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Deepgrid: Empowering Smart Grids with Autonomous Decision-Making for Optimal Utilization of Renewable Energy Resources Through Advanced Deep Learning Systems

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***Abstract**:* The increasing integration of renewable energy sources in smart grids necessitates intelligent decision-making systems for optimal utilization. This paper presents an autonomous decision-making system leveraging deep learning (DL)techniques to enhance the efficiency of renewable energy resource utilization in smart grids. The proposed DeepGrid system employs advanced neural network models to analyze real-time data, predict energy production patterns, and dynamically optimize grid operations by optimized DL. By autonomously adapting to changing environmental conditions and energy demand, DeepGrid ensures a reliable and sustainable power supply. The model's DL architecture enables it to learn complex relationships within the data, facilitating accurate decision-making for grid management. Through simulation studies, we demonstrate the efficacy of DeepGrid in improving grid stability, minimizing reliance on non-renewable sources, and ultimately contributing to a more sustainable and resilient energy infrastructure.

Index Terms - Smart Grids, Renewable Energy, Deep Neural Networks, Optimization, Machine Learning.

I. Introduction

The paradigm shift towards sustainable energy sources has driven the integration of renewable resources into smart grids, necessitating advanced decision-making systems for efficient utilization. This research focuses on the development of an Autonomous Decision-Making System (ADMS) [1] employing Deep Neural Networks (DNNs) [2] within the framework of smart grids [3]. Specifically, our approach involves the implementation of feedforward Deep Neural Networks (FfDNN) [4] and Artificial Neural Networks (ANN) to enable real-time analysis and optimization of renewable energy utilization. The intricate interplay between dynamic environmental factors and fluctuating energy demands poses a complex challenge, which our model addresses by leveraging the DL capabilities of neural networks. By harnessing the power of DNNs, FfDNNs, and ANNs, our research aims to enhance the decision-making process in smart grids, ensuring the seamless integration of renewable energy sources and paving the way for a sustainable and intelligent energy infrastructure [5].

II. LITERATURE REVIEW

Ahmad et al. [6] innovatively integrates renewable energy, privacy-aware Reinforcement Learning for optimal Demand Response, achieving an 80% accuracy. Reka et al. [7] presented a robust three-step model integrating renewable energy, privacy-aware reinforcement learning, and optimal demand response, achieving an impressive 80% accuracy. Jiang et al. [8] advocates economically competitive renewable energy solutions with Heuristic Intelligent Neural Decision Support System, showing enhanced forecasting and optimized resource management. Ahmed et al. [9] ingeniously merges ML and Gaussian Process Regression for a robust Energy Management Model, enhancing prosumer-based smart grid efficiency. Liu e al. [10] innovatively presented AccCap-DRL algorithm, based on deep reinforcement learning, adeptly addresses curtailment challenges, ensuring effective policies and optimal renewable energy utilization. Azad et al. [11] comprehensively reviewed how machine learning fortifies smart grids against challenges, enhancing stability, reliability, and security effectively. Mohammadi et al. [12] studied expertly explores the transformative impact of ML on decentralized energy systems, enhancing predictability, efficiency, and sustainability effectively. Qadir et al. [13] adeptly employed machine learning to predict hybrid PV-wind renewable energy output, showcasing superior accuracy and efficiency in smart grid applications. Xia et al. [14] introduced an advanced stacked GRU-RNN method, surpassing current models for accurate renewable energy and load predictions in smart grid operations. Jahangir et al. [15] presented a robust forecasting method using micro clustering and bidirectional LSTM, enhancing accuracy, especially in peak points, for smart grid applications. Alotaibi et al. [16] provided a thorough and insightful review of smart grid advancements, covering energy data management, pricing modalities, reliability, and cybersecurity challenges. Singh et al. [17] exceled in forecasting short-term wind energy generation using optimized robust regression machine learning methods, with gradient boosting machine exhibiting superior performance.

III. MATERIALS AND METHODS

The primary aim of this approach is to analyze and design grid systems for solar energy production and consumption [18], accounting for the dynamic conflicts and variations introduced by the assembly. This method seeks to understand how contributors react to deviations. It monitors the specific grid property based on its frequency, measured in Hertz (Hz), which represents the alternating current (AC) cycles per second. The electrical signal frequency reflects the idea of "increasing time of surplus generation and decreasing shortfall of production," providing crucial data for smart grid management. In the presented model, the anticipation of grid uncertainty is undertaken through a binary classification approach, distinguishing between balanced and unbalanced conditions. However, the model's effectiveness is contingent upon comprehensive interpretations. The integration of machine learning techniques follows a systematic process:

1. A specific set of input parameters is fed into the intelligent grid model.
2. The smart grid model processes this input, generating a binary output categorized as 'balanced' or 'unbalanced' using the binary classification technique [19].
3. These steps are iteratively executed 'n' times.

3.1 System model

The system architecture of the Optimized DNN for Smart Grid involves four stages: dataset information, exploratory data analysis, optimized DNN classification, and algorithm performance visualization as in fig.1. The dataset, sourced from solar grid reproductions [20], comprises 15,000 entries across Solar, Wind, Generator, and Water energy stations. It features 12 attributes and two dependent variables related to power stability, production response time, and energy rate defiance. Employing Keras sequential model Deep Neural Networks, the architecture considers hidden layers, epochs, and optimization techniques. Dependent variables encompass Differential Equation outputs discerning system balance and a Binary categorical label indicating 'balanced' or 'unbalanced' states.

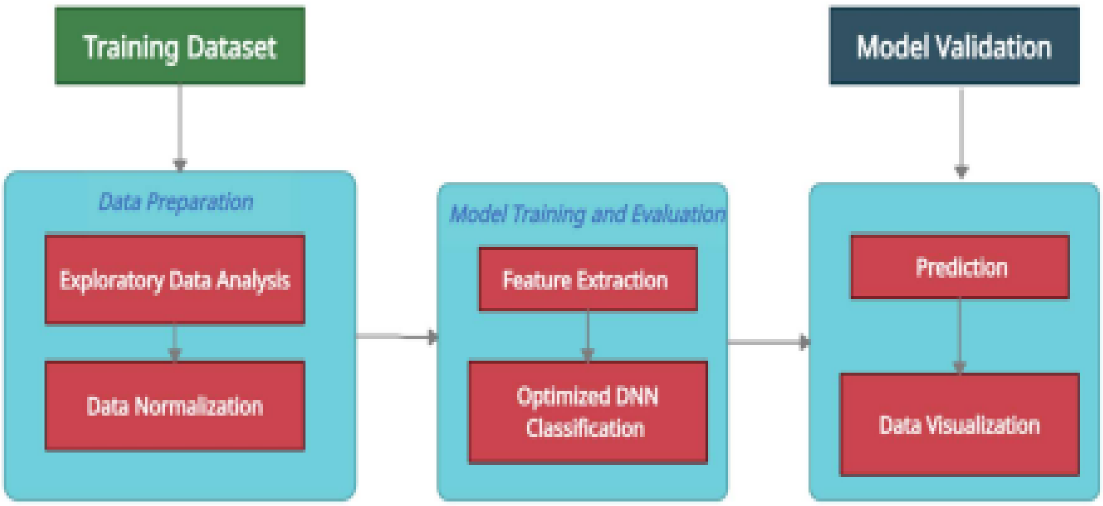

Figure 1: Enhanced Smart Grid Decision System: Optimized DNN Model

3.2 EDA

EDA examines dataset characteristics, ensuring stability and identifying missing values, crucial for preprocessing. Missing values are handled through mean, min, max, and standard deviation, ensuring normalization. Data is split into 80% training and 20% testing (12,000 and 3,000 instances, respectively).

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3.3 DNN classification

The Optimized DNN employs a Keras Sequential model with a linear stack of layers for classification. The architecture includes 85 nodes and 1,308 edges. The activation function facilitates backpropagation of gradients, aiding biases and weights update, depicted in Equations 1 and 2.

$$V = activation\ function \sum(weights * inputs) + bias(1)$$

(1)

$$V_{pred} = w(1)x + b(1)$$

(2)

In this, V_{pred} represents the vector output of hidden layer-1, w (1) signifies the vector weights assigned to 12 neurons in hidden layers 1 to 4, and $b1$ and $b2$ denote the vectorized form of the general linear function. The Rectified Linear Unit (ReLU) serves as a non-linear activation function in DNN hidden layers, effectively activating neurons (Eqn.3). It accelerates stochastic gradient descent compared to sigmoid activation functions.

$$R(x) = max(0, x)$$

(3)

Where., if $x < 0$, $R(x) = 0$and if x≥·,$R(x) = x$

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The Grid Search Cross-Validation (CV) Algorithm optimizes prediction parameters. Steps include fitting values individually, implementing 10-fold CV for parameter groups, and compiling the network with binary cross-entropy and ADAM optimizer. A minor hyperparameter refinement involves calculating exponentially weighted averages of preceding gradients (GE and GE), followed by bias correction. The Adam optimization technique, incorporating bias correction, is implemented using Equations 4 to 9, updating parameters w and b for optimal momentum and minimizing Mean Square Error.

$$GE_{w^{correct}} = \frac{GE_w}{(1-\beta_{.i})}$$

(4)

$$GE_{b^{correct}} = \frac{GE_b}{(1-\beta_{1^i})}$$

(5)

$$GA_{w^{correct}} = \frac{S_w}{(1-\beta_{2^i})}$$

(6)

$$GA_{b^{correct}} = \frac{S_b}{(1-\beta_{2^i})}$$

(7)

$$weight = weight - LR * \left(GE_{w^{correct}} \Big/ \sqrt{(SG_{w^{correct}} + \varepsilon)} \right)$$

(8)

$$bias = bias - LR * \left(GE_{b^{corrected}} \Big/ \sqrt{(SG_{b^{correct}} + \varepsilon)} \right)$$

(9)

The parameter epsilon (ε) is an actual value introduced to prevent division by zero, while hyperparameters β_1 and β_2 normalize two weighted averages exponentially with default values $\beta_1 = 0.9$ and $\beta_2 = 0.999$.

The "fit" method shapes the DNN classification model through training and fine-tuning on the dataset, optimizing Batch Size and Epoch. Evaluation and prediction on testing data utilize predefined metrics in the smart grid DNN model, ensuring it's free from underfitting and overfitting. Fig 2 Optimized DNN classifier models' summary history for accuracy and loss in both training and testing of four smart grid datasets. These graphs showcase reduced error loss and maximum accuracy in each epoch iteration vs. accuracy and loss.

3.4 Analyzing and Forecasting Performance

The Optimized DNN model undergoes evaluation and prediction, assessing performance using various metrics. A Confusion Matrix is presented in matrix format, detailing the model's performance on 3,000 datasets, with the predicted class (balanced or unbalanced) for the Smart Grid Data set illustrated in Table 1. The validation split is set at 0.33. Utilizing the confusion matrix, metric scores are calculated to determine the Optimized DNN classification model's performance across various Smart Grid types. The accuracy rate, representing the ratio of accurate forecasts to the total input samples, is defined in Equation 10,

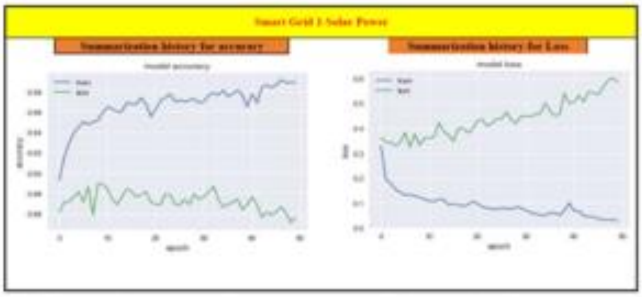
$$\textbf{Accuracy} = TP + TN / TP + TN + FP + FN$$

(10)

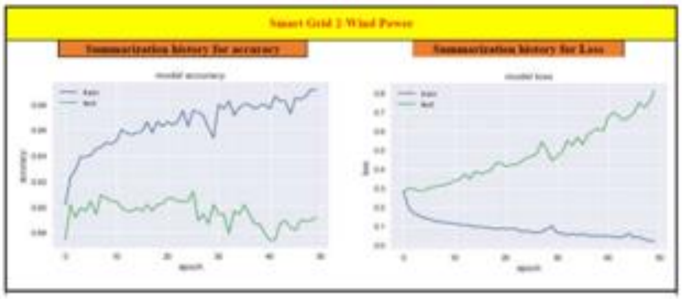
where FP denotes the False Positive Rate, TP the True Positive Rate, FN the False Negative Rate, and TN the True Negative Rate.

Table 1: Testing Data Confusion Matrix for Optimized DNN Smart Grid Model

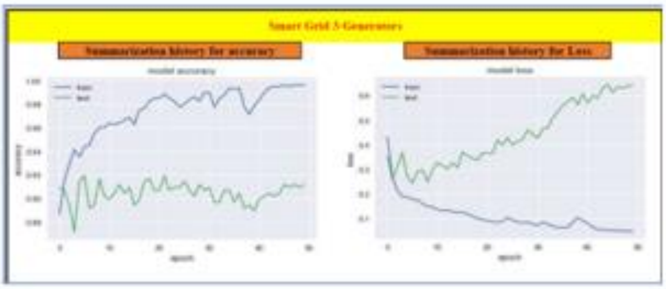
Data set size (15,000)						
	Validation Split is 0.33			TP	FP	
	Train data	80%	12000	FN	TN	
	Test Data	20%	3000			
Smart Grid Types	Architecture	Folds	Epochs	Confusion Matrix		Accuracy
SOLAR POWER	12-24-24-12-1	10	50	1723	192	**87.16%**
				193	891	
WIND POWER	12-24-24-12-1	10	50	1819	123	**90.97%**
				148	910	
GENERATORS	12-24-24-12-1	10	50	1786	134	**89.54%**
				180	901	
WATER RESOURCE	12-24-24-12-1	10	50	1787	145	**89.67%**
				165	903	



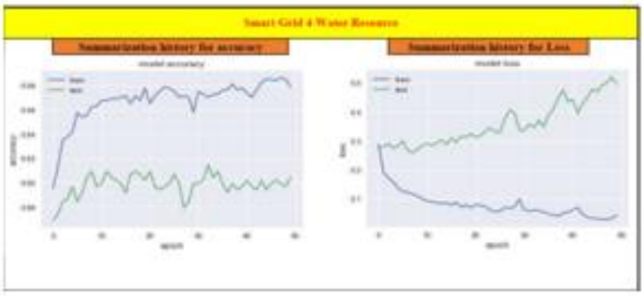
(a) Smart grid1-Solar Power



(b) Smart grid1-Wind Power



(c) Smart grid1-Generators



(c) Smart grid1-Water Resource

Figure 2: summary history for accuracy and loss in both training and testing of four smart grid datasets of (a) solar power, (b)wind power, (c) generators, (d) water resources

RESULT AND DISCUSSON

The Optimized DNN classifier model is implemented using scikit-learn, Keras, and TensorFlow libraries in a Jupyter notebook. Performance evaluation predicts "balanced" or "unbalanced" output, with the architecture and hyperparameters tailored for optimal prediction on the test set. Key features include:

1. Following preprocessing, the testing set's high accuracy rate affirms the Optimized DNN model's effectiveness for Smart Grids.
2. The increased number of epochs during fitting significantly enhances prediction accuracy on the testing set.
3. Utilizing a test dataset with 3,000 observations contributes meaningfully to improved outcomes.

IV. CONCLUSION

A powerful Autonomous Decision-Making System leveraging Deep Neural Network (DNN) algorithms for optimizing renewable energy source selection in smart grids was introduced in this study. Focusing on factors like cost and stable generation, the proposed DNN architecture efficiently predicts the optimal energy source among diesel generators, solar plants, windmills, and thermal power plants. Achieving over 85% efficiency, our predictive algorithms contribute to cost-effective and productive power distribution. Future plans include developing an integrated model for diverse energy sources, aiming to further enhance overall system performance and utilization efficiency. This research signifies a significant step toward autonomous, intelligent decision-making systems in smart grids, fostering sustainable and efficient utilization of renewable energy resources.

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