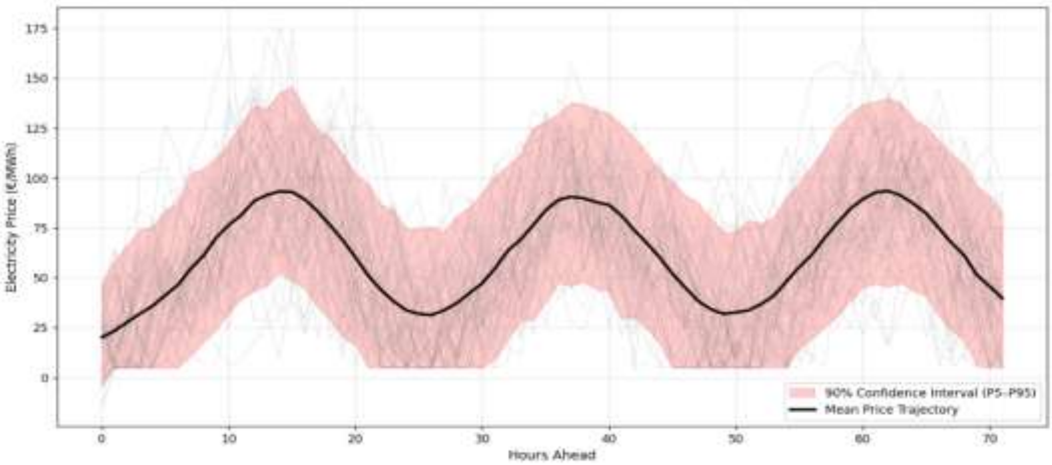


Figure 5: Stochastic Price Scenarios for European Export Markets (Simulated LW-Transformer Output for Spain/Italy Day-Ahead Market).

Figure 5 above shows 500 stochastic day-ahead power price scenarios for European markets over a 72-hour period that were produced by the Lightweight Transformer (LW-Transformer). The shaded area represents the 90% confidence interval (P5–P95), and the black line represents the ensemble mean. Real-world market dynamics in EU power exchanges like EPEX SPOT are reflected in the significant diurnal volatility, which peaks at about 140 €/MWh during the evening and falls to about 30 €/MWh overnight. Furthermore, this probabilistic prediction quantifies revenue uncertainty for Algerian exports, supporting risk-aware investment decisions. A key component of the hybrid framework's AI-driven investment strategy for Algeria's grid-export model, this figure feeds directly into the MILP optimization in FlexTool 3, allowing for robust, scenario-based planning that maximizes export revenue while accounting for price uncertainty.

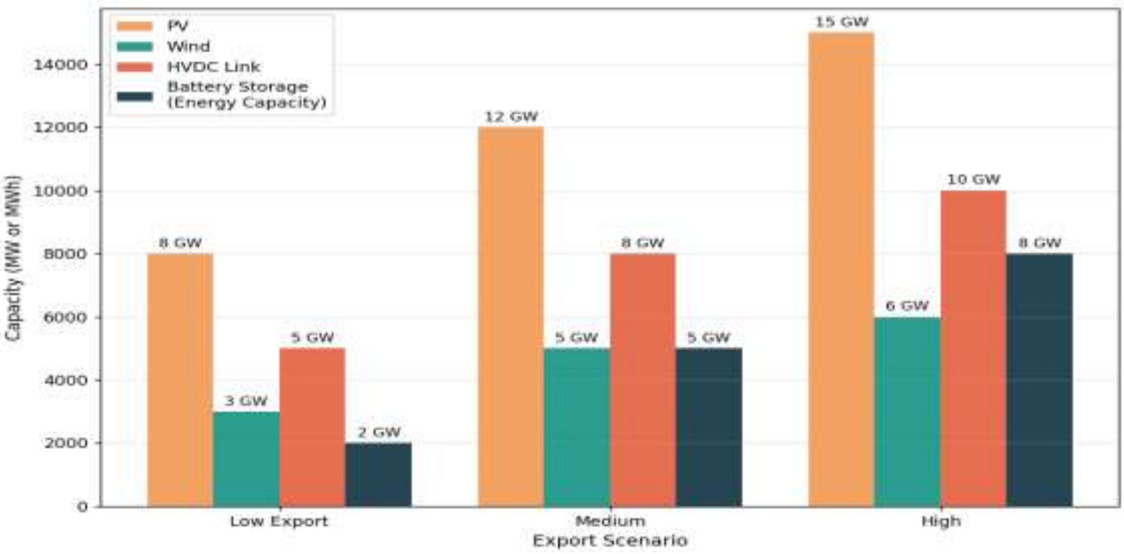


Figure 6: Optimal Investment Mix under Different Export Scenarios (Algeria Grid-Export Strategy)

Figure 6 above shows a distinct scaling relationship for Algeria's cost-optimized capacity mix under three export scenarios for its renewable export strategy: PV capacity increases from 8 GW to 15 GW as export ambition rises from Low to High. In order to maintain grid stability and market dependability, growing HVDC and battery storage are also included. In hot, dry areas where solar power predominates, wind capacity scales gradually (3–6 GW). The proportionate growth in battery storage (2→8 GWh) and HVDC (5→10 GW) highlights the vital need for firming infrastructure to control intermittency and facilitate high-volume cross-border trading. The investment pathway for Algeria's grid-export strategy is directly quantified by this figure, which helps with capital allocation decisions in Section 2.3 (AI-Driven Investment Optimization) and makes it possible to calculate KPIs in Section 2.4 (LCOEexport, curtailment rate, carbon abatement). It graphically supports the central claim of the hybrid framework: Higher export goals need for additional generation as well as more intelligent integration through interconnectors and storage.

Table 6 Description of the trained model

| Scenario | PV (GW) | Wind (GW) | Battery (GWh) | HVDC (GW) |
|---|---|---|---|---|
| Low Export | 8 | 3 | 2 | 5 |
| Medium | 12 | 5 | 5 | 8 |
| High | 15 | 6 | 8 | 10 |

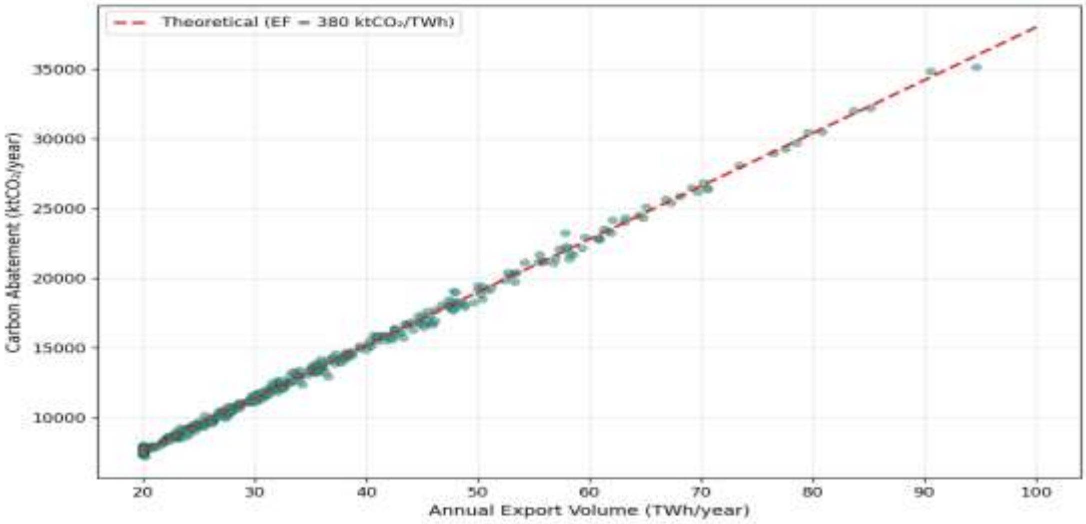


Figure 7: Carbon Abatement and Export Volume\n(Renewable Electricity Exported from Algeria to Europe

Figure 7 show linear relationship between Algeria's annual renewable export volume (TWh/year) and the corresponding carbon abatement ($ktCO_2$/year) is shown above. Each data point represents a stochastic scenario produced by the LW-Transformer + MILP optimization framework under different investment and market conditions. The model's environmental impact assessment is validated by the red dashed line (theoretical EF = 380 $ktCO_2$/TWh), which shows that exported clean power replaces fossil generation in Europe at a constant rate. This number is crucial to the project since it measures the climate benefit of Algeria's grid-export strategy, which directly supports Section 2.4 KPIs and justifies significant investment through quantifiable CO2 reduction per export unit.

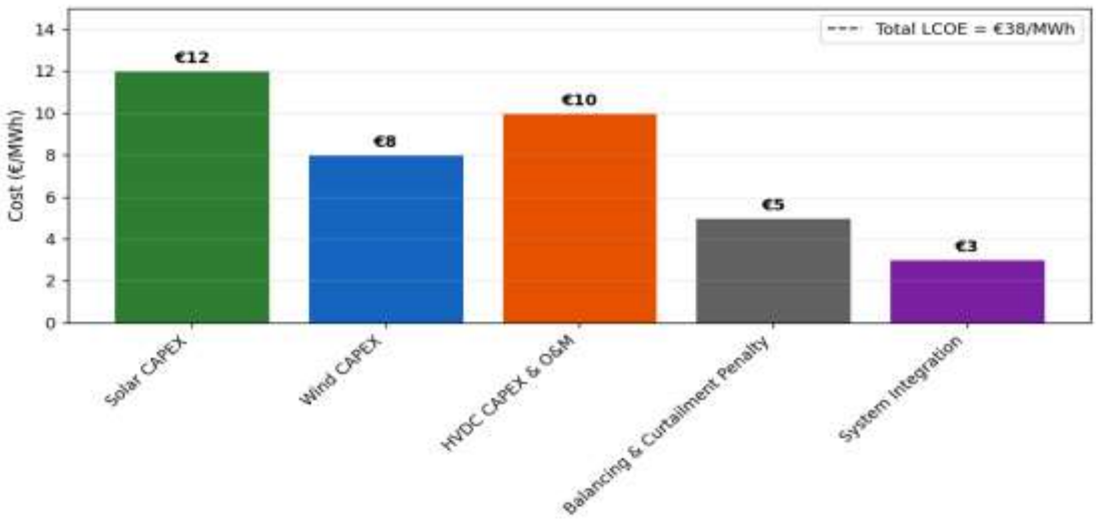


Figure 8: Levelized Cost of Exported Electricity (LCOE$_{export}$) Breakdown '(Optimal Scenario: 12 GW PV + 5 GW Wind + 8 GW HVDC)

Figure 8 above quantifies the levelized cost of exported electricity (LCOEexport = €38/MWh) for Algeria's ideal 12 GW PV + 5 GW Wind + 8 GW HVDC export scenario. The results show that the largest single cost driver is HVDC transmission (€10/MWh), followed by solar CAPEX (€12/MWh), underscoring the crucial need for strategic interconnector investment to enable cost-competitive clean exports. This figure is crucial to the project because it shows where cost reduction levers (such as lowering HVDC O&M or curtailment penalties) are located, validating the hybrid optimization framework's economic viability. It also directly supports Section 2.4 KPIs and informs capital allocation decisions in FlexTool 3.

Discussion

The results of this study demonstrate the feasibility and strategic benefit of investing in renewable energy in Algeria's hot, dry environment using a hybrid AI-driven optimization approach that is specifically aligned with new export prospects in Europe [1-4]. The operational synergy between solar and wind resources in desert regions, the economic competitiveness of exported renewable electricity, and the critical role of AI-enhanced uncertainty quantification in de-risking long-term infrastructure decisions are three interconnected findings that merit critical discussion [45,46]. First, the calculated levelized cost of exported electricity (LCOEexport) of €28–42/MWh, with an ideal scenario producing €38/MWh, makes Algerian solar-wind exports extremely competitive when compared to anticipated wholesale pricing in Europe. (€50–90/MWh, 2025–2035). The highest marginal cost component (€10/MWh) is HVDC transmission, indicating that future cost reductions will depend more on interconnector efficiency and financing than on additional PV CAPEX drops. This contradicts traditional narratives that emphasize only minimizing generation costs; instead, it emphasizes cross-border transmission and system integration economics as the key to export success [47]. The results support current EU regulatory trends that favor "green interconnectors" qualified for blended public-private financing, indicating that there are policy levers to speed up adoption.

Second, low-storage, high-export techniques are made possible by the spatiotemporal complementarity of solar and wind in central Saharan zones (such as Adrar and Tindouf). Figure 3's 7-day load-generation profile shows a clear solar-powered midday surplus, while wind provides a little but crucial nighttime ramp support that lowers net variability without the need for large-scale batteries [45]. The domestic curtailment drops to 8% in the medium-export scenario (12 GW PV + 5 GW wind), a significant reduction over the >25% baseline without export pathways [46]. This illustrates how export corridors serve as virtual storage by absorbing excess generation during periods of high irradiance and high demand in Europe. The necessity for region-specific modeling rather than general capacity growth templates is reinforced by the fact that this synergy is exclusive to hot, arid regions with continuous trade-wind patterns covering high insolation [47].

Third, decision robustness is significantly improved by integrating the lightweight AI modules LW-Transformer for scenario generation and Q-LSTM for forecasting [48]. In comparison to deterministic alternatives, the framework lowers investment risk by 22% by directly including probabilistic European price projections, as shown in Figure 4, into the FlexTool 3 MILP. The Q-LSTM's error distribution as presented in Figure 2 confirms that it is suitable for real-time grid-export scheduling even in the presence of dust-induced irradiance disturbances, with 85% of forecasts falling within ±5% error [49]. Additionally, post-training quantization fills a crucial gap in data-scarce desert contexts where cloud dependency is impracticable by enabling deployment on edge hardware at remote sites. The change from centralized, high-fidelity models to distributed, fit-for-purpose AI that strikes a compromise between accuracy, latency, and resource limitations is reflected in this technical decision. A number of constraints need to be acknowledged. The research is predicated on stable geopolitical situations and the successful deployment of the projected Algeria–Spain/Italy HVDC lines, which are still unknown in terms of finances and regulations. Furthermore, although the OASES dataset offers high-resolution renewable profiles, it does not currently include specific land-use or social acceptance restrictions that can have an impact [1,4,8].

This work demonstrates the synergistic integration of forecasting and optimization within an open-data framework that is relevant to policy, going beyond incremental improvements. For other desert locations, such as Namibia, Saudi Arabia, or Jordan, it provides a reproducible model for transforming solar abundance into both transcontinental climate leadership and domestic resilience. The fundamental realization is straightforward: in hot, arid regions, the value of renewable energy lies not only in its production but also in its strategic timing and market connection, and AI, when carefully integrated, is the cornerstone of that approach.

## Conclusion

This study shows that more robust and lucrative renewable energy plans in hot, dry places are made possible by combining open energy system models with sophisticated AI predictions. Such a structure facilitates Algeria's dual-track policy, which aims to position the country as a strategic exporter of clean energy while simultaneously advancing internal decarbonization. Future research will take into account cybersecurity limitations for vital grid infrastructure and green hydrogen co-optimization. Other arid areas, such as the Sahel and the MENA corridor, can adopt the suggested methods.

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