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MIXED REFRIGERANTS SUITABILITY ANALYSIS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This paper presents an artificial neural network approach with back propagation algorithm (BPA) to find an alternative to Chloroflurocarbon (CFC) by considering the mixture of Hydro fluorocarbon (HFC) and Hydrocarbon (HC). The thermodynamic properties of refrigerants are obtained using REFPROP 9. Correspondingly, the Coefficients of Performances (COPs) of the mixed refrigerants have been obtained. The testing of the ANN shows high performance in estimating the closest COP.

Keywords: back propagation algorithm, artificial neural network, mixed refrigerant, coefficient of performance.

INTRODUCTION

Cryogenic refrigerators operating with refrigerant mixtures were developed under classified and proprietary programs for many years, and it was only after 1991 that the world realized the importance of the mixed refrigerant systems for cryogenic refrigeration. Mixed refrigerant cryogenic processes are also used in most large base load natural gas liquefaction plants. Hundreds of patents exist on different aspects of mixed refrigerant processes for liquefaction of natural gas, as well as the composition of mixtures for Joule-Thomson and other refrigerators. Still, the fundamental aspects of these processes continued to not receive the attention they deserve in open literature in the view of these commercial interests (Venkatarathnam *et al*., 2008).

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

They are in research for an improvement as R134a itself is found to contribute to global warming. These refrigerants must 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 because they are two different compounds with different temperature to pressure characteristics. The mixture is called azeotrope. Though the low temperature to pressure characteristics of azeotrope may be close to 134a, the high temperature high pressure characteristics vary considerably. The symptoms of this blend result in high system and head pressures. High head pressure will cause the compressor and other system components to fail prematurely. (http://freeasestudyguides.com/refrigerant-idendifier.html).

Mixing different refrigerants can cause big problems. For one, it will increase the system operating pressure. This can result in a loss of cooling performance and may overtax the compressor to the point where it fails. R134a and mineral oil will not mix. So, if somebody recharges an R12 system with R134a and does not add a compatible lubricant, the compressor will soon fail.

ANNs are also used in modeling energy systems such as ejector-absorption cycles (Sozen *et al*., 2003), refrigeration systems using different refrigerant mixtures (Arcaklioglu, 2004), heat exchangers used in refrigeration applications (Pacheco *et al*., 2001), long-term prediction of daily energy use (Olofsson *et al*., 2001), estimations of vapor-liquid equilibrium data (Sharma *et al*., 1999), and performance analysis of heat pumps using R12/R22 refrigerant mixtures.

Refrigeration is one of the important industries needed to keep the world's population fed, (Erol *et al*., 2004). However, the last two decades put this industry on the world's agenda due to its use of chemicals harmful to the ozone layer. This caused numerous efforts to find substitutes for these chemicals (i.e., CFCs and HCFCs). An overview, laying out this problem along with the possible directions for the solution can be found in (McMullan, 2002).

The problem is, finding alternatives to these harmful fluids without changing the traditional components of a cooling system. Up to now, a pure refrigerant that can match the properties of R12, R22, and R502 has not been found. However, various mixtures (substitutes) have been suggested (Camporese *et al*., 1997; Richardson *et al*., 1995; Gunthur *et al*., 1997). The use of mixtures poses other problems: for instance, at a given pressure they have different boiling points, their saturation temperature changes during evaporation, etc. Therefore, making a choice between these mixtures needs some compromises and finding the most suitable mixture ratio, under a wide range of operating 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 have been calculated for a vapor-compression refrigeration system with a liquid/suction line heat-exchanger. Changing the mole percentages of the mixtures enables us to reach the desired thermodynamic properties of the fluids, (Didion, 1999). Therefore, various values of the COPs with different mixture concentrations refrigerants, were used to train and test the ANN algorithm.

ARTIFICIAL NEURAL NETWORK

ANN is an abstract simulation of a real nervous system that contains a collection of neuron units communicating with each other via axon connections. Such a model bears a strong resemblance to axons and dendrites in a nervous system. Due to this self-organizing and adaptive nature, the model offers potentially a new parallel processing paradigm. This model could be more robust and user friendly than the traditional 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 problems in a manner which is different from conventional mapping. Neural networks are used to mimic the operational details of the human brain in a computer. Neural networks are made of artificial neurons which are actually simplified versions of the natural neurons that occur in the human brain. It is hoped that it would be possible to replicate some of the desirable features of the human brain by constructing networks that consist of a large number of neurons. A neural architecture comprises massively parallel adaptive elements with interconnection networks which are structured hierarchically.

Artificial neural networks are computing elements which are based on the structure and function 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. Each node in the successive layer receives the inner product of synaptic weights with the outputs of the nodes in the previous layer. The inner product is called the activation value. The activation value is passed through a non-linear function.

When the vectors are binary or bipolar, hard-limiting non-linearity is used. 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 called discrete and the same with a continuous output is called analog. In a discrete network at a particular time the state of every 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 is 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 the current 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 updation of the networks can be carried out by supervised methods or by unsupervised methods 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 in the fixed weight association networks methods, inputs and outputs are used along with pre-computed and pre-stored weights.

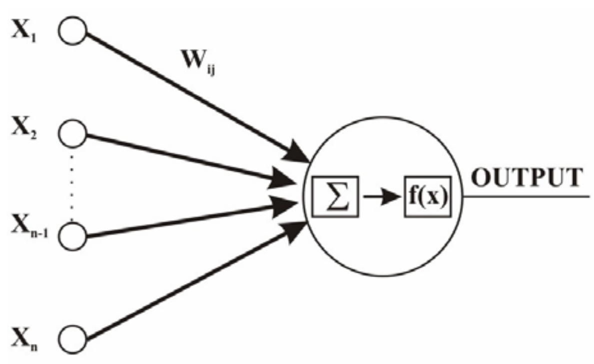

Figure-1. Operation of a neuron.

Some of the supervised learning algorithms are the perceptrons, decision based neural networks, adaptive linear element (ADALINE) (Figure-1), multilayer perceptrons, temporal dynamic models and hidden Markov analysis. The various unsupervised learning algorithms are neo-cognition, self-organizing feature map, competitive learning, adaptive resonance theory. The fixed weight networks are Hamming net, Hopfield net and the combinatorial optimization. The total pattern recognition system constitutes instantiation space, feature extraction, training the network, and the testing the network. Rumelhart *et al*. (2008) has made the concept of ANN widely known through their publications.

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 by:

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

where

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

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

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network. The patterns selected for training the network should be, such that they represent the entire population of the data.
The selection of patterns is done using equation (2):

$$E_i^2 = \frac{\sum_{j=1}^{nf} (x_{ij} - \bar{x}_j)^2}{\sigma_i^2} \qquad (2)$$

where

E_i^2 is maximum variance of a pattern
nf is number of features

$$\sigma_i^2 = \frac{\sum_{j=1}^{nf} (x_{ij} - \bar{x}_j)^2}{L} \qquad (3)$$

$\bar{x}$ = mean for each feature

L = total number of patterns

The value of E_i^2 is found for each pattern. Patterns with maximum E_i^2 are chosen from each class for training the network.

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.

o (output of a node) = $1/(1+\exp(\sum w_{ij} x_i))$ (4)

where

w is the weight matrix
x is inputs to the nodes

Step 4: The error of a pattern is calculated

$E(p) = (1/2) \sum(d(p) - o(p))^2$ (5)

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

Reverse propagation

Step 5: The error for the nodes in the output layer is calculated.

δ(output layer) = o(1-o)(d-o) (6)

Step 6: The weights between output layer and hidden layer are updated.

W (n+1) = W (n) + $\eta\delta$(output layer) o (hidden layer) (7)

Step 7: The error for the nodes in the hidden layer is calculated.

δ (Hidden layer) = o (1-o) $\sum\delta$ (output layer) W (updated weights between hidden and output layer) (8)

Step 8: The weights between hidden and input layer are updated.

W (n+1) = W (n) + $\eta\delta$(hidden layer) o (input layer) (9)

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 displayed on the monitor as the mean squared error (MSE).

MSE = $\sum$ E(p) (10)

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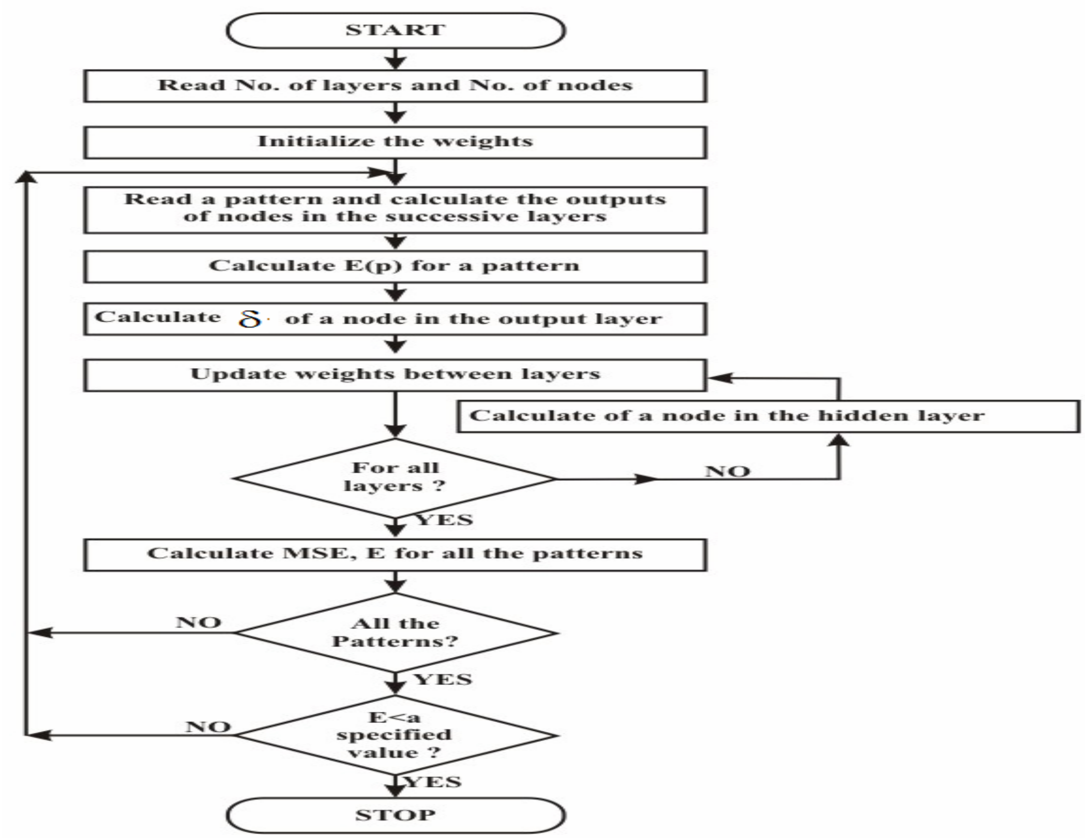
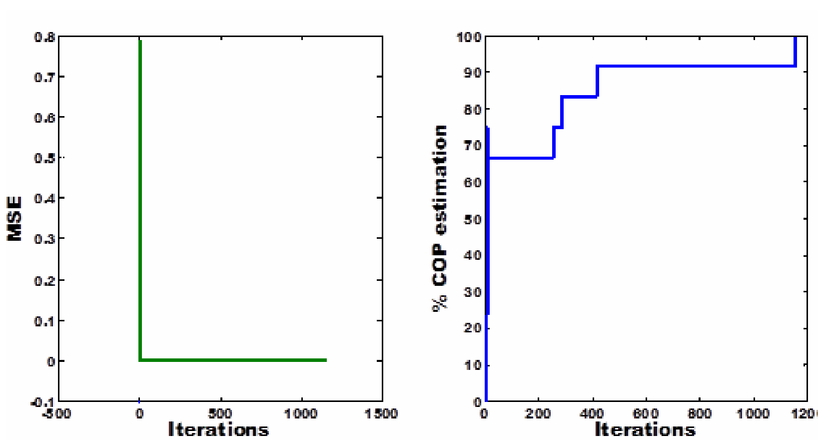


Figure-2. Flow chart of the back propagation algorithm.

RESULTS AND DISCUSSIONS

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-3(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-3(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 been estimated correctly.



(a) **(b)**

Figure-3. Training / testing of BPA.

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The COP is the ratio of the cooling capacity power to the compressor power.

Table-1. Patterns used for testing the ANN with BPA.

S. No.	Inputs to BPA , Erol *et al*., (2004)							Target output
	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

CONCLUSIONS

This paper presents an implementation of back propagation algorithm to find out an optimum mixed refrigerant that gives high COP. It takes 1154 iterations to learn all the 50 patterns for 3 nodes in the hidden layer. More number of mixed refrigerants has to be considered for evaluating the performance of the BPA ANN.

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