Mansoura Engineering Journal, (MEJ), Vol. 36, No. 4, December 2011. M. 39

A Proposed Performance Prediction Approach for Manufacturing Process using Artificial Neural Networks

التنبؤ بأداء عمليات التصنيع بإستخدام الشبكات العصبية الإصطناعية

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ملخص:

يقدم هذا البحث طريقة للتنبؤ بأداء الأجزاء المنتجة خلال عمليات تصنيع متعددة المراحل، تهدف للتحكم في مدخلات ومخرجات العملية وتحديد العلاقة بينهما ومن ثم يصبح مهندس العمليات قادراً على التنبؤ بأداء مخرجات العملية بناءاً على مدخلاتها بدقة أكثر. يسير هذا العمل وفق منهجية سيجما ستة (Six-Sigma) لتحسين أداء كلا من العمليات والمنتج.

يعرض البحث دراسة حالة في تصنيع الضواغط الترددية محكمة الغلق، حيث أن كل مرحلة من مراحل التصنيع المختلفة تؤثر في وظيفة المنتج النهائي، وهنا نقدم تطبيقاً لاستخدام الشبكات العصبونية الاصطناعية (Artificial Neural Networks) بغرض تحسين التنبؤ بأداء المنتج خلال هذه البيئة الصناعية. النتائج توضح أن الطريقة المقترحة قادرة على التنبؤ بدقة وفاعلية.

ABSTRACT

This paper aims to provide an approach to predict the performance of parts produced after multi-stages manufacturing processes, as well as assembly. Such approach aims to control and subsequently identify the relationship between the process inputs and outputs so that a process engineer can more accurately predict how the process output will perform based on the system inputs. The work is guided by a six-sigma methodology to obtain improved performance.

In this paper a case study of the manufacture of a hermetic reciprocating compressor is presented. Each of manufacturing stages is separate and affects to the functionality of the end product. The application of artificial neural networks (ANNs) technique is introduced to improve performance prediction within this manufacturing environment. The results demonstrate that the approach predicts accurately and effectively.

Keywords: Performance prediction, Six Sigma, Artificial neural networks, Quality control, Hermetic reciprocating compressor manufacturing.

Accepted November 2, 2011.

1. Introduction

Performance prediction of manufacturing process and products is one of the important manufacturing processes improvement tools. Product performance measurements are difficult and expensive, as these measurements are often destructive tests done via selecting samples from the production volume of product which requires more time and high costs.

Rapidly evolving technologies, that employ advanced techniques, such as lasers, machine vision, and pattern recognition, are incentives to develop general and accurate prediction methodologies for product performance [1].

Prediction systems are implemented as a proactive rather than a reactive manufacturing process improvement tool. Several researchers investigate the usage of statistical process control (SPC), such as regression model and design of experiments (DOE) and ANN as prediction systems.

Predictive systems are utilized as proactive rather than reactive procedures in manufacturing environment. Stochastic optimization is adoptive rather than deterministic in many situations within manufacturing environment [2]. Therefore ANNs are deployed in several applications through manufacturing environment. ANNs are used to monitor and recognize the abnormal patterns situations on SPC chart [3]. Application of the ANNs as a prediction model is presented in many publications [4], [5] ,[6], [7].

The main advantage for using ANNs is that they have the ability to ''learn'' arbitrary nonlinear mappings between noisy sets of input and output data. The most popular applications of ANNs in the fields of automation and manufacturing control are in pattern recognition and economics.

Several researchers utilized ANNs as a prediction model in several manufacturing fields. It predicts important information about the manufacturing processes, such as, extrusion process parameters, welding characteristics, boring process, machine tool failure and surface roughness [7-14].

Prasad and Khong utilized ANNs to predict the quality of a plastic injection molding process utilizing several process inputs. They used statistical tools to identify the input variables to predict process injection time. The resulting value is utilized as an input parameter to a second neural network to predict injection molding process quality [4].

Ghiassi and Nangoy presented the development of a dynamic architecture for ANN (DAN2) model for solving nonlinear forecasting and pattern recognition problems. They showed DAN2 to be more accurate and to perform consistently better than alternative approaches employed in forecasting nonlinear processes [15].

Radial basis function network and Taguchi method were combined by Huang and Hung to structure a well-trained prediction model and further to search for the optimal hard disk drive packaging process parameter design through genetic algorithm [16].

A practical method is presented to estimate IC product performance and parametric yield by Cho, Kim et al from a well-chosen set of existing electrical measurements intended for technology monitoring at an early stage of manufacturing [17].

A neural network model was developed by Chang and Jiang to probe the dependency between the quality of finished product and sensor measurements which were collected to monitor the failure (sudden fracture) of a tool in the manufacturing process. The quality information of finished product can be further obtained from the on line tooling sensor measurements utilizing the trained neural network [1].

Johnston et al. introduced research on the integration of intelligent techniques and a Six Sigma methodology for the performance prediction in a manufacturing environment. They developed a model for downstream prediction based on the writing parameters of the R/W head of hard disc drive (HDD), to predict how each *individual head* would perform in a finished HDD based on parametric measurements during manufacturing stages of HDD head [18].

Many authors discussed the off-design simulation or after operating at customer of the behavior of one equipment (compressor, pump, turbine, etc.) utilizing statistical forecasting methods and/or ANNs mentioned in the references [5, 19-21]. There are no results about prediction model for part or product performance within manufacturing environment of equipment such as hermetic compressor, except some researches in semiconductors industry [7, 16-18].

Several business improvement methodology and techniques were developed recently. One such technique is the Six Sigma. Six-Sigma is defined as "a strategic initiative to boost profitability, increase market share and improve customer satisfaction through statistical tools that can lead to breakthrough quantum gains in quality."As a methodology it uses existing problem solving tools to eradicate system variations. The methodology of Six Sigma is to identify the key input variables of a process and subsequently controlling them will ensure that the key output variables of a process will also remain in control. This is contrary to common manufacturing policy and many process engineers concept where they tend to monitor process outputs (e.g. final product) and then react to out of control situations as they occur [22, 23].

Case study in this work is the manufacturing of hermetic reciprocating compressors from parts casting to overall assembly processes of the compressor with its controlling mechanisms through machining operations. For developing and manufacturing of higher compressor performance, the challenge of non-contaminant refrigerants, the need for higher efficiency, optimal design and noise reduction are strong incentives to develop general and accurate prediction methodologies.

In this work , the ANNs is developed to predict the manufacturing performance via the quality control data of machined parts which impact on performance of finished product through the proposed approach. Section 2 describes the manufacturing environment of reciprocating compressor. Experiments implementation is described in section 3. A proposed ANN model is presented within an industrial case study in section 4. Section 5 presents the Sigma quality level improvement. The conclusions of research are highlighted in section 6.

2. Manufacturing environment of hermetic reciprocating compressors

The strategy of hermetic reciprocating compressor manufacturers is to develop the smallest and lightest with intended performance with the most cost-effective pricing plan and delivered to the market on time with highest quality.

The reciprocating compressor is the workhorse of the refrigeration and air conditioning industry. Fig. 1 shows a detailed scheme of a hermetic reciprocating compressor. Reciprocating compressors consist of a piston moving back and forth in a cylinder, with suction and discharge valves to achieve suction and compression of the refrigerant vapor. The suction side is connected to the exit of the evaporator, while the discharge side is connected to the condenser inlet. The suction and discharge valves open and close due to pressure differences between the cylinder and inlet or outlet manifolds respectively. The valves used are of plate type.

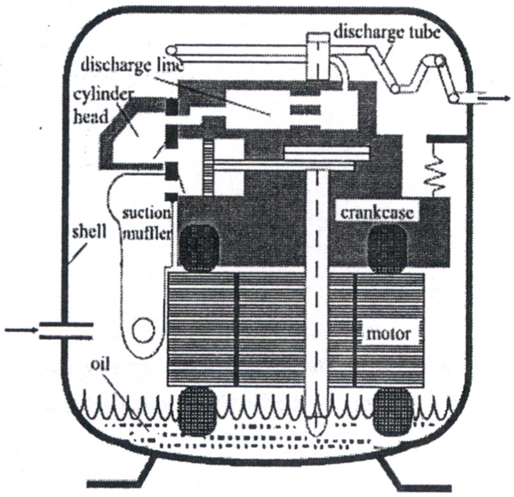

Fig. 1: General hermetic reciprocating compressor scheme

It is extremely difficult to develop a defect free manufacturing process in a high-volume reciprocating compressor environment. There are so many operations of manufacturing processes for each part. A more viable option is to attain the ability to predict how a part may perform after assembly operations. This will aid production planning, fault finding and improve time to market/volume.

Within this manufacturing environment, Six-sigma methodology opportunities exist to improve the area of parametric data and thus quality prediction. However, the manufacturing of hermetic reciprocating compressor parts has complex relationship within its multi-stages operations. This work is done involving six-sigma project development, its objective is determining and using prediction approach for compressor performance based on quality parameters of parts. It aims to predict how each part of unit (valve unit) will perform in a finished compressor based on quality parameters of assembled parts of unit. The test of one compressor takes about two hours, so sampling technique is used. Therefore, the prediction of performance of parts (units) before arriving to final manufacturing stage would save time and improve both quality and production yield.

The challenge of non-contaminant refrigerants, the need for higher efficiency, optimal designs and noise reduction are strong incentives to develop general and accurate prediction methodologies.

In this case study, the outputs of calorimeter test will be considered to study with respect to influencing of valve unit on compressor performance. The compressor may be divided to three units, motor and starting equipment, piston/cylinder unit and valve unit. In this research, the valve unit is concerned for determining and verifying the proposed prediction model.

3. Experimental procedures

3.1. Experimental facilities

The manufacturing and assembly equipment used is stable and in control statistically. The measurement equipment used is the calorimeter tester Microline SRL. The experimental compressor used in this study is GL 70AA made by

MCMC, Egypt. The samples are drawn from the same production lot with the same geometrical parameters to minimize differences in part qualities. All presented cases correspond to a domestic hermetic reciprocating compressor of 6.64 cm^3cylinder capacity, working with refrigerant *R134a* and a nominal frequency of 50 Hz.

Suction, compression and discharge are the main processes to compressor perform its function. All these processes are done through valve plate orifices such as suction and discharge orifices. This experiment aims to determine the valve unit metrology influencing compressor performance. Consequently, this study would be considered a guide for implementing the same procedures with the rest units of the compressor to determine importance each part for compressor performance.

3.2. Experimental design

The experiments are focused on the valve unit (including valve plat, valve gaskets, cylinder head and muffler). The selected control factors for valve unit are valve thickness (V_t), discharge orifice diameter of valve plate (D_v) and discharge orifice diameter of crank case (D_{cc}) shown in Figs. 2 and 3. The factor levels are lower and upper tolerance limits as listed in Table 1 as inferred from geometrical parameters. The experiments are performed with the full factorial method (i.e. 2^3 trails for 3 factors in 2 levels).

Table 1- the control factors and levels of the experiments

Control factors	Level	
	lower	upper
(V_t) valve thickness (mm)	2.75	2.85
(D_{cc}) discharge orifice diameter of crank case (mm)	2.88	3.12
(D_v) discharge orifice diameter of valve (mm)	2.275	2.525

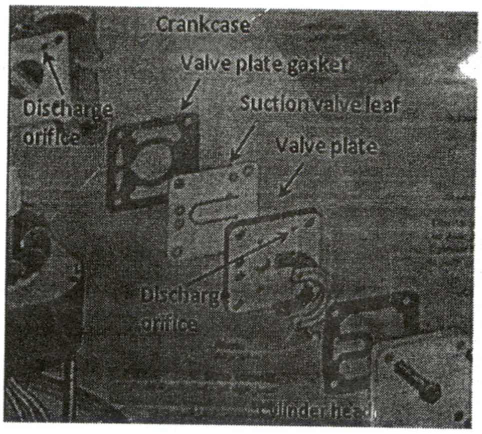

Fig. 2: Schematic valve unit of compressor.

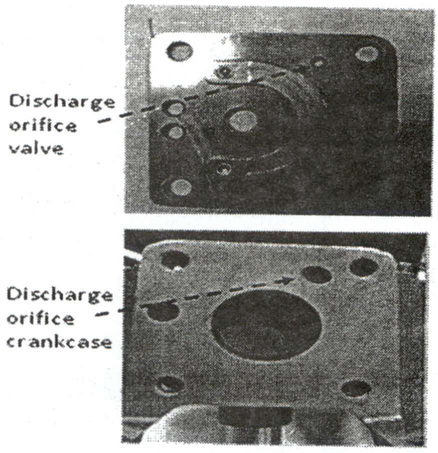

Fig. 3: Discharge orifice of valve plate and crankcase.

This method is selected to study the effects of all the factors on the final responses. This methodology provides a suitable tool for screening various factors with limited experimental results.

3.3. Quality characteristics (performance indicators)

The manufacturer considers several quality characteristics of hermetic reciprocating compressor at quality tests stage. These quality characteristics conform to global working values such as cooling capacity (CC), power consumption (PC), coefficient of performance (COP), etc. In this study, CC, PC and COP are chosen as the compressor performance indicators, and measured from a calorimeter test. CC and COP as a quality characteristics are the larger-the better. Conversely, manufacturer strives for lowest PC.

The quality characteristics value for this case study transfer to ratio of the best value could be calculated from historical data of our compressor model. The CC ratio (CCR) and COP ratio (COPR) are computed according to the relationship;

$$Ratio = \frac{\textit{actual value of Quality Characteristic}}{\textit{max expected value of Quality Characteristic}} \quad (1)$$

For PC ratio (PCR), *1/Ratio* is used, as the target is the lowest value.

3.4. Experimental results and analysis

To handle the experiments, the data of 24 compressors are collected based on eight samples of data of a two-level DOE 2^k full factorial analysis with 3 replicate. All the samples are manufactured and tested in real manufacturing environment maintaining of rest parameters of other parts. The performance indicators selected for this study and their calculated values from results for each combination of factors are given in Table 2.

3.4.1. Cooling capacity

The interactions factors shown in Fig.4 influence the response (cooling capacity) as shown in ANOVA test demonstrated in Table 3 and Pareto chart shown in Fig. 5. Contour plot in Fig. 6 shows the relationship of this manufacturing process where just two input parameters, discharge valve diameter (D_v) and discharge crankcase diameter (D_{cc}) were altered with hold input parameter (V_t) versus one of compressor performance characteristics (CC) as a response. This contour is produced with two parts of compressor. It may be more complex for more parts.

Cube plots can be used to show the relationships among two to eight factors for two-level factorial designs. The cube plot shown in Fig. 7 illustrates the three-factor (V_t, D_v and Dcc) cube plot with response variable CC. This cube plot shows the cooling capacity means at each point on *the* cube where observations were measured.

Table 2- The control factors combinations and their responses of experiments

no.	Control factors			Performance indicators ratio		
	Vt	Dcc	Dv	CCR	COPR	PCR
1	Min	Min	Min	0.955	0.931	0.963
2	Min	Min	Min	0.931	0.924	0.924
3	Min	Min	Min	0.948	0.934	0.916
4	Min	Max	Max	0.961	0.937	0.908
5	Min	Max	Max	0.932	0.920	0.917
6	Min	Max	Max	0.953	0.938	0.915
7	Min	Min	Max	0.964	0.934	0.901
8	Min	Min	Max	0.946	0.924	0.908
9	Min	Min	Max	0.951	0.958	0.936
10	Min	Max	Min	0.957	0.951	0.924
11	Min	Max	Min	0.993	0.935	0.875
12	Min	Max	Min	0.963	0.930	0.899
13	Max	Min	Max	0.959	0.951	0.923
14	Max	Min	Max	0.963	0.938	0.906
15	Max	Min	Max	0.949	0.938	0.919
16	Max	Max	Min	0.941	0.925	0.913
17	Max	Max	Min	0.982	0.929	0.880
18	Max	Max	Min	0.941	0.935	0.924
19	Max	Min	Min	0.936	0.917	0.911
20	Max	Min	Min	0.918	0.932	0.944
21	Max	Min	Min	0.923	0.919	0.926
22	Max	Max	Max	0.933	0.935	0.932
23	Max	Max	Max	0.951	0.934	0.913
24	Max	Max	Max	0.9388	0.9306	0.921

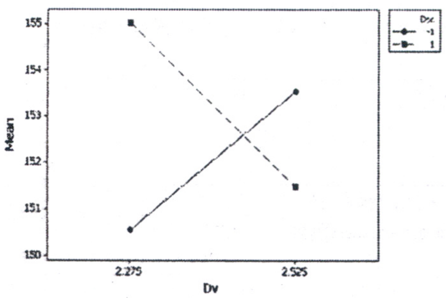

Fig. 4: Interaction plot for CC Vs. D_v and D_{cc}.

Regression analysis is used to identify the relationship between independent variables and the associated dependant variables, and to predict the trend of dependant variables as a function of independent variables. The regression analysis is applied based on the results of experiments and the correlation coefficient R^2 is used to justify the validity of regression model. MINITAB package is used for the regression analyses in this work.

Table 3- ANOVA for Cooling capacity of the experiments

Source	DF	Seq. SS	Adj. SS	Adj. MS	F	P
Main Effects	3	33.56	33.45	11.1523	3.07	0.060
2-Way Interactions	3	60.885	60.884	20.2949	5.59	0.009
3-Way Interactions	1	0.000	0.0001	0.0001	0.00	0.996
Residual Error	15	54.45	54.4517	3.6301		
Pure Error	15	54.45	54.4517	3.6301		
Total	22	148.89				

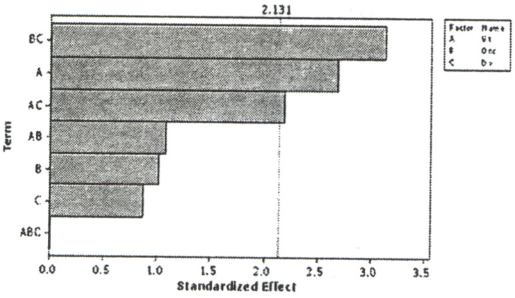

Fig. 5: Pareto chart of the effects on CC (Alpha=0.05).

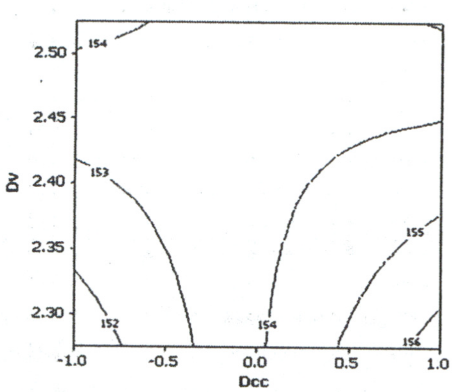

Fig. 6: Contour plot of CC Vs. Dv and Dcc

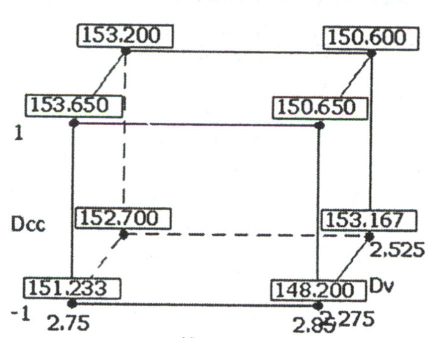

Fig. 7: Cube plot fitted means for CC Vs. V_t, D_v and D_{cc}.

The regression model obtained of DOE analysis is for the cooling capacity is:

$$CC = 718.76 - 207.6\,Vt - 378.4Dcc - 212.47Dv + 141.2Vt\,Dcc + 78VtDv + 166.67DccDv - 62VtDccDv \quad (2)$$

The R^2 value of this model is 0.72.

In general the prediction of the compressor performance parameter is very difficult using the regression model in manufacturing environment. Therefore, the proposed ANN model will be implemented in next section.

The proposed ANN model is used to predict the performance parameter of compressor within quality parameters measured during manufacturing and assembly processes. Specifically, the study uses calorimeter test as a quality test which gives the compressor performance indicators: cooling capacity, power consumption, and COP.

4. Artificial neural network model

Principally, to obtain a successful model of ANN, it based mainly on a process of trial and error with some factors to consider. Although ANNs are widely used for modeling purposes in various different areas, until now there are no clear rules that could serve as a basis to follow in producing the most efficient model [13]. This study considers the factors which could be that affect the effectiveness of the ANN developed model.

4.1. Network structure

In this study, the network structure shown in Fig. 8 is selected as a result of many iterations. Table 4 gives the results of using different network structures. The structure that gives best results (given in last raw) is selected. This structure can be described as:

- *Input layer*: Five nodes for the input layer corresponds to the five predictors which are valve thickness (V_t), discharge crankcase diameter (D_{cc}), discharge valve diameter (D_v), gasket thickness (G_t) and air gap (A_{gap}) between the piston and cylinder hole.

Table 4- Networks results summary

Network structure	# Hidden layer(s)	Transfer Function	MSE (*mean Square error*)	Correlation Coefficient R		
				Training	validation	Test
5-7-1	1	tansig	0.13	1.000	0.798	0.887
5-8-1	1	tansig	0.20	0.971	0.798	0.820
5-8-1	1	logsig	0.20	0.873	0.673	0.634
5-20-5-1	2	tansig, tansig	0.027	0.999	0.806	0.890
5-6-10-1	2	tansig, tansig	0.089	1.000	0.825	0.897
5-15-12-1	2	tansig, tansig	0.025	0.999	0.974	0.807

- *Hidden layers*: two hidden layers. First layer contains 15 neurons. Second layer contains 12 neurons. The hyperbolic tangent sigmoid transfer function (tansig) is used for these hidden layers, according to the relationship;

$$Output = \frac{2}{1+\exp(-2\times input)} - 1 \quad (3)$$

- *Output layer*: consists of one neuron that gives its output as estimated value of cooling capacity. The used transfer function for this layer is linear function (purelin).

4.2. Training and testing data

- *Data collection,* the training set contains 29 examples collected from experiments, divided into 70% for training, 15% for validation and 15% for testing. These data are used as inputs to the proposed ANN prediction model and its output is the estimated cooling capacity as valve unit performance.

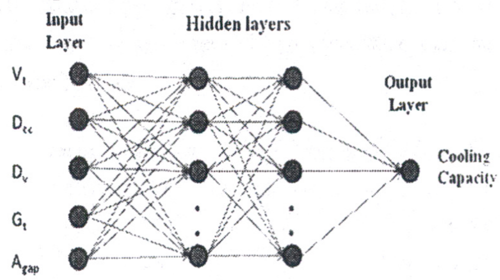

Fig. 8: ANN structure used 5-15-12-1.

- *Normalization,* is used to scale down the range of input data to a range between −1 and +1 using the following equation:

$$x_{normalized} = 2\,\frac{x - x_{min}}{x_{max} - x_{min}} - 1 \quad (4)$$

Where, x is the input value of network, x_{min} and x_{max} are the minimum and the maximum values in a given set for each quality characteristic, respectively.

4.3. Network application

- *Training Results*; the accepted performance with the 5-15-12-1 structure was achieved with training performance MSE of 0.001. The regression analysis was performed on training data set to determine highly accuracy network performance with correlation coefficient (R) between target and output of simulation of trained ANN of 0.999. It has best validation performance MSE of 0.027 at epoch 3 and correlation coefficient (R) between target and output for validation data of 0.974.

- *Test Results*; the results of testing the ANN used in this work using unseen data are shown in Fig. 9. The convergence condition is considered achieved when the R between actual values and predicted output is greater than 0.80 referred to limitation of the training data set.

Fig. 10 illustrates the actual value vs. output plot for the trained ANN simulated by all training data set. Performance of network can be improved if training data is increased. Data collection is very difficult as it is done in the manufacturing environment actual production takes place not in laboratory environment.

5. Sigma quality level improvement

5.1. Current sigma level of CC

Utilizing a measure of part-per-million (PPM) as a defect rat measure, in our case study, manufacturer determined the PPM of 59,000 defective units per million for four critical to quality characteristics (CTQs) named cooling capacity, COP, Power and current. This corresponds to the 3.07 sigma level and the percentage of yield (Y) is 94.17 % according to this formula [23, 24],

$$Y = \left(1 - \frac{\mathrm{PPM}}{1{,}000{,}000}\right) \times 100 \qquad (5)$$

Where, Y is yield percentage and PPM is parts-per-million.

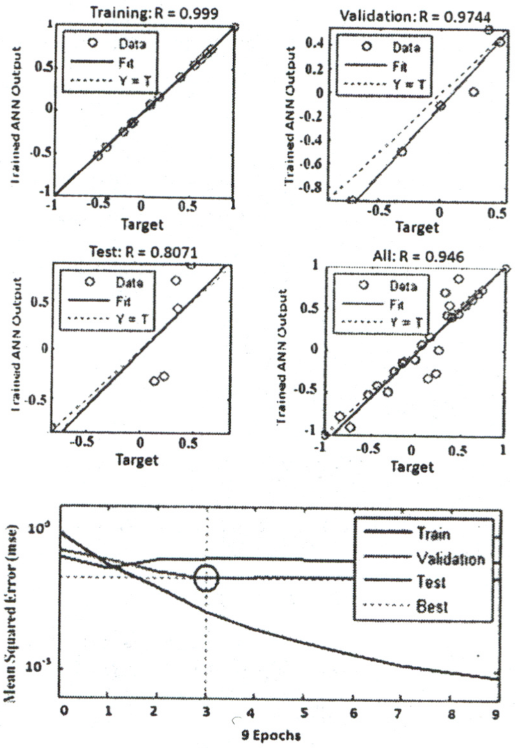

Fig.9: Training result of proposed ANN structure.

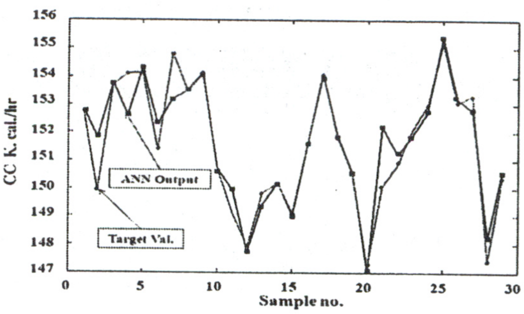

Fig. 10- Trained ANN output vs. target plot.

Assuming every one of the four CTQs has equal yield, then the yield of production caused by cooling capacity test result is 0.985 which corresponds to PPM of 15,000 defective unit per million. This corresponds to the 3.67 sigma level. The cooling capacity readings from calorimeter test show the assembly operations performance as shown in Fig. 11, with *Cpk* (process capability index) of 0.72.

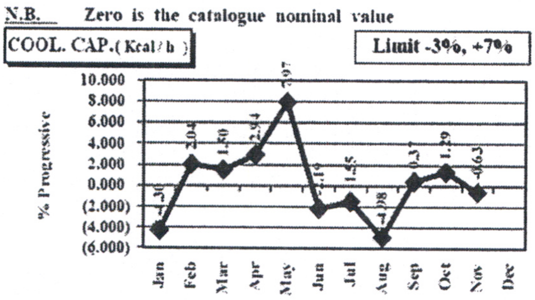

Fig. 11- Average values of cooling capacity for a year.

5.2. Process improvement

After appling the proposed approach integrated with tracing and quality control systems in order to improve the classification and assembly parts with appropriate dimension and geometrical tolerances. This is expected to improve the assembly processes capability at least 15% with respect to cooling capacity characteristic, so that *Cpk* becomes 0.828 coresponding to the 4 sigma level, and PPM of 6,200 defective part per million from tables in [23].

6. Conclusions

This paper describes a proposed approach for performance prediction of product within manufacturing environment. The ANN is utilized to predict the performance indicators such as CCR, COPR and etc. Then, Six Sigma techniques are used to evaluate the manufacturing system integrating ANNs.

DOE analysis and historical data of industrial case are utilized to determine most factors influencing quality characteristics of compressor such as the CC and COP. For the valve unit of the compressor, valve thickness, gasket thickness, valve discharge orifice diameter, crank case discharge orifice diameter and piston/cylinder clearance were determined to influence both CC and COP of compressor performance indicators.

The proposed ANN model gives acceptable results to predict the cooling capacity ratio and identifies the performance parameter levels with real data. The performance of trained ANN would be improved further with increasing the amount of data collected from manufacturing environment. It is further determined that the proposed approach increases the throughput yield, and improves sigma quality level for the process and organization.

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