DEVELOPMENT AND COMPARATIVE EVALUATION OF MACHINE LEARNING ALGORITHMS FOR PERFORMANCE APPROXIMATION OF AIR-TO-REFRIGERANT HEAT EXCHANGERS

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ABSTRACT

Tube-fin heat exchangers (TFHXs) are omnipresent within the air-conditioning and refrigeration industry. Computationally expensive, physics-based models and sometimes even simple lumped parameters models are conventionally used to conduct performance simulations, optimization, and design selection of such devices. But both these approaches have their challenges. In this research, a comparative evaluation of machine learning based regression techniques to predict the heat transfer and refrigerant pressure drop of TFHXs for different applications is conducted. Ridge Regression (RR), Support Vector Regression (SVR) and Artificial Neural Network (ANN) models are trained and analysed. Compared to studies from the literature, this research also includes multiple refrigerants, applications, and flow path configurations. Results show that the baseline full-domain SVR and ANN models predict more than 90% of the test dataset within a 20% error for 5 out of 6 applications. Subsequently, the potential of SVR and ANN models to deliver previously exhibited levels of prediction accuracy when trained on datasets consisting of fewer samples is examined. As a result, reduced-domain ANN and SVR models with training times that are 2 to 3 orders of magnitude lower than baseline models with little to no degradation in prediction accuracy are obtained. The trained ML models facilitate rapid exploration of the design space significantly reducing engineering time to arrive at near optimal designs.

1. INTRODUCTION

Heat exchanger (HX) design optimization and its subsequent integration into heat transfer systems is made possible through performance predictions. Reliable physics-based HX models such as Jiang et al. [1], are typically utilized to meet this requirement. These models demand detailed information pertaining to HX geometry, circuiting, and associated operating conditions. While such models are both accurate and precise, they suffer from computational intractability (Huang et al. [2]). To alleviate this shortcoming, machine learning (ML) based models have been satisfactorily adopted by several researchers – Diaz et al. [3], Wu et al. [4] to approximate HX performance. The ability of these black-box models to yield accurate predictions with minimal cost of computation at times overshadows their inability in explaining the underlying heat transfer phenomena. However, most machine learning models in the literature are essentially performance maps, i.e., they predict the performance of a given heat exchanger as a function of operating conditions.

Additionally, to keep up with the heating, ventilation, and air-conditioning industry's progression towards adopting lower-GWP refrigerants, consideration of a variety of refrigerants and a comprehensive set of geometry, flow circuitry and operating conditions must be incorporated into the ML models. A literature review indicates a lack of such inclusive models. To fill this void, three supervised ML algorithms – ridge regression (RR), support vector regression (SVR) and artificial neural network (ANN) are implemented to predict the heat load (Q) and refrigerant pressure drop (ΔP) of three different HXs. Further investigations are then conducted to check for variation in performance when resources available for model development are reduced. This is done to understand the cost associated with a model to deliver a certain degree of prediction accuracy. The remainder of this work is organised as follows: Section 2 describes the ML model-building methodology; Section 3 presents and discusses results pertaining to model performance and prediction behaviour; Conclusions are drawn in section 4.

2. MACHINE LEARNING MODEL-BUILDING METHODOLOGY

The model-building methodology is comprised of the following steps: Step 1 is the identification of the input domain for each HX and is shown in Tables 1 - 3. Step 2 involves sampling the design space for training and test datasets. The training dataset is sampled through a combination of full factorial and Latin Hypercube sampling (Simpson et al. [5], McKay et al. [6]) while the test dataset is randomly sampled within the design space. Step 3 involves generation of performance data corresponding to the design points sampled in step 2. This data generated using a finite volume physics-based model [1]. Step 4 comprises of an exploratory data analysis followed by data pre-processing. These steps are performed to investigate possible correlation between the input variables. In Step 5, optimal hyperparameter values for each model type are obtained using an iterative k-fold cross validation with k=5. Step-6 involves model training. This is followed by model testing where each model predicts Q and ΔP for each HX design from the test dataset. Finally, the performance of each model is expressed using the following metrics: Relative Mean Absolute Error (RMAE), Maximum Absolute Percentage Error (MAPE), percentage of designs predicted within ±20% of true values (β), Standard deviation of absolute errors (σ_{error}), Train time and Prediction time.

Table 1: Radiator input domain

Application	Model Inputs	Units	Range/Category
Radiator	Refrigerant	[-]	Water
Training data	Tubes per bank	EA	10-100
points = 167716	Tubes per bank per circuit (i.e., circuitry)	EA	1-4
Testing data	Tube banks	EA	1-4
points = 72000	Tube length	[m]	0.25-2
	Fins per inch	$inch^{-1}$	11-20
	Air velocity	ms^{-1}	0.5-3
	Refrigerant temperature	K	338.15-353.15
	Refrigerant mass flux	$kgm^{-2}s^{-1}$	200-800

Table 2: Condenser input domain

Application	Model Inputs	Units	Range/Category
Condenser	Refrigerant	[-]	R32, R410A, R454B
Training data	Tubes per bank	EA	10-100
points = 378511	Tubes per bank per circuit (i.e., circuitry)	EA	1-4
Testing data	Tube banks	EA	1-4
points = 142840	Tube length	[m]	0.25-2
	Fins per inch	$inch^{-1}$	11-20
	Air velocity	ms^{-1}	0.5-3
	Refrigerant dew point temperature	K	313.15-323.15
	Refrigerant inlet superheat	K	2-30
	Refrigerant mass flux	$kgm^{-2}s^{-1}$	300-1200

3. RESULTS AND DISCUSSIONS

3.1 Baseline Model Results

Verification plots for the baseline model predictions on the test dataset for the condenser heat load and refrigerant pressure drop are shown in Figs. 1 and 2 respectively. Baseline models are defined as those which have been trained using the entire training dataset available. Further displayed in the plots are values of the tuned hyperparameters. Since RR models fare poorly, the decision to develop more sophisticated ML models to predict HX performance is justified. In the interest of space, baseline results pertaining to each HX is communicated in tabular form in tables 4-9.

Table 3: Evaporator input domain

Application	Model Inputs	Units	Range/Category
Evaporator	Refrigerant	[-]	R32,410A, R454B
Training data	Tubes per bank	EA	10-50
points = 210008	Tubes per bank per circuit (i.e., circuitry)	EA	4-20
Testing data	Tube banks	EA	1-8
points = 74870	Tube length	[m]	0.25-2
	Fins per inch	$inch^{-1}$	11-20
	Air velocity	ms^{-1}	0.5-3
	Refrigerant bubble point temperature	K	278.15-288.15
	Refrigerant inlet quality	%	10-30
	Refrigerant mass flux	$kgm^{-2}s^{-1}$	300-1200

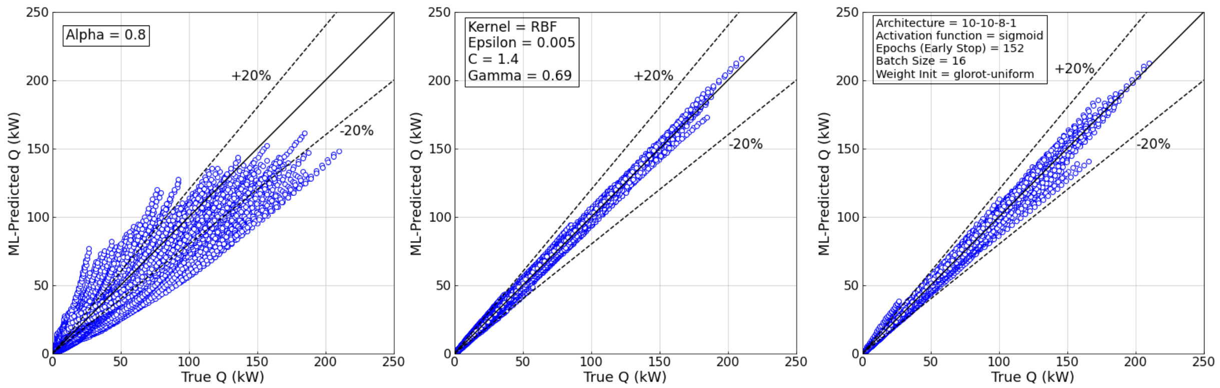

Figure 1: Verification plot for condenser heat load. Left: RR, centre: SVR, right: ANN

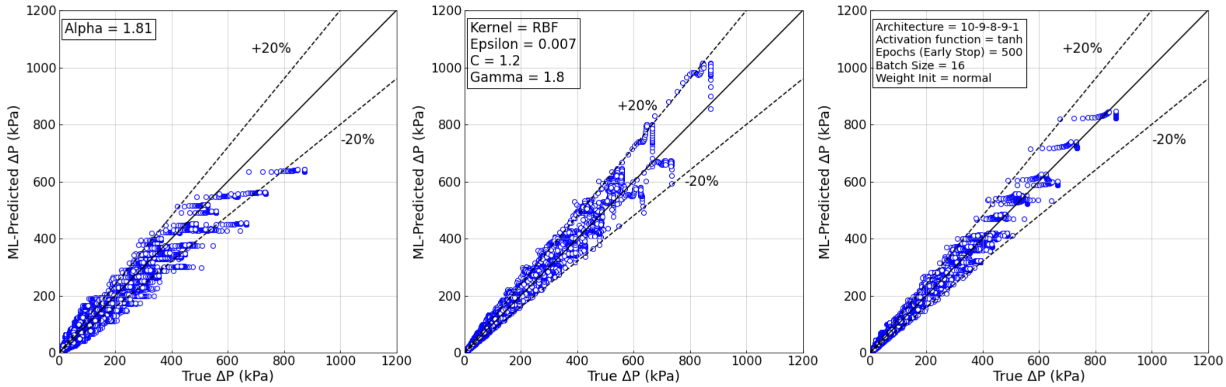

Figure 2: Verification plot for condenser pressure drop. Left: RR, centre: SVR, right: ANN

Table 4: Radiator baseline ML model comparison

Predicted Parameter	Metric	RR	SVR	ANN
Heat load	RMAE [%]	23.4	2.6	4.2
	MAPE [%]	412.6	22.4	59.1
	σ_{error}	58.5	15.8	247.8
	β	52.1	99.9	99.2
	Training time [s]	1.3	4355	1041
	Prediction time [s]	0.002	49.6	1.3
Refrigerant	RMAE [%]	18.4	3.7	1.8
pressure drop	MAPE [%]	131.1	27	25.5
	σ_{error}	1.4	4.1	13.1

	β	60.3	99.9	99.9
	Training time [s]	1.1	5604	289
	Prediction time [s]	0.001	44.4	1.3

Table 5: Condenser baseline ML model comparison

Predicted Parameter	Metric	RR	SVR	ANN
Heat load	RMAE [%]	22.1	3.1	2.7
	MAPE [%]	336.1	29.3	56.2
	σ_{error}	18.6	16.2	104.4
	β	50.2	99.7	99.9
	Training time [s]	4.5	53571	1812
	Prediction time [s]	0.005	152	1.6
Refrigerant pressure drop	RMAE [%]	19.9	6.4	4.5
	MAPE [%]	187.8	58.9	119.4
	σ_{error}	47.6	154.6	87.7
	β	55.5	96.6	98.9
	Training time [s]	2.9	68087	6163
	Prediction time [s]	0.007	513	1.5

Table 6: Evaporator baseline ML model comparison

Predicted Parameter	Metric	RR	SVR	ANN
Heat load	RMAE [%]	33.4	7.8	6.9
	MAPE [%]	335.1	159.8	67.4
	σ_{error}	19.1	23	80.7
	β	30.8	92.4	94.4
	Training time [s]	2.1	65898	946.2
	Prediction time [s]	0.003	174	0.4
Refrigerant pressure drop	RMAE [%]	44	11	8
	MAPE [%]	980.6	284	124.2
	σ_{error}	475	726	784
	β	34.9	83.1	91.4
	Training time [s]	1.6	29630	2564
	Prediction time [s]	0.004	137	1.5

3.2 Physical Verification of ML Models

The ability of the trained ML baseline models to capture heat transfer and refrigerant ΔP trends as physics-based models do is carried out to deem the appropriateness of ML models in not only predicting accurately a set of points, but in correctly predicting heat transfer and refrigerant pressure drop trends one would expect to observe during HX operation.

Parametric Analyses

A sample radiator design as shown within the input domain shown in table 2 is considered. Parametric analyses are conducted to investigate the impact of tube length on heat load and refrigerant ΔP respectively at different refrigerant mass flux values (G). Figs. 3 and 4 show the variation in heat load and refrigerant ΔP as calculated by a physics-based HX model [1] and ML models (SVR and ANN) for various tube lengths. While there does exist a clear deviation in prediction it is evident that both ML models predict physical trends of heat load and refrigerant ΔP in accordance with the physics-based HX model.

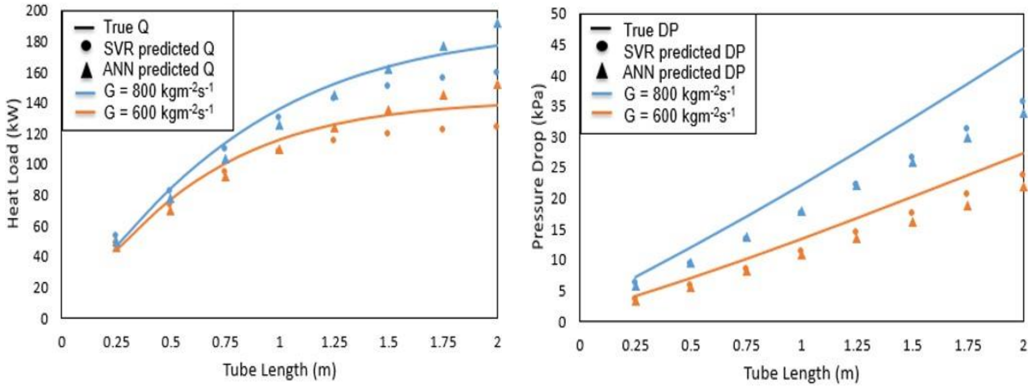

Figure 3: Radiator parametric analyses. Left: heat load, right: refrigerant pressure drop

3.3 Impact of Training Dataset Size

Shown in Figs. 4 and 5 are the performance trends in terms of prediction accuracy and training time of the SVR and ANN for condenser heat load and refrigerant pressure drop as a function of the percentage of the overall training dataset size (378511) used for ML model building. This percentage is represented by α. The absence of a significant increase in performance with an increase in training dataset size across both the models is noticed. Another key point of observation is the drastic increase in engineering time for the ML building procedure as the value of α increases. This informs us that for the current study, an increase in dataset size is not necessary to achieve better model performance.

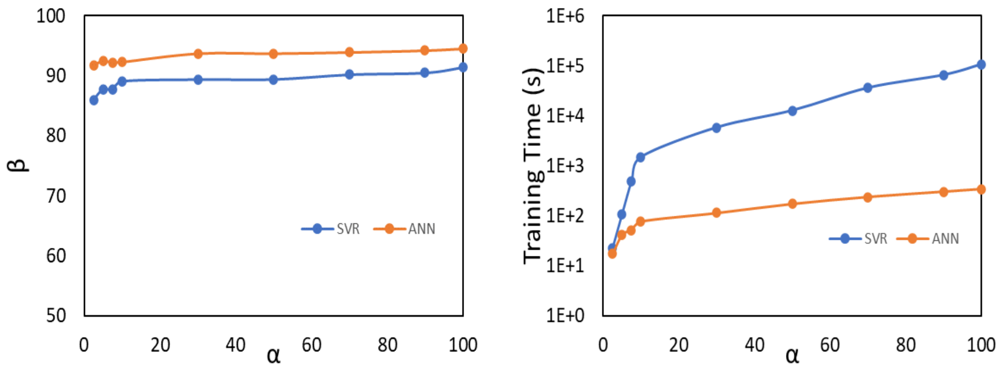

Figure 4: Dataset size impact on condenser heat load prediction

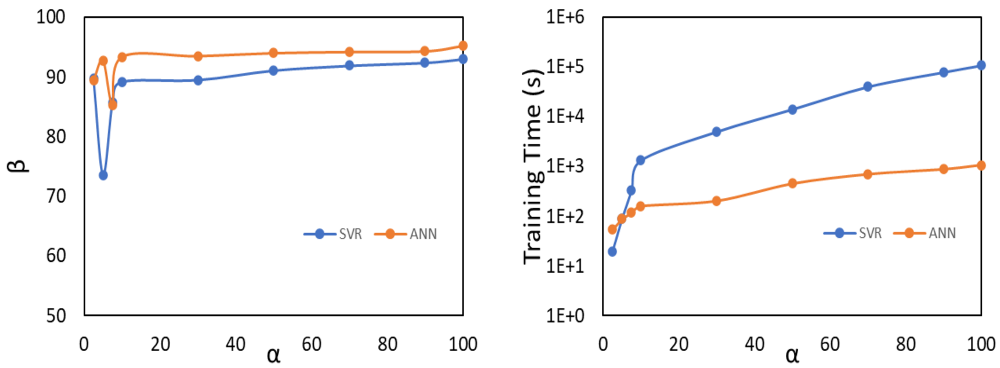

Figure 5: Dataset size impact on condenser refrigerant pressure drop prediction

4. CONCLUSIONS

This study develops and compares three machine learning models to approximate HX performance as a function of geometry and operating conditions. They were then verified against results from a validated finite-volume heat exchanger model [1]. It is found that support vector regression and artificial neural network models predict greater than 90% of the test dataset within ± 20% for 5 out of 6 heat exchanger application cases. Additionally, the machine learning models developed can predict heat exchanger operational trends satisfactorily. Marginal degradation in performance is observed accompanied by significant reduction in engineering time for machine learning model building when minute proportions of the original dataset size are implemented for model training Compared to literature, the models developed here not only include operating conditions but also comprehensive geometry and circuiting. For the applications studied, these machine learning models could potentially eliminate the need for expensive simulations and even performance maps for screening and optimization studies. However, it is recommended that final designs be verified using high-fidelity models.

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