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A Novel Optimization Approach for Sustainable Renewable Energy Distribution and Multi-Source Resource Integration

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***Abstract*— *The rapid expansion of renewable energy systems has introduced new challenges in ensuring the sustainable, efficient, and reliable distribution of electricity. Variability in generation from sources such as solar, wind, and hydro, combined with fluctuating demand, necessitates the development of intelligent optimization methods for multi-source resource integration. This research presents a novel optimization approach that integrates solar, wind, and hydro resources with energy storage and auxiliary backup systems to achieve efficient and sustainable distribution within microgrids. The proposed framework employs a hybrid machine learning-driven optimization model, combining Ladybug Beetle-driven Weighted Random Forest Regression (LB-Weighted RFR) for accurate power generation forecasting and optimized energy distribution. The forecasts enable dynamic scheduling that balances supply and demand, reduces peak loads, and maximizes renewable energy utilization. Forecasting incorporates historical production data, weather patterns, and grid conditions, achieving low error metrics such as MSE (0.00008) for energy sources. Simulation results demonstrate significant improvements of the proposed model over conventional approaches, including reductions in operating costs, decreases in peak demand, enhanced supply-demand balance, and increased renewable energy utilization.*

I. INTRODUCTION

Renewable energy distribution refers to the process of delivering electricity generated from sustainable sources such as solar, wind, hydro, and biomass to end-users in an efficient, reliable, and environmentally friendly manner [1]. In conventional fossil-fuel-based power systems, renewable energy generation is often decentralized, with multiple small-scale generation units connected to microgrid or the main grid. This decentralization offers opportunities for cleaner energy production and reduced carbon emissions, but it also introduces challenges in maintaining a stable and continuous electricity supply [2]. The unpredictability and intermittency of renewable resources are caused by seasonal weather variability and are subject to variability of power output, creating supply-demand mismatches and risk for instability for the grid [3]. In addition, many electrical grids are designed as centralized generation by default and therefore, face issues of fair incorporation of distributed generation. Infrastructure deficiencies, coupled with the high operational and maintenance costs associated with managing multiple variable energy sources, make it difficult to distribute renewable energy [4]. Integrating multiple sources is emerging as a key strategy to address these issues by combining various renewable resources with energy storage solutions and backup providers. This approach enhances supply consistency and reliability; what one source may lack, others can compensate, such as wind or hydro (water), can complement solar energy during cloudy conditions. The reliability with many sources is increased, more energy is produced efficiently, and it relies less on fossil fuels; additionally, it can provide dynamic scheduling when required from the microgrid in heavy-load periods [5]. Some disadvantages of multi-source implementation are high initial cost, higher complexity of systems, additional management and forecasting requirements, and a broader range of diverse components to maintain. Although there are disadvantages to utilizing multiple renewables, it is not unreasonable to consider, as the multi-source approach may provide the best opportunity to achieve a sustainable, efficient, and reliable energy service provision. The efficiency of these complex and variable sources of energy is best managed through intelligent forecasting and optimization techniques, where the ultimate goal is to facilitate the transition to a low-carbon, resilient energy system and infrastructure [6].

The use of solar, wind, and hydro generation is creating challenges to achieve an efficient energy scheme. Conventional ways create high costs, peak loads, and use few renewable resources. Intelligent optimization is needed to match supply with demand and effectively use sustainable resources. This research presents a new optimization method that extracts solar, wind, and hydro resources into energy storage and backup systems to distribute efficiently and sustainably in a microgrid.

II. RELATED WORKS

Multi-source information fusion was applied in smart distribution power systems using advanced data fusion techniques to integrate heterogeneous sources [7]. The approach enhanced grid reliability and improved fault detection accuracy. Simulation results demonstrated significant improvements in system monitoring metrics. Computational complexity and real-time implementation remained challenging.

A risk assessment model addressed multi-perspective vulnerability in distribution networks using multi-source heterogeneous data and probabilistic analysis [8]. The model improved the identification of vulnerable nodes with a detection accuracy reaching 92%. The approach provided actionable insights for network reinforcement. However, real-time adaptability was limited, and network dynamics were simplified.

A multi-time-scale coordinated scheduling method was implemented for complementary multi-source power generation under uncertain load and source conditions [9]. The technique reduced energy imbalance and operational costs by approximately 15%. Coordinated scheduling improved the overall system efficiency. The method relied heavily on accurate forecasting and faced scalability constraints.

A hybrid imperialist competitive algorithm–particle swarm optimization framework was used for energy management in multi-source residential microgrids [10]. Results showed operational cost reductions of 12% and higher renewable energy utilization. Optimization enhanced scheduling efficiency and reliability. Convergence speed and parameter sensitivity posed practical challenges.

Frequency-constrained scheduling was integrated to coordinate multi-source converters and enhance frequency regulation [11]. Frequency stability improved, and deviation was reduced by 8–10%. The method supported dynamic scheduling under multiple constraints. Limitations included assumptions of uniform converter performance and restricted dynamic evaluation.

A Cokha algorithm-based approach optimized renewable energy-based multi-source systems in deregulated environments [12]. Efficiency and cost performance improved by 10–15% compared to baseline strategies. Scheduling optimization enhanced power distribution and system reliability. Effectiveness decreased under highly volatile market conditions and uncertain input data.

2.1 Research Gab

Existing multi-source energy optimization approaches have scalability, adaptability to real-time, and forecast accuracy limitations. Even with simplified assumptions, these gaps hinder their use in dynamic and uncertain grid settings. Comprehensive optimization will be necessary to assure sustainable and efficient renewable energy use.

III. METHOD AND MATERIALS

This research optimizes sustainable renewable energy distribution through multi-source integration. The dataset includes historical solar, wind, and hydro production records along with weather and grid condition data. A hybrid LB-Weighted RFR method is applied for forecasting and optimized scheduling to balance supply-demand and maximize renewable utilization. Figure 1 illustrates the distribution of renewable energy sources.

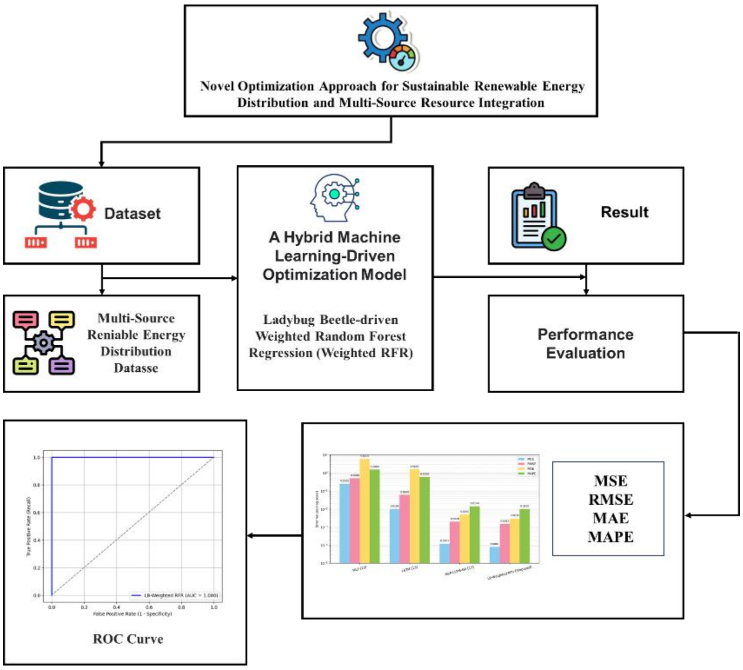

Fig.1: Proposed Hybrid Optimization Framework for Sustainable Renewable Energy Distribution and Multi-Source Resource Integration

3.1 Dataset

The Multi-Source Renewable Energy Distribution Dataset is gathered for Kaggle: https://www.kaggle.com/datasets/programmer3/multi-source-renewable-energy-distribution-dataset. This dataset represents a realistic multi-source renewable energy microgrid, integrating solar, wind, and hydro generation with influencing factors such as weather conditions, energy storage, backup systems, demand, and grid stability. It includes target columns for forecasted solar, wind, load, and optimal distribution, enabling effective training and evaluation of machine learning and optimization models, including the proposed Ladybug Beetle–Weighted Random Forest Regression (LB-Weighted RFR).

3.2 A Ladybug Beetle-driven Weighted Random Forest Regression (LB-Weighted RFR)

LB-Weighted RFR uses bio-inspired LB optimization to improve renewable energy forecasting with WRFR. The LB-driven weighting components consider the most important features of the generation decision tree when forecasting renewable energy generation, thereby improving the accuracy and robustness of predictions. WRFR components are averaged based on the decision trees, collecting distribution over time to provide efficient, sustainable, reliable, and multi-source generation of energy.

- **Random Forest Regression (RFR):** RFR is used to forecast solar, wind, and hydro power generation, enabling dynamic energy scheduling and optimal multi-source distribution within the microgrid; it builds an ensemble of decision trees trained on random data subsets, with predictions averaged across all trees to improve accuracy, reduce overfitting, and support efficient parallel forecasting.
- **Weighted Random Forest Regression (WRFR):** The WRFR method extends standard RFR by assigning weights to decision trees or data samples based on their importance or reliability. It averages predictions, making internally weighted contributions to allow for more accurate and robust predictions without losing the ensemble or parallel processing benefits of traditional RFR. Here, WRFR is developed and used to allow for the distribution of multi-sourced energy loads for efficiency, sustainability, and reliability in microgrid systems.

$$Random\ forest\ prediction = \frac{1}{L}\sum_{l=1}^{L} g_l(w) \quad (1)$$

$$MSE_{OOB} = \frac{1}{m}\sum_{j=j}^{m}(z_j - \bar{z}_{j_{OOB}})^2 \quad (2)$$

$$Q^2_{OOB} = 1 - MSE_{OOB}/Var_z \quad (3)$$

In these equations (1 and 3), L is the number of trees, and $g_l(w)$ is the prediction from the tree l.

Here, m is the total samples, $z_j$actual value, and $\bar{z}_{j_{OOB}}$the out-of-bag prediction.

MSE_{OOB} is the mean squared error, Var_z variance of observed values, and Q^2_{OOB} indicates predictive accuracy.

- **Ladybug Beetle Optimization:** The LBO algorithm plays a key role in enhancing microgrid performance by optimizing the allocation of multi-source renewable energy. LBO is a bio-inspired metaheuristic algorithm modeled on the coordinated movement of ladybugs searching for optimal heat locations. It iteratively evaluates, updates, and ranks candidate solutions to converge on the optimal objective function. Here, LBO is applied to achieve efficient, sustainable, and reliable multi-source energy distribution by dynamically optimizing the allocation of solar, wind, and hydro resources within the microgrid, represented by Equations (4 and 5).

$$m_n = round(m * \mu_n) \quad (4)$$

$$M(l+1) = round(M(l) - qand \times M(L)(\frac{l}{l_{max}}) \quad (5)$$

m_n is the adjusted iteration count using the mean factor μ_n. $M(l+1)$ updates population size based on the reduction factor $qand$, current size $M(L)$, iteration l, and maximum iterations $(\frac{l}{l_{max}})$.

The LB-Weighted RFR method incorporated a novel, useful way to improve renewable energy forecasting by adaptively weighting the features from solar, wind, and hydro inputs. Its optimization-based design improved convergence stability and prevented over-fitting. The ensemble provided highly accurate, reliable, and interpretable predictions of microgrid energy distribution.

IV. RESULT

This research aimed to create a hybrid LB-weighted RFR optimization framework to reduce multi-sourced renewable energy distribution in microgrids. The experimental design was programmed in Python 3.10 with NumPy, Pandas, Scikit-learn, and PyTorch on a computer with a 16-core CPU, 64GB RAM, and RTX 3080 GPU, and Windows 11 Pro as the OS. This framework provides a functional and scalable framework for accurate forecasting, scheduling, reducing costs, and optimizing the use of renewable energy under various grid conditions.

- **Experimental Assessment**

This section presents the experimental evaluation, confirming the LB-Weighted RFR framework's effectiveness. The result demonstrates improved accuracy, cost reduction, and renewable energy utilization.

The ROC curve for the LB-Weighted RFR model proposed here demonstrates remarkable prediction performance with an AUC of 1.0 or perfect classification ability. Figure 2 depicts the ROC curve of the proposed model.

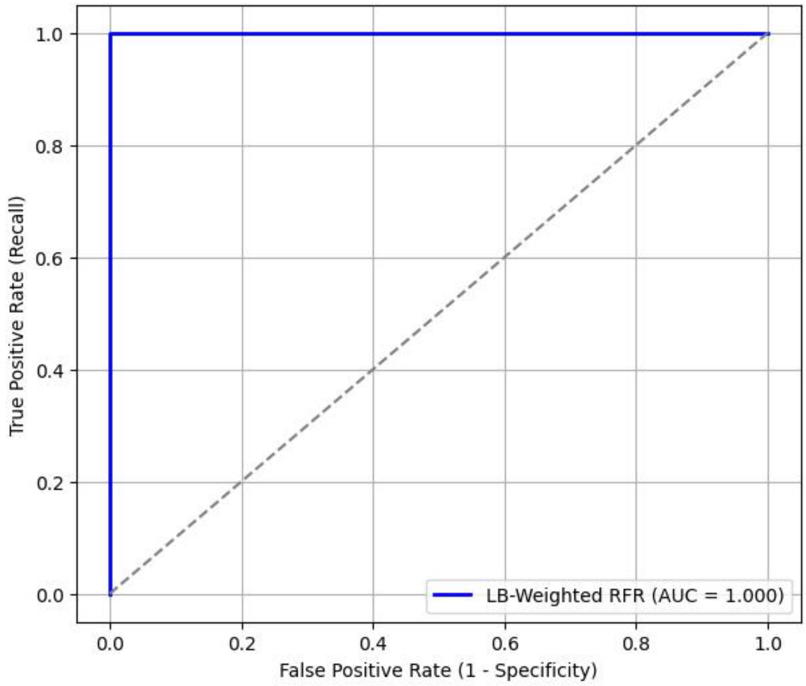

Fig.2: ROC Curve for Proposed LB-Weighted RFR Model

The ROC curve lies entirely along the top boundary and the left boundary, which means the LB-Weighted RFR model achieves a true positive rate of 100% with no false positives; thus, this result supports the robustness and accuracy of the framework and its strong discriminative ability.

❖ **Comparative Assessment**

The proposed LB-Weighted RFR framework was compared with existing methods, including MLP [13], LSTM [13], and MLP-LSTM-GA [13], using metrics such as MSE, RMSE, MAE, and MAPE. This demonstrates enhanced renewable energy utilization compared to baseline models.

- **Mean Squared Error (MSE):** Measures the average squared difference between predicted and actual energy outputs. A lower MSE indicates higher accuracy in forecasting renewable generation. It ensures reliable scheduling for multi-source integration.
- **Root Mean Squared Error (RMSE):** Represents the square root of MSE, giving error values in the same unit as energy output. It highlights large deviations more strongly. Lower RMSE supports stable energy distribution in microgrids.
- **Mean Absolute Error (MAE):** Calculates the average absolute difference between predicted and actual outputs. It directly reflects forecasting precision. Lower MAE reduces mismatches in supply-demand balancing.
- **Mean Absolute Percentage Error (MAPE):** Expresses prediction errors as a percentage of actual values. It allows easy comparison of accuracy across solar, wind, and hydro sources. Lower MAPE ensures higher utilization of renewables.

Table 1: Performance Comparison of Different Models

Method	MSE	RMSE	MAE	MAPE
MLP [13]	0.25	0.50	5.82	1.5
LSTM [13]	0.01	0.06	1.56	0.6
MLP-LSTM-GA [13]	0.00012	0.002	0.005	0.014
LB-Weighted RFR[Proposed]	0.00008	0.0015	0.003	0.010

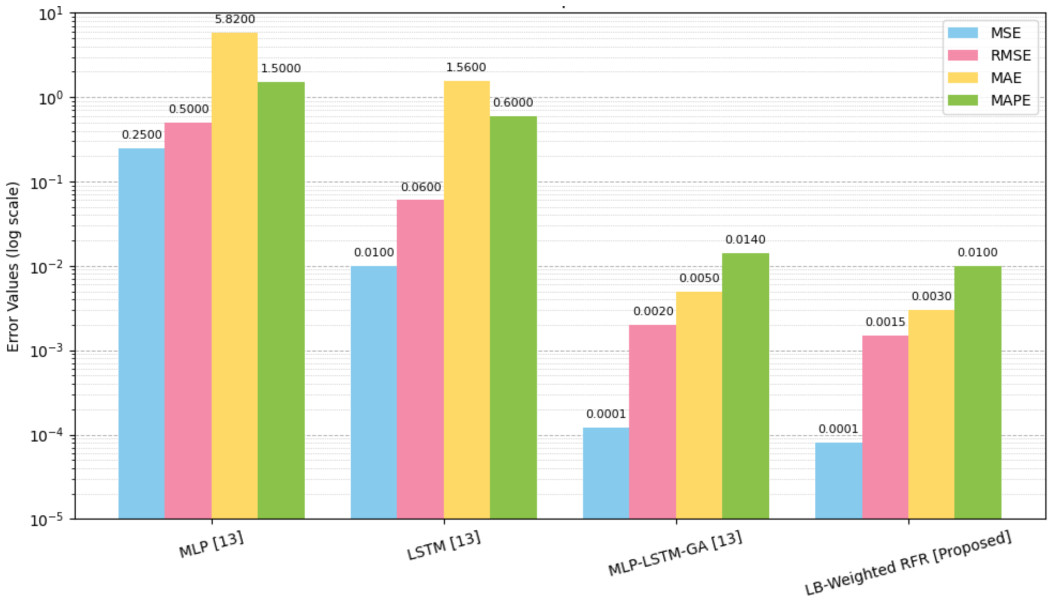

Fig.3: Comparative Performance of Forecasting Models

Table 1 and Figure 3 compare multiple forecasting models across standard error metrics (MSE, RMSE, MAE, and MAPE). Traditional MLP [13] exhibited relatively high errors, while LSTM [13] significantly improved predictive performance by effectively capturing temporal dependencies. Hybrid models such as MLP-LSTM-GA [13] further reduced errors by combining deep learning with optimization. The proposed LB-Weighted RFR achieved the lowest errors overall, highlighting its superior accuracy, robustness, and adaptability for renewable energy microgrid forecasting tasks.

V. DISCUSSION

The research evaluated renewable energy forecasting and optimal distribution using the proposed LB-Weighted RFR framework, ensuring accurate and robust performance across solar, wind, and hydro sources. Existing approaches, such as MLP [13], LSTM [13], and hybrid MLP-LSTM-GA [13], demonstrate limitations in scalability, sensitivity to noise, and handling non-linear dependencies. The LB-Weighted RFR [proposed] effectively addresses these issues by combining adaptive and ensemble learning, which improves accuracy in forecasting, lowers error rates, and produces assured stability in dynamic environmental conditions, reduces the chance of inefficient resource allocations, assures grid reliability, and informs a more operational model when considering or exploring new decisions in microgrid operation environments. More practically, the framework assists with sustainable microgrid operation by tracking supply, demand, and storage while providing a solution to transition into an energy system of the future. 'Scalability' is built into the design of the LB-Weighted RFR.

VI. CONCLUSION

This research enhanced the renewable energy forecasting and optimal distribution in a multi-source microgrid. A dataset integrating solar, wind, hydro, demand, and storage parameters was utilized. The purpose of this research lies in the LB-Weighted RFR model, which integrates adaptive weighting with ensemble learning to enhance performance. The proposed model yielded better results than all benchmark approaches, with $MSE = 0.00008, RMSE = 0.0015, MAE = 0.003, and\ MAPE = 0.010$. A limitation of this research is that the larger datasets and computational complexity limit scalability. Future work includes adapting the model to assess and design in a practical environment. Design the assessment to support that real-time deployment, as well as implementation within integrated situation in a larger-scale smart grid to enhance efficiency, adaptability, and reliability.

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