Applied Thermal Engineering 77 (2015) 113–120

Contents lists available at ScienceDirect

Applied Thermal Engineering

journal homepage: www.elsevier.com/locate/apthermeng

Research paper

Hybrid ANN–PLS approach to scroll compressor thermodynamic performance prediction

Z. Tian [a], B. Gu [a, *], L. Yang [b], Y. Lu [c]

[a] Institute of Refrigeration and Cryogenics, Shanghai Jiao Tong University, Shanghai 200240, China
[b] School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China
[c] New Energy Vehicle Division of SAIC, Shanghai 201804, China

HIGHLIGHTS

- Hybrid ANN–PLS is utilized to predict the thermodynamic performance of scroll compressor.
- ANN–PLS model is determined with 5 hidden neurons and 7 latent variables.
- ANN–PLS model demonstrates better performance than ANN and PLS working separately.
- The values of *MRE* and *RMSE* are in the range of 0.34–1.96% and 0.9703–0.9999, respectively.

ARTICLE INFO

Article history:
Received 4 December 2013
Accepted 9 December 2014
Available online 18 December 2014

Keywords:
Scroll compressor
ANN
PLS
Hybrid model
Performance prediction

ABSTRACT

In this paper, a scroll compressor thermodynamic performance prediction was carried out by applying a hybrid ANN–PLS model. Firstly, an experimental platform with second-refrigeration calorimeter was set up and steady-state scroll compressor data sets were collected from experiments. Then totally 148 data sets were introduced to train and verify the validity of the ANN–PLS model for predicting the scroll compressor parameters such as volumetric efficiency, refrigerant mass flow rate, discharge temperature and power consumption. The ANN–PLS model was determined with 5 hidden neurons and 7 latent variables through the training process. Ultimately, the ANN–PLS model showed better performance than the ANN model and the PLS model working separately. ANN–PLS predictions agree well with the experimental values with mean relative errors (*MREs*) in the range of 0.34–1.96%, correlation coefficients (R^2) in the range of 0.9703–0.9999 and very low root mean square errors (*RMSEs*).

1. Introduction

Scroll compressors, a type of positive displacement compressor, have been successfully utilized in a variety of applications, such as heat pump systems, supermarket racks, truck transports and marine containers on account of quiet operation, reduced vibration, compact structure and superior performance [1]. The knowledge about the scroll compressor performance is of vital importance in refrigeration system preliminary design, cycle performance prediction and optimization, system control and management, which help designers to figure out alternative solutions to reduce energy consumption [2–4]. Therefore, different kinds of models have been proposed by numerous researchers to handle the compressor performance prediction.

With respect to the compressor performance prediction models, the distinction can be made between numerical models, empirical correlation models and artificial intelligence models. Numerical models are based on the geometrical parameters, the mechanical principle, and thermodynamic and heat transfer mechanisms [5–7]. However, a numerical model requires the geometry of the scrolls, scroll dynamics and internal leakage, which are only known by manufacturers [8,9]. In addition, results of numerical models established by professional designers are typically not open for engineers [10,11]. As numerical compressor model demands high computing time, it is generally avoided in transient system simulations. An empirical correlation model takes physically meaningful equations into consideration and is less time-consuming and more numerically robust than a numerical model [12–14]. However, the

* Corresponding author. Tel.: +86 21 34 20 62 60; fax: +86 21 34 20 68 14.
E-mail address: gubo@sjtu.edu.cn (B. Gu).

http://dx.doi.org/10.1016/j.applthermaleng.2014.12.023
1359-4311/

Nomenclature

B	regression coefficient matrix
b	bias
c, **w**	weight coefficient
d	data point
F	residual matrix
h_{f1}	evaporator inlet enthalpy (kJ kg^{-1})
h_{f2}	TXV inlet enthalpy (kJ kg^{-1})
h_{g1}	compressor inlet enthalpy (kJ kg^{-1})
h_{g2}	evaporator outlet enthalpy (kJ kg^{-1})
K_1	thermal leakage factor (kW°C^{-1})
m	mass flow rate (kg h^{-1})
N	compressor speed (rpm)
P_{con}	power consumption (W)
p	pressure (kPa)
q, **u**	latent variable
SS	variance
t	temperature (°C)
t_a	environment temperature (°C)
t_s	saturated temperature (°C)
V	volume (m^3 s^{-1})
W_1	heater input power (kW)
X, **Y**	variable matrix
z	variable array

Greek letters

α, β	fitting coefficients
ε	permissible error
η_v	volumetric efficiency
ξ	variance ratio
φ	prediction error
Φ	prediction parameter

Subscript

aver	average
comp	compressor
cond	condensing
dis	discharge
evap	evaporating
exp	experimental
lin	linear
max	maximum
min	minimum
nlin	non-linear
pre	prediction
r	refrigerant
suc	suction
sup	superheat
th	theoretical

feasibility of the empirical correlation model is generally constrained by the experimental conditions and experimental subjects.

The application of artificial intelligent methods in prediction is growing due to their fast, reliable, and computationally inexpensive response. Lazzaretto and Toffolo [15] and Yu et al. [16] showed the possibility of an applying artificial neural network (ANN) method to model the compressor map. Penz et al. [17] predicted the compressor refrigerating capacity using Bayesian networks and Fuzzy-Bayesian networks. Sanaye et al. [18] implemented a rotary vane compressor (RVC) performance prediction with the ANN method, which agreed well with experimental values with R^2 in the range of 0.962–0.998, *MRE* in the range of 2.79–7.36% and *RMSE* in the range of 0–10.59 kg h^{-1} and 0–12 K for refrigerant mass flow rate and discharge temperature, respectively. The ANN method has an undeniable advantage in compressor performance prediction. Nevertheless, ANN approximates a non-linear function without considering the linear correlation among input variables, which will result in an uncertain extrapolation performance. Meanwhile, ANN is lacking of the background principles to explain the performance of the compressor model.

Partial least squares (PLS) regression is a technique for modeling a linear relationship between a set of output variables and a set of input variables, which can realize the regression modeling, data structure simplification and correlation analysis at the same time. Chu et al. [19] demonstrated the ability of PLS in predicting centrifugal compressor performance with data from a simulation study and a real case. As for the validation data, the PLS model exhibited better performance than the back propagation (BP) network model. What calls for special attention is that the choice of the latent variable (LV) will make the regression analysis restricted.

From the literature review, it should be obvious that the hybrid model making up the inadequacy has not been proposed for compressor performance prediction, especially not for scroll compressor. The hybrid ANN–PLS model for scroll compressor thermodynamic performance prediction was structured in this paper as a linear combination of ANN and PLS. Totally 148 experimental samples were used to train and test the ANN–PLS model in predicting the volumetric efficiency (η_v), refrigerant mass flow rate (m_r), refrigerant discharge temperature (t_{dis}) and power of consumption (P_{con}). Statistical error measures such as *MRE*, *RMSE* and R^2 were calculated. Moreover, the hybrid ANN–PLS model was compared with the ANN model and the PLS model working separately.

This paper is organized as follows. Section 2 describes theories and methods used in this study. The experimental setup and test procedure are presented in Section 3. After obtaining the experimental data, application of the hybrid ANN–PLS model in scroll compressor thermodynamic performance prediction is introduced in Section 4. Section 5 includes results and discussions for both training data and test data. Section 6 concludes and suggests perspectives.

2. Theories and methods

2.1. Artificial neural network (ANN)

ANN is a massively parallel distributed processor, which contains a large number of simple neurons and a large number of weighted connections encode the knowledge of a network. An ANN-model makes it possible that correlations can solve physical phenomena in engineering application without explicit mathematical relations [20]. A typical three layer ANN architecture consists of an input layer, a hidden layer and an output layer. The neuron arranged in layers links up to others through adaptable weights. Each neuron receives multiple inputs from former neurons and delivers an output signal to subsequent neurons.

Among various forms of an ANN, the back propagation neural network (BPNN) has caused great interest. As shown in Fig. 1, there are a training stage and a back propagation stage in the neuron working process. In the training stage, the network learns from a training data set without the necessity of confirmable arithmetical relationship between input and output variables. After being