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Data Mining Approach for Analysis of Variable Speed Refrigeration System

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Abstract: The aim of this study is to carry out performance modeling of an experimental refrigeration system driven by variable speed compressor using Data Mining techniques with small data sets. In order to vary the capacity of the refrigeration systems, one of the best methods is controlling the rotational speed of the compressor motor with a frequency inverter. For this aim, an experimental refrigeration system is setup with a frequency inverter for controlling the speed of compressor electric motor. The experiments are made for 35 Hz to 50 Hz electric motor frequencies. Data mining technique is applied to determine the system performance parameters using actual data obtained from the measurements. From the results, it is observed that data mining procedure is suitable for forecasting the system characteristics for different compressor frequencies and cooling loads instead of making several experiments.

Değişken Hızlı Soğutma Sisteminin Analizi İçin Veri Madenciliği Yaklaşımı

Anahtar Kelimeler
Veri madenciliği
Değişken hız
Soğutma
Frekans

Özet: Bu çalışmanın amacı, veri Madenciliği tekniği kullanılarak değişken hızlı kompresörlü deneysel bir soğutma sisteminin performansının modellenmesidir. Soğutma sisteminin kapasitesinin değiştirilmesi için, Soğutma sistemlerinin kapasitesini değiştirmenin en iyi yöntemlerinden birisi kompresör motor hızının bir frekans invertörü ile kontrol edilmesidir. Bu amaçla, kompresör elektrik motorunun hızının frekans invertörü ile ayarlanabildiği bir deneysel soğutma sistemi kurulmuştur. Deneyler elektrik motorunun frekansının 35 Hz ile 50 Hz aralığında yapılmıştır. Sistem performansının belirlenmesi deneysel ölçümlerden alınan gerçek veriler kullanılarak veri madenciliği tekniği uygulanmıştır. Sonuç olarak, farklı kompresör frekansları ve soğutma yüklerindeki sistem karakteristiklerini belirlenmesinde birçok deney yapmak yerine veri madenciliği tekniğinin kullanılmasının uygun olduğu tespit edilmiştir.

1. Introduction

A refrigeration system generally works by indirectly transferring thermal energy from low-temperature sources to high-temperature sinks at the expense of electricity or mechanical work to lower or maintain the source temperature at a certain value (Zhang and Xu, 2011). These kinds of refrigeration applications generally operate at part-loads for much of their life by regulating on-off type compressors. Nominal frequency of on-off type compressors is usually 50 Hz, and the system includes a thermostatic control valve increasing causing high energy consumption. In addition, the inefficient electricity usage for driving the refrigeration compressors is considered as an indirect contribution to the greenhouse gases emitted in the atmosphere. These emissions can be reduced by improving the energy conversion efficiency of the above mentioned systems (Aprea et al, 2004a). Because of the refrigeration systems are broadly utilized in a wide range of commercial applications, any efficiency improvement of refrigeration systems would represent a significant energy economy (Buzelin et al, 2005). The variable speed compressor which continuously matches the compressor refrigeration capacity to the load is theoretically the most efficient method of refrigeration capacity control (Aprea et al, 2004b).

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2. System Description

The experimental variable speed refrigeration system is composed of a semi hermetic compressor, an evaporator, a condenser and an externally equalized thermostatic expansion valve. The schematic overview of the experimental system is given in Figure 1. Evaporation and condensation processes take place in air cooled heat exchanger type evaporator and condenser. As seen from Figure 1, condenser is mounted in an isolated channel in order to avoid the effects from ambient conditions. Some electrical heaters are used at the entrance of the channel to fix the temperature of the inlet air constant. The cold room is made of insulated panels and the dimension of the cold room is 2.1××1.2×1.35 m. At the bottom of the inner cold room, flat type electrical heaters are located to simulate the heat load. There 18 flat type heaters and each one is 0.045 kW which is controlled by means of a variable transformer. The power consumption is also measured using a wattmeter. The evaporator is located at the top of the cold room. A frequency inverter is mounted on the compressor in order to vary the compressor electrical motor speed.

The temperature and pressure values are measured from different parts of the experimental system to evaluate the system performance by varying the compressor speed. A flowmeter is used to measure the refrigerant flow rate which is designed for refrigerant R404a. Additionally, humidity of air at the inlet and outlet of the condenser channel are measured using compact humidity measuring instrument. Temperature measurements are collected from 12 points of the system, pressure measurements are collected from 7 points and refrigerant mass flow rate measured after the condenser. All the measurement devices are connected to a data logger which has 20 channels for collecting the data.

The experiments are made up for compressor electrical motor frequencies of 35 Hz, 40 Hz, 45 Hz and 50 Hz. Minimum frequency range is selected to be 35 Hz for avoiding problems for the compressor lubricating by splash. Additionally, compressor vibrations increase at lower frequencies. At each adjusted frequency, cold room refrigeration duty is simulated by electrical heaters. Experimental setup is operated for each adjusted frequency and cooling loads. All measurements are made for every 5 seconds and the data is transferred to the computer by means of data logger.

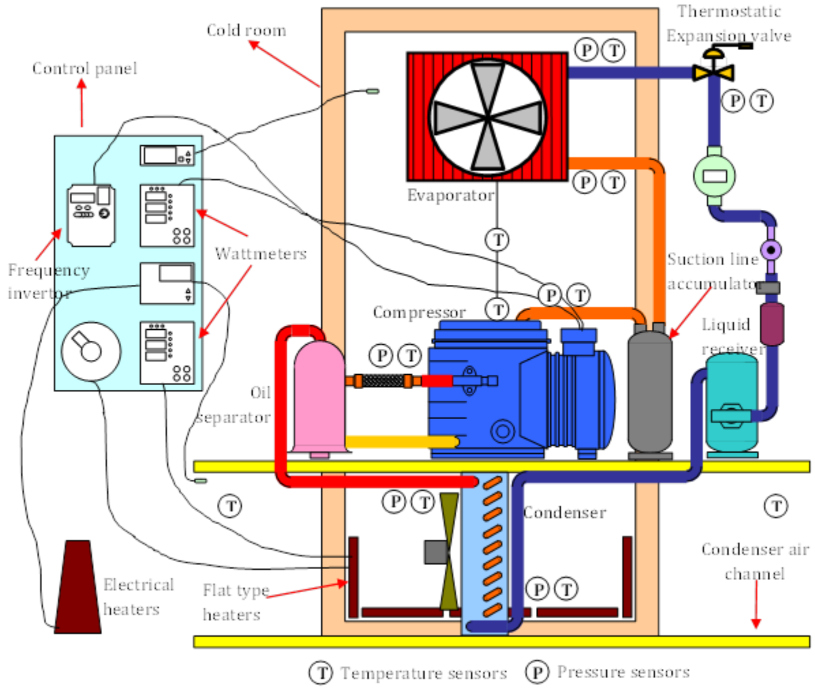

Figure 1. Schematic overview of the experimental setup

3. Thermodynamic Equations

For determining the system performance of the experimental system before data mining application, thermodynamic analysis is applied by using the measured data from the experiments. A general mass balance equation for a steady-state and steady-flow processes can be written as (Cengel and Boles, 1994):

$$\sum \dot{m}_{in} = \sum \dot{m}_{out} \quad (1)$$

where $\dot{m}$ is the mass flow rate, the subscripts in and out are inlet and outlet respectively. The general energy balance for a steady-flow system can be written as;

$$\dot{Q} + \sum \dot{m}_{in} h_{in} = \dot{W} + \sum \dot{m}_{out} h_{out} \quad (2)$$

where, $\dot{Q}$ is the heat transfer rate, $\dot{W}$ is the work, and h is the specific enthalpy. The performance of the refrigeration system can be determined using the Coefficient of Performance (COP) equation:

$$COP = \frac{\dot{Q}_E}{\dot{W}_C} \quad (3)$$

where $\dot{Q}_E$ is the evaporator capacity and $\dot{W}_C$ is the compressor work.

The general exergy balance equation can be written as (Dincer and Rosen, 2007);

$$\sum \dot{Ex}_{in} = \sum \dot{Ex}_{out} + \sum \dot{Ex}_{dest} \quad (4)$$

Here $\dot{Ex}_{dest}$ is exergy destruction rate. The exergy balance in steady state can be expressed in more detail as:

$$\dot{Ex}_Q - \dot{Ex}_W = \sum \dot{m}_{in} e_{in} - \sum \dot{m}_{out} e_{out} + T_0 \dot{S}_{gen} \quad (5)$$

In Equation 5, $\dot{Ex}_Q$ is the exergy rate of heat, $\dot{Ex}_W$ is the exergy rate of work, e is the specific exergy, T_0 is the reference state temperature and $\dot{S}_{gen}$ is the rate of entropy generation. Exergy of heat and work are given below:

$$\dot{Ex}_Q = \dot{Q}\left(\frac{T - T_0}{T}\right) \quad (6)$$

$$\dot{Ex}_W = \dot{W} \quad (7)$$

The rate of entropy generation can be calculated according to the exergy destruction rate:

$$\dot{Ex}_{dest} = T_0 \dot{S}_{gen} \quad (8)$$

The specific exergy which is also called thermomechanical or flow exergy can be expressed relative to the reference environment conditions (T_0, P_0):

$$e = (h - h_0) - T_0(s - s_0) \quad (9)$$

where s is entropy and the subscript 0 stands for reference conditions.

The general exergy efficiency can be written as the ratio of total exergy output to total exergy input (Dincer and Rosen, 2007):

$$\eta_{ex} = \frac{\dot{Ex}_{out}}{\dot{Ex}_{in}} \quad (10)$$

For determining the exergy efficiency of the variable speed refrigeration system, Equation 10 can be rearranged as:

$$\eta_{ex} = \frac{\dot{Ex}_{Q,E}}{\dot{Ex}_W} \quad (11)$$

where $\dot{Ex}_{Q,E}$ is the exergy of evaporator capacity (refrigeration capacity) and $\dot{Ex}_W$ is the exergy of compressor capacity (power consumption of compressor).

Using the equations given above, the performance parameters of the system, namely, compressor power consumption, mass flow rate of refrigerant, experimental and theoretical COP (COP_{exp} and COP_{the}), exergy efficiency and exergy destruction rate are determined.

4. Data Mining

Data mining is the process of uncovering the hidden patterns in the large amounts of data. Parallel to the developments in information technology, there have been improvements in data collection and information about storage. Data are collected from not only business processes the organization but can also be collected from the internet and printed sources. A large amount of the collected data is a valuable information resource that should be evaluated and analyzed. The obtained information can be used to model, classify, and make predictions for numerous applications (Harding et al. 2006).

Data mining procedure can be applied many applications such as information management systems, query processing, decision making, process control, etc. Researchers in many different fields, including database systems, knowledge-based systems, artificial intelligence, machine learning, knowledge acquisition, statistics, spatial databases, and data visualization, have shown great interests in data mining (Chen et al. 1996; Zhang et al. 2010). CRISP-DM (Cross Industry Standard Process for Data Mining), SEMMA, SolEuNet, Kensington Enterprise Data Mining and Data Mining Group have created methodologies, developed languages and software tools for the standardization of industrial applications of data mining (Harding et al. 2006). CRISP-DM process is used in this study. The steps of this process respectively; Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, Deployment (Chapman et al. 2000). Figure 2 shows the CRISP-DM process which defines the basic stages of DM.

The application of data mining process consists of six steps which are explained in brief in the next parts. The implementation of procedure to the performance evaluation of variable speed refrigeration system is carried out using eight predictive modeling techniques as described in modelling section.

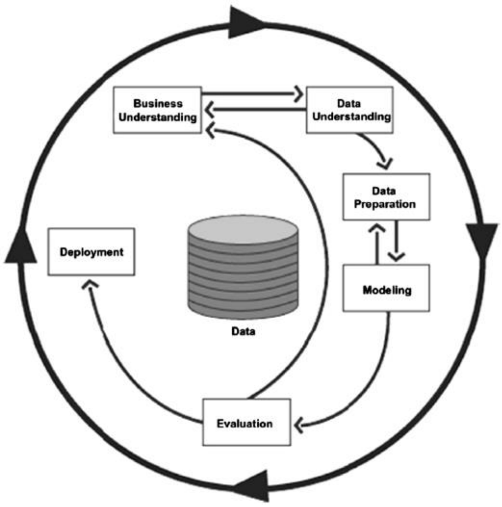

Figure 2. Basic steps of CRISP-DM process (Chapman et al. 2000)

4.1. Business Understanding

The performance parameters of the system such as compressor power consumption, mass flow rate, coefficient of performance (experimental and theoretical), exergy efficiency and exergy destruction rates can be evaluated with this initial phase for different system inputs.

4.2. Data Understanding

For achieving the goal in the first step, the input data which should be collected are investigated. Compressor frequencies, cooling loads, evaporator and condenser temperatures and pressures are determined to be the input parameters.

4.3. Data Preparation

For obtaining the data in second step, the experimental setup shown in Figure 1 is used. Using the experimental setup, the values of cooling load, evaporator temperature, condenser temperature, evaporator pressure and condenser pressure were measured and collected. After this process, compressor power consumption, mass flow rate, coefficient of performance, exergy efficiency and exergy destruction values are calculated using thermodynamic equations.

4.4. Modeling

In this stage, different models are established for each output value using Linear Regression, MultiLayer Perceptron, SMOReg, KStar, Additive Regression, Decision Table, M5Rules, RepTree algorithms. The modelling process is carried out by WEKA software (Weka, 2012). Additionally, 80 % of the values are used for training and 20 % of the values are used for test procedure.

Linear regression (LR): Linear regression is a commonly known method of modeling of the relationship between a dependent variable and independent variables. The regression model uses existing values to forecast the dependent values. In the simplest case, the regression model employs standard statistical techniques such as linear regression. However, many daily life problems cannot be solved by using a linear regression since everything does not change linearly in daily life. Therefore many different techniques (e.g., logistic regression, neural networks) may be necessary to forecast the dependent values (Read, 1999).

MultiLayer Perceptron (MLP): Artificial neural network modeling technique is widely used nowadays and one of the best learning algorithms used in this technique is known as backpropagation. In this algorithm, each piece of data are processed depending on the amount of error between the obtained results with the expected results and learning is performed by changing the connection weights (Alam et al. 2009).

SMOReg: SMOReg (Self-Organizing Maps (SMO) algorithm for regression) is applied to support vector machine for regression. This application replaces all missing global values and converts nominal variables into binary ones. At the same time, it normalizes all the attributes by default. (Chiu et al. 2008).

KStar: KStar is the class of a test instance and is based on the class of those training instances similar to it, as determined by some similarity function. KStar uses entropy based distance function (Wu et al. 2007).

Additive Regression (AR): In this algorithm, prediction is performed by adding prediction of each classifier. Reducing the learning rate helps prevent over-fitting but increases the learning time. Meta classifiers improve the performance of regression-based classifiers (Friedman, 2002; Weka, 2012).

Decision Table (DT): Decision Table shows the data set with a decision table. Decision table uses the wrapper method to find the best subset of attributes to be added to the table. Data set with little or no effect on the attributes of the model by eliminating, the algorithm creates a smaller and more intense decision table. (Cunnigham & Holmes, 1999).

M5Rules: The model M5Rules creates rules from the model trees. All the instances that are covered by the created rule are removed from the dataset. This process continues until all instances in the data set by covered a rule or rules (Goodwin et al. 2003; Hall et al. 1999).

RepTree: Quinlan (1987) first introduced Reduced Error Pruning (REP) as a method to prune decision trees. REP is used with many samples can be very powerful. Using information gain and reduced error pruning creates a decision tree (Licamele & Getoor, 2006).

4.5. Evaluation

In evaluation process, for assessment of the established models explained in previous sections, R^2 (Determination Coefficient), MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), RAE (Relative Absolute Error) and RRSE (Root Relative Squared Error) values are determined. These values are calculated using the equations given below (Akdag et al. 2009; Arcaklioglu et al. 2004; Sozen et al. 2007; Li, & Liu, 2009).

$$R^2 = 1 - \frac{\sum_i (t_i - o_i)^2}{\sum_i (o_i)^2} \quad (12)$$

$$MAE = \frac{1}{p} \sum_i \left| \frac{t_i - o_i}{o_i} \right| \quad (13)$$

$$RMSE = \sqrt{\frac{1}{p} \sum_i |t_i - o_i|^2} \quad (14)$$

In above equations, t is the target value, o is the output value and p is the number of patterns.

4.6. Deployment

In this stage, a computer program is developed using Java programming language and WEKA classes for evaluating each output value. The interface of the designed program is given in Figure 3. As can be seen from the figure, one can easily enter the system parameters and the program evaluates the targets according to the data mining techniques, simplifying the procedure.

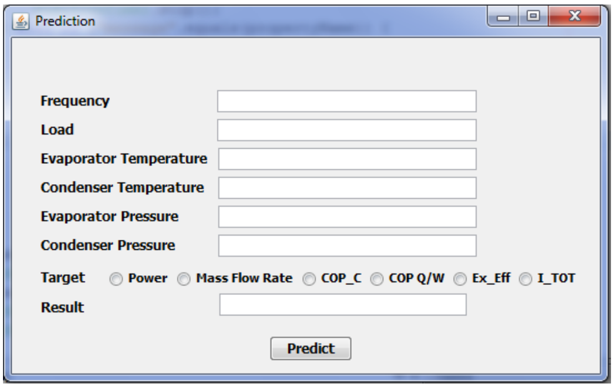

Figure 3. The interface of developed computer program

5. Result and Discussion

Data mining approach is employed to determine the performance of the variable speed refrigeration system. The input variables are namely, frequency, cooling capacity, condenser temperature and pressure, evaporator temperature and pressure. The output parameters to be predicted are power consumption of compressor, mass flow rate of refrigerant, experimental and theoretical COP values (COP_{exp}, COP_{the}), exergy efficiency and exergy destruction rate of the system. For the evaluation of variable speed refrigeration system, eight different data mining techniques that is to say Linear Regression, MultiLayer Perceptron, SMOReg, KStar, Additive Regression, Decision Table, M5Rules, RepTree are used. Furthermore, a comparison of these different modeling techniques is presented.

Statistical values such as R^2, MAE, RMSE, RAE and RRSE are given in Tables 1 to 6 for different system outputs for all modelling techniques. It can be seen from the results of the different modelling techniques that the best results are obtained using Linear Regression for power consumption (Table 1) and exergy efficiency (Table 5), RepTree for mass flow rate (Table 2), Multilayer Perceptron for COP_{exp} (Table 3) and for COP_{the} (Table 4) and for exergy destruction (Table 6).

Table 1. Comparison of prediction models for power consumption

	R^2	MAE	RMSE	RAE(%)	RRSE(%)
Linear Regression	**1**	**0.0003**	**0.0005**	**0.7606**	**0.8854**
Multilayer Perceptron	0.999	0.0007	0.0009	1.5608	1.6551
SMOReg	0.999	0.0006	0.0007	1.2818	1.2723
KStar	0.981	0.0058	0.0077	13.1316	14.8425
Additive Regression	0,947	0.0101	0.012	22.8677	23.2754
Decison Table	0.990	0.0047	0.0052	10.5373	10.0647
M5Rules	0.999	0.0011	0.0013	2.3986	2.5673
RepTree	0.99	0.0021	0.0024	4.672	4.6349

Table 2. Comparison of prediction models for mass flow rate

	R^2	MAE	RMSE	RAE(%)	RRSE(%)
Linear Regression	0.999	0	0	2.742	2.8362
Multilayer Perceptron	0.999	0	0	2.5804	2.778
SMOReg	0.999	0	0	2.6409	2.7218
KStar	0.984	0	0	11.89	13.5527
Additive Regression	0.823	0.0001	0.0001	41.4256	43.1595
Decison Table	0.991	0	0	9.5897	9.4129
M5Rules	0.999	0	0	1.2362	1.2831
RepTree	**1**	**0**	**0**	**0**	**0**

Table 3. Comparison of prediction models for COP_{exp}

	R^2	MAE	RMSE	RAE(%)	RRSE(%)
Linear Regression	0.995	0.0017	0.0053	2.6714	7.2534
Multilayer Perceptron	**0.997**	**0.0015**	**0.0041**	**2.4416**	**5.6039**
SMOReg	0.995	0.0014	0.0049	2.2058	6.7693
KStar	0.983	0.008	0.0104	12.641	14.3453
Additive Regression	0.946	0.0149	0.0172	23.6699	23.5987
Decison Table	0.952	0.012	0.0163	19.0913	22.3788
M5Rules	0.993	0.002	0.0059	3.2179	8.1038
RepTree	0.944	0.0116	0.017	18.3821	23.4311

Table 4. Comparison of prediction models for COP_{the}

	R^2	MAE	RMSE	RAE(%)	RRSE(%)
Linear Regression	0.975	0.007	0.0185	7.052	16.1464
Multilayer Perceptron	**0.986**	**0.0069**	**0.0135**	**6.985**	**11.7955**
SMOReg	0.973	0.0059	0.0189	6.013	16.5728
KStar	0.952	0.0185	0.0268	18.7251	23.4192
Additive Regression	0.884	0.0356	0.0434	36.1169	37.9542
Decison Table	0.616	0.0473	0.0723	48.0023	63.2185
M5Rules	0.964	0.0076	0.0221	7.7586	19.3026
RepTree	0.871	0.0393	0.0475	39.8772	41.5224

Table 5. Comparison of prediction models for exergy efficiency

	R^2	MAE	RMSE	RAE(%)	RRSE(%)
Linear Regression	**1**	**0.0001**	**0.0001**	**0.8091**	**1.1285**
Multilayer Perceptron	0.999	0.0001	0.0002	2.0554	2.108
SMOReg	1	0.0001	0.0001	0.9066	0.963
KStar	0.985	0.0008	0.001	12.2029	13.3079
Additive Regression	0.911	0.0019	0.0023	29.8724	31.3924
Decison Table	0.868	0.0023	0.0027	36.2441	36.7926
M5Rules	0.990	0.0005	0.0007	7.6326	10.1909
RepTree	0.941	0.0017	0.0019	26.1958	26.2694

Table 6. Comparison of prediction models for exergy destruction

	R^2	MAE	RMSE	RAE(%)	RRSE(%)
Linear Regression	0.999	0.0005	0.0014	1.1564	2.7814
Multilayer Perceptron	**0.999**	**0.0005**	**0.0009**	**1.1848**	**1.7293**
SMOReg	0.999	0.0006	0.0008	1.2968	1.5875
KStar	0.979	0.0058	0.0078	13.4891	15.6277
Additive Regression	0.948	0.0099	0.0115	23.2653	23.0854
Decison Table	0.989	0.0047	0.0054	10.9761	10.7626
M5Rules	0.999	0.0008	0.001	1.7626	2.0268
RepTree	0.987	0.0044	0.006	10.2038	11.9651

The comparisons of the results of actual and predicted parameters using data mining approach are given in Figures 4-9. In Figure 4, a comparison of measured and predicted values of power consumption is given. In Figure 5, a comparison of actual mass flow rate and predicted one is given. Figure 6 and 7 show the comparison of actual and measured COP_{exp} and COP_{the} values. In Figure 8, actual and predicted exergy efficiency values are compared. In the last Figure, actual and calculated exergy destruction rate of the system are compared. It can be seen from the figures that, the regression curves for the actual values agree well with the predicted ones for output parameters. It should be noted that these data are completely unknown for the model. The R^2 value obtained for power consumption is 0.999, for mass flow rate is 1, for COP_{exp} is 0.997, for COP_{the} 0.9861, for exergy efficiency is 0.999 and for exergy destruction is 0.9998. From the results it can be understood that the results are very satisfactory.

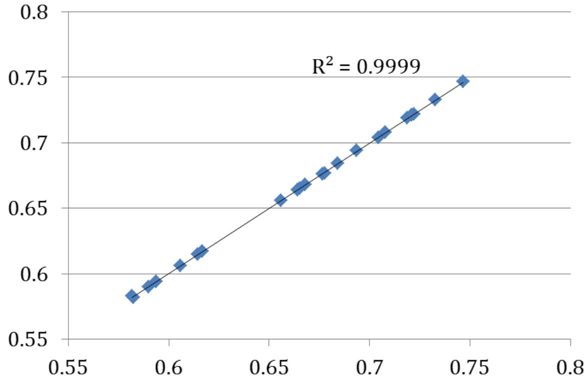

Figure 4. Comparison of the measured and predicted values for the power consumption of compressor

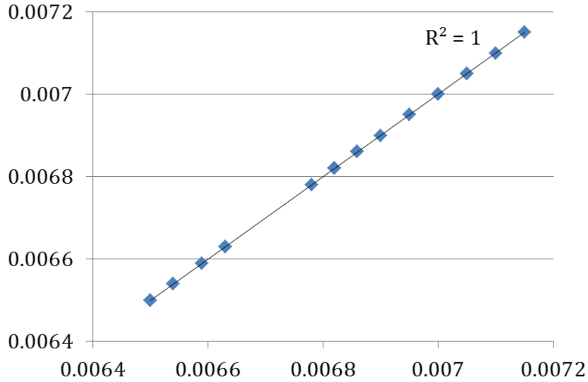

Figure 5. Comparison of the measured and predicted values for the refrigerant mass flow rate

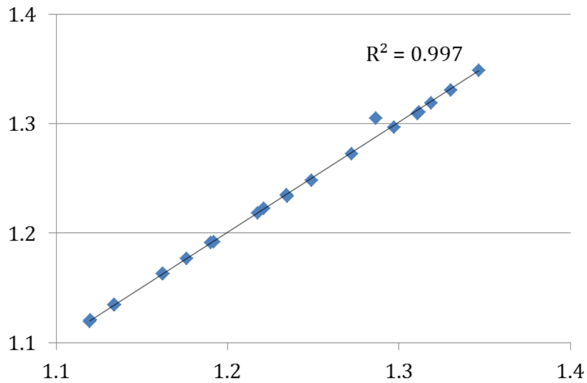

Figure 6. Comparison of the measured and predicted values for the COP_{exp}

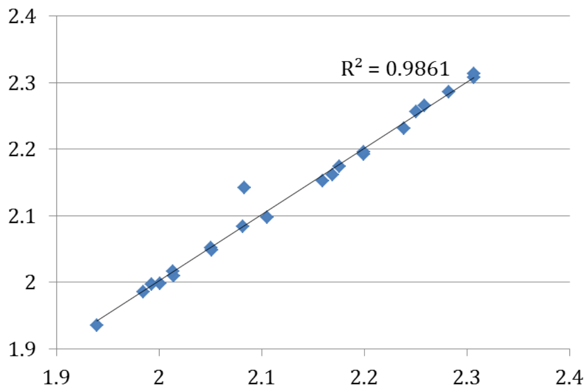

Figure 7. Comparison of the measured and predicted values for the COP_{the}

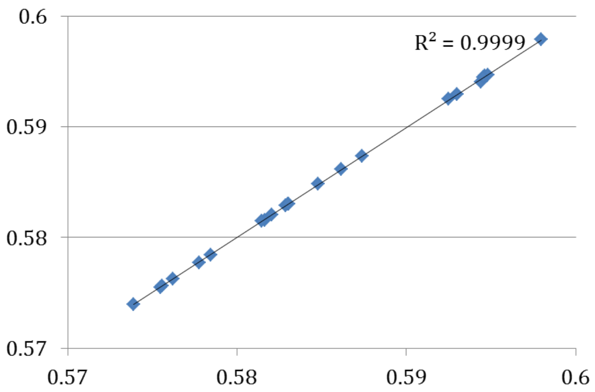

Figure 8. Comparison of the measured and predicted values for the exergy efficiency

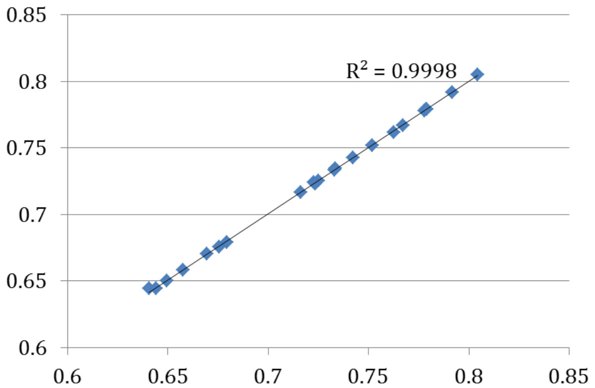

Figure 9. Comparison of the measured and predicted values for the exergy destruction

6. Conclusions

In this study, thermodynamic performance analysis of variable speed refrigeration system was successfully carried out using data mining technique. Eight different algorithms were used for the analysis namely, Linear Regression, Multilayer Perceptron, SMOReg, KStar, Additive Regression, Decision Table, M5Rules, RepTree. The statistical error values namely R^2, MAE, RMSE, RAE, RRSE were determined to compare the results of analyses. From the results, it was examined that the predicted performance indicators of the refrigeration system using data mining approach exhibited excellent accuracy. With the help of this approach, one can determine the system characteristics for the unmeasured compressor frequencies instead of making several experiments. The use of data mining approach is found to be satisfactory for the analysis of refrigeration systems.

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