Reducing Mirror Slippage of Nightstand with Plackett-Burman DOE and ANN Techniques

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Additional information is available at the end of the chapter

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1. Introduction

Understanding the behaviors of the systems is possible by conducting some experiments. But, experiments have to give all needed information in a reasonable manner; especially time and budget for the experiments are main constraints in a system observation. Identifying the key factors of experiments which have impact on the process and conducting all trials relevant with key factors are very difficult. It is difficult to make analytical and numerical modeling in complex processes and the real life problems which have many parameters that affect the systems. To prevent all these negativities, design of experiment (DOE) is an indispensable method which observes systems behavior. It is a systematic approach to find how inputs affect the system outputs and also provides a continuous improvement for processes and explores relationship between key input variables and output performance characteristics by existing and performing a designed set of experiments. Key input variables can be defined as factors (independent variables) and outputs can be defined as response (dependent variables)[1]. A well organized experimental design needs a design matrix (Orthogonal) prior to experiment. The design matrix contains all the settings of factors at different levels and also gives the order of experiments. The number of factors and interactions, levels of factors, budget and resources define the size of experiment[2]. Design of experiment was firstly used for agricultural applications in 1920s and became a popular tool observing systems and processes. Many books and journals have been published about the applications of Chemistry[3], Biology[4], Statistics[5] and Engineering[2] for years. Optimizing the levels of factors, finding interaction relationship between factors and response, making a fast decision, improving the system performance are some advantages of DOE[6].

Some design of experiment methods used in the literature are Full Factorial Design, Fractional Factorial Design, Plackett-Burman Design, Central Composite Design, Box-

Behnken Design, Robust Parameter Design, Computer Aided Design and Taguchi. Taguchi method has a wide usage in the engineering applications but criticized in the literature about not concerning with the interactions between factors while focusing on evaluation of main effects totally[7]. It is one of the most important tools that can be used for improving steps of Six Sigma loop[8].

This application study which was done in furniture manufacturing firm in TURKEY to prevent the mirror slippage of nightstand is analyzed from the point of Six Sigma philosophy view. The structure of the rest of the paper is given as follows: In Section 2, it is described in detailed about the concept of six sigma. In Section 3, the application of the artificial neural network is presented. In Section 4, conclusion is given as evaluation of the results.

2. Application of Six Sigma

Manufacturing sector has to provide perfect products and produce fast, quality and economical products to their consumers because of severe competition in the market. As all businesses reach this purpose, their processes must be stabilized or kept under control with continuous improvement. Six Sigma that provides continuous improvement is a key to being successful in business. This management philosophy which uses some statistical and systematic approaches will prevent defects. Providing continuous improvement in a system is a result of applying the loop of Six Sigma in correct order and identifying relations between inputs and outputs. This loop is made up of the steps of Define, Measure, Analyze, Improve and Control. Some quality and statistical methods are being applied in all these steps[9]. The most used Six Sigma tools are Design of Experiments, Response Surface Method, Robust Design, Statistical Process Control, Quality Function Deployment, Failure Mode and Effect Analysis, Capability Analysis, Hypothesis Testing, Analysis of Variance, Regression Analysis[10]. Sigma (σ) is a letter which represents the variability and standard deviation in the processes. On the other hand, Six Sigma identifies how a deviation is shown from the perfect conditions[11]. The significant factor in six sigma process is to share responsibility in an organization. For this reason, everyone has different responsibilities depending on their education[10]. Organization structure can be addressed as Leadership, Champions and Sponsors, Black Belt, Green Belt, and Master Black Belt[12]. Applying Six Sigma tools in manufacturing processes provides reduction of defect rate, cycle time, manufacturing costs and improvement in quality and productivity[13].

A Six Sigma application study was done in a furniture manufacturing firm in TURKEY. Steps following for the application of Six Sigma by considering DMAIC loop is given below.

This six sigma application study was simulated with a mechanism which rotates the mirror nightstand (Figure 2) having constant speed. Thus, slippage resistant of mirror was measured. While running the system, if it stands out against slippage more than 72 hours (based on expert opinion), this situation is called as “no slippage”.

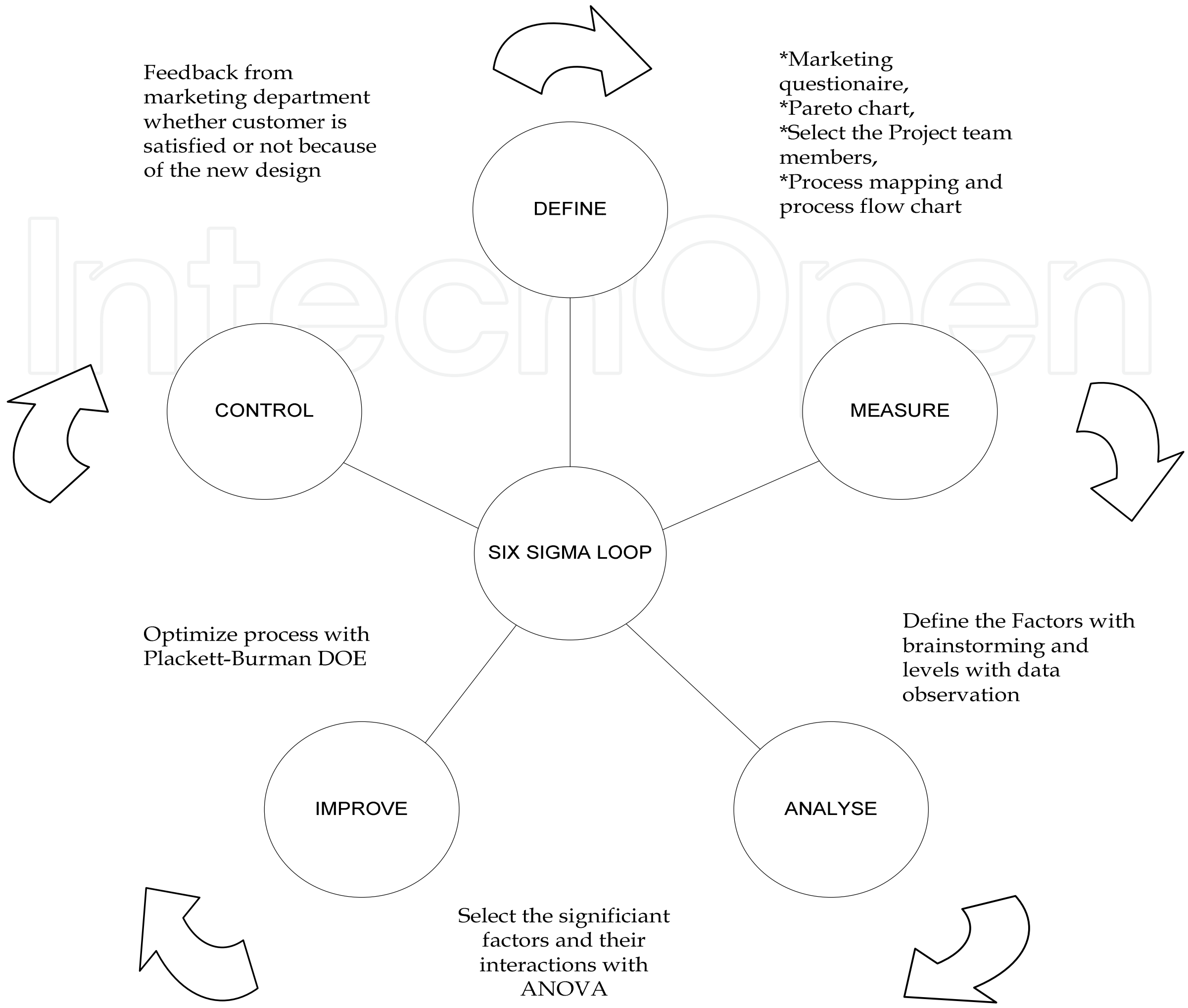

Figure 1. Six sigma loop

Figure 2. A Nightstand Sample

2.1. Define

In this stage, following steps should be applied;

- Required studies are done to define systems' problem,
- A team is constructed for solution,
- Follow-up method is selected
- Goal is defined by analyzing process carefully.

In the application, a marketing questionnaire was applied to customers of the firm to find the reason of the problem. This project's objective is reducing the customer complaints of the manufacturing firm about nightstand mirror slippage. As a result of questionnaire, pareto chart shown in Figure 3 was constructed by using data about product returns. It is seen that one of the significant complaints (%7) are dealing with slippage of glass on the nightstand and we selected this problem for obtaining a fast improvement. A quality engineer, a foreman from the plant and two persons from university were formed a team for this six sigma application.

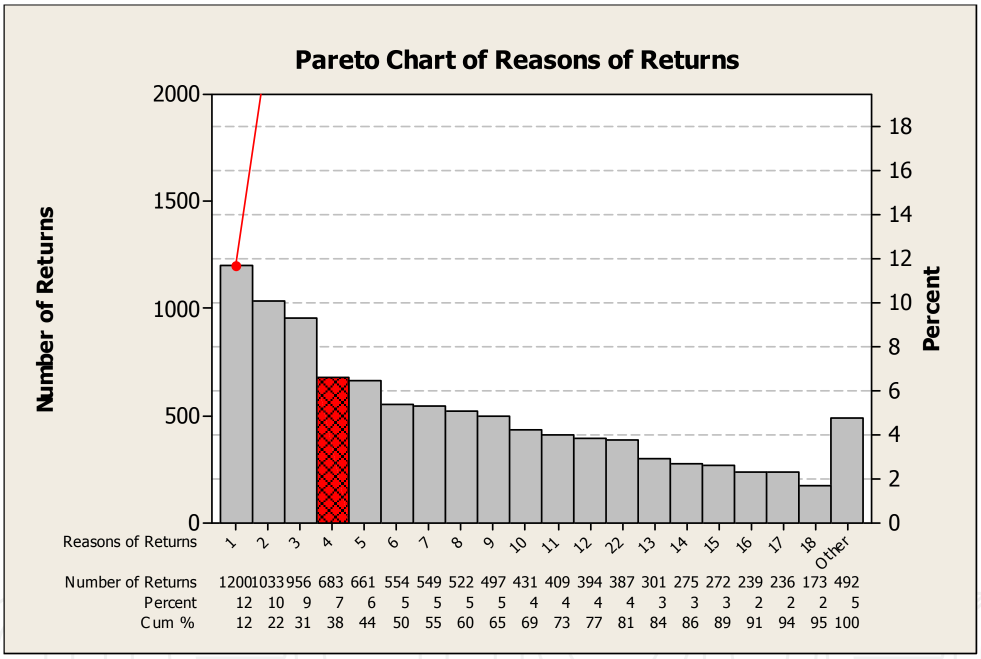

Figure 3. Pareto chart of Returns

Slippage of mirror nightstand is a reason of customer dissatisfaction. The aim is to increase customer satisfaction by reducing variance and maximizing mirror slippage time. After problem definition and forming a team, the next step is to perform a detailed process analysis. A process chart was constructed by the team and is given in Figure 4.

Figure 4. Process chart

2.2. Measure

Key input variables (factors) and their levels are defined to determine impacts of variables on process performance. The steps which will be followed in this phase are:

- Identifying key quality characteristics (dependent and independent variables),
- Measuring system capability,
- Finding a solution to data collection.

In measure phase, most important factors and levels were defined clearly for the slippage problem. The number of independent variables (or factors) were found as 13 and given in Table 1. 13 factors which are affected glass-mirror slippage were decided by brainstorming of team members and it was decided to evaluate all factors as two levels.

Control Factors	Factor Effects	Min. Level (-1)	Max. Level (+1)
Environment temperature (C^o)	A	- 20	60
Surface Cleanliness	B	Dirty	Clean
Temperature Difference in working place (C^o)	C	14	28
Storage Position	D	Bottom	Top
Mirror Cleanliness	E	Dirty	Clean
Waiting time (hours)	F	0	2
Anti slip tape quality	G	ELSEM*	TESA*
Styrofoam	H	Nonexistence	Existence
Cleaning liquid	J	Existence	Nonexistence
Dust in the working place	K	Dirty	Clean
Double sided anti slip tape quality	L	Existence	Nonexistence
Anti slip tape usage	M	Undismantle	Dismantle
Anti slip tape usage rate (centimeter)	N	6	12
*ELSEM and TESA are the names of anti-slip tapes			

Table 1. List of experimental control factor

2.3. Analyse

Which tools will be used is defined and factor analyzes are done by using some statistical methods. The steps which will be followed in this phase are:

- Identifying causes of defects and variation,
- Conducting multi-variable analysis,
- Collecting process data about dependent and independent variables,
- Using regression analysis to define relationship between dependent and independent variables.

Exp. Number	A (Co)	B	C (Co)	D	E	F (hours)	G	H	J	K	L	M	N (cm)	Slippage (hours)
1	60 (1)	Clean (1)	14 (-1)	Bottom (-1)	Clean (1)	2 (1)	Tesa (1)	Existence (1)	Existence (-1)	Dirty (-1)	Existence (-1)	Undismantle (-1)	12 (1)	No slippage
2	-20 (-1)	Clean (1)	28 (1)	Top (1)	Dirty (-1)	2 (1)	Elsem (-1)	Existence (1)	Nonexistence (1)	Dirty (-1)	Existence (-1)	Undismantle (-1)	6 (-1)	No slippage
3	60 (1)	Dirty (-1)	28 (1)	Bottom (-1)	Clean (1)	2 (1)	Elsem (-1)	Existence (1)	Nonexistence (1)	Dirty (-1)	Nonexistence (1)	Dismantle (1)	12 (1)	16
4	-20 (-1)	Dirty (-1)	28 (1)	Top (1)	Dirty (-1)	0 (-1)	Tesa (1)	Nonexistence (-1)	Existence (-1)	Dirty (-1)	Nonexistence (1)	Dismantle (1)	12 (1)	No slippage
5	-20 (-1)	Clean (1)	14 (-1)	Bottom (-1)	Dirty (-1)	2 (1)	Elsem (-1)	Nonexistence (-1)	Nonexistence (1)	Clean (1)	Nonexistence (1)	Undismantle (-1)	12 (1)	No slippage
6	-20 (-1)	Clean (1)	28 (1)	Top (1)	Clean (1)	0 (-1)	Tesa (1)	Existence (1)	Existence (-1)	Clean (1)	Nonexistence (1)	Undismantle (-1)	12 (1)	No slippage
7	-20 (-1)	Dirty (-1)	14 (-1)	Top (1)	Dirty (-1)	2 (1)	Tesa (1)	Existence (1)	Nonexistence (1)	Dirty (-1)	Existence (-1)	Dismantle (1)	6 (-1)	No slippage
8	-20 (-1)	Clean (1)	28 (1)	Bottom (-1)	Clean (1)	2 (1)	Tesa (1)	Nonexistence (-1)	Nonexistence (1)	Clean (1)	Nonexistence (1)	Dismantle (1)	6 (-1)	No slippage
9	60 (1)	Clean (1)	14 (-1)	Top (1)	Dirty (-1)	2 (1)	Tesa (1)	Nonexistence (-1)	Nonexistence (1)	Clean (1)	Existence (-1)	Dismantle (1)	12 (1)	No slippage
10	-20 (-1)	Clean (1)	14 (-1)	Bottom (-1)	Clean (1)	0 (-1)	Tesa (1)	Nonexistence (-1)	Existence (-1)	Dirty (-1)	Nonexistence (1)	Dismantle (1)	6 (-1)	No slippage
11	-20 (-1)	Clean (1)	28 (1)	Top (1)	Clean (1)	2 (1)	Elsem (-1)	Nonexistence (-1)	Existence (-1)	Clean (1)	Existence (-1)	Undismantle (-1)	6 (-1)	No slippage
12	-20 (-1)	Dirty (-1)	28 (1)	Bottom (-1)	Dirty (-1)	2 (1)	Elsem (-1)	Existence (1)	Existence (-1)	Clean (1)	Existence (-1)	Dismantle (1)	12 (1)	No slippage
13	60 (1)	Dirty (-1)	28 (1)	Top (1)	Clean (1)	0 (-1)	Tesa (1)	Nonexistence (-1)	Nonexistence (1)	Dirty (-1)	Existence (-1)	Undismantle (-1)	12 (1)	No slippage
14	-20 (-1)	Dirty (-1)	14 (-1)	Top (1)	Clean (1)	0 (-1)	Tesa (1)	Existence (1)	Nonexistence (1)	Clean (1)	Existence (-1)	Undismantle (-1)	6 (-1)	No slippage
15	60 (1)	Dirty (-1)	14 (-1)	Bottom (-1)	Clean (1)	0 (-1)	Elsem (-1)	Existence (1)	Existence (-1)	Clean (1)	Existence (-1)	Dismantle (1)	6 (-1)	2-3
16	60 (1)	Dirty (-1)	28 (1)	Top (1)	Dirty (-1)	2 (1)	Tesa (1)	Existence (1)	Existence (-1)	Clean (1)	Nonexistence (1)	Dismantle (1)	6 (-1)	No slippage
17	60 (1)	Clean (1)	28 (1)	Bottom (-1)	Dirty (-1)	0 (-1)	Tesa (1)	Nonexistence (-1)	Nonexistence (1)	Dirty (-1)	Existence (-1)	Dismantle (1)	6 (-1)	72
18	60 (1)	Clean (1)	14 (-1)	Top (1)	Clean (1)	2 (1)	Elsem (-1)	Nonexistence (-1)	Existence (-1)	Dirty (-1)	Existence (-1)	Dismantle (1)	12 (1)	16
19	60 (1)	Dirty (-1)	14 (-1)	Bottom (-1)	Dirty (-1)	2 (1)	Tesa (1)	Nonexistence (-1)	Existence (-1)	Clean (1)	Nonexistence (1)	Undismantle (-1)	6 (-1)	72
20	60 (1)	Dirty (-1)	14 (-1)	Top (1)	Dirty (-1)	0 (-1)	Elsem (-1)	Nonexistence (-1)	Nonexistence (1)	Clean (1)	Nonexistence (1)	Undismantle (-1)	12 (1)	2-3
21	-20 (-1)	Dirty (-1)	28 (1)	Bottom (-1)	Clean (1)	0 (-1)	Elsem (-1)	Nonexistence (-1)	Nonexistence (1)	Clean (1)	Existence (-1)	Dismantle (1)	12 (1)	No slippage
22	60 (1)	Clean (1)	28 (1)	Bottom (-1)	Dirty (-1)	0 (-1)	Elsem (-1)	Existence (1)	Nonexistence (1)	Dirty (-1)	Nonexistence (1)	Undismantle (-1)	6 (-1)	2-3
23	60 (1)	Clean (1)	28 (1)	Bottom (-1)	Dirty (-1)	0 (-1)	Tesa (1)	Existence (1)	Existence (-1)	Clean (1)	Existence (-1)	Undismantle (-1)	12 (1)	No slippage
24	-20 (-1)	Dirty (-1)	14 (-1)	Bottom (-1)	Clean (1)	2 (1)	Tesa (1)	Existence (1)	Nonexistence (1)	Dirty (-1)	Nonexistence (1)	Undismantle (-1)	12 (1)	No slippage
25	60 (1)	Clean (1)	14 (-1)	Top (1)	Clean (1)	0 (-1)	Elsem (-1)	Existence (1)	Nonexistence (1)	Clean (1)	Nonexistence (1)	Dismantle (1)	6 (-1)	2-3
26	-20 (-1)	Dirty (-1)	14 (-1)	Bottom (-1)	Dirty (-1)	0 (-1)	Elsem (-1)	Nonexistence (-1)	Existence (-1)	Dirty (-1)	Existence (-1)	Undismantle (-1)	6 (-1)	No slippage
27	60 (1)	Dirty (-1)	28 (1)	Top (1)	Clean (1)	2 (1)	Elsem (-1)	Nonexistence (-1)	Existence (-1)	Dirty (-1)	Nonexistence (1)	Undismantle (-1)	6 (-1)	16
28	-20 (-1)	Clean (1)	14 (-1)	Top (1)	Dirty (-1)	0 (-1)	Elsem (-1)	Existence (1)	Existence (-1)	Dirty (-1)	Nonexistence (1)	Dismantle (1)	12 (1)	No slippage

Table 2. Orthogonal Matrix of PB design

In this phase, we need to collect data about process variables to find the resource of variation in the system. By this way, an experimental design will be performed. If a full factorial experimental design is run, we need 2^{13} (8192) experiment for trying all possibilities. This condition takes too much time and effort. On the other hand, a Plackett Burman fractional factorial design can give faster results in a short time. For this reason, application of fractional factorial experimental design was decided and by considering all the advantages above, Placket-Burman L_{28} experimental design was used in this study. Orthogonal (Design) matrix is given in Table 2.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	***1***	***11100,2***	***11100,2***	***11100,2***	***35,12***	***0,000***
B	1	110,0	110,0	110,0	0,35	0,565
C	1	279,7	279,7	279,7	0,89	0,363
D	1	118,1	118,1	118,1	0,37	0,551
E	1	885,9	885,9	885,9	2,80	0,116
F	1	390,0	390,0	390,0	1,23	0,285
G	***1***	***8349,0***	***8349,0***	***8349,0***	***26,42***	***0,000***
H	1	325,7	325,7	325,7	1,03	0,327
J	1	299,0	299,0	299,0	0,95	0,347
K	1	18,1	18,1	18,1	0,06	0,814
L	1	1627,9	1627,9	1627,9	5,15	0,040
M	1	157,9	157,9	157,9	0,50	0,491
N	1	192,9	192,9	192,9	0,61	0,448
Error	14	4424,6	4424,6	316,0		
Total	27	28279,2				

Table 3. ANOVA for factors

ANOVA was performed to verify whether the main effects exist or not between variables and given in Table 3. Confidence level of the model was selected as 99 %. Main effects plotted for mean response is as shown in Figure 5.

2.4. Plackett-burman in screening design

This design is used for screening a large number of process factors to identify the most important parameters that have a significant impact on the process performance. It provides a reduction in the number of factors that needed to be observed. PB design includes in a family of screening design. The natures of interactions among the factors are not interested in screening designs. Geometric PB designs contain M number of experiment which is a power of two (4, 8, 16…etc.). On the other hand, non-geometric designs contain M number of experiment which are multiples of four but not power of two (12, 20, 24, 28…etc.)[2]. All main effects have same precision in PB designs.

After defining the key parameters, if necessary, full factorial, fractional factorial designs and response surface method, subsequent experiments can be run. Full factorial design needs all possible combinations of levels for all factors. PB designs which focus on the main effects by

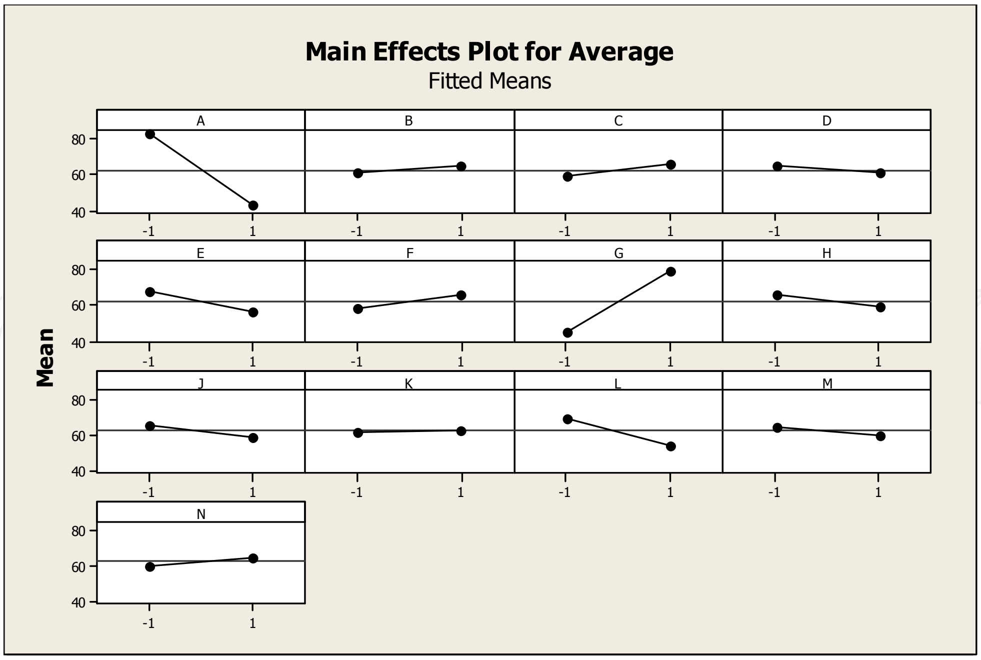

Figure 5. Main effects plot for average

considering the interactions among the factors are negligible[14]. It can be applied effectively to industrial studies which need to analyze many factors in the same manner[15]. The main aim is not to see interactions among the factors, but this doesn't mean that we couldn't have any idea about the interactions among factors. It is proved that, PB can be used even two sided interactions and main effects are confounded[16]. In PB designs, M+1 experiment are conducting to analyze M factors and generally it is advised to use for main effects.

The 12, 20, 24, 28- run PB designs have a special importance, because they fill the gap in the standard design. On the other hand, these designs have a high alias structure. If it is assumed that there are no interactions between the factors, this alias structure can be prevented. But this assumption is not possible in real life systems. To get away with alias structures, it is provided to make a second run, but not an exact replication[17]. In a research, it is proved that using 28-run PB gives best results for a system between 32-run design fractional factorial, 28 experiment design PB and 28 experiment design a random balance[18].

2.5. Improve

Improvement points which yield an optimum process are selected and system model is constructed by considering the optimum condition. The steps which will be followed in this phase are:

- Conducting design of experiments.
- Trying to improve process by eliminating variation.
- Optimizing process.

Slippage time of mirror was analyzed by using Plackett-Burman experimental design matrix. After the experiments were conducted, some statistical analyses were done to define parameters which have a great variance. Also, two way interactions were taken into consideration. An optimum setting which contains different factor levels was found. This provides maximum slippage time and extracted data was used in the real manufacturing of mirror nightstand.

Our main goal in this study is decreasing process variability by defining most effective factors and levels on quality characteristics. PB experimental design module of MINITAB 15.0 software was used. As a result, optimal factor setting obtained is -1,1,1,1,-1,1,1,1,-1,1,-1,-1,1 (Environmental Temperature= -20 C^o; surface cleanliness = clean, temperature difference (C^o) in working place = 28 C^o; storage position= top; mirror cleanliness= dirty; waiting time= 2 hours; anti slip tape quality= Tesa; styrofoam= existence; cleaning liquid= existence; dust in the working place = clean; double-sided tape usage = existence; anti slip tape usage= undismantle; anti slip tape usage rate= 12cm). If these conditions are applied to process/product, a quality product having a new design reducing complaint of customers comes out and mirror nightstand slippage will not occur.

Factors	Effect Values	Coef.	Interaction	Effect Values	Coef.
Fixed values		56,82	Fixed Values		56,82
A	***-32,36***	***-16,18***	A*B	1,48	0.74
B	1,48	0,74	A*C	3,48	1,74
C	3,48	1,74	A*D	-1,26	-0,63
D	-1,26	-0,63	A*E	2,40	1,20
E	2,40	1,20	A*F	2,07	1,04
F	2,07	1,04	***A*G***	***31,62***	***15,81***
G	***31,62***	***15,81***	A*H	-3,05	-1,52
H	-3,05	-1,52	A*J	-1,71	-0,86
J	-1,71	-0,86	A*K	1,00	0,50
K	1,00	0,50	A*L	1,50	0,75
L	1,50	0,75	A*M	1,33	0,67
M	1,33	0,67	A*N	2,17	1,08
N	2,17	1,08	B*C	-0,00	-0,00
			B*D	-0,00	-0,00

Table 4. Factors and interaction table

When Table 4 is analyzed, A, G factors and their interaction values have a significant difference from others. In order to decide which effects are statistically meaningful, normal plot of standardized effects was used. While interpreting the normal plot of standardized effects, important factors can be shown under the plot and left of the line, or above the plot and right of the line. As shown in the Figure 6, A (Environment temperature), G (Anti slip tape quality) and A-G interaction are significant factors for this study. While optimizing dependent variable, these factors must be considered together.

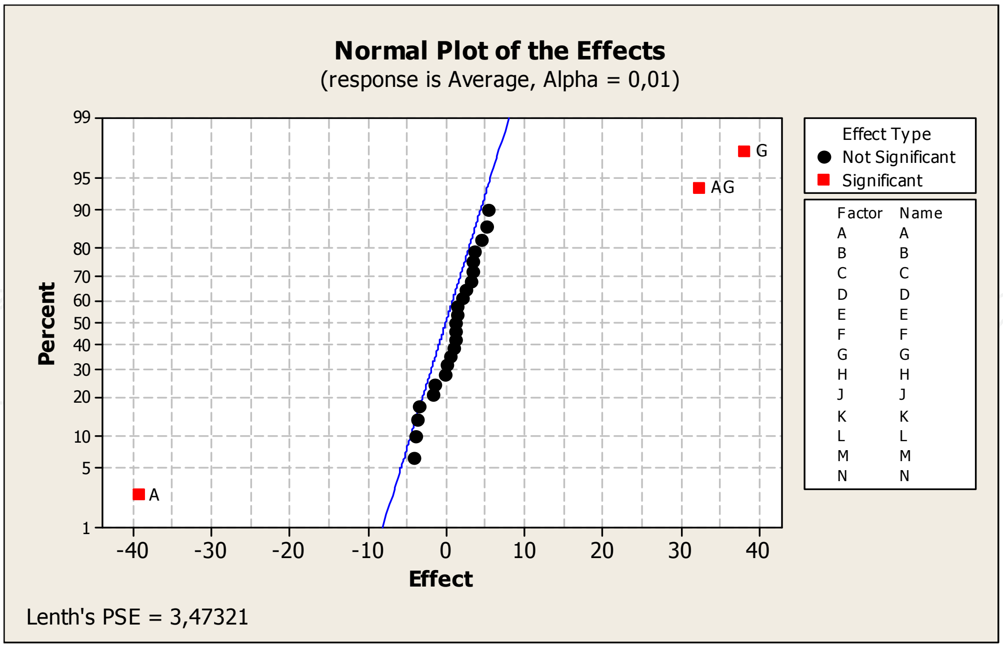

Figure 6. Normal plot of standardized effects

We can also see the importance of A and G factors from pareto chart of standardized effects as shown in Figure 7.

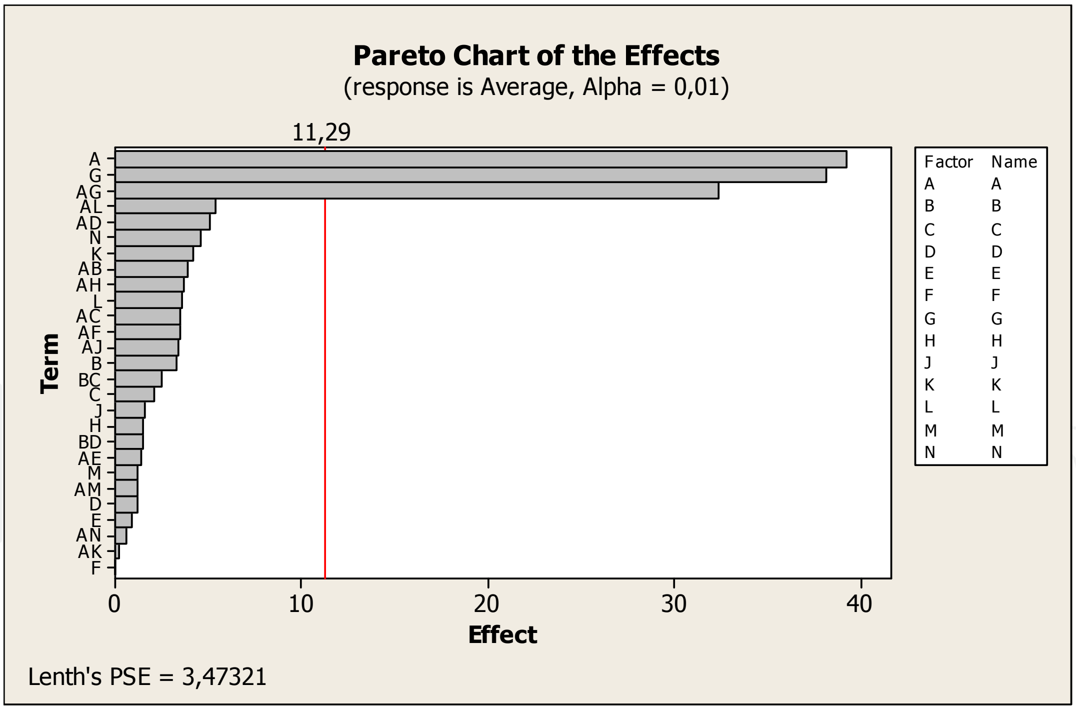

Figure 7. Pareto chart of effects

2.6. Control

New responsibility distribution is done as a result of optimization, and data is collected to achieve continuous improvement[2]. The steps which will be followed in this phase are:

- Checking new system performance,
- Monitoring improvements,
- Implementing control plans and trying to construct continuous improvements in the system.

In order to test the model verification regarding whether this design gives optimal result or not, optimal factor setting was applied in the process and process data of 6 months were collected. We realized that Product-complaints were reduced by 60 %.

3. Application of ANN (Artificial Neural Network)

ANN can perform modeling in nonlinear systems as well as linear systems. Nonlinear relations between data are extracted by ANN which is inspired with human nervous system. In a neural network, three have been three types of units: input units which receive data from outside, output units which send data out of the neural network, and hidden units where the signals are transferred inside of the neuron. Weights can be represented as the strength of the connection between an input and a neuron. The neuron can be defined as processing units, the place where actual activity occurs. An activation function controls the value of the input while transferring it from the layers, until it reaches to output. Each neuron receives input from neighbours and use these inputs while computing an output signal[20]. When this data flow occurs between the units, weights are adjusted. There can be different types of ANN. Multilayer Perceptron (MLP) and Radial Basis Function are the most known types of ANN. MLP networks consist of typically an input layer, single or more hidden layers, and one output layer. Hidden layers have one or more hidden neurons which perform nonlinear mapping between inputs and outputs[21]. Relationship between input and output is constructed by using some methods that is needed for adjusting the weights during the training session. This can be represent as learning algorithm. Choosing the proper learning algorithm is also very important while training the networks. The most common learning algorithm is called Back Propagation (BP). There are several types of optimization techniques for ANN using the backpropagation algorithm such as gradient descent method, gradient descent with momentum, conjugate gradient method (Fletcher-Reeves, Polak-Ribiere), quasi-newton method (Broyden-Fletcher-Goldfarb-Shanno - BFGS). Generally, levenberg-marquardt method is used for the networks which contain up to a few hundred weights, converges faster and uses second derivatives for solutions. For the moderate size networks, quasi-newton method are often the next fastest algorithms[22]. BFGS is the most successful quasi-newton method employed in our study[23].

The optimal number of nodes in the hidden layer is generally computed by a trial-and-error approach[24]. To find the best neural network, networks which contain different number of hidden neurons are compared with each other[25]. Mean square error (MSE) is the basic criteria while judging the capability of networks. If we use too much hidden neurons, this leads us too much flexibility and over fitting. On the other hand, if we use too few hidden neurons, this prevents the learning capability[26]. Therefore, one of the biggest problems is to find the proper number of hidden neurons. Furthermore, the simplest architecture is better than others[27]. Thus, single hidden layer can be chosen and it is sufficient for many continuous nonlinear mapping.

In this study, after the design of experiment study was conducted, ANN application was done for modeling the system. PB experiment data were used as input to ANN. To prevent alias structure of PB, a second run was used as input; but not an exact replication. Data were divided into two parts as training (80%), and testing (20%), respectively. The Neural Network module of STATISTICA 9.0 software was employed in modeling the ANN. In the network, there were 13 inputs and one output as defined before. A trial and error method was used in deciding the best model for the system. 500 different combinations of activation functions and neuron numbers were tried by considering the fitted model MSE. The performance of best five models was evaluated and MLP 13-5-1 model was chosen as shown in Table 5. The MAE and MSE of the selected topology are 2.957247 and 15.54706, respectively. Generally, using the sigmoid (logistic) function in ANN topology provides a good nonlinear input–output mapping capability[28]. A weight decay method was used to reduce the overfitting problem. This option encourages the development of smaller weights, so it potentially improves performance of the network and modifies the network's error function to penalize large weights[29].

Network Architecture	Training perf.	Test perf.	Training error	Test error	Training algorithm	Hidden activation function	Output activation function
MLP 13-7-1	0.986217	0.988856	21.77105	8.85785	BFGS	Exponential	Logistic
MLP 13-11-1	0.986836	0.989038	20.68673	10.50230	BFGS	Exponential	Logistic
MLP 13-9-1	0.980550	0.987936	23.20724	11.52654	BFGS	Exponential	Logistic
MLP 13-10-1	0.984314	0.986702	18.20639	12.64308	BFGS	Exponential	Logistic
MLP 13-5-1	***0.986941***	***0.990763***	***23.59058***	***7.77353***	***BFGS***	***Exponential***	***Logistic***

Table 5. Best Network Architecture

ANN model was controlled whether the slippage occurs or not for PB's optimal set. We showed that slippage time was predicted as 89 hours in the ANN. We wanted to see which parameters are significant for ANN as in PB. On account of this, sensitivity analysis was performed in ANN. There have been some researches about determining the effects of the input parameters on the response variable[30] in terms of sensitivity. Sensitivity analyzes can be applied to a network after the training session is completed. It tries to see what the effect would be of changing the inputs of the model on the overall model fit. While an input of the artificial neural network model is eliminated from the model, sums of squares residuals for the model are analyzed and the inputs can be sorted by their importance[29]. The larger the variance in the error after the parameter is omitted, the more important the variable is[31]. As a result of the sensitivity analysis, it proves that A and G are really the most important parameters for the ANN model. This sensitivity analysis values were normalized as given in Figure 8.

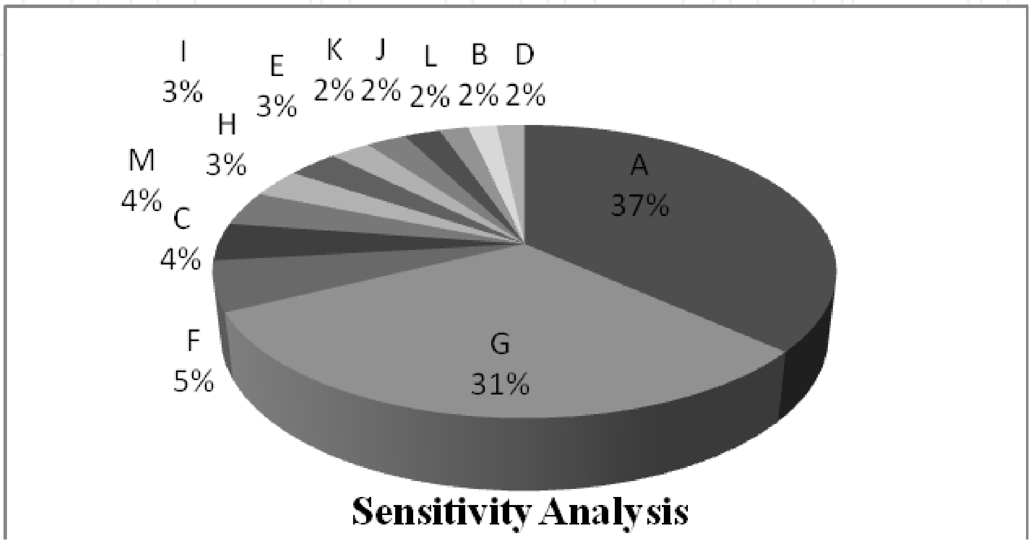

Figure 8. Pie chart of normalized sensitivity analysis

4. Conclusion

In this study, PB experimental design method was used from the point of view of Six Sigma philosophy. Besides, ANN was employed for the solution of same problem and results were compared whether nightstand mirror slippage occurs or not. If the mirror of nightstand can stand out against rotate without slipping as long as 72 hours, it is called as 'no slippage'. In this context, the modeling of PB and ANN came to conclusion as 'no slippage'. This is the first time we used PB and ANN in the literature for a furniture manufacturing firm.

We defined significant factors with ANOVA used for PB and sensitivity analysis of ANN was performed for verification. Environment temperature, anti slip tape quality and their interactions were the significant factors for both modeling. Customer complaints were decreased by 60 % in products / processes with real production of optimal factor settings. Thus, we found applicability of PB and ANN for nightstand mirror slippage problem. In the future, optimum solutions can be compared by using different meta- heuristics such as Genetic algorithm, Particle swarm optimization and Bees Algorithm.

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