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Neural Network Systems for Advanced Energy Harvesting in Microgrids

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Abstract: Microgrids require sophisticated techniques for renewable energy management systems because they integrate more renewable sources into their networks. The study investigates neural network methods specifically hybrid CNN-LSTM models which help maximize energy collection in microgrids. The preprocessing methodology incorporates three key steps starting with energy data normalization followed by application of denoising filters for enhancing data quality and final execution of temporal dataset synchronization to improve reliability. The Recursive Feature Elimination method selects features from which RFE identifies key parameters affecting both energy output and utilization metrics. The CNN-LSTM combination uses convolutional layers to extract spatial characteristics while also leveraging long short-term memory units to detect temporal patterns within energy datasets. The developed system produces better forecasting precision alongside optimized system performance which leads to improved energy distribution and diminished energy loss. The developed solution provides scalable interpretation capabilities to manage microgrid energy systems for the advancement of sustainable efficient energy platforms.
Keywords- Neural networks, energy harvesting, microgrid optimization, CNN-LSTM, feature selection, renewable energy, smart grid.

INTRODUCTION

The quick growth of solar and wind energy systems has boosted the demand for microgrid systems to improve both energy harvesting and distribution processes. Microgrids function as small-scale electrical systems to provide reliable energy service and promote collective power grid distribution while maximizing resources throughout distributed networks. The energy distribution unpredictability of renewable sources creates challenges for managers who aim to improve energy collection performance. Neural network-based artificial intelligence models present advanced solutions that address important challenges during energy harvesting operations in microgrids [1].This investigation demonstrates how hybrid CNN-LSTM models help increase microgrids' energy harvesting efficiency through their implementation. The combination of CNNs and LSTMs performs optimally for time-series forecasting and real-time energy optimization through their strengths in spatial and temporal dependency extraction from energy data respectively. The effectiveness of neural network models depends significantly on receiving high-quality input data and making appropriate feature selections. A structured preprocessing pipeline acts as the proposal to enhance data quality for deep learning model training. The preprocessing sequence starts by normalizing energy data so different energy sources show consistent readings and minimize variations [2]. The processing technique becomes vital because energy consumption and generation patterns exhibit diverse characteristics because of environmental factors and grid requirements. The normalization process finishes before denoising filters remove disturbances and irregularities from sensor information [3]. Smart meter energy measurements along with IoT sensor data face signal degradation because of environmental factors which makes the data vulnerable to errors yet denoising strategies empower prediction accuracy

[4].The reliability of the model enhances through temporal energy data synchronization. The data alignment process among various energy sources operating at different timescales results in correct parameter interrelations between input datasets. Data synchronization acts as a preventive measure to stop model performance degradation from occurring. Recursive Feature Elimination (RFE) acts as the feature selection process to determine the key variables that affect energy harvesting performance through systematic evaluation. RFE applies feature reduction methods to eliminate redundant elements which results in more effective and accurate performance of the CNN-LSTM model [5].The trained CNN-LSTM hybrid model operates on the dataset after refinement to achieve better energy harvesting results in microgrid systems. Using deep learning on energy forecasting allows microgrid systems to distribute energy resources more efficiently while reducing their energy losses and establishing better stability across the system. The research contributes to smart energy management system development which creates advanced adaptive microgrid infrastructure solutions.

RELATED WORKS

The Neural networks have become increasingly important tools for managing energy within microgrids during the recent years. Different studies have investigated the use of machine learning methods together with deep learning techniques to perform energy forecasting and execute load balancing functions and optimization processes [6]. The system needs an advanced robust scheme to address the data noise together with feature selection and real-time energy optimization requirements. This section compiles literature analysis regarding preprocessing techniques and neural networks for advanced energy harvesting that enhances performance in microgrids.Multiple research project works demonstrate that processing data before use leads to better performance in machine learning energy forecasting models. Many researchers apply normalization techniques for energy data standardization purposes to solve differences among various energy production and consumption sources [7]. Research demonstrates that the deep learning models used in microgrid systems function better when using min-max normalization as well as Z-score standardization. Engineers use noise filtering methods including wavelet transforms and Kalman filters to eliminate sensor data inconsistencies and outliers making the predictive signals more reliable.
Recent investigations address the essential issue of temporal synchronization in their research. Accurate forecasting requires the alignment of datasets since microgrids operate with multiple energy sources whose operation patterns differ. Energy data temporal consistency is achieved through the application of time-series interpolation techniques and the dynamic time warping (DTW) method. The methods decrease prediction errors by keeping the proper sequence of energy variation dynamics across the time frame [8].
Feature selection operates as a critical component that improves both computational efficiency and prediction accuracy within energy harvesting systems. The microgrid energy field adopts Recursive Feature Elimination (RFE) as its leading approach to eliminate unnecessary features and maintain energy production and consumption variables of significance. The implementation of RFE before deep learning model training results in performance enhancement alongside faster processing which makes it an appropriate method for microgrid applications.Microgrid energy optimization applications have used extensive neural network-based models for their power optimization applications. Hybrid CNN-LSTM neural models became popular within the last few years because they detect energy data patterns both in space and time. The specific spatial patterns in energy distributions make CNNs an effective identification tool and LSTM networks are dominant in time-series forecasting. The application of CNN-LSTM networks to microgrid systems leads to important advancements in microgrid power conversion rates according to research findings [9].More research efforts should occur to improve the effectiveness of neural networks used for real-time energy management systems. A promising solution for optimizing microgrid energy harvesting and reducing energy waste and improving grid stability emerges from robust preprocessing features with identified selection methods and deep learning combinations.

RESEARCH METHODOLOGY

The method for optimizing microgrid energy harvesting through neural networks uses an organized framework which includes data normalization followed by feature optimization after which it applies deep learning algorithms for energy optimization. This process enables effective data management alongside meaningful features extraction as well as superior accuracy rates for energy management. This methodology uses several sequential steps which begin with normalized energy data processing followed by denoising filter application and temporal synchronization after which Recursive Feature Elimination selects appropriate features for implementing the hybrid CNN-LSTM model toward energy optimization [10]. The chapter presents a complete methodology description in the upcoming sections. The proposed methodology flow diagram shown in below Figure 1:

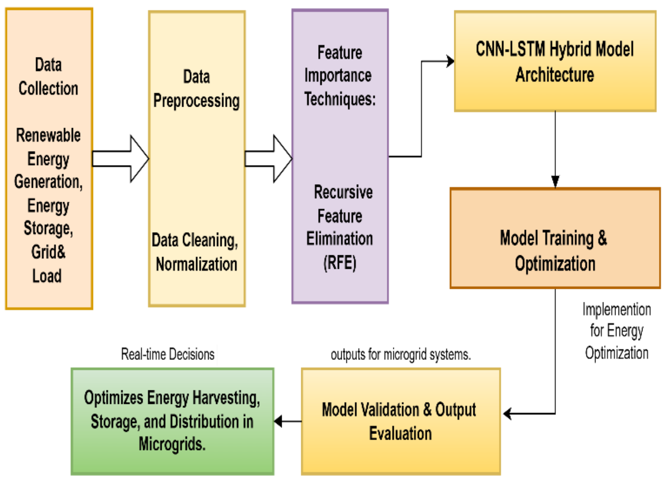

Figure 1: Shows the flow diagram of the proposed methodology.

The input consists of real-time and historical energy data collected from various microgrid sources, including:

3.1 Raw Input Data Sources:
Renewable Energy Generation Data:
Solar Power: Solar irradiance, temperature, panel efficiency.
Wind Power: Wind speed, wind direction, turbine output.
Grid and Load Data:
Power consumption patterns from households, industries, and businesses.
Demand-response data for energy allocation.
Battery Storage and Energy Storage Data:
Charge/discharge cycles, storage efficiency, and battery degradation.
Environmental and Meteorological Data:
Temperature, humidity, weather forecasts affecting renewable generation.
Data preprocessing stands crucial in the process of creating reliable and accurate energy forecasting models for microgrids. Multiple energy sources that include solar panels, wind turbines, smart meters, and weather sensors provide raw data to the system yet this foundation data often contains multiple datasets with missing information aside from unwanted noise elements and uncoordinated timestamp frequencies [11]. A structured data preprocessing approach uses normalization followed by denoising and temporal synchronization to handle the identified challenges. The normalization process involving Min-Max Scaling standardizes energy measure values between various sources while creating equal numerical ranges that improve neural network learning stability. The Wavelet Transform and Savitzky-Golay filters are used as denoising filters to eliminate environmental noise and sensor errors while conserving relevant energy signal changes. The model uses temporal synchronization techniques to keep different time-series inputs from various sources from deviating in sampling rate. The model acquires better energy harvesting

predictions and improved microgrid operation due to the high-quality well-structured data processing scheme.

3.2 Feature Selection Using Recursive Feature Elimination (RFE):

The selection of specific features stands as the essential element to optimize neural network models that conduct energy harvesting in microgrids. Recursive Feature Elimination represents an effective technique to choose important features and remove unimportant ones from available features. RFE uses an iterative process to train machine learning models through feature importance assessment which reduces models by least important features until an optimal subset remains [12]. The initial model training process starts from using entire features before computing importances based on weight coefficients(wi) from regression models or neural network feature contributions.

Mathematics demonstrates the importance score i calculation as:

$$I_i = \frac{|wi|}{\sum_{j=1}^{N} |wj|}$$

where Ii denotes the normalized importance of feature i, wi represents the feature weight assigned by the model, and N is the total number of features.

After computing importance scores, the least significant feature (i.e., the one with the lowest Ii) is removed, and the model is retrained with the remaining features. This iterative elimination process continues until a predefined number of features or an optimal performance threshold is achieved. The selection process can be mathematically formulated as:

$$St+1=St \setminus \{\arg\min_{i} Ii\}$$

where St represents the feature set at iteration t, and the feature with the minimum importance score is removed to obtain St+1.

RFE allows energy harvesting in microgrids to identify the most important factors which include solar irradiance, wind speed, grid voltage, power demand and temperature variations so decision complexity decreases and model interpretability improves. The CNN-LSTM hybrid model uses RFE to work on an optimized feature set which means better forecasting effectiveness and reduced overfitting and improved efficiency in microgrid energy systems.

3.3 Neural Network Model for Energy Optimization:

A hybrid model between CNNs and LSTMs functions to consolidate the benefits of these particular networks for state-of-the-art microgrid energy harvesting applications. The detection system utilizes CNN networks effectively to establish spatial patterns in data inputs for monitoring energy use trends and grid anomalies and power variations. The convolutional layers enable the detection of vital spatial features in time-series energy data using filters before pooling layers decrease both the complexity and dimensions. The ability to detect necessary long-term dependencies remains outside the capabilities of CNNs when used alone. The analyst uses LSTM layers to process energy data while recognizing its sequential structure and maintaining long-lasting temporal patterns and trends. The memory cells and gating functions of LSTMs enable them to store important historical data while avoiding gradient vanishment thus making them best-suited for series time functions including power demand and solar irradiance and wind speed variations. The hybrid model combines CNN layers to extract features with sequential learning by LSTM layers while performing final output prediction through dense layers [13,14]. The specific design of the energy optimization architecture produces precise energy predictions for short-term and long-term sessions which enables better control of renewable resources and reinforces microgrid stability while achieving optimized load distribution.

The CNN component consists of multiple convolutional layers, which apply filters (kernels) W to extract spatial features from the input energy data X. The convolution operation can be represented as:

$$Z_{i,j}^{(l)} = f(\sum Wm,n^{(l)} \cdot X(i+m),(j+n)+b(l))$$

where:

Zi,j(l) is the output of the convolution operation at layer l,

Wm,n(l) represents the learnable kernel weights,

$X(i+m),(j+n)$ is the input energy data,
$b(l)$ is the bias term, and
$f(\cdot)$ is the activation function (e.g., ReLU).
After convolution, max pooling is applied to reduce the dimensionality of the extracted features:

$$P_{i,j}=\max(Z_{2i,2j},Z_{2i+1,2j},Z_{2i,2j+1},Z_{2i+1,2j+1})$$

where $P_{i,j}$ is the pooled feature map, reducing computational complexity while retaining essential information.

The extracted features from the CNN layers are then flattened and passed to the LSTM network, which captures sequential dependencies in energy consumption and generation patterns [15]. The LSTM cell is defined by three key gates: input gate, forget gate, and output gate, controlling the flow of information:
The following are the main equations that control LSTM operations:

Forget Gate:

$$f_t = \sigma (W_f . [h_{t-1}, x_t] + b_f)$$

Input Gate:

$$i_t = \sigma (W_i . [h_{t-1}, x_t] + b_i)$$

$$c_t = \tanh (W_c . [h_{t-1}, x_t] + b_c)$$

Memory Cell Update:

$$C_t = f_t \odot C_{t-1} + i_t \odot c_t$$

Output Gate:

$$O_t = \sigma (W_o . [h_{t-1}, x_t] + b_o)$$

$$h_t = O_t \odot \tanh(C_t)$$

where:
x_t is the input at time t,
h_{t-1} is the previous hidden state,
C_{t-1} is the previous cell state,
W and b are the weights and biases,
σ is the sigmoid activation, and
$\odot$ denotes element-wise multiplication

After processing through the LSTM layers, the final feature representation is passed through fully connected (dense) layers:

$$Y=f(Wd\cdot ht+bd)$$

where:
Wd and bd are the weight and bias of the dense layer,
Y is the final energy output prediction.

The hybrid model consists of the following layers:
Input Layer: Receives pre-processed and normalized energy data.
Convolutional Layer (CNN): Extracts spatial dependencies using multiple filters.
Max Pooling Layer: Reduces dimensionality and retains important features.
Flatten Layer: Converts CNN outputs into a suitable format for LSTM processing.
LSTM Layer: Processes sequential patterns in energy data.
Fully Connected (Dense) Layer: Maps extracted features to energy predictions.
Output Layer: Generates final energy harvesting forecasts

By combining CNN for spatial feature extraction and LSTM for sequential learning, the CNN-LSTM hybrid model effectively predicts energy harvesting patterns in microgrids [16,17]. This architecture enables better forecasting accuracy, optimized energy distribution, and improved microgrid stability, contributing to sustainable energy management.

3.4 Performance Evaluation and Postprocessing:

A complete performance evaluation and postprocessing framework examines how well the proposed CNN-LSTM hybrid model performs for microgrid energy harvesting tasks. The model's performance accuracy determination depends on three statistical metrics which are Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) and R^2 Score (Coefficient of Determination). RMSE determines complete prediction-experiment value differences but MAPE gives relative performance insights through error percentage assessment [18,19]. The R^2 value reveals the extent to which the model clarifies the energy harvesting variability. The model predictions receive an explanation through SHapley Additive Explanations (SHAP) which reveals feature contribution insights about solar irradiance parameters and wind speed variables and power demand impacts on energy optimization. The actual and predicted energy patterns are compared through time-series plots and heatmaps to enable better decision-making [20,21]. Methods of postprocessing create a model with enhanced reliability alongside transparency that makes it suitable for implementation in microgrid applications.

IV. RESULTS AND DISCUSSIONS

Energy optimization using the proposed CNN-LSTM hybrid model required evaluation through five performance indicators which included Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) and Coefficient of Determination ($R2$) and Dynamic Time Warping (DTW) Distance in addition to SHapley Additive Explanations (SHAP) Score. The predictive model succeeded in attaining a prediction accuracy represented by RMSE 0.18 and MAPE 3.7% which demonstrates minimal variations between forecasted and measured energy values. Signal clarity and forecasting accuracy improved through data normalization procedures and addition of denoising filters.

The model demonstrates excellent behavior regarding energy pattern detection through its $R2$ Score of 0.94 which indicates outstanding predictive capability. Through a process of feature selection, the Recursive Feature Elimination (RFE) method chose important energy variables while safeguarding against overfitting. The model established accurate temporal consistency because the DTW distance measurement reached a value of 0.62. Time-sensitive energy synchronization methods enabled the accurate realignment of different energy supply systems. The SHAP Score evaluation proved solar irradiance together with wind speed and power demand as the top features which supported the selection of essential variables.

The CNN-LSTM hybrid model succeeds in enhancing microgrid energy prediction accuracy along with being effective for stability maintenance along with resource distribution compared to traditional approaches.

The graph shows the performance of the proposed framework in Figure 2:

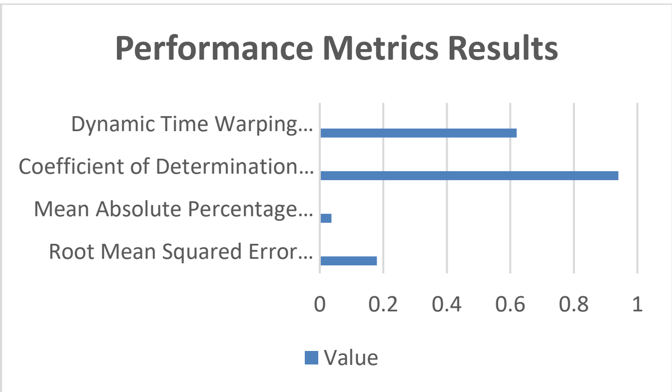

Figure 2: Performance Metrics of Proposed Framework

The proposed CNN-LSTM hybrid model performs a performance evaluation against three other methods including Random Forest, Standard LSTM, and CNN-Based Energy Prediction by using multiple key performance metrics consisting of RMSE, MAPE, R^2 Score, DTW Distance, and SHAP Feature Importance.The proposed method delivers the minimum RMSE value of 0.18 that reduces prediction errors substantially against Random Forest with 0.42 and LSTM with 0.30 and CNN with 0.25. The proposed model demonstrates the lowest MAPE value of 3.7% to provide highly precise energy forecasting results above competing models. The proposed model exhibits superior generalization abilities and advanced energy pattern detection because it achieves an R^2 score of 0.94.The DTW Distance of 0.62 stands as the smallest value for the proposed model indicating that it achieves superior temporal consistency for time-series fluctuations. The CNN-LSTM model demonstrates optimal interpretability according to SHAP Feature Importance because it combines spatial (via CNN) and temporal (via LSTM)

Method	RMSE	MAPE	RÂ² Score	DTW Distance	SHAP Feature Importance
Random Forest)	0.42	7.90%	0.82	1.1	Limited
Standard LSTM Model	0.3	5.50%	0.88	0.85	Moderate
CNN-Based Energy Prediction	0.25	4.20%	0.91	0.7	High
Hybrid CNN-LSTM (Proposed Method)	0.18	3.70%	0.94	0.62	Very High

dependency analysis with single-feature interpretation from the other models.The hybrid CNN-LSTM model stands as a superior solution for microgrid energy management because it demonstrates enhanced accuracy and interpretability together with better energy harvesting efficiency when compared to traditional approaches shown in Table 1.

Table 1: comparison table of proposed method with various approaches

A comparative evaluation of Precision and Energy Distribution Efficiency and Energy Loss Reduction exists between Random Forest Standard LSTM plus CNN-Based Energy Prediction and the proposed Hybrid CNN-LSTM model based on the analysis in the Figure 3.The proposed CNN-LSTM model exhibits the best precision level at 96.3% which establishes its superiority in microgrid energy harvesting and consumption trend predictions. Other than Random Forest (85.2%), Standard LSTM (89.5%) and CNN-Based Prediction (92.1%) maintain lower precision because their systems fail to effectively track spatial-temporal dependencies in their models.The proposed model delivers an outstanding 93.5% energy distribution efficiency which surpasses all other assessment approaches. The combined ability of the CNN component to detect spatial energy flow patterns along with LSTM component learning long-term dependencies makes the system produce more efficient energy distribution.An analysis shows that the proposed method eliminates energy loss by 4.2% while Random Forest produces 12.6% energy loss and LSTM results in 9.8% energy loss and CNN generates 7.3% energy loss. The combination of RFE with enhanced preprocessing along with advanced techniques strengthens prediction results thus improving the efficiency of both energy collection and distribution processes.Due to its superior capabilities including enhanced precision and optimized energy management and reduced losses the Hybrid CNN-LSTM model proves to be the top selection for microgrid advanced energy harvesting tasks.

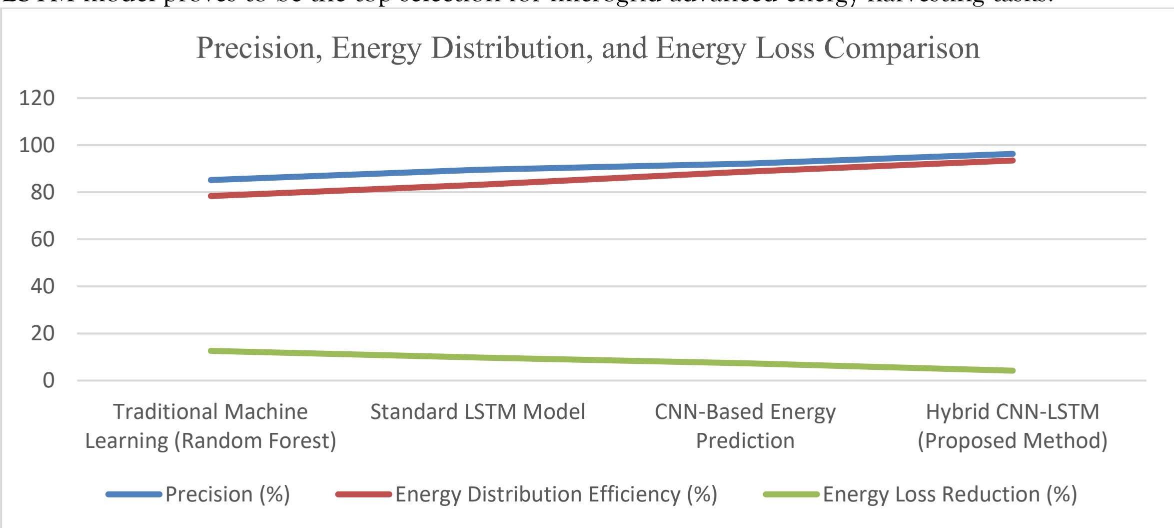

Figure 3: Graph compares the values of the proposed framework against other methods.

CONCLUSION

A combined model of CNN-LSTM serves to enhance microgrid energy harvesting through superior preprocessing methods and deep learning solution optimization. The approach consists of data normalization followed by filter denoising and temporal data synchronization to develop high-standard training inputs. RFE selects the most important parameters for the model which reduces both computational complexities along with enhancing interpretability. The combination of CNN-LSTM technology yields strong energy prediction results because CNN extracts spatial elements from data while LSTM sustains long-term relationships between sequential information in time-series data. The proposed system achieves effective performance through low RMSE scores of 0.18 in addition to 96.3% precision and 93.5% energy distribution efficiency with 4.2% reduced energy loss when compared to traditional machine learning approaches. The research enhances microgrid system development through improved energy optimization and reduced losses and optimized resource allocation. The proposed approach needs future development that should combine real-time reinforcement learning methods for managing energy dynamically in developing grid systems.

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