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An Adaptive Neuro-Fuzzy Inference System (ANFIS) modelling of oil retention in a carbon dioxide air-conditioning system

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ABSTRACT

In a closed loop vapor compression cycle, a small portion of the oil circulates with the refrigerant flow through the cycle components while most of the oil stays inside the compressor. The worst scenario of oil circulation in the refrigeration cycle is when large amounts of oil become logged in the system. Each cycle component has different amounts of oil retention. Because oil retention in refrigeration systems can affect performance and compressor reliability, it receives continuous attention from manufactures and operators. In this paper, an Adaptive Neuro Fuzzy Inference System (ANFIS) is used for modeling the effect of important parameters on oil retention in a carbon dioxide air-conditioning system is trained and tested with the experimental data taken from the experimental work by Lee (2003). In this way, we considered oil retention in a carbon dioxide air-conditioning system when oil injection occurs at evaporator (OREO) as target parameter, refrigerant mass flow rate (RMFR), oil mass flow rate (OMFR), oil circulation ratio (OCR), gas cooler inlet pressure (P_{GCI}), evaporator inlet pressure (P_{EI}), gas cooler inlet temperature (T_{GCI}), gas cooler outlet temperature (T_{GCO}) and evaporator outlet temperature (T_{EO}) as input parameters. Then, we randomly divided empirical data into train and test sections in order to accomplish modeling. We instructed ANFIS network by 75 percent of empirical data. 25 percent of primary data which had been considered for testing the appropriativity of the modeling were entered into ANFIS model. Results were compared by two statistical criterions (R^2 , RMSE) with empirical ones. Considering the results, it is obvious that our proposed modeling by ANFIS is efficient and valid and it can also be promoted to more general states.

1. INTRODUCTION

The compressor in a refrigeration system needs oil to lubricate its mechanical parts. The function of a lubricant is to prevent surface-to-surface contact in the compressor, to remove heat, to provide sealing, to keep out contaminants, to prevent corrosion, and to dispose of debris created by wear (Vaughn, 1971). In a closed loop vapor compression cycle, a small portion of the oil circulates with the refrigerant flow through the cycle components while most of the oil stays in the compressor. The lubricant is necessary for the compressor, but is not necessary for the other components of the refrigeration system. To fulfill its duty, the dynamic viscosity of the refrigerant/oil mixture must be high enough to provide the proper lubrication and sealing effects. On the other hand, it is important that the viscosity of the refrigerant/oil mixture in the heat exchangers and tubes is not too high, so that an adequate feedback of the oil into the compressor is possible (Kruse and Schroeder, 1984).

Successful operation of the refrigeration system requires sufficient oil return into the compressor to avoid eventual trouble from a lack of proper lubrication that may cause compressor failure. In fact, the oil return behavior is a complex function of fluid properties as well as system components and configuration aspects. Since the temperature and pressure conditions are varied depending upon each system component, such as the gas cooler, the evaporator and the suction line, the oil return characteristics in the cycle components are also specific to the system component. The circulating oil, which is missing from the compressor, exists as an oil film on the tube wall, and the oil film thickness is affected by the system conditions. Thus, each cycle component has different amounts of oil retention. Large amounts of oil retention cause a decrease in heat transfer and an increase in pressure drop. As a

result, the system performance can be degraded. Because oil retention in refrigeration systems can affect performance and reliability, it receives continuous attention from manufactures and operators.

In a few recent years, theoretical research about information processing has been increasingly developed in order to use it in applied aspects, particularly for problems that are not soluble or easily solved. This interest has been specially displayed much more in the development of intelligent systems which are based on the empirical data. Artificial neural networks are among the systems which transfer the knowledge and rules exist beyond the empirical data into the network structure by their processing. Because artificial neural network don't consider any presuppositions about statistical distribution and characteristics of the data, they are practically more efficient than common statistical methods. On the other hand, they use a non-linear approach to create a model, so when encountered with the complicated and non-linear data, these networks may express such a data much more accurately as a defined model. High learning abilities of artificial neural network has converted the method into a superior choice when combined with fuzzy systems. The combination of artificial neural network with fuzzy method can create an efficient approach for various modelling systems, so that each of these two methods may recover the weakness of another and increase the efficiency of the neuro-fuzzy system. A neuro-fuzzy system uses learning methods derived from artificial neural network in order to find the parameters of fuzzy system which includes appropriate membership functions and fuzzy rules. One of the neuro-fuzzy systems in which learning algorithm is coincided with integrates learning approaches is ANFIS system. In recent years, many investigations have been performed to apply the ANFIS system for modelling of the engineering processes (Li et al, 2009), (Sun et al, 2005) and (Hasiloglu et al, 2004).

Considering the complexity of analytical and numerical methods as well as very high costs of empirical experiments, artificial intelligence methods are appropriate choice to model oil retention in a carbon dioxide air-conditioning system. In this study, a model was created for oil retention in a carbon dioxide air-conditioning system when oil injection occurs at evaporator outlet by ANFIS system. In this model, OREO was the target variable (output parameter) and RMFR, OMFR, OCR, P_{GCL} , P_{EL} , T_{GCL} , T_{GCO} and T_{EO} were chosen as designing variables (input parameters).

2. EXPERIMENTAL FACILITY

Experiments and measurements have already been performed by Lee (2003). A brief description of the test section and the procedure are given below. The experimental facility was designed and constructed to investigate oil retention characteristics of each system component. The test facility for oil retention mainly consists of a refrigeration loop and an oil loop. These two loops are connected to or disconnected from each other by a three-way valve in such a way that the refrigerant flow direction can be controlled. The refrigeration loop was modified from an existing carbon dioxide automotive air-conditioning system. The air-conditioner was operated between two temperature conditions, indoor and outdoor. Air-side test conditions were provided by a closed air loop and an environmental chamber, which simulate the indoor and outdoor conditions, respectively. The evaporator was located in the indoor-side air loop, while the other components (i.e. compressor, gas cooler) were in the environmental chamber. The refrigeration loop consisted of a compressor driven by an electric motor, a gas cooler, a manual expansion valve, and an evaporator.

PAG (Polyalkylene Glycol) was studied by Lee (2003) as a lubricant for a carbon dioxide air-conditioning system because the compressor manufacturer recommended PAG oil to guarantee reliability and compatibility with compressor materials. PAG that was used in this study has a viscosity of 43 cSt at 40°C, 9.2 cSt at 100°C, and a density of 996 kg/m³ at 25°C. The dielectric constant, which is measured by the level sensor to calculate the oil amount, is around 6 at 20 °C.

3. ARCHITECTURE OF ANFIS

ANFIS system uses two neural network and fuzzy logic approaches. When these two systems are combined, they may qualitatively and quantitatively achieve an appropriate result that will include either fuzzy intellect or calculative abilities of neural network. As other fuzzy systems, the ANFIS structure is organized of two introductory and concluding parts which are linked together by a set of rules. We may recognize five distinct layers in the structure of ANFIS network which makes it as a multi-layer network. A kind of this network, which is a Sugeno type fuzzy system with two inputs and one output, is indicated in Figure 1. As shown in Figure1, this system contains two inputs namely x and y and an output or Z which is associated with the following rules:

Rule 1 If (x is A_1) and (y is B_1) then $Z_1=p_1x+q_1y+r_1$
 Rule 2 If (x is A_2) and (y is B_2) then $Z_2=p_2x+q_2y+r_2$

In this system, A_i , B_i and Z_i are fuzzy sets and system's output respectively. p_i , q_i and r_i are designing parameters which are obtained during the learning process. If we consider the output of each layer in the ANFIS network as

O_i^j (i_{th} node output in j_{th} layer) then we may explain the various layers functions of this network as follows:

Layer 1: In this layer, each node is equal to a fuzzy set and output of a node in the respective fuzzy set is equal to the input variable membership grade. The parameters of each node determine the membership function form in the fuzzy set of that node. Since we used the Gaussian membership function in this study, so will have:

$$\mu_{A_i}(x) = e^{-\frac{1}{2}(\frac{x-c_i}{\sigma_i})^2} \tag{1}$$

In which x is the input value of the node and C_i and σ_i are the membership function parameters of this set which explain Gaussian membership function center and Gaussian membership function width respectively.

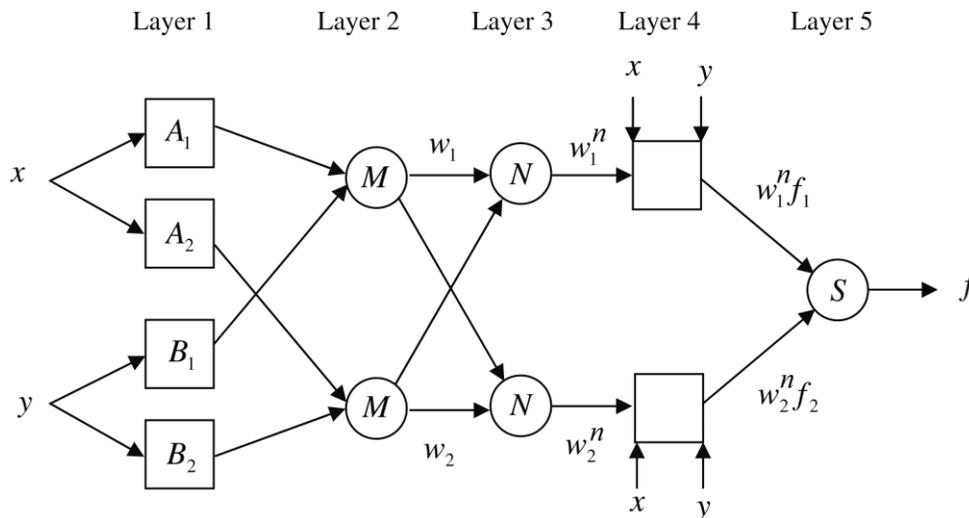


Figure 1. Architecture of ANFIS.

Layer 2: In this layer the input signals values into each node are multiplied by each other and a rule firing strength is calculated.

$$O_i^2 = \omega_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2 \tag{2}$$

In which μ_{A_i} is the membership grade of x in A_i fuzzy set and μ_{B_i} is the membership of y in fuzzy set of B_i .

Layer 3: This layer nodes calculate rules relative weight. In which ω_i^n is the normalized firing strength of i_{th} rule.

$$O_i^3 = \omega_i^n = \frac{\omega_i}{\omega_1 + \omega_2}, \quad i = 1, 2 \tag{3}$$

Layer 4: This layer is named rules layer which is obtained from multiplication of normalized firing strength (has been resulted in the previous layer) by first order of Sugeno fuzzy rule.

$$O_i^4 = \omega_i^n f_i = \omega_i^n (p_i x + q_i y + r_i), \quad i = 1, 2 \quad (4)$$

Layer 5: This layer is the last layer of the network and is composed of one node and adds up all inputs of the node.

$$O_i^5 = \sum_{i=1}^2 \omega_i^n f_i = \frac{\omega_1 f_1 + \omega_2 f_2}{\omega_1 + \omega_2}, \quad i = 1, 2 \quad (5)$$

Briefly, the first layer in ANFIS structure performs fuzzy formation and second layer performs fuzzy AND and fuzzy rules. The third layer performs the normalization of the membership functions and the fourth layer is the conclusive part of fuzzy rules and finally, the last layer calculates the network output. According to these, it is obvious that the first and fourth layers in ANFIS structure are adaptive layers in which C_i and σ_i in layer 1 are known as premise parameters that are related to membership function of fuzzy input. In layer 4 r_i , q_i and p_i are adaptive parameters of the layer and are called consequent parameters (Hanbooy *et al*, 2009) and (Cordero *et al*, 2000).

There are adaptive and consequent parameters sets in ANFIS structure. In fact, when the simulation has been conducted correctly, provided that both sets of parameters are estimated so as the model error function has the lowest value in training and experimental sections. These parameters are obtained two passes: In first pass, we assume that the adaptive parameters set are constant and the consequent parameters set are calculated by least square error algorithm; this pass is called forward pass. In the second pass which is named backward pass, the consequent parameters are assumed to be constant and the adaptive parameters set is obtained by gradient descent algorithm. When we obtained the parameters sets of the model, we can calculate the value of the model output for each orderly pair of training data and compare them with values that have been anticipated by the model. Consequently, the error function of the model instruction is determined. After considering the appropriate of this error function, the training process is stopped and the final model is achieved (Jang, 1993).

4. RESULTS AND DISCUSSION

Grid partition method of fuzzy inference systems was tried to generate the fuzzy rule base sets. A number of 80 epochs for training was applied to obtain the minimum root mean square error (RMSE) and maximum square of correlation coefficient (R^2) that the perfect agreement is achieved when RMSE and R^2 are equal to 0.0 and 1.0 respectively.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (Q_i - P_i)^2} \quad (6)$$

$$R^2 = \frac{\left(\sum_{i=1}^N (Q_i - Q_m)(P_i - P_m) \right)^2}{\sum_{i=1}^N (Q_i - Q_m)^2 + (P_i - P_m)^2} \quad (7)$$

Where Q_i is observed and P_i is predicted value. Q_m and P_m represents the average value of observed and predicted values. RMSE and R^2 represent differences observed and predicted data and square of correlation coefficient respectively.

Some experimental data by Lee (2003) were used for the model. This data set was divided randomly into two subsets as 75 % for training and 25% for testing purposes. More data were used in the training phase because ANFIS is more adapted nonlinear functional dependency between input and output variables. The minimum and maximum ranges of the parameters used in modelling were given in Table 1.

Generally, fuzzy rules were described by an expert. Instead of consulting an expert, the rules were automatically generated in this study. The optimum ANFIS structures were obtained by trial and error of grid partition fuzzy inference system and the lowest RMSE and highest R^2 values were obtained with grid partition system. Input variables were fuzzified with two membership functions, which were labelled MF1 and MF2 with Gaussian membership function. The parameters of these membership functions were given in Table 2. The 256 rules base of this model reflected the physical property of the system along with membership functions with the optimum consequent parameters obtained after the ANFIS training.

Table 1. Ranges of parameters that used in OREO modelling

Input variable	Minimum levels	Maximum levels
Refrigerant mass flow rate (RMFR)	13.4	27.4
Oil mass flow rate (OMFR)	0.09	1.19
Oil circulation ratio (OCR)	0.6	6.8
Gas cooler inlet pressure (P_{GCI})	7.7	9.2
Evaporator inlet pressure (P_{EI})	3.7	4
Gas cooler inlet temperature (T_{GCI})	75	100.8
Gas cooler outlet temperature (T_{GCO})	36.1	40.4
Evaporator outlet temperature (T_{EO})	9.4	17.8

Table2. Parameters of membership functions for OREO modelling

Membership function		RMFR	OMFR	OCR	P_{GCI}	P_{EI}	T_{GCI}	T_{GCO}	T_{EO}
MF1	n	5.945	0.4647	2.633	0.6373	0.172	10.83	1.698	3.3
	m	13.4	0.08861	0.5998	7.701	3.735	75	36.1	9.392
MF2	n	5.945	0.5067	2.632	0.6203	0.0888	10.83	1.706	3.315
	m	27.4	1.172	6.8	9.207	4.037	100.5	40.1	17.2

n represents Gaussian MFs width, m determines Gaussian MFs center

4.1 Model Validation

Some statistical data was used to determine how well the FIS model could predict the OREO in a carbon dioxide air-conditioning system corresponding to various values of inlet variables. Figure 2, show plots of the experimental data by Lee (2003) and ANFIS modeled OREO utilizing of testing data. These diagrams demonstrate that the predicted values are close to the experimental values, as many of the data points fall very close to the diagonal (dotted) line in scatter plot. Clearly the models created by ANFIS have an agreement with the experimental data. Amount of R^2 and RMSE for this modeling was given in Table 3.

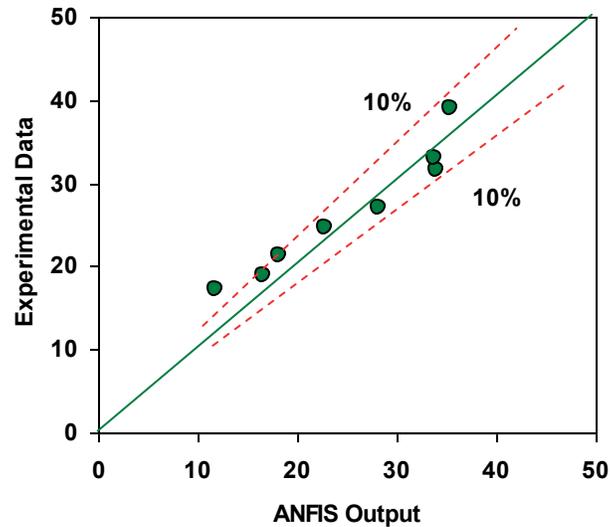


Figure 2. Comparison between experimental data by Lee (2003) and ANFIS model for OREO (mL) modeling.

Table 3 .Amount of R^2 and RMSE for OREO modelling

R^2	0.9306
RMSE	2.5791

5. CONCLUSIONS

This study suggests that how we may use ANFIS network for modeling the OREO in a carbon dioxide air-conditioning system. Results analysis and figure clearly demonstrate that this system is more effective for our proposed model. This study also indicates the high ability of ANFIS network for modeling the more complicated engineering processes which there is no an obvious mathematical relationship to express their behavior. Whereas the system dose not requires clear and definite and a large sample data, it is more appropriate method than classical modeling approaches. However, whatever the effective parameters are identified and applied better in the modeling, surely improved results will be obtained.

NOMENCLATURE

RMFR	refrigerant mass flow rate	(g/s)		
OMFR	oil mass flow rate	(g/s)	GCI	gas cooler inlet
OCR	oil circulation ratio	(wt.%)	GCO	gas cooler outlet
P	pressure	(MPa)	EI	evaporator inlet
T	temperature	($^{\circ}C$)	EO	evaporator outlet
OREO	oil retention when oil injection (mL) occurs at evaporator outlet			

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