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A Proposed Performance Prediction Approach for Manufacturing Processes using ANNs

M. S. Abdelwahed, M. A. El-Baz and T. T. El-Midany

***Abstract*—**this paper aims to provide an approach to predict the performance of the product produced after multi-stages of manufacturing processes, as well as the 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 shall perform based on the system inputs. The approach 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. 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*—**Artificial neural networks, Reciprocating compressor manufacturing, Performance prediction, Quality improvement

I. Introduction

PERFORMANCE prediction of manufacturing process or product is one of the important for quality improvement. Product performance measurements are difficult and cost, as these measurements are often done via selecting samples from the production volume of product. It consumes more time and cost.Rapidly evolving technology, which employs 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 usage of statistical process control (SPC), such as regression model and design of experiments (DOE) and ANN as prediction systems.Tsai et al. presented a study to determine the effects of process parameters on optical quality of lenses during injection molding. They used the Taguchi method to perform screening experiments to identify the significant process parameters affecting quality of lenses. From their results that the highest accuracy prediction of surface waviness as a quality characteristic was from a nonlinear regression model [2].

M. S. Abdelwahed is with the King Abdulaziz University, Faculty of Engineering, Jeddah, Saudi Arabia, on leave from, Workers University, Egypt, (phone: +966-558-818-275; e-mail: ms_wahed@ yahoo.com).

M. A. El-Baz is with Industrial Engineering Department, Zagazig University, Egypt, (e-mail: elbaz@2mail.com).

T. T. El-Midany is with the faculty of Engineering, Mansoura University, Egypt, (e-mail: elmidany@mans.edu.eg).

The ANNs have the ability to ‘‘learn’’ arbitrary nonlinear mappings between noisy sets of input and output data. Several researchers are utilizing ANNs as a prediction model for several manufacturing fields. It predicts important information about the manufacturing processes, such as, extrusion process parameters, welding characteristics, machine tool failure and surface roughness. It is deployed in several applications within manufacturing environments [3]-[8].

Chen and al [9] presented an innovative self-organizing map plus a back-propagation neural network model for creating a dynamic quality predictor for a plastic injection molding process too.

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 [10]. An example of how ANNs have been deployed within semiconductor specific problem domains. The application developed was to replace necessary experimentation on semiconductor chips in an effort to determine critical process parameters (i.e. melting point and band gap). The modeling capabilities within manufacturing is the ability to predict processing yield [11].

A neural network model was developed by Chang and Jiang to probe the dependence 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. 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 [12].

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 [13]-[16]. There are no results about prediction model for part/product performance within manufacturing environment of finished product such as hermetic compressor, except some researches in semiconductors industry [3], [10], [12], [17].

Several business improvement methodology and techniques were developed recently. One such technique is the Six Sigma. Harry (1998) defines Six Sigma to be “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 [12], [18]-[20].

Case study in this research 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 research, 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.

II. MANUFACTURING ENVIRONMENT OF HERMETIC RECIPROCATING COMPRESSORS

Since the end of the 19th century, compressor design and improvement have been subordinated to continuous experimentation and learning. 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.

The reciprocating compressor is the workhorse of the refrigeration and air conditioning industry. Figure 1 shows the 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.

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 valves used are shown in Fig. 2. 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.

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.

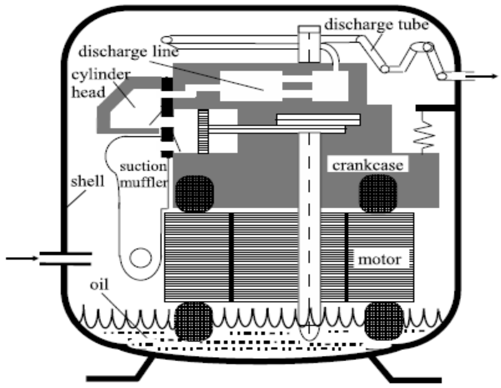

Fig. 1 General hermetic reciprocating compressor scheme

Predictive systems are utilized as proactive rather than reactive procedures in manufacturing environment. Stochastic optimization is adopted rather than deterministic optimization in many situations within manufacturing environment [21]. Therefore ANNs are deployed in several applications through manufacturing environment. ANNs are utilized as a prediction model that is demonstrated in many aspects of researches [2], [3], [15].The manufacturing of hermetic reciprocating compressor parts has complex relationship within the operations of multi-stages. 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 product before arriving to final testing stage would save time and improve both quality and production yield.

III. EXPERIMENTAL PROCEDURES

A. Experimental Facilities

The experimental facilities can be divided into; 1) the manufacturing and assembly equipment used is stable and in control statistically and 2) 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 produced from the same production lot with same geometrical parameters to minimize deference in part qualities. All cases herewith presented correspond to a domestic hermetic reciprocating compressor of a cylinder capacity 6.64 cm^3, working with R134a and a nominal frequency of 50 Hz.

Suction process, compression process and discharge process 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 work aims to determine the influencing of valve unit metrology on finished compressor performance. Consequently, this study would be considered a guide for implementing the same procedures with the rest units and parts to determine importance each part for compressor performance.

B. *Experimental Design*

The experiments are focused on 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}) as illustrated in Fig. 2 and 3. The factor levels are two, at lower tolerance limit and upper tolerance limit as listed in Table 1 selected from geometrical parameters. The experiments are executed according to full factorial method in 2^3 trails (3 factors in 2 levels). During experiments, full factorial designs were used to study the effects of all the factors on the final responses.

C. *Quality characteristics (performance indicators)*

Number Several quality characteristics of hermetic reciprocating compressor are considered by the manufacturer at quality tests stage 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 are 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 produced from historical data of our compressor model. The Cooling capacity ratio (CCR) and COP ratio (COPR) are computed according to the relationship;

$$\text{Ratio} \equiv \frac{\text{actual value of Quality Characteri stic}}{\text{max. expected value of Quality Characteri stic}} \qquad (1)$$

For power consumption ratio (PCR), 1/Ratio is used, where the target is lowest value.

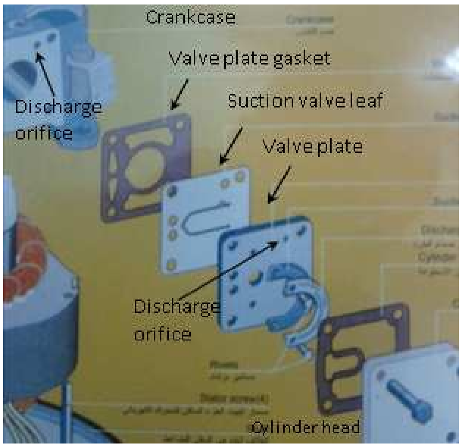

Fig. 2 Schematic valve unit of compressor

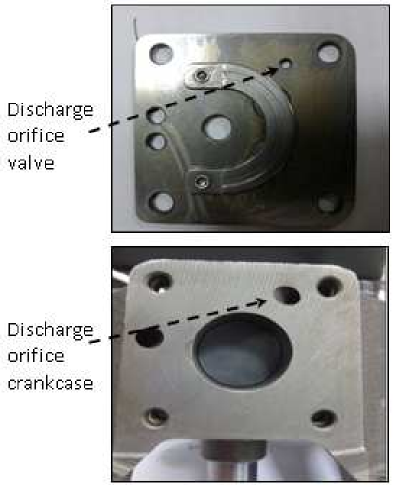

Fig. 3 Discharge orifice of valve plate and crankcase

TABLE I
CONTROL FACTORS AND LEVELS OF EXPERIMENTS

Control factors	Levels	
	1(lower)	**2**(upper)
(A) valve thickness (V_t)[mm]	2.75	2.85
(B) discharge orifice diameter of crank case (D_{cc}) [mm]	2.88	3.12
(C) discharge orifice diameter of valve (D_v) [mm]	2.275	2.525

D. *Experimental Results and Analysis*

To handle the experiment, 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.

E. *Cooling capacity*

The interactions factors shown in Fig.4 have the influencing in the response (cooling capacity) as shown in ANOVA test demonstrated in Table 2 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 holding 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 shown in Fig. 7 can be used to show the relationships among three-factor (V_t, D_v & D_{cc}) with response variable CC. This cube plot shows the cooling capacity means at each point on the cube where observations were measured. Regression analysis is used to identify the relationship between independent variables and the associated dependent variables, and to predict the trend of dependent variables as a function of independent variables.

TABLE II
ANOVA FOR COOLING CAPACITY OF EXPERIMENTS

Source	DF	F	P
Main Effects	3	3.07	0.060
2-Way Interactions	3	5.59	0.009
3-Way Interactions	1	0.00	0.996
Residual Error	15		
Pure Error	15		
Total	22		

The regression analysis is applied based on the results of experiments and the correlation coefficient R^2 (R-squared) is used to justify the validity of regression model. The regression analyses in this work are performed in a software MINITAB. The regression model obtained of DOE analysis is referred to "(2),"

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

The R^2 value of this model is 0.72.

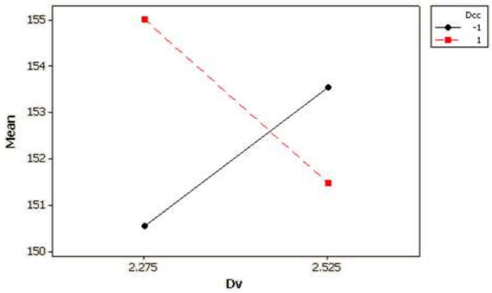

Fig. 4 Interaction plot for cooling capacity Vs. D_v & D_{cc}.

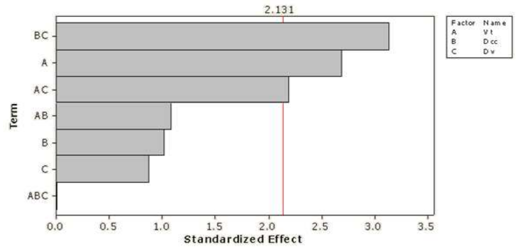

Fig. 5 Pareto chart of the effects on CC

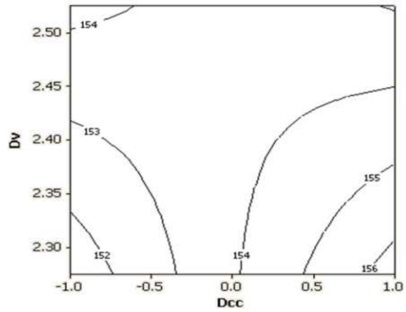

Fig. 6 Contour plot of CC Vs. Dv & Dcc

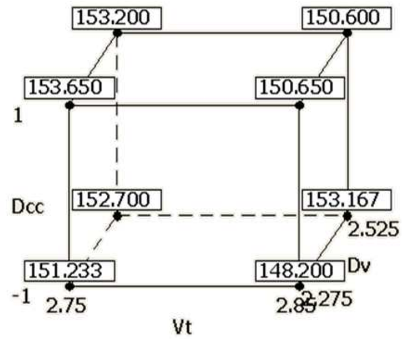

Fig. 7 Cube plot for cooling capacity Vs. V_t. D_v & D_{cc}.

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

IV. ARTIFICIAL NEURAL NETWORK

The effectiveness of the ANN model developed is fully dependent on the trial-and-error process in some factors; this study considers the factors which could be influencing the effectiveness of the ANN model developed based on the item required by the MATLAB ANN toolbox in order to develop the ANN model.

A. Network Structures

An ANN network structure principally consists of layers and nodes. ANN structure consists of three layers which are the input layer, hidden layer and output layer. It is also possible to have an ANN structure with no hidden layers. In this study, the network structure shown in Fig. 8 is selected after many trails are illustrated in Table 3. It is as the following;

- *Input layer*: Five nodes for the input layer stand for the five predictors of the case study which are V_t, D_{cc}, D_v, gasket thickness (G_t) and air gap (A_{gap}) between the piston and cylinder hole.
- *Hidden layers*: Contain 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;

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

TABLE III
NETWORKS RESULTS SUMMARY

Network structure	Trans. Fun.	MSE	R_{tr}	R_{test}
5-7-1	tansig	0.13	1.00	0.89
5-8-1	tansig	0.20	0.97	0.82
5-8-1	logsig	0.20	0.87	0.63
5-20-5-1	tansig, tansig	0.02	0.99	0.89
5-6-10-1	tansig, tansig	0.09	1.00	0.90
5-15-12-1	tansig, tansig	0.03	0.99	0.81

- Output layer: it has one neuron, where the output is estimated value of cooling capacity, so the used transfer function for this layer was linear function (purelin).

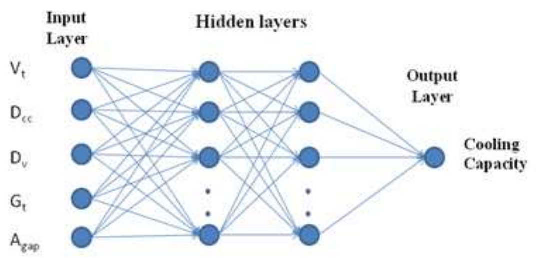

Fig. 8: ANN structure

B. Training and Testing Data

- *Data collection*, the training set contains 29 examples collected for experiments, divided into 70% for training, 15% for validation and 15% for testing. This data is used as inputs to proposed ANN prediction model for output of cooling capacity as valve unit performance.
- *Normalization*, as used here, simply scales down the range of input data to a new range between –1 and +1 using the following equation,

$$\text{Normalized Value} = 2 \times \frac{x - Min}{\text{Max - Min}} - 1 \tag{4}$$

Where, x is the input value for a, *Min* is the minimum value in a given set for each quality characteristic, and *Max* is the maximum value in a given set for each quality characteristic.

C. 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 was 0.974.
- Test Results; the results of testing for 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 the limitation of the training data set.

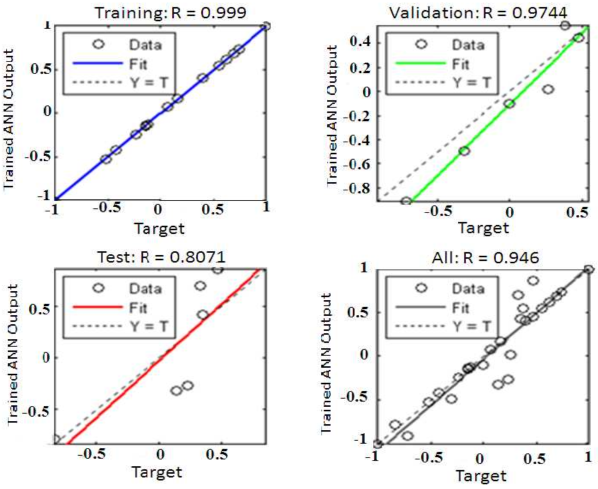

Fig. 9 Training result of proposed network

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, where authors suffered for collecting the data, where it is collected in manufacturing environment, not laboratory environment.

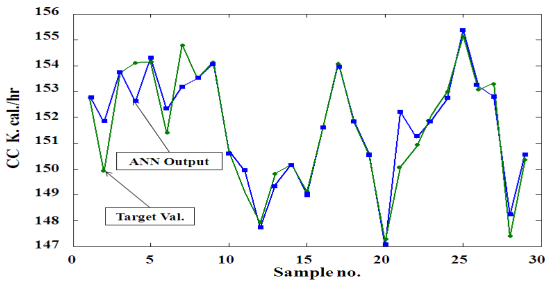

Fig. 10 Trained ANN output vs. target plot

V. Sigma Quality Level Improvement

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 equation 5 stated in [19], [22].

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

Assuming every one of the four CTQs has equal throughput 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 with *Cpk* (process capability index) of 0.72.

After appling the proposed approach integrating with tracing and quality control systems in order to improve the classification and assembly parts with appropriate dimension and geometrical tolerances. This will improve the assembly process 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 using tables in [19].

VI. Conclusions

This paper describes an 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 CTQs 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 accurately predicts the cooling capacity ratio and identifies the performance parameter level(s) 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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