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An Integrated LSTM and RNN Forecasting with Genetic Algorithm Scheduling and Reinforcement Learning Control for Smart Grid Demand Prediction, Peak Shaving, and Distribution Loss Minimization

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Abstract- Modern electricity networks face increasing complexity due to renewable variability, electrification, irregular consumer behavior, and rising peak loads, which collectively intensify the need for accurate short term forecasting and intelligent load management. This paper presents a hybrid framework that couples deep learning based energy demand prediction with evolutionary day ahead load redistribution. Using more than 6,800 hourly consumption records from 2023, the study applies temporal alignment, anomaly treatment, interpolation, feature engineering, and sliding window transformation to construct supervised learning sequences for forecasting. The Long Short Term Memory model achieves the best predictive performance with MAE of 16.19 kWh, RMSE of 20.36 kWh, and MAPE of 86.58%, outperforming the Recurrent Neural Network with MAE of 16.64 kWh and RMSE of 20.85 kWh, while the RNN's slightly lower MAPE of 82% is linked to sensitivity under very low night time loads. For load management, daily profiles are clustered via K Means, and 20% of shiftable load is redistributed within a 2 hour window using a Genetic Algorithm. The optimization runs for 120 generations with a population of 60 candidate schedules and produces a noticeable reduction in peak demand and operational cost while maintaining total daily energy consumption. Overall, the framework demonstrates stable convergence, lower performance variance, and practical peak shaving capability for smart grid decision support, with clear extension paths to multi horizon forecasting and real time pricing integration. (smart grid, energy forecasting, LSTM, RNN, genetic algorithm)

I. INTRODUCTION

The global power sector is rapidly transforming as demand rises with population growth, urbanization, and technological expansion, while sustainability pressures expose weaknesses in conventional centralized grids. Smart grids address these pressures by embedding digital communication, automation, and analytics into the grid, enabling two way utility consumer interaction and improved reliability, efficiency, and renewable integration. However, smart grid operation depends on accurate forecasting, demand side management, and optimization, tasks where artificial intelligence and deep learning can extract patterns from high volume energy data and drive intelligent decisions.

Despite this promise, a central practical gap remains, many distribution systems still struggle to match supply and demand, conventional forecasting fails to capture nonlinear consumption dynamics, and peak periods amplify voltage fluctuations and losses. This paper therefore targets an integrated solution that does not stop at prediction alone, it connects forecasting to actionable day ahead load shifting through evolutionary optimization, and it further considers robustness under conditions representative of fragile grids.

Hybrid deep learning forecasting using LSTM and RNN, with benchmarking against classical models and additional evaluation dimensions like peak load error.

Genetic Algorithm based load shifting with explicit real world constraints, 20% shiftable load and 2 hour maximum shift window.

Reinforcement learning distribution agent evidence, reporting a 6.5% distribution loss reduction relative to heuristic baselines.

Transferability and robustness simulation concept under Sub Saharan like instability, using mathematical perturbations such as voltage sags on test data.

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II. REVIEW AND RESEARCH GAPS

Prior studies show that deep learning, especially LSTM architectures, often outperforms classical statistical models for load forecasting and better captures nonlinear consumption patterns, enabling improved load balancing and reliability, yet resilience under extreme grid conditions is frequently under explored. Similarly, demand response and scheduling approaches using reinforcement learning can reduce peak hour costs and adapt to price and load changes, but real world deployment and robustness under complex conditions remain common limitations.

Genetic Algorithms have also been applied for dispatch optimization and microgrid scheduling, achieving meaningful cost and emission reductions, but many studies rely on manual parameter tuning that limits scalability and generalization. In addition, broader reviews highlight persistent barriers such as interpretability and standardization challenges, plus privacy and communication overhead issues in federated and distributed learning settings.

Gap addressed by this paper: the literature often treats forecasting and optimization as separate layers, or evaluates models under stable conditions only. This paper based approach unifies forecasting with constrained day ahead load shifting, adds comparative benchmarking, and explicitly introduces a transferability simulation for fragile grid behavior.

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III. METHODOLOGY

A. Dataset and features

The study uses an hourly dataset with 6,806 records and multi dimensional building and grid related features including historical energy consumption, HVAC related variables, occupancy indicators, local energy production, grid stability score, solar irradiance, and peak demand reduction indicator among others. The study also frames this as a curated feature rich dataset across 39 building and grid level features.

	Timestamp	Building Type	Energy Consumption (kWh)	Temperature (°C)	Humidity (%)	Occupancy Rate (%)	Lighting Consumption (kWh)	HVAC Consumption (kWh)	Energy Price ($/kWh)	Carbon Emission Rate (g CO2/kWh)	...	Energy Savings Target (%)	Room-Level Energy Consumption (kWh)
0	2018-01-01 00:00:00	Residential	74.679912	31.357437	62.472886	49.293544	9.892054	9.073339	0.053297	341.764320	...	16.208574	13.341547
1	2018-01-01 01:00:00	Industrial	46.592761	30.229121	63.067770	65.039117	11.063696	26.487881	0.019031	427.270057	...	16.081108	11.750894
2	2018-01-01 02:00:00	Commercial	58.836657	19.182581	65.030972	-16.599946	0.582297	10.385565	0.060282	278.064969	...	17.463861	24.297381
3	2018-01-01 03:00:00	Residential	53.586516	16.700048	67.405643	27.398152	3.580005	8.199913	0.209318	691.906306	...	14.132527	24.586379
4	2018-01-01 04:00:00	Residential	37.800448	29.620051	55.069770	74.220380	17.823608	12.268133	0.225335	620.526286	...	20.960512	24.482306

Figure 1 Figure 3.3: Top Five (5) Rows of the southern California consumption dataset

B. Preprocessing and supervised transformation

Your pipeline includes temporal alignment, anomaly treatment, interpolation, feature engineering, and sliding window transformation to convert time series into supervised sequences for deep learning.

Let the multivariate input at hour (t) be $(x_t \in \mathbb{R}^d)$, then with lookback window (L):

$$X_t = [x_{t-L+1}, x_{t-L+2}, \ldots, x_t], \quad y_{t+1} = \text{Energy Consumption}_{t+1}$$

This supports day ahead or one step ahead forecasting depending on how (y) is defined.

C. Forecasting models

Recurrent Neural Network (baseline deep model)

$$h_t = \phi(W_x x_t + W_h h_{t-1} + b_h), \quad \hat{y}_t = W_y h_t + b_y$$

where$(\phi(\cdot))$ is a nonlinear activation.

Long Short Term Memory (primary deep model)

Using standard gate equations:

$$\tilde{c}t = \tanh(W_c[x_t, ht-1] + b_c), \quad c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}t$$

$$o_t = \sigma(W_o[x_t, ht-1] + b_o), \quad h_t = o_t \odot \tanh(c_t)$$

The results indicate LSTM produced the best predictive performance relative to RNN on the 2023 dataset.

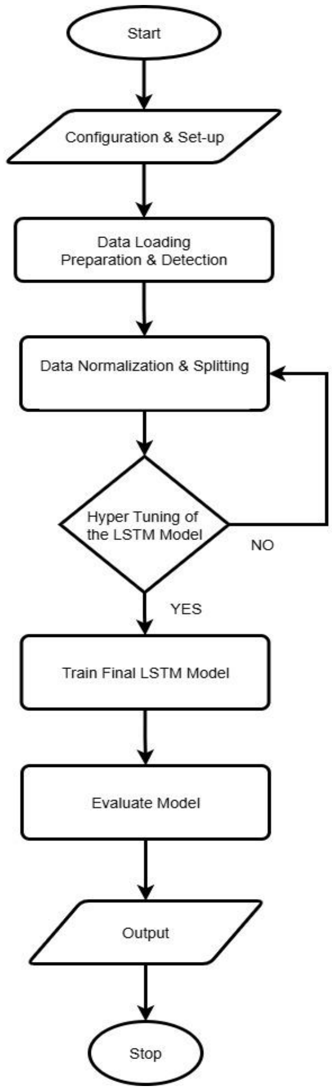

Figure 2: Model architecture diagram, input window, stacked LSTM, dense output, aligned with deep learning pipeline.

D. Load profiling via K Means clustering

Daily load shapes are clustered using K Means before optimization, to group similar day patterns and improve schedule manipulation realism.

$$\min_{\mu_k k=1^K} \sum i = 1^N \min_k |p_i - \mu_k|_2^2$$

where (p_i) is a daily profile vector and (μ_k) is centroid (k).

E. Genetic Algorithm load shifting optimization

The GA shifts 20% of loads within a maximum of 2 hours, and balances peak shaving with cost reduction using peak weight 0.5 and cost weight 0.5.

A practical objective consistent with your parameter definitions can be expressed as: $\min_s; J(s) = w_p \cdot \max_t(L_s(t)) + w_c \cdot \sum_t \pi(t), L_s(t)$

Subject to:

Shift constraint: $(|\Delta t| \leq 2)$ hours for shiftable items

Shiftable ratio: only 20% of total load is movable

The GA runs 120 generations with population size 60 candidate schedules.

Recommended Figure 3 (from thesis): "GA load shifting" plot with base curve vs optimized curve, as already described in Chapter 4.

F. Evaluation metrics

For predicted values (\hat{y}i) and true values (y_i):

$$\text{MAE} = \frac{1}{n} \sum i = 1^n |y_i - \hat{y}i|, \quad \text{RMSE} = \sqrt{\frac{1}{n} \sum i = 1^n (y_i - \hat{y}i)^2}$$

$$\text{MAPE} = \frac{100}{n} \sum i = 1^n \left| \frac{y_i - \hat{y}_i}{y_i} \right|, \quad R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

This study explicitly uses RMSE, MAE, MAPE, and (R^2) for benchmarking and model evaluation.

G. Robustness simulation under Sub Saharan conditions

Because high resolution Nigerian grid data is limited, the study perturbs the Southern California test set to emulate fragile grid behavior and tests robustness under instability conditions. One explicitly stated perturbation is voltage instability introduced by reducing the voltage feature by 15% for 10% of timestamps to simulate brownouts.

IV. RESULTS AND DISCUSSION

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A. Forecasting performance, LSTM vs RNN

The LSTM achieved MAE 16.19 kWh, RMSE 20.36 kWh, and MAPE 86.58%, outperforming the RNN in MAE and RMSE, while the RNN's lower MAPE is explained by sensitivity to very low night time loads. Practically, MAE and RMSE are more operationally useful for grid scheduling because they penalize absolute deviations that directly translate into dispatch and reserve errors.

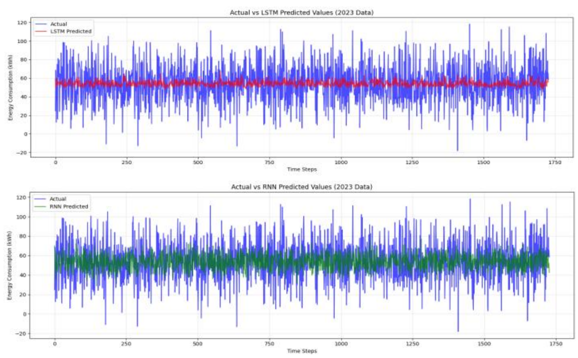

Figure 4: Actual vs predicted curves for both LSTM and RNN,

B. Benchmarking against classical models and peak load error

Our study includes a comparative evaluation table showing error, (R^2), and peak load error across multiple models. In that benchmark, Gradient Boosting and MLP report stronger scores than linear regression and random forest, and peak load errors range from 12.3% for linear regression down to 7.8% for MLP. The RL distribution agent reports a 6.5% loss reduction.

Model	MAE (kWh)	RMSE (kWh)	R^2 Score	Peak Load Error (%)
Linear Regression	0.15	0.22	0.72	12.3
Random Forest	0.12	0.18	0.81	9.1
Gradient Boosting	0.11	0.17	0.83	8.7
MLP Neural Network	0.10	0.16	0.86	7.8
RL Distribution Agent	N/A	N/A	N/A	6.5 (loss reduction)

Table 1: Benchmark summary

C. Genetic Algorithm peak shaving and schedule reshaping

The GA successfully reduces a dominant peak at hour 15 from 110 kWh to 85 kWh, which is a reduction of (25/110 = 0.2273), approximately 22.7% peak shaving at the highest hour. To preserve total daily energy, the algorithm redistributes part of the demand into adjacent hours, for example increasing hour 14 from 59 kWh to 82 kWh, which is consistent with constrained shifting behavior.

The GA parameters reinforce realism, only 20% of loads are shiftable, and shifting is capped at 2 hours, preventing impractical long deferrals. The Study also reports that the optimization completed 120 generations with population size 60 and produced noticeable reduction in peak demand and operational cost while keeping total daily energy consumption stable.

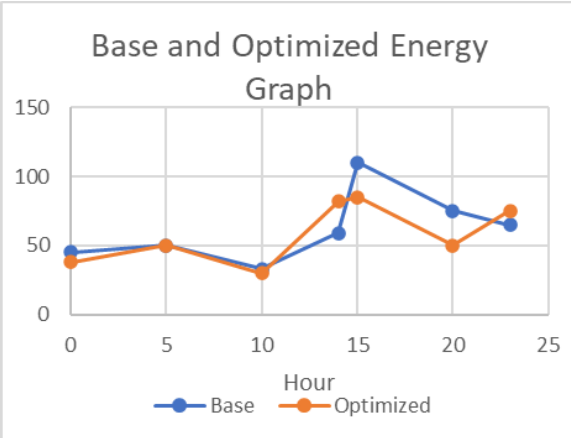

Figure 5: Base vs optimized hourly bar or line chart to visualize the hour by hour redistribution.

D. Robustness and transferability insight

The robustness simulation introduces explicit voltage instability patterns, which is a direct nod to the operational reality of fragile grids, and the methodology positions the framework as transferable even when local high resolution data is absent. In a publication, this is a defensible and practical contribution, it acknowledges constraints, but still tests behavior under a controlled stress model rather than claiming unrealistic deployment readiness.

V. CONCLUSION

This paper developed an integrated smart grid decision support framework that unifies short term demand forecasting with constrained day ahead load shifting. Using an hourly 2023 dataset of more than 6,800 records, the LSTM model achieved superior predictive accuracy relative to an RNN in MAE and RMSE, establishing it as the preferred forecasting core for operational planning. On the optimization layer, a Genetic Algorithm redistributed 20% of shiftable demand within a 2 hour window and demonstrated tangible peak shaving behavior, including a 22.7% reduction at the dominant peak hour while maintaining comparable daily energy totals. Comparative benchmarking further supported the value of advanced learning models through reduced peak load error, and the RL distribution agent reported a 6.5% loss reduction, reinforcing the wider case for learning driven grid intelligence. Finally, the robustness simulation under Sub Saharan like voltage instability strengthens the argument for transferability into resource constrained contexts.

Forward looking extension (paper ready): multi horizon forecasting, cross regional validation, spatial modeling, and coupling the GA schedule with real time tariff signals.

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