IMPROVE CHARACTERISTICS OF MANUFACTURED PRODUCTS USING ARTIFICIAL NEURAL NETWORK PERFORMANCE PREDICTION MODEL

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ABSTRACT

This work aims to improve the characteristic of the manufactured products using a performance prediction model. The proposed approach consists of two phases. The first phase explains how to determine the factors affecting the performance of the manufactured part by designing experiments and derive a model for measuring performance using artificial neural networks. The second phase explains how to take advantage from this predicted model to get the largest number of manufactured products which have the better qualities through parts allocation to the matched assembled parts. This approach is explained through a case study for the manufacturing of hermetic reciprocating compressors. Results have been clarified through illustrative example and showed that the proposed approach is effective.

KEYWORDS

Performance Prediction, Artificial Neural Networks, Assembly Parts Allocation, Product Performance Improvement

1. INTRODUCTION

Measurements of product performance are difficult and expensive. Prediction of product performance is one of the major improvement tools for manufacturing process. Although all quality characteristics of each part assembled in a product are under statistical control (through specification limits), the final product does not have the same expected performance. Consequently, predicting the performance of a product during multi-stage operation is important to reduce process variability and to improve yield of production.

Rapidly evolving technologies, which employ advanced techniques, such as lasers, machine vision and pattern recognition, are incentives to develop general and accurate prediction methodologies for product performance [1-3]. A more viable option is to attain the ability to predict how parts may perform after assembly operations. This will help production planning and fault finding and improve time to market/volume. Moreover, it will help to control the assembly processes to achieve improved performance of the final product.

Stochastic optimization is adopted more than deterministic in many situations within manufacturing environment [4] and prediction systems are implemented as a proactive rather than a reactive manufacturing process improvement tool. Several researchers investigated the use of statistical process control (SPC), such as regression model, design of experiments (DOE), and artificial neural networks (ANNs) as prediction systems [5-9].

The use of ANN as a prediction model in several manufacturing fields was investigated by several researchers including prediction of important information about the manufacturing processes, such as, extrusion process parameters, welding characteristics, boring process, machine tool failure and surface roughness [7, 10-16]. Johnston et al.[3], for example, developed a prediction model to predict the performance of the head of hard disc drive as a finished product based on parametric measurements through manufacturing stages.

ANNs are deployed in several applications in manufacturing environments. The most popular applications of ANNs in the fields of automation and manufacturing control are in pattern recognition and economics. They are used to monitor and recognize abnormal pattern situations on SPC charts [17] and as a prediction model [16, 18, 19].

Many authors [19-22] discussed prediction of equipment behaviour using statistical forecasting methods or ANNs in design simulations or operation. Nevertheless, the prediction model for product performance within manufacturing processes is not sufficiently addressed through literature [3, 16, 23-25]. Moreover, the use of prediction systems for improving performance of product during manufacturing is not thoroughly addressed in literature. This work introduces an approach to improve the manufactured product characteristic using performance prediction model and matched parts allocation.

2. Proposed Approach

The approach presented in this work consists of two major phases as shown in Fig. 1. The first phase aims to provide a prediction model of product performance as a result of the conducting DOEs. Experiments are conducted after determination of critical to quality (CTQ) as a performance index (PI) then the significant factors are identified. Performance prediction model is developed according to the procedures illustrated in the flow chart shown in Fig. 2.

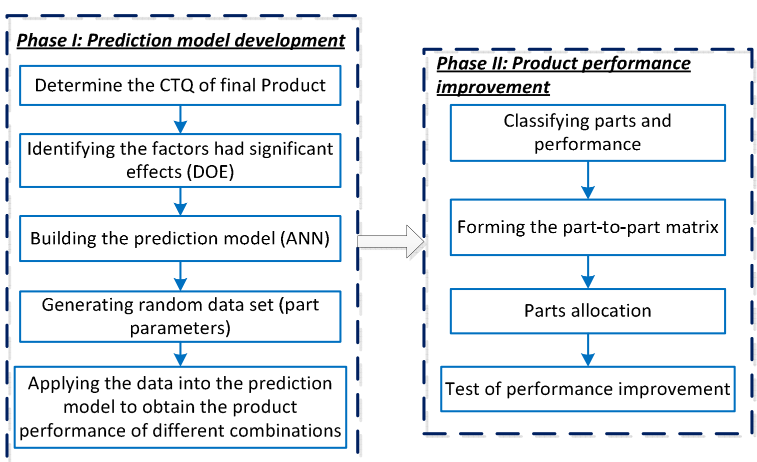

Fig. 1: The overall structure of the proposed approach

In the second phase the matched parts are classified based on the tolerances. The parts are represented in part-to-part matrix which shows different levels of product performance. Consequently, part allocation procedure is used to identify the appropriate parts to assemble for achieving the higher performance level of assembled product.

3. PHASE I: PREDICTION MODEL DEVELOPMENT

3.1. Experiments Procedure

Experiments are designed using DOE as a statistical tool to develop a linear or nonlinear model to represent a system. Experiments are conducted to determine the significant factors that are influencing PI. These factors will be the predictors for prediction model developed in next step. The two-level modelling experiments (factorial and fractional factorial) can be used for this purpose. Response surface design and Taguchi method also can be used for same purpose [26, 27].

The difficulty with The conventional method involves constructing a predictive model using simple regression or correlation tools is that they may be unable to adequately capture the non-linear relationships between data [28]. ANNs have the ability to model linear and non-linear systems without the need to make assumptions implicitly as in most traditional statistical methods. They becoming increasingly popular in the last two decades due to its short development and fast processing speed [8].

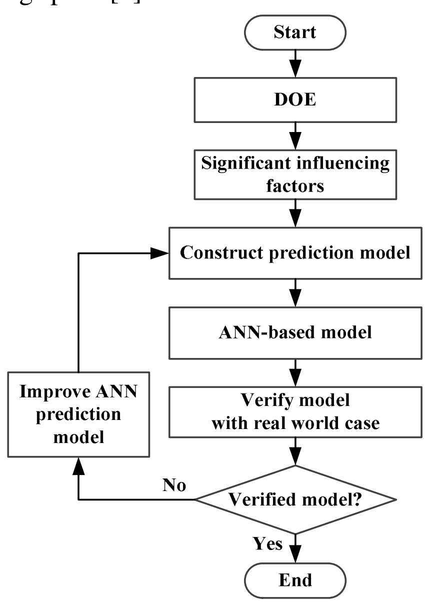

Fig. 2: Flow chart for performance prediction model development.

3.2. Network Structure

ANNs is built on a number of simple processing elements as shown in Fig. 3. These processing elements are often organized into a sequence of layers. All layers of the network are linked by weights, which are adapted by learning. The structure of a neural network could be characterized by the interconnection architecture among processing elements [29].

The network structure was itself determined by three factors:(i) Size of the input data, which was set equal to number of predictors which results from designed experiments, (ii) Number of hidden layers and the number of hidden neurons are determined by iterative method until it gives a satisfactory performance of training, and (iii) The type of coding used to express the target data will determine the number of output layer neurons and type of transfer function used.

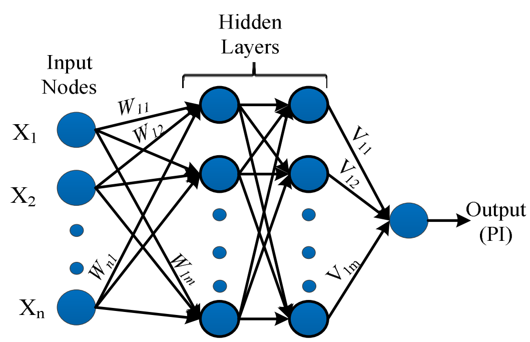

Fig. 3: ANN Structure

The transfer function used in the hidden layers was a hyperbolic tangent sigmoid (tansig) which is selected based on better training performance. The tansig function calculates layer output by transforming its input between -1 and +1, according to the equation 1;

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

The output layer's transfer function was a linear function (purelin), thus making the layer's output can take on any value and the layer has one neuron, where the output is one value for intended performance index (PI).

3.3. Training Data

The training set is collected from experiments, divided into subsets for training, validation and for testing. These data are used as inputs to the proposed ANN prediction model and its output is the estimated PI. Normalization is used to scale down the range of input data to a range between –1 and +1 using the following equation:

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

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 variable, respectively.

3.4. Network Training Cycle

In the training cycle, the training examples were presented in a random fashion to the neural network. The learning rate was initially set to 0.1. The connection weights were initialized with small random values before training and were adjusted after each example was presented into network. As the training progressed, these parameters were slowly decreased to allow for fine tuning of the network solutions. Mean Square Error (MSE) as statistical criterion is commonly utilized to evaluate accuracy of training results according to following equation 3.

$$MSE = \frac{1}{n}\sum_{j=1}^{n}\left(t_j - o_j\right)^2 \tag{3}$$

Where, t and o are target and output of ANN respectively. Also n is the number of the network outputs. The training session was stopped either when the MSE fell below 0.02 or the number of epochs reaches to 50.

4. REAL CASE STUDY

4.1. Manufacturing environment

In this paper, the manufacturing of hermetic reciprocating compressors is presented as a case study. During this manufacturing environment, the parts have complex relationship within its multi-stage operation. For developing and manufacturing of higher compressor performance, the need for higher efficiency and optimal design are strong incentives to develop general and accurate prediction methodologies. This study is focused on the valve unit (including valve plat, valve gaskets, cylinder head and muffler). Several influencing and control factors were identified and measured.

In a high-volume compressor manufacturing, the defect–free manufacturing process is extremely difficult to be developed during many operations for each part. A more viable option is to attain the ability to predict how parts may perform after assembly operations. This will aid control the assembly processes to obtain improved performance of final product. Although all parts are within statistical control limits, variation of final performance occurs.

4.2. Experimental work

The selected control factors for valve unit are valve thickness (T_v), discharge orifice diameter of valve plate (D_v) and valve plate gasket thickness (T_g) as shown in in Fig.4. The discharge orifice diameter of crank case (D_{cc}) is also considered with previous factors. The factor levels are lower and upper tolerance limits as inferred from geometrical parameters (i.e. within specification limits).

The progressive of performance index is expressed as a percentage from the designed value. The cooling capacity (CC) progressive percentage (% of Progressive of CC) is computed according to equation 4.

$$\%\ progressive\ of\ CC = \frac{Measured}{Designed} \times 100 \tag{4}$$

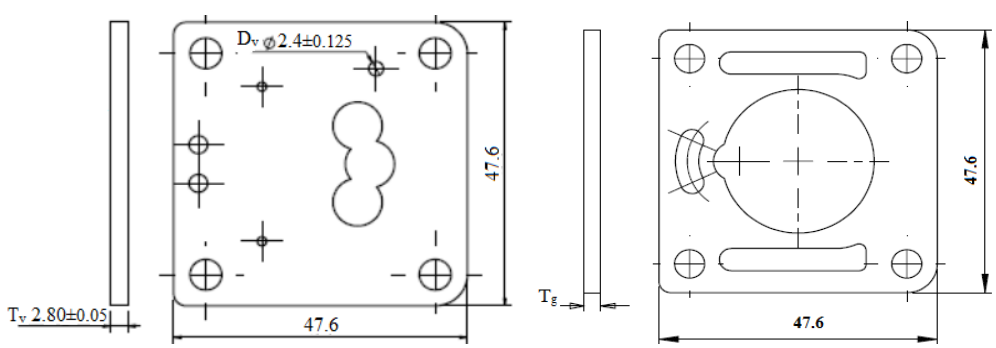

Fig. 4: Valve plate and gasket valve plate

By classifying the allowed tolerance area of CC% into three classes A, B and C as shown in Fig. 5, it is obvious that class A is preferred over class B and class B is preferred over class C. When the compressor performance lies in Zone C, it is in the worst quality level. Although this compressor of class C is accepted according to quality control system, this is not sufficient for competition in world markets.

From the historical records of quality test results over a year, 74.49% of tested compressors are in class C (not desired class) and 24.16% classified as B class, while only 1.3% in the best class (A class). The experiment aims to substantiate a valid relationship between the parameters of parts and the corresponding response variable, and hence, to identify the critical parameters having a significant contribution in influencing the performance of compressor.

The manufacturing and assembly equipment used is stable and in control statistically. The measurement equipment used is the calorimeter tester Microline SRL. All presented cases correspond to a domestic hermetic reciprocating compressor. The samples are drawn from the same production lot with the same geometrical parameters to minimize differences in part qualities.

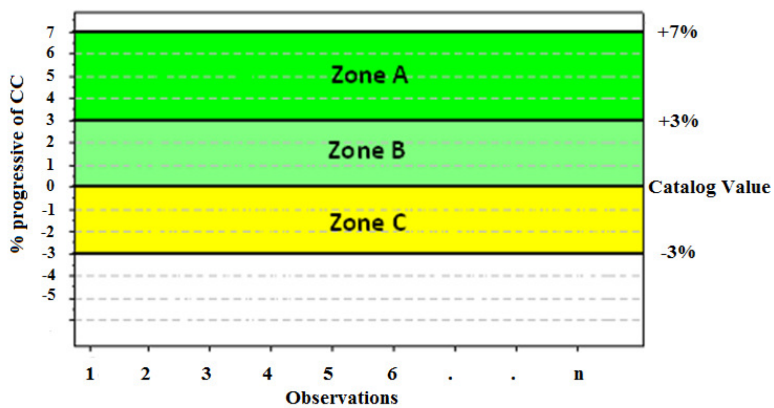

Fig. 5: Classes of CC performance index

Interactions analysis reveals that when the D_v is minimum diameter, the larger D_{cc} increases the cooling capacity (CC) and vice versa. The main effect plot shown in Fig. 6 illustrates that T_g and T_v have the biggest influence on cooling capacity, then, D_{cc} comes next in effect. Finally, the D_v has the lowest influence.

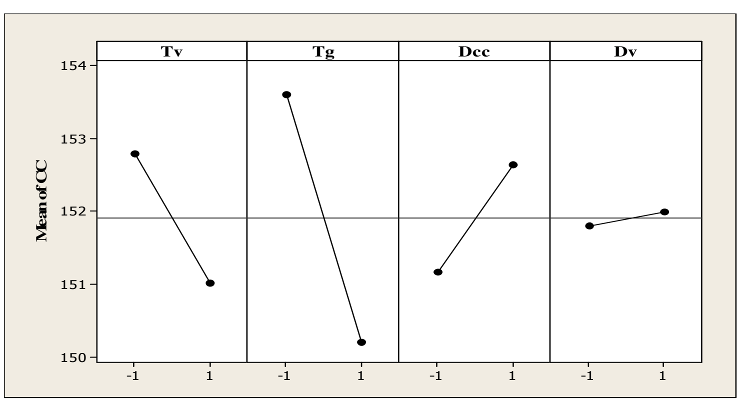

Fig. 6: Main effects plot for means of CC

4.3. ANN Performance Prediction Model

1) *Neural network model*: The network structure is selected based on a number of iterations illustrated in Table 1. Input layer consists of four nodes for the inputs corresponds to the four predictors which are T_v, D_{cc}, D_v and T_g. Output layer consists of one neuron that gives its output as estimated value of cooling capacity ratio. The used transfer function for this layer is *purelin*. Finally, one hidden layer is selected and it contains 18 neurons. The *tansig* is used for this hidden layer.

The training set contains 32 examples collected from experiments, divided into 85% for training and validation and 15% for testing and normalized according to equation 2.

Table 1: Training of networks result summary

Network structure	# Hidden layer(s)	Transfer Fun.	MSE	Correlation Coefficient R		
				Training	Validation	Test
4-14-1	1	Tansig	0.0128	0.9938	0.8786	0.9813
4-16-1	1	Tansig	0.0100	0.9953	0.9564	0.9156
4-18-1	1	Tansig	0.0083	0.9906	0.9457	0.9800
4-26-1	1	Tansig	0.0086	0.9897	0.9787	0.9722
4-28-1	1	Tansig	0.0084	0.9893	0.9832	0.9100

2) *Training results*: the accepted performance with the 4-18-1 structure was achieved with training performance MSE of 0.0083. 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 0.99 as shown in Fig. 7.

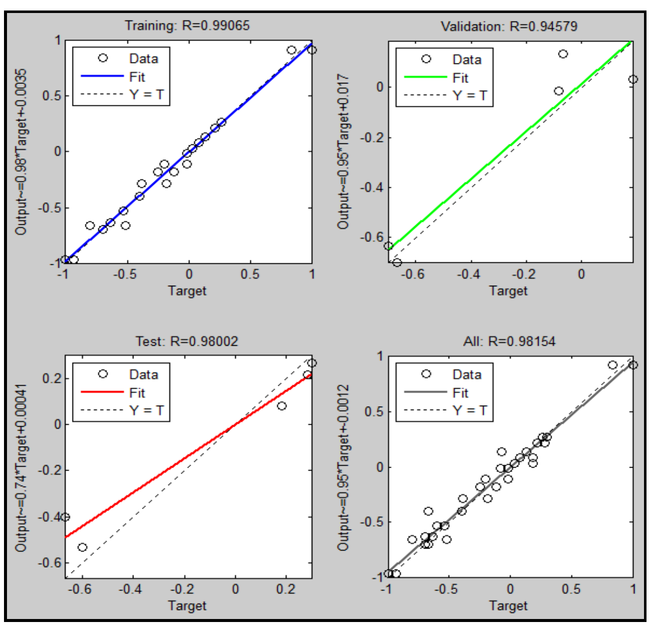

Fig. 7: ANN training results

3) *Test results*: the results of testing the ANN used in this work using unseen data are shown in Fig. 7. The convergence condition is considered achieved when the R is greater than 0.97 with limitation of the training data set.

5. PHASE II: PRODUCT PERFORMANCE IMPROVEMENT

5.1. Classification and Allocation of Parts

After manufacturing stage, the parts have to be classified into classes before starting the assembly operation. The matched parts are classified based on predicted performance value obtained by the prediction model. The more levels or classes for each factor have to be identified and applied to the prediction model. The followed steps to generate a set of data which represents the most cases of combinations are: (1) determine number of levels of each factor, (2) identify the combinations of full factorial design, (3) apply prediction model on all combinations, (4) sort and classify the results into number of levels (e.g. three levels; A, B, C), (5) form part-to-part matrix in which is a classification matrix.

The factor combinations are generated as full factorial experiments to cover several alternative matched parts. Assuming that **X** is first part and Y is second part and control factors of each one as illustrated in Table 2. The predicted value of product performance from each combination between the parts (i.e.5^2 x 3^2) is classified into three levels (A, B and C) as in part-to-part matrix illustrated in Table 3.

Table 2: Control factors and levels of 1st and 2nd parts

Parts	Control factors	Levels				
		1	2	3	4	5
X	T_g (12:19 thickness classes)	-1	-0.5	0	+0.5	+1
	D_{cc} (3.12:2.88 mm)	-1	0	+1	-	-
Y	T_v (2.75:2.85 mm)	-1	-0.5	0	+0.5	+1
	D_v (2.275:2.525 mm)	-1	0	+1	-	-

Table 3: Scheme of matched parts classification based on the performance prediction model

Assembled parts		Tv	1	1	1	0.5	0.5	0.5	0	0	0	-0.5	-0.5	-0.5	-1	-1	-1
		Dv	1	0	-1	1	0	-1	1	0	-1	1	0	-1	1	0	-1
Tg	Dcc																
1	1		C	C	B	C	B	B	C	B	B	C	B	B	C	B	B
1	0		B	C	C	B	C	C	B	B	B	B	B	B	B	B	B
1	-1		B	C	C	B	C	C	B	C	C	B	B	C	B	B	C
0.5	1		C	B	B	B	B	B	B	B	B	B	B	B	B	B	A
0.5	0		B	B	C	B	B	B	B	B	B	B	B	B	B	B	B
0.5	-1		B	C	C	B	B	C	B	B	C	B	B	C	B	B	B
0	1		B	B	B	B	B	B	B	B	A	B	B	A	B	B	A
0	0		B	B	B	B	B	B	B	B	B	B	B	B	B	B	B
0	-1		B	B	C	B	B	C	B	B	C	B	B	B	B	B	B
-0.5	1		B	B	B	B	B	A	B	B	A	B	A	A	B	A	A
-0.5	0		B	B	B	B	B	B	B	B	B	B	B	B	B	B	A
-0.5	-1		B	B	C	B	B	C	B	B	B	B	B	B	B	B	B
-1	1		B	B	A	B	A	A	B	A	A	B	A	A	B	A	A
-1	0		B	B	B	B	B	B	B	B	B	B	A	A	B	A	A
-1	-1		B	B	C	A	B	C	A	B	B	A	B	B	A	B	B

To complete the process of allocating matched parts, the parameter of number of parts from each class of part is added to the matrix. The classification matrix is populated by adding column for quantity of part X and one row for quantity of part Y.

Proposed method to allocate the parts to find largest number of higher performance product by concentrating on the cells which have highest performance is as the following:

(i) Assign as much as possible to the cell with the highest performance level.
(ii) Next, satisfied row or column is crossed out and the amounts of part X and Y are adjusted accordingly. If both a row and a column are satisfied simultaneously, only one is crossed out.
(iii) Look for the uncrossed-out cell with the highest performance level and repeat the process until exactly one row or column is left uncrossed out.

This solution is considered as a better starting solution to get the largest number of assembled products that have the highest performance level. For dealing with another objective function, there are other methods to solve the assignment problem as illustrated in literature [30, 31].

6. Numerical Example

To present the advantage from the proposed approach, a comparative analysis is performed between this proposal and the random assembly method that is usually used. The approach is applied to 200 parts to be assembled (100 of each part).

The matrix is filled using one of the two methods followed in such situation. The first is traditional method where assembly of parts is randomly processed without consideration of product performance level. On the other hand, the second one is carried out by matching parts based on their performance levels through the proposed procedure for parts allocation.

Number of parts obtained from each quality level of the proposed method is illustrated in Table 4. Table 5 illustrates the predicted performance of product assembled randomly according to traditional method and also predicted performance values produced by applying the proposed approach. Obviously, the results obtained from new method reveals that the achieved improvement is 15% transferred from lowest level into 9% of highest performance level and 6% of medium performance levels.

Table 4: Amount of parts on classification matrix using proposed method

part Y / part X		Tv	1	1	1	0.5	0.5	0.5	0	0	0	-0.5	-0.5	-0.5	-1	-1	-1	Quantity of part X
		Dv	1	0	-1	1	0	-1	1	0	-1	1	0	-1	1	0	-1	
Tg	Dcc																	
1	1				1													1
1	0		4															4
1	-1		4															4
0.5	1			1														1
0.5	0					4	5		13	2								24
0.5	-1									6								6
0	1										1							1
0	0				7			2										9
0	-1									1		6						7
-0.5	1							2										2
-0.5	0							4			13							17
-0.5	-1										9	1						10
-1	1																	0
-1	0												3	2	1			6
-1	-1					8												8
Quantity of part Y			8	1	8	12	5	8	13	9	23	7	3	2	1	0	0	100

Table 5: Results of parts allocation using proposed approach vs. random assembly

Performance level	**Parts allocation**		**Improvement**
	Using random assembly	Using proposed approach	
A	7	16	9%
B	78	84	6%
C	15	0	15%

The results of this example are represented in Fig.8 that shows both distributions of performance values for assembled compressors applying the two methods. The distribution of the intuitive method for product assembly takes up about 72% of the width of the specifications. In contrast, the new method produced products take up about 54% of the specification band. As a result, there is considerably less variability in the performance of product assembled by the proposed approach.

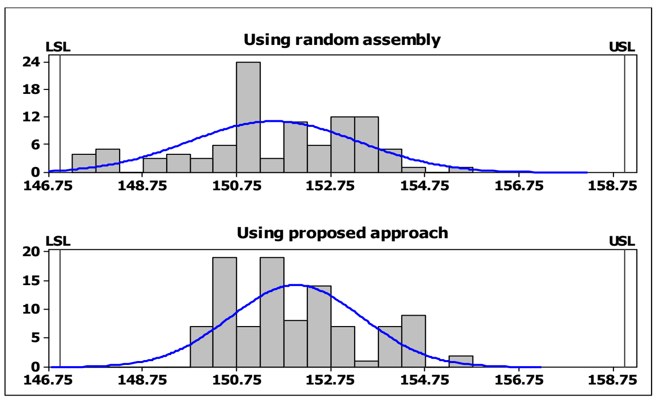

Fig. 8: histograms of compressor performance from both methods

7. CONCLUSIONS

The paper presented an approach to improve the characteristics of the manufactured products during manufacturing processes utilizing a prediction model built using ANNs technique. The proposed approach consists of two phases. The first phase decided the factors affecting the performance of the manufactured parts by designing experiments, as well as derives a model to predict product performance using artificial neural networks. The second phase explained how to take advantage from this predicted model to get the largest number of manufactured products have better qualities. The performance of the approach evaluated using a real case study. The approach successfully allocated larger number of assembled matched parts that achieved higher performance levels.

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