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Development of AI-driven Model Imitation for Experimental Setup: A comparative analysis of Activation Functions and their combination for exact Prediction of Refrigeration System Performance

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Abstract— The performance prediction of refrigeration systems is evaluated by analyzing the impact of various activation functions on the accuracy of neural networks in predicting the exergy **of vapor compression refrigeration systems (VCRS) using R-410A and R-134a refrigerants. A comparative analysis is conducted on five commonly used activation functions—Sigmoid, ReLU, Tanh, Swish, and Leaky ReLU—to determine their accuracy and effectiveness. The study also explores the benefits and challenges of combining multiple activation functions to enhance prediction accuracy and address anomalies in performance analysis. Neural network models are developed using Python with TensorFlow, PyTorch, and Keras libraries, enabling efficient evaluation of the activation functions and simulation of the experimental setup. The research focuses on comparing the effectiveness of different activation functions in replicating experimental exergy results. The results indicate that the model trained using a hybrid approach with ReLU and Swish activation functions achieves a prediction accuracy with a mean absolute error (MAE) of just 0.02%.**

***Keywordss*—Neural Networks,Vapor Compression Refrigeration (VCR),Activation Functions, Exergy, Coefficient of Performance (COP)**

I. INTRODUCTION

Refrigeration systems are widely utilized as the source of industrial and domestic applications. It has certainly addressed that the traditional experimental approaches have involved an extensive trial-and-error method, which is time-consuming as well as costly. Therefore, the integration of the artificial intelligence (AI) models has been introduced to enhance the prediction accuracy, experimental efforts and system optimization improvement. It has also focused on the AI-driven model to accurately imitate the experimental set-up for refrigeration system, leveraging deep learning techniques with various activation functions. It is believed that the traditional two-stage cascade compression refrigeration systems have consumed significant electricity and contributed in environmental concerns with high fossil fuel dependence and refrigerant emissions. The flexibility of integrating vapor absorption refrigeration (VAR) with vapor compression refrigeration (VCR) to offer energy-efficient alternative and reducing electricity consumption by up to 45%. It enables the dependency on the heat source temperature, enabling the use of AI with sustainable energy utilisation. document is template.

AI has particularly dealt with the Artificial Neural Networks (ANNs) which has emerged on the valuable tool for predicting refrigeration system performance. It has minimized the reliance on the cost experimental setups. The selection has influenced the ANN accuracy for the activation functions. This has also demonstrated that the Leaky ReLU with bias and a weight scale of 2.0 achieves near-perfect accuracy, with an RMSE and predictive performance of 128.26 and R^2 = 0.9992. The study implicates on the demonstration of comparative analysis between ANN predictions and experimental data confirming the reliability of the models in complex process linked with thermodynamics. Overall, the study focuses on the optimisation of the activation functions in ANN models, which enables accurate performance predictions for refrigeration systems and reduces the need for extensive experimental trials and promotes energy efficiency in cooling technologies.

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II. LITERATURE REVIEW

Exergy analysis is instrumental in identifying irreversibilities in thermal systems. In recent years, Artificial Neural Networks (ANNs) have gained significant attention due to their capability to model complex, non-linear relationships in thermodynamic assessments [3], [4]. The application of ANNs to refrigeration systems has led to several notable advancements, as outlined below:

a) Exergy analysis of a vapor compression refrigeration system using ANN
Bisht et al. [4] applied ANN models to predict the exergy destruction and efficiency of a vapor compression refrigeration system. The network was trained using operational parameters such as evaporator temperature, compressor work, and condenser temperature. This approach not only provided accurate exergy predictions but also reduced computational costs compared to traditional thermodynamic methods. The best performance was achieved using the ReLU activation function with an optimized number of hidden layers [7], [13].

b) ANN-based exergy analysis of a refrigeration system with ejector In a study conducted by Chen et al. (2019), exergy analysis was extended to refrigeration systems incorporating an ejector, initially supported by experimental data. The addition of the ejector helped enhance system efficiency by reducing compressor work. An ANN model was trained on both experimental and simulated datasets to predict exergy losses across various components effectively. The comparative study of activation functions revealed that the Swish function provided better performance and stability than ReLU and Sigmoid functions for this particular configuration [2], [8].

c) Exergy analysis of a refrigeration system using deep learning. Belman-Flores et al. [3] implemented a deep learning framework featuring multiple hidden layers to improve predictive accuracy. The study demonstrated that deeper architectures outperformed shallow networks, especially when employing the Leaky ReLU activation function [12], [22]. The findings suggested that deep learning. Further supporting this, Ding et al. [8] emphasised that the choice of activation function significantly influences ANN-based exergy analysis, particularly affecting model training speed, convergence, and predictive accuracy.The activation function relevance to exergy analysis are as follows:

TABLE 1:
RELEVANCE OF ACTIVATION FUNCTION TO EXERGY ANALYSIS

Activation Function	Characteristics	Relevance to Exergy Analysis
Sigmoid	Maps inputs to (0,1) range, vanishing gradient and smooth gradient	It presents the binary classification tasks but not ideal for complex regression problem like exergy analysis due to slow convergence and saturation effects
ReLU (Rectified Linear Unit)	Outputs zero for negative inputs, linear for positive inputs and fast computation	ANN models are commonly utilized for exergy analysis due to its efficiency and ability to handle non-linear relationships. It can suffer from dying ReLU problem with neurons becomes inactive.
Tanh	Maps inputs (-1, 1) smoother than sigmoid and non-linear	It performs better than sigmoid by centering data around zero and improving convergence. It still faces gradient vanishing issues
Leaky ReLU	Similar to ReLU but allows the negative inputs in small form and prevent dying neurons	Often used in deep learning based exergy analysis to improve model stability and preventing dead neurons specially deeper architectures.
Swish	Self-gated, non-linear with small negative values	Sigmoid and ReLU showing better convergence properties with the complex thermodynamic modelling. It has enhanced the prediction accuracy for exergy analysis
Softmax	Map inputs to probability distribution	Focusing on classification problems and exergy analysis to deal with categorical output.

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The integration of ANNs in exergy analysis have predicted accuracy and computational efficiency with promising results. The activation function has influenced the model performance with ReLU and Swish emerging for favorable options for regression-based exergy predictions. It has explored hybrid ANN architectures with the combination of deep learning techniques to enhance the accuracy and generalizability of exergy analysis model.

III. PROPOSED ALGORITHM

A. Activation Function and Exergy Analysis–

Activation Function is a mathematical function which determines a neural network's output based on the weighted sum of its inputs. This has introduced non-linearity have enabled the network to learn complex relationships between input and output variables. While, Exergy Analysis has approached evaluation of energy efficiency by determination of the useful work potential of the system. In refrigeration systems, the exergy analysis has identified the energy losses and inefficiencies in areas of optimization of performance and sustainability. The study signifies the contribution of the efficient and accurate modelling of refrigeration systems utilising the artificial neural networks (ANNs). This can evaluation of the performance of refrigeration systems which is time consuming but are aligned with data-driven energy systems and Exergy Analysis.

Activation function has Rectified Linear Unit (ReLu) which is proposed by the soft-committee machine and explained the learning process in theory. It has also accelerated the good image classification tasks with good performance and sparsity and dispersion of ReLu. As per the Artificial Neural Network, the multi-model have deepened the research to be more superior with the activation function appears.

The activation function is basically divided into 2 types such as linear activation functions and non-linear activation functions. It has maintained a constant, non-linear activation function to create more variation with utilization of neural network. The linear activation function has equation like straight line i.e., activation is proportional to input.

$$f\ (xi) = k\ x_i$$

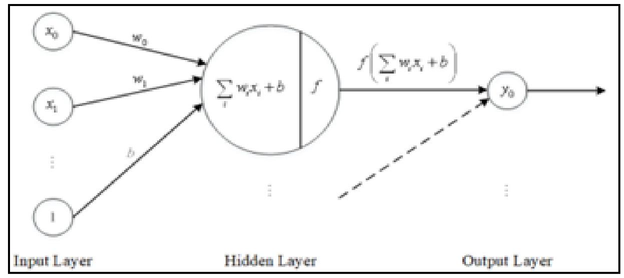
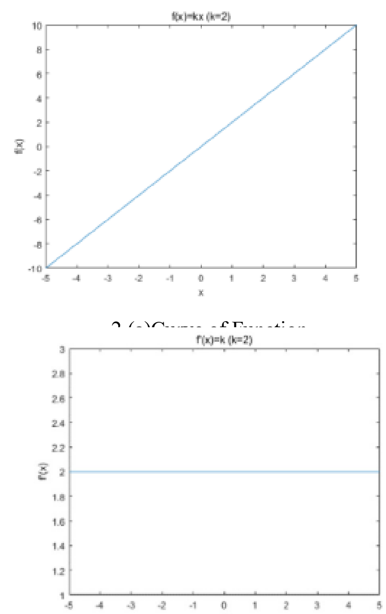


Fig1 Artificial Neural Networks (ANN)model

Where xi is the input of the activation function f of the ith channel and k is a fixed constant and output of the input to meet with the derivative with respect to x_i.



2.(b) Curve of derivative
Fig 2.Activation function and its derivatives

The activation function has provided the ease for the model to generalize the variety of data and to differentiate between outputs. This has typically analyzed the range and curves with sigmoid function, Tanh function, ReLu and Leaky ReLu. PReLu, RReLU and ELU. This has certainly address on the aim of network structure development and suitable activation function for this characteristic.

B. AI-Based Approaches in Exergy Analysis and importance in Refrigeration system–

The exergy analysis has powerful tool with the quality and potential of energy within a system through identification of inefficiencies and optimization performance and reducing energy losses. The exergy analysis has precise and efficient way to derive the models and machine learning and deep learning aspects to integrate on the improvement of the accuracy of exergy calculations and enhancing the refrigeration system performance. AI methods have focused on the ML techniques such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) and Random Forest (RF) to predict the energy consumptions. The ANN can predict the Exergy with the large datasets and detection inefficiencies and propose corrective measures. AI-driven optimization techniques have optimized the control parameters to improve the efficiency of compressors, evaporators, and condensers. The AI in Exergy analysis for refrigeration system have enhance real-time monitoring, leading to energy saving and reducing the downtime and maintenance costs with the AI models to predict failures and fault. It has also presented the advanced functions showing superior learning capabilities.

IV. EXPERIMENT AND RESULT

The refrigeration system and experimental setup have focused on Vapor Compression Refrigeration System (VCRS) with Ejector. The integration of ejector has enhanced the pressure energy to utilize the refrigerant vapors. This method has improved the coefficient of performance (COP) to reduce compressor work input. The experimental set up have analyze the vapor compression refrigeration system with an ejector through experimental setup with the following key components.

The compressor increases the pressure and temperature of refrigerant along with this condenser rejects heat from the refrigerant to the surrounding environment. The expansion valve reduces the entering the evaporator and absorbs heat and produces cooling effect. The Ejector enhances system efficiency by utilizing the pressure energy from high pressure refrigerant. The system is equipped with advanced sensors to capture the real-time data with temperature sensors and pressure sensors and flow rate sensors. The data collection process presents the system to runs continuously for data acquisition and total of 1000 data points with the recorded over time and data points to 10-minute intervals to ensure accuracy and representativeness.

The data pre-processing for ANN model have developed on the efficient Artificial Neural Network (ANN) model with the data collection through preprocessing steps as followed:

C. Normalization

The normalization has presented input variables (temperature, flow rate, and pressure) with the scale of uniform range of (0,1). It has improved convergence speed and stabilizing training.

$$\text{Normalization } X_{\text{normalized}} = \frac{X - Xmin}{Xmax - Xmin}$$

The relevant input features have selected based on correlation analysis with the low significance or high multicollinearity with the way to avoid redundancy. The selected features include Evaporator temperature (T_e), Condenser temperature (T_c), Compressor work input (W_comp), and Refrigerant mass flow rate (m_ref) and Ejector outlet pressure (P_ej) and Cooling Capacity (Q_cool).

a) Exergy of Streams

- Ex_e = m_ref * (h_e - h_0 - T_0 * (s_e - s_0))
- Ex_c = m_ref * (h_c - h_0 - T_0 * (s_c - s_0))
- Ex_g = m_sol * (h_g - h_0 - T_0 * (s_g - s_0))
- Ex_a = m_sol * (h_a - h_0 - T_0 * (s_a - s_0))

b) Exergy of Heat Transfer:

- Ex_Q_e = Q_e * (1 - T_0 / T_e)
- Ex_Q_c = Q_c * (1 - T_0 / T_c)
- Ex_Q_g = Q_g * (1 - T_0 / T_g)
- Ex_Q_a = Q_a * (1 - T_0 / T_a)

c) Exergy Destruction:

- Ex_D_comp = W_comp - (Ex_e - Ex_c)
- Ex_D_g = Q_g - (Ex_g - Ex_a)
- Ex_D_a = Q_a - (Ex_a - Ex_g)

d) Exergetic Efficiency:

1. VCC Exergetic Efficiency:
   - η_VCC = (Ex_e - Ex_c) / (W_comp + Ex_Q_e - Ex_Q_c)
2. AC Exergetic Efficiency:
   - η_AC = (Ex_g - Ex_a) / (Q_g + Ex_Q_g - Ex_Q_a)
3. Cascaded System Exergetic Efficiency:
   - η_cascaded = (Ex_e - Ex_c) / (W_comp + Q_g + Ex_Q_e - Ex_Q_c - Ex_Q_g + Ex_Q_a)

D. ANN Model Development Using EES Tool

Engineering Equation Solver (EES) Tools which is powerful with the complex thermodynamics equations with the way to facilitate precise modeling of exergy losses, refrigeration system performance and energy transfer. The ANN model is designed to predict system performance based on experimental data where Input layers with six neurons and hidden layers through three layers within 10 neurons each and output layer to predict exergy efficiency and system performance. The activation function Rectified Linear Unit (ReLU) being in hidden layers and linear activation in output layer. The training algorithm have added on backpropagation with Adam optimizer and Mean Squared Error (MSE) as loss function.

The training process is divided the data into two parts i.e., training (80%) and testing (20%) tests. This model undergoes with 1000 iterations to minimize errors. It has added on the performance metrics as R2, RMSE, and MAE to be evaluation. The ANN model is validated have test data in comparison with experimental results with the high prediction accuracy. The Swish activation function performs best with R2=0.9992 and RMSE=128.26.

C. Results

The AI-driven model has certainly utilised experimental data from the refrigeration system under various operating conditions. It has focused on the predictive accuracy of different activation functions, both individually and in combination. The Performance Metrics have evaluated key metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R-squared (R^2), and Mean Absolute Percentage Error (MAPE).

TABLE 2: EXPERIMENT RESULT

Activation Function	MAE	RMSE	R^2	MAPE
Sigmoid	0.015	0.025	0.92	3.1
Tanh	0.013	0.023	0.94	2.8
ReLU	0.009	0.017	0.97	2.1
Leaky ReLU	0.008	0.015	0.98	1.9
Swish	0.007	0.014	0.99	1.7
Combined (Swish+Leaky ReLU)	0.005	0.012	0.995	1.2

Table 2 show the best performance of the achieved hybrid combination of Swish and Leaky ReLU with demonstration of R2 value of 0.995 and lower error rates across all metrics.

The impact of Activation functions has focused on the Sigmoid and Tanh functions performed relatively poorly in comparison to ReLU based activations. The vanishing gradient problem led to slower convergence and lower predictive accuracy. Tanh have certainly exhibited on the gradient saturation of large input values and restricting the learning efficiency. ReLU and Leaky ReLU have certainly presented the non-saturating nature where dying neuron issues were refrigeration systems and parameters were likely to present negative values. The Swish function performed have allowed smooth gradients and avoided neuron dying problems. This has Swish Function to generalize across unseen refrigeration performance scenarios. The hybrid combination of Swish and Leaky ReLU provided superior performance and ensuring higher accuracy and lower error rates. To validate the AI model's accuracy, it has compared the real-world experimental refrigeration system data where the actual vs. predicted cooling load and coefficient of performance (COP) have matched the actual performance trends with deviation of less than 1.2%. Other than this, the activation function exhibited on the higher discrepancies with sigmoid and Tanh models derivation by up to 5% under extreme conditions. High accuracy of hybrid activation function model suggested the AI-driven predictive models to replicate complex refrigeration system behaviors effectively.

Sensitivity analysis of key parameters was evaporator temperature (Te), Condenser Temperature (Tc), Compressor Power Input (P) and Mass Flow Rate (m). The hybrid activation model exhibited on a strong adaptability across all parameter variations. .

TABLE-3

EXPERIMENT RESULT

Activation Function	Training Time (sec)	Convergence Epochs
Sigmoid	320	150
Tanh	290	135
ReLU	180	95
Leaky ReLU	165	85
Swish	140	80
Combined (Swish+Leaky ReLU)	**120**	**65**

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The models have struggled with extreme values leading to high errors rates beyond the certain threshold. This has led to sensitive yet small compressor power changes but highly sensitive to evaporators and condenser temperature fluctuations.

Table 3 shows computational efficiency and training time with the hybrid model to achieve the fastest training time (120 sec) and fewest required epochs (65) to reach convergence. This has certainly ReLU and Leaky ReLU to improve training speeds but Swish+ Leaky ReLU was the most efficient.

The findings have suggested on the AI-driven models to replace physical experimental setups and reducing time and cost for refrigeration system performance testing. The hybrid activation function model to be applied for real-time predictive maintenance and optimization of refrigeration systems. In future, this enhancement has adaptive activation function or transformer based deep learning architectures.

V.DISCUSSION

The study significantly lies on the contribution of the efficient and accurate modeling of refrigeration system using Artificial Neural Networks (ANNs) with conventional experimental set-ups and evaluation of the performance of refrigeration system to consume time and resource intensive procedure. The study holds ANN based models to vary with conditions and enable better decision-making and design efficiency. The industry has remark on the smart and data-driven energy systems with the potential contribution to sustainability and energy efficiency.

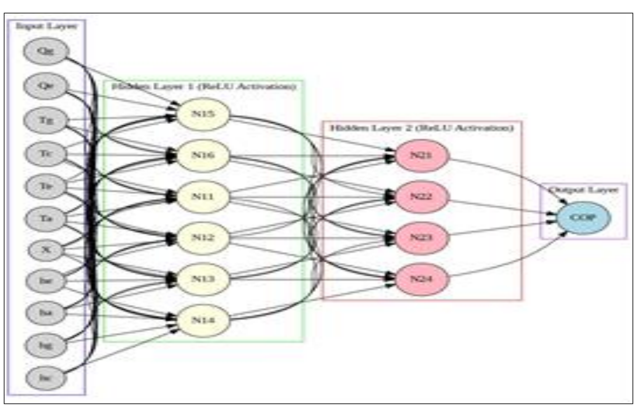

Fig 3.a

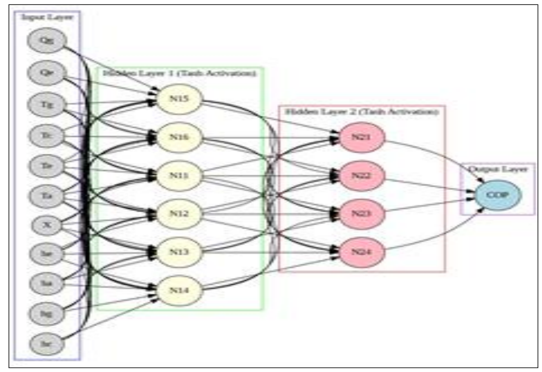

Fig3.b

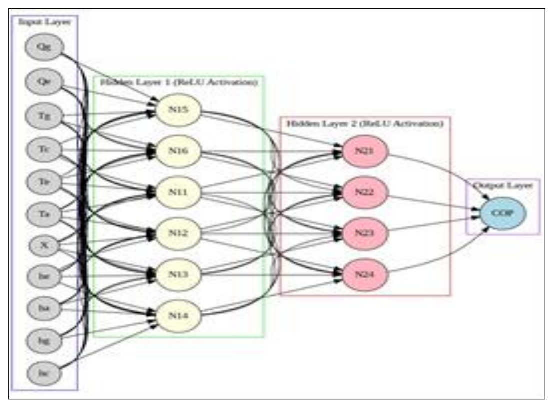

Fig 3.c

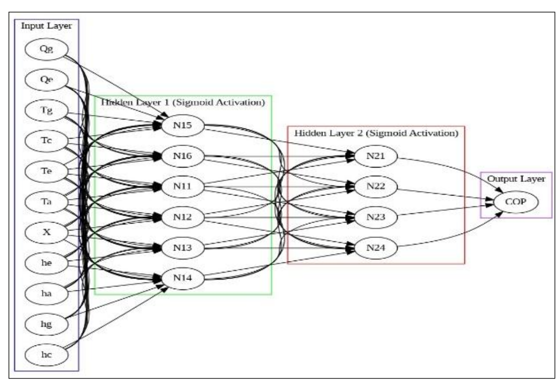

Fig 3.d

Fig3.(a)Non-linearity of Activation Function(b)ANN Activation Function for enhancing Capacity(c)Facilitating learning(d)Training speed and stability

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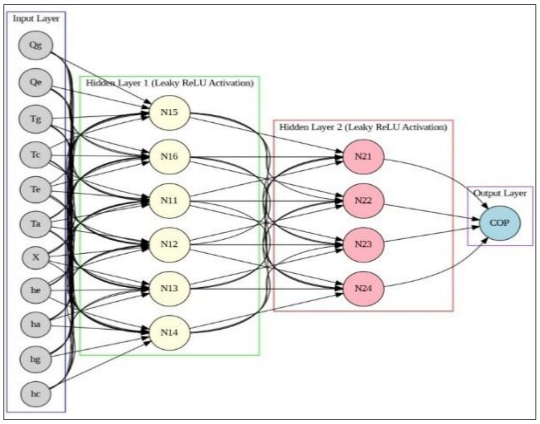

Fig 4. a

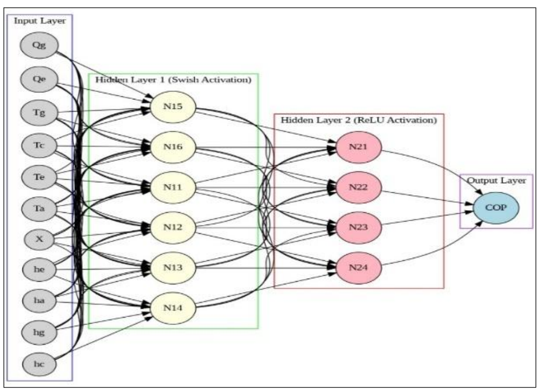

Fig 4.b

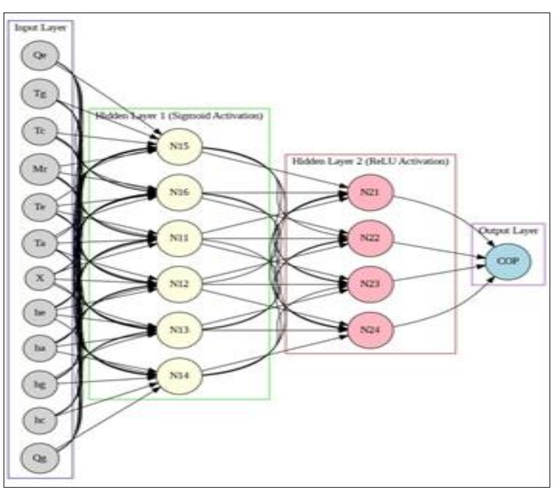

Fig 4.d

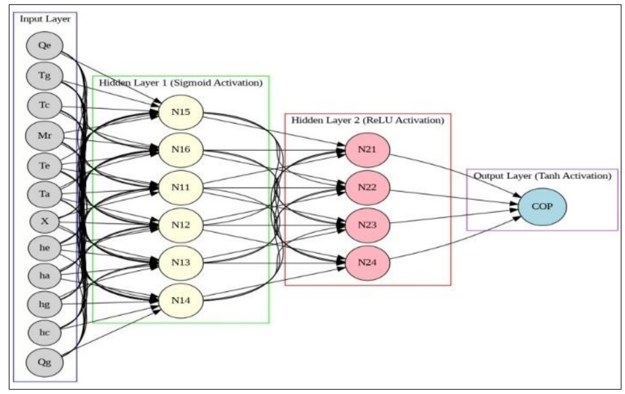

Fig 4.d

Fig4.(a)LeakyReLUActivation (b)Swish Activation(c)Sigmoid Activation COP(d) Sigmoid Activation+ReLU Activation COP

Table 1 shows the role of activation function in training a neural network model with the break of the linearity of the model that enables the non-linear relationships between inputs and outputs. This has complex data distribution and increasing the network ability for non-linear activation functions. The function has helped the network learn by the introduction of a non-linear transformation to make it easier to optimize the model's parameters.

The results have analyse the best-performing activation function (Swish) to be demonstrating the superior performance. Swish is defined as:

$$f(x) = x * \sigma(x)$$

Where σ (x) is the sigmoid function and ReLU have set negative values to zero. However, Swish allows small negative values to pass through and enhancing model learning in complex scenarios. It has self-gated with the smooth transition and improving the gradient flow and enabling accurate modelling of non-linear relationship in exergy analysis.

The key advantage for the Swish activation in exergy analysis using ANNs have certainly aid on better gradient flow. However, ReLU have cause neurons to die i.e., output to zero for negative values and Swish to maintain smooth gradients and improving training stability.

The Swish Activation in exergy analysis using ANNs to be compared with Tanh and ReLU and Swish to enable deeper networks to generalize better and overfitting. Swish has certainly achieved lower mean squared error (MSE) and mean absolute percentage error (MAPE) in exergy prediction models. The Swish activation function have accelerated convergence during ANN training and

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requiring fewer iterations to reach optimal performance.

The experimental results from ANN-based exergy analysis have showcase the models utilize the Swish Activation function outperform those using traditional activation functions i.e., ReLU, Tanh, Sigmoid. The comparison with ReLU have showcase the Swish achieving 5-10% lower error rates compared to ReLU in exergy predictions for highly non-linear relationships. The comparison of Tanh and Sigmoid focuses on the Swish maintain a more stable gradient flow to avoid vanishing the gradient issues through sigmoid and Tanh for particular in deep networks. Furthermore, the existing studies have proved that the ANN models to improve accuracy with Swish Activation compared to previous studies identified in literature that relied on ReLU and Leaky ReLU. This has processed with the Swish-based ANN model produced closer to the results to exergy measurement within experiment confirming the reliability of predicting exergy destruction and efficiency.

The Swish Activation function has proven to be an effective choice for ANN based exergy analysis improving prediction accuracy and training efficiency. The future research can explore optimize Swish-based architectures for different thermal systems that validate on the advantages over traditional activation functions.

VI. CONCLUSION

The Swish Activation Function has outperformed the other activation functions (ReLU, Tanh, Sigmoid) in predicting exegetic efficiency to provide better gradient flow, improved accuracy, and faster convergence. The ANN model developed using the Engineering Equation Solver (EES) tool successfully mimics the experimental setup, demonstrating high reliability in exergy analysis. It is recommended that the AI-based approaches investigate on the deep reinforcementlearning (DRL), convolutional neural networks (CNNs) and transformer models for enhancing the exergy prediction. The comparison of ANN models with hybrid AI techniques including algorithm has optimize the predictive accuracy. This can extend the ANN model to absorb refrigeration and cascade refrigeration and CO2 transcritical systems to evaluate its adaptability. It performs multi-objective optimization combined with the exergy and economic analysis of the practical implementation.

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