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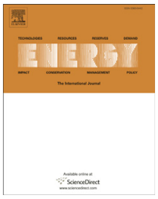

Sparsity-enhanced optimization for ejector performance prediction

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ABSTRACT

Within a model of the ejector performance prediction, the influence of ejector component efficiencies is critical in the prediction accuracy of the model. In this paper, a unified method is developed based on sparsity-enhanced optimization to determine correlation equations of ejector component efficiencies in order to improve the prediction accuracy of the ejector performance. An ensemble algorithm that combines simulated annealing and gradient descent algorithm is proposed to obtain its global solution for the proposed optimization problem. The ejector performance prediction of a 1-D model in the literature is used as an example to illustrate and validate the proposed method. Tests results reveal that the maximum and average absolute errors for the ejector performance prediction are reduced much more when compared with existing results under the same experimental condition. Furthermore, the results indicate that the ratio of geometric parameters to operating parameters is a key factor affecting the ejector performance.

1. Introduction

Ejector refrigeration systems (ERSs) have been known since early twentieth century. A study of applying ERS to air-conditioning and refrigeration was reported in mid-1950s. For ERSs, there are many advantages, such as simple construction, high reliability and low maintenance cost in comparison with other refrigeration systems. Although the coefficient of performance (COP) of ERSs is relatively low when compared with that of vapor compression refrigeration systems, ERSs can be powered by low-grade energy, such as solar energy, biomass energy and waste heat. Therefore, there are many research activities on the study of ERSs and their performance in the literature.

For an ERS, it basically consists of a generator, evaporator, condenser, ejector, expansion valve and a pump. The ejector can be regarded as its heart, playing a key role for the performance of the ERS. The ejector design can be classified into two types according to the position of the nozzle [1]: constant-area mixing ejector; and constant-pressure mixing ejector. Both the constant-area mixing model and the constant-pressure mixing model are developed for the prediction of the ejector performance. The predicted results obtained for the constant-area mixing model are found to be consistent with the experimental results. On the other hand, the predicted results obtained for the constant-pressure mixing model do not agree well with the experimental results [2]. However, the performance of a constant-pressure mixing ejector is, in practice, superior to that of a constant-area mixing ejector [3]. Therefore, an intensive effort has been devoted to the study of performance prediction of the constant-pressure mixing ejector. For constant-pressure mixing ejector, there are several models developed to improve its performance prediction. The model proposed by Huang et al. [4] is used to predict the ejector performance at critical mode with dry refrigerant R141b. It is assumed that the primary flow mixes with the secondary flow under constant-pressure inside the constant-area section of the ejector after the choking of the secondary flow. Four empirical component efficiencies are introduced in the model by matching the test data. As a result, the prediction accuracy is improved and the prediction results agree well with the experimental data. The maximum relative error on prediction entrainment ratios is −22.99%. In Ref. [5], a model is developed for the ejector performance prediction of both dry and wet refrigerants. The real velocity distribution inside the ejector is approximated by a simple linear function. The mass flow rates of the two flows are derived by intergrading the velocity function at

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Nomenclature

A	Area (m^2)
C_p	specific heat at constant pressure (kJ/kg K)
C_v	specific heat at constant volume (kJ/kg K)
d	diameter (m)
E_r	relative error
m	mass flowrate (kg/s)
M	mach number
P	pressure (MPa)
R	gas constant (kJ/kg K)
T	temperature (K)
u	entrainment ratio
V	velocity (m/s)
η	efficiency relating to isentropic efficiency
ϕ	efficiency account for losses
β	sparsity weight factor
γ	$=C_p/C_v$

Superscripts

c	critical mode of ejector

Subscripts

c	to condenser, exit of ejector
d	diffuser
i	ideal, with no loss
m	mixing flow
p	primary flow, from section1-1 to y-y
p_0	primary flow at inlet of ejector
p_1	primary flow at nozzle exit
r	ratio
s	secondary flow
s_0	secondary flow at inlet of ejector
y	position of the hypothetical throat

Abbreviations

COP	coefficient of performance
ERS	ejector refrigeration system
GDA	gradient descent algorithm
SAA	simulated annealing algorithm
SW	sparsity weight

the inlet of the constant-area section. Three empirical component efficiencies are introduced to account for the losses in the ejector. As a result, the maximum relative error is reduced to 13.8%. In Ref. [6], it is assumed that the secondary flow is choking in the hypothetical throat at critical mode and that there is an effective area of the secondary flow at sub-critical mode. Based on the assumptions, the model can predict ejector performance at both critical mode and sub-critical mode with improved prediction accuracy. The maximum relative error on entrainment ratios is 14.2%. It can be seen that the prediction accuracy of these models has been improved by developing novel physical description of the ejector.

In fact, besides the physical description of the ejector, the ejector component efficiencies have dramatic influence on the validity of a 1-D ejector model [7]. The efficiencies are either selected as constant value empirically based on experimental data [8] or taken from literature [9]. However, it is found that ejector component efficiencies relied on the ejector configurations [4] or operating conditions [5] or both of them [10]. Therefore, ejector component efficiencies were presented as empirical correlations in some models, but only empirical methods are introduced to determine the correlation equations of the efficiencies in the models. The question on how to optimize ejector component efficiencies such that simple correlation equations with better prediction accuracy are obtained appears to remain open in the literature.

The aim of this paper is to develop a unified method to determine correlation equations of ejector component efficiencies in order to pick out and analyze the key factors which affect ejector performance. To begin with, the ejector performance prediction is formulated as a sparsity-enhanced optimization problem [11]. The objective in our optimization problem includes not only the prediction accuracy, but also the number of active terms in the correlation equations. A hybrid algorithm is developed to solve this formulated optimization problem. To illustrate the effectiveness of our proposed method, 1-D model of the ejector performance prediction proposed in Ref. [4] is used as an example.

2. Mathematical modelling and optimization formulation

In this section, we will take 1-D model proposed in Ref. [4] as an example to illustrate how to formulate the corresponding performance prediction as a sparsity-enhanced optimization problem. The flow characteristic of the model is illustrated in Fig. 1.

2.1. Ejector component efficiencies

In order to account for losses at critical mode in ejector, ejector component efficiencies are introduced in most of 1-D ejector models. Four efficiencies, η_p, η_s, ϕ_p and ϕ_m, are taken into consideration in Ref. [4]. In the model, the efficiencies, η_p and η_s, relate to the isentropic efficiency of the primary flow from inlet to the nozzle throttle and the secondary flow from inlet to section y-y, respectively. As far as η_p, it is used to account for the loss of the primary flow from section 1-1 to y-y. Huang et al. [4] think the loss may result from the slipping or viscous effect of the primary and the secondary flows at the boundary. However, recent studies have shown that, the loss is due to a series of oblique shocks which the primary flow undergoes as it expands from section 1-1 to y-y [12]. But no matter what reason the loss results from, it can be taken into account by isentropic efficiency.

However, there is some diversity on how to account for losses in the mixing chamber in different ejector models. Huang et al. [4] defined mixing efficiency, ϕ_m, as a momentum transfer efficiency, namely

$$\phi_m = \frac{(m_p + m_s)V_m}{m_p V_{py} + m_s V_{sy}} \tag{1}$$

This definition is the same as that in literature [8] and [13]. However, Yu et al. [14] and Xu et al. [15] present another definition of mixing efficiencies, it is

$$\phi_m = \frac{V_m^2}{V_{m,i}^2} \tag{2}$$

Cizungu et al. [16] and Selvaraju and Mani [17] use friction at wall surface of mixing chamber to account for mixing losses. The friction factor f_m is expressed as