Enhancing Renewable Energy Storage Conversion Efficiency using ERFE with FFNN

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Abstract – The 21st century witnesses a pivotal global shift towards Renewable Energy Sources (RES) to combat climate change. Nations are adopting wind, solar, hydro, and other sustainable energy forms. However, a primary concern is the inconsistent nature of these sources. Daily fluctuations, seasonal changes, and weather conditions sometimes make renewables like the sun and wind unreliable. The key to managing this unpredictability is efficient Energy Storage Systems (ESS), ensuring energy is saved during peak periods and used during low production times. However, existing ESSs are not flawless. Energy conversion and storage inefficiencies emerge due to temperature changes, inconsistent charge rates, and voltage fluctuations. These challenges diminish the quality of stored energy, resulting in potential waste. There is a unique chance to address these inefficiencies using the vast data from renewable systems. This research explores Machine Learning (ML), particularly Neural Networks (NN), to improve REES efficiencies. Analyzing data from Palm Springs wind farms, the study employs an Entropy-Based Recursive Feature Elimination (ERFE) coupled with Feed-Forward Neural Networks (FFNN). ERFE utilizes entropy to prioritize essential features, reducing redundant data and computational demands. The tailored FFNN then predicts energy conversion rates, aiming to enhance energy storage conversion and maximize the usability of generated Renewable Energy (RE).

Keywords – Renewable Energy, Energy Storage System, Feature Elimination, Entropy, FFNN, Machine Learning.

I. INTRODUCTION

The global transition to Renewable Energy Sources (RES) is one of the most critical undertakings of the 21st century. As nations rally to reduce their carbon footprints, the focus is increasingly on harnessing the power of wind, solar, hydro, and other sustainable resources. While adopting renewable energy systems has been encouraging, a foundational challenge remains: addressing the intermittent nature of these energy sources [1]. Unlike conventional energy sources, renewables are highly dependent on environmental conditions. The sun and wind, two primary sources of Renewable Energy (RE), are inconsistent and fluctuate based on time of day, seasons, and weather patterns [2]. This intermittent poses a significant challenge regarding how energy can be reliably provided when the primary sources are not always available. The answer lies in the efficiency and reliability of Energy Storage Systems (ESS).

Practical energy storage is vital for ensuring that energy generated during peak periods of renewable source availability is captured, stored, and then efficiently dispatched during periods of low or no generation [3]. Current storage systems, however, have their own sets of challenges. Inefficiencies arise during the energy conversion and storage processes due to numerous factors like temperature variations, charge rate inconsistencies, and fluctuating voltage levels. These inefficiencies can significantly reduce the quantity and quality of stored energy, leading to wastage and reduced effectiveness of RE installations [4]. Given the vast amount of data generated by renewable energy systems and storage units, there lies a unique opportunity. By applying advanced computational methods, it is possible to understand these inefficiencies in-depth, predict them, and even rectify them in real-time. Enter the Machine Learning (ML) domain, which has shown immense promise in numerous sectors, from healthcare to finance [5].

In this research, the potential of ML, specifically neural networks, is tapped to address the inefficiencies of Renewable Energy Storage Systems (RESS). By collecting and analyzing data from wind farms in Palm Springs, California, this study introduces an innovative approach that integrates the Entropy-Based Recursive Feature Elimination (ERFE) technique with Feed-forward Neural Networks (FFNN). ERFE, as the name suggests, uses entropy, a measure from information theory, to rank features based on their importance. By recursively eliminating fewer key features, the model is streamlined, reducing computational complexity while retaining data integrity. The FFNN, tailored to the unique demands of this dataset and problem, is trained to predict energy conversion efficiencies. This integrated model aims to optimize energy storage conversion efficiency, ensuring the maximum amount of generated RE is stored and made available for future use.

The paper is organized as follows: Section 2 presents the literature review, Section 3 presents the proposed methodology, Section 4 presents the experiment analysis, and Section 5 concludes the work.

II. LITERATURE REVIEW

ML and Artificial Intelligence (AI) utilization in RES and management has seen considerable attention in recent literature. [6] emphasize the potential of Reinforcement Learning (RL) in energy management, particularly concerning hydrogen production and storage. Their study highlights the advantages of incorporating energy and price forecasts within the RL paradigm. However, they also underline a prevailing challenge in this domain: defining a reward function that can cater to multiple objectives in an environment with limited freedom.

Another intriguing development in the field is captured by [7-10], focusing on ML's efficiency in modeling material interfaces. His discourse underscores the advantages of ML models over traditional first-principles methods, given their computational prowess. Such models have proven invaluable in understanding the structure, stability, and dynamics at materials interfaces, offering insights into interfacial reactions and mass transport.

Parallelly, [11-12] introduced an energy management model rooted in the performance metrics of lithium batteries. Their study employed DDPG and genetic algorithms, emphasizing such advanced methods' cost and performance benefits. [13] utilized various ML models to predict power conversion efficiencies, highlighting the high prediction accuracy of selected models. In contrast, [14] accentuated the efficacy of simple AI tools in improving the predictability and efficiency of domestic PV grids.

Lastly, the works of [15-17] signify the ever-increasing utility of ML in predicting power conversion efficiencies and the short-term predictability of household PV systems, respectively.

These contributions underscore the evolving landscape of RE management, driven by advanced computational methods. They also collectively spotlight the existing challenges and knowledge gaps, emphasizing the pressing need for further exploration, such as the present work, aiming to optimize energy storage efficiency through integrated ML approaches.

III. METHODOLOGY

Problem Statement

Given the context of ESS and their inherent inefficiencies, the problem can be formulated as an optimization challenge. Consider the following notations:

- E_i : Energy input to the storage system at time i.
- E_o : Energy output from the storage system at time i.
- L_i : Conversion loss at time i.
- $P(T, R, V)$: Conversion efficiency function dependent on temperature T, charge rate R, and voltage V.

The conversion efficiency η at time i is EQU (1)

$$\eta_i = \frac{E_0}{E_i - L_i} \tag{1}$$

Given that the loss L_i is a function of the input energy, temperature, charge rate, and voltage EQU (2)

$$L_i = E_i - P(T, R, V) \times E_o \tag{2}$$

The primary problem is to optimize the efficiency function P using a feed-forward neural network to minimize the loss L_i.

Objective Function:

The objective is to maximize the overall efficiency η over a period T, which is equivalent to minimizing the total loss L over the same period, EQU (3)

$$\min_{P} \sum_{i=1}^{T} L_i \tag{3}$$

Subject to:

$0 \leq L_i \leq E_i$

$E_o \leq E_i$

Where:

- The first constraint ensures that the loss is non-negative and does not exceed the input energy.
- The second constraint ensures that the output energy does not exceed the input energy.

By leveraging the FFNN model, an optimal $P(T, R, V)$ that achieves the objective is sought.

Data Collection Setup

The data for this study was sourced from a selected set of wind farms in Palm Springs, California. Recognized for its consistent solar exposure and prominence in wind energy, Palm Springs presents an environment rich in renewable energy resources, making it a typical location for this research [18-19]. The data was collated over 12 months to capture the seasonal variations intrinsic to Palm Springs. An hourly sampling frequency was employed to delineate the day-to-day energy dynamics. The detailed data description is presented in **Table 1.**

Data Sources

- Renewable Energy Generation Data: Hourly energy generation metrics from solar panels and wind turbines include power generated (in kWh) and the precise generation time. Additional source-specific metrics encompass solar irradiance for photovoltaic systems and wind speed metrics for the turbines.
- Energy Storage System Data: This dataset provides insights into the energy storage devices, detailing their charging and discharging rates, the cumulative stored energy at various time intervals, the health and efficiency of the storage system, and the associated conversion losses.
- Operational Parameters Data: Key operational parameters, pivotal in influencing conversion efficiency, include:
    - Temperature (T): Acquired from local weather stations and on-site sensors.
    - Charge Rate (R): Metrics detailing the pace at which the energy storage devices are charged or discharged.
    - Voltage (V): Data detailing the voltage level during various storage or retrieval processes.

Data Collection Tools and Infrastructure

- Sensors: Deployed across the energy generation and storage facilities in Palm Springs, these tools capture real-time data, ranging from current and voltage readings to wind speed and solar irradiance measurements.
- Data Loggers: Devices stationed on-site, consistently recording data over extended durations and set to capture data at precise hourly intervals.
- Centralized Data Repository: An integrated platform where all data streams converge, ensuring ease of access and comprehensive analysis.

Data Refinement

- Noise Mitigation: To ensure data integrity, techniques like rolling averages were employed to mitigate sensor noise.
- Data Imputation: Gaps in the dataset, resulting from missing entries, were addressed using data extrapolation techniques.
- Standardization: Before neural network input, normalization techniques ensured a consistent dataset, ready for analysis.

The data collected over a year-long period resulted in a dataset that was approximately 8,760 records (reflecting hourly data points). Post the rigorous data refinement processes, which involved noise mitigation, data imputation, and standardization, a cleaned dataset comprising 8,532 records was obtained. To ensure an unbiased approach in subsequent stages, this dataset was split into a 70:30 ratio, resulting in 5,972 records for training and 2,560 records for testing. This refined dataset not only maintains the integrity and authenticity of the original data but is also optimized for subsequent neural network input and analysis.

Entropy-Based Recursive Feature Elimination (ERFE)

- Given the complexity and multifaceted nature of RESS data, it is essential to identify the most salient features that significantly influence the outcome – in this case, conversion efficiency. By narrowing down the feature set, the model can focus on the most crucial data points, thereby improving efficiency, reducing overfitting, and simplifying interpretability.

Table 1. Data Description for RESS

Feature Name	Data Type	Units	Sample Value	Description
Date	Date	YYYY-MM-DD	2023-05-15	Date of data recording
Time	Time	HH: MM	14:30	Hourly timestamp of data recording
Power_Solar	Numeric	kWh	45.8	Power generated from solar panels
Power_Wind	Numeric	kWh	72.1	Power generated from wind turbines
Solar_Irradiance	Numeric	W/m^2	600	Solar irradiance impacting photovoltaic systems
Wind_Speed	Numeric	m/s	7.3	Speed of wind for turbines
Charge_Rate	Numeric	kWh	12.5	The rate at which energy storage devices are being charged
Discharge_Rate	Numeric	kWh	8.4	The rate at which energy is being discharged
Stored_Energy	Numeric	kWh	250.6	Cumulative energy stored in the system
Storage_Health	Numeric	Percentage	96	Percentage indicating the health and efficiency of the storage system
Conversion_Loss	Numeric	kWh	1.5	Energy lost during the storage conversion process
Temperature	Numeric	°C	27.5	Ambient temperature recorded at the site
Voltage	Numeric	V	450	Voltage level during the storage or retrieval processes
Noise_Level	Numeric	dB	1.2	Noise level or interference in the recorded data

This work proposes a novel, "Entropy-based Recursive Feature Elimination (ERFE)". The ERFE technique integrates entropy, a foundational concept from information theory, with the recursive feature elimination process to optimize Feature Selection (FS) for predictive models [20-22]. Entropy measures the amount of uncertainty or randomness in a dataset, and by applying it recursively, the algorithm aims to identify and retain only the most informative features for model training.

Given a dataset with n features, the entropy H for a specific feature f_i is calculated using the EQU (4)

$$H(f_i) = -\sum_{j=1}^{m} p\left(f_{i,j}\right)\log_2 p\left(f_{i,j}\right) \tag{4}$$

Where:

- $p\left(f_{i,j}\right)$ represents the probability of the j^{th} the unique value of the feature f_i.
- m is the number of unique values in the feature f_i.

A feature with high entropy indicates higher unpredictability, whereas a feature with low entropy suggests it imparts more distinctive information about the output variable. Once entropy values are computed for all features, they are ranked in ascending order EQU (5)

$$R(f_i) = \text{rank of } H(f_i) \text{ in } [H(f_1), H(f_2), \ldots, H(f_n)] \tag{5}$$

Features with lower entropy values (and thus lower rank values) are deemed more valuable for the prediction task. The essence of recursive elimination lies in systematically training the model and evaluating its performance by excluding one feature at a time:

1 Start with the complete feature set $F = \{f_1, f_2, \ldots, f_n\}$.
2 Train the model using F and evaluate its performance.
3 Remove the feature with the highest rank (and thus the highest entropy) from F. Let us denote this feature as f_{remove}, such that $f_{\text{remove}} = \text{argmax}\left(R(f_i)\right)$.
4 $F = F - \{f_{\text{remove}}\}$
5 Repeat steps $2-4$ until F is empty.

Throughout the recursive elimination, performance metrics (like accuracy mean squared error) are recorded. The optimal feature set is identified at the iteration with the highest model performance metric EQU (6)

$$F_{\text{optimal}} = \text{argmax Performance } (F) \tag{6}$$

Where "Performance" can be any relevant metric, such as accuracy for classification tasks or RMSE for regression tasks. Following the ERFE method, the final model is equipped with a subset of features that provide the maximum predictive power, thereby ensuring optimal performance with minimal complexity.

Feed-Forward Neural Network (FFNN) Design

The optimization of renewable energy storage conversion efficiency necessitates an advanced learning model. The chosen model for this task is the FFNN [23-24]. Its design and architecture are intricately shaped by the problem's distinctive requirements and the refined feature set derived from the ERFE technique. The FFNN, as shown in **Fig 1,** is structured with an input layer, several hidden layers, and an output layer. The input layer's size directly corresponds to the optimal feature set obtained from ERFE, with each node symbolizing a particular feature, such as temperature, charge rate, or voltage. Hidden layers are pivotal, allowing the network to discern nonlinear relationships and intricate interactions between features. The number of nodes in these layers and the count of layers themselves are typically determined through rigorous experimentation, seeking a balance between the model's accuracy and its computational demands. Finally, the output layer, tailored to this problem, contains a singular node dedicated to outputting the predicted conversion efficiency value.

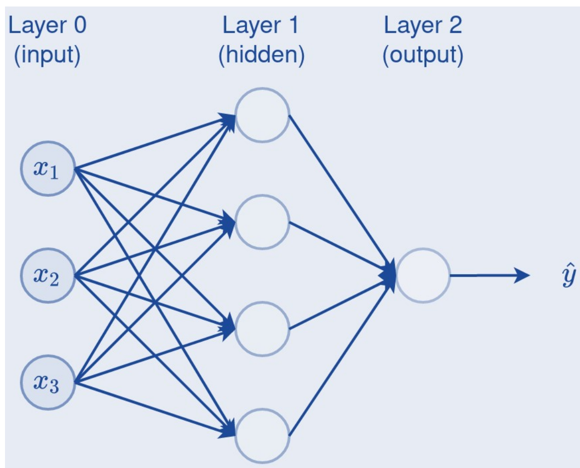

Fig 1. FFNN

Within the network, activation functions play a crucial role. For the hidden layers, the Rectified Linear Unit (ReLU) function is favored due to its computational efficiency and its ability to mitigate the vanishing gradient problem. Mathematically, ReLU is represented as EQU (7)

$$f(x) = \max(0, x) \tag{7}$$

In contrast, the output layer employs a sigmoid activation function, ensuring that the network's output values maintain a range between 0 and 1. This function can be expressed as EQU (8)

$$\sigma(x) = \frac{1}{1+e^{-x}}, \tag{8}$$

They are effectively representing the conversion efficiency as a proportional value. Training the FFNN revolves around several components. The chosen loss function is the Mean Squared Error (MSE), which strives to ensure the network's predictions closely align with the actual conversion efficiency values. The EQU (9) for MSE is

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2, \tag{9}$$

where y_i denotes the actual efficiency, $\hat{y}_i$ is its predicted counterpart, and N signifies the number of data points. For weight adjustments, the Adaptive Moment Estimation (Adam) optimizer is employed, merging the advantages of both AdaGrad and RMSProp for rapid and efficient convergence. To thwart overfitting, due to potential intricacy, dropout layers are interspersed between the hidden layers. These layers sporadically "drop out" a fraction of nodes in each training iteration, safeguarding the model from excessive dependence on specific nodes.

Additionally, an adaptive learning rate schedule is instituted, diminishing the learning rate progressively to ensure swifter convergence initially and more meticulous fine-tuning as training progresses. For model validation, a portion of the data is exclusively earmarked. Hyperparameters spanning the number of hidden layers, nodes in each layer, the learning rate, and the dropout rate undergo meticulous tuning using this validation subset. This ensures that the FFNN is primed to offer a real-time, adaptive solution to augment the efficiency of renewable energy storage systems.

ERFE + FFNN Enhanced Conversion Efficiency

The "ERFE + FFNN Enhanced Conversion Efficiency" algorithm presents a dual-phase approach to harnessing the optimal predictive power of the available features in renewable energy storage datasets. Initially, the ERFE method is employed. During this phase, the algorithm calculates the entropy of each feature, systematically removing the one with the highest entropy, which implies the highest unpredictability. This iterative process ensures the retention of the most informative features and effectively reduces the feature space, enhancing the efficiency of subsequent modeling. Once the optimal feature set, termed as $F_{optimal}$, is derived through ERFE, and the FFNN is initialized. The FFNN's architecture is carefully tailored with an input layer matching the size of $F_{optimal}$, multiple hidden layers with ReLU activation functions to capture non-linear relationships, and an output layer with a sigmoid activation to predict the conversion efficiency, η, which is intrinsically bounded between 0 and 1. Using the MSE as the loss function, the algorithm seeks to model the efficiency function $P(T, R, V)$ such that the predicted efficiency closely aligns with the actual values. The incorporation of the Adam optimizer ensures rapid convergence during training. After iterative training and validation on reserved subsets of the training data, the model's performance is assessed on the test data to ascertain its prowess in minimizing conversion loss over time T. The following algorithm presents the step-wise description of the proposed model

Algorithm ERFE + FFNN Enhanced Conversion Efficiency

Input : TRAIN_DATA, TEST_DATA

Output : Optimized model for P(T,R,V)

Begin

Step 1. F = All features in TRAIN_DATA // ERFE)
Step 2. Function ComputeEntropy (Feature)->value //Calculates and returns entropy of a given feature
Step 3. While F is not empty
Step 4. For Each feature f in F
Step 5. Entropy = ComputeEntropy(f)
Step 6. End For
Step 7. f_maxEntropy = feature with the highest entropy from F
Step 8. Remove f_maxEntropy from F
Step 9. FFNN_Model = Train FFNN using remaining features in F to predict η
Step 10. Record model performance
Step 11. End While
Step 12. F_optimal = Subset of features in F giving best model performance
Step 13. // Design & Training of FFNN to model P(T,R,V) for conversion efficiency η
Step 14. Initialize FFNN with input layer size as the size of F_optimal
Step 15. Define hidden layers with ReLU activation
Step 16. Define the output layer with sigmoid activation to predict η (bounded between 0 and 1)
Step 17. Define loss function as MSE between predicted η and actual η
Step 18. Use Adam optimizer for training
Step 19. For Each epoch
Step 20. Train FFNN using TRAIN_DATA with features F_optimal
Step 21. Validate FFNN using validation subset from TRAIN_DATA
Step 22. End For
Step 23. Evaluate FFNN using TEST_DATA to ensure minimized L over the period T
Step 24. Return FFNN
Step 25. End

IV. EXPERIMENTAL ANALYSIS

The experimental setup utilized a system with an Intel Core i9-10900K processor, 64 GB DDR4 RAM at 3200MHz, and an NVIDIA RTX 3080 GPU for efficient neural network training. This system operated on Ubuntu 20.04 LTS. The primary development environment was Python 3.8, incorporating libraries such as TensorFlow 2.6 and sci-kit-learn 0.24 to aid in neural network modeling and data processing. For the evaluation of the model, several metrics were employed. The MSE was crucial for quantifying the difference between the predicted and actual conversion efficiencies. Accuracy served to provide a percentage representation of correct predictions. In addition to these, the Root Mean Squared Error (RMSE) was computed to give an understanding of the prediction error magnitude. Lastly, the R^2, or the coefficient of determination, was used to determine the proportion of the variance for the dependent variable explained by independent variables in the model.

For the training of the ERFE + FFNN model, various hyperparameters were meticulously tuned to ensure optimal performance. The number of hidden layers in the FFNN was set to three, with the number of nodes in each layer being 128, 64, and 32, respectively. A dropout rate of 0.25 was applied between the hidden layers to prevent overfitting. The learning rate, a critical parameter dictating the adjustment magnitude of the network weights, was initialized at 0.001 and was adapted using a learning rate decay factor of 0.9 after every 10 epochs. This adaptive learning rate ensures a faster convergence during the initial epochs and a more refined tuning during the later stages of training. The Rectified Linear Unit (ReLU) served as the activation function for the hidden layers, while the output layer employed a sigmoid function. For the optimization process, the batch size was set to 32, and the training process spanned 50 epochs. Weight initialization was done using the He-normal initializer, which is particularly effective for layers with ReLU activations. Lastly, the Adaptive Moment Estimation (Adam) optimizer was chosen for its efficiency in converging, with a beta1 value of 0.9 and a beta2 value of 0.999, ensuring momentum and adaptive learning rates, respectively.

For a comprehensive evaluation of the proposed ERFE + FFNN model's effectiveness in optimizing conversion efficiency, several baseline models were chosen for comparison. These models represent a mix of traditional ML algorithms and neural architectures:

- Linear Regression (LR): A simple and interpretable model that assumes a linear relationship between the input features and the output.
- Decision Trees (DT): Non-linear models known for capturing intricate patterns in the data by recursively splitting the feature space.
- Random Forest (RF): An ensemble of DT that aggregates predictions to reduce variance and improve accuracy.
- Gradient Boosting Machines (GBM): Boosting-based ensemble learning that optimises previously mispredicted instances.
- Support Vector Machines (SVM): Powerful for finding the optimal hyperplane separating the classes in a transformed feature space.
- Simple FFNN: A basic neural network architecture without the FS steps to gauge the impact of the ERFE process.

By contrasting the performance of the proposed model against these baselines, the study aims to determine the relative advantages of the integrated ERFE + FFNN approach in the context of renewable energy storage efficiency optimization.

The experimental results, as presented in **Fig 2 to Fig 4,** provide a comprehensive insight into the performance of the proposed ERFE + FFNN model compared to the baseline models across varying epoch sizes. For the MSE, it is evident that the ERFE + FFNN model consistently outperforms the other models, achieving the lowest error rates. This indicates that the proposed model is more adept at closely predicting conversion efficiencies than its counterparts. Throughout increased training epochs, this model demonstrated a significant reduction in MSE, indicating the benefits of prolonged training. In terms of RMSE, which provides a measure of the average magnitude of errors between predicted and observed values, the ERFE + FFNN model's superiority remains consistent. Notably, while all models seem to benefit from extended training, the rate of improvement in RMSE for the proposed model is commendable.

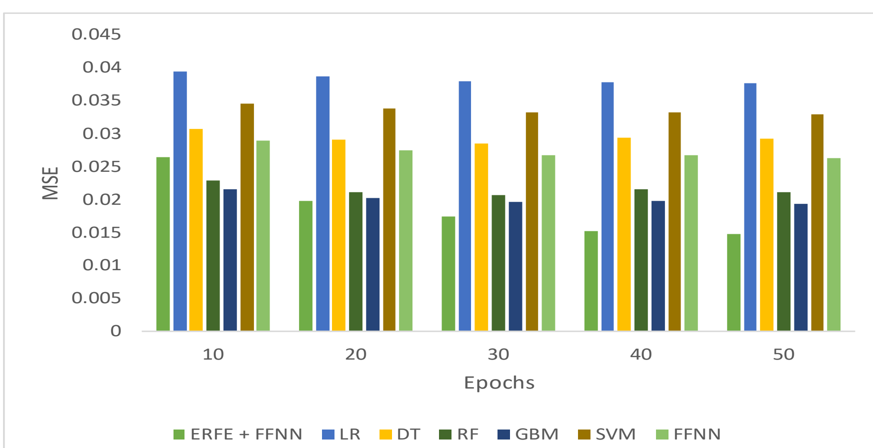

Fig 2. MSE for all Models

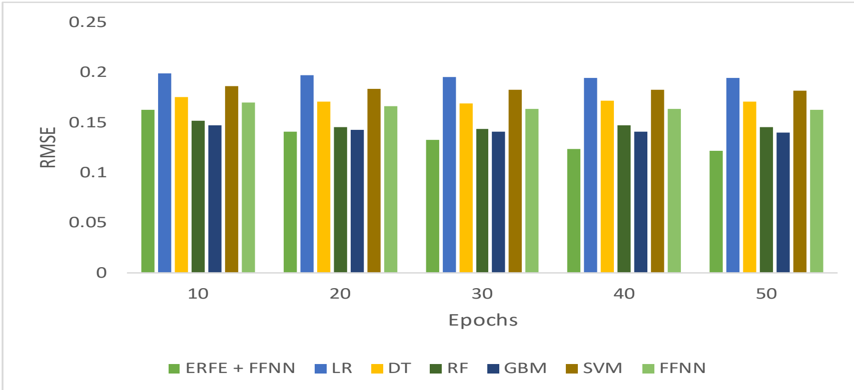

Fig 3. RMSE for all Models

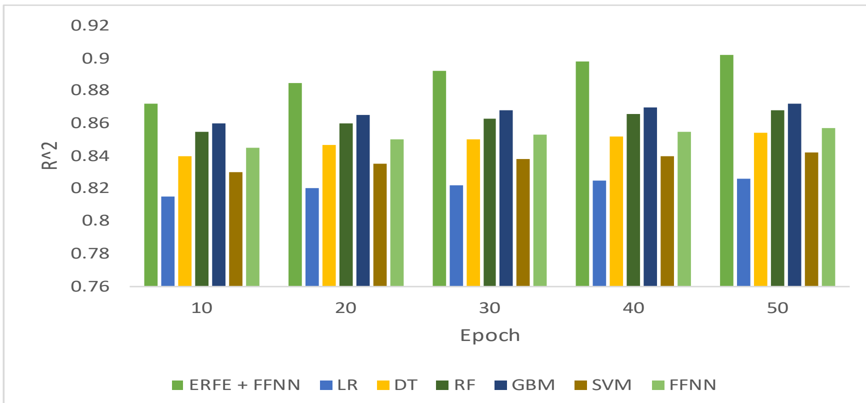

Fig 4. R^2 for all Models

The R^2 values, which measure the proportion of the variance for the dependent variable explained by the independent variables in the model, further validate the prowess of the ERFE + FFNN model. Across the board, its R^2 values are highest, suggesting that it captures the underlying data trends most effectively. As epoch counts increase, there is a discernible enhancement in the model's explanatory power. One interesting observation across all metrics is that while traditional machine learning models like Linear Regression (LR), Decision Trees (DT), and SVMs show minor improvements with more epochs, models harnessing ensemble or neural techniques, such as Random Forests, GBMs, and FFNNs, demonstrate more pronounced benefits from extended training. The ERFE + FFNN model, tailored specifically for the unique characteristics of the RES dataset, showcases its potential as an advanced tool for optimizing conversion efficiency. Its consistent performance superiority across MSE, RMSE, and R^2 metrics, combined with the empirical evidence from extended training epochs, affirms its robustness and aptness.

V. CONCLUSION AND FUTURE WORK

The shift towards Renewable Energy (RE) sources is essential for a sustainable future. However, the inherent intermittent of these sources demands innovations in Energy Storage Systems (ESS). This research successfully leverages the power of Machine Learning (ML), particularly the synergy between ERFE and FFNN, to address storage inefficiencies. Integrating these advanced techniques, applied to data from wind farms in Palm Springs, reveals a promising approach to optimize energy storage conversion efficiency. By prioritizing data features using entropy and accurately predicting energy conversion rates, the model aims to ensure that generated RE is maximized for storage and subsequent use. The experimental analysis, benchmarked against contemporary models, highlights the superiority of the proposed model in various performance metrics. As we look to the future, several avenues exist for further research and exploration. First, the model can be extended and tested across various renewable energy sources beyond wind farms, like solar fields and hydropower stations. This would ascertain its adaptability and scalability. Secondly, integrating real-time feedback mechanisms could allow for immediate adjustments to storage systems based on predictions, further enhancing efficiency. Lastly, as technology evolves, there will be opportunities to combine this approach with other emerging AI and data analytics techniques. Such interdisciplinary collaborations could pave the way for holistic solutions to the global energy challenge.

Data Availability
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interests
The author(s) declare(s) that they have no conflicts of interest.

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Competing Interests
There are no competing interests.

References
[1]. W. Strielkowski, L. Civín, E. Tarkhanova, M. Tvaronavičienė, and Y. Petrenko, "Renewable Energy in the Sustainable Development of Electrical Power Sector: A Review," Energies, vol. 14, no. 24, p. 8240, Dec. 2021, doi: 10.3390/en14248240.
[2]. D. Yang et al., "A review of solar forecasting, its dependence on atmospheric sciences and implications for grid integration: Towards carbon neutrality," Renewable and Sustainable Energy Reviews, vol. 161, p. 112348, Jun. 2022, doi: 10.1016/j.rser.2022.112348.
[3]. C. O'Dwyer, L. Ryan, and D. Flynn, "Efficient Large-Scale Energy Storage Dispatch: Challenges in Future High Renewable Systems," IEEE Transactions on Power Systems, vol. 32, no. 5, pp. 3439–3450, Sep. 2017, doi: 10.1109/tpwrs.2017.2656245.
[4]. I. E. Atawi, A. Q. Al-Shetwi, A. M. Magableh, and O. H. Albalawi, "Recent Advances in Hybrid Energy Storage System Integrated Renewable Power Generation: Configuration, Control, Applications, and Future Directions," Batteries, vol. 9, no. 1, p. 29, Dec. 2022, doi: 10.3390/batteries9010029.
[5]. V.-D. Păvăloaia and S.-C. Necula, "Artificial Intelligence as a Disruptive Technology—A Systematic Literature Review," Electronics, vol. 12, no. 5, p. 1102, Feb. 2023, doi: 10.3390/electronics12051102.
[6]. A. Dreher et al., "AI agents envisioning the future: Forecast-based operation of renewable energy storage systems using hydrogen with Deep Reinforcement Learning," Energy Conversion and Management, vol. 258, p. 115401, Apr. 2022, doi: 10.1016/j.enconman.2022.115401.
[7]. N. Artrith, "Machine learning for the modeling of interfaces in energy storage and conversion materials," Journal of Physics: Energy, vol. 1, no. 3, p. 032002, Jul. 2019, doi: 10.1088/2515-7655/ab2060.
[8]. Y. Gao, J. Li, and M. Hong, "Machine Learning Based Optimization Model for Energy Management of Energy Storage System for Large Industrial Park," Processes, vol. 9, no. 5, p. 825, May 2021, doi: 10.3390/pr9050825.
[9]. N. Alwadai, S. U.-D. Khan, Z. M. Elqahtani, and S. Ud-Din Khan, "Machine Learning Assisted Prediction of Power Conversion Efficiency of All-Small Molecule Organic Solar Cells: A Data Visualization and Statistical Analysis," Molecules, vol. 27, no. 18, p. 5905, Sep. 2022, doi: 10.3390/molecules27185905.
[10]. I. Rojek, D. Mikołajewski, A. Mroziński, and M. Macko, "Machine Learning- and Artificial Intelligence-Derived Prediction for Home Smart Energy Systems with PV Installation and Battery Energy Storage," Energies, vol. 16, no. 18, p. 6613, Sep. 2023, doi: 10.3390/en16186613.
[11]. "Grid Integration of Renewable Energy Sources using GA Technique for Improving Power Quality," International Journal of Renewable Energy Research, no. v11i3, 2021, doi: 10.20508/ijrer.v11i3.12292.g8283.
[12]. "Application of Artificial Intelligence to DFIG based wind farm for Reactive Power Compensation," International Journal of Renewable Energy Research, no. v10i2, 2020, doi: 10.20508/ijrer.v10i2.10684.g7962.
[13]. J. F. Roseline et al., "Neural Network modelling for prediction of energy in hybrid renewable energy systems," Energy Reports, vol. 8, pp. 999–1008, Nov. 2022, doi: 10.1016/j.egyr.2022.10.284.
[14]. A. H. Elsheikh et al., "Low-cost bilayered structure for improving the performance of solar stills: Performance/cost analysis and water yield prediction using machine learning," Sustainable Energy Technologies and Assessments, vol. 49, p. 101783, Feb. 2022, doi: 10.1016/j.seta.2021.101783.
[15]. A. M. Gandhi et al., "Performance enhancement of stepped basin solar still based on OSELM with traversal tree for higher energy adaptive control," Desalination, vol. 502, p. 114926, Apr. 2021, doi: 10.1016/j.desal.2020.114926.
[16]. A. M. Gandhi et al., "SiO2/TiO2 nanolayer synergistically trigger thermal absorption inflammatory responses materials for performance improvement of stepped basin solar still natural distiller," Sustainable Energy Technologies and Assessments, vol. 52, p. 101974, Aug. 2022, doi: 10.1016/j.seta.2022.101974.
[17]. P. Chithaluru, F. Al-Turjman, T. Stephan, M. Kumar, and L. Mostarda, "Energy-efficient blockchain implementation for Cognitive Wireless Communication Networks (CWCNs)," Energy Reports, vol. 7, pp. 8277–8286, Nov. 2021, doi: 10.1016/j.egyr.2021.07.136.
[18]. A. Gayathri et al., "Cooperative and feedback based authentic routing protocol for energy efficient <scp>IoT</scp> systems," Concurrency and Computation: Practice and Experience, vol. 34, no. 11, Feb. 2022, doi: 10.1002/cpe.6886.
[19]. R. C. Bheemana, A. Japa, S. S. Yellampalli, and R. Vaddi, "Negative capacitance FETs for energy efficient and hardware secure logic designs," Microelectronics Journal, vol. 119, p. 105320, Jan. 2022, doi: 10.1016/j.mejo.2021.105320.
[20]. P. Thamizharasu et al., "Revealing an OSELM based on traversal tree for higher energy adaptive control using an efficient solar box cooker," Solar Energy, vol. 218, pp. 320–336, Apr. 2021, doi: 10.1016/j.solener.2021.02.043.
[21]. T. Vino et al., "Multicluster Analysis and Design of Hybrid Wireless Sensor Networks Using Solar Energy," International Journal of Photoenergy, vol. 2022, pp. 1–8, Oct. 2022, doi: 10.1155/2022/1164613.
[22]. B. B. Sharma et al., "Designing and implementing a smart transplanting framework using programmable logic controller and photoelectric sensor," Energy Reports, vol. 8, pp. 430–444, Nov. 2022, doi: 10.1016/j.egyr.2022.07.019.
[23]. L. Sathish Kumar et al., "Modern Energy Optimization Approach for Efficient Data Communication in IoT-Based Wireless Sensor Networks," Wireless Communications and Mobile Computing, vol. 2022, pp. 1–13, Apr. 2022, doi: 10.1155/2022/7901587.
[24]. R. Thirumuru, K. Gurugubelli, and A. K. Vuppala, "Novel feature representation using single frequency filtering and nonlinear energy operator for speech emotion recognition," Digital Signal Processing, vol. 120, p. 103293, Jan. 2022, doi: 10.1016/j.dsp.2021.103293.