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ABSTRACT

Ejectors have found its application in improving the performance of carbon dioxide refrigeration systems over the last three decades. As the cycle complexity increases with the addition of an ejector, it is imperative to design the ejector cycle after thorough system analysis. The system model requires accurate heat exchanger models, and therefore, detailed Finite Volume (FV) models are needed. Though the FV heat exchanger models are accurate, they can be computationally expensive which hampers an extensive component analysis during the design phase. In this study, a computationally efficient Artificial Neural Network (ANN) evaporator model is developed from the wide range of experimental data of a given evaporator, operated in a standard ejector cycle. Usually, several number of temporal data points are collected for a single steady state data point. Though, the steady state data has less uncertainty than the temporal data, it is difficult and time consuming to collect large number of steady-state performance data points. This limits the number of neurons in the ANN, as the model run into an overfitting problem. In this study, the ANN evaporator model is developed using both the steady state (331 data points) and the temporal data (28,853 data points). The ANN model is developed after optimizing the neural network topology while using different activation functions and backpropagation techniques. The study finds that the ANN based on temporal data does not show any improvement over ANN based on steady state data. The ANN model with 2 layers (4 neurons in the first layer, and 16 neurons in the second layer) is found to have the minimum residual. The ANN model is trained using Bayesian Regularization backpropagation technique with symmetric sigmoid as the activation function. The ANN model predicts 99.7% of the data points, whereas the FV model with 100 elements, predicts 91.2% of the data points within $\pm$10% accuracy for the capacity when compared with the experimental data. The ANN model takes around 15milliseconds, whereas FV model with 10 elements, takes around 12-19 seconds to compute evaporator performance. Later, both the ANN and the FV evaporator models are used in a standard ejector cycle system model. The system model with FV (100 elements) predicts 79% of the data points, whereas the system with ANN evaporator model predicts 100% of the data points within $\pm$10% accuracy. The system using ANN model is found to be 139 times faster than the FV (10 elements) based system model. This shows that the developed ANN model can be useful in conducting an extensive component selection analysis as it is not only computationally fast, but also accurate. The applicability of the technique extends to other refrigerant systems as well.

1. INTRODUCTION

Ejectors, as work recovery device, have been widely studied for improving the performance of carbon dioxide refrigeration systems (Elbel and Hrnjak, 2008). The research has also found that the ejectors can also improve the performance of other low and medium pressure refrigerant systems like R1234yf (Lawrence and Elbel, 2014) and R410A (Lawrence and Elbel, 2016). However, with the addition of ejector, the complexity of the system increases as compared to the conventional vapor compression system. This makes the design and control of an ejector system a challenging task. It is, therefore, important to develop detailed ejector system models that allow system designers to carry out thorough component selection analysis in which different combinations and cycle architectures can be evaluated numerically with high level of confidence (Haider and Elbel, 2021b).

The heat exchangers performance prediction accuracy is important in determining the overall prediction accuracy of the cycle performance. There are different approaches to the heat exchanger modeling. One of the basic approaches is the thermodynamic state analysis in which only the inlet and outlet conditions of the refrigerant are considered. Similarly, fixed UA values are considered for modeling heat exchangers that include the effects of heat transfer fluid conditions. The highest fidelity models available are Finite Volume (FV) models that discretize the heat exchangers into small discrete elements and solve mass, energy, and momentum balances within each volume. The FV models can give insights into the heat exchanger design. They are accurate; however, they are computationally expensive.

Other components of the vapor compression cycle are usually modeled using computationally efficient methods. For example, variable speed compressors can be modeled using ten coefficient polynomials (Haider and Elbel, 2020), and recently ejectors have been modeled using performance map (Haider and Elbel, 2021a). In this line of argument, heat exchangers for system analysis can also be modeled using computationally efficient approaches. The Artificial Neural Network (ANN) based heat exchangers model have been studied extensively (Mohanraj et al., 2015). However, their utility in component analysis of an ejector system has not been studied so far in the literature.

An additional inquiry is to figure out if ANN based on temporal data can give better prediction over steady state data. During experiments, several number of temporal data points are collected for a single steady state data point. Though, the steady state data has less uncertainty than the temporal data, it is difficult and time consuming to collect large number of steady-state performance data points. Less number of steady state data points mean the number of neurons in NN remain limited, else the model can run into an overfitting problem. One solution to this problem could be use of the temporal data for training the ANN. Therefore, ANN based on both steady state and temporal data are developed and analyzed.

In this study, only evaporator is considered among other heat exchangers. It is modeled using FV and ANN. The two models are compared for accuracy and computational cost both at component and system level. The study is divided into three sections. The first section introduces the experimental facility used to collect the evaporator performance data. The second section introduces the modeling methodologies and different procedures that are adopted. The third section discusses the results while comparing FV and ANN evaporator models.

2. EXPERIMENTAL FACILITY

The experiments for measuring evaporator capacity are conducted using an air conditioning system working on a transcritical CO_2 standard ejector cycle with internal heat exchanger (IHX). The detailed system layout and description can be found in Lawrence and Elbel (2016). The microchannel gas cooler and the evaporator are housed inside two separate closed loop wind tunnels. In the evaporator side wind tunnel, an electric heater is installed for controlling inlet air temperature, and thus, the cooling capacity of the evaporator. Similarly, the gas cooler wind tunnel is equipped with a chilled water heat exchanger which helps in controlling inlet air temperature and heat transfer rate. The compressor used in the study is a variable speed radial piston compressor. The IHX is a microchannel heat exchanger with a high and low-pressure line.

The detailed uncertainties in temperature, pressure and mass flow rate sensors installed in the experimental facility, along with the geometry specification of the evaporator can be found in Zhu et al. (2018). A total of 331 steady state data points are available for the evaporator. Similarly, a total of 28,853 data points is available for temporal data. **Table 1** shows the input and output variables used in the study for evaporator model with their minimum and maximum values. The data is normalized using min-max approach. The simulations/training in the study are conducted on a desktop computer with Intel® Core™ i7-2600 CPU @3.4GHz and 16GB installed memory.

3. MODELING METHODOLOGY

3.1 Finite Volume (FV) evaporator model

The microchannel evaporator with four slabs has been modeled by discretizing it into finite volumes. It is assumed that there is no temperature gradient due to the conduction resistance. The flow inside the evaporator is counter-crossflow with dry conditions on the air side as shown in the **Figure 1**. A hybrid scheme is used in solving evaporator, in which air side temperatures are updated after each iteration, whereas the energy and the momentum balances are solved simultaneously in each finite volume as the solution is marched from one finite volume to the other.

MATLAB's lsqnonlin function available in Optimization Toolbox is used to solve each finite volume using four variables, namely, P_{ro}, h_{ro}, T_{ao}, and T_f. The refrigerant and air-side heat transfer coefficients are calculated using the empirical correlations specified in **Table 2**. The pressure drop is only considered on the refrigerant side, while fixed mass flow rate is assumed for the air side flow. The iterations are repeated until the change in predicted capacity between two consecutive iterations are less than the set tolerance for all the finite volumes. It is important to note that in finite volume model, the pressure drop predictions are usually not good, as significant part of pressure drop is expected to occur in headers, which have not been modelled. As a results, fixed scaling factor is used to improve the pressure drop predictions.

Table 1 Input and output variables used for evaporator models with minimum maximum values, and uncertainty

Variable	Unit	Variable type	max	min	Uncertainty
T_{ai}	ºC	Input	27.5	26.5	± 0.5
$\dot{m}_{ai}$	kg/s	Input	0.427	0.251	± 0.005
RH_{ai}	-	Input	0.465	0.109	± 0.025
T_{ri}	ºC	Input	17.1	0.1	± 0.5
$\dot{m}_r$	kg/s	Input	0.049	0.0086	$\pm 0.2\%$
X_{ri}	-	Input	0.068	0	0.002
$\dot{Q}_e$	kW	Output	7.419	1.997	$\pm 6\%$
ΔP_{er}	kPa	Output	86.7	9.7	± 0.9

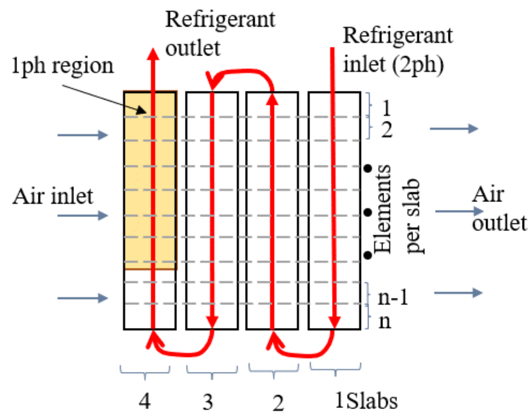


Figure 1 Schematics of microchannel evaporator in a counter-crossflow conditions

Table 2 Empirical correlations used for modeling evaporator

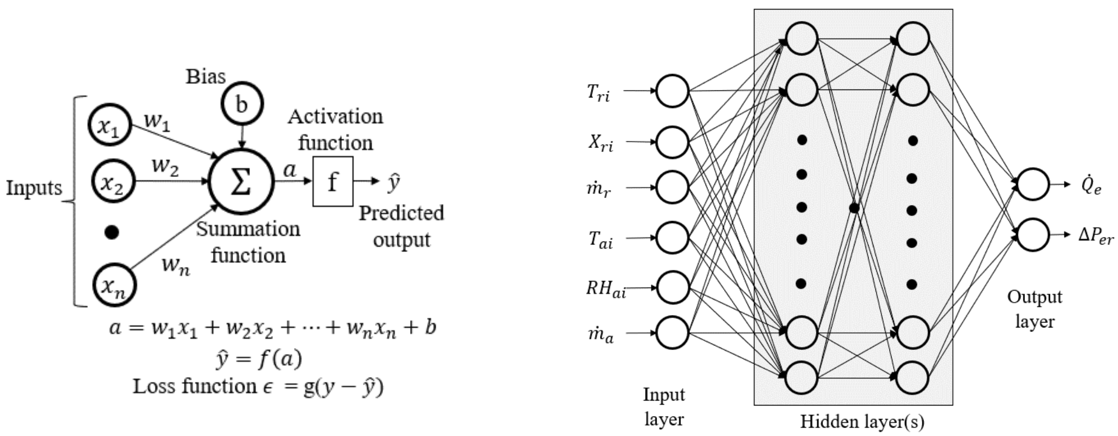
	Parameter	Reference
Pressure drop	1ph refrigerant ΔP	Churchill (1977)
	2ph refrigerant ΔP	Friedel (1979)
HTC	1ph refrigerant HTC	Gnielinski (1976)
	2ph refrigerant HTC	Shah (2017)
	Air-side HTC	Park and Jacobi (2009)

3.2 Artificial Neural Network (ANN) evaporator model

Key concepts related to ANN are briefly introduced here. These include single perceptron ANN, multi-layer feedforward ANN, activation function, loss function, training of the ANN, topology optimization of ANN etc. A more detailed description of ANN can be found here (Priddy and Keller, 2005).

3.2.1 Artificial Neural Network (ANN)

Perceptron is the basic building block of ANN. **Figure 2**(a) shows a single perceptron Artificial Neural Network with multiple inputs and a single output. The perceptron is combination of summation function that sums the weighted inputs with a bias value, and an activation function that determines the contribution of a particular perceptron to the output value. The ANN also has a loss/error function which is a function that relates measured output value and the predicted output value. The training of ANN with backpropagation technique is the process of reducing the loss function by adjusting the weights NN using gradient methods. The method calculates the gradient of the loss function with respect to the NN's weight. The gradient is calculated backwards through the network, i.e., the gradient of the last hidden layer's weights is calculated first, and the gradients of the first layer's weight is calculated last. **Figure 2**(b) shows a multi-layer feedforward neural network (MLFNN) comprising of multiple perceptron arranged in multiple hidden layers. In developing evaporator model, six input and two output variables are used. These variables are first normalized using min-max method.



(a) (b)

Figure 2 Artificial Neural Network (a) single perceptron ANN (b) multiple perceptron ANN

3.2.2 Activation function

The summation function is a linear combination of weights, inputs, and biases. The activation function adds non-linearity in the ANN. The activation plays important role in determining the accuracy and training time for the ANN. In this study, three different activation functions are used after carrying out analysis which is presented in section 4.2. These activation functions are symmetric sigmoid (tansig, ts), logarithmic sigmoid (logsig, ls), and radial basis (radbas, rb). These functions are shown in **Figure 3**.

3.2.3 Training function:

MATLAB offers several backpropagation techniques for training feedforward neural network. After conducting simulations using single layer ANN, presented in the section 4.2, two of the training functions are shortlisted for training rest of the NNs. These training functions are Levenberg-Marquardt (LM) and Bayesian Regularization (BR) algorithms. LM updates the next set of weight using the Equation (1)

$$x_{k+1} = x_k - (J^TJ + \mu I)^{-1}\mathrm{J}\epsilon \tag{1}$$

where, ϵ is the loss function, J is the Jacobian matrix, μ is the factor that allows LM to switch between Gradient Descent (GD) method and Newton method. When μ is large, LM acts as GD, whereas if it is small then LM acts as Newton method. The Newton method offers fast convergence as it uses Hessian. However, the Hessian matrix is not calculated as it can be computationally expensive, rather it is estimated through Jacobian. In BR, the loss function ϵ not only contains the error term from the output variables ϵ_y, but also a term that sums the weights ϵ_w as given by Equation (2).

$$\epsilon = \epsilon_y + \alpha\epsilon_w \tag{2}$$

α is usually a small number. In this study, $\alpha = 0.005$ is considered. BR performs better at avoiding over-fitting. The loss function for the output variables for the training is chosen to be mean square error.

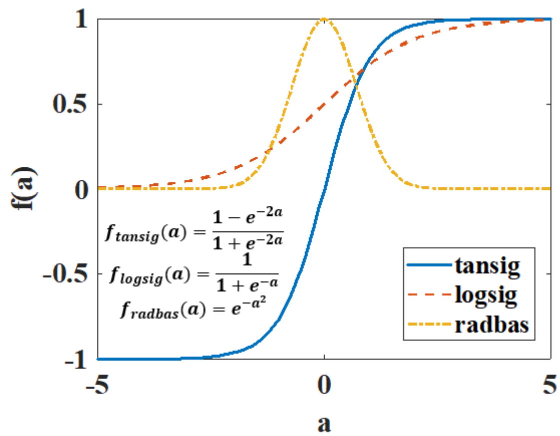


Figure 3 Three activation functions used in the study

3.2.4 Shortlisting training and activation functions

MATLAB has several built-in activation and training functions. It is not straight-forward to answer which of these functions will be appropriate for the ANN evaporator model. The analysis is limited to only single layer ANN evaporator model in shortlisting training and activation functions. A total combination of 195 while considering thirteen training functions and fifteen activation functions, are tested with 4,8,12,16 neurons. The steady state experimental data is first normalized. The number of neurons is selected such that the number of weights and biases, N_{wb} of the NN remains less than half the number of sample data points. This is done to avoid over-fitting. The N_{wb} is a function of number of layers, number of neurons in each layer, number of inputs and outputs. After generating a NN with set number of neurons, multiple trials are run for training and performance prediction. This is done because weights and biases are initialized randomly. Also, 70% of the data is randomly selected for training, while 15% is used for cross-validation, and 15% as test data. Multiple trials help in getting a statistical data. The prediction performance is evaluated by summing the absolute error (sae) terms for all the data points. The cumulative normalized error sums the error (sae) from all the trials. The combination of training and activation functions with minimum mean cumulative normalized error from all the number of neurons is shortlisted for further analysis.

3.2.5 Topology optimization

Topology optimization is to find the number of layers and number of neurons of the ANN that gives the best performance prediction. A brute force method is adopted where all the possible combinations are tested. The NN with number of layers 1, 2, 3, 4 and 5 are evaluated. The number of neurons in each layer can be 4, 8, 12, and 16. The number of layers and neurons in each layer are selected such that the N_{wb} is lower than the half of the number of the steady state data points. NN training is carried out by considering both steady state and temporal data. However, performance prediction is done considering steady state data points only. The NN with same number of neurons are used for training with steady state and temporal data.

3.3 System model

A system model for a standard ejector cycle with internal heat exchanger (IHX) has been developed in MATLAB for predicting system performance using different combinations of the system components. Fluid properties are obtained using CoolProp (Bell et al., 2014). The ejector is modeled using recently developed ejector performance map (Haider and Elbel, 2021a). The compressor is modeled using ten coefficient polynomials for each of the three efficiencies (Haider and Elbel, 2020). The gas cooler and IHX is modeled by heat exchanger effectiveness obtained from experimental data. It is assumed that there is not pressure drop inside gas cooler, IHX, and the separator. The quality at the vapor port of the separator is set from the experimental data. The same code is used to switch between FV and ANN evaporator model for fair comparison in computational speed and accuracy.

The MATLAB function lsqnonlin with trust-region-reflective algorithm is used for solving the set of nonlinear equations. A total of four variables P_{cpro}, P_{cpri}, P_{eri} and P_{ero} are used for finding the solution of the ejector system. The model does not fix the high side pressure, rather it takes the pressure drop across the expansion valve before the motive nozzle as an input. This reflects the control of high side flow more realistically than fixing the high side pressure. For incorporating this, an additional equation is introduced that related the ejector motive inlet pressure with suction inlet pressure as function of motive nozzle characteristics and operating conditions. It is given by Equation (3)

$$P_{mn} - P_{sn} = C_v \frac{\dot{m}_{mn}^2}{\rho_{mn}} + C_0 \tag{3}$$

where, C_v and C_0 are coefficients estimated by using experimental data for the fixed geometry ejector.

4. RESULTS AND DISCUSSION

4.1 Accuracy and computational speed of Finite Volume evaporator model

The FV model is initially developed using CoolProp's MATLAB wrapper for calling refrigerant properties (Haider and Elbel, 2021b). The MATLAB's profiler feature shows that more than 60% of the computational time is spend in calling CoolProp wrapper. As a result, in the updated FV evaporator model, the fluid properties are called by interpolating fluid property tables which are populated using CoolProp wrapper. The FV model becomes 10-15 times faster using tabular fluid properties.

The FV model is simulated for all the 331 steady state data points. **Figure 4** shows the prediction accuracy for the capacity and the pressure drop of the FV model using $N_{elements} = 10$. **Table 3** compares the FV model for two different $N_{elements}$, i.e., 10 and 100. The FV model with 100 elements is almost six times more computationally expensive than the model with 10 elements. The accuracy improvement from 10 elements to 100 elements is appreciable, but not significant. For example, with 10 elements, FV model can predict capacity for the 84.3% of the data points within 10% accuracy, whereas with 100 elements it is 91.2%. There is a clear tradeoff between the accuracy and computational cost. For practical reasons, small number of elements are desirable. The accuracy of the FV model may be improved by using tuning factors.

4.2 Shortlisting activation and training functions

Figure 5 shows the cumulative normalized residual for all the 195 combinations of the training and the activation functions using only single layer ANN. The reported residual is the mean value for all the NNs evaluated for the given combination of training and activation function. The Box 1 contains NN trained by BR, whereas Box 2 contains NN trained by LM. These two training functions are shortlisted for further analysis as the NN trained by these functions has relatively smaller mean cumulative normalized residual. In general, the training time and accuracy using BR as training function is more than that of LM. Similarly, the activation functions against the three lowest mean cumulative normalized residual are shortlisted for further analysis. These include symmetric sigmoid, logarithmic sigmoid, and radial basis function. The rest of the analysis considers the six combinations from these two training and three activation functions.

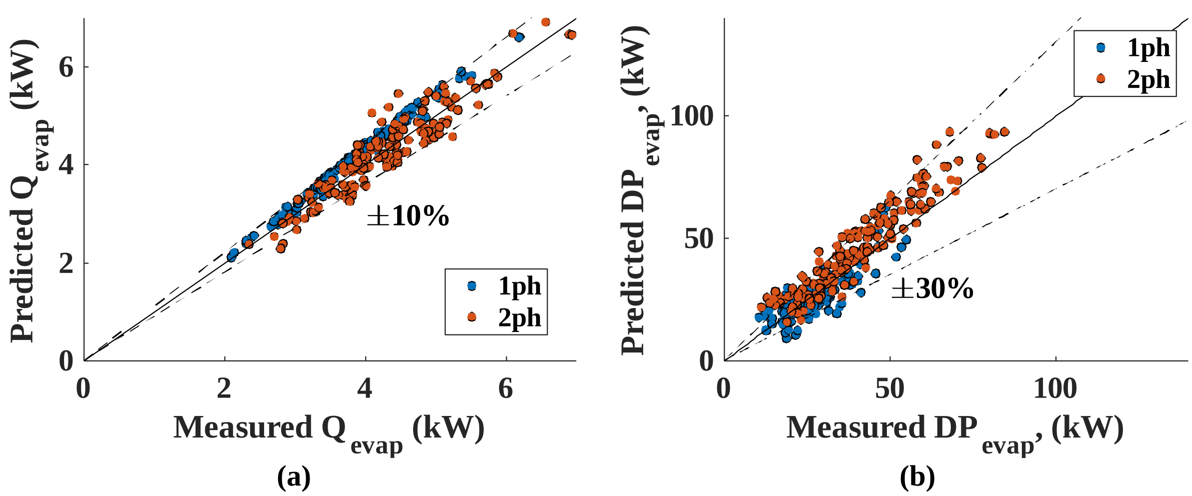


Figure 4 Prediction of the FV model (a) capacity (b) pressure drop

Table 3 Computational speed and prediction accuracy of FV model with two different number of elements

$N_{elements}$	$t_{comp,avg}$ (s)			Accuracy					
	1ph	2ph	% Data	±5%	±10%	±15%	±20%	±25%	±30%
10	19.1	12	Q_e	27.8	84.3	98.2	100	100	100
			ΔP_{er}	20.9	42	60.4	75.5	82.8	87.3
100	129.4	65.3	Q_e	32.3	91.2	98.2	100	100	100
			ΔP_{er}	21.3	42.5	60.6	75.5	82.8	87.3

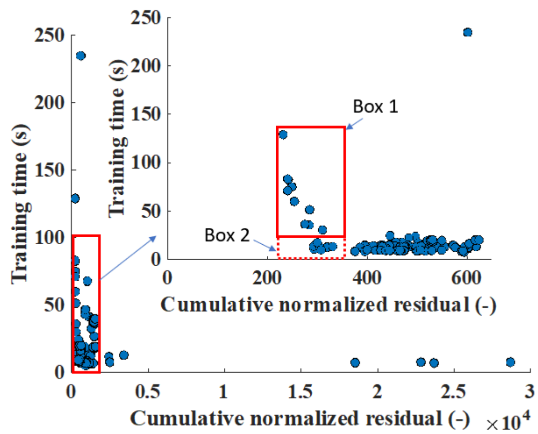


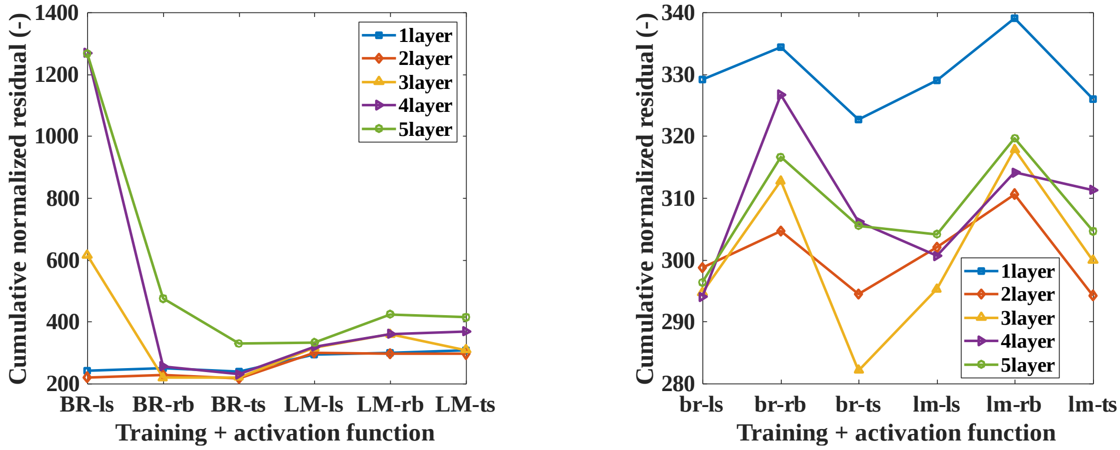
Figure 5 Cumulative normalized residual from single layer ANN models

4.3 Topology optimization for the ANN evaporator model

The six combinations of training and activation functions are used to evaluate several NN with different number of layers and number of neurons in each one of them. **Figure 6** shows the comparison of the cumulative normalized residual using both the steady state and temporal data points. The reported residual is the minimum residual obtained by a certain NN against the given combination of training and activation function. The NN with steady state data have relatively large variation in residuals as compared to the NN with the temporal data, however, the NN with steady state data gives the minimum cumulative normalized residual. The NN with minimum residual has 2 layers with 4 neurons in the first layer and 16 layers in the second layer. It has BR as training function and tansig as the activation function. It can be observed that the temporal data based NN does not have higher prediction accuracy than the steady state data based NN, but it appears to be less sensitive to the choice of neurons in the NN. The temporal data may be helpful if the number of steady state data points are less. Moreover, it can be observed in both steady state and temporal data that typically the residual decreases as number of layers are increased from single layer. However, the residual increases again when the number of layers exceed the third layer.

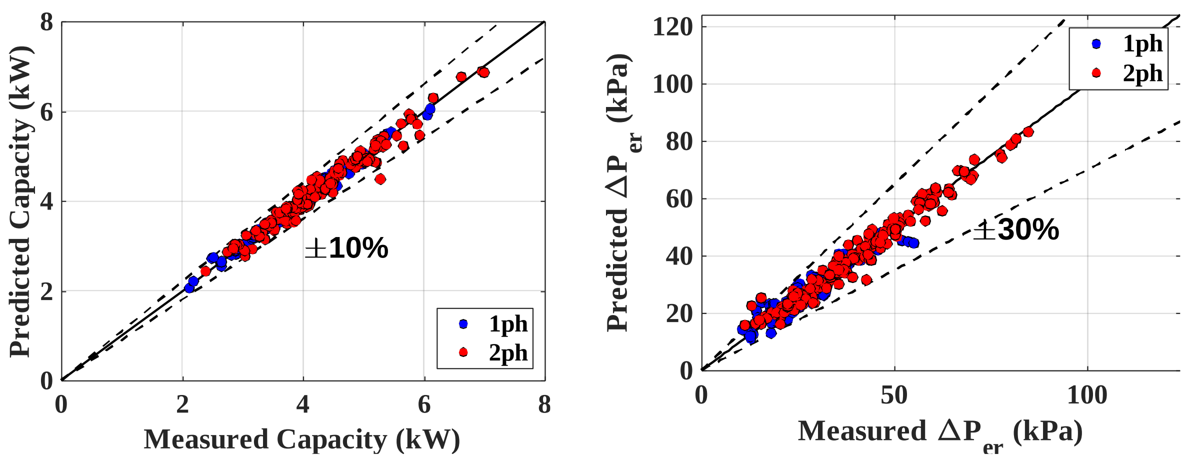
4.4 Accuracy and computational speed of ANN evaporator model

The selected ANN is trained ten times and the NN in the trials that gives the minimum residual is selected for reporting the final result. **Figure 7** shows the prediction accuracy of ANN evaporator model. **Table 4** gives the computational speed and prediction accuracy in terms of the percentage data. The ANN has relatively significant training time, but has neglible computational cost which matters in the system level simulations. The prediction accuracy of ANN is better than the FV i.e, the FV model could predict 91.7% (100 elements) of the data with 10% accuracy, whereas ANN can predict 99.7% of the data with the same accuracy.



(a) (b)

Figure 6 Residuals for different layers against six combinations of training and activation functions (a) steady state data (b) temporal data



(a) (b)

Figure 7 Prediction accuracy of ANN evaporator model (a) capacity (b) pressure drop

Table 4 Computational speed and prediction accuracy of ANN evaporator model

Time (s)			Accuracy					
Training	Comp.	% Data	5%	10%	15%	20%	25%	30%
105	0.014	Q_e	92%	99.7%	99.7%	100%	100%	100%
		ΔP_{er}	51.4%	76.4%	88.2%	95.2%	96.4%	97.6%

4.5 System level comparisons for accuracy and computational speed

The data for system level validation contains 24 data points. The data points have both single and two-phase evaporator exit conditions. The ambient temperature is in the range of 35-45ºC, while compressor speed is in the range of 900-1500min^{-1}. The suction inlet quality for IHX is not considered to be one, rather it is considered as one of the parameters, taken from experimental data after doing energy balance across IHX, for each of the simulation point. **Table 4** compares the accuracy and computational cost of the three system models: the two using the FV evaporator model with 10 and 100 elements respectively, and the third using the ANN evaporator model. It can be observed that not only ANN model gives accurate prediction, but also the computational time is significantly less. The system model using ANN evaporator model is 139 times faster the FV model with 10 elements.

Table 5 Computational cost and accuracy of three ejector system models

	FV 10elements	**FV 100elements**	**ANN**
% Data within $\pm$10% COP	66%	79%	100%
$t_{avg}(s)$	598.4	5684	4.3
$t_{avg}/t_{avg,ANN}(-)$	139	1321	1

5. CONCLUSIONS

This study has explored the ANN evaporator model as computationally efficient, yet accurate modeling approach which can be utilized in ejector system model analysis. The study has developed two types of evaporator models: the first one is the detailed FV model, and the second is the ANN model. The ANN model has been developed using both the steady state and the temporal data, however, it has been found that the ANN using steady state data gives better performance prediction. The selected ANN model has two layers (4 neuron in the first layer, and 16 neurons in the second layer) with Bayesian Regularization backpropagation as training function and symmetric sigmoid as the activation function. Both the FV and the ANN models are compared with 331 steady state data points. The ANN evaporator model is found to be more accurate than the FV model, i.e., it predicted 99.7% of the data within 10% accuracy compared to 91.2% for the FV model with 100 elements. Furthermore, a system model for an ejector system working on a standard ejector cycle is developed for comparing the prediction accuracy using these two different evaporator models. The ejector system with the ANN evaporator model was not only more accurate, but also 139 times faster than the FV model with 10 elements. This has proved that the ANN heat exchanger models can be useful tool in conducting thorough component system analysis for an ejector system design. This study is conducted for carbon dioxide system; however, it can also be applicable to other refrigerant systems.

NOMENCLATURE

BR	Bayesian Regularization	(-)
J	Jacobian	(-)
LM	Levenberg-Marquardt	(-)
$\dot{m}$	mass flow rate	(kg/s)
N	number of quantity	(-)
P	pressure	(kPa)
$\dot{Q}$	heat transfer rate	(kW)
RH	relative humidity	(-)
t	time	(s)
T	temperature	(°C)
x	normalized input variable vector	(-)
X	quality	(-)
y	normalized output	(-)
ϵ	loss function	(-)

Subscript

a	air
comp	computational
cp	compressor
e	evaporator
i	inlet
mn	motive nozzle
o	outlet
sn	suction nozzle
r	refrigerant
wb	refer to number of weights and biases in NN

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