SIMULATION OF TEMPERATURE OF R744/ R290 REFRIGERANT AT EVAPORATOR OUTLET IN AUTOCASCADE REFRIGERATION SYSTEM

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Abstract :

The objective of present work is to predict the temperature of refrigerant mixture at evaporator outlet using fuzzy modeling in autocascade refrigeration system. The fuzzy model is presented in this paper for the prediction refrigerant mixture temperature at evaporator outlet. The autocascade refrigeration system provides the possibility of keeping the highest pressure within a limit by selecting the composition of the refrigerant mixture as compared to vapor compression system which uses pure carbon dioxide. The refrigeration system uses R744/R290 as refrigerant mixture. Pressure (kPa), temperature (°C) and concentration of CO_2 are taken as input variable parameters for developing fuzzy model and the output is taken as the refrigerant mixture temperature at outlet of evaporator (°C). The model predictions are compared with a set of reliable experimental data available in the literature for the validation of fuzzy model and it is found that proposed fuzzy model gives the results which are well in agreement with experimental results.

***Keywords**: Autocascade refrigeration, refrigerant mixture R744/R290, FIS modelling.*

1. Introduction

Autocascade refrigeration systems are complete, self-contained systems in which multiple stages of cascade cooling occur simultaneously. This is accomplished by means of several steps of vapor/liquid separation and adiabatic expansion of the different refrigerants contained in the refrigerant charge. The low temperature may be achieved with a reciprocating type compressor in conjunction with the appropriate mixture of two or more refrigerants. Autocascade systems are typically much smaller than custom-designed equipment, and they use standard hermetic compressors ranging up to about 10 hp (7.5 kW) [1].

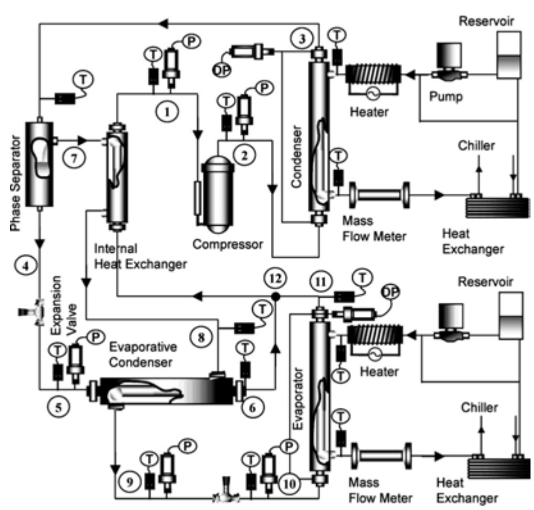

Figure1. Autocascade refrigeration system.

These systems have a surprisingly low compression ratio and a high volumetric efficiency. The components of an autocascade refrigeration system basically include a compressor, a phase separator, a condenser (water- or air-cooled), an evaporator, and a mixture of refrigerants with varying boiling points, an evaporative condenser and an internal heat exchanger. Figure1. Show a typical view of autocascade refrigeration system.

Yu et al. [2] suggested an autocascade refrigeration system using an ejector system for the performance improvement to obtain low temperature conditions. They presented a novel autocascade refrigeration cycle with an ejector system. In this system, the ejector is used to recover some available work to increase the compressor suction pressure. The system enables the compressor to operate at lower pressure ratio, which improves the cycle performance. Du et al. [3] presented a characteristics cycle of an auto-cascade refrigeration system using zeotropic mixture as refrigerant, which achieves cascade between high and low boiling point components by an evaporative condenser for the purpose of obtaining a lower evaporation temperature comparing with single refrigerant system. The coefficient of performance, cooling capacity, evaporation temperature, and pressures and temperatures of refrigerant at the inlet and outlet were measured and parameter analyses were conducted with different charging concentrations, different temperatures of cooling water and different matches of cycle flux between high and low boiling point components under the same evaporating pressure. Kim and Kim [4] presented an experiment and simulation on the performance of an autocascade refrigeration system using carbon dioxide as a refrigerant. This work investigates the performance of an autocascade refrigeration system using zeotropic refrigerant mixtures of R744/R134a and R744/R290. The present work has been planned to model outlet temperature of refrigerant mixture R744/R290 at evaporator outlet in autocascade refrigeration system using fuzzy modeling.

2. Fuzzy Modeling

FUZZY LOGIC is a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems. It can be implemented in hardware, software, or a combination of both. FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. FL's approach to control problems mimics how a person would make decisions, only much faster.

2.1 Fuzzy inference system (FIS)

The heart of a fuzzy logic controller/modeling is the inference engine, which contains knowledge of the control strategy in the form of ‘‘if-then” rules. Since the fuzzy logic rules involve linguistic variables, but the inputs and outputs of a process are generally continuous crisp values, the translation of crisp values into fuzzy values and vice versa are necessary and is the function of the fuzzification and defuzzification respectively. The initial step of the fuzzy modeling system is to decide the input and output variables of the fuzzy logic controller. Mamdani-type fuzzy inference system is taken for the purpose. A typical direct fuzzy inference system is shown in Fig. 2. This FIS system is designed for multi input single output (MISO) system. In the present study, this MISO system includes three inputs and one output.

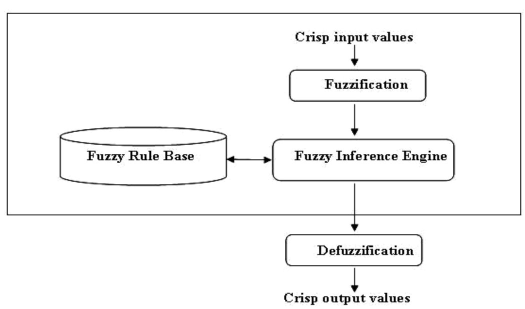

Fig. 2 Block diagram of fuzzy inference system.

2.2 Need of fuzzy modeling

Many researchers have worked on fuzzy modeling in various engineering fields. Singh et al. [5] have worked on fuzzy modeling of a vapor compression system in air conditioning system. They proposed fuzzy models of refrigerating compressor, expansion valve, evaporator and condenser. Fuzzy model of all the elements has been compared with their respective mathematical models for their validation. Ertunca and Hosoz [6] presented a comparative analysis of an evaporative condenser using artificial neural network and adaptive neuro-fuzzy inference system. In this paper the performance of an evaporative condenser using both artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) techniques are predicted. The condenser heat rejection rate, refrigerant temperature leaving the condenser along with dry and wet bulb temperatures of the leaving air stream are predicted by these models. The adaptive network based fuzzy inference system (ANFIS) is a useful neural network approach for the solution of function approximation problems. An ANFIS gives the mapping relation between the input and output data by using hybrid learning method to determine the optimal distribution of membership function. This system is based on Mamdani-type system and can simulate and analyze the mapping relation between the input and output data through a hybrid learning to determine the optimal distribution of membership function. The fuzzy model uses ''if-then" rules to obtain the crisp results.

Emami et al. [7] suggested that fuzzy modeling is an expert tool to model any complex system. They proposed a systematic approach of fuzzy modeling and system identification. The methodology considers the inference mechanism as a computation ground for fuzzy systems as well as the structure and parameter identification of the fuzzy system. For reasoning process, a unified parameterized formulation is applied by which the suitable inference mechanism is adjusted for the system based on its input–output data. Li and Gatland [8] proposed a systematic analysis and design for conventional fuzzy control system. A general robust rule base is proposed for fuzzy two-term control, and leave the optimum tuning to the scaling gains, which greatly reduces the difficulties of design and tuning. The digital implementation of fuzzy control is also presented for avoiding the influence of the sampling time. Kim et al. [9] presented an application of fuzzy logic to control the refrigerant distribution for the multi type air conditioner. In this paper they have compared the control result of two systems that applied to the conventional control algorithm and the fuzzy control algorithm. Fodil et al. proposed a fuzzy model to control a pressurized water nuclear reactor. In their work they found that the fuzzy controller runs as efficiently as an expert operator for the control of a pressurized water nuclear reactor. Ryoo et al. [10] developed a fuzzy model to control of convergence in a computational fluid dynamics simulation system. Adaptive-network-based fuzzy inference system (ANFIS) was used to control convergence of a computational fluid dynamics (CFD) algorithm. Normalized residuals were used to select the relaxation factors on each iteration of the computation. The ratio between the residual of the current iteration and of the previous iteration was used as a control input.

Flores et al. [11] gave a fuzzy control for a solar power plant. The proposed predictive controller uses fuzzy characterization of goals and constraints, based on the fuzzy optimization framework for multi-objective satisfaction problems. This approach enhances model based predictive control (MBPC) allowing the specification of more complex requirements. Two fuzzy predictive controllers using different membership functions are designed for a solar power plant, and they are compared with a classical predictive controller. The simulation results show that the fuzzy MBPC formulation, based on a well proven successful algorithm, gives a greater flexibility to characterize the goals and constraints than classical control. Gill & Singh [12] presented that the parameters associated with the membership functions will change through the learning process. The computation of these parameters is facilitated by gradient vector, which provides a measure of how well fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of the several optimization routines could be applied in order to adjust the parameters so as to reduce some error measure.

Chen and Saif [13] presented a novel base fuzzy system with dynamic rule base system. The focus of this article was mainly on the approximation capability of this fuzzy system. The proposed system was capable of approximating any continuous function on an arbitrarily large compact domain. A new type of fuzzy system which has a dynamic rule base and fixed number of fuzzy rules was proposed in this article. It was proved that the proposed fuzzy system can approximate any continuous function to arbitrary degree of accuracy on any compact domain. Moreover, it can even approximate any uniformly continuous function on infinite domains. Buragohain & Mahanta [14] suggested that adaptive network based fuzzy inference system (ANFIS) is also an useful neural network approach for the solution of function approximation problems. Ying & Pan [15] proposed that an ANFIS gives the mapping relation between the input and output data by using hybrid learning method to determine the optimal distribution of membership functions. Avci [16] presented that both artificial neural network (ANN) and fuzzy logic (FL) are used in ANFIS architecture. Sengur and Ubeyli [17] proposed that framework makes the ANFIS modeling more systematic and less reliant on expert knowledge.

Gill and Singh [18] reported an adaptive neuro-fuzzy inference system modeling for material removal rate in stationary ultrasonic drilling of sillimanite ceramic. In their work had presented an adaptive neuro-fuzzy Inference System (ANFIS) technique to model and simulate the material removal rate in stationary ultrasonic drilling of sillimanite ceramic. They had taken the depth of penetration, time for penetration and penetration rate as model input features. The model combined modeling function of fuzzy inference with the learning ability of artificial neural network and a set of rules has been generated directly from experimental data. The proposed modeling approach is verified by comparing the predicted results with the actual practical results obtained by conducting the confirmation experiments.

From the above literature it is found that fuzzy modeling is an expert type of modeling which can be used for modeling of different types of systems in many engineering fields. Now in present investigation fuzzy modeling of evaporator system in autocascade refrigeration is presented in this paper. The predicted values from the fuzzy model are compared with the experimental data for validation of the work and χ^2-test has also been applied for the accuracy of predictions.

3. Modeling of evaporator system

Fuzzy logic technique contains a potential to give a simplified control of various engineering and non-engineering applications. The rule-based character of fuzzy models allows for a model interpretation in a way that is similar to the one humans use to describe reality. Conventional methods for statistical validation based on numerical data can be complemented by the human expertise that often involves heuristic knowledge and intuition.

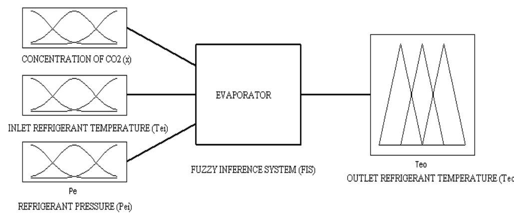

Fig.3 Modeling of evaporator system

In the present study the modeling of evaporator system in autocascade refrigeration system has been done using Fuzzy Inference System (FIS) by considering three input parameters and one output parameter.

3.1. *Identification of input and output variables*

The fuzzy logic is based on the identification of the fuzzy-set that represents the possible values of the variables. Fig. 4 shows real inputs and real output for evaporator system using R744/R290. Fuzzy model described in this paper is a MISO system with three input parameters**;** concentration of carbon dioxide (x), temperature of refrigerant mixture at evaporator inlet (Tei) and pressure of refrigerant mixture (Pei) and the output as the outlet temperature of refrigerant mixture at evaporator outlet (Teo). Possible universe of discourse for the input parameters is given below:

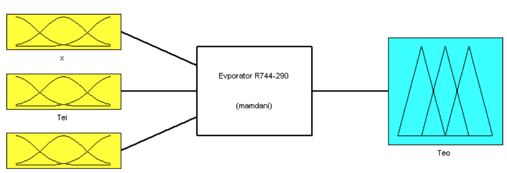

Fig.4 Fuzzy model for evaporator system showing inputs and output.

Concentration of carbon dioxide (x) = 0.13 to 0.31
Temperature of refrigerant mixture at evaporator inlet Tei) = −17.2 ºC to −5.5 ºC.
Pressure of refrigerant mixture (Pei) = 633.3 kpa to 976.3 kpa.
Output parameter:
Outlet temperature of refrigerant mixture at evaporator outlet (Teo) = predicted depending upon input parameters (°C).

3.2. Membership functions for the input and output variables

This step is to define linguistic values assigned to the variables and that was done via fuzzy subsets and their associated membership functions. A membership function assigns numbers between zero and one, called the grades of membership, to the range of the possible values of the variable. Zero membership value indicates that it is not a member of the fuzzy-set; one represents a complete member. A membership function can have any shape but preferably symmetric. The standard shapes of membership functions include trapezoidal, triangular and bell shaped. Three membership functions were generated for each input variable of concentration of CO_2 (x), temperature of refrigerant mixture at evaporator inltet (Tei), pressure of refrigerant mixture (Pei) based on ANFIS as shown in Figs. 5(a), 5(b), 5(c). Membership function of output variable of refrigerant mixture temperature at evaporator outlet (Teo) is given in Fig. 6. The span of each function was equally divided within the specified range. Tests were conducted to evaluate the response parameters and the span was varied accordingly for improvement. After a few iterations, the final membership functions for the system were determined as shown in respective figures.

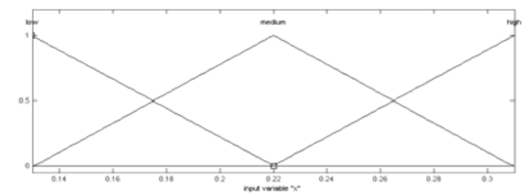

Fig.5 (a) Membership function plots of input variable concentration of CO_2 (x).

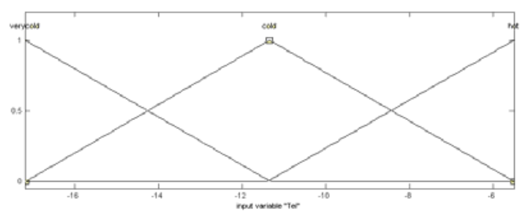

Fig.5 (b) Membership function plots of input variable temperature of refrigerant mixture at evaporator inlet (Tei).

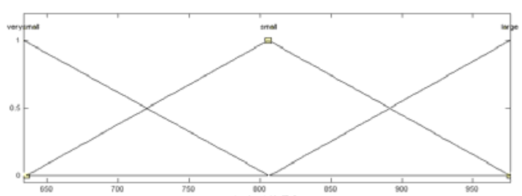

Fig.5(c) Membership function plots of input variable pressure of refrigerant mixture (Pei).

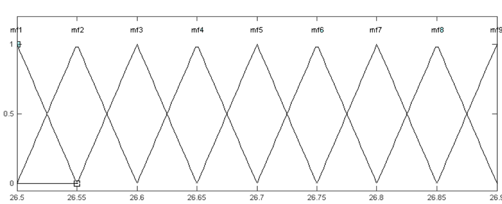

Fig.6 Membership function plots of output variable refrigerant mixture temperature at evaporator outlet (Teo).

3.3. FIS rules employed in model

The fuzzy modeling of the evaporator in an autocascade refrigeration system uses three input parameters concentration of CO_2 (x), temperature of refrigerant mixture (Tei), pressure of refrigerant mixture (Pei), and one

output parameter of temperature of refrigerant mixture (Teo), each of which correspond to three linguistic variables. These variables can generate number of rules, but these rules have been reduced to 18 for R744/R290 mixture refrigerant, since there are many rules that correspond to ‘not applicable’ conditions and have not been included in the designed control rules of the system. The applicable control rules formulated for the model are given below:
For R744/R290:

1. If (x is low) and (Tei is verycold) and (Pe is verysmall) then (Teo is mf1)
2. If (x is low) and (Tei is cold) and (Pe is small) then (Teo is mf2)
3. If (x is low) and (Tei is hot) and (Pe is large) then (Teo is mf3)
4. If (x is medium) and (Tei is verycold) and (Pe is verysmall) then (Teo is mf4)
5. If (x is medium) and (Tei is cold) and (Pe is small) then (Teo is mf5)
6. If (x is medium) and (Tei is hot) and (Pe is large) then (Teo is mf6)
7. If (x is high) and (Tei is verycold) and (Pe is verysmall) then (Teo is mf7)
8. If (x is high) and (Tei is cold) and (Pe is small) then (Teo is mf8)
9. If (x is high) and (Tei is hot) and (Pe is large) then (Teo is mf9)
10. If (x is low) and (Tei is verycold) and (Pe is large) then (Teo is mf1)
11. If (x is low) and (Tei is cold) and (Pe is verysmall) then (Teo is mf2)
12. If (x is low) and (Tei is hot) and (Pe is small) then (Teo is mf3)
13. If (x is medium) and (Tei is verycold) and (Pe is large) then (Teo is mf4)
14. If (x is medium) and (Tei is cold) and (Pe is verysmall) then (Teo is mf5)
15. If (x is medium) and (Tei is hot) and (Pe is small) then (Teo is mf6)
16. If (x is high) and (Tei is verycold) and (Pe is large) then (Teo is mf7)
17. If (x is high) and (Tei is cold) and (Pe is verysmall) then (Teo is mf8)
18. If (x is high) and (Tei is hot) and (Pe is small) then (Teo is mf8)

These set of rules along with membership function are also shown in rule viewer of fuzzy model (Fig. 7). This figure clearly shows that at x=0.22, Tei=−13.9 and Pei=755 maximum rules are fired and it predicts Teo=26.7. Similarly for the different set of data points in the identified universe of discourse of undertaken parameters various others values of refrigerant mixture temperature Teo can also be predicted from the fuzzy models.

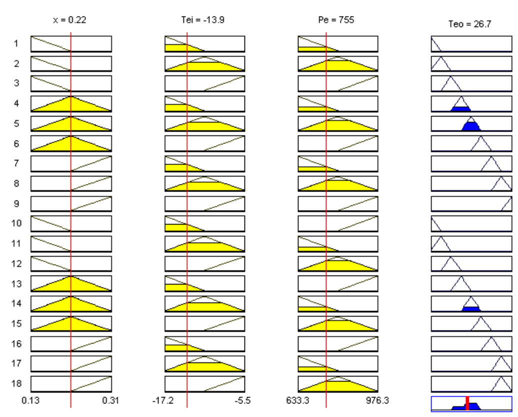

Fig.7 Rule viewer of fuzzy model (R744/R290).

Control surface as shown in Figs. 8 and 9 gives the interdependency of input, and output parameters guided by the various rules in the given universe of discourse. It has already been finalized that there are 18 rules for R744/R290 refrigerant mixture to predict the outlet temperature of refrigerant mixture at evaporator outlet depending upon the input parameters; concentration of CO_2 (x), temperature of refrigerant mixture at evaporator inlet (Tei) and pressure of refrigerant mixture (Pei), for MISO fuzzy model. These rules were implemented in MATLAB environment using Mamdani-type of fuzzy inference system in fuzzy logic toolbox. Control surface given in Fig. 8 shows dependency of Teo on x and Tei and Fig.9 shows dependency of Teo on x and Pei for R744/R290 refrigerant mixture.

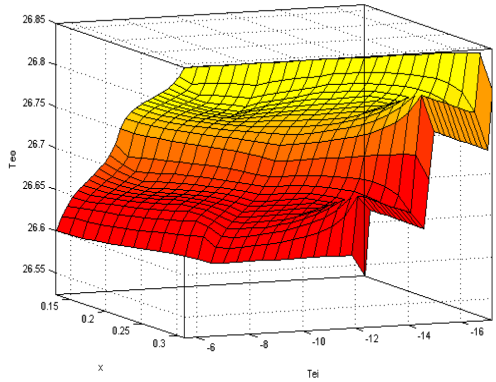

Fig.8 Control surface of fuzzy model showing interdependency of Teo on x and Tei

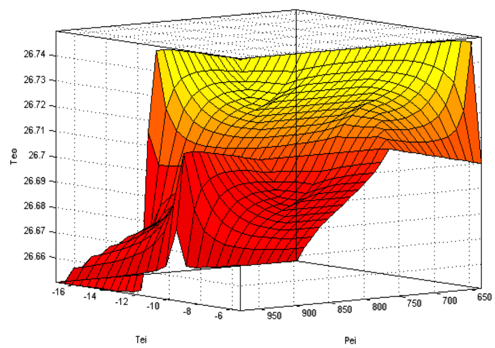

Fig.9 Control surface of fuzzy model showing interdependency of Teo on Tei and Pei

Results predicted from this fuzzy model of evaporator in autocascade refrigeration system have been compared with the experimental results for its validation in the following sections.

4. Results and discussions

Fig. 10(a), (b) and (c) gives the comparison of the predicted refrigerant mixture temperature Teo using developed fuzzy model and reported experimental.

Fig. 10(a) shows the plot between outlet refrigerant mixture temperature (Teo) and CO_2 concentration, 10(b) shows the plot between outlet refrigerant mixture temperature (Teo) and inlet temperature of refrigerant mixture (Tei) and 10(c) outlet refrigerant mixture temperature (Teo) and pressure of refrigerant mixture for refrigerant mixture of R744/R290.

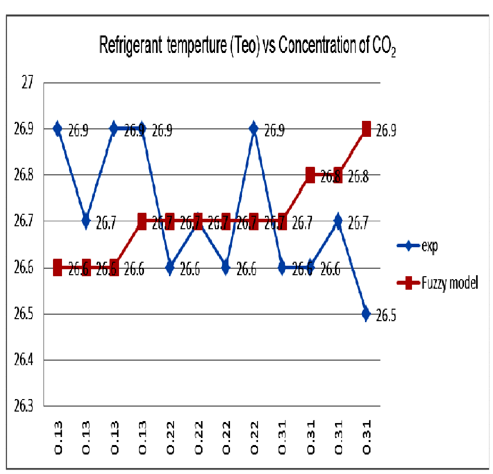

Fig. 10 (a) outlet refrigerant mixture temperature vs. concentration of CO_2

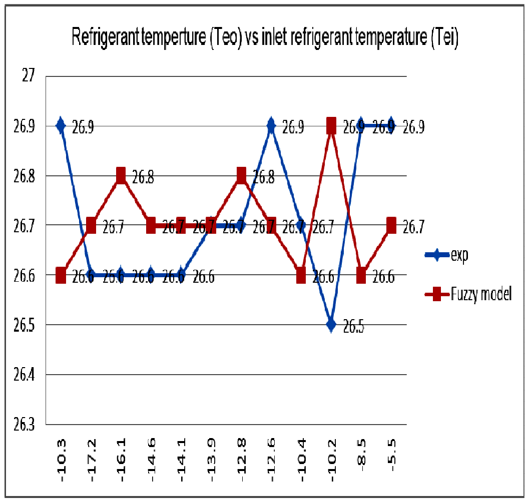

Fig. 10 (b) outlet refrigerant mixture temperature vs. inlet refrigerant mixture temperature

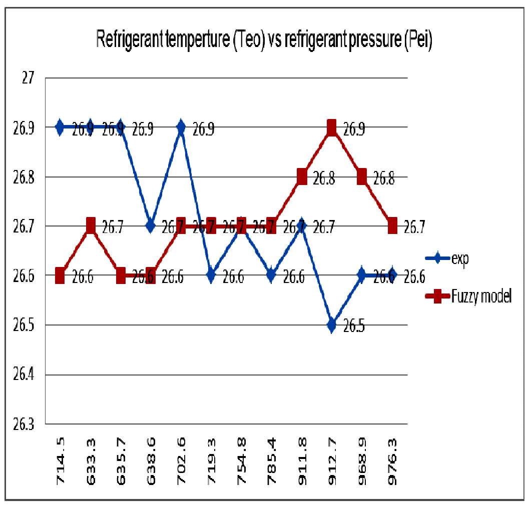

Fig. 10 (c) outlet refrigerant mixture temperature vs. pressure of refrigerant

Table 1.

Number of degrees of freedom	12-1=11
Calculated values of χ^2	0.000662218
Tabulated values of χ^2 at 0.1% level of significance	56.893

Out of the various outputs generated by fuzzy model, only one data point crosses the individual error of mere then 2% (1.5%). The total average error is 0.681%. In the present study total number of data points involved was 12. The system gave an overall 98% accuracy. Thus it can be conducted that there is a close relation between the experimental and simulated results to obtain the refrigerant mixture temperature at evaporator outlet.

To check whether there is any significant difference experimental and theoretical values of fuzzy model; χ^2-test has been used. This test is used for the test of goodness of fit, comparison of a number of frequency distribution and finding association and relationship between attributes. The calculated values of χ^2, tabulated values of χ^2 and degrees of freedom are listed in Table 1. Since the calculated values of χ^2-test is much less than the tabulated values of χ^2 at 0.1% level of significance, there is no significant difference between the outlet temperature of refrigerant mixture at evaporator outlet values generated by fuzzy model and experimental values. Hence the probability of generating values of refrigerant mixture temperature at evaporator outlet by fuzzy model is 99%.

5. Conclusion

1. This paper has set out to apply the fuzzy logic to predict the refrigerant mixture temperature at evaporator outlet using R744/R290 mixture. In this paper, MISO fuzzy model is developed using ANFIS and validated with experimental results for given conditions. It has been found that results generated by the designed fuzzy model are close to the experimental results with 98% accuracy.

2. After investigating the significance of developed model, it has been concluded that the probability of the model to predict accurate results is 99% as validated by the application of χ^2-test. With this much accuracy, model can be used by the practicing engineer who would like to get quick answers for on-line intelligent control and/or optimization.

3. Fuzzy logic system was found to be very flexible and easy to comprehend and hence can act as an alternative to the conventional modeling techniques. Present study supports that fuzzy logic technique can be introduced as a viable alternative to carry out analysis without conducting actual experiments. Fuzzy logic allowed the modeling and on-line control problem to be treated simultaneously.

In this paper, we design MISO fuzzy model for liquid desiccant based air dehumidification system**.** The result of fuzzy model has very nice features. The advantage of this fuzzy model is that we can take a parametric form for highly non- linear process. So, it can analysis the model for robustness view point in frequency domain. Especially, the proposed type of identifier can cover the unmodelled dynamics which can be generated by nonlinearity in self-tuning control. However, remaining problem is that we should find the efficient clustering method even if measuring the set of input and output cannot sufficiently represent the all of input and output space.

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