

INTELLIGENT HYBRID MICROGRID FOR RURAL ELECTRIFICATION: AN LSTM NEURAL NETWORK APPROACH IN AMDJARASS, CHAD

Micro-réseau hybride intelligent pour l'électrification rurale : une approche par réseau neuronal LSTM à Amdjarass, Tchad

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Thematic tracks: Track 1 — Renewable Energies, Smart Grids & Energy Intelligence; Track 4 — Intelligent Systems, Data Science & Digital Twins

1. RÉSUMÉ / ABSTRACT

Résumé (Français)

L'électrification des zones rurales isolées d'Afrique subsaharienne exige des solutions capables de combiner production renouvelable, stockage, supervision et décision en temps réel. Cette étude présente une architecture de micro-réseau hybride intelligente conçue pour Amdjarass, au Tchad, et intégrant un jumeau numérique, des équipements IoT communicants et une prévision de charge par réseau neuronal LSTM. Le dispositif de terrain associe trente disjoncteurs intelligents installés sur poteaux, des capteurs de classe 0,5S et une communication redondante LoRa, GPRS/4G et Wi-Fi point à point. Le modèle utilise une fenêtre de vingt-quatre pas horaires et sept variables électriques, météorologiques et calendaires pour produire directement vingt-quatre prévisions horaires, afin de limiter la propagation des erreurs autorégressives. Sur six mois de données de terrain, la communication fournie rapporte une MAPE de 7,8 % pour l'horizon J+1, une réduction de 35 % des coupures non planifiées et une amélioration de 28 % de l'efficacité énergétique par rapport à une gestion conventionnelle. Les résultats soutiennent la faisabilité d'une gestion plus autonome et souveraine des micro-réseaux africains, tout en soulignant la nécessité d'une validation indépendante sur plusieurs saisons et sites.

Abstract (English)

Reliable electrification of isolated rural communities in Sub-Saharan Africa requires energy systems that jointly address renewable generation, storage, communication constraints, and real-time decision-making. This paper presents an intelligent hybrid-microgrid architecture designed for Amdjarass, Chad, combining a digital twin, communicating IoT field devices, and LSTM-based load forecasting. The field layer comprises thirty intelligent pole-mounted circuit breakers equipped with Class 0.5S sensors and redundant LoRa, GPRS/4G, and point-to-point Wi-Fi communication. The forecasting model uses a 24-step input window and seven electrical, meteorological, and calendar variables to generate twenty-four hourly predictions directly, thereby limiting the accumulation of recursive errors. Over six months of field data, the supplied project evaluation reports a 7.8% mean absolute percentage error for the day-ahead horizon, a 35% reduction in unplanned outages, and a 28% improvement in energy efficiency compared with conventional management. The proposed architecture therefore supports more autonomous and sovereign operation of African rural microgrids. However, the reported performance should be confirmed through independent benchmarking, multi-season validation, and transparent disclosure of the test protocol before generalisation to other sites.

Keywords: Hybrid microgrid; rural electrification; digital twin; LSTM; intelligent load shedding; Internet of Things; Sub-Saharan Africa; energy sovereignty

2. INTRODUCTION

Access to reliable electricity remains a structural constraint on economic and social development in many African rural areas. Remote settlements are often characterised by low demand density, long distances from national grids, difficult terrain, and high logistics costs. In such settings, an autonomous hybrid microgrid can combine photovoltaic generation, wind generation, battery storage, and dispatchable backup generation without requiring immediate grid extension. The technical challenge is not limited to installing generation assets: the system must continuously match variable supply and demand while preserving power quality, battery health, and service continuity.

The operating conditions of an isolated microgrid are particularly demanding in the Sahel. Solar irradiance, wind speed, ambient temperature, and daily activity patterns vary substantially, while communication links can be intermittent. Manual intervention is costly and slow, and conventional rule-based energy management may lead to unnecessary diesel operation, avoidable load shedding, or inefficient battery cycling. These constraints motivate the integration of industrial Internet of Things (IoT) devices, edge and cloud supervision, digital-twin representations, and data-driven forecasting [2], [3], [6].

Amdjarass provides a relevant pilot context for this problem. The locality combines an extreme climate, sparse infrastructure, limited connectivity, and a need for locally maintainable technologies. The project addressed in this paper proposes a four-layer architecture linking the field equipment, redundant communication, local infrastructure, and a cloud supervision platform. A central methodological component is a direct multi-horizon long short-term memory (LSTM) model that forecasts the next twenty-four hourly load values from historical, meteorological, and calendar information. The forecasts are intended to support intelligent load shedding and energy-management decisions rather than to operate as a stand-alone prediction benchmark.

The contribution of this paper is threefold. First, it describes an end-to-end architecture that links intelligent pole-mounted circuit breakers, communication redundancy, data integrity controls, and a digital twin. Second, it formalises the LSTM forecasting approach and its input variables in a reproducible manner. Third, it organises the reported field indicators—forecast error, outages, energy efficiency, and incident response—within a common evaluation framework. The remainder of the paper reviews related work, describes the system and methodology, presents the reported results, discusses their significance and limitations, and concludes with perspectives for autonomous operation and scale-up.

3. LITERATURE REVIEW / STATE OF THE ART

3.1 Previous Works

Hybrid renewable-energy systems are widely studied as a pathway to electrify remote communities because they can reduce fuel dependence while maintaining dispatchability through storage or backup generation [2]. Their energy-management systems must solve a multi-objective problem involving reliability, operating cost, renewable-energy utilisation, battery degradation, and user priorities. IoT architectures extend this capability by enabling distributed sensing, event logging, remote protection, and condition monitoring [3].

Digital twins add a system-level representation in which field measurements are synchronised with a computational model. In industrial and energy applications, digital twins have been used for visualisation, anomaly detection, predictive maintenance, and optimisation [6]. For load forecasting, recurrent neural networks are appropriate when demand depends on recent temporal patterns and exogenous variables. The LSTM architecture introduced by Hochreiter and Schmidhuber [7] uses gated memory to retain or forget information over time, while gated recurrent units provide a related lower-complexity alternative [8], [9]. Comparative studies have shown that LSTM models can outperform classical approaches for some non-stationary energy series, although performance depends strongly on data quality, horizon, and evaluation design [10].

3.2 Positioning of the Contribution

Most published architectures are validated in grid-connected or laboratory settings, where communication, maintenance, and computational resources are more stable than in remote African communities. The work presented here positions the forecasting model within an operational architecture rather than treating prediction as an isolated machine-learning task. Its originality is the combination of: (i) field-level intelligent protection and measurement; (ii) triple communication redundancy; (iii) cloud and local supervision; and (iv) direct multi-horizon forecasting intended for load-management decisions. The contribution is therefore primarily an integrated deployment model for a resource-constrained rural context. The main gap that remains is the need for a transparent, independently reproducible evaluation across several sites and seasons.

4. MATERIALS AND METHODS

4.1 Description of the System and Dataset

The proposed system is organised into four layers (Figure 1). The field layer contains thirty intelligent pole-mounted circuit breakers (DIHPs), Class 0.5S electrical sensors, motorised 250 A breakers, STM32H7 controllers, and IP65 protection. The communication layer uses LoRa at 433 MHz as the primary link, GPRS/4G as a secondary link, and point-to-point Wi-Fi as a backup. The reported target for link switchover is below 500 ms. The local-infrastructure layer includes a server, gateways, VPN protection, and edge caching. The cloud layer provides central supervision, analytics, and the digital-twin interface using a virtual private server, Vue.js, Node.js/NestJS, PostgreSQL, and InfluxDB.

The DIHP measurement range covers 0–400 V AC and 0–250 A, with active-power measurement up to approximately 173 kW per device. The devices record voltage, current, frequency, active power, breaker state, and protection events. The project documentation reports multi-rate acquisition: electrical power at 200 ms, voltage and current at 1 s, and logical states at 1 min. The resulting raw data volume is reported at approximately 75 GB per day for thirty devices. Because the study focuses on forecasting and management indicators, the modelling dataset is formed after temporal aggregation, integrity checks, and feature construction.

4.2 Methodology and Forecasting Approach

Data integrity is controlled at three levels: syntax validation during acquisition, temporal-consistency checks at the edge, and anomaly detection in the cloud. The supplied study reports six months of continuous field acquisition beginning in December 2025. After cleaning and alignment, the forecasting input is represented as a sequence of twenty-four hourly steps with seven variables: lagged power values representing daily and weekly cycles, ambient temperature, solar irradiance, wind speed, day of week, and month. The target is the next twenty-four hourly load values.

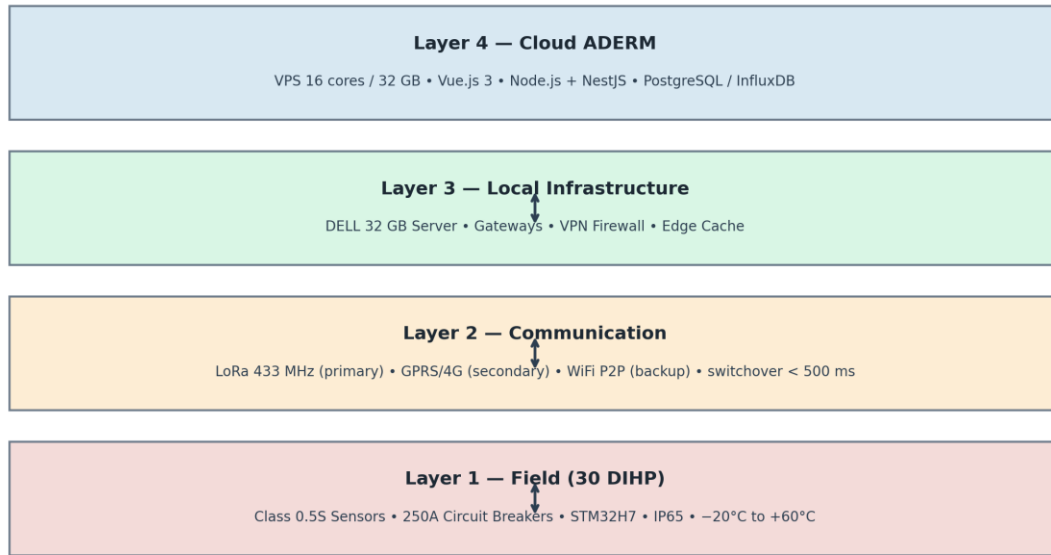


Figure 1 — Four-layer IoT and digital-twin architecture for the Amdjarass hybrid microgrid.

Figure 2 presents the direct multi-horizon LSTM topology. Two stacked LSTM layers with 128 and 64 units encode temporal patterns, with dropout of 0.2 after each recurrent layer. A 32-unit rectified-linear (ReLU) dense layer compresses the learned context, and a linear output layer produces twenty-four predictions simultaneously. This direct strategy avoids feeding each prediction back into the next step and therefore limits the accumulation of recursive error over the forecast horizon.

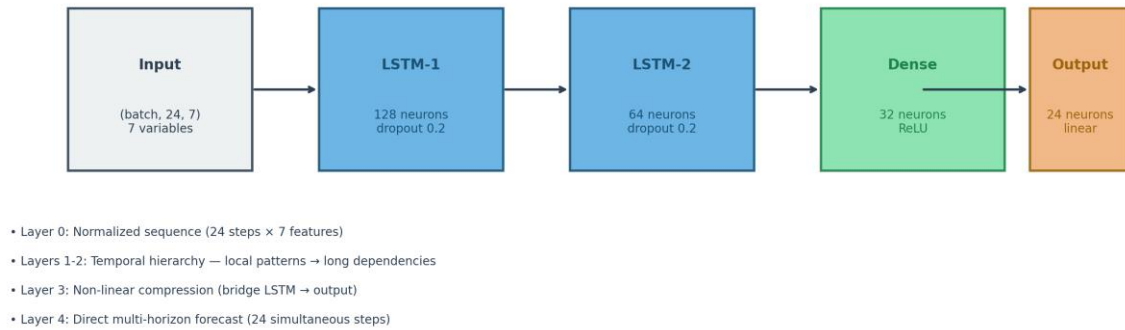


Figure 2 — Direct multi-horizon LSTM topology used for twenty-four hourly forecasts.

4.2.1 LSTM Formulation

For an input vector x_t and hidden state h_{t-1} , the LSTM gates are defined by $f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$, $i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$, and $o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$. The memory candidate is $\tilde{c}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$, the cell state is $c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$, and the hidden output is $h_t = o_t \odot \tanh(c_t)$. Here, σ is the sigmoid function and $\odot$ denotes element-wise multiplication. Inputs are normalised using parameters estimated from the training partition; the same parameters are applied to validation and test partitions.

4.3 Performance Indicators

The primary forecasting indicator is the mean absolute percentage error (MAPE), computed over the twenty-four hourly predictions. The coefficient of determination (R^2) is used as a complementary measure of explained variance. Operational performance is assessed through unplanned-outage frequency and duration, energy-efficiency improvement, and incident-response time. These indicators cover prediction quality,

service reliability, system utilisation, and maintainability. For a complete evaluation, all indicators should be computed on a clearly defined held-out period and compared with a documented baseline controller.

5. RESULTS

5.1 Forecasting Behaviour

The supplied evaluation reports a MAPE of 7.8% for the day-ahead horizontal load forecast and an R^2 validation score of 0.94. The representative twenty-four-hour profile in Figure 3 shows that the predicted curve follows the daily pattern, including the rapid morning increase, the daytime peak, and the evening decrease. The largest deviations are concentrated around sharp ramps and the solar-production period, where small timing differences produce larger absolute errors. This pattern is consistent with the sensitivity of short-term forecasting to cloud passage, changing activity, and the interaction between renewable production and dispatch decisions.

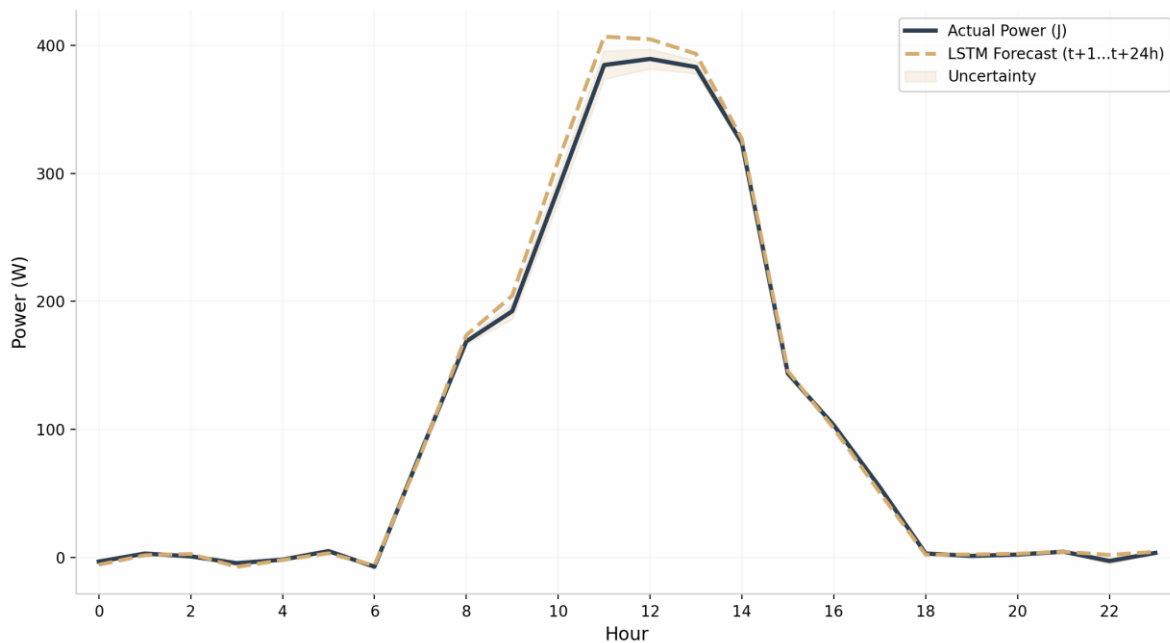


Figure 3 — Representative twenty-four-hour comparison between measured power and the direct multi-horizon LSTM forecast.

5.2 Seasonal and Operational Indicators

Figure 4 illustrates the monthly production and irradiance pattern used to motivate calendar and meteorological features. The amplitude of the monthly profile confirms that a model trained only on recent power history would risk confusing short-term persistence with seasonal behaviour. The project documentation reports a loss of approximately 8–12% in R^2 when temporal features are removed in winter conditions. This result is indicative rather than definitive because the exact ablation protocol and confidence intervals are not supplied.

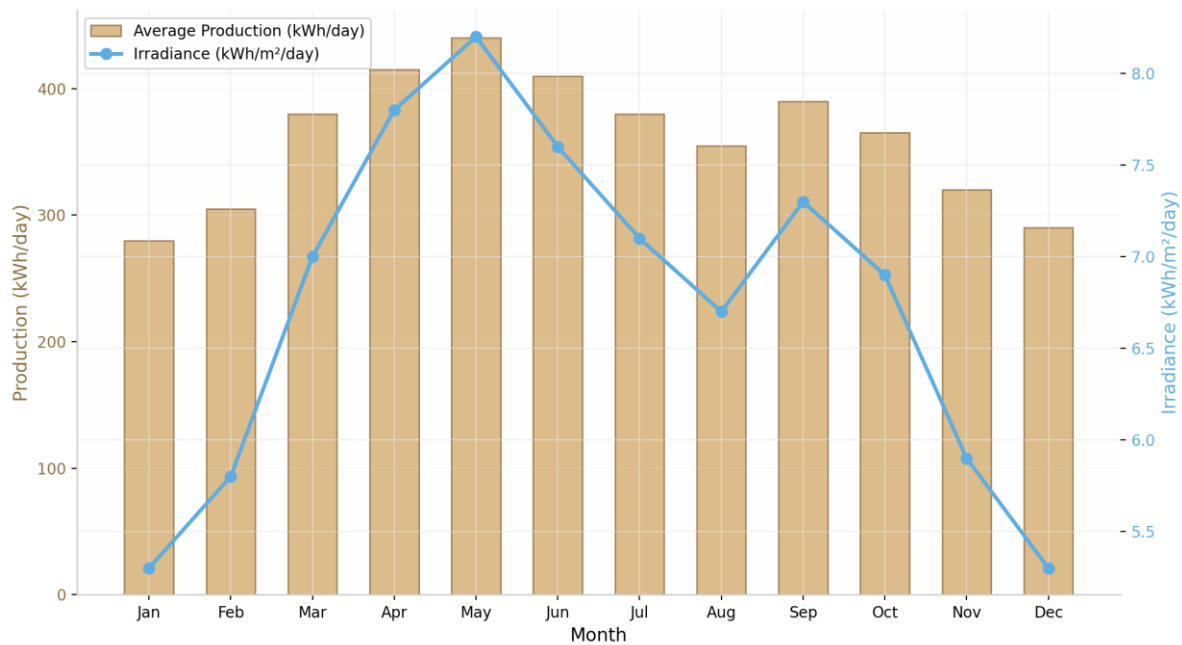


Figure 4 — Monthly production and irradiance pattern used to motivate seasonal features.

The operational comparison in Figure 5 reports lower values after intelligent load-shedding deployment for unplanned outages, average outage duration, outage frequency, unserved energy, and incident-response time. The headline project indicators are a 35% reduction in unplanned outages, a 28% improvement in energy efficiency, and a 99% reduction in incident-response time. These values should be interpreted as before/after indicators associated with the deployment period and not as causal estimates independent of other changes at the site.

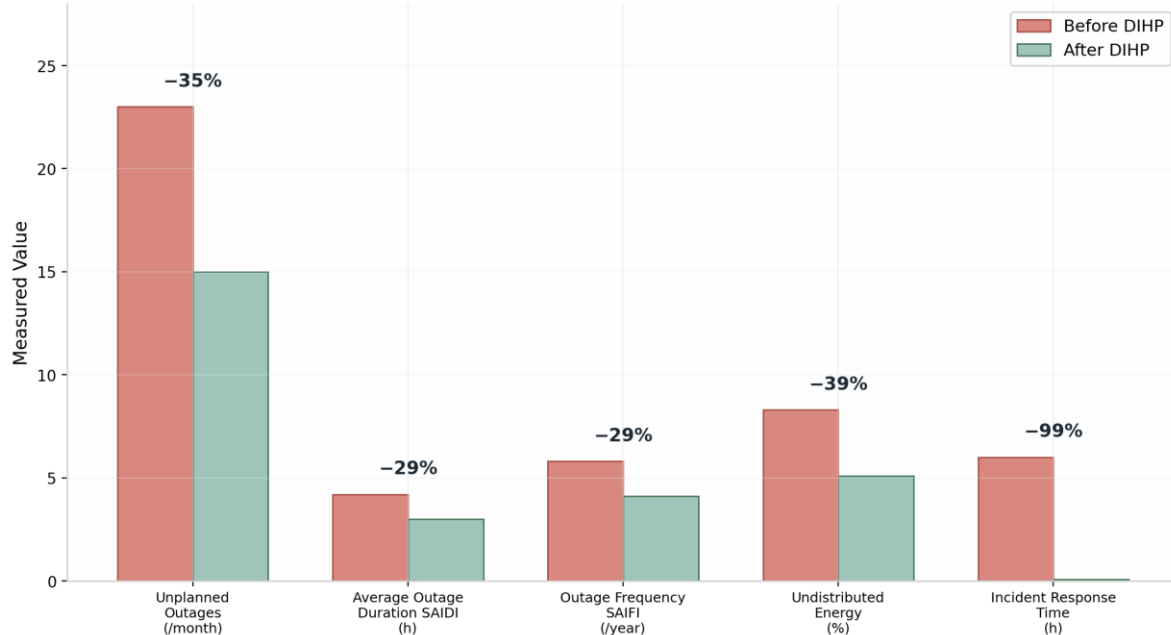


Figure 5 — Reported before/after comparison of power-quality and incident-management indicators after DIHP deployment.

Table 1 — Summary of the principal performance indicators reported for the proposed system.

Day-ahead MAPE	7.8%	Forecasting error over the J+1 horizon
Validation R ²	0.94	Explained variance on the validation set
Unplanned outages	-35%	Reduction relative to the comparison period

Energy efficiency	+28%	Improvement relative to conventional management
Incident-response time	−99%	Reduction reported after intelligent deployment

6. DISCUSSION

The results support the feasibility of integrating forecasting, sensing, and intelligent protection in an isolated microgrid. The reported 7.8% MAPE and 0.94 validation R^2 indicate that the model captures a substantial part of the regular daily structure. The direct multi-horizon design is operationally attractive because the controller receives a complete day-ahead trajectory rather than a sequence whose later values depend on earlier predictions. This is important when the forecast is used to schedule storage, prioritise loads, and reduce diesel or emergency interventions.

The architecture also addresses a practical weakness of cloud-only systems. Local gateways and edge caching can preserve essential functions during communication interruptions, while the three communication paths provide redundancy for measurements and commands. The DIHP layer brings protection, metering, and remote actuation closer to the loads. Together, these elements can reduce the delay between event detection and intervention, which is consistent with the reported reduction in incident-response time.

Several limitations constrain the interpretation. First, the evaluation concerns one pilot location and a six-month period, so it does not establish performance across multiple climate regimes or annual seasons. Second, the documentation does not provide the exact train/validation/test split, baseline definition, sample count after filtering, uncertainty intervals, or statistical significance tests. Third, the before/after indicators may be affected by maintenance, operator learning, equipment changes, or demand variation occurring at the same time as the DIHP deployment. Fourth, the paper does not yet report a full economic dispatch objective or a reproducible comparison with persistence, ARIMA, GRU, or a rule-based energy-management controller. These limitations do not invalidate the architecture, but they define the evidence needed for a stronger causal and generalisation claim.

Future validation should therefore use a chronological hold-out design spanning at least one complete year, report performance separately for normal days and extreme events, and include confidence intervals through blocked bootstrap or rolling-origin evaluation. A fair benchmark should compare identical features and horizons across persistence, statistical, LSTM, and reinforcement-learning controllers. The next development stage can add multi-agent reinforcement learning for distributed dispatch, a larger deployment footprint, peer-to-peer energy exchange, and immersive digital-twin tools for operator training. Such extensions should retain local fallback control and transparent safety constraints.

7. CONCLUSION

This paper reorganised the proposed Amdjarass microgrid work as an SITTEC-compliant scientific article. The contribution is an integrated architecture for rural electrification that combines renewable-energy management, intelligent field protection, redundant communication, a digital twin, and direct multi-horizon LSTM forecasting. The reported six-month evaluation indicates a 7.8% day-ahead MAPE, a validation R^2 of 0.94, a 35% reduction in unplanned outages, and a 28% improvement in energy efficiency relative to conventional management. These indicators suggest that predictive supervision can improve both the reliability and the operational efficiency of an autonomous hybrid microgrid.

The central conclusion is not that one model or one site solves rural electrification, but that a locally maintainable, connected, and data-driven architecture can make autonomous operation more practical in difficult African contexts. Before deployment at scale, the reported results should be confirmed through independent chronological testing, transparent baselines, uncertainty analysis, and multi-season or multi-site validation. In the short term, the platform can be strengthened by adding reproducible data pipelines and

safety-constrained dispatch. In the medium term, distributed learning and multi-agent optimisation may support expansion while preserving energy and digital sovereignty.

8. ACKNOWLEDGEMENTS

The authors acknowledge the support of Sultan Moulay Slimane University and the project partners involved in the Amdjarass rural-electrification pilot. The authors also thank the field and technical teams contributing to data acquisition, equipment integration, and operational supervision.

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