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Simulation and Prediction of Thermodynamic Performance of Reciprocating Compressor utilizing Physical Models Combining with Generalized Regression Neural Network

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Simulation and Prediction of Thermodynamic Performance of Reciprocating Compressor utilizing Physical Models Combining with Generalized Regression Neural Network

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Abstract. Thermodynamic performance of a reciprocating compressor is generally evaluated or predicted by its physical models (PM). However in conventional PM, some key parameters are not easy to be determined and most time they can only be set values empirically. This article presented and experimentally verified physical models combining with generalized regression neural network (PMCGRNN) for the simulation and prediction of reciprocating compressor thermodynamic performance including the discharge temperature, and the volume flow rate. In PMCGRNN model of the compressor, firstly, the key parameters of compression polytropic exponent n and the volume efficiency λ_d were obtained by generalized regression neural network (GRNN) with the input variables of suction temperature, suction pressure, discharge pressure, compressor rotate speed. Then the discharge temperature and the volume flow rate of the compressor were simulated respectively by their physical models (PM). The simulation results of discharge temperature and the volume flow rate by PMCGRNN were validated by a test bench of an air compressor. It was found that PMCGRNN has reliable prediction accuracy, and the relative errors of two PMCGRNN models are between -3.5% and $+1.5\%$, and between -5% and 4% , respectively.

1. Introduction

Reciprocating compressors are important equipment in many gas industries. Hence, the accurate prediction of the thermodynamic parameters in preliminary design process is crucial to prevent compressor matching mistakes. Besides, in reciprocating compressor failure diagnosis procedure, we usually identify the fault through the comparisons of the parameters in failure conditions and in normal conditions. Therefore, it is vital to evaluate the key thermodynamics parameters of reciprocating compressor actually, such as the discharge temperature, the volume flow rate and the shaft power in normal conditions.

In earlier stage, thermodynamic parameters of a reciprocating compressor is generally evaluated or predicted by simplifying its physical models (PM) to mathematical formulas. A global model for the thermodynamic analysis of reciprocating compressors is presented by Pascal Stouffis [1]. Expressions for the volumetric effectiveness, the work per unit volume and the indicated efficiency are derived. In



the model of indicated efficiency, the author considered the pressure variations during the discharge and the suction process and the gas-to-wall heat transfer. For example, Bin Zhao[2] presented a 3-dimensional (3D) computational fluid dynamics (CFD) model of a double acting reciprocating compressor, which considered the valve motion and pressure pulsation. A numerical model considering reciprocal interaction between compressor and suction chamber, cylinder volume and discharge chamber is performed by Liu Zhan[3]. These CFD models can predict the performance of compressor accurately, but the calculation will consume a lot of time. So some authors predicted the key characteristics of compressors by artificial neural network (ANN). A three-layer back-propagation neural-network applied Levenberg–Marquardt algorithm is discussed by Youhong Yu[4] to predict the characteristic performance map of a compressor. But omitting the physical models is adverse to guide the design of compressor.

So this article presented and experimentally verified physical models combining with generalized regression neural network (PMCGRNN) for the simulation and prediction of reciprocating compressor thermodynamic performance including the discharge temperature and the volume flow rate. The two models are validated with experimental data, and the relative errors are between -3.5% and $+1.5\%$, and between -5% and 4% , respectively.

2. Thermodynamic performance of a reciprocating compressor

2.1. Discharge temperature

In thermodynamic process of gas compression, temperature will increase with the pressure ratio rising. So if pressure ratio of compressor is high, discharge temperature will be out of range. While the cylinder is usually cooled by lubricating oil, exorbitant temperature will result in its low viscosity and deterioration. Therefore, discharge temperature is an important indicator of a compressor.

In preliminary design of a reciprocating compressor, discharge temperature is determined by (1):

$$T_d = T_s \varepsilon^{\frac{n-1}{n}} \quad (1)$$

where T_d is discharge temperature, T_s is suction temperature, ε is pressure ratio, n is polytropic exponent. n is variable in actual compression process, most time it can only be set values empirically. In this article, it was determined by GRNN.

2.2. Discharge temperature

The volume flow rate of a reciprocating compressor is calculated by (2):

$$Q = V_{th} \lambda_v \lambda_p \lambda_T \lambda_l r = \lambda_d V_{th} r \quad (2)$$

where Q is the volume flow rate, V_{th} is the theoretical stroke volume, λ_v is the volume coefficient, λ_p is the pressure coefficient, λ_T is the temperature heating coefficient, λ_l is the leak coefficient, r is the rotate speed of compressor, and λ_d is volumetric filling efficiency of the compressor.

According to the expression, the volume flow rate is related to many factors, such as suction pressure, suction temperature, rotate speed, clearance volume and leakage. In design stage, the four coefficients λ_v , λ_p , λ_T , and λ_l are decided by empirical formulas, and λ_d is discharge coefficient, which is product of the four coefficients. In this paper, λ_d is obtained through GRNN.

3. The PMCGRNN model

3.1. The GRNN Structure

GRNN is based on nonlinear regression analysis, and the regression analysis of non-independent variable y relative to independent variable x is actually to calculate the y with the greatest probability. The prediction of the y is calculated by (3) [5][6]:

$$\hat{Y} = \frac{\int_{-\infty}^{\infty} y f(x,y) dy}{\int_{-\infty}^{\infty} f(x,y) dy} \quad (3)$$

where \hat{Y} is the prediction of y , X is the observation of x , and $f(x, y)$ is the joint probability density function of x and y . And the joint probability density function is estimated applying Parzen Probability Density Estimator [7].

The structure of GRNN is shown in Figure 1, it constitutes four layers. The input variable of neural network is $X=[x_1, x_2, \dots, x_n]^T$, and the output variable is $\hat{Y}=[y_1, y_2, \dots, y_k]^T$. The number of the samples is assumed to be m .

(1) Input Layer

The number of neuron in input layer is equal to the dimension of the input variable. The neurons in input layer are only simple distribution units.

(2) Pattern Layer

The number of neuron in pattern layer is equal to the size of sample, and each neuron corresponds to one sample. The transfer function of the units in pattern layer is:

$$p_i = \exp\left(-\frac{(X-A_i)^T(X-A_i)}{2\sigma^2}\right) \quad i = 1, 2, \dots, m \quad (4)$$

where A_i is the i th input sample. σ is the width factor of Gaussian function.

(3) Summation Layer

The summation layer includes two kinds of neurons. The transfer function of one of them is shown as (5).

$$S_D = \sum_{i=1}^m p_i \quad (5)$$

The other kind of transfer function is shown as (6).

$$S_{Nj} = \sum_{i=1}^m y_{ij} p_i \quad j = 1, 2, \dots, k \quad (6)$$

where y_{ij} is the j th element of the i th output sample.

(4) Output Layer

The number of neuron in output layer is equal to the dimension of the output variable. The j th neuron of the output layer corresponding to the j th element of the prediction is calculated by (7).

$$\hat{Y}_j = \frac{S_{Nj}}{S_D} \quad j = 1, 2, \dots, k \quad (7)$$

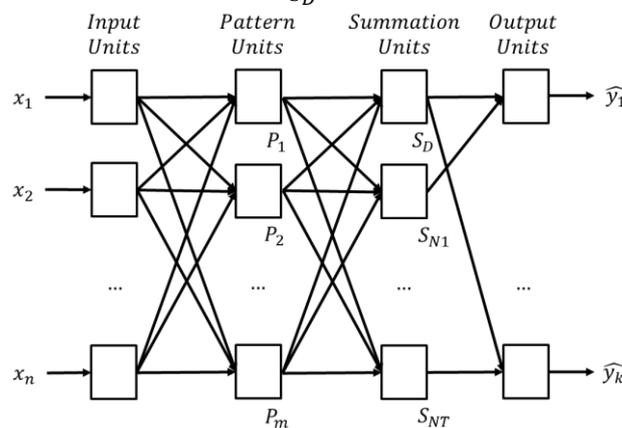


Figure 1. The structure of GRNN.

3.2. The PMCGRNN model

Two GRNN models are built respectively to predict polytropic exponent n and the discharge coefficient λ_d . According to the analysis of influence factor of n and λ_d , the suction temperature, suction pressure, discharge pressure and compressor rotate speed are selected as the input variable for both two GRNN models.

The number of the samples for two GRNN models is 32 which are small, so 5-fold cross validation was applied to train the two GRNN models. In the models, 29 samples acted as training set, and the other 3 samples acted as validation set.

After the prediction of polytropic exponent n and the discharge coefficient λ_d with GRNN model, the physical model (1) and (2) are used to calculate discharge temperature and volume flow rate. The whole method is called physical model combining with general regression neuron network (PMCGRNN) model.

4. Results and discussion

In the current study, two PMCGRNN models were developed to predict the discharge temperature and volume flow rate of an air labyrinth reciprocating compressor working with air. The parameters of the compressor are listed in Tab.1.

Table 1. The parameters of the compressor

| Category | Vertical |
|--------------------|----------------------|
| Type of action | Single |
| Stroke | 90mm |
| Rotate speed | 450-800 r/min |
| Suction pressure | 0.1 MPa |
| Discharge pressure | 0.1-0.4 MPa |
| Volume flow rate | 3.16-104.34 Nm^3/h |

Figure 2 shows regression plots of the discharge temperature predicted by PMCGRNN with respect to the actual values for both training and validation data. As can be seen, all of the data fall besides the diagonal lines, showing that the PMCGRNN model is capable of predicting discharge temperature with a good precision. To be more accurate, the relative percentage deviation as a function of the actual values is depicted in Figure 3 and lie in a reasonable range between -3.5% and $+1.5\%$.

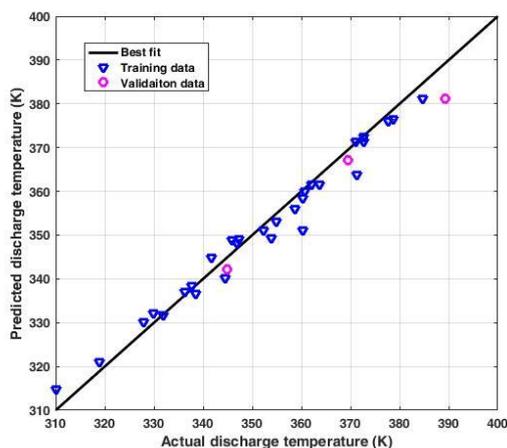


Figure 2. Regression plots of predicted and actual discharge temperature for testing and training data.

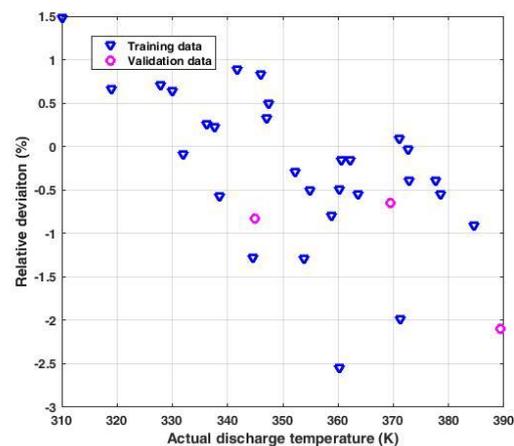


Figure 3. Scatter plots of relative deviation between predicted and actual discharge temperature for testing and training data.

Regression plots between the compressor volume flow rate predicted by the PMCGRNN model and the actual values are presented in Figure 4. In this figure, the predicted data are plotted on the vertical axes as a function of the actual values. As can be seen, there is excellent agreement between the predicted and actual values, as almost all of the data are along a straight line, which highlights the integrity of the model in the estimation of compressor volume flow rate. The relative percentage deviation as a function of the actual values is depicted in Figure 5 and most data also lie in a reasonable range between -5% and 4% .

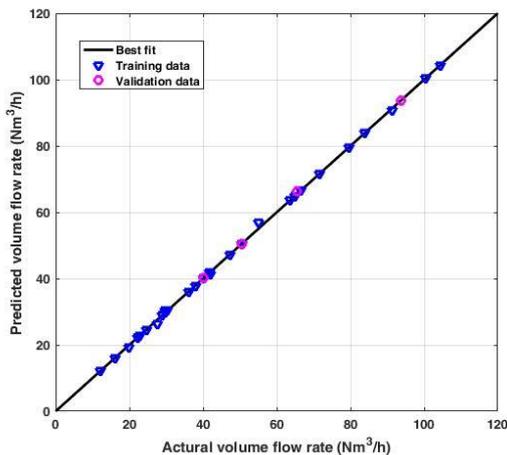


Figure 4. Regression plots of predicted and actual volume flow rate for testing and training data.

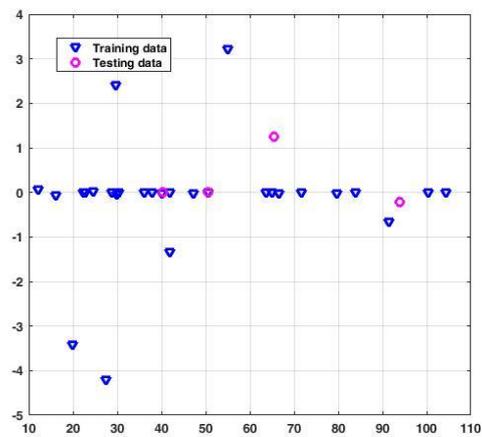


Figure 5. Scatter plots of relative deviation between predicted and actual volume flow rate for testing and training data.

5. Results and discussion

Due to the importance of evaluation of thermodynamic performance of a reciprocating compressor, PMCGRNN models were built for prediction of the thermodynamic parameters of discharge temperature and volume flow rate of an air reciprocating by taking 32 experimental data samples. In the PMCGRNN models, the discharge temperature and the volume flow rate were considered as the outputs of the models and suction temperature, suction pressure, rotate speed and discharge pressure were considered as inputs. To appraise the reliability of the proposed method, the comparisons between predicted results by PMCGRNN models and experimental results were made, and it was shown that predicted results by PMCGRNN models were accurate with small relative deviation. It was concluded that a high level of accuracy and efficiency could be obtained for thermodynamic performance prediction by utilizing the PMCGRNN model.

6. References

- [1] Stouffs P , Tazerout M and Wauters P 2001 *Int J Therm Sci* Thermodynamic analysis of reciprocating compressors **40(1)** 52-66
- [2] Zhao B, Jia X, Sun S, Wen J and Peng X 2018 *Appl Therm Eng* Fsi model of valve motion and pressure pulsation for investigating thermodynamic process and internal flow inside a reciprocating compressor **131** 998-1007
- [3] Liu Zhan, Longhui Liang and Zhenya Duan 2018 *Energy Procedia* A non-linear reciprocating compressor model representing the interaction between thermodynamic process and unsteady flow **152** 125-130
- [4] Yu Y, Chen L, Sun F and Wu C 2007 *Appl Energy* Neural-network based analysis and prediction of a compressor' s characteristic performance map **84(1)** 48-55
- [5] Heimes F and Heuveln B V 1998 *IEEE International Conference on Systems* The normalized radial basis function neural network **2** 1609-14
- [6] Övünç Polat and Tülay Yıldırım 2008 *Expert Syst Appl* Genetic optimization of GRNN for pattern recognition without feature extraction **34(4)** 2444-48
- [7] Parzen E 1962 *Ann Math Statist* On estimation of a probability density function and mode **33** 1065–1076

7. Acknowledgments

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