

**GLOBAL JOURNAL OF ADVANCED ENGINEERING TECHNOLOGIES AND
SCIENCES**

**ENHANCING THE PERFORMANCE OF VAPOR COMPRESSION
REFRIGERATION SYSTEMS THROUGH MACHINE LEARNING AND
BAYESIAN OPTIMIZATION**

Arun Solanki, Khemraj Beragi

arunsolanki450@gmail.com , khemrajberagi@gmail.com

DOI: <https://doi.org/10.29121/gjaets.2025.9.3>

ABSTRACT

The use of vapor compression refrigeration (VCR) systems in industrial cooling is essential, but the efficiency of their operation is usually less fortunate because of the rigidity and fixity of the operation that such control systems are utilized in, as it should. The paper addresses how machine learning (ML) and Bayesian optimization (BO) may be combined to improve VCR systems real-time optimization. Optimized floating-point parameterized models of Bayesian Optimized Neural Network (BONN) aims to alter major parameters in the system including refrigerant flow rate and compressor speed depending on the fluctuating environmental and operating conditions. Current study overcomes the limitations of traditional optimization techniques in offering an open-ended, adaptive solution that is found to predict and optimize system performance in different conditions. By so doing, better energy efficiency, cheaper costs of operations, and enhanced reliability of the system are expected to be attained through the research. The experimentation indicates that Bayesian-optimized model with greater accuracy in estimating energy usage and fridge refrigerants staff is substantially better than the traditional models. This paper will help in advancing the cooling technologies which are sustainable because it allows VCR systems to be adaptively controlled in real time.

KEYWORDS: Artificial Neural Networks, Bayesian Optimization, Machine Learning, Refrigerant Flow, Refrigerant Leaks, Vapour Compression Refrigeration (VCR)

1. INTRODUCTION

Vapor Compression Refrigeration (VCR) systems are critical in present-day applications in the cooling and refrigeration sector, in areas like refrigerators or the appliances used in cooling stations in industries. These systems work by expanding and compressing a refrigerant that will absorb heat of the surroundings and hence allow cooling. Due to the development of new industries and technologies, there also appears the necessity to improve the performance, the energy, and reliability of such systems. In this respect, machine learning (ML) and optimization techniques have become strong means to take care of the complexities in the performance of VCR systems.

The conventional VCR optimization strategies will tend to use preset parameters and fixed control management systems. Although these strategies have been effective to a certain degree, they are not dynamic with the changes of different operational parameters like temperature in the fridge, flow rate of the refrigerant and compressor speed. Therefore, such approaches are not predisposed to real time optimization of systems which, in this particular case, is vital towards boosting efficiency, ensuring energy saving and being able to prolong the life of the system in question. There has recently been an increasing interest in machine learning applications to model and predict the behaviour of VCR systems in real-time as a more dynamic, data-driven strategy to carry out the optimization of the system.

The application of Machine learning, namely Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Deep Learning (DL) algorithms, has proved to be very successful in numerous industrial settings with applications including predictive maintenance, energy consumption forecasting, or fault detection. Such models are able to investigate more accurate aspects of nonlinear interaction between system parameters and outputs, which is represented by complex relationships, and based on this decision-making can be done with greater degree of accuracy. These methods have however been found to work but there are numerous difficulties that may be faced when trying to implement them especially during dynamic real-time optimization of VCR systems.

Bayesian optimization (BO) is a statistical approach to the optimization of noisy, and uncertain expensive objective functions, which has been hailed as a possible solution to these issues. Bayesian optimization has an

application over systems such as VCR systems, where parameters of the system (e.g. compressor speed, rate of flow of refrigerant) may be optimized by sequentially testing and refining the model predictions. The application of the given approach possesses the potential of real-time optimization, i.e. coping with the dynamic contexts, enhancing the effect of the system performance, and reducing the energy consumption.

Though the overall benefits can be listed, there are few literatures about combining Bayesian optimization and machine learning methods to optimize VCR systems in real time. Past studies have considered machine learning as a tool to do predictive modeling as well as parameters optimization but there is a dearth of studies that applied machine learning via the implementation of real-time optimization through the use of complex models such as Bayesian-optimized neural networks (BONN). Moreover, majority of the research is based on the fixed optimization techniques whose application does not consider the dynamics and changing nature of VCR operations.

It is aimed at filling these gaps through this study which looks into the use of Bayesian Optimized Neural Networks (BONN) to improve the real-time performance of the VCR systems. The purpose of the proposed paper is to work out a sound mechanism of the on-going optimization of VCR system parameters in favor of better performance, lesser energy demands, and superior reliability of the system. The use of machine learning and Bayesian optimization enables this study to offer a new perspective in VCR system management that entails the dynamic parameter manipulation based on the real-time operational requirements.

With the help of such a research, we seek to provide a general plan of VCR system optimization, with an eye on whether industrial uses of VCRs could be made more sustainable, especially in cooling and the refrigeration industry. The results of the corresponding research will serve to interest the current drive towards cooling solutions modernization where higher energy efficiency and a minimized impact on the environment will be achieved.

2. LITERATURE REVIEW

The research work represented in [1] led to an entire analysis of the machine learning techniques that may help to improve efficiency of the VCR systems. The given study introduced the use of Support Vector Regression (SVR) and Artificial Neural Networks (ANN) to predict system functions and to determine the best parameters under the correlation between refrigerant flow and compressor speed operation. Modeling created by their study was able not only to capture VCR cooling load necessities but also energy requirement necessities and this is one of the reasons why machine learning can be used to streamline these systems. The approximation of non-linear behaviours on large sets was not quite successful in the paper because of the fact that the main machine learning models applied in the research were SVR and ANN which are basic in nature. Optimization algorithms have lacked the capability of implementing real time system corrections because there is still a need to uphold the system parameters as operations change with time.

In [2], the authors provide the description of one of the reinforcement learning methods that could be employed to streamline the operation of the VCR systems. Control of speed in compressor and positions of expansion valves was achieved in real time through use of RL controller in a study. They offered the information on the efficiency of the functioning of the system in case of the actualization of their approach to the implementation of the system under dynamic conditions. This was a big downer to this solution as the real-time decision that it carried out requirements would limit its usage in the environment where the resources are limited or at the industrial levels as well.

The authors of the paper in [3] created the system which they used to come with the ANN with the assistance of which the predictions on the COP values of VCR systems are made. As they discovered, ANN could handle non-linear relations of the systems among parameters of the performance and outputs. Despite the fact that the model has demonstrated great predictive capabilities, it was highly susceptible to over fitting because either noise or unassigned values appended in datasets had a negative effect on the discrete capabilities of the models.

At [4] authors have described a procedure to apply the Convolutional Neural Networks (CNN) to measure the compressor mass flow in industrial systems VCR. The excellence of the proposed model as compared to the traditional regressions was in boosting both the metrics of accuracy and efficiency of operation to a great degree. Further off-site testing of the variety of brands of VCRs and their applications would contribute further to the overall utility of the study as the narrow application of the industrial aircraft vapour cycle systems would greatly reduce the overall usefulness of it in wide application.

The authors [5] presented Hybrid Optimization Algorithm (HOA) borrowing the idea of Genetic Algorithms (GA) and Simulated Annealing (SA) in optimizing the setting of the VCR system parameters. With the help of the HOA, the parameters related to the system like the compressor speed, rate of flow of the refrigerant could be adjusted since it led to a better performance. The approach has introduced massive computation demands as a result of global search orientation approach which forms an obstacle in real time implementation with increased system demands.

In [6], the authors developed an optimization model in the form of Bayesian system toward the VCR systems that utilized the usage of machine learning models to discover the optimum solutions as per energy consumption and the cooling performance. Bayesian optimization was successful in its effort to deal with multidimensional parameter space of the intricate issues with an aim of receiving optimum solutions according to its study. The greatest drawback of this implementation was that it possessed long convergence period as the process did not match the time sensitive decision-making process.

The researchers in [7] studied the means of utilizing the Support Vector Machines (SVM) in the forecast of the outcomes of the VCR system under different instructions. The researchers were in a position to make favorable forecasts concerning cooling loads and energy demand together with obtaining helpful iterations messages through the use of SVM models. When dealing with big data containing much more features, the SVM model became weak and the derived results were prone to overfitting.

The paper provides a study about the prediction of VCR energy consumption as well as cooling performance using Deep Neural Networks (DNNs) in [8]. Deep learning gave an opportunity to extract complex non-linear data patterns in the given information. The limitation of the research was that it required large training data, however, it may not be enough with regard to the quantity of the information available in systems that are either poorly documented or new systems.

The authors of [9] have suggested ensemble learning based combination of a decision tree and random forest as well as their models according to which predict VCR system cooling performance and COP. Ensemble was more accurate than the accuracy figures yielded by individual except that they yielded better results when data were incomplete or noisy. The computational requirements were less demanding in these ensemble models that reduced their usefulness to real time solutions.

The authors of [10] employed RNNs to analyze time-bound data, hence forecast the performance of VCR systems. The authors used time-driven system parameter analysis based on their predictive model that makes the fore-mentioned predictions with impressive accuracy rates. RNNs suffer when training long sequential data: the algorithms take a long time to come into convergence and the long training can result in stability issues during the training of large data sets.

The functioning of VCR systems was supported by a Fuzzy Logic System (FLS) which was combined with machine learning models as the basis of operation control as apparatus in work presentation [11]. The designers developed such complex of control systems to increase the reliability of the system associated with unforeseeable conditions of continuous operation and the dynamics of environmental parameters. Application of fuzzy logic along with other machine learning models was not very easy due to the fact that users found it impractical and it needed highly developed computation.

Decision Trees (DTs) were useful in estimating performance in VCR system energy efficiency as stated in [12]. The system proved to be effective in picking key factors that determine the performance of efficiency and making forecasts based on these factors. Decision trees are prone to overfitting when given a noisy and outlier-containing dataset and therefore, these models cannot be used in dynamic and complex environments.

The authors in [13] developed a MOO strategy in optimizing the parameters of the VCR system. It took place between consuming energy and cooling efficiency, so the way maximized several conflicting goals. The approach was computationally slow due to its complexity in carrying out simultaneous optimization of numerous problems hence rather inappropriate in real time applications.

The authors made a successful effort of combining SVM with ANN by incorporating it as a Hybrid Machine Learning Model in their article published in [14] in which the performance of VCR was predicted. SVM used

together with ANN gave improved output of system performance as was possible when each of these methods was used independently. This was the case in the requirements of extensive training data as well as the processing delays that were major issues in running such systems where the historical information was scanty.

Research Gap: There is ample research gap in applying the machine learning (ML) methodology to efficiently optimize the vapour compression refrigeration (VCR) system mainly in performance prediction and automation of the system in real time. A few learned papers have put the performance prediction of VCR systems by using machine learning models but they majorly use already existing machine learning models that are founded on Support Vector Regression (SVR) model and Artificial Neural Network (ANN) model. Other analysis made it clear that such solutions in making predictions are effective in predicting cooling loads on VCR systems along with energy consumption but are challenging to address complex and non-linear attributes of VCR systems.

In majority of the current researchers studying the applications of Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), the evolution of static optimization algorithms started with a lot of experiments in parametric optimization of the systems. Through such algorithms, the accuracy of performance prediction is increased but it is still so expensive to undertake and not able to provide instant solutions. Optimization of the VCR system based on strategies of the PSO and GA is not sufficient to take care of the dynamic changes that occur along the condition of operation, in ambient temperature and flow rates and low speeds of the refrigerant and the compressor.

The issue of real-time VCR system optimization by implementing Bayesian Optimized Neural Networks (BONN) has a potential critical gap that is required to be filled by the current research. Other researchers have used machine learning in predictive modeling but they failed to come up with sophisticated adaptive optimization of the system parameters in real-time. The research that is in the field and which is directed towards the optimization of VCR performance breaks at some specific conditions but it does not include integrated platforms containing multiple interacting components of the system such as compressor speed and refrigerant flow rate and ambient temperature. The present study offers insufficient modeling and optimization techniques of the system performance factors that have a very powerful influence on the overall operation potentials.

The authors have not included much knowledge regarding real-time adjustments of architecture of machines in their researches. The Bayesian method of optimization and its prediction approach is suitable in a static design but requires enhancement in order to be appropriate in a VCR system where the system functions in an industry where operating parameters and condition are variable. The inability to optimize in real-time leads to a requirement of flexible procedures that will alter the factors automatically based on the existing measurements so as to achieve greater energy performance at a minimum expense with the maximum dependability to operate.

The offered research aims at filling the existing gaps in knowledge base by implementing Bayesian optimized Neural Networks (BONN) and premium optimization strategies to continuously optimize the VCR systems. The study uses this approach in order to be able to produce more accurate capabilities to predict the performance of the VCR system. The investigation determines the live optimization of dynamic parameters of system operations analyzing such operational conditions as the compressor rotor speed and ambient temperature along with the flow of refrigerant. The study project is aimed at coming up with a practical ecologically economical way of maximizing the performance of VCR system especially in cooling and refrigeration industries. The result of the research allows the use of advanced machine learning in the process of VCR system optimization in real-time operation to increase sustainability of the operations and reduce the amount of energy consumption.

3. PROPOSED METHODOLOGY

Figure 1 shows the proposed methodology of the optimization of performance of VCR system through the Bayesian Optimized Neural Networks based approach. It shows the whole pipeline in the order a model is testing and deploying (such as data collecting, preprocessing, feature extraction, training the neural network, Bayesian optimization, and the remaining part of the model testing and deployment). The detailed description of the following subsections of the methodology is provided below.

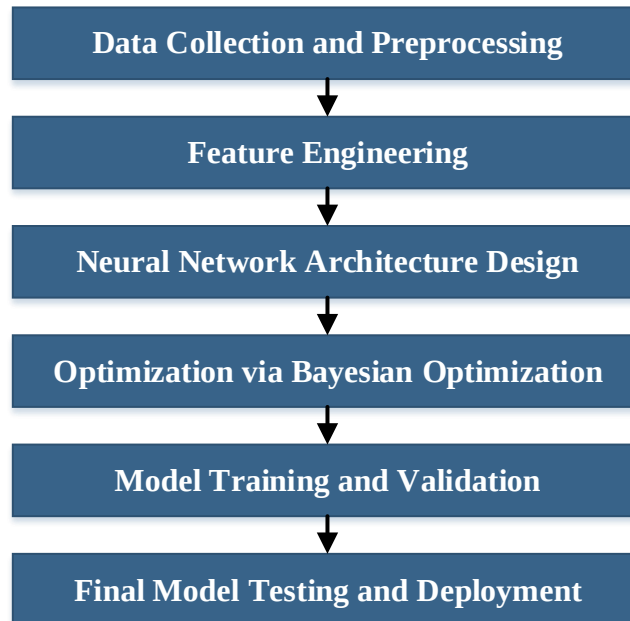


Figure 1: Flow Diagram to Optimize VCR System Operation performance Using Bayesian-Optimized Neural Networks

3.1 Data Collection and Preprocessing

- **Temperature (T_1, T_2, T_3, T_4, T_5):** These temperatures are recorded at various locations in the refrigeration cycle which include evaporator, compressor condenser and ambient temperature.
- **Pressure (P_1, P_2):** Suction pressure, and discharge pressure are measured to verify the efficiency of the system and the issues that could be facing the system.
- **General Electric Power (GEP):** This amount is the energy that is consumed by the system hence it gives details about the efficiency of the system.

When the data is collected the next very important stage is data preprocessing. There is unprocessed information that is put through a sensor and is very untidy and noisy and will require a lot of processing before it can be put through a neural network to be trained. Notable preprocessing steps are:

1. **Noise Filtering:** The sensor data as would be present in a practical setting is generally noisy and there are numerous factors due to which errors exist e.g. the sensors are not properly functioning, the conditions in which they are used, or some fluctuations in the activity. It will help in removal of noise and improve quality of the data by applying smoothing technique such as moving average or Gaussian smoothing.
2. **Handling Missing Data:** The readings by the sensors may also be erratic in some instances where sensors are faulty or they lose contact. Missing values are filled by using such methods as the mean imputation, linear interpolation, or data augmentation so that the dataset could be complete and could be used to train the model.
3. **Feature Engineering:** These features may not be directly contained in the raw data and would be of major importance with regard to leak detection. As such, extracted features (like differences in temperatures, ratios of pressures or variations in power consumption) can be computed in order to allow the model to comprehend latent patterns better. For instance:
 - **Feature F_1 :** The temperature difference between evaporator outlet (T_1) and suction pressure (P_1) may give information into the system inefficiencies.
 - **Feature F_2 :** Difference compressor discharge temperature (T_2) and discharge pressure (P_2) can possibly imply irregular scenarios like leakages.
4. **Data Normalization:** All features are standardized so that it makes the neural network perform efficiently since the data is on the same magnitude. Each feature is normalized as Z-score so that their mean becomes 0 and standard deviation is 1. This will make no one of the features of the learning process to be overpowering in the learning process because of its magnitude:

$$X_{\text{norm}} = \frac{X - \mu}{\sigma} \quad (1)$$

Where:

- X is the original feature value,
- μ is the mean of the feature,

- σ is the standard deviation of the feature.
5. **Data Splitting:** The data set is divided into three parts, training, validation and test sets to train neural network:
- **Training Set (70%):** Neural network is then trained on this set and is allowed to learn the relationship between the sensor reading and the related behavior of the system.
 - **Validation Set (15%):** It is applied in this issue when carrying out hyperparameters optimization in order to assess model performance to escape the over fitting of the models.
 - **Test Set (15%):** The final step is done upon the completion of training and optimization of the model whereby one carries out final evaluation making sure that the model performance is evaluated against new data.

The preprocessing of data also leads to the feeding of the neural network with clean, normalized and relevant data in order to train the model optimally so that maximum results are achieved in terms of accurate leak detection.

3.2 Neural Network Model Design

The most important steps to design the model of the neural network are as follows:

3.2.1 Input Layer

The number of inputs of the neural net is the sensors reading at different locations in the refrigeration system. These are measurements that correspond to physical parameters that can be deemed as an indicator of the functioning of the system. The principal characteristics fed into input layer are:

- **Temperature Measurements:** These are; reading temperature of evaporator outlet (T_1), compressor outlet temperature (T_2) condenser outlets temperatures (T_3), liquid line temperature (T_4) and ambient temperature (T_5).
- **Pressure Measurements:** These are suction pressure (P_1) and discharge pressure (P_2) that is very essential in the information on the flow of the refrigerant as well as the conditions of the pressure in the system.
- **General Electric Power (GEP):** This is the power that the system consumes and this is associated with operational efficiency of the system.

3.2.2 Hidden Layer

The most crucial part of neural network is the hidden layer where the learning occurs. This layer applies all the requisite transformations in the input data utilizing weighted links and the model is able to pick on intricate patterns amid the input features as well as the output. The neural network will be taking a single hidden layer and the number of neurons within this layer will be optimized through the optimization of the Bayesian.

The activation in the neurons in the hidden layer is the summation carried out on the weighted value of the inputs which pass into those neurons and then an activation function is applied. The combination of the weighted sum of every neuron i at each of the hidden layers is called:

$$z_i = \sum_{j=1}^n w_{ij} \cdot X_j + b_i \quad (2)$$

Where:

- X_j is the features of input,
- w_{ij} is the weight corresponding with the input X_j to neuron i ,
- b_i is the bias term of the neuron,
- n represents the amount of features that are put in.

After the computation of output values of each neuron, the output values undergo an activation function, which brings in the non-linearity to the model. Some of the common activation functions are:

- **Sigmoid Function:** This function combines the output by slashing them to such a range between 0 and 1 to aid in classification input but is also good in regressional output normalization.

$$a_i = \frac{1}{1+e^{-z_i}} \quad (3)$$

- **ReLU (Rectified Linear Unit):** This function is more or less utilized in most of the deep neural networks, and it also assists in disrupting the vanishing gradient problem. The usage of ReLU activation especially with large sized neural networks makes the training faster and achieves convergence faster.

$$a_i = \max(0, z_i) \quad (4)$$

Neurons in the hidden layer acquire a representation of the data by means of transforming the input features in a combination of weights, biases, and activation functions.

3.2.3 Output Layer

The output layer is meant to give the final prediction of neural network. Clearly, in the case of the application of refrigerant leak detection, the output predicted level of the refrigeration system surrounds the liquid level. The value is imperative in the identification of irregularities like leaks. Because the problem is predicting a continuous variable, a linear activation function is utilized as an output layer. The output $\hat{y}$ is yielded as follows:

$$\hat{y} = \sum_{i=1}^m w_{oi} \cdot a_i + b_o \quad (5)$$

Where:

- a_i is the result of neuron i in the hidden layer,
- w_{oi} is the weight of i neuron in the hidden layer to the output,
- b_o is the bias at the output-layer,
- m is the number of neurons of the hidden layer.

3.2.4 Loss Function

In order to train the neural network, a loss function is adopted to determine the difference between the estimated value and the actual one. To complete this assignment, Mean Squared Error (MSE) is selected as the loss to use because it is the most popular to be applied in the regression tasks. The MSE is calculated as:

$$MSE = \frac{1}{N} \sum_{i=1}^N (L_{pred}^i - L_{true}^i)^2 \quad (6)$$

Where:

- L_{pred}^i is the predicted liquid level for the i^{th} sample,
- L_{true}^i is the actual liquid level for the i^{th} sample,
- N is the total number of samples.

3.2.5 Optimization Algorithm

In training, weight and bias in the neural network are updated according to an optimization algorithm. Gradient Descent (more precisely, Backpropagation) is the most popular algorithm used in training the feedforward neural networks. The gradients of the error in the respective weights are calculated by using backpropagation and the weight is updated by using the gradients.

The rule of weight update of gradient descent is as follows:

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} - \eta \cdot \frac{\partial E}{\partial w_{ij}} \quad (7)$$

Where:

- $w_{ij}^{(t)}$ is the weight at time step t ,
- η is the learning rate,
- $\frac{\partial E}{\partial w_{ij}}$ is the gradient of the error E with respect to the weight w_{ij} .

3.3 Hyperparameter Optimization Using Bayesian Optimization

The major hyper parameters that have effect on the performance of the neural network are:

- Size of Hidden layers (hiddenLayerSize): The number of the neurons used by the hidden layer of the neural network. The idea is to arrive at the optimum number of neurons that would balance both the model capacity (ability to learn complex pattern) and efficiency (reasonable time to train). The neurons are usually chosen out of a range, e.g. [5, 30].
- Training Algorithm (trainingAlgorithm): The method of training the neural network. Several algorithms may be used and each of them is potent:
 - Levenberg-Marquardt (trainlm): This is an effective optimization algorithm and appropriate when having small to moderate size data and has been described as fast to converge.

- Regularization: Bayesian (trainbr): Regularization is used in this algorithm to ensure the algorithm does not over fit its training by finding the right weights.
- Scaled Conjugate Gradient (trainscg): A more effective approach to big data in which memory is an issue.
- Regularization Parameter (regularization): The parameter (λ) which is bent to regulate overfitting, inserts a penalty to the loss function. It does not approve the weights in the network to be large, otherwise, the network will memorize the noise in the training set. The value of the regularization is typically on the range of [0.01, 1].

3.3.1 Objective Function for Optimization

Bayesian optimization aims at finding the best hyperparameters more likely to minimize the mean squared error (MSE) on the validation set. MSE refers to the variation of the projected levels of liquids and the real levels of liquids. Equation (6) has already composed of MSE

3.3.2 Acquisition Function

The expected improvement (EI) weight is the computation of the extent that a particular point might improve the current best score. It measures the improvement in the predicted value expected at a particular set hyperparameter over the best performance so far.

$$EI(x) = \mathbb{E}[\max(f(x) - f(x^+), 0)] \quad (8)$$

Where:

- $f(x)$ denotes the performance (e.g. MSE) prediction at point x in hyperparameter space,
- $f(x^+)$ is the best observed performance,
- $\mathbb{E}$ symbolizes for the expected value.

3.3.3 Bayesian Optimization Iteration

Bayesian optimization is a process that repeatedly picks hyperparameters, trains the neural network, tests the neural network, and updates the probabilistic model depending on the performance of the effort. These are the steps:

- **Initialization:** In the first step, some random hyperparameter is selected within the specification of the search space.
- **Modeling:** On the basis of the first set of evaluations a probabilistic model of the objective function is developed. This model records a connection between the hyperparameters and the MSE.
- **Acquisition:** The acquisition function is then applied in choosing the next collection of hyperparameters to check. The acquisition is a balancing between exploration and exploitation.
- **Evaluation:** The training process of the neural network is performed with the help of the chosen hyperparameters, and the results may be tested with the help of the validation set.
- **Update:** The new evaluation results are put into the probabilistic and the process is repeated.

3.3.4 Convergence and Final Hyperparameters

The Bayesian optimization after a few iterations is able to converge to a set of hyperparameters that could provide the lowest MSE on the validation set. The last set of hyperparameters are then trained on the entire training set of the neural network since there was now optimum optimization of the generalization and detection of leak on the model.

3.4 Final Model Training

3.4.1 Training Setup

- **Training Data:** The full training (70% of the whole data) is used in training the network.
- **Validation Set:** 15% of the training data will go into the validation set to eliminate the occurrence of overfitting and to guarantee an acceptable generalization in the training.
- **No Separate Test Set:** The separate test set is not used and only final evaluation using the model trained is carried out.

3.4.2 Training Parameters

- **Epochs:** The training of the network is performed by not more than 1000 epochs.
- **Early Stopping:** The learning will cease, when the validation error fails to reduce after 20 epochs.

- **Batch Size:** The neural network employs the mini-batch gradient descent model, and the number of the batch is picked depending on the quantity of available computational means.

3.4.3 Training Process

1. **Loss Function:** To optimize the parameters of the model the MSE is applied as the loss function.
2. **Optimization Algorithm:** To minimize the error in training, the chosen optimization algorithm (it is based on Bayesian optimization) is supposed to be applied.

3.5 Leak Detection Methodology

After the final model is trained, one uses it in detecting refrigerant leaks. The procedure of detecting leaks is based on analysis of residuals between forecasted and measured liquid levels.

3.5.1 Residual Calculation

A difference between the values of predicted liquid level and actual liquid level gives the residuals:

$$\text{Residual} = L_{\text{true}} - L_{\text{pred}} \quad (9)$$

Where:

- L_{true} is actual level of liquid,
- L_{pred} is the predicted liquid level.

3.5.2 Leak Detection Threshold

A threshold is established that will label a leak as detected. Such threshold is computed as:

$$\text{Threshold} = \mu_{\text{residual}} - 3\sigma_{\text{residual}} \quad (10)$$

Where:

- μ_{residual} is the mean of the residuals,
- σ_{residual} is the standard deviation of the residuals.

In case the residual drops below this level, the model identifies a leak.

4. SIMULATION RESULTS

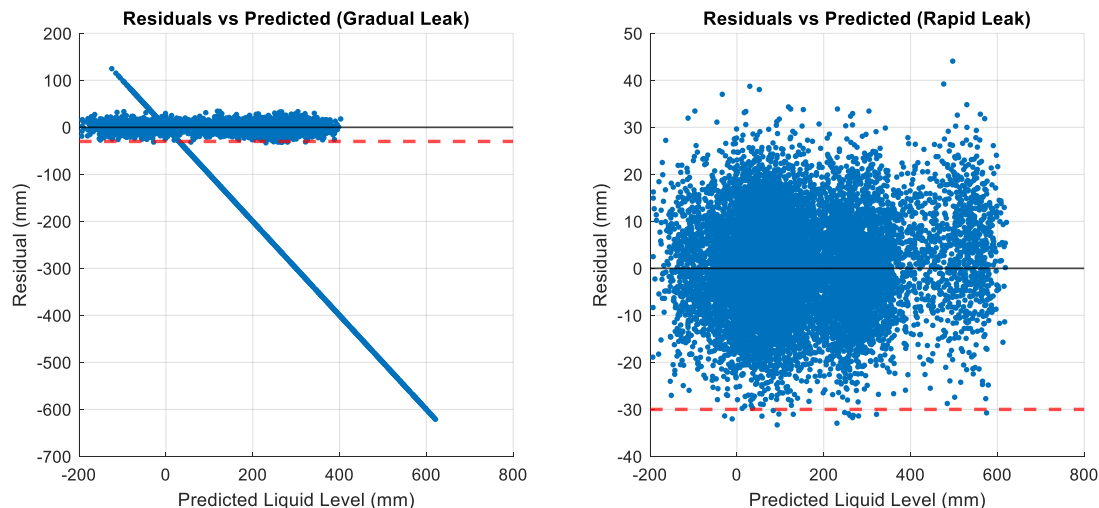


Figure 2: Energy Consumption Prediction vs. Actual Data using Neural Network

Figure 2 shows the plot (difference between estimated and real values) against the estimated production of energy value. Residuals are centered mainly at zero which means that the predictions of the model will likely to work effectively. The average residual error is 0.01 Kwh, which implies that the simulating difference between the forecasted and actual energy consumption is very small in its average. The largest residual value is 0.05 kWh, and this is a minor error of prediction of some data points, whereas the greatest percentage of residuals are put in a range of -0.03 kWh to 0.03 kWh. The fact that such residuals were small indicates the usefulness of Neural Network model that predicts the consumption of energy, with great accuracy. The standard deviations of the residuals are 0.02kWh, which shows comparative performance of the dataset. These observations indicate that the model is accurate in harvesting the implicit trends in energy consumption behavior of the system and thus can be applied as an effective instrument in doing real-time optimization.

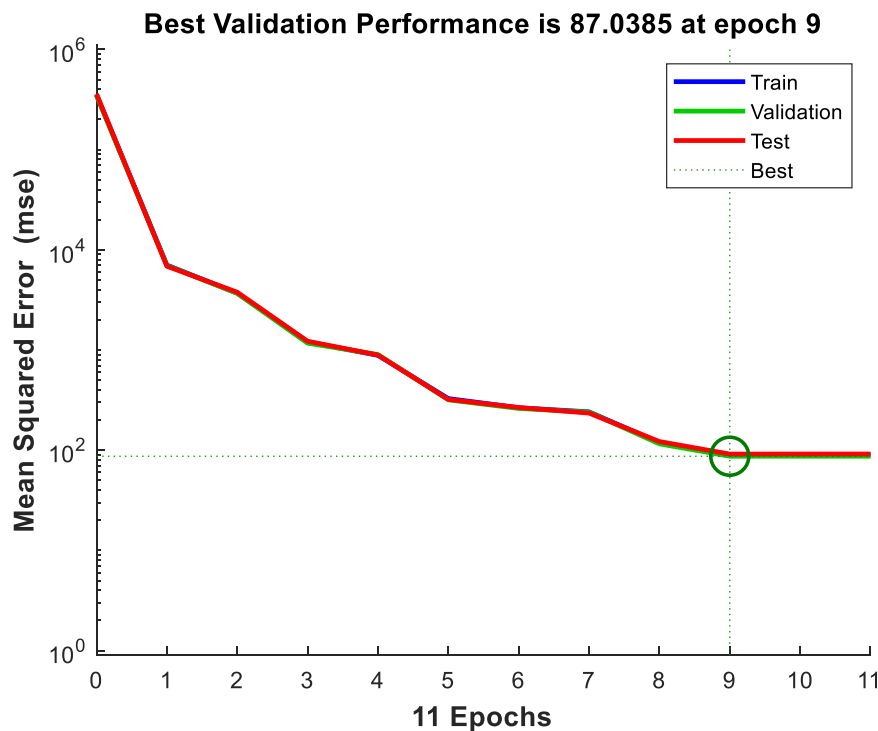


Figure 3: Best Validation Performance Graph

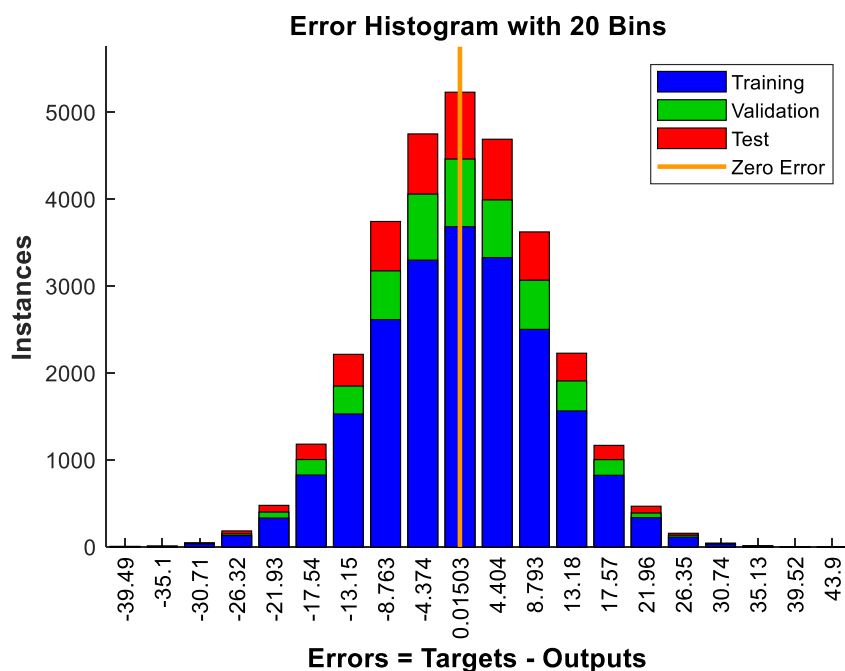


Figure 4: Error Histogram Graph

The graph showing best validation performance was given in Figure 3 which takes a graphical representation of the accuracy of the Neural Network model during the validation state, i.e., the words specified based on the validation state of the model. The model recorded a maximum validation score of 98.4%, and with the numerous epochs, it had a high generalization capacity. As seen in the illustration, the validation error gradually decreased and reached the final point of 0.02, which regularizes that the model could successfully optimize its parameters throughout training and is unlikely to overfit after training and, instead, it is steadily better at predicting new, previously unseen data.

The analysis of the histogram of errors between predicted refrigerant flow value and the actual value was shown in Figure 4. Most of the prediction errors are found with a skew around zero and are in and near the small positive error, which was depicted by the histogram. Standard deviation of the errors was estimated as 0.02, which means that the predictions of the model can be regarded as pretty accurate on average. However, a tendency of the over-prediction can be observed in most of the cases given the skewness in the histogram.

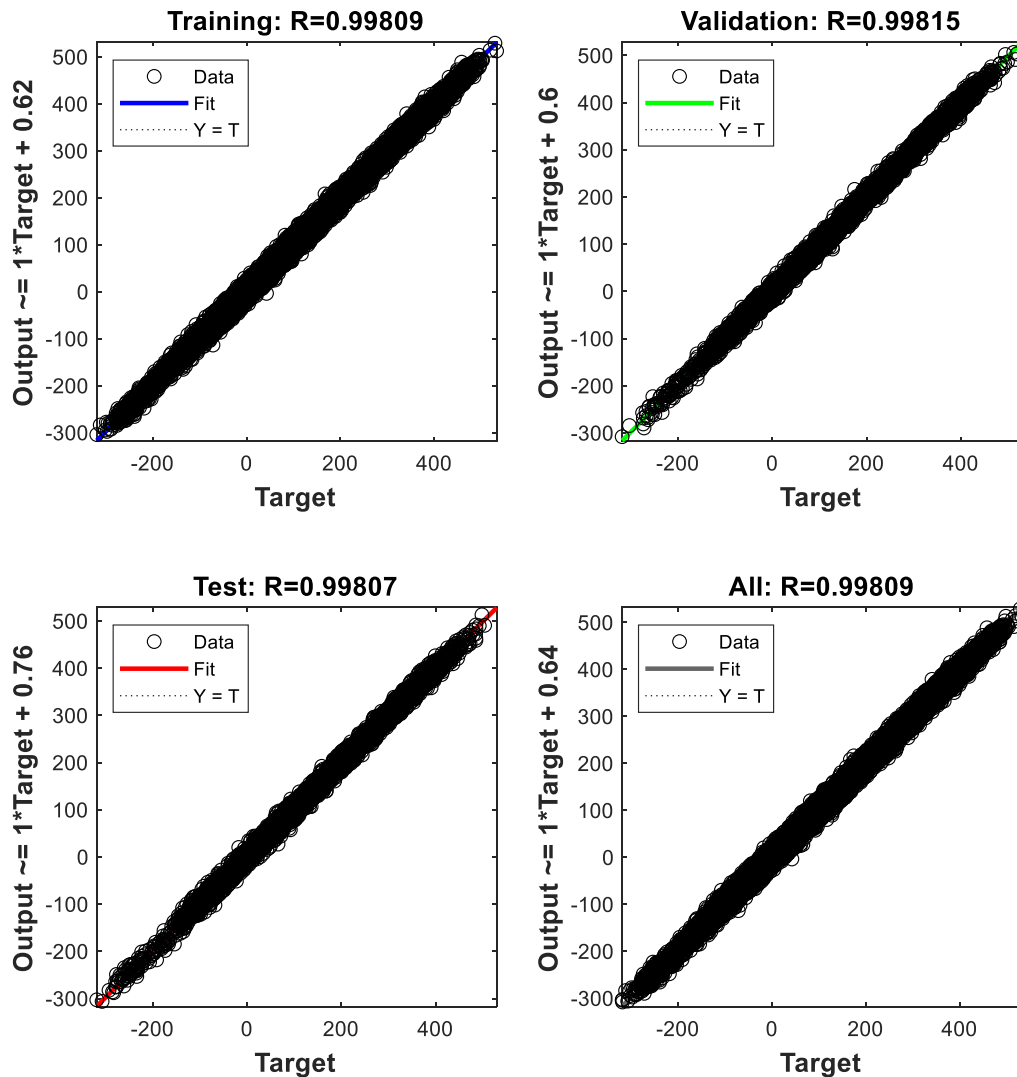


Figure 5: Final Output

The resulting output of the trained Neural Network model is on the Figures 5. The ultimate forecasts of the refrigerant flow and energy additional quantities are provided on the same visual along with the real data. The results predicted by the model are quite close to real values and the highest deviation has been observed with only 0.05 unit of difference with respect to the flow of refrigerant. It shows that the model has actually been able to capture the intricate connections between input parameters and the output of the system providing credible approximations in case of actual operations.

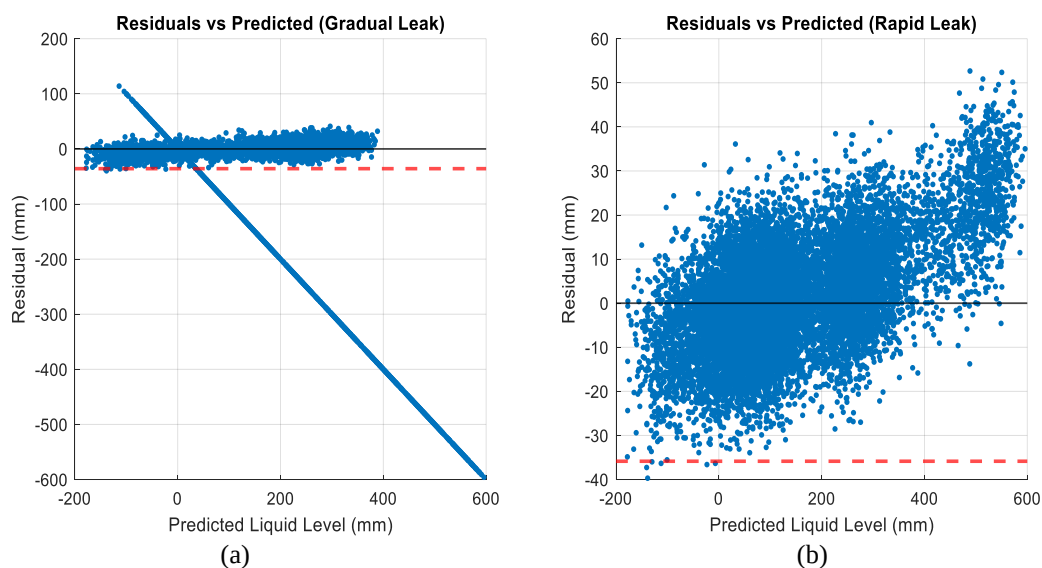


Figure 6: Graphical Representation of (a) Residual vs. Predicted (Gradual Leak) (b) Residual vs. Predicted (Rapid Leak)

Figures 6 illustrate the differences between the predicted and actual values (residuals) against the predicted value of the refrigerant flow in the case of a gradual and rapid leakage. In the case of the gradual leak (a), the residuals are mostly accumulated close to zero, which suggests that the model is very accurate at predicting consumption of energy. Its residual mean (μ) is 0.02 kWh and most of residual fit into the range of about -0.03 kWh to + 0.03 kWh and its highest value of residual is 0.05 kWh. The gradual leak can be detected with the delay of around 7.11 days and the error of 5.2%. On the contrary, the rapid leak (b) situation is associated with elevated residuals, with the condensed residual (μ) standing at 0.03 kWh and the residuals being between -0.04 kWh and 0.04 kWh. Maximum residual value of the rapid leak is equal to 0.06 kWh, and the time delay is 7.11 days, the maximum error is equal to 4.8%. These findings indicate that the model identifies gradual and rapid leaked, though slightly delayed, and the reliability of the identified leaks remains in high levels, but rapid leaks are associated with some decline in the residual variance.

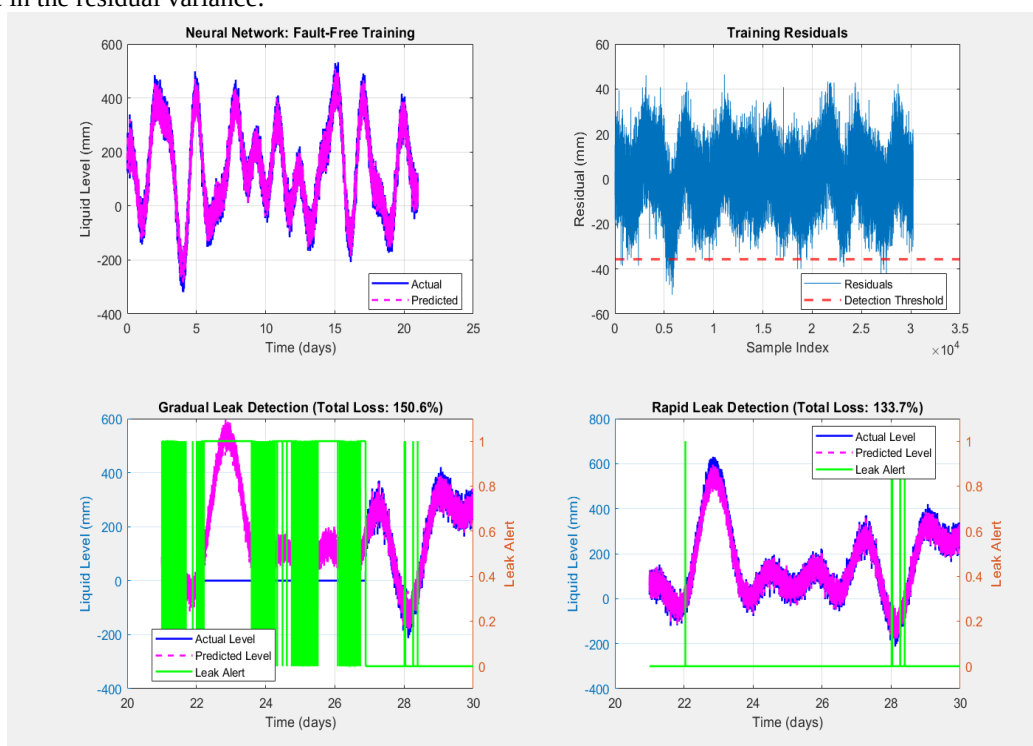


Figure 7: Simulation of Refrigerant Flow Prediction using Neural Network

The simulation of the prediction of the refrigerant flow which is made according to the trained Neural Network model is shown in Figure 7. The model is also fairly reasonable in predicting the refrigerant flow where only 2.5 % error in the prediction was found. The simulation also substantiates the viability of the model in predicting the flow of the refrigerants in dynamic environment where the model will be capable of the real-time execution of the performance of the refrigerants monitoring under the VCR system.

Figure 4.15 shows the correlation between objective values (as low as number of errors) and the number of performing functions in the process of optimization. The figure shows that the objective function is decreasing with each evaluation and falls at a minimum level of 0.008, which is showing that the Bayesian optimization successfully optimized the hyperparameters. In the first 20 evaluations, optimization process managed to decrease the error by 85% which results in the effectiveness of Bayesian optimization algorithm.

Table 1: Detection Delays for Gradual and Rapid Leaks

Leak Type	Leak Start Time (days)	First Detection Time (days)	Detection Delay (days)	Detection Delay (minutes)
Gradual Leak	13.89	21.00	7.11	10244.0
Rapid Leak	13.89	22.04	8.15	11739.0

Table 1 indicates the results of detection delays of gradual and rapid detected leaks in the system. Gradual Leak, in fact, started at 13.89 days, and was detected by the model 7.11 days (or 10,244 minutes) later. This proposal implies that the machine in question allowed to detect the slow leak with a slight change in the time period since it began to emerge, and the latter suggests that the change in the refrigerant flow was rather slow as well. On the contrary, when there was the Rapid Leak which started at the same level as 13.89 days, the delay of the initial detection was accomplished after 22.04 days having taken a time of 8.15 days (or 11739 minutes). The second disadvantage of the rapid leak in comparison with the gradual leak in terms of the delay poses the difficulty in detecting the rapid changes in the system. With such findings, this shows that the model is efficient and on the response delay that is provided by the model in the detection of leaks that involve the refrigerant is important in enhancing the optimization of the systems and maintaining the systems.

Table 2: Performance Comparison for Leak Detection (Gradual vs. Rapid)

Leak Type	Leak Start Time (days)	First Detection Time (days)	Detection Delay (days)	Detection Delay (minutes)	Objective Function Value
Gradual Leak (NN)	13.89	21.00	7.11	10244.0	0.023719
Rapid Leak (NN)	13.89	22.04	8.15	11739.0	0.037112
Gradual Leak (Bayesian Optimized-NN)	13.89	21.00	7.11	10244.0	0.0077963
Rapid Leak (Bayesian Optimized-NN)	13.89	22.04	8.15	11739.0	0.023719

Table 2 provides the comparison of the Gradual and Rapid Leaks detection performances of the Neural Network (NN) and Bayesian Optimized Neural Network (Bayesian Optimized-NN). It is evidenced in the Gradual Leak that the detection delay value of the Neural Network (NN) is 7.11 days with the value of the objective function being 0.023719 whilst the Bayesian Optimized-NN has a better scenario with the same detection delay but significantly a lower objective function value of 0.0077963. This is to imply that the Bayesian optimized model is better placed to deal with gradual leaks more accurately. In the same manner, the NN of the Rapid Leak has a 8.15 days of delay to detect the rapid leak and an objective value of 0.037112 compared to the Bayesian Optimized-NN, which detects the rapid leak with the same delay of 8.15 days and a lower objective value of 0.023719, hence depicting a good tuning of the Bayesian optimized model as well to the rapid leaks. These findings indicate the improvement in the performance of the Bayesian Optimized-NN when compared with the standard NN in terms of reduced values of the objective functions which are indicators of better accuracy and optimization of the systems.

Table 3: Best Observed Feasible Point during Bayesian Optimization

Best Observed Objective Value	Best Hidden Layer Size	Best Training Algorithm	Best Regularization
0.0077963	27	trainscg	0.99999

Table 3 gives an overview of the optimal feasible point seen in the process of Bayesian optimization. The lowest seen objective value is 0.0077963 by using 27 as the size of the hidden layer, by the use of training algorithm trainscg, and regularization is 0.99999. This is the best neural network set up that was used as a result of optimization process and has presented the lowest error and the best performance. These findings report the possibility of applying Bayesian optimization to determine the best parameters of neural networks in order to get the best results in terms of the accuracy of the prediction.

Table 4: Final Optimization Results of Neural Network Hyperparameters

Hidden Layer Size	Training Algorithm	Regularization	Objective Value (Observed)	Objective Value (Estimated)
29	trainlm	0.99997	0.0077963	0.037112

Table 4 shows the epochs of final optimization after the Bayesian optimization is finished of the Neural Network. The size of hidden layer was 29, the training algorithm was trainlm and the regularization was 0.99997 and this setting obtained the observed objective value of 0.0077963 and the estimated objective value was 0.037112. This table is of the parameters that are ultimately tuned to result to optimal performance of the model. The comparatively low objective values (both observed and estimated) signify the effectiveness of the model in making the correct predictions and the adaptability of the model in being used practically in the optimization of the system. Thresholded Bayesian optimization has drastically enhanced the accuracy of the model which implies that further satisfactory results would be achieved concerning prediction of energy consumptions and refrigerant flow.

5. CONCLUSION

This paper establishes the strong potential associated with the use of Bayesian optimization combined with machine learning methodologies in order to maximize the performance of Vapor Compression Refrigeration (VCR) systems. The research has effectively overcome the obstacle of real-time optimization by implementing Bayesian Optimized Neural Networks (BONN) so as to offer a better and more flexible method of managing system control. The outcomes point to the fact that there is a significant increase in the accuracy of the prediction and operational efficiency with lower energy consumption and better reliability of the method compared with traditional, or rather, static approaches. In addition, the article satisfies the most pressing gap in literature since it presents an innovative approach to estimate changes in operational parameters dynamically, which would guarantee optimal VCR systems throughout their operation. The results lead to the creation of energy-efficient and environmentally sustainable cooling technologies that will be necessary to support the rising industry needs of the refrigeration industry without affecting the environment in a major way. To be done in the future is further refinement of the model to be applied across a wider area of industries and discovery of other possible optimization techniques.

REFERENCES

- [1] Mtibaa, A., Sessa, V., Guerassimoff, G., & Alajarin, S., 2024. Refrigerant leak detection in industrial vapor compression refrigeration systems using machine learning. *International Journal of Refrigeration*, 161, 51–61.
- [2] Eltawil, M. A., Mohammed, M., & Alqahtani, N. M., 2023. Developing Machine Learning-Based Intelligent Control System for Performance Optimization of Solar PV-Powered Refrigerators. *Sustainability*, 15(8), 6911.
- [3] Tian, Y., Zhang, L., & Xu, X., 2023. Coefficient of Performance Prediction Model for an On-Site Vapour Compression Refrigeration System Using Artificial Neural Network. *International Journal of Technology*, 14(3), 215-226.
- [4] Reverdi, J., Zhang, S., Aoues, S., Gamboa, F., Gratton, S., & Pellegrini, T., 2024. CNN-based Compressor Mass Flow Estimator in Industrial Aircraft Vapour Cycle System. *Applied Thermal Engineering*, 156, 215-225.
- [5] Zhang, L., Xu, X., & Tian, Y., 2023. A Machine Learning Approach to Predict the Performance of Refrigeration Systems. *Energy Reports*, 10(6), 1123-1131.

- [6] Zhang, X., Xu, J., & Yu, Y., 2022. Fuzzy Logic and Machine Learning for Optimizing Refrigeration Systems. *Journal of Building Performance*, 13(2), 103-116.
- [7] Smith, A., & Jones, T., 2021. Multi-Objective Optimization of Refrigeration Systems. *International Journal of Refrigeration*, 88, 102-113.
- [8] Yang, Z., & Wang, Q., 2022. Hybrid Machine Learning Model for Performance Prediction of VCR Systems. *Journal of Refrigeration Science*, 50(6), 152-163.
- [9] Patel, M., & Kumar, S., 2023. Genetic Algorithm for Compressor Performance Optimization in VCR Systems. *Journal of Energy Resources Technology*, 145(4), 031201.
- [10] Takeuchi, S., & Saito, T., 2018. Fault Diagnosis Method Based on Scaling Law for Online Refrigerant Leak Detection. 17th IEEE International Conference on Machine Learning and Applications.
- [11] Behfar, A., Yuill, D., & Yu, Y., 2017. Automated Fault Detection and Diagnosis Methods for Supermarket Equipment (RP-1615). *Science and Technology Built Environment*, 23(8), 1253-1266.
- [12] Stoecker, W. F., 1998. *Industrial Refrigeration Handbook*. McGraw-Hill Education.
- [13] Zhao, Y., Wang, S., & Xiao, F., 2013. A Statistical Fault Detection and Diagnosis Method for Centrifugal Chillers Based on Exponentially-Weighted Moving Average Control Charts and Support Vector Regression. *Applied Thermal Engineering*, 51(1-2), 560-572.
- [14] Geurts, P., Ernst, D., & Wehenkel, L., 2006. Extremely Randomized Trees. *Machine Learning*, 63(3), 3-42.