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TECHNICAL NOTE

Artificial Neural Network Involved in the Action of Optimum Mixed Refrigerant (Domestic Refrigerator)

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ABSTRACT

This analysis principally focuses on the implementation of Radial basis function (RBF) and back propagation (BPA) algorithms for training artificial neural network (ANN) to get the optimum mixture of Hydro fluorocarbon (HFC) and organic compound (Hydrocarbons) for obtaining higher coefficient of Performances (COPs). The thermodynamical properties of mixed refrigerants are observed using REFPROP 9 software system that contains details of refrigerants. Totally different mixtures of the refrigerants along with their COP are obtained by the REFPROP 9. This task consumes time in getting the right combination of refrigerants as lot of menu choices have to be compelled to be chosen within the REFPROP 9. In order to form the method of checking out the correct mixed refrigerants with minimum manual intervention, RBF is trained and tested with the different patterns of mixed refrigerants. The RBF / BPA mixed refrigerant analysis software has been developed by using MATLAB 11a.

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1. INTRODUCTION

Cryogenic refrigerators operative with mixed refrigerants were developed under classified and proprietary programs for several years, and it was solely after 1991 that the globe realized the importance of the mixed refrigerant systems for cryogenic refrigeration. Mixed refrigerant cryogenic processes are utilized in most massive base load fossil fuel liquefaction plants. Many patents exist on completely different aspects of mixed refrigerant processes for phase transition of natural gas, also as well as composition of mixtures for Joule-Thomson and different refrigerators. Still, the elemental aspects of those processes continued to not receive the attention they merit in open literature within the view of these industrial interests.

Refrigerants should never be deliberately mixed. The foremost common cross contamination are the two most typical refrigerants, R12 and R134a. This is often the mixture of the older R12 refrigerant that contains chlorine with R134a. Chlorine was found to cause harm to the earth's ozone layer and has been replaced with the newer and environmentally safer R134a.

These are still in experimental stage for improvement as R134a itself is found to contribute to global warming. These refrigerants should be contained as it is unlawful and unethical to release them into the atmosphere. Today's manufacturers use R134a as their preferred refrigerant. These two should not be mixed in an AC system since they are two completely different compounds with different temperature to pressure characteristics. The mixture is termed azeotrope. Although the low temperature to pressure characteristics of azeotrope could also be close to 134a, the hot temperature high pressure characteristics vary significantly. The symptoms of this blend lead to high system and head pressures. High head pressure can cause the compressor and other system elements to fail prematurely.

Mixing completely different refrigerants will cause massive issues. For one, it will increase the system

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operative pressure. This can result in a loss of cooling performance and may tax the compressor to the point wherever it fails. R134a and mineral oil won't combine. So, if somebody recharges an R12 system with R134a and does not add a compatible lubricant, the compressor can permanently fail.

Refrigerants were taken into assessment are R22, R32, R290, R125, R134a, R404A, R600a, propane butane mixture, etc. Refrigerants with Maximum temperature glide (temperature change during evaporation / condensation) are not discussed in this paper. For this assessment two conditions were preferred: 1- It should represent the operation of a marketable freezer display case, and 2- a container cooler at maximum ambient temperature.

- LBP - Freezer evaporating / condensing / return (suction) gas at -35/50/20 °C.
- MBP - Bottle cooler evaporating / condensing / return (suction) gas at -10/55/20 °C.

In several assessments the condensing temperature or suction gas temperature are different. Current Scenario all researchers are focusing on is to substitute refrigerant for domestic and marketable refrigerators. R290 has a long history in refrigeration. It has been in use before CFCs were developed and was re-introduced for use in heat pumps after the CFC phased out. Its thermodynamic data efficiency is well known. In some countries, refrigerator manufacturers and food producers began using R290 as a replacement for R404A or R134a in appliances shortly after 2000, due to environmental concerns and global warming potential. At present they are focusing the propane butane mixture as a substitute for the current refrigerant.

ANNs also are employed in modeling energy systems like ejector-absorption cycles [1], refrigeration systems using completely different refrigerant mixtures [2], heat exchangers used in refrigeration applications [3], long-run prediction of daily energy use [4], estimations of vapor-liquid equilibrium information [5], and performance analysis of heat pumps using R12/R22 refrigerant mixtures.

Refrigeration is among important industries required to keep the world's population fed, [6] .However, for the last 20 years put this industry on the world's attention due to its use of harmful chemicals to the ozone layer. This caused various efforts to seek out substitutes for these chemicals (i.e., CFCs and HCFCs). A summary, laying out this drawback along with the attainable directions for the solution is found in [7].

The drawback is finding alternatives to these harmful fluids without changing the normal components of a cooling system. Up to now, a pure refrigerant which will match the properties of R12, R22, and R502 has not been found. However, numerous mixtures (substitutes) have been recommended [8-10]. The utilization of mixtures poses different problems: for example, at a given pressure they need different boiling points, their saturation temperature changes throughout evaporation, etc. Therefore, creating a selection between these mixtures needs some compromise and finding the foremost suitable mixture ratio under a wide range of operative conditions depends on analytical and experimental studies.

In this study, by using various concentrations of refrigerant mixtures of HFCs and HCs, the coefficient of Performances (COPs) of refrigerant mixtures are calculated for a vapor- compression refrigeration system with a liquid/suction line heat-exchanger. Changing the mole percentages of the mixtures permits us to achieve the specified thermodynamic properties of the fluids, [11]. Therefore, various values of the COPs with completely different mixture concentrations refrigerants were accustomed train and check the ANN algorithmic rule.

2. ARTIFICIAL NEURAL NETWORK

ANN is an abstract simulation of a true nervous system that contains a set of neuron units that act with one another via axon connections. Such a model bears a powerful resemblance to axons and dendrites in a nervous system. Because of this self-organizing and adaptative nature, the model offers potentially a brand new parallel processing paradigm. This model might be more robust and user friendly than the standard approaches. ANN can be viewed as computing elements, simulating the structure and function of the biological neural network. These networks are expected to solve the issues in a manner that is completely different from standard mapping. Neural networks are used to mimic the operational details of the human brain in a computer.

Neural networks are manufactured from artificial neurons which are actually simplified versions of the natural neurons that occur within the human brain. It is hoped that it might be attainable to duplicate some of the fascinating options of the human brain by constructing networks that consist of a large number of neurons. A neural design comprises massively parallel adaptive components with interconnection networks which are structured hierarchically.

Artificial neural networks are computing components that are supported by the structure and performance of the biological neurons. These networks have nodes or neurons, which are described by difference or differential equations. The nodes are interconnected layer wise or intra-connected among themselves. Every node within the consecutive layer receives the inner product of synaptic weights with the outputs of the nodes within the previous layer. The inner product is termed the activation value. The activation value is a more matured non-linear function.

When the vectors are binary or bipolar, hard-limiting non-linearity is employed. When the vectors are analog, a squashed function is used. Some of the squashed functions are sigmoid (0 to 1), tanh (-1 to +1), Gaussian, logarithmic and exponential. A network with two states of a neuron 0 or 1 and -1 or 1 is termed discrete and therefore the same with a continuous output is termed analog. In a discrete network at a selected time the state of each neuron is updated, the network is said to be synchronous. If the state of only one neuron is updated, the network is said to be asynchronous. A network is feed forward, if there's no closed chain of dependence among neural states. The same network is feed backward, if there is such a closed chain. When the output of the network depends upon this input, the network is static. If the output of the network depends upon past inputs or outputs, the network is dynamic. If the interconnection among neurons changes with time, the network is adaptive. The synaptic weight updating of the networks are often carried out by supervised strategies or by unsupervised strategies or by fixed weight association networks methods. In the case of the supervised methods, inputs and outputs are used in the unsupervised methods, only the inputs are used and within the fixed weight association networks methods, inputs and outputs are stored weights.

Some of the supervised learning algorithms are the perceptions; decision based mostly neural networks, adaptive linear element (ADALINE) (Figure 1), multilayer perceptions, temporal dynamic models and hidden Markova analysis. The different unsupervised learning algorithms are neo-cognition, self-organizing feature map, force learning, and adaptive resonance theory. The mounted weight networks are hamming net, Hopfield net and the combinatorial optimization.

The entire pattern recognition system constitutes instantiation space, feature extraction and also the testing the network.

3. NORMALIZATION OF THE PATTERNS

The patterns are normalized so that the values of the features are in the range of 0 to 1 and the computational complexity is reduced. The normalization of the patterns is done as per Equation (1).

$$x_i = x_i / x_{max} \qquad (1)$$

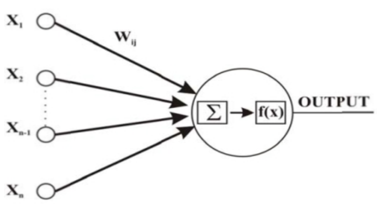

Figure 1. Operation of Neuron

where, x_i is the value of a feature, and x_{max} is the maximum value of the feature.

3.1. Selection of Patterns for Training

The numbers of classes (Range of COPs), which are based on the classification range of the outputs, are decided. If only one output is considered the range of classification is simple. If more than one output is considered a combination criterion has to be considered. The total number of patterns is decided for each class. Out of these patterns, the number of patterns to be used for training the network is decided. The remaining patterns are used for testing the classification performance of the network. The patterns selected for training the network should be such that they represent the entire population of the data.

3.2. Back Propagation Algorithm

The BPA uses the steepest-descent method to reach a global minimum. The flow-chart of the BPA is given in Figure 2. The number of layers and number of nodes in the hidden layers are decided. The connections between nodes are initialized with random weights. A pattern from the training set is presented in the input layer of the network and the error at the output layer is calculated. The error is propagated backwards towards the input layer and the weights are updated. This procedure is repeated for all the training patterns. At the end of each iteration, test patterns are presented to ANN and the classification performance of ANN is evaluated. Further training of ANN is continued till the desired classification performance is reached.

Steps for training and testing BPA Forward propagation

Step 1: The weights of the network are initialized.

Step 2: The inputs and outputs of a pattern are presented to the network.

Step 3: The output of each node in the successive layers is calculated using Equation (2)

$$o \text{ (output of a node)} = 1/(1+\exp(\textstyle\sum w_{ij}.\ x_i)) \qquad (2)$$

where, w is the weight matrix/ x is inputs to the nodes

Step 4: The error of a pattern is calculated using Equation (3):

$$E(p) = (1/2) \textstyle\sum (d(p) - o(p))^2 \qquad (3)$$

where p is pattern number and d is the desired output and o is outputs of nodes in hidden and output layers

Reverse propagation

Step 5: The error for the nodes in the output layer is calculated using Equation (4).

$$\delta(\text{output layer}) = o(1-o)(d-o) \qquad (4)$$

Step 6: The weights between output layer and hidden layer are updated using Equation (5).

$$W(n+1) = W(n) + \eta\delta \text{ (output layer) } o \text{ (hidden layer)} \qquad (5)$$

Step 7: The error for the nodes in the hidden layer is calculated using Equation (6).

$$\delta \text{ (Hidden layer)} = o\,(1\text{-}o) \sum \delta \text{ (output layer)} \qquad (6)$$

W (updated weights b/w hidden and output layer)

Step 8: The weights between hidden and input layer are updated using Equation (7).

$$W(n+1) = W(n) + \eta\delta(\text{hidden layer})o(\text{input layer}) \qquad (7)$$

where, η is the learning factor (>0 and <=1), the above steps complete one weight updation.

Step 9: Second pattern is presented and the above steps are followed for the second weight updation.

Step 10: When all the training patterns are presented, a cycle of iteration or epoch is completed.

Step 11: The errors of all the training patterns are calculated and used as stopping criteria (MSE) using Equation (8).

$$MSE = \sum E\,(p) \qquad (8)$$

3. 3. Radial Basis Function For each function 't', the approximation to this function, is essentially stored in the coefficients and centers of the RBF, Cowan et al. [12], Grant et al. [13] ,Chen et al. [14], Moody et al. [15], Robert et al. [16]. These parameters are in no way unique, since for each function 't' is approximated, many combinations: of parameter values exist. RBFs have the following mathematical representation (9)

$$F(x) = co + \sum_{i=0}^{N-1} ci\ \Phi(\| x - R \|) \qquad (9)$$

where c is a vector containing the coefficients of the RBF, R is a vector containing the centers of the RBF, and φ is the basis function or activation function of the network. F(x) is the approximation produced as the output of the network. The coefficient Co, which is a bias term, may take the value 0, if no bias is present. The norm used is the Euclidean distance norm. Equation (10) shows the Euclidean distance for a vector 'x' containing n elements:

$$\|x\| = \sqrt{\sum_{i=1}^{n} {x_i}^2} \qquad (10)$$

Each centre Rj has the same dimension as the input vector 'x', which contains 'n' input values. The centers are points within the input data space and are chosen so that they are representative of the input data. When a RBF calculates its approximation to some input data point, the distance between the input point and each centre is calculated in terms of the Euclidean distance. The distances are then passed through the basis function φ. The results of the basis functions are weighted with the coefficients Ci and these weighted results are then linearly summed to produce the overall RBF output.

One of the most common choices for the basis function is that of the Gaussian as given in Equation (11):

$$\Phi(x) = \exp(- x\ 22\sigma) \qquad (11)$$

where 'σ' is a scaling parameter. Other choices for the basic functions include the thin plate spline, the multi-quadric and the inverse multi-quadric. Flow chart for RBF is given in Figure 3. The following program presents training algorithm for RBF and following as testing algorithm for RBF. In the RBF topology, the hidden layer has activation functions as exp (-x).

Training RBF

Step 1: Apply Radial Basis Function.

No. of Input = 7

No. of Patterns = 10

No. of Centre = 10

Calculate RBF as

RBF = exp (-X) Calculate Matrix as G = RBF

A = GT * G Calculate B = A-1

Calculate E = B * GT

Step 2: Calculate the Final Weight. F = E * D

Step 3: Store the Final Weights in a File.

Testing RBF

Step 1: Read the Input

Step 2: Read the final weights

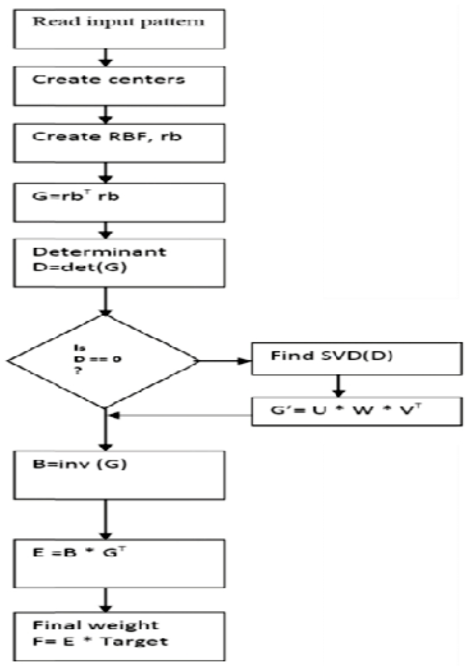

Figure 2. Radial Basis Function Flow Chart

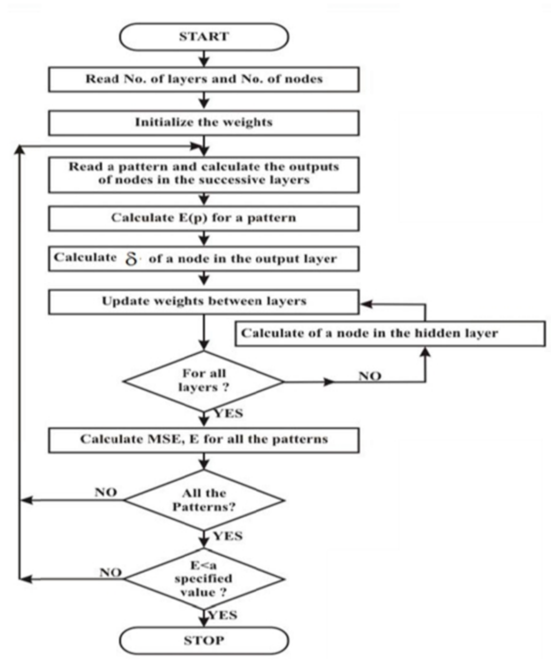

Figure 3. Back Propagation Algorithm Flow Chart

TABLE 1. Patterns used for Testing the ANN with BPA / RBF

Inputs to BPA / RBF , Erol et al. [17]								Target output
S.No.	R32	R125	R290	R134a	R143a	R152a	R600a	COP
1	0	15	0	4	81	0	0	2.181
2	0	25	0	15	60	0	0	2.185
3	0	40	10	50	0	0	0	2.158
4	0	60	15	25	0	0	0	2.113
5	10	30	0	0	60	0	0	2.178
6	35	5	0	60	0	0	0	2.239
7	0	0	20	80	0	0	0	2.159
8	0	0	0	70	0	0	30	2.223
9	0	0	0	40	0	60	0	2.243
10	0	80	0	0	20	0	0	2.144

4. RESULTS AND DISCUSSIONS

The input data of the Table 1 is plotted in Figure 4.

4.1. Training and Testing of BPA Table 1 presents test patterns using 7 combinations of pure refrigerants. Ten patterns are used for testing the BPA. To train the BPA , 50 patterns have been used. Figure 5(a) presents the convergence of MSE for increased iterations while training the 50 patterns with 3 nodes in the hidden layer of the network. The topology of the ANN is 7 x 3 x 1. Higher number of nodes in the hidden layer can also be preferred depending the rate of convergence of MSE. Figure 5(b) presents the number of test patterns presented in Table 1 during the testing process by using the final trained weights. During the process of testing the ANN, only forward propagation of the BPA have been used. The plot shows the percentage of patterns for which COP has estimated correctly. The COP is the ratio of the cooling capacity power to the copmpressor power.

4. 2. Training and Testing of RBF Table 1 is used for training the ANN with RBF. The performance of RBF is shown in Figure 6. Red color marker shows the actual target COP. The blue color marker shows the RBF output during testing. The number of RBF centres used is 10.

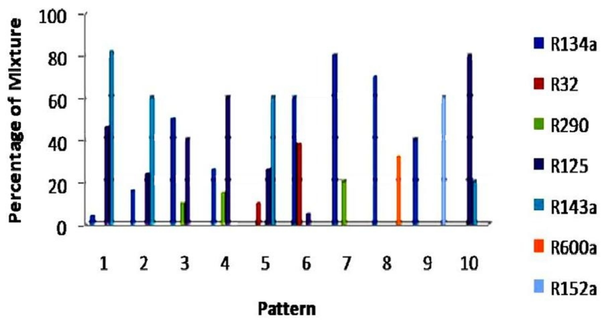

Figure 4. Refrigerant Mixture Composition

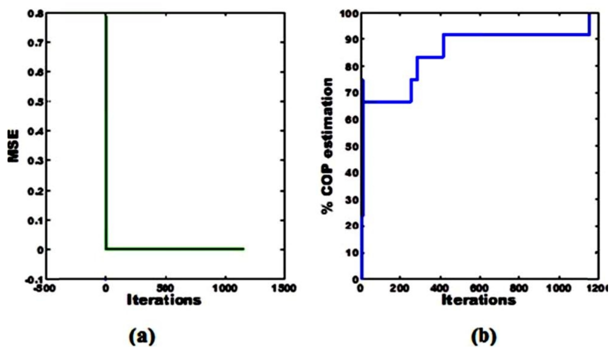

Figure 5. Testing of BPA

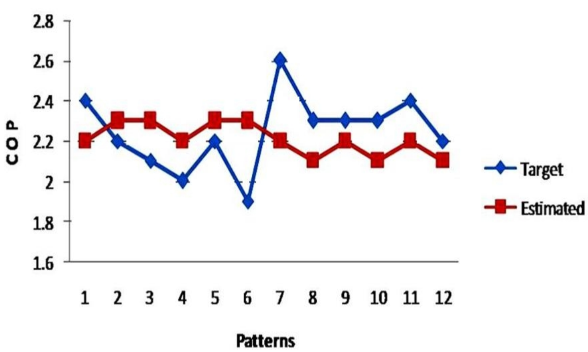

Figure 6. Performance of RBF

5. CONCLUSIONS

This paper presents training and testing of ANN with BPA/RBF for finding out optimum mixed refrigerants to achieve very high COP. Data have been simulated to train and test the performance of ANN algorithms.
1. The BPA requires some iterations for learning the data. However, RBF requires only one iteration to learn all the training patterns. This is a major advantage of RBF over BPA is learning the data.
2. Some times BPA may not converge due to the property of data. However, RBF can produce a better result when compared to BPA in estimation of COP.
3. The number computational complexity is more for BPA than that of RBF.

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چکیده

این تحلیل اساساً بر کاربرد الگوریتم‌های تابع پایه‌ی شعاعی (RBF) و پس انتشار خطا (BPA) برای آموزش شبکه عصبی مصنوعی (ANN) برای به دست آوردن مخلوط بهینه از هیدرو فلوروکربن (HFC) و مواد آلی (هیدروکربن ها) برای به دست آوردن بالاتر متمرکز است. خواص ترمودینامیکی از مبرد مخلوط REFPROP 9 با استفاده از سیستم نرم افزاری حاوی جزئیات مبرد مشاهده شده است. مخلوط‌های کاملاً متفاوت از مبرد همراه با ضریب‌های کارایی‌شان بر اساس REFPROP 9 به دست آمده است. تعیین ترکیب مناسبی از مبرد زمان زیادی لازم دارد زیرا باید گزینه‌های بسیاری از درون REFPROP 9 انتخاب شود. به منظور پیدا کردن یک روش چک کردن مخلوط صحیح مبرد با حداقل مداخله‌ی دستی، RBF آموزش دیده و با الگوهای مختلف مبرد مخلوط مورد آزمایش قرار می‌گیرد. نرم افزار تجزیه و تحلیل مخلوط مبرد RBF / BPA با استفاده از MATLAB 11A توسعه یافته است.

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