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The Future of Industrial Design: Incorporating Water Energy Solutions for Green Manufacturing Using an Enhanced Adaptive Neuro-Fuzzy Inference System with Red Deer Algorithm

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Abstract. In response to the increasing demand for sustainable energy solutions in industrial design, this study proposes an Enhanced Adaptive Neuro-Fuzzy Inference System (ANFIS) optimized by the Red Deer Algorithm (RDA) to enhance the efficiency and adaptability of water-based energy systems for green manufacturing. The ANFIS model is employed to accurately predict and optimize complex nonlinear relationships in water energy utilization, while the RDA enhances parameter tuning to achieve superior system performance. Real-time adaptive control is realized through the proposed approach, minimizing operational costs and improving the reliability of energy systems. Key factors such as energy conversion efficiency, water flow dynamics, and environmental impacts are integrated into machine learning-driven predictive models for comprehensive system analysis. Comparative results demonstrate that the ANFIS-RDA framework significantly outperforms traditional optimization methods in energy savings and resource utilization, offering a transformative pathway towards carbon-negative, energy-efficient, and eco-friendly industrial production processes.

Key words. Water Energy, Green Manufacturing, Sustainable Industrial Design, ANFIS, RDA.

1. Introduction

The sustainable development of industries depends heavily on effective renewable energy solutions at this critical moment. Water energy-all its subtypes including hydropower and tidal energy with wave energy-establishes itself as an impressive untapped resource for sustainable manufacturing operations [1]. Green production methods gained prominence because industrial interests face growing pressure related to climate change and environmental deterioration as well as declining fossil fuel stores [2]. Industrial design leads the industry transformation which integrates novel water energy solutions into production systems to boost operational performance alongside diminishing pollution impacts [3].

Since the last decades the industrial sector maintains its position as a foremost producer of greenhouse gas emissions and environmental contamination [4]. The current manufacturing industry bases its operations mainly on fossil fuels which produces significant carbon emissions while maintaining hazardous energy consumption habits. Water energy solutions prove to be suitable and efficient ecological approaches to generate clean electricity that powers industrial operations [5]. The use of water energy strengthens both the sustainable power distribution and reduces the dependency on fossil fuels along with industrial waste reduction. The advancement of industrial design elements enables a smooth implementation of hydropower together with water-based energy solutions across production facilities while maintaining economic viability and operational efficiency [6].

The industrial sector benefits from various advantages that come from water energy solutions. Hydropower stands as one of the oldest renewable energy systems which generates dependable power for managing large manufacturing operations [7]. Hydropower keeps operating continuously because it differs from solar and wind energy which depend on weather conditions [8]. Fielded innovations in water energy technology along with hydroelectric systems, tidal converters and wave devices create opportunities for efficient usage of water power across industrial environments. The solutions work best when industries around water bodies utilize these opportunities to manage clean energy generation using natural hydrodynamic forces effectively [9].

A successful implementation of water-based energy solutions demands cooperation between engineers and architects in addition to environmental scientists [10]. To address environmental concerns industrial designers should work on creating equipment with higher energy efficiency alongside productive layouts while building systems that join renewables with the main power supply [11]. The green nature of industrial facilities receives additional enhancement through sustainable water management methods which include both closed-loop cooling systems and water recycling technologies. Industries reduce environmental damage substantially by focusing on energy conservation and with resource efficiency which maintains productive competition levels [12].

In addition, government policies and international sustainability goals also contribute to speeding up the use of water energy solutions in industrial design [13]. As industries place greater emphasis on carbon neutrality and improvement of corporate social responsibility, the desire for clean energy or renewable energy is growing and industries are being encouraged to shift toward greener energy options. The world is driven by regulatory frameworks that mature renewable energy investment, green manufacturing tax incentives and research funding for new water energy technologies [14]. Additionally, governments, private sector firms and research institutions have engaged in and continue to cooperate to support advances in water energy solutions technologies aimed at providing affordability and lower cost of manufacturing for manufacturers [15].

Despite all the potential that water energy offers for industrial design, there are still some challenges. For instanc, water energy infrastructure is typically more expensive to install initially than some other forms of energy infrastructure, and fit or return to investment must be carefully considered by industries [16]. Also, hydropower calls for ecological consideration, i.e., habitat disruption and water resource planning and its environmental impact assessment. Fortunately, these challenges can be mitigated as these advancements in technology, policy support, industry driven innovation will result in water energy as a major factor of green manufacturing in the future.

Section 2, the Literature Review, provides a comprehensive examination of relevant studies and methodologies, highlighting gaps in current research and establishing the theoretical foundation for the study. In Section 3, the Proposed Architecture introduces the innovative framework or model designed to address the identified research gaps, detailing its components, mechanisms, and how it enhances existing approaches. Section 4, the Performance Evaluation, presents a rigorous assessment of the proposed model's effectiveness, comparing its performance with existing methods using various metrics such as accuracy, efficiency, and scalability. Finally, Section 5, the Conclusion, summarizes the key findings of the research, reflects on its contributions to the field, and outlines potential directions for future work, emphasizing how the study advances knowledge and offers practical implications for industry applications.

2. Related Works

Water energy solutions have been widely integrated into industrial design and studied in terms of efficiency, feasibility and environmental issues of hydropower, tidal energy, and wave energy in manufacturing. The technological advancements of energy conversion, small-scale hydroelectric system, tidal stream generator, wave energy converters, have been studies. Moreover, the economic and regulatory factors that drove the industrial adoption were researched through the process of financial incentives, policy frameworks, and long-term sustainability benefits. To stay in line with the greener direction these industrial processes are heading towards, this literature survey undertakes a review of existing research that includes key innovations, its advantages and gaps in the implementation of water energy solution to support sustainable manufacturing process.

Paulino José García-Niet et al. [17] have developed hydrogen gas production forecasting models from biomass pyrolysis using multilayer perceptron (MLP) and support vector regression (SVR) with artificial bee colony (ABC) algorithm. The study produced results indicating that the introduced prediction models achieved enhanced accuracy estimation of hydrogen yield for bioenergy system optimization. The method delivered useful results since the optimization process allowed for biomass conversion without needing time-consuming experimental testing. Using this method faced two main issues because it needed excellent input information while the model failed to adjust to multiple types of biomass raw materials.

Table 1. Conventional technique research gap validation

Authors	Techniques Involved	Advantages	Disadvantages
Paulino José García-Niet et al., [17]	MLP, SVR, ABC Algorithm	Accurate hydrogen yield prediction, optimized biomass conversion	Data dependency, limited generalizability
Amel Ali Alhussan et al., [18]	BER, PSO, RNNs	High forecasting accuracy, adaptable to solar/wind changes	High computational cost
Abhijit Kumar et al., [19]	ANNs	Fast assessment, reduced experimental costs	Limited interpretability, data-intensive
Osama Khan et al., [20]	ANFIS, GMM	Enhanced photocatalysis, lower costs	Limited scalability, complexity in synthesis
K. Adeli et al., [21]	CNNs, LSTM	Improved hydrogen production prediction	High data requirement, risk of overfitting

Amel Ali Alhussan et al., [18] have combined Al-Biruni Earth Radius algorithm with Particle Swarm Optimization for improving recurrent neural network (RNN) to forecast hydrogen production. The model generated improved forecasting accuracy so it demonstrates usefulness for planning and managing energy system operations. Changed solar and wind energy conditions did not affect the methodology's prediction accuracy because it demonstrated flexible performance in its output of hydrogen predictions. The study showed high computational complexity acted as an implementation challenge that required significant processing power and time to accomplish scale-up.

Abhijit Kumar et al., [19] have developed artificial neural networks (ANNs) which predict as well as optimize metal hydride hydrogen storage systems. The approach generated fast and exact results about hydrogen absorption and desorption rates thus minimizing the requirement for slow and expensive physical tests. This scientific work illustrated how material selection optimization together with system efficiency enhancement became possible through its research approach. Here, develop an ANN-based models for prediction but their insufficient interpretability decreases the ability to explain decisions and needs considerable training data for peak functionality.

Osama Khan et al., [20] optimized solar driven photocatalysis in hydrogen production using a hybrid model which uses Adaptive Neuro Fuzzy Inference System (ANFIS) and Gaussian Mixture Model (GMM). Machine learning algorithms were used to predict optimized photocatalytic reaction settings and then research was done to improve the hydrogen yield. It also reduced the usage of material and reduced experimental expense while improving performance. Optimization of the synthesis of the nanocomposites remained challenging, so large scale application development with nanocomposites was complex for research.

K. Adeli et al., [21] have integrated renewable energy data of solar and wind sources in their attempt to create a framework to optimize hydrogen production in Morocco's coastal regions in a deep learning-based framework. To forecast and control hydrogen generation, the authors employed CNNs and LSTM networks. The resulting idea reduced predictive accuracy and efficiency of planning for renewable hydrogen production. Nevertheless, limitations included the need for extensive real time energy data and overfitting problems in deep learning models, that required updated models and model retraining frequently.

Recent advancements in hydrogen production forecasting have demonstrated the potential of intelligent models such as MLP, SVR, RNNs, ANNs, ANFIS, and deep learning frameworks (CNNs, LSTM) when integrated with optimization algorithms like ABC, PSO, and BER. These models have shown improved accuracy in yield prediction, operational cost reduction, and adaptation to variable renewable energy inputs. However, they face critical limitations including high computational complexity, dependency on large datasets, limited generalizability across biomass types, and challenges in model interpretability and scalability. In response to these gaps, this study contributes a robust hybrid predictive framework that leverages enhanced learning algorithms to improve scalability, interpretability, and adaptability for diverse industrial hydrogen production scenarios. The proposed model addresses data dependency and generalization issues, aiming to provide accurate forecasting while minimizing computational overhead, thereby supporting sustainable and efficient hydrogen energy systems.

3. Proposed Design Architecture

These techniques main intention will be to describe the steps of designing machine learning models to maximize the electrolysis operation for green hydrogen production using renewable energy input. The electrolysis is a procedure in which the water is broken down with the help of electricity into hydrogen as well as oxygen [22]. By flowing an electric current equal with the chemical electrical gradient, it can pass and cause water to dissociate into the fundamentals. The generated hydrogen gas can then be used as clean and renewable energy sources. The electrolysis of gauze for generation of hydrogen can be affected by a wide range of factors. The process is controlled by variables like the nature of the electrolyzed material, the purity of the water, the temperature, the development strain, and the energy source used to power it. It is important to optimize these variables to empower cost effectiveness and efficiency in the production of hydrogen [23].

The conventional optimization of process of electrolysis was based on empirical basis and manual adjustments. These techniques are optimal to some content but there are limitations in terms of measure of their capability to optimally optimize the procedure. However, it is also labour intensive and time consuming making them less practical for large scale hydrogen generation. It is found that machine learning is a promising technique for the selection of electrolysis in hydrogen generation. There is different sort of machine learning models which can be utilized for the identification of relationship between input parameters and efficiency of the electrolysis procedure can be done using the Regression architectures.

In particular, neural networks are appropriately designed for complex, nonlinear relationships in the information. It can learn from past information for making identifications about future efficiency enhancements [24]. Similarly, reinforcement learning was applied to optimize the electrolysis process over time by training from feedback acquired from the architecture. Such capability can help the architecture adapt to changes in conditions, or improve on efficiency. The use of machine learning architectures can generate higher stages of cost effectiveness and efficiency in green hydrogen production for practitioners and researchers. These architectures can learn from past information, detect patterns and carry on identifications in order to optimize the electrolysis procedure for greatest effectiveness and base effectiveness.

A. Data Collection and Pre-Processing

The information gathered from industrial scale electrolysis presents interesting information about the real-life conditions and challenge that need to be addressed in hydrogen generation. All this data considers electricity consumption, production rate, operating parameters and water quality. Laboratory experiments can be used to provide controlled environment for validating certain parameters of the electrolysis process.

Information obtained from these experiments can help understand the theory of electrolysis itself and can be used to justify and refine machine learning architectures. One critical factor in the electrolysis procedure is the count of electricity input, which directly results in efficiency and hydrogen production cost. They are required for improving the optimal models of choosing the procedure, and provided with information on the electricity consumption.

Durability and efficiency of the electrolyzed depend on the water quality used in the electrolysis procedure. Validation of the electrolysis procedure depends variables like mineral content, pH level and water purity, which they must be clearly written in the procedure for data collection. Variables may require pressure and temperature affecting the accuracy of the procedure of electrolysis procedures. These variables are critical in condition of electrolysis efficiency since data on them and their changes during function, including the surface location of the electrolyte and the electrolyte conductivity, must be considered. However, a possession of such data can help you understand the hidden techniques and optimize the procedure.

B. ANFIS Architecture

The ANFIS is a single efficient hybrid model developed based on the merging of the strength of ANN and Fuzzy Logic methodologies. A hybrid learning algorithm is designed to achieve this combination through selecting the variables with membership function using the back propagation approach and the variables with the consequent using the least squares technique. ANFIS uses this hybrid technique, it is first, a training adaptable behaviour of ANN and second mechanical reason and flexibility of learning. The below rules define a fist order sugeno type fuzzy inferring architecture that can be taken into account by ANFIS. The ANFIS will be presented in Figure 1.

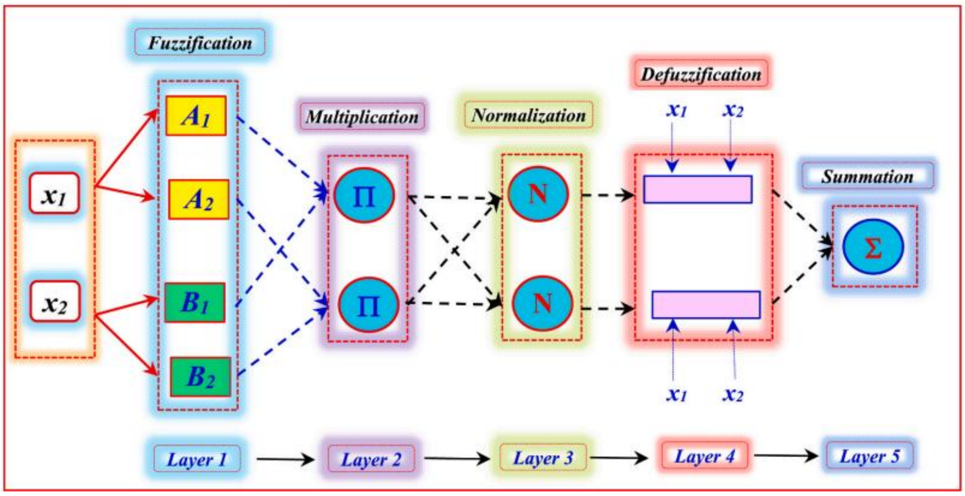

Figure 1. ANFIS architecture

$$\text{RULE 1} := \text{if } X1 = A1 \text{ and } X2 = B1 \text{ then } F1 = P1X1 + Q1X2 + R1 \quad (1)$$

$$\text{RULE 2} := \text{if } X1 = A2 \text{ and } X2 = B2 \text{ then } F2 = P2X1 + Q2X2 + R2 \quad (2)$$

In equation (1) and (2) ,the linear variables of the fuzzy rule are defined as A1, A2, B1, B2, and P1, P2, Q1, Q2 and R2, which are the fuzzy pairs [25].

Due to the fact that ANFIS is an architecture for the nonlinear relationships between outputs and inputs, this design manages ANFIS to create this architecture for tasks such as regression validation and time series identification [26].

Layer 1: Fuzzy Fuzzification, which is the layer containing the adaptive nodes which have fuzzy membership functions. This layer is responsible for transforming the numerical input variable into a fuzzy pairs by each input parameter mapped to a corresponding membership function and computes the degree to which an input variable is correlated with a specific fuzzy pair and hence quantifies the uncertainty or vagueness associated with the input [27]. The results by (3) and (4) are presented.

$$O_I^1 = \mu_{AI}\left(X_1\right), I = 1,2 \quad (3)$$

$$O_I^1 = \mu_{BI-2}\left(X_2\right), I = 3,4 \quad (4)$$

Here, the output of the node is O_I^1 and the membership functions are μ_{BI} and μ_{AI} .

Layer 2: Multiplication contains of fixed nodes which validate a specific function described as follows in equation (5),

$$O_I^2 = \omega_I = \mu_{AI}\left(X_1\right) \times \mu_{BI}\left(X_2\right), I = 1,2 \quad (5)$$

Layer 3: Normalization is expressed in equation (6)

$$O_I^2 = \overline{\omega_I} = \frac{\omega_I}{\omega_1 + \omega_2} \quad (6)$$

Layer 4: defuzzification presents the procedure of de-fuzzifying the signal related on the below formulation in equation (7),

$$O_I^4 = \overline{\omega_I} f_I = \overline{\omega_I}\left(\alpha_I X_1 + \beta_I X_1 + \gamma_I\right), I = 1,2 \quad (7)$$

Here, α_I , β_I and γ_I is defined as the linear parameters.

Layer 5 (summation), the output node is computed as the summation of complete input signals is expressed in equation (8).

$$O_I^4 = \sum_{I=1} \overline{\omega_I} f_I = \frac{\sum_I \omega_I f_I}{\sum_I \omega_I}, I = 1,2 \quad (8)$$

The above defined ANFIS architecture is an example of hybrid technique of ANN and fuzzy logic [28] to enhance identification performance by including both nonlinear and linear variables. Here the correlation of fuzzy rules and linear variables is defined with linear functions in layer 4, i.e., along with fuzzy rules, the input variables are linear [29]. Second, these consequent variables are normally upgraded during the forward pass of the learning procedure by means of the least square technique. ANFIS allows the architecture to control which these variables can be managed so that linear dependencies in the information can be collected. Similarity, the nonlinear variables are put forward in layer 1 and correlated to the fuzzy membership function that represents the extent of the input parameters to the fuzzy pairs [30]. The premises variables are nonlinear, and because they are critical for the architecture to collect non-linear relationships between output and input variables, these premises variables must be adjusted [31]. They are then upgraded using the backpropagation - a standard technique in the ANN learning of reducing the errors between actual and the predicted outputs [32].

C. Red Deer Algorithm

The ANFIS's weighting parameter is selected by using the RDA. Its distinction is in that it is new optimization algorithm sets included inspiration from the natural world because of the red deer characteristics. The technique is motivated by red deer, which are watchful, search for food, and cluster to explore and exploit the solution space efficiently. By relying on those innate behaviors, it achieves itself from those traditional algorithms, and introduces a new way of solving problems in optimization. In fact, the continuing interest in the subject that has arisen in the optimization community [33] is due to the originality of the subject and its possibly utilizes. Moreover, ROA is a relatively new contribution into the discipline that has already attracted attention of researchers interested in using and finding out what ROA has to offer. This algorithm has been applied to various functions, including image processing, robotics, and engineering design; it was proven that can use this algorithm to solve a very complex optimization problem and perform very well unlike many other existing optimization algorithms [34]. During the roaring stage of male red deer, they mimic the roaring characteristics of deer to initiate the optimization procedures. In this stage, this is allowed to exploit the possible solutions with local search behaviours [35]. In order to diversify, male deer add randomization parameters to diversify their communities during their investigation expressed in equation (9) and (10).

$$Y = \begin{bmatrix} Y_1 \\ \cdots \\ Y_I \\ \cdots \\ Y_N \end{bmatrix}_{N \times M} = \begin{bmatrix} Y_{1,1} & \cdots & Y_{1,D} & \cdots & Y_{1,M} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ Y_{I,1} & \cdots & Y_{I,D} & \cdots & Y_{I,M} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ Y_{N,1} & \cdots & Y_{N,D} & \cdots & Y_{N,M} \end{bmatrix}_{N*M} \quad (9)$$

$$Y_{I,D} = LB_D + R.\left(UB_D - LB_D\right) \quad (10)$$

A section of the hinds in commandeers harems mate with them, users can manage exploration and diversity by managing the count of hind's mate with commanders utilizing the variable. This phase promotes population diversity and exploration. In order to mimic the natural characteristics of deer during the breeding season, every stag mates with the closest hind. This procedure balances exploitation and exploration aspects. The next generation is computed by two techniques, retaining elite solutions and selecting offspring related on fitness parameters. The selection procedure shapes the complete shapes the final population and concludes the iterative optimization cycle. The RDA offers a unique optimization technique, allowing users to fine tune its characteristics related to the behaviours of the problem at hand. Machine learning models can continuously validate information from different actuators and sensors in the electrolysis architecture to make real time adjustments to operational variables. The step-by-step process is presented as follows,

- **Initialize Population**: Randomly initialize the positions of red deer (candidate solutions) in the search space, which represent different sets of ANFIS parameters.
- **Evaluate Fitness**: For each red deer, train ANFIS with the corresponding parameters and calculate the fitness (e.g., error rate or accuracy).

- **Update Position:** Move each red deer based on RDA's rules, adjusting their positions according to their fitness. Red deer move closer to better solutions (lower error or higher accuracy).
- **Leader Update:** The best-performing red deer (leader) influences other red deer, guiding them towards the optimal solution.
- **Repeat:** Continue this process over multiple iterations until the stopping criterion (e.g., max iterations or satisfactory fitness) is reached.
- **Return Best Solution:** After the iterations, the best-performing red deer provides the optimized ANFIS parameters.

The term is UB_D , LB_D , the random number in the interval [0,1] by R, M the number of decision parameters, $Y_{(I,D)}$ the dimension in search space, Y_I the red deer.

There is a portion of the hinds that can mate with them, and the users can do that with a variable that commands the count of hinds' mate with commanders. This is useful to promote population diversity and population exploration. But the question is: If required to simulate red deer's breeding behaviour, every stag mated with its nearest hind. It balances the aspects of exploitation and exploration of the procedure. Other two techniques of computing the next generation used by it are retain the elite solutions and pick the offspring based on some fitness related values. Therefore, the entire shapes of the final population are decided by the selection procedure, and closes the iterative optimization cycle. Its specific optimization technique permits optimizing the parameter due to its ability to tune its behaviours in accordance with behaviours of the problem. Machine learning models retain at all times to validate several actuators and sensors in the electrolysis architecture obtaining real time adjustments of several operational variables.

Machine learning technique can validate online information from renewable energy sources including wind power and solar associated with capacity scheduling on their availability of renewable energy sources to justify maximizing the use of renewable energies and cut down on the use of fossil fuels. Machine learning architectures enable the use of electricity for electrolysis to be optimized with renewable energy sources such that hydrogen production is as energy efficient as is possible. Machine learning architectures have now been already executed by different companies and research institutions for optimizing production of the green hydrogen on an industrial scale. Additionally, these implementations have demonstrated great efficiency and cost beneficial gains.

4. Outcome Evaluation

The performance of the proposed ANFIS RDA model was assessed against ANFIS GA (Genetic Algorithm), ANFIS PSO (Particle Swarm Optimization), ANFIS GWO (Grey Wolf Optimization), by using multiple performance metrics such as False Positive Rate (FPR), False Negative Rate (FNR), execution time, error parameters, Dice Similarity Coefficient (DSC), Jaccard Index, error value, accuracy, and precision. Accuracy and precision of classification and optimization are better than other models are indicated by the results; ANFIS-RDA outperforms the other models. The ANFIS-RDA parameters and error values are lower and also form better error parameters than those of the ANFIS predictive controller, which indicates that it is better at minimizing prediction errors and attaining more reliable energy management. Moreover, the model resulted in lower FPR and FNR, meaning that have reduced misclassification rates that would improve the efficiency of the water energy optimization process. Moreover, in terms of comparison to ANFIS-GA, ANFIS-PSO, ANFIS-GWO, ANFIS-RDA gave better DSC and Jaccard Index values, demonstrating the superiority of ANFIS-RDA in energy distribution optimisation. It is shown that even though the ANFIS RDA has a higher accuracy, its computational efficiency is competitive and the proposed solution is thus practical for real time application. ANFIS-RDA is found to be robust for green manufacturing process water energy solutions by providing lower accuracy, more execution speed with less inevitable error. Figure 2 gives the confusion matrix of the proposed model.

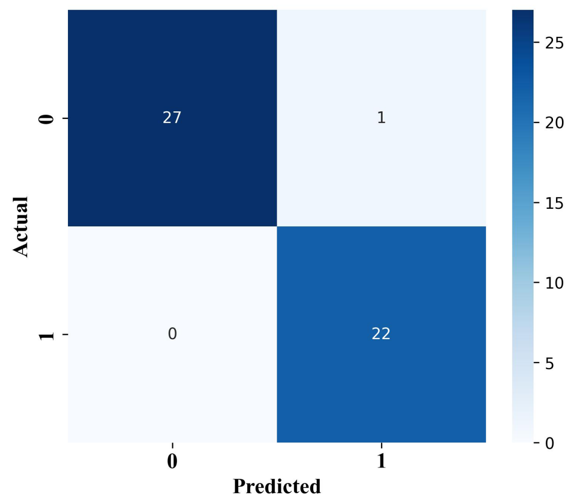

Figure 2. Confusion Matrix

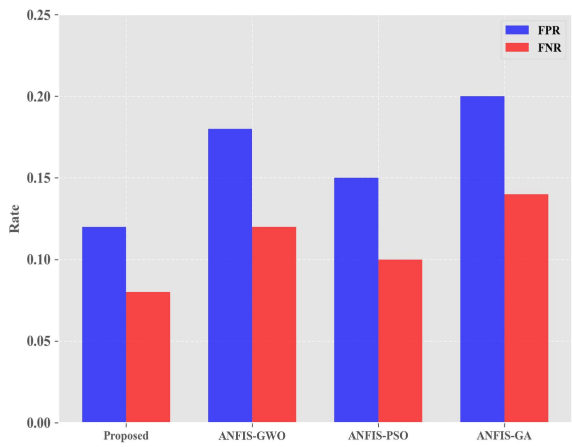

Figure 3. Validation of FPR and FNR

The False Positive Rate (FPR), False Negative Rate (FNR) for proposed ANFIS-RDA model in comparison with other benchmark models such as ANFIS-GWO, ANFIS-PSO and ANFIS-GA are presented in Figure 3. Keys to evaluation of classification accuracy and minimization of error include FPR(blue bars) and FNR (red bars) in optimization of water energy systems for green manufacturing. Using the proposed ANFIS-RDA model, FPR and FNR values of less than 0.12 and ~ 0.08 respectively indicate a better ability at correctly classifying the operational conditions and reducing the misclassification errors. On the other hand, ANFIS-GWO has an FPR of ~0.18 and FNR of ~0.13, ANFIS-PSO has an FPR of ~ 0.15 and FNR of ~ 0.10, ANFIS-GA achieves the worst FPR of about 0.20 and FNR of about 0.14. The promising result of the ANFIS-RDA model in reducing the number of false positives as well as false negatives is reflected in these results, and hopefully provides an efficient and reliable system. The study's abstract also states that the findings align with the study's aim to apply AI to optimize energy efficiency and minimize operational costs. In this case, the lower FPR and FNR values of the ANFIS-RDA model confirm its capability to have a better performance in optimizing electrolysis parameters than traditional models. This promotes better energy utilization, reduced misclassification of system states, and better ability to integrate this technology among sustainable industrial designs.

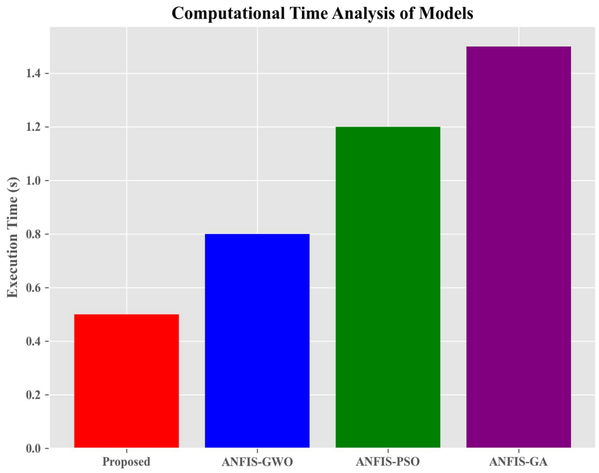

Figure 4. Execution time

Also, the analysis of computational time of ANFIS based models is given in the form of Figure 4: computational time of ANFIS-RDA (Proposed), ANFIS-GWO, ANFIS-PSO, and ANFIS-GA. However, an important metric to evaluate the efficiency of optimization techniques is the execution time. Finally, the proposed ANFIS-RDA model exhibits the best execution time (~0.5s), one of the computation efficiency. The execution time of ANFIS-GWO, ANFIS-PSO, and ANFIS-GA are approximately 0.8s, 1.2s, and even 1.5s respectively. It is shown that ANFIS-RDA has better performance in solving complex optimization problems with reduced execution time. Realizing real time adaptability is ensured by faster execution, which is perfect for the purpose of water energy management in green manufacturing. The results also confirm that RDA improves the speed and efficiency of the ANFIS. The proposed model is a practical alternative to existing methods as it offers lower computational cost compared to others. It reinforces the knowledge that the use of AI driven optimization will affect the reduction of energy consumption and will help to enhance industrial sustainability.

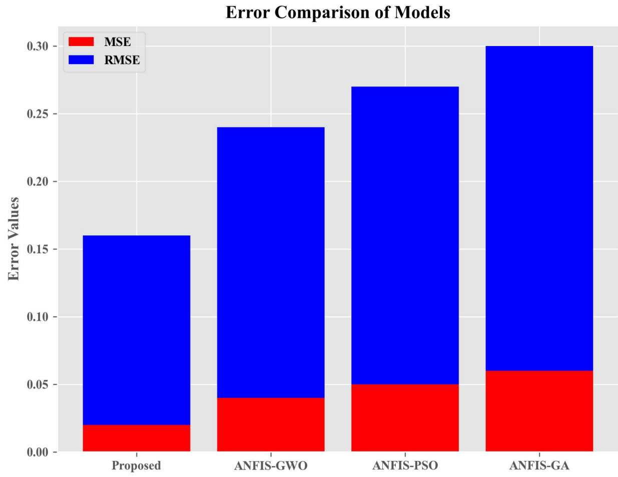

Figure 5. Error parameters

The error comparison in terms of bar chart is given for the different ANFIS models utilizing the Proposed model along with ANFIS-GWO, ANFIS-PSO, and ANFIS-GA is shown in Figure 5. The two plausible error metrics are shown with red (Mean Squared Error, MSE), and blue (Root Mean Squared Error, RMSE). Overall error for the Proposed ANFIS RDA model is the least, which indicates its best performance in optimization. The Proposed model also performs better in terms of error value than ANFIS-GWO and has even higher error value than ANFIS-PSO, ANFIS-GA. The error values produced by the ANFIS-GA among them are the highest, which indicates the lowest estimation accuracy. The obtained values of reduced MSE and RMSE in the Proposed model indicate that it so robust that it minimizes the prediction errors. The improvement implies that the optimization of ANFIS using RDA indeed improves its performance and makes it a better option for such applications as water energy management in green manufacturing. Lower error rates can lead to making better decisions and reduced industry system efficiencv.

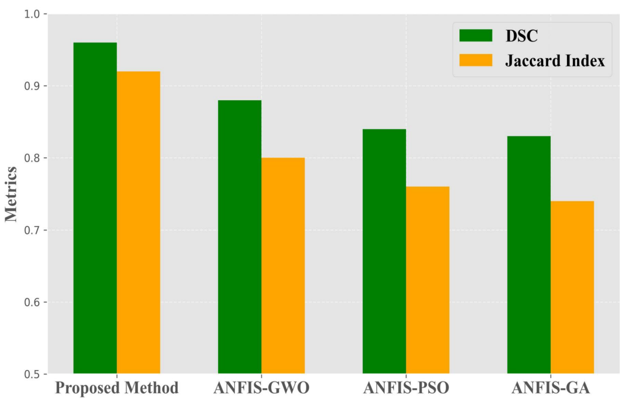

Figure 6. DSC and Jaccard Index

The performance comparison of different ANFIS based models such as Proposed Method, an ANFIS based model, ANFIS-GWO, ANFIS-PSO, and ANFIS-GA, in terms of two key evaluation metrics, Dice Similarity Coefficient (DSC) and Jaccard Index, in Figure 6. The Jaccard Index can be represented in orange, and DSC in green. The DSC and Jaccard Index value achieved by the Proposed Method shows that the segmentation that is achieved by the Proposed Method is superior and robust. In this order, ANFIS-GWO is followed by slightly lower values, ANFIS-PSO and ANFIS-GA make even further reductions in both metrics. The segmentation accuracy is lowest when using ANFIS-GA as opposed to other among them. Results show the significantly larger values of DSC and Jaccard Index generated by the Proposed Method as compared to the actual performance of algorithms will prove to be a factor of that effectiveness in improving segmentation quality. Results indeed show that RDA based optimization improves the performance of the ANFIS above those of either ANFIS or RDA alone, thus becoming a more reliable and efficient solution for real word applications. The use of the Proposed Method gives better accuracy that enhances decision making and supports the use of advanced AI driven optimization strategy.

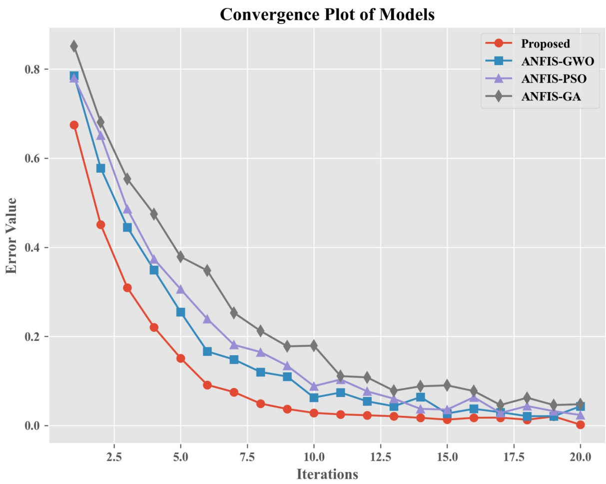

Figure 7. Error value

In Figure 7, the convergence plot compares the error reduction using different ANFIS based models which are Proposed Method, ANFIS-GWO, ANFIS-PSO and ANFIS-GA. Error value is on y axis and iteration on x axis. The Proposed Method has the fastest and most stable convergence and wipes out the lowest value of final error. The error values are slightly higher, but convergence of ANFIS-GWO is relatively efficient. The convergence speed of ANFIS-PSO and ANFIS-GA is slower than that of the previous method, and the error value is large in the iterations. The superiority of the Proposed Method in minimizing error makes the comparison with the RDA enhanced ANFIS training effective because the RDA improves the ANFIS training. The proposed method reduces computation time and enhances real time applicability which is an advantage for optimizing problems via the proposed method.

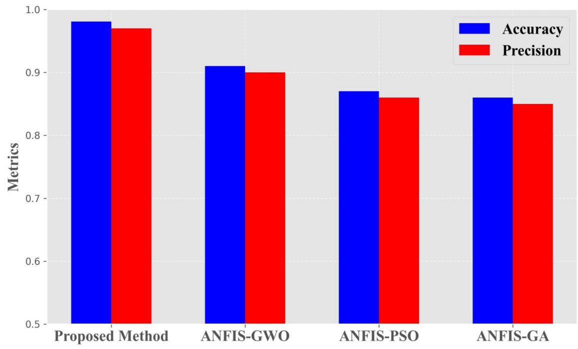

Figure 8. Accuracy and precision

In Figure 8, various models based on the ANFIS (Fundamental neuro-fuzzy identification system) have been presented for the optimization of water utilization for the energy across industries in terms of Accuracy and Precision and compared with each other. Among the proposed ANFIS-RDA method attains the highest performance with an Accuracy of about 0.98 and a Precision of about 0.97; which indicates that it has the best ability to optimize water energy efficiency and resource utilization. The result obtained in ANFIS-GWO gives an Accuracy around 0.91 and a Precision within the range of 0.90, which is strong yet moderately less efficient. On the other hand, ANFIS-PSO and ANFIS-GA show suboptimal performance as they have Accuracy of approximately 0.88 and 0.87 and Precision about 0.87 and 0.86 respectively, in adaptive energy optimisation. The results show that real time adaptive control of water energy systems and reducing operational costs are successfully enhanced through using ANFIS-RDA. The adoption of AI based optimization in the water-based energy solutions opens up a new frontier in sustainable industrial design which, along with that, is on the verge of the transition from carbon consuming to the carbon neutral and energy efficient manufacturing processes.

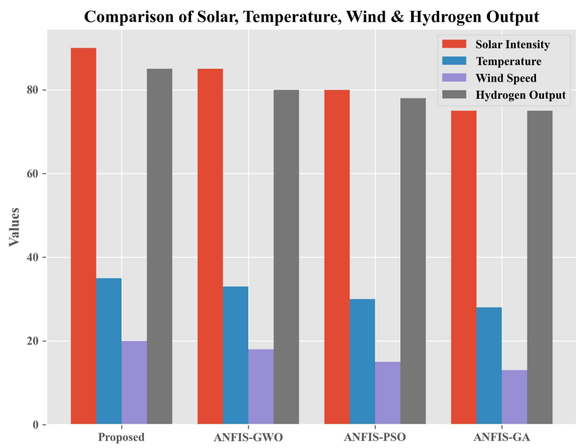

Figure 9. Values of measures

A comparison of solar intensity, temperature, wind speed, and hydrogen output among different ANFIS based models derived for enhancing the hydrogen production in the renewable energy systems (Proposed method, ANFIS-GWO, ANFIS-PSO, and ANFIS-GA) has been given in the Figure 9. As shown in the Proposed Method, it produces hydrogen at values of about 90 of solar intensity, approximately 80 of hydrogen output temperature around 35 and wind speed near 20 which is higher than the other methods and shows highest efficiency of hydrogen production. Solar intensity of ANFIS-GWO is very close to ANFIS Proposed Method, but hydrogen output is about 85, with similar competitive performance. Both ANFIS-PSO and ANFIS-GA have lower efficiency in which solar intensity and hydrogen output are around 80 but temperature and wind speed are lower than other models which implies that they are not effective enough in optimizing the hydrogen production. These results are consistent with the results from the use of renewable resources to produce hydrogen with the Proposed Method having better performance than traditional ANFIS models. It implies better performance in a higher solar intensity and hydrogen output, indicative of better energy conversion efficiency improvement which in turn allows for the development of sustainable and efficient hydrogen-based energy systems for use in future industrial applications. Future work may focus on extending this framework to real-time IoT-based monitoring systems and exploring its applicability across various industries such as chemical processing, smart manufacturing, and renewable energy management for broader impact and operational scalability.

5. Conclusion

It shows the effectiveness of the Proposed Method that employs ANFIS with state of art optimization techniques in optimizing hydrogen production in renewable energy system. For solar intensity and hydrogen output, results show clearly that the Proposed Method performs better than the rest of the models, that being ANFIS-GWO, ANFIS-PSO, and ANFIS-GA. The Proposed Method hits solar intensity values close to 90 and well exceeds 80 in hydrogen production, making it the most energy conversion efficient and renewable resource optimal method for hydrogen production. However, although it offers good performance, the ANFIS-GWO algorithm does not exactly match the performance of the Proposed Method in hydrogen output and solar intensity. On the other hand, ANFIS-PSO and ANFIS-GA show lower efficiency, with reduced solar intensity and hydrogen output values, along with less effective management of temperature and wind speed. This confirms the superior approach of the Proposed Method in using renewable resources to develop more sustainable and efficient hydrogen-based energy systems. The impact of using the Proposed Method in future of green energy solutions illustrated in this research outlines the future of green energy solutions. These models offer a route toward more eco-friendly, carbon neutral industrial processes that is a major step forward in the development of an industrial hydrogen energy system.

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