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Coefficient of Performance Prediction Model for an On-Site Vapor Compression Refrigeration System Using Artificial Neural Network

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Abstract. Refrigeration system is essential in ensuring the comfort of people, preserving food for extended periods, and supporting the functionality of technological devices. However, refrigeration system accounts for approximately 17% of global electricity consumption due to the substantial energy requirement of compression work. This high consumption rate shows the need to reduce operational and maintenance costs by monitoring the efficiency of refrigeration system using Coefficient of Performance (COP). Currently, there are two methods of monitoring COP, namely substituting actual values into theoretical formulas, and developing artificial intelligence model for COP values. Therefore, this study aimed to develop COP prediction model using Artificial Neural Network (ANN) at a room set point temperature of -25°C. The results showed that through the analysis of ANN parameters, prediction model was successfully developed with an RMSE of 0.0621, an R^2 value of 0.8162, and a training speed of 27.3 seconds. The developed prediction model had a CvRMSE value of 3.41 and an MBe of 0.14 which falls within the acceptable values. The prediction model was able to predict COP values of other CDUs, with the same specification, for set point temperature of -21°C. This study showed a promising strategy for monitoring COP of an on-site vapor compression refrigeration system using a data-driven method.

Keywords: Artificial Neural Network; Coefficient of Performance; Machine Learning; Refrigeration; Vapor compression system

1. Introduction

Refrigeration system is essential in modern lives, ensuring comfort, preserving food for extended periods, and supporting the functionality of technological devices (Poggi *et al*., 2020). Whether for air conditioning, heat pumps, or refrigeration purposes, all these applications require a vapor compression system, accounting for approximately 17% of global electricity consumption due to the substantial energy requirement of compression work (Ustaoglu *et al*., 2020). In the Philippines, there is a projected doubling of overall energy demand by the year 2035 compared to the 2010 levels, with an average annual increase of 2.9%. Moreover, the Energy Policy and Planning Bureau of the Department of Energy has prioritized energy efficiency as a fundamental aspect of the Filipino way of life, targeting a 10% reduction in energy consumption by 2030 (Martinez, 2017).

The Energy Efficiency and Conservation Act, also known as the Republic Act 11285 of 2019, has established energy efficiency and conservation as a legal obligation to people.

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This law unites various sectors to make energy efficiency and conservation a way of life for Filipinos. Apart from establishing an inter-agency energy efficiency and conservation committee as well as implementing a certification system for Energy Conservation Officers (CECO) and Energy Managers (CEM), this act also directs establishments to integrate Energy Management Systems into the operations, promoting strategic measures and initiatives.

The development and implementation of monitoring system as well as integration of predictive model are essential steps to reduce energy consumption and predict potential failure of a system (Noorsaman *et al*., 2023; Sari *et al*., 2023; Louhichi, Sallak, and Pelletan, 2022; Katipamula and Brambley, 2005). To ensure the efficient operation of cooling system, there is a need to implement energy efficiency measures to effectively reduce electricity consumption while sustaining the desired temperature for the cooled area (Ahmed *et al.*, 2021; Olughu, 2021). This phenomenon can be achieved by monitoring and analyzing Coefficient of Performance (COP) of system, as a common method of determining the efficiency of cooling applications. Several studies conducted by Yu and Chan underscore the importance of monitoring COP in decreasing the electricity consumption of cooling system. These studies analyzed changes in COP under different operating conditions, investigating whether low values can be improved through design and operational control adjustment. For example, COP was increased from 11.4% to 237.2% by identifying the optimum set point for condensing temperature, resulting in an electricity consumption reduction of approximately 14.1 kWh/m^2 of area in an HVAC application. These results showed that simulation studies could offer valuable insights for HVAC engineers to optimize the operation of cooling system (Yu and Chan, 2008; Yu, Chan, and Chu, 2006; Yu and Chan, 2005).

Monitoring COP is crucial for developing predictive approaches to conduct necessary maintenance activities. For instance, a study by Yu, Chen, and Chen (2020) explored the application of the Internet of Things (IoT) in COP forecasting using a Long Short-Term Memory (LSTM) network, a deep learning model, in the context of predictive maintenance (Yu, Chen, and Chen, 2020). This study showed that a good COP prediction could facilitate timely maintenance of cooling system to reduce unnecessary energy and cost losses. Breuker from the ASHRAE journal has also showed the impact of machine fault on COP (Breuker, Rossi, and Braun, 2000). Through performance indices, it was observed that refrigerant leakage reaching a fault level of 14% could lead to 4.6% reduction in COP. Additionally, condenser fouling was found to have a greater effect on COP compared to capacity, potentially indicating a looming failure. Consequently, as equipment function decreases severely, the need for maintenance activity increases significantly.

A Systematic Literature Review (SLR) conducted by Dalzochio explored the challenges and application of Machine Learning (ML) in predictive maintenance in the context of Industry 4.0 (Dalzochio *et al*., 2020). Obtaining early insight into the physical system using predictive model offers various benefits including productivity improvement, reduction of system faults, minimization of unplanned downtimes, increased efficiency in financial and human resources, as well as optimization in planning the maintenance interventions (Nacchia *et al*., 2021). The study also explored predictive maintenance challenges in the business context, emphasizing the importance for companies to adopt predictive model capable of providing early indications of potential anomalies according to the impact of failure on the plant operations. Despite the advantages, some companies opt for redundant equipment that can take over when the primary hardware fails, rather than investing in predictive maintenance approach.

For the development of COP prediction model for cooling or heating system, several studies have been carried out using different types of ML. Through statistical analysis of parameters, ANN-based COP prediction model was developed for a heat pump. The results showed that ANN produced the lowest Mean Bias Error (MBE) of -3.6 compared to the Support Vector Machine (SVM), Random Forest, and K-nearest neighbor. Due to the superior accuracy and fast calculation time, the trained model was applied to a Building Automation System (BAS) to monitor system performance in real-time (Shin and Cho, 2021). Similarly, Tian developed COP prediction model for an on-site screw compressor cooling system in a cinema setup (Tian *et al*., 2019). The result showed that ANN produced a maximum error of 5.8% and the prediction from experimental data ranged between positive or negative 5%, indicating the significance of ANN on water-cooled screw cooling system.

Several studies have applied ML to predict COP in energy efficiency and predictive maintenance contexts. In this study, ANN is proposed for predicting COP of an on-site refrigeration system as a promising approach to address the challenges of monitoring COP of decentralized industrial cooling system. Specifically, the objectives of this study include developing a ML-based COP prediction model for a vapor compression refrigeration system using ANN. The experiment was carried out to manually determine the effectiveness and limitations of model in predicting COP for other decentralized condensing units with similar specifications. The input variables used were selected using statistical analysis, with COP theoretically measured using evaporation temperature and pressure, as well as condensing and subcooled temperature. In conclusion, ANN showed a high accuracy and fast training time, indicating the effectiveness in predicting COP of an on-site vapor compression refrigeration system.

2. Methods

2.1. System description

The equipment used is in a decentralized cold storage facility in Paranaque City, Philippines. Specifically, the equipment has been operating for 4 years and consists of a Mitsubishi ECOV-EN270VC1 brand of Condensing Unit (CDU), with a scroll inverter type compressor that uses R410a refrigerant. Furthermore, it is known for energy saving, high efficiency, and compactness, which is typically used in air conditioning or refrigeration applications (Wang *et al*., 2021). In this study, the equipment is set to maintain a room temperature of -25°C. The cooling unit is installed with a water defrost system, which is scheduled every 2:00 AM and 2:00 PM. The system includes an inverter scroll compressor, an evaporator, an expansion valve, and an air-cooled condenser.

2.2. Data collection

Currently, there are two major methods used in the industry for monitoring COP. The first is by fitting the actual refrigeration parameters to a theoretical formula, while the second method entails training artificial intelligence model to predict future values (Tian *et al*., 2019). In this study, the second method was used, proposing the use of ANN model trained on data from an on-site refrigeration system. The model is expected to predict COP of other condensing units with similar model and specification. Specifically, 3770 data points for each refrigeration parameter were used, with 70% allocated for training Machine learning (ML) model while the 30% remaining were applied for testing. The equipment was located on the machine deck above the cold room facility on an outdoor setup. Data were extracted through XWEB Evo at an interval of 5 minutes for the entire month of June. Subsequently, to capture the system COP, a theoretical method was used. By applying parameters such as evaporating temperature, suction pressure, condensing temperature, and subcooled temperature, the enthalpies of refrigerant were interpolated from the saturated and superheat property table of R410A refrigerant to calculate COP using the formula from the ASHRAE (2013) Handbook: Fundamentals. The following formula was used to obtain the value of COP (see Equation 1).

$$COP = \frac{Q_{in}}{W_{comp}} = \frac{h_1 - h_4}{h_2 - h_1} \tag{1}$$

COP of vapor compression system serves as a measure of compressor efficiency. Furthermore, it is the ratio of cooling effect achieved by system to energy supply under certain conditions (Jani *et al.,* 2017; Jani *et al.,* 2016). Equation 1, shows the theoretical formula for obtaining COP of the system. Where COP represents the coefficient of performance of the system, Q_{in} indicates the heat absorption in evaporator, Q_{out} is the heat rejection in the condenser, W_{comp} is the work input from the compressor, and h_1 to h_4 [kJ / kg – K] denotes the enthalpy in the four stages of the vapor compression cycle.

2.3. Input value selection

An effective ML prediction model depends on the quality and significance of input data used in training (Fenza *et al.,* 2021). Therefore, statistical analysis was used to identify refrigeration parameters with the most significant relationship to COP. This could help reduce the amount of data to be collected by extracting relevant information (Jittawiriyanukoon and Srisarkun, 2018). In this context, COP is the dependent variable while suction pressure, suction temperature, evaporation temperature, condensing temperature, condensing pressure, EXV opening, subcooled temperature, and superheat are independent variables. Table 1 shows the summary of regression analysis and ANOVA conducted on all variables. Among the input variables, suction pressure and temperature, including evaporation temperature have the highest R^2 values. Moreover, R^2 shows the extent to which changes in dependent variables are explained by independent variables, as values closer to 1 indicate a better explanatory power (Chicco, Warrens, and Jurman, 2021). In this case, the three variables have the highest values and the most significant relationship with the dependent variable, namely COP. Meanwhile, the p-value is a measure that gives credibility to statistical analysis, with a lower value indicating a greater significance in the observed variances (Maheshwarappa and Majumder, 2023).

Table 1 Summary of statistical analysis for the input variable selection

Input variable	*P* value	ANOVA			Importance score
		R^2	F	Sig	
Suction Pressure	<0.05	0.81	16122	<0.001	~300
Suction Temperature	<0.05	0.72	9746	<0.001	~300
Evaporation Temperature	<0.05	0.81	15962	<0.001	~300
Condensing Temperature	<0.05	0.19	901	<0.001	~270
Condensing Pressure	<0.05	0.19	900	<0.001	~260
EXV Opening	<0.05	0.05	213	<0.001	~90
Subcooled Temperature	0.76	<0.01	0.09	0.76	~60
Superheat	<0.05	0.02	67	<0.001	~40

All input variables, except subcooled temperature, showed a statistically significant value of below 0.05. Additionally, a separate feature ranking algorithm was used in MATLAB to identify input variables with the most significant relationship to the output variable. Based on the results, suction pressure, suction temperature, and evaporation temperature have the highest importance scores in the F-test conducted, indicating the most significant refrigeration parameters regarding COP.

2.4. Prediction model development

ANN is a ML model used to determine the significant relationship between input and output variables. This model is composed of interconnected neurons containing an activation function with three structural layers, namely input, hidden, and output (Fagbola, Thakur, and Olugbara, 2019). In this study, three fully connected (FC) layers comprising 10 nodes each, excluding the final fully connected neurons, are used for model training. Neurons are interconnected with weight reflecting the output of neurons relative to others (Pérez-Gomariz, López-Gómez, and Cerdán-Cartagena, 2023). Some of the common activation functions used in ANN are the Sigmoid and the Rectified Linear Unit (ReLU) to address the “expansion as well as disappearance” problem usually encountered in sigmoid and tanh functions. The use of the ReLU introduces sparsity to the computation, improving efficiency regarding time and space complexity (Bai, 2022). Therefore, the ReLU activation function was used in this study with an iteration limit of 1000, training only suction pressure, suction temperature, and evaporation temperature among the 8 input variables.

2.5. Accuracy Metrics

The two main parts of developing a prediction model using ANN are training and testing. Similar to other ML, ANN uses a high percentage of data for training by arriving at an optimal weight of the network. In this study, 70% of data was used to train the model while the remaining 30% was used for testing (Genç, and Tunç, 2019). To analyze the accuracy of prediction model relative to each other, several metrics were used such as Coefficient of determination (R^2) and Root Mean Squared Error (RMSE). In ML, R^2 is a metric that shows how effectively model explains the fitted data in the regression model, with higher values representing better explanatory power. Meanwhile, RMSE shows a clear view of the model performance by indicating the dispersion degree of the data. The lower the RMSE value the better the ML model and its prediction (Tyagi *et al.*, 2022). Both metrics can be calculated using the formula shown below, as expressed in Equations 2 and 3 (Tian *et al.*, 2019).

$$R^2 = \frac{Variance\ explained\ by\ the\ model}{Total\ variance} = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \quad (2)$$

$$RMSe = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

In the equations, n represents the sample size, y_i is the actual value, and $\hat{y}_i$ is the predicted value. In addition to the metrics, this study used the coefficient of variation for root mean squared error (CvRMSE) and Mean Bias Error (MBE) to evaluate the application of the trained prediction model. ASHRAE guideline 14 provided a standard of 10% for MBE and less than 30% for CvRMSE (Shin and Cho, 2021). Equations 4 and 5 are the formulas for CvRMSE and MBE.

$$CvRMSe = \frac{RMSe}{\bar{y}} \quad (4)$$

$$MBE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n} * 100 \quad (5)$$

2.6. Comparison of the prediction model

Currently, there are several regression ML model that can be used to predict desired parameters such as Regression trees, Support Vector Machine (SVM), Gaussian Process Regression, and kernel approximation regression (Sarker, 2021). An analysis using

MATLAB, compared the effectiveness of ANN to other ML models. Table 2 shows the comparison of accuracy metrics and learning speed between different models.

Table 2 Comparison of different regression models' metrics and learning speed

Machine learning (ML) Model	RMSE	MSE	R^2	Training time	Learning speed
Artificial Neural Network	0.0621	0.0039	0.8162	27.3 Sec	~77000 obs/sec
Gaussian Process Regression	0.0621	0.0039	0.8162	199.78 Sec	~7900 obs/sec
Regression Tree	0.0625	0.0039	0.8138	2.7 Sec	~79000 obs/sec
Support Vector Machine	0.0629	0.0040	0.8115	29.9 Sec	~26000 obs/sec
Kernel Approximation Regression	0.0667	0.0045	0.7880	145.7 Sec	~24000 obs/sec

In this study, the Gaussian process regression used for analysis is a matern 5/2 kernel function, with an isotropic kernel and a constant function. The regression tree is a course tree with a minimum leaf size of 36, while the support vector machine model is a medium Gaussian SVM with a kernel scale of 1.7. Additionally, the last model is SVM Kernel with an iteration limit of 1000. Although ANN and Gaussian process regression have the same significance in terms of accuracy, there is a difference in terms of learning speed and training time. Approximately, 69,100 observations per second and a difference of 172.48 seconds are identified between the two models. Based on the results, the lowest RMSE value and highest observation rate of ANN show a better prediction model compared to others.

2.7. Optimization, validation, and testing

In addition to the feature selection conducted, ANN model was analyzed using different numbers of nodes and types of activation functions. Table 3 shows that RMSE and R^2 value changes based on variation in the number of hidden nodes. The results showed that RMS error was smallest when there were 10 hidden nodes under the ReLU function, leading to an RMSE of 0.0621 and an R^2 value of 0.8162. Therefore, a hidden layer node of 10 was used in training ANN prediction model.

Table 3 Predicted error with different hidden nodes and function

Hidden nodes number	ReLU Function		Sigmoid Function	
	RMS error	R^2	RMS error	R^2
6	0.0673	0.7844	0.0628	0.8121
7	0.0651	0.7981	0.0629	0.8113
8	0.0635	0.8082	0.0702	0.7648
9	0.0645	0.8017	0.0642	0.8038
10	0.0621	0.8162	0.0624	0.8148

2.8. Automation Concept

Apart from accuracy, ANN is also capable of a higher learning rate compared to other ML models (Shin and Cho, 2021). Figure 1 shows the complete process flow in developing, testing, and applying ANN-based COP prediction model used in this study. The first part includes the development of prediction model by training 70% of the data and testing 30%. The second part includes an automation concept for the deployment of prediction model. Using refrigeration data at a normal operating condition, this study also proposes a future improvement integrating a fault detection and diagnosis ML model. Moreover, several studies, including Han *et al.* (2010) have developed an automated Principal Component Analysis (PCA) – Support Vector Machine (SVM) based AFDD of a vapor compression refrigeration system. (Han *et al.*, 2010).

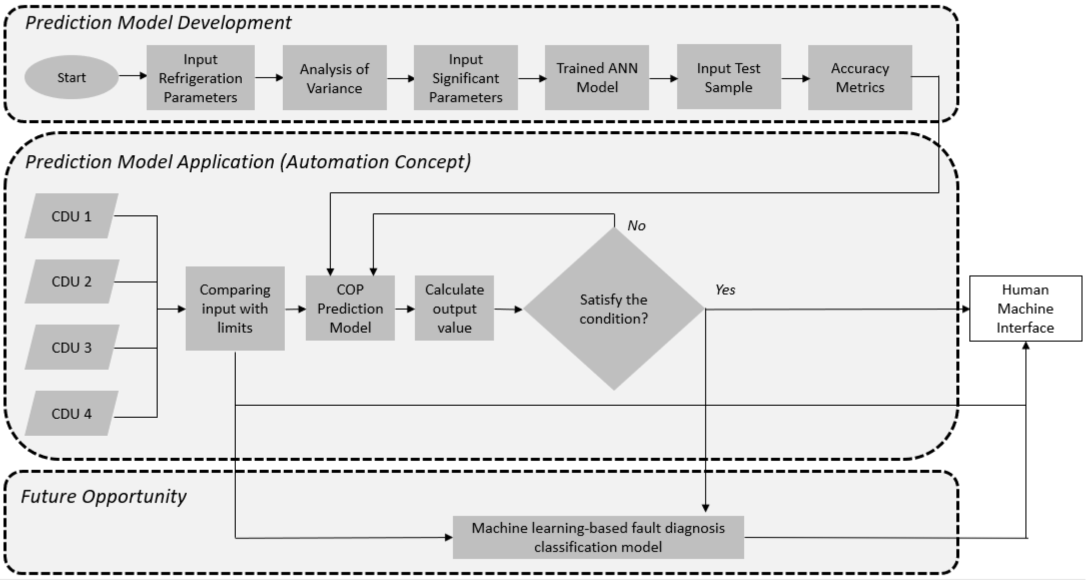
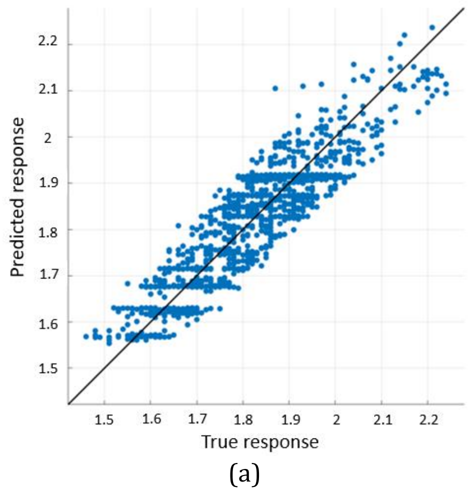


Figure 1 Procedure and automation concept for COP prediction model

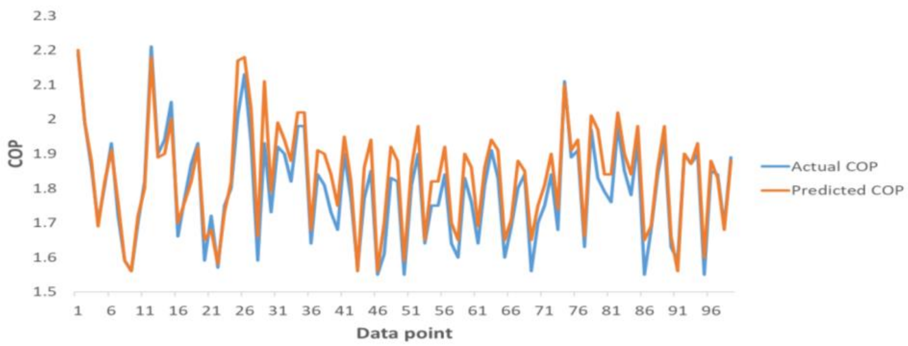
3. Results and Discussion

3.1. Performance of prediction model

Figure 2 shows the graph of the actual COP value relative to the predicted response. The straight diagonal line shows the perfect prediction, with closer values representing better results. The graph shows that the predicted values are close to the perfect prediction line. This indicates that the trained ANN prediction model can predict the test data with a small amount of error.



(a)



(b)

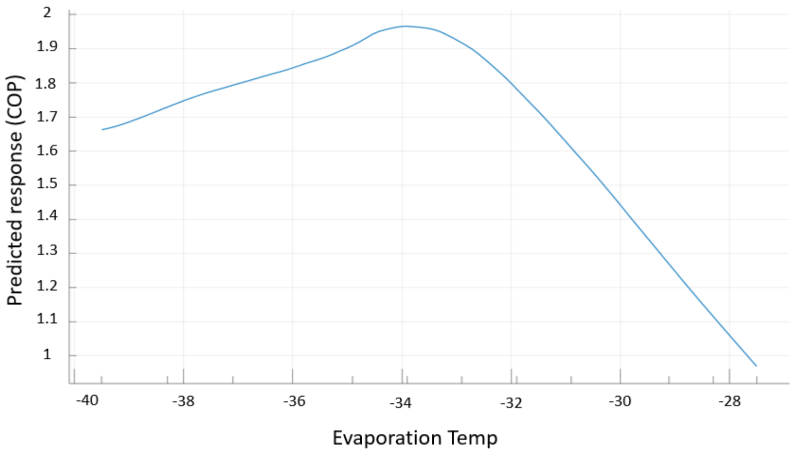
Figure 2 True and predicted result (a) and comparison of predicted values to actual (b)

The second graph shows the predicted and actual COP against each data point used during model testing. The slight disparity in RMSE, MSE, CvRMSE, and MBE along with the positive graph of the predicted and actual COP, shows the effectiveness of ANN model developed. Table 4 also depicts the accuracy metrics of the trained ANN prediction model, with a detailed comparison between the different accuracy metrics conducted for the two tests. Compared to standard set by ASHRAE (2014) guideline 14, the table shows that CvRMSE of 3.41 is below 30%, while the MBE of 0.18% does not meet the threshold of 10%. These results show the effectiveness of the prediction model.

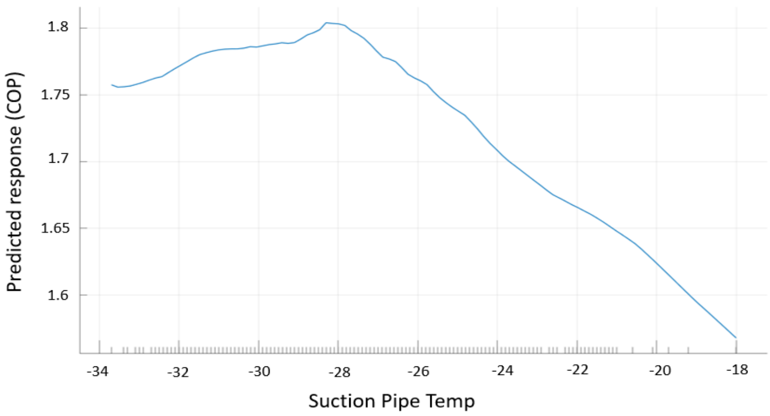
Table 4 Accuracy of testing the prediction model using a similar machine

Prediction Model Accuracy Metrics	CDU 1	CDU 2	Training/ testing
RMSE	0.1441	0.0615	0.0621
MSE	0.0208	0.0038	0.0039
CvRMSE	6.90%	3.17%	3.41
MBE	-10.6%	0.58%	0.18%
R^2	-0.4	0.75	0.8162
Set point temp	-18	-21	-25

Figure 3 shows a partial dependence plot and the relationship between each variable in the COP to understand the model and its three input variables. Evaporation temperature and suction pipe temperature show similar characteristics that increase as COP decreases. However, suction pressure increases as the COP of the system rises.

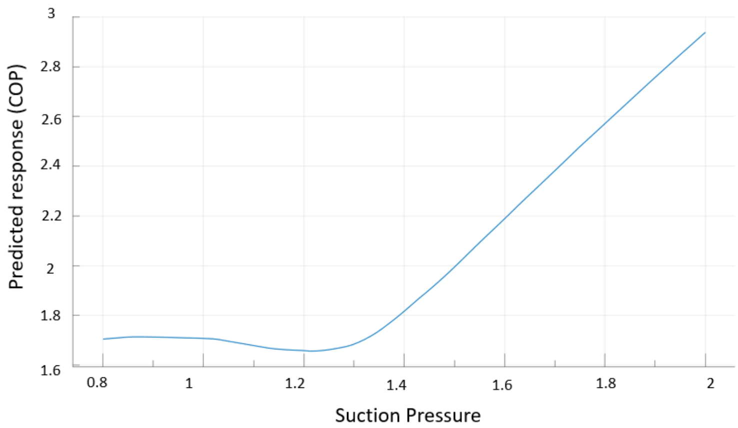


(a)



(b)

Figure 3 Partial dependence plot of evaporation temperature (a), suction pipe temperature (b), and suction pressure (c), respectively

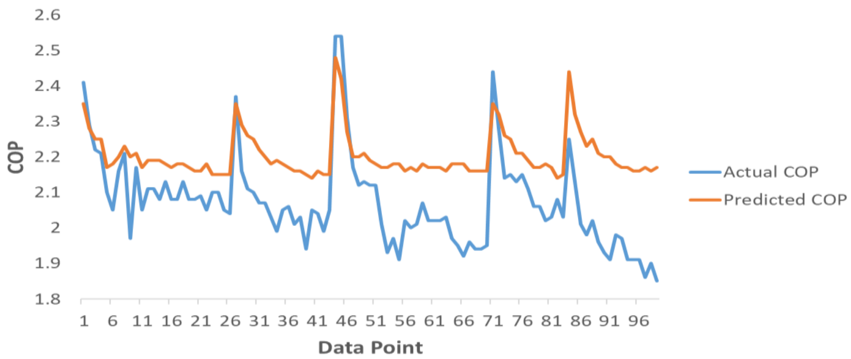


(c)

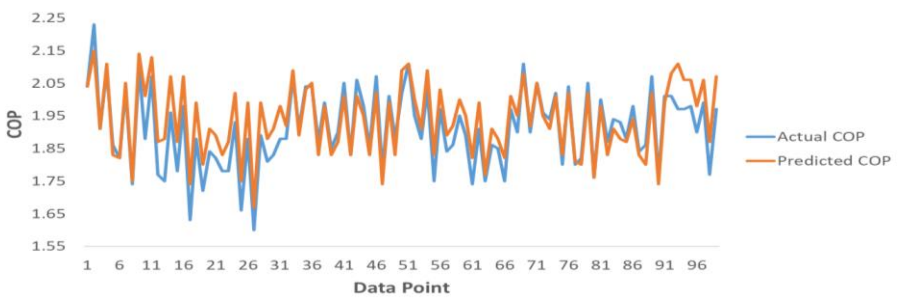
Figure 3 Partial dependence plot of evaporation temperature (a), suction pipe temperature (b), and suction pressure (c), respectively (Cont.)

3.2. Prediction model application

An additional test was conducted using input data from two different condensing unit (CDU) of the same model and brand. CDU 1 was set at -18°C cooled temperature while CDU 2 was set at -21°C temperature. CDU 2 showed better prediction results compared to CDU 1 in terms of RMSE with a value lower than the training metrics. For the R^2 value, CDU 1 has a significantly low value of -0.4 compared to the R^2 value of 0.75 of CDU 2. The CvRMSE for both CDUs falls within the standard set by ASHRAE (2014) guideline 14, which is below 30%. Meanwhile, the MBE for CDU1 falls slightly below the standard of 10%, which is contrary to the MBE of CDU2. With different set point temperatures, the results show that room temperature and equipment condition are factors in the prediction capability of model. This is attributed to the compressor functioning at different pressures based on the operating condition. Figure 4 shows the comparison chart of the actual and predicted values for CDU 1 and CDU 2, respectively.



(a)



(b)

Figure 4 Comparison between predicted and actual COP of CDU 1 (a) and CDU 2 (b)

4. Conclusions

In conclusion, this study successfully developed a machine learning-based COP prediction model using the actual operating data from an on-site scroll-type compressor refrigeration system with a vapor compression refrigeration cycle. A total of 3770 data for each parameter was used, where 70% was allocated for prediction model training and 30% for testing. Statistical analysis was conducted on the 8 refrigeration parameters to improve the result. Among these parameters, suction temperature, suction pressure, and evaporation temperature with the highest RMSE, MSE, and R^2 values were selected as input variables for training ANN model. By comparing the trained ANN model at -25C set point temperature to other ML algorithms, ANN has the highest RMSE value of 0.06, MSE of 0.004, and R^2 of 0.82, indicating a good prediction capability of COP. Through the change of nodes number and activation function type, the result showed that the ReLU function with 10 nodes for each hidden layer produced the lowest RMSE value. Furthermore, the prediction model developed was tested using data from another condensing unit (CDU) with the same model, showing the potential to predict COP at approximately -21 set point temperature. This study showed a promising strategy for monitoring COP of decentralized refrigeration system using a data-driven method.

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