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Technical Note

Application of artificial neural network method for performance prediction of a gas cooler in a CO_2 heat pump

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ABSTRACT

The objective of this work is to train an artificial neural network (ANN) to predict the performance of gas cooler in carbon dioxide transcritical air-conditioning system. The designed ANN was trained by performance test data under varying conditions. The deviations between the ANN predicted and measured data are basically less than ±5%. The well-trained ANN is then used to predict the effects of the five input parameters individually. The predicted results show that for the heat transfer and CO_2 pressure drop the most effective factor is the inlet air velocity, then come the inlet CO_2 pressure and temperature. The inlet mass flow rate can enhance heat transfer with a much larger CO_2 pressure drop penalty. The most unfavorable factor is the increase in the inlet air temperature, leading to the deterioration of heat transfer and severely increase in CO_2 pressure drop.

1. Introduction

As the global warming potential (GWP) value of most of HFCs is still high, the application of HFC refrigerants in a refrigeration or heat pump system cannot solve the green house problem completely [1]. Typically, a release of 1 kg of an HFC gas contributes 1000–3000 times more to global warming than the release of 1 kg CO_2 [2]. This is the reason why HFC refrigerants are included in the Kyoto-agreement as compounds to be regulated. Due to the carbon dioxide's outstanding thermodynamic, transport, and other environmentally friendly properties [3], it has being investigated ever-increasingly as an alternative to CFC and HFC refrigerants since the publication of Lorentzen's paper [2].

Heat pump is one of the CO_2 application areas where theoretical and experimental investigations are now performed by an increasing number of research institutions and manufacturers [2,4–10]. Great achievements have been obtained, and the remaining issues are to improve the energy utilization efficiency and reduce the cost of the systems to an acceptable level. Different kinds of heat pumps applying CO_2 as the working fluid are investigated both in theoretical analysis and in laboratory experimental measurement [2,7–10]. Within all the thermodynamic cycles, the transcritical CO_2 cycle has been well known for a long time and was revisited by Lorentzen and Pettersen [2,4].

One way to increase the transcritical CO_2 system efficiency is to improve heat transfer performance of the gas cooler. This is because the system capacity can be maximized by reducing the refrigerant temperature at the gas cooler exit to approach the ambient temperature, while keeping the refrigerant side pressure drop in the gas cooler at an acceptable level. In such CO_2 system, the operating pressures range from sub-critical to 150 bar, and the thermophysical properties vary strongly in the critical region, where specific heat approaches infinity. Cycle COP is very sensitive to the gas cooler outlet state. In an actual cycle, the refrigerant temperature at the gas cooler exit changes with different operating conditions, and a good design of gas cooler can bring it closer to the ambient temperature.

An analysis of the thermal resistance through the overall heat transfer of the gas cooler reveals that the dominant thermal resistance for an air-cooled heat exchanger is generally on the airside, which may account for 85% or more of the total resistance. As a result, to effectively improve the thermal performance and to significantly reduce the size and weight of air-cooled heat exchangers, airside enhanced surface geometries are often encountered in practical applications. And the plate fin-and-tube surfaces are the most widely-used ones. Among many types of plate fin-and-tube heat transfer surfaces, the wavy-fin is one of the widely-used enhanced configurations. The wavy surface can lengthen the path of the airflow and cause better airflow mixing. Consequently, higher heat transfer performance is expected compared with a plain plate fin surface. Many investigations, both experimental and numerical, have been conducted for the heat exchangers with fin-and-tube surface of wavy type. In [11,12] reviews and experimental results of friction factor and heat transfer coefficient are presented for the wavy-type fin surfaces. For the simplicity of presentation we will not go into the details of this subject.

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Nomenclature

f	data
MRE	mean relative error
d	output for exemplars
$\dot{m}$	CO_2 mass flow rate
N	number of sets of data for testing network; number of exemplars
p	pressure
P	number of the output processing elements
Q	heat transfer rate
rms	root mean-squares error
T	temperature
v	velocity
y	network output for exemplars
Δp	pressure drop in tube side
ΔT	temperature difference

Subscripts

e	experimental
in	inlet
out	outlet
p	predicted

However, heat exchangers are complex devices. The complexities of heat exchangers come from their geometrical configurations and manufacturing technologies. Even for the same design, the minor differences in manufacturing technologies may lead to products whose outer appearance looks like the same but many details are actually different. For example, the sharpness of the wavy crest and trough may different which affects the heat transfer and pressure drop characteristics. As such the experimental correlations are useful tools for a general design but actual heat transfer and pressure drop characteristics still should be measured individually after the heat exchanger had been manufactured. This is especially important for a batch of products in order to have a general understanding of their thermal performance within a wide range of parameter variation. Since experimental study is usually cost-expensive, it is important that from limited number of test data we can have a quite comprehensive understanding of the heat exchanger performance. In this regard, the artificial neural network (ANN) method is a useful tool.

Take the gas cooler in the CO_2 system as an example. For a given CO_2 gas cooler, its major output parameters are outlet air temperature, outlet CO_2 temperature, CO_2 pressure drop and airside pressure drop. The five input parameters are inlet air temperature and velocity, input CO_2 temperature, pressure, and mass flow rate. From engineering operation point of view the most important output parameters are the heat transfer rate and the CO_2 pressure drop. In order to have a general understanding of how the five input parameters may affect the two output quantities for a given gas cooler with a limited number of test data, the ANN method may be adopted. In general, ANN is widely-used in function estimation since it is able to estimate virtually any function in a stable and efficient manner [13–20]. Therefore, it is expected that the ANN approach can predict the major performance of gas cooler at random input conditions without too many experiment measurements.

The rest of this paper is organized as follows. First a brief introduction to the CO_2 heat pump experiment system set up in the authors' lab and the type of gas cooler are presented, followed by the presentation of some typical measurement heat transfer and friction factor data of the gas cooler. Then the process of obtaining an adequate ANN is briefly introduced, and the trained ANN is used to predict the two major output quantities for a systematic variation of the five input parameters. Finally some conclusions are drawn.

2. Experimental equipment and range of parameters

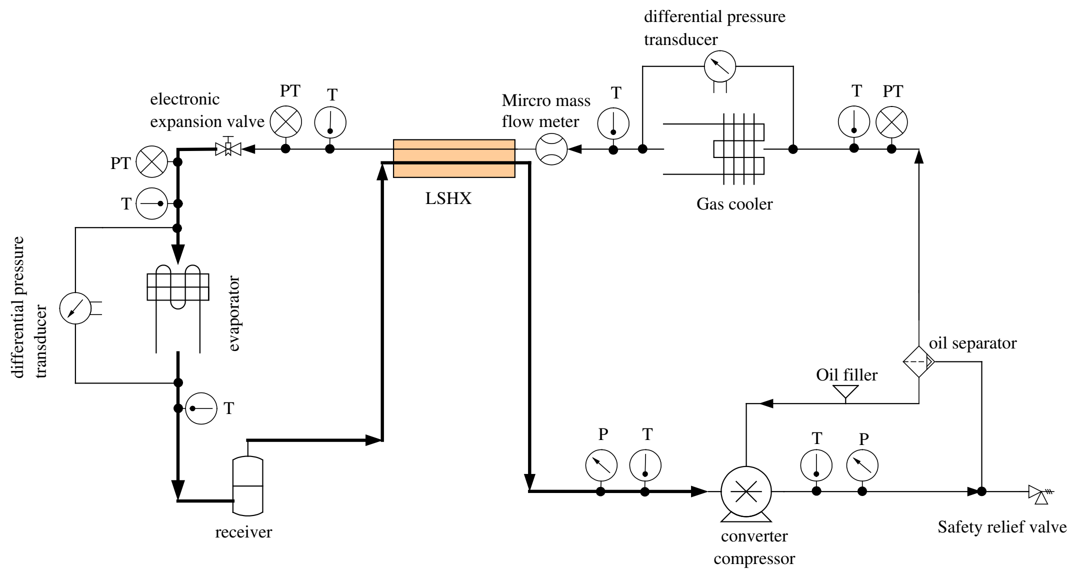
The experimental trancritical heat pump system of CO_2 was built in 2005 in the authors' lab according to the modifications to the basic air-conditioning cycle proposed by Lorentzen and Pettersen [2,4]. Additional components are shown in Fig. 1a, including the control elements to regulate the system's operating conditions. The operating condition can be regulated in two ways. In one method of control, the suction gas temperature is controlled by the low-pressure receiver added just after the evaporator (see Fig. 1a), which will ensure very little superheat of the suction gas by storing liquid and allowing only vapor to enter the compressor. The other control means are for the high pressure and the mass flow rate. The manual electronic expansion valve and the manual control converter of the compressor control the high-side pressure and CO_2 mass flow rate. The function of the oil separator is to purify the CO_2 flow in the system and to realize high heat transfer coefficients inside tube. A safety relief valve is used to protect the system from too high pressure in emergency. Also connected to the system are the following test instruments: temperature transmitters (T, specification: ±0.2 °C), pressure transducers (PT, specification: 0.075%), differential pressure transducers (specification: ±0.075%), and micro-motion mass flow meter (specification: ±0.50%).

In the experimental system 3-row staggered wavy-fin heat exchanger is employed as gas cooler. The gas cooler is set in a wind-duct with a cross section of $340 \times 640\ mm^2$. In the wind-duct, as shown in Fig. 1b, there are a heater, a grid at the duct inlet, three thermopiles (for the air outer temperature and temperature difference, specification: ±0.2 °C), and an air mass flow meter(specification: ±1.0%). The heater is used to adjust the inlet air temperature. The grid is used to create a uniform airflow. A frequency converter is also equipped to adjust the fan speed for altering the airflow rate. The air duct is constructed with plastics and packed with thermal insulation material. The room air is pumped into the duct by centrifugal blower positioned at the end of the duct (not shown in Fig. 1b). During system operation, through altering the inlet air temperature and velocity, the performance of gas cooler and system are tested.

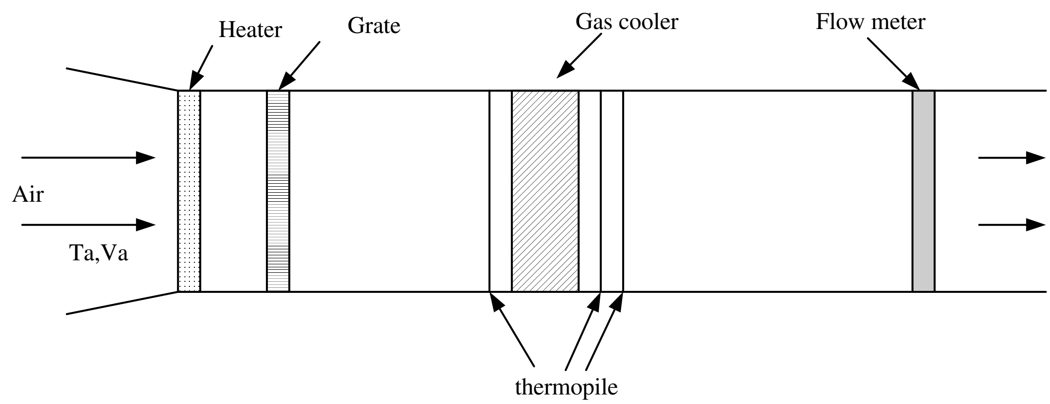
During the experimental procedure a number of parameters are changed systematically. These include: the gas cooler inlet CO_2 pressures ranged from 7.5 to 10.5 MPa, the gas cooler inlet CO_2 temperatures from 78 to 104 °C, the CO_2 mass flow rate from 0.75 to 1.30 kg/min, the air inlet temperature from 25 to 45 °C, and the air inlet velocity from 0.5 to 2.5 m/s. The objective of the present experimental series is to test the performance of the wavy-fin gas cooler and training an artificial neural networks to predict the major performance of gas cooler: how the five input parameters affect the two major output parameters. With this trained ANN the effects of the inlet parameters on the heat transfer rate and the pressure drop of CO_2 will be investigated systematically.

3. Artificial neural network

Before presenting the training of our artificial neural network, two related issues showing the significance of the ANN technique



(a) Experimental trancritical system of CO_2



(b) Gas cooler wind duct

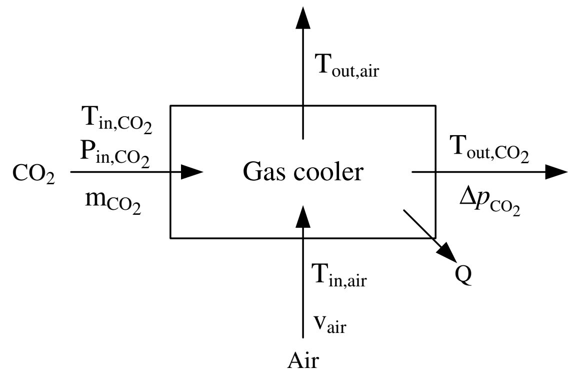
Fig. 1. Experimental system for testing gas cooler performance.

will be presented. In Fig. 2a, the lumped parameter physical model of the CO_2 heat exchanger is presented. For a given heat exchanger, when the five input parameters shown in the figure are given, a unique output of the four parameters can be obtained. However, the functional relationships inherently included within the nine parameters can not be obtained via straightforward mathematic functions [18,19]. And the relationships about the nine parameters within the full heat exchanger are definitely different from both the relationships among Re, Nu and f for the airside fin pattern studied and relationships among Re, Nu and f for the CO_2-side. It is at this point that the artificial neural network technique may play a significant role.

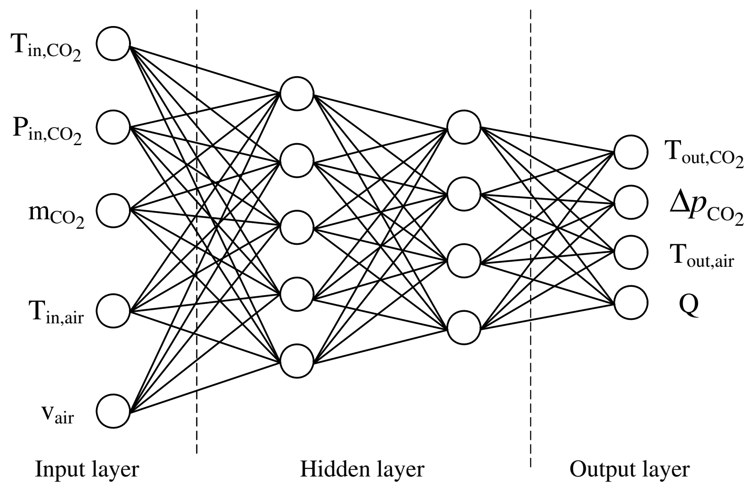
A further notable character of the ANN technique is the possibility of showing the effect of changing one input parameter on the four output parameters while keeping the other four input parameters constant. Such variation trend may be obtained by experimental measurement through fixing four input parameters and varying the fifth one. However, this kind of experiment is very difficult to carry out. For example, when the inlet air velocity for gas cooler changes, all the operational parameters of CO_2 system will change subsequently. Thus to keep the other four inlet parameters constant, the test facility must be adjusted in a complicated way, and sometime even can not reach the required test condition.

As indicated above the artificial neural network method is good at many-to-many relationship analysis [13]. Through training and testing the designed ANN by measurements data, the trained ANN can predict the performance of gas cooler. Fig. 2b illustrates a typical full-connected network configuration. Such an ANN consists of a series of layers with a number of nodes. As one of the most widely implemented neural network topologies, in this paper, the multilayer perceptron (MLP) [13] is employed. When the MLP model is applied to forecast the performance of the gas cooler, it can reveal the highly nonlinear relationship between the five input parameters and four output parameters, by searching an optimal weight in its weighting space. The optimal weights of MLP model store the information, which can best represent such highly nonlinear relationships. Mathematically, searching the optimal weight or training the MLP model aims to minimize a cost function with respect to the training data set. The mathematical background, the details of training and testing the ANN can be found in [13,21,22] and will not be represented here for simplicity.

The authors conducted more than 450 heat transfer performance measurement experiments with the inlet parameters varying in a wide range indicated in Section 2. For all the selected data the heat balance of gas cooler between airside and CO_2 side is within 5%. In developing an ANN model the test data are divided into



(a) Lumped parameter physical model



(b) Four -layer MLP neural network model

Fig. 2. Physical and ANN model for prediction.

two sets: one to be used for training the network and the rest for test its performance. After input a number of the experimental data the test of the ANN was performed with new measurement data. If the deviation between prediction and measurement was larger than an allowable percentage, push these measurement data for training again and retesting by newer measurement data until the deviation between new prediction and measurement data was within ±5%. Totally, more than 350 experiment data were used for training. Once the trained ANN is good enough, the performance of gas cooler can be predicted without further validation by measurement data.

During the training process, the performance of the neural network was evaluated by calculating root mean square error (rms) values of the output data [13]. The rms is defined as

$$\mathrm{rms} = \sqrt{\frac{\sum_{j=0}^{P}\sum_{i=0}^{N}(d_{i,j} - y_{i,j})^2}{N \cdot P}} \tag{1}$$

where, P is the number of the output processing elements; N is the number of exemplars in the data set; $y_{i,j}$ is network output for exemplars at processing elements j; and $d_{i,j}$ is the output for exemplars at processing elements j. At the end of training process, the rms is only 0.062. It makes sure that the trained ANN has satisfactory performance within the trained data.

In Table 1 ten data at the input side of gas cooler are selected from our measured results for testing the trained neural network. In Table 2 the comparisons and the percentage deviations between ANN predicted and measured results of the output side of gas cooler are presented. As shown in Table 2, the prediction is in good agreement with experiment data. For most of the predicted output data, the deviation is far less than 5%. Among 40 data, only 8 data have their relative deviation larger than 5%, with the maximum deviation being of 9.65% for the air temperature difference. And mean relative error (MRE) is defined as

Table 1
Selected experiment data for testing the trained ANN (Five input parameters)

Case	p_{in,CO_2} (MPa)	T°_{in,CO_2} C	$\dot{m}_{CO_2}$ (kg/min)	v_{air} (m/s)	$T_{in,air}$ °C
1	9.02	95.68	0.944	1.39	33.23
2	8.94	93.28	0.995	1.39	33.27
3	9.07	97.77	0.921	1.39	33.18
4	8.83	90.26	1.023	1.39	33.27
5	9.56	92.75	0.994	1.00	35.07
6	8.65	94.63	0.749	1.02	33.31
7	8.66	88.79	0.775	1.03	31.82
8	8.66	92.17	0.774	1.10	32.04
9	8.64	86.81	0.778	1.10	31.94
10	8.96	93.10	1.002	0.98	35.56

$$\mathrm{MRE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{f_{i,p} - f_{i,e}}{f_{i,e}}\right| \tag{2}$$

where, N is the number of the selected testing data, $f_{i,p}$ and $f_{i,e}$ are the predicted value and the corresponding measurement data, respectively. For these 40 data, MRE is 2.96%. Such an agreement should be regarded satisfactory from engineering point of view.

Table 2
Comparison and deviation (%) between experiment and prediction

	T°_{out,CO_2} C			Δp_{CO_2} (kPa)			$T_{out,air}$ °C			Q (W)		
Case	Exp	Pre	Dev	Exp	Pre	Dev	Exp	Pre	Dev	Exp	Pre	Dev
1	38.15	38.16	0.01	175.9	175.6	0.20	41.70	42.01	−3.50	2781	2679	3.81
2	38.35	38.24	−0.21	186.1	188.0	−1.00	41.70	41.76	−0.63	2746	2636	4.20
3	38.08	38.11	0.05	171.7	170.6	0.63	41.74	42.24	−5.58	2805	2748	2.07
4	38.32	38.02	−0.57	193.7	197.6	−1.95	41.48	41.16	3.98	2610	2533	3.03
5	41.71	42.61	1.81	185.2	190.7	−2.85	46.03	45.71	3.03	2540	2373	7.03
6	38.09	37.97	−0.21	154.0	161.5	−4.64	41.64	41.36	3.47	1896	1993	−4.90
7	37.43	37.76	0.66	153.9	162.6	−5.34	40.49	39.81	8.51	2023	1949	3.76
8	37.37	37.48	0.19	154.2	161.7	−4.63	40.38	39.96	5.32	2093	2065	1.37
9	37.18	37.56	0.79	154.1	162.9	−5.40	40.04	39.33	9.65	2025	1925	5.20
10	40.98	41.71	1.42	203.0	207.0	−1.94	45.33	45.17	1.61	2182	2114	3.22

Note: The case numbers are correspondent to those in Table 1, and temperature deviations are calculated by $(\Delta T_{in,out,exp}\text{-}\Delta T_{in,out,pre})/\Delta T_{in,out,exp}\text{-}100\%$.

4. Predicted effect of the five input parameters

Here, the trained ANN is adopted to predict the performance of gas cooler when one of the five input data is a variable. The typical predicted results are presented in Fig. 3. In this figure among the five input parameters (p_{in,CO_2}, T_{in,CO_2}, $\dot{m}_{CO_2}$, v_{air} and $T_{in,air}$) only one parameter: v_{air} is changed systematically, and the corresponding curves illustrate the two most important output parameters, pressure drop of CO_2 and heat transfer rate.

From Fig. 3 and other predicted results, the effects of the five input parameters on the heat transfer rate and the pressure drop of CO_2 can be summarized as follows. For the heat transfer, the inlet air velocity, the inlet CO_2 temperature and pressure, and the CO_2 mass flow rate have positive effects. While the inlet air temperature has negative effect. These effects can be well understood from basic heat transfer theory. For example the increase in the inlet CO_2 temperature leads to a larger overall temperature difference between air and CO_2, thus enhancing the overall heat transfer process. On the contrast, the increase in the inlet air temperature decreases this overall temperature difference. Hence, the heat transfer rate is reduced. As for the pressure drop of CO_2, the increase in the inlet air velocity, the inlet temperature of CO_2 and the inlet pressure of CO_2 are all favorable to reduce the pressure drop of CO_2, while the increase in CO_2 mass flow rate and temperature will lead to the increase in pressure drop. These predicted results are not so straightforward and should be understood from a comprehensive analysis of the overall process. Taking the effect of the increase in the inlet air velocity as an example, the effect of the inlet air velocity on the CO_2 pressure drop can be understood as follows. In the overall heat transfer process, the air side thermal resistance is dominated. Hence, the increase in the air velocity will appreciably reduce the overall thermal resistance. Meanwhile, the outlet air temperature will also be reduced, leading to some reduction in the outlet temperature of CO_2. The reduction in the averaged temperature of CO_2 will decrease the CO_2 density. At a fixed mass flow rate, this will decrease the volumetric velocity of CO_2, hence the pressure drop will be decreased. The effects of the other input parameters can be explained in a similar way, and for the simplicity of presentation, detailed discussion is omitted here.

From Fig. 3 and above analysis, it is easily found that air velocity is the most effective factor to the heat transfer performance of gas cooler. A larger air velocity could both enhance the heat transfer and reduce the pressure drop of CO_2 inside tube. Next effective factors are the inlet CO_2 pressure and temperature. These two parameters' effects are not so large as that of air velocity, and they can improve the performance of gas cooler quite appreciably. Though increasing CO_2 mass flow rate can increase heat transfer, it makes the pressure drop increase more significant, leading to a more severe working condition of the compressor. The most despondent situation is the increase in the inlet air temperature.

5. Conclusion

This paper demonstrates the applicability and feasibility of the artificial neural network (ANN) for estimating the performance of a wavy-fin gas cooler in CO_2 transcritical system. A well-trained and tested ANN by a lot of measurement data is employed to predict its performance at off-design conditions. Especially, the effect of the

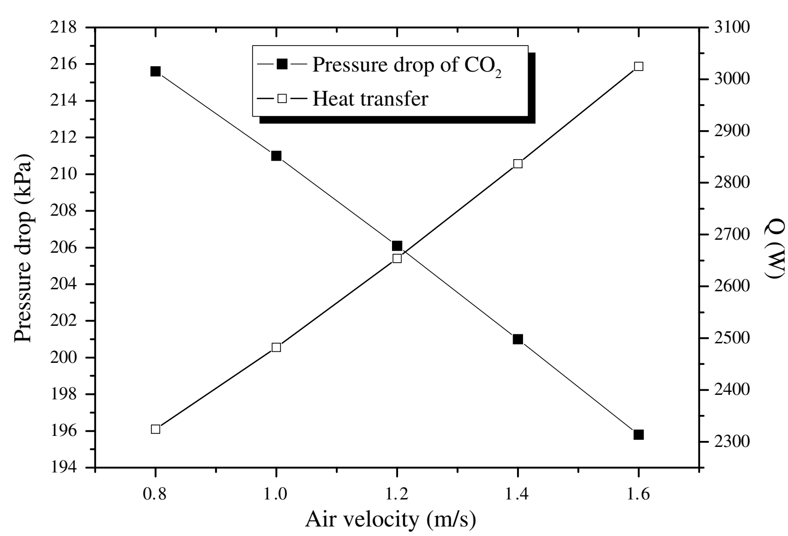


Fig. 3. Predicted effect of inlet air velocity on CO_2 pressure drop and heat transfer rate ($p_{in,CO_2} = 9.5$ MPa, $T_{in,CO_2} = 93$°C, $\dot{m}_{CO_2} = 1.08$kg/min, $T_{in,air} = 35$ °C).

five input parameters (p_{in,CO_2}, T_{in,CO_2}, $\dot{m}_{CO_2}$, v_{air} and $T_{in,air}$) has been examined individually by keeping the other four parameters constant. The predicted results show that among the five parameters the most effectively positive influence is the inlet air velocity, then come the inlet CO_2 pressure and temperature. The mass flow rate of CO_2 can also enhance heat transfer with a much bigger penalty in pressure drop. The increase in the inlet air temperature will deteriorate the heat transfer and increase the pressure drop of CO_2.

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