Prediction of Refrigeration System Performance Using Artificial Neural Networks

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Abstract

In this research, a review of the previously conducted simulation approaches for estimating the performance of the vapor pressure refrigeration systems has been performed. It was found that some researchers have followed the mathematical approaches, which are based on the principles of thermodynamics, to measure the performance, while many others investigated the use of artificial intelligence methods. The artificial neural network (ANN) is one of the most widely used methods in this research field. It showed that the ANN could predict the effect of almost all parameters that significantly impact the performance of compressed vapor refrigeration systems. Also, ANN was efficient and rapid in reducing time and costs, and most of the obtained results were close to the experimental results. However, most of the accomplished research considered the effect of no more than three to four parameters simultaneously. Thus, it is recommended to investigate the concurrent influence of more and different parameters.

Keywords

artificial neural networks, refrigeration systems, energy efficiency,

1. Introduction

Refrigeration system production has been significantly rising in recent decades, has become increasingly vital in people's everyday lives. As a result, improving the refrigeration system design process's efficiency and product performance is critical. One of the most useful tools for achieving this goal is a computer simulation. The working circumstances and configuration parameters of the product are supplied first, then the performance is anticipated, and finally, the configuration parameters of the product are evaluated based on the performance prediction. If the anticipated performance does not match the requirement, the configuration settings should be tweaked, and the simulation should be run again with the tweaked structural parameters. The process of changing the parameters and simulating with those changes will be continued until a set of the best-suited settings is found [1, 2, 3, 4, 5, 6, 7, 8]. This paper describes some of the modeling approaches for vapor compression refrigeration systems research that have been published in various journals or conferences. The findings of these studies will be deliberated, and the essential elements influencing the cooling system performance and stability are evaluated. The results of simulation approaches will be examined and discussed, and the conclusions made by the researchers are discussed. Finally, recommendations for future work are provided.

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2. Application of ANN for Refrigeration Systems Performance Predication

Artificial intelligence (AI), machine learning (ML) and many other statistical approaches have widely being used for different prediction and automation applications [9, 10, 11, 12, 13, 14, 15, 16, 17, 18]. However, in terms of cooling and refrigeration systems, Prabha, et al. [19] used mathematical models to investigate the impact of refrigeration system characteristics such as evaporating temperature, condensing temperature, and the mass of the refrigerant charge utilized on the system's performance. The researchers constructed such mathematical models to conduct the needed tests utilizing three variables (evaporating temperature, condensing temperature, and mass of the refrigerant charge) and two levels factorial method refrigerating effect and compressor power. The impact of various system variables and their substantial interaction effects on answers were estimated using MINITAB software, based on these mathematical models established for predicting the values of replies. For the refrigerants R290/R600, R290/R600a, and LPG, the performance was determined. The influence of system factors on performance may be explained using mathematical models. However, the following was concluded:

- The models created for a refrigeration system's performance parameters were simple first-order quadratic equations correlating the system's performance parameters. These created models may be used to forecast system performance based on any collection of system factors.
- The evaporating temperature has a greater impact

on refrigerating capacity than refrigerant mass or condensing temperature.

- The power consumed by the compressor increases as the evaporating temperature increases.
- Changes in refrigerant mass and condensing temperature have comparable effects on compressor power but are less substantial.

The vapor compression refrigeration system (VCRS) components (compressor, condenser, capillary tube, and evaporator) were tested for irreversibility employing R134 a/LPG refrigerant as a replacement to R134a [20]. Various experiments were conducted for different temperatures of evaporator and condenser under restricted settings to achieve this goal. Under identical experimental settings, irreversibility in the components of VCRS using R134a/LPG (liquefied petroleum gas) was lower than irreversibility in the components of VCRS using R134a. The second law of efficiency and total irreversibility of the refrigeration system were predicted using artificial neural network (ANN) models. The absolute fraction of variance in the range of 0.980–0.994 and 0.951–0.977, root-mean-square error in the range of 0.1636–0.2387 and 0.2501–0.4542, and mean absolute percentage error in the range of 0.159–0.572 and 0.308–0.931 percent, respectively, were anticipated using the ANN and ANFIS (adaptive neuro-fuzzy inference system) models. The results reveal that the ANN model outperforms the ANFIS model in terms of statistical prediction.

OUYANG and KANG [21] developed a model for forecasting the COP of a supermarket refrigeration system. For this purpose, ANN models were created utilizing onsite testing data. The BP (Back Propagation) and RBF (Radial Basis Function) neural networks were trained, and the BP network model was optimized using the genetic algorithm (GA). The results showed that both the BP and RBF neural networks could estimate the refrigeration system's COP, and the prediction results are extremely close to the real data. The BP and the BP-based GA models' mean relative error (MRE) is 1.82 percent and 0.62 percent, respectively, and their R2 is 0.9518 and 0.9889, demonstrating that the BP network can be efficiently optimized using the genetic algorithm. However, the RBF model outperformed the other two techniques. It has the lowest training time and the highest prediction accuracy with a mean relative error of 0.21 percent and an R2 of 0.9996. To determine the input variables of ANN models, all variables from operating data are analyzed, and it was found that COP is related to all variables. In another research, the ANN was employed to model a micro-cooling system [22]. The primary goal of this research was to compare the energy efficiency of three refrigerants: R134a, R450A, and R513A. The ANN was used to estimate three common energy metrics as a function of evaporating and condensing temperatures. These

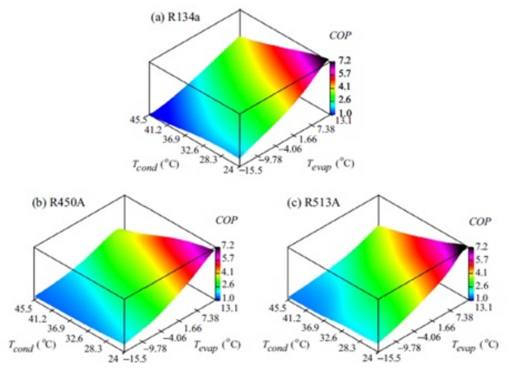

Figure 1: Figure 1 ANN results for COP [22]

matrics arr cooling capacity, power consumption, and COP. Cross-validation was used to validate each model, resulting in minimum relative errors of 0:15 for cooling capacity and coefficient of performance and 0.05 for power consumption. Computer simulations were conducted based on the required validation results to create 3D colored figures, as shown in Figure 1. After examining these 3D color surfaces, it was determined that R450A had a little lower cooling capacity than R134a, with a 10% drop in cooling capacity calculated. Similar findings were found in power usage, with R450A using around 10% less electricity than the other two refrigerants. R134a and R513A, conversely, were shown to have extremely comparable energy characteristics. In terms of COP, it was determined that all three refrigerants behaved in a relatively comparable manner. After using ANNs and 3D surface color to analyze the data, it was determined that R450A and R513A are suitable refrigerants to substitute R134a in medium evaporation temperature applications in the short term.

Instead of CFCs (R12, R22, and R502), HFC- and HC-based refrigerants and their blends were studied by Arcaklioğlu [23]. The COP values of vapor-compression refrigeration systems were obtained through the ANN with different refrigerants and their abovementioned mixtures. In a vapor compression refrigeration system with a liquid/suction line heat exchanger, ternary and quartet mixtures of various ratios were calculated to train the network. The input layer consisted of refrigerant mixing ratios and evaporator temperature, while the output layer outputs the COP value. The outcomes demonstrate that the absolute proportion of variance (R2) values were about 0.9999, and the root means square error (RMSR) values are less than 0.002.

An ANN was used to analyze the COP for a compression vapor system using R1234yf [24]. A laboratory test was created to evaluate many parameters at the refrigeration system's input and output. The temperature, compressor rotation speed, and volumetric flow in the secondary fluids were the input variables. The behavior of the refrigeration system was modeled using the ANN. To test the effect of these parameters on the COP, a uniformly distributed random variable was applied to one of the ANN's inputs. The refrigeration system was analyzed, and the optimum performance was observed utilizing computer simulations employing artificial neural networks. A data set comprising 54650 values, counting input and output variables, was built, resulting in an output set of values for each input set. The data were arbitrarily divided into two sets: one for training and the other for verification. 70% of the measurements were utilized to create the training set, while the remaining 30% were used for validation. The following conclusions were drawn from the simulation results: •The energy performance is substantially influenced by the temperature variation of the coolant condenser liquid. • The volumetric flow rates of the coolant condenser liquid have only a little impact on energy efficiency (COP). • Variations in the coolant condenser liquid temperature significantly impact the installation's energy performance variability.

Kamar, et al. [25] investigated the use of the ANN to forecast the cooling capacity, compressor power input, and coefficient of performance in a conventional air-conditioning system for a passenger car. The evaporator, condenser, compressor, and expansion valve are the four primary components of the system. Temperature sensors were utilized to measure the cooling fluid, air inside and outside temperatures on the evaporator and the condenser. Also, a flow meter, a compressor's speed meter, and a pressure gauge were used to collect the experimental data. The compressor speed, air temperature at the evaporator inlet, air temperature at the condenser inlet, and air velocity at the evaporator inlet were all varied at steady-state conditions in the experimental setup. The correlation between the ANN model's anticipated outputs and the experimental data has a good agreement in forecasting the system performance.

In another research, ANNs were utilized to build and validate a variable speed vapor compression device [26]. The experimental test bench is made up of one vapor compression circuit and two secondary fluids circuits. The R134a working fluid is used in the vapor compression circuit, which is a single-stage compression system. Compressor rotation speed, volumetric flow rates, and secondary fluid temperatures are the model's input parameters. The coefficient of performance, compressor power consumption, cooling capacity, the water temperature at the condenser outlet, and water-glycol temperature at the evaporator outlet are the model's output parameters. Sensors in the experimental facility measure pressure, temperature, volumetric flow rate, mass flow rate, compressor speed, and energy usage. To collect 38071 system samples, encompassing transient and stationary states, all sensors' signals and those given by measuring equipment were utilized. A variable speed vapor compression system was monitored, and numerous variables were measured and stored to prepare the training set. These metrics were utilized to create both the training and validation sets. The samples were separated into two groups: 85 percent (32360) were utilized for training, while the remaining 15% (5711) were used for validation. The findings show that the ANN can accurately envisage the actual operative behavior of this type of installation. The following were predicted: COP, compressor power consumption, cooling capacity, the water temperature at the condenser outlet, and water-glycol temperature at the evaporator outlet. Ertunc and Hosoz [27] developed an experimental R134a vapor-compression refrigeration unit to test an ANN model. K-type thermocouples were used for all temperature measurements. The intake and exit of each component were fitted with refrigerant thermocouples. The airstream entering and leaving the evaporative condenser was measured for both dry and wet bulb temperatures. At the compressor's input and outflow, refrigerant pressures were recorded. Variable-area flow meters were used to measure the refrigerant and water mass flow rates. In the experimental work, 60 distinct steady-state test runs were performed to collect training data and evaluate the proposed ANN. The evaporator load, air mass flow rate, water mass flow rate, air dry bulb, and wet bulb temperatures at the condenser intake are all inputs to the ANN. The condenser heat rejection rate, refrigerant mass flow rate, compressor power absorbed by the refrigerant, electric power spent by the compressor motor, and coefficient of performance are the ANN's outputs. Various system performance characteristics were computed from thermal analysis equations based on the experimental results and utilized to create and test the ANN model. The available data set from the experimental work was divided into training and validation sets to create the ANN for the experimental refrigeration system. The training set was assigned to 70% of the data, while the remaining 30% was used for network testing and validation. For performance evaluation, the projected output parameters were compared to the experimental ones. The RMSE values for the predicted parameters were quite low when compared to the experimental ranges. The significance of what was discovered in this study is that a refrigeration system with an evaporating condenser, which is perhaps the most difficult to predict using traditional methods, can be modeled using ANNs with excellent accuracy. This assists application engineers and makers of these systems in quickly determining their performance without the need for extensive testing.

For illustrating mass flow rate through straight and helical coil adiabatic capillary tubes in a vapor compression refrigeration system, an experimental investigation was done with R134a and LPG refrigerant mixture [28]. Various studies were carried out under steady-state settings, varying the length of the capillary tube, the inner diameter, the coil diameter, and the degree of subcooling. The system's primary components are as follows: compressor, condenser, expansion valve, evaporator, and other accessories. The results showed that the mass flow rate through helical coil capillary tubes was 5-16% lower than straight capillary tubes. Dimensionless correlation and Artificial Neural Network (ANN) models were constructed to forecast the mass flow rate, which was found to be in good agreement with the experimental results, with absolute fractions of variance of 0.961. The results indicated that the ANN model performed statistically better because ANN model predictions were closer to experimental values than the dimensionless correlation model.

Based on using artificial neural networks and limited data sets, a study was conducted to estimate the thermodynamic performance of an experimental refrigeration system driven by a variable speed compressor [29]. A semi-hermetic compressor, an evaporator, a condenser, and an externally equalized thermostatic expansion valve make up the experimental variable speed refrigeration system. The evaporator and condenser were finned tube heat exchangers that are air-cooled. The evaporator was housed in a specially built cold room with electric heaters to simulate the refrigeration demand. Temperature and pressure measurements were taken from specific points of the experimental system to evaluate the system performance by modulating the compressor capacity with an inverter. A flow meter built for refrigerant R404a was used to measure the mass flow rate of the refrigerant. A tiny humidity measurement equipment was also used to measure air humidity at the intake and outflow of the condenser channel. Temperatures were taken at 12 places throughout the system, the pressure was taken at seven places, and the refrigerant mass flow rate was measured after the condenser. All of the measurement equipment is wired into a data logger with 20 channels for data collection. A computer was also attached to the data recorder. All measurements were taken every 5 seconds, and the data was recorded on a computer using a data logger. ANNs were employed to study the performance of the variable speed refrigeration system, which was the major goal of this research. Compressor frequency, cooling load, condenser and evaporator temperatures, and condenser and evaporator pressures are all input parameters. The output parameters were the compressor power consumption, refrigerant mass flow rate, and experimental and theoretical COP values. Instead of conducting numerous studies, it was discovered that using a neural network approach was more efficient. This research showed that using neural networks to determine the best compressor frequency can save substantial energy. The thermodynamic analysis of refrigeration systems can be simplified using this methodology, and the predicted values were extremely similar to the actual values.

An experimental configuration of a single-door household refrigerator working with R134a and a total capacity of 175L was utilized to predict the performance of a domestic refrigeration system employing R436A as an alternate refrigerant to R134a [30]. This method can be used to calculate the cooling effect, power consumption, and performance coefficient of a domestic refrigerator. Seven thermocouple sensors were employed inside the freezer, refrigerator cabin, evaporator, compressor, condenser inlets, and outlets. The investigation started by charging R436A mass into the system and calculating cooling capacity, compressor effort, and COP for various capillary tube lengths. However, the same capillary tube length was used throughout the R134a tests. Continuous tests were conducted throughout the conditions described above, with the evaporator temperature reaching -15°C. The pull-down properties and performance factors such as cooling capacity, power consumption, and system performance can be determined first. For reference, the ambient temperature should be kept at about 29°C when changing capillary tubes and refrigerant weights. After establishing steady-state conditions, total experimental values were collected. With the experimental data, the ANN forecasts for compressor power provide an average inaccuracy of 2.51% . These results show that, despite the wide range of operating conditions, the ANN accurately forecasts the power absorbed by the refrigerant in the compressor. Compared to the experimental COP, the ANN forecasts are the average error for these predictions is 1.23. The COP forecasts of the ANN were as accurate as those of the other performance metrics predictions. The results showed that in a household refrigeration system, the hydrocarbon refrigerant mixture R436A performs better than R134a. For a few input values, the ANN provides a good response with a significant amount of error. As a result, the R436A could be a more energy-efficient, ozone-friendly, safe, and long-term replacement fluid for R134a in a system. All of the hardware in a residential refrigerator remains the same, except the length of the capillary tubes, and there was no need to change the lubricating oil when using R436A as the refrigerant.

Yilmaz and Atik [31] established an experimental vapor compressor refrigeration setup to explore using R134A as a refrigerant in a vapor compression refrigeration system (Figure 2). The data received from the test results were then utilized to simulate the system performance Based on the outcomes of the trials and the accompanying computed coefficient of performance, an Artificial Neural Network was created. In this case, a hermetically sealed compressor was used. The power consumed by the compressor was measured with an energy meter. After

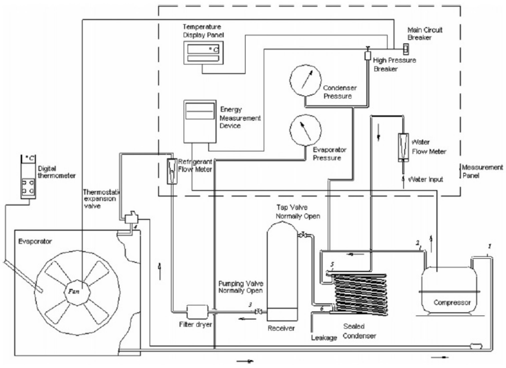

Figure 2: Figure 2 The developed experimental set-up by [31]

the compressor, an air-cooled condenser with a water-cooled evaporator was installed, with air cooling and a thermostatic expansion valve. The parameters were the refrigerant temperatures entering and leaving the compressor, condenser, and evaporator, the air temperatures entering and leaving the condenser, and the water temperatures entering and leaving the evaporator inlet and outlet pressures evaporator and condenser. The ANN model has excellent statistical performance as measured by the correlation coefficient (R) and the MSE. With a coefficient of correlation higher than 0.988 and a maximum percentage of error of less than 5% , the outputs predicted by the ANN model match with experimental data. The results show that the ANN model can be used successfully to estimate the performance of a very accurate and dependable vapor compression refrigeration system. Swider, et al. [32] have applied the neural networks were to compress vapor in two hermetic vapor-compression liquid chillers, a single-circuited single-screw (Chiller A) and a twin-circuited twin-screw (Chiller B) (Chiller B). The chilled water outlet temperature is the most important factor in determining the cooling capability of each chiller. In order to anticipate chiller performance, the neural network used the chilled water outlet temperature from the evaporator, the cooling water inlet temperature from the condenser, and the evaporator capacity as input parameters for both chillers. The neural network chiller models have statistical findings for both the chiller's COP and the electrical work. In the lab, the mass flow rates, inlet and outlet temperatures of chilled and cooling water, and compressor input were all measured. The cooling water mass flow rate changed during various combined chiller operations. This is done for 450 of the 500 measured data patterns in Chiller A and 342 of the 380 observed data patterns in Chiller B. Only the final validation of the model requires the remaining 50 and 38 data patterns for Chiller A and B, respectively. Chiller A had a coefficient of variation of less than 1.5 percent, while Chiller B had a coefficient of variation of 3.9 percent, precisely forecasting the COP.

The dynamics of a vapor compression cycle were also modeled using artificial neural networks [33]. A semi-hermetic reciprocating compressor, an air-cooled finned-tube condenser, three electronic expansion valves, and three evaporators make up the vapor compression cycle system (one air-cooled finned-tube evaporator and two electronic evaporators). The input air temperature of the condenser is controlled by one air duct heater to simulate outdoor conditions, while the inlet air temperature of the evaporator is maintained at 25 C by the HVAC system. R134a is the working fluid in the system. The compressor, condenser fan, and evaporator fan all have inverters to modify their respective frequencies. To adjust the condenser's incoming air temperature, a heater was mounted in front of the condenser. These components are connected in a closed-loop so that the working fluid can be circulated constantly throughout the system. Compressor rotation speed, evaporator fan frequency, condenser fan frequency, expansion valve opening percentage, outdoor temperature, and indoor temperature are input parameters, condensing pressure, evaporating pressure, subcool, superheat, and system power consumption is examples of output parameters. The artificial neural networks model may achieve the minimum modeling error and significantly robustness against input disturbances and system uncertainties. The testing and comparing results using experimental data have further proven the neural model's remarkable performance.

Hosoz, et al. [34] The operation of a vapor-compression refrigeration system using R134a as the working fluid and a counter-flow cooling tower was estimated using artificial neural networks. The model was then used to predict numerous performance variables of the refrigeration system, including the evaporating temperature, compressor power, coefficient of performance, and the temperature of the water stream leaving the tower. The refrigeration system consists of a reciprocating compressor, a water-cooled condenser coupled to the cooling tower, a thermostatic expansion valve, and an electrically heated evaporator. The system was charged with 600 g of R134a. For all temperature measurements, K-type thermocouples were employed. The dry and wet bulb temperatures of the air stream were measured at the cooling tower's entrance and output. The evaporating and condensing pressures were monitored using Bourdon tube gauges. The refrigerant and water mass flow rates were measured using variable-area flow meters. To build an artificial neural networks model for the experimental refrigeration system, the available data set, which consisted of 64 input vectors and their corresponding output vectors from the experimental work, was separated into training and test sets. The training set was randomly assigned to 75% of the data set, while the remaining 25% evaluated the network's performance. Evaporator load, dry bulb temperature and relative humidity of the air stream entering the tower, air mass flow rate, and water mass flow are the five input factors that determine the refrigeration system's outputs. The refrigerant mass flow rate, compressor, condenser heat rejection, coefficient of performance, evaporating temperature, compressor discharge temperature, water temperature at the cooling tower outlet, and water mass flow rate refrigeration system with the cooling tower are all output parameters. Artificial neural networks could adequately depict refrigeration systems with cooling towers, according to the findings. This novel technique requires a modest number of experiments rather than extensive experimental study or dealing with a large mathematical model. Datta, et al. [?] used the ANN to forecast the thermal performance of a vehicle air conditioning system was examined. A finned tube condenser and evaporator, as well as a swashplate fixed displacement compressor (driven by the engine) and a thermostatic expansion valve, make up the primary refrigerating unit. During start-up and stop, the compressor's speed fluctuates in lockstep with the engine's. A three-phase motor with variable frequency drive was employed as the compressor's primary mover to explore the influence of speed fluctuation. R134a, the same refrigerant used in vehicle air conditioning systems, is also used in the test rig. Separate ducting has been built at the input and outlet plenums of the evaporator and condenser to guide and measure the air streams' flow rate and temperature. A variac-controlled electrical heater is installed downstream of the evaporator duct to create variable heat loads similar to that of a driving car. The compressor and blower speeds, as well as the refrigerant temperature and pressure at various locations, the refrigerant mass flow rate, the air dry-bulb temperature and relative humidity at the evaporator and condenser inlet and outlet, and the airflow rate through both the evaporator and the condenser are all measured. All of the system's input parameters are the refrigerant charge, compressor speed, and blower speed. The output parameters are the cooling capacity, compression work, and COP. The experimental outcomes are used to build the training, testing, and validation data sets. The following metrics were randomly chosen: training takes up 70% of the budget (42), while testing and validation take up the remaining 30% . The system's performance can be accurately predicted by the ANN. RMSE, MRE, and EI were 0.48-0.74 percent, 5.00-6.50 percent, and 0.80-2.01 percent, respectively, in the performance measuring parameters. When compared to the experimental results' ranges, the MSE values are incredibly low. The correlation coefficient of all performance parameters is extremely close to unity. The largest differences between ANN forecasts and experimental observations are 8.03 percent, 1.68 percent, and 11.85 percent, respectively, for cooling capacity, compression work, and COP of the system. It suggests that a properly configured ANN could be a useful tool for predicting the performance of automobile air conditioning systems. This saves time and money in the simulation by avoiding the complexity of a first principle-based simulation. Hosoz, et al. [35] used artificial neural networks to model several mobile air conditioning (MAC) system performance metrics. Instead, soft computing techniques, such as the ANNs, can be employed to simulate MAC systems and estimate their performance under various operating scenarios. The performance of a MAC system using the alternative refrigerant R1234yf was modeled using the ANN technique. The created ANN model's predictions were then compared to experimental results using statistical performance measures. A five-cylinder swash plate compressor, a parallel-flow micro-channel condenser, a laminated type evaporator, a receiver/filter/drier, and a thermostatic expansion valve were designed for the proposed ANN model from the original components of an R134a MAC system of a compact car (TXV). A data collection system was often used to collect the measured variables, which were then recorded on a computer. The compressor speed, intake temperatures of the evaporator and condenser air streams, and relative humidity of the air at the evaporator inlet were used as input parameters for the proposed ANN model. The cooling capacity, power absorbed by the refrigerant in the compressor, condenser heat rejection rate, coefficient of performance, conditioned air temperature, compressor discharge temperature, refrigerant mass flow rate, and pressure ratio across the compressor were the output parameters, on the other hand. The generated ANN model gives quite accurate predictions, with correlation coefficients in the range of 0.9159–0.9962 and mean relative errors in 2.24–7.46 percent. The findings suggested that an ANN technique can be utilized to predict the performance of R1234yf MAC systems. The ANN model produced very accurate predictions for the performance characteristics of the MAC system. These findings showed that MAC systems could be effectively represented using an ANN technique rather than comprehensive experiments or complex mathematical modeling.

In [36], the ANN approach was used to predict various performance parameters of a cascade vapor compression refrigeration system using R134a in lower and higher-temperature refrigeration circuits. The suggested ANN was trained and tested using steady-state test runs of an experimental cascade refrigeration system. The ANN was used to forecast the evaporation temperature in the lower circuit, compressor power for each circuit, COP for the lower circuit, and COP for the overall cascade system was developed using the backpropagation algorithm. The correlation coefficient, mean relative error, and root means square error were used to evaluate the ANN predictions' performance. The ANN forecasts for the cascade refrigeration system usually performed statistically well, with correlation coefficients ranging from 0.953 to 0.996 and MREs ranging from 0.2 to 6.0 percent and extremely low RMSE values compared to the experimental data' ranges. The ANN was utilized outside of the experimental range to estimate system performance, and satisfactory prediction curves were obtained. This research indicates that the ANN approach may be used to model cascade vapor compression refrigeration systems instead of traditional modeling techniques. As a result, instead of undertaking an intensive experimental investigation or dealing with a complicated mathematical model, the performance parameters of these systems can be simply identified by doing only a minimum number of test runs. Tian, et al. [37] presented research on utilizing an artificial neural network (ANN) to predict the thermal performance of a parallel flow (PF) condenser using R134a as the working fluid. The condenser was divided into three sections: refrigerant side, tube side, and air side. The following assumptions were made to make the research easier: Under steady conditions, all parameters are constant, and the refrigerant and airflow are one-dimensional. Heat conduction along the axial direction and radiation heat transfer is not considered; the system comprises a refrigerant, air cooling, and heating loop to ensure that the system automatically responds to the presetting parameters. The four key components of the refrigerant loop section are the compressor, PF condenser, electric expansion valve, and evaporator. These four components were thought to be operating in a steady-state mode. The vacuum pump ran for two hours before circulating R134a through the system to empty the refrigerant loop. ANN takes into account the dry temperature, wet bulb temperature, and velocity of the incoming air stream, mass flow rate, and the temperature and pressure of the refrigerant entering the condenser. All of the performance parameters' R2 values were very close to unity, demonstrating that the ANN model can reliably predict the performance parameters of the PF condenser. Finally, Tian, et al. [38] utilized an ANN technique to forecast the performance of an electric vehicle air conditioning system. Experiments were carried out by altering the scroll compressor speeds, EEV apertures, and ambient temperatures. 119 experimental data sets were acquired for ANN training and testing. Scroll compressor speed and EEV were used as input variables to the ANN. The condenser inlet air temperature, and evaporator inlet air temperature were used. The output variables included refrigerant mass flow rate, condenser heat rejection, refrigeration capacity, and compressor energy consumption. In the established ANN, mean relative errors for refrigerant mass flow rate, condenser heat rejection, refrigeration capacity, and compressor power consumption were 1.87 percent, 2.71 percent, 1.79 percent, and 1.64 percent, respectively. For refrigerant mass flow rate, condenser heat rejection, refrigeration capacity, compressor power consumption, root mean square errors were 0.0133 kg h1, 0.0141 kW, 0.0140 kW, and 0.0106 kW, respectively. The refrigerant mass flow rate had a correlation coefficient of 0.9983, the condenser heat rejection had a correlation coefficient of 0.9980, the refrigeration capacity had a correlation coefficient of 0.9975, and the compressor power consumption had a correlation coefficient of 0.9979.

3. Conclusion

This paper has conducted a thorough investigation of the literature and published research from various sources, including research papers, conference papers, and earlier investigations conducted to estimate refrigeration systems' performance. The ANN technique was widely applied to determine the performance of an air conditioning system; however, most of the studies looked at the impact of some parameters that affect the system performance. The considered parameters were about three or four. Thus, it is recommended to consider more variables that could affect the refrigeration systems. These parameters include, for example, the system's cooling fluid before and after each component, the air temperature in contact with the evaporator and condenser, the refrigerant flow rate, the compressor rotation speed, and the system's high and low pressure. Also, the quantity of chilled airflow to the condenser and the ambient and external temperatures affecting the condenser should be simulated using a heat source to adjust the amount of heat passed on the condenser to examine its influence. The system's performance, the compressor's volumetric efficiency, the compression ratio, and the amount of deep chilling were projected to replicate most of the system's characteristics. It should be emphasized that ANN outperforms other nonlinear data approaches significantly. Without a prior understanding of the relationships between input and output variables, ANN can conduct nonlinear models. This will benefit designers in their decision-making and provide them with more flexibility in adjusting design criteria.

References

[1] M. Hosoz, H. M. Ertunç, H. Bulgurcu, Performance prediction of a cooling tower using artificial neural network, Energy Conversion and Management 48 (2007) 1349–1359.

[2] E. Pasqualotto, S. Federici, A. Simonetta, M. Olivetti Belardinelli, Usability of brain computer interfaces, in: Everyday Technology

for Independence and Care, IOS Press, 2011, pp. 481–488.

[3] A. Simonetta, M. C. Paoletti, Designing digital circuits in multi-valued logic, International Journal on Advanced Science, Engineering and Information Technology 8 (2018) 1166–1172.

[4] R. Brociek, G. De Magistris, F. Cardia, F. Coppa, S. Russo, Contagion prevention of covid-19 by means of touch detection for retail stores, volume 3092, 2021, p. 89 – 94.

[5] F. Mazzenga, A. Simonetta, R. Giuliano, M. Vari, Applications of smart tagged rfid tapes for localization services in historical and cultural heritage environments, in: 2010 19th IEEE International Workshops on Enabling Technologies: Infrastructures for Collaborative Enterprises, IEEE, 2010, pp. 186–191.

[6] E. Pasqualotto, A. Simonetta, S. Federici, M. Olivetti Belardinelli, Usability evaluation of bcis (2009).

[7] G. Capizzi, F. Bonanno, C. Napoli, Hybrid neural networks architectures for soc and voltage prediction of new generation batteries storage, in: 2011 International Conference on Clean Electrical Power (ICCEP), IEEE, 2011, pp. 341–344.

[8] G. De Magistris, S. Russo, P. Roma, J. Starczewski, C. Napoli, An explainable fake news detector based on named entity recognition and stance classification applied to covid-19, Information (Switzerland) 13 (2022). doi:10.3390/info13030137.

[9] R. Giuliano, G. C. Cardarilli, C. Cesarini, L. Di Nunzio, F. Fallucchi, R. Fazzolari, F. Mazzenga, M. Re, A. Vizzarri, Indoor localization system based on bluetooth low energy for museum applications, Electronics 9 (2020) 1055.

[10] F. Fallucchi, M. Coladangelo, R. Giuliano, E. William De Luca, Predicting employee attrition using machine learning techniques, Computers 9 (2020) 86.

[11] F. Bonanno, G. Capizzi, S. Coco, C. Napoli, A. Laudani, G. Sciuto, Optimal thicknesses determination in a multilayer structure to improve the spp efficiency for photovoltaic devices by an hybrid fem - cascade neural network based approach, 2014, p. 355 – 362. doi:10.1109/SPEEDAM.2014.6872103.

[12] F. Fallucchi, H. Steffen, E. W. De Luca, Creating cmdi-profiles for textbook resources, in: Research Conference on Metadata and Semantics Research, Springer, 2018, pp. 302–314.

[13] A. A. Jaber, A. A. Saleh, H. F. M. Ali, Prediction of hourly cooling energy consumption of educational buildings using artificial neural network, Space 10137 (2019) m3.

[14] S. Russo, C. Napoli, A comprehensive solution for psychological treatment and therapeutic path planning based on knowledge base and expertise sharing, volume 2472, 2019, p. 41 – 47.

[15] A. A. Jaber, K. M. Ali, Artificial neural network based fault diagnosis of a pulley-belt rotating system, Int J Adv Sci Eng Inform Technol 9 (2019) 544–551.

[16] G. C. Cardarilli, L. D. Nunzio, R. Fazzolari, D. Giardino, A. Nannarelli, M. Re, S. Spanò, A pseudo-softmax function for hardware-based high speed image classification, Scientific Reports 11 (2021). doi:10.1038/s41598-021-94691-7.

[17] S. Brusca, G. Capizzi, G. Lo Sciuto, G. Susi, A new design methodology to predict wind farm energy production by means of a spiking neural network–based system, International Journal of Numerical Modelling: Electronic Networks, Devices and Fields 32 (2019) e2267.

[18] N. Brandizzi, V. Bianco, G. Castro, S. Russo, A. Wajda, Automatic rgb inference based on facial emotion recognition, volume 3092, 2021, p. 66 – 74.

[19] G.-l. Ding, Recent developments in simulation techniques for vapour-compression refrigeration systems, International Journal of refrigeration 30 (2007) 1119–1133.

[20] J. Gill, J. Singh, O. S. Ohunakin, D. S. Adelekan, Ann approach for irreversibility analysis of vapor compression refrigeration system using r134a/lpg blend as replacement of r134a, Journal of Thermal Analysis and Calorimetry 135 (2019) 2495–2511.

[21] W.-l. OUYANG, R.-q. KANG, Ann methods for cop prediction of supermarket refrigeration system, DEStech Transactions on Computer Science and Engineering (2019).

[22] J. Belman-Flores, A. Mota-Babiloni, S. Ledesma, P. Makhnatch, Using anns to approach to the energy performance for a small refrigeration system working with r134a and two alternative lower gwp mixtures, Applied Thermal Engineering 127 (2017) 996–1004.

[23] E. Arcaklioğlu, Performance comparison of cfcs with their substitutes using artificial neural network, International Journal of Energy Research 28 (2004) 1113–1125.

[24] S. Ledesma, J. M. Belman-Flores, Analysis of cop stability in a refrigeration system using artificial neural networks, in: 2016 International Joint Conference on Neural Networks (IJCNN), IEEE, 2016, pp. 558–565.

[25] H. M. Kamar, R. Ahmad, N. Kamsah, A. F. M. Mustafa, Artificial neural networks for automotive air-conditioning systems performance prediction, Applied Thermal Engineering 50 (2013) 63–70.

[26] J. M. Belman-Flores, S. Ledesma, M. Garcia, J. Ruiz, J. L. Rodríguez-Muñoz, Analysis of a variable speed vapor compression system using artificial neural

networks, Expert systems with applications 40 (2013) 4362–4369.
[27] H. M. Ertunc, M. Hosoz, Artificial neural network analysis of a refrigeration system with an evaporative condenser, Applied Thermal Engineering 26 (2006) 627–635.
[28] J. Gill, J. Singh, Use of artificial neural network approach for depicting mass flow rate of r134a/lpg refrigerant through straight and helical coiled adiabatic capillary tubes of vapor compression refrigeration system, International Journal of Refrigeration 86 (2018) 228–238.
[29] Ö. Kizilkan, Thermodynamic analysis of variable speed refrigeration system using artificial neural networks, Expert Systems with Applications 38 (2011) 11686–11692.
[30] M. V. Reddy, C. C. Sekhar, D. R. Reddy, Performance prediction of domestic refrigeration system using r436a refrigerant as alternative refrigerant to r134a with ann, International Journal of Innovative Research in Science, Engineering and Technology 6 (2017) 19008–19017.
[31] S. Yilmaz, K. Atik, Modeling of a mechanical cooling system with variable cooling capacity by using artificial neural network, Applied Thermal Engineering 27 (2007) 2308–2313.
[32] D. Swider, M. Browne, P. Bansal, V. Kecman, Modelling of vapour-compression liquid chillers with neural networks, Applied thermal engineering 21 (2001) 311–329.
[33] L. Zhao, W.-J. Cai, Z.-H. Man, Neural modeling of vapor compression refrigeration cycle with extreme learning machine, Neurocomputing 128 (2014) 242–248.
[34] M. Hosoz, H. M. Ertunc, H. Bulgurcu, An adaptive neuro-fuzzy inference system model for predicting the performance of a refrigeration system with a cooling tower, Expert Systems with Applications 38 (2011) 14148–14155.
[35] M. Hosoz, M. S. Kaplan Kaplan, M. C. Aral, H. M. Ertunc, Artificial neural network modelling of a mobile air conditioning system using refrigerant r1234yf, in: 5th International Symposium on Innovative Technologies in Engineering and Science 29-30 September 2017 (ISITES2017 Baku-Azerbaijan), 2017.
[36] M. Hosoz, H. Ertunc, Modelling of a cascade refrigeration system using artificial neural network, International Journal of Energy Research 30 (2006) 1200–1215.
[37] Z. Tian, B. Gu, L. Yang, F. Liu, Performance prediction for a parallel flow condenser based on artificial neural network, Applied Thermal Engineering 63 (2014) 459–467.
[38] Z. Tian, C. Qian, B. Gu, L. Yang, F. Liu, Electric vehicle air conditioning system performance prediction based on artificial neural network, Applied Thermal Engineering 89 (2015) 101–114.