Taguchi Based Design of Experiments for Optimization of Closed Loop Production Systems

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Abstract

Sustainable production system requires optimal utilization of resources. Raw material acquisition is one of the costly processes in a production system. End-of-Life (EOL) and products re-manufacturing through reverse logistics can help in decreasing excessive raw material cost. In this study, we consider production system of closed loop supply chain in which both forward and reverse production systems are active. Design of experiments (DOE) methodology is incorporated which is a statistical approach adopted in dealing with complex workplace problems. We employ L_9 orthogonal array using Tagouchi experiment in Minitab 17 and Design experts for plotting the results. Dependent variable used in this study is quality accuracy of product (measured in percentage of deviation from reference standards. Control variables used in the analysis are tools employed in production system (tu), number of machines being used (m) and dedicated manufacturing cells (dc). We use three levels of analysis for each control factor. Optimum result conditions are calculated using signal to noise ratio with smaller-the-better criteria and study is concluded with main effects of the mean plots.

Keywords
Closed loop supply chain, Design of experiments, Productivity, Tagouchi experiment, Signal to noise ratio.

1. Introduction

Production systems are faced with enormous business challenges where resource efficient utilization and cost minimization are more prominent. Resources of production system include raw materials, energy, technology, tools and man-power. If resources are optimally utilized then cost minimization can be accomplished. Due to competitive market dynamics, cost optimality is of no use if it comes as a result of compromise on quality. It is thus in the best interest of a business to optimize a production system once it is assessed for quality. In this article, we discuss one of the efficient ways to optimally use resources in the form of raw material usage by considering case of a closed loop supply chain. Supply chain involves multiple business activities such as acquisition of raw materials, production, logistics management & distribution of the product to customer (Paksoy et al., 2011). A normal supply chain moves the product line in one direction starting from accessing raw material from supplier and delivering to the end customer; however in closed loop supply chain, both forward and reverse movements of the product (to and fro from the customer) are considered. Closed Loop Supply Chain (CLSC) is implemented to moderate the economic and environmental consequences of the products, for instance minimization of products containing Carbon contents (environmental degradation) (Kumar et al., 2013). CLSC is defined as "*design, control and operation of a system to maximize value creation over the entire life cycle of a product with dynamic recovery of value from different types and volumes of returns over time*" (Guide et al., 2003). Reverse logistics deal with collection of products from customer once they serve their useful life which is quite opposite of the traditional logistic services (Beamon et al, 1999).

Reverse logistic operations have created more hype in the wake of corporate social responsibility (Tai et al., 2014) and it is one of the leading practices adopted by businesses such as BMW, Howard Packard and General

Motors (Srivastava, 2007). Closed loop supply chain containing both forward and reverse logistics brings about phenomenal advantages to the business such as green design & manufacturing, product life cycle assessment, waste management, formation of sustainable & eco-friendly environment. Forward loop of CLSC is more stagnant and predictable in a sense that an orthodox method is followed for processing a product on assembly line. However, in the case of reverse logistics, it is hard to tell that product would retrieve back into the system at what point. For instance reversed product might need repair, recondition, re-manufacturing and/or recycling depending upon the state of the product as shown in Figure 1 (Khor et al., 2012). If repair is needed, product would pass through post-assembling facility where minor adjustment are provided and if it is to be re-conditioned, it is fed into the assembly line. This makes the process more uncertain for balancing between the forward and reverse assembly line. Similarly, an evaluation needs to be performed for the assessment of productivity of the CLSC and quality of the products being produced.

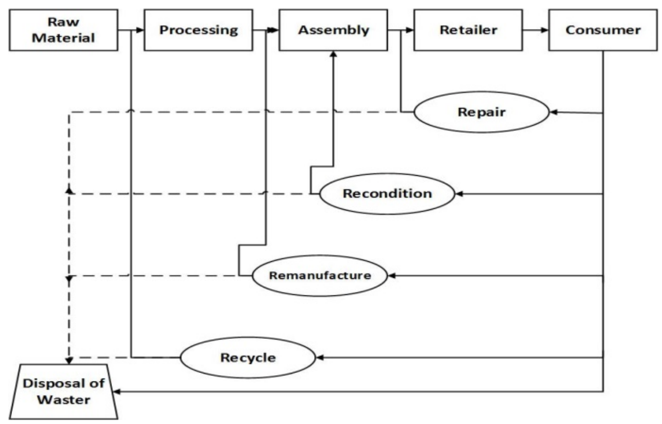

Figure1. Schematic of Closed Loop Supply Chain (CLSC) (Khor et al., 2012)

Reverse logistics provides with efficient centralized system for controlling, implementing and planning in accordance with requirements of the production system (Kolk et al., 2014). To re-emphasize, it is not necessary that the product through reverse chain enters into the system from the start but rather it can enter into the production system at any point depending upon the condition of the product and processes needed to be performed. Reverse Logistics serves for extracting value from the collected items and thus it follows start to a new supply chain (Wilson et al., 2009), which in connection to the existing supply chain creates problems such as productivity, quality of production, work scheduling and demand completion (Tibben, 2002; Tibben et al., 2002). We use Tagouchi method for examining the quality aspect of a product in closed loop supply chain. In the next section, methodology of the study is outlined.

2. Methodology

We analyze manufacturing line of closed loop supply chain using Tagouchi method which is a statistical robust technique for process parameters examination. Tagouchi method has been in practice for more than 3 decades now and its utility can be found in contexts such as manufacturing, process design and supply chain (Mahfouz et al., 2010). Tagouchi method starts with identification of the study control variables and their salience, followed by selection of noise factors (factors which are un-controllable). In the third step we define the objective function and explicate the levels of control factors. On the basis of levels of identified factors, orthogonal array is constructed for experimentation and validation purposes (Athreya et al., 2012). Figure 2 below shows the flow diagram of the process.

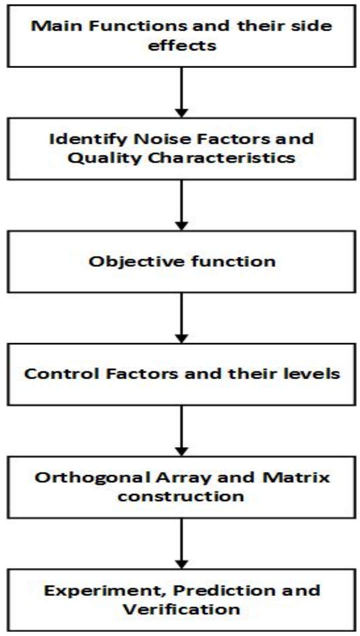

Figure2. Six steps approach towards Tagouchi Method (Athreya et al., 2012)

For analysis of the study, we considered a French manufacturing assembly line of automotive engines and performed statistical analysis of parts in high need of repair and replacement through reverse logistics. We considered three parts for the study investigation which are; Piston, Case and Connecting rod as shown in Figure 3.

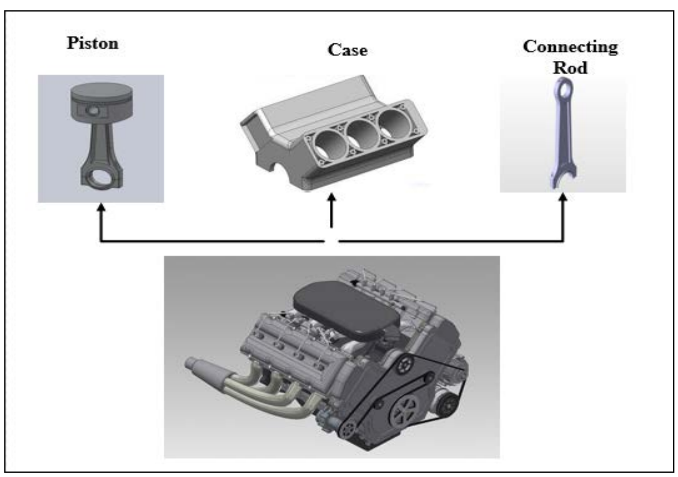

Figure3. Selection of parts for study analysis

As a result of both forward and reverse channeling; enterprises needs to investigate an effect on adopting variation in their production strategy such as tooling, machines and work-cells on quality of the product produced. A cellular layout was designed in the assembly line for dedicated manufacturing cells indulged in the closed loop production. We considered three control factors and one noise factor (un-controllable and observed variable) for the study. Control factors were Tools employed, *tu* in the production process, machines in use, *m* and dedicated manufacturing cells, *dc* while noise factors was dimensional accuracy *da*. Dimensional accuracy is defined in terms of deviation of overall dimensions from the specified standards and it is measured in percentage.

Table 1
List of control and noise factors considered for the study analysis

Control Factor	**Noise Factor**
Tools employed, *tu*	Dimensional accuracy, *da*
Machines in use, *m*	
Dedicated manufacturing cells, *dc*	

Next, identification of levels for the factors is performed. For tool employment, number of tools varies from 24 to 38 in different machines. Similarly, number of machines used is 24 in level 1, 32 in level 2 while 38 in third level. Lastly, machines are designated to manufacturing cells which are3 in level 1, 6 in second level while 11 in third level. Main objective of carrying out this research is to identify mix of factors for which quality is in optimum condition.

Table 2
Factors and their three levels

Factors	**Levels**		
	1	**2**	**3**
Tools employed, *tu*	24	32	38
Machines in use, *m*	8	14	22
Dedicated manufacturing cells, *dc*	3	6	11

Table 3 below contains list of nine (9) experiments and combination of independent/control factors level in that particular experiment. Also, values of control variables are provided in the brackets for particular experiments. For instance, experiment 7 contains level 3 value for tools, level 1 value for machines used while level 3 value manufacturing cells which are translated as 38 tools, 8 machines and 11 manufacturing cells.

Table 3
Number of experiments and combination of the factors

Experiments	**Factors** **1(tools)** **2(machines)** **3(cells)**		
1	1(24)	1(8)	1(3)
2	1(24)	2(14)	2(6)
3	1(24)	3(22)	3(11)

4	2(32)	1(8)	2(6)
5	2(32)	2(14)	3(11)
6	2(32)	3(22)	1(3)
7	3(38)	1(8)	3(11)
8	3(38)	2(14)	1(3)
9	3(38)	3(22)	2(6)

Tagouchi method applies full factorial design on the orthogonal array defined in analysis. Since we had 3 control factors, we applied L_9 orthogonal array with three runs on each experiment, making in total 27 iterations of the experiments. Tagouchi can be used for analysis of Signal to Noise (S/N) ratio with one of the three performance characteristic; Larges the better, Smaller the better and Nominal the better. Larger the better is a performance characteristic used when the desire is to maximize the value of outcome (productivity in this case) while smaller the better indicator is used for minimization of the outcome, i.e., dimensional deviation in this case. The formula smaller the better are given below.

As mentioned earlier, total of 27 experiment runs were performed for analysis of productivity with the mean values also tabulated. Dimensional accuracy in this case is defined in terms of deviation of overall dimensions from standard specifications. It is expressed in terms of percentage and smaller the value of deviation (*da)*, the better it is. S/N criteria of smaller the better is considered and table5 below exhibits deviation values for all 27 experiments with mean value and S/N ratio. Formula for S/N normal the better is given as;

$$\pi = 10 \log(y/s^2)$$

Where, π = S/N ratio;
y= mean of dimensional accuracy and
S^2= Variance between S/N ratio and y.

Table 4
Iterations for *da* & S/N ratio

Exp.	**Dimensional accuracy, *da***				**S/N ratio**
	1	**2**	**3**	**Mean**	
1	1.5	2	1.2	1.57	-9.27
2	1	1.5	1	1.16	-6.82
3	1.2	1	1.5	1.23	-11.58
4	1.5	1	2	1.50	-9.04
5	2.5	2	1	1.83	-14.92
6	1	2	2.5	1.83	-14.92
7	1.5	2.5	2.5	2.16	-17.27
8	2	2.5	1	1.83	-14.92
9	2.5	2.5	1	2.00	-19.03

In Table 5 below, sum and average of S/N ratios for all control variables is presented for dimensional accuracy for which the criteria used was smaller the better. Graphical depiction through design experts is provided in Figure 4 where data of S/N for control variables is plotted on y axis against levels on x-axis.

Table 5
Sum and average of three levels for control factors

Level	Tools employed, *tu*		Machines in Use, *m*		Manufacturing cells, *dc*	
	Sum	Average	Sum	Average	Sum	Average
1	-27.89	-9.29	-28.82	-9.60	-25.57	-8.52
2	-25.42	-8.47	-27.19	-9.06	-28.36	-9.45
3	-28.16	-9.39	-29.32	-9.77	-29.49	-9.83

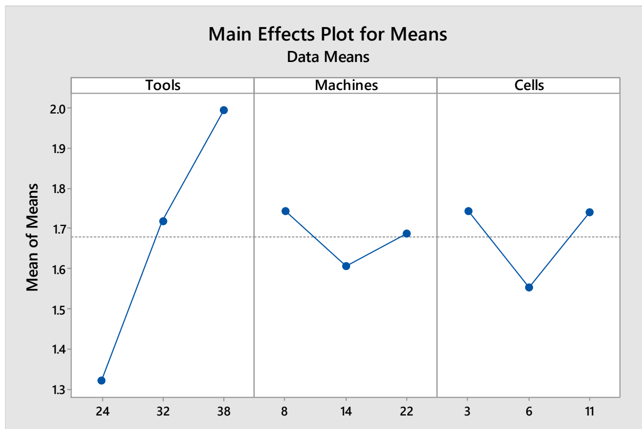

Figure4. Main Effects plot for Means

In Table 6, parameters variation analysis results are presented. Variation explanation in "dimensional accuracy" is accounted for by "machines" equal to 35.8%, "tools" factor explains it by 30.6% while manufacturing cells by 28.8%.

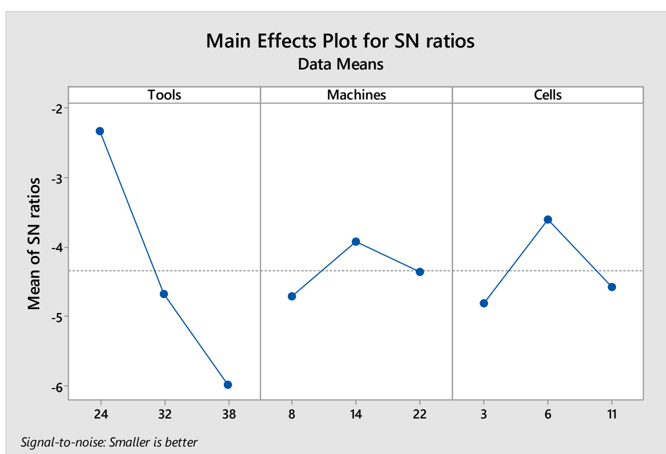

Figure5. Main Effects Plot for Signal to Noise ratios

Table 6
ANOVA statistics of the control factors

Parameter	**S. Squares**	**Mean Square**	***F*-ratio**	**Variation**
Dimensional Accuracy, *da*				
Tools employed, tu	6.24	3.78	9.42	30.6%
Machines in Use, m	7.31	3.95	10.36	35.8%
Manufacturing cells, dc	5.88	3.24	8.54	28.8%
Error	0.99	0.64		4.8%
Total	**20.42**			**100%**

From table below, we can assess that tools (Delta 3651, Rank=1) has larges effect on S/N ratio compared to both Machines (Delta= 0781, Rank=1) and Cells (Delta=1195, Rank=2).

Table 7
Response table for S/N ratio

Level	**Tools**	**Machines**	**Cells**
1	-2.335	-4.710	-4.805
2	-4.673	-3.929	-3.611
3	-5.986	-4.356	-4.579
Delta	3.651	0.781	1.195
Rank	1	3	2

Similarly from Table 8, we can posit that Tools have a strong effect on the value of mean results of Taguchi experiment (Delta=0677, Rank=1), compared to Machines (Delta=0.137, Rank=3) and also Cells (Delta =0190, Rank=2).

Table 8
Response Table for Means

Level	**Tools**	**Machines**	**Cells**
1	1.320	1.743	1.743
2	1.720	1.607	1.553
3	1.997	1.687	1.740
Delta	0.677	0.137	0.190
Rank	1	3	2

Lastly in Table 9, optimized results of Tagouchi method for “dimensional accuracy” are reported. We chose smaller the better criteria and accordingly, smaller value of S/N is -6.82 which corresponds to second arrangement of experiment and tools employed are 24, machines used are 14 while manufacturing cells are 3 in number. Literature reveals that most of study undertaken for quality assessment considers orthodox control parameters while we have considered a non-conventional approach by incorporating variables such as tools, machines and manufacturing cells. In mass customization environment where more focus is upon production quantity, through this study we can suggest that maximum resource mobilization is not an ideal approach and it can create havoc in terms of quality. With more tools and machines, worker focus might get disrupted. Also, it can cause in resource management and transportation in the work facility hence a compromise on achieving good quality product.

Table 9
Optimized values of control factors

Parameter	**Optimal Value**
Tools employed, *tu*	24
Machines in Use, *m*	14
Manufacturing cells, *dc*	6

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Biography

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