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A Sequential Procedure for Manufacturing System Design

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ABSTRACT Experimental design is a powerful approach to study the impact of potential variables affecting systems and provides spontaneous insight for continuous improvement possibilities. Most research in system design has focused on problems with a single characteristic or response. This paper is concerned with the application of a design method to problems with multiple characteristics. The study sequentially employs two optimum-seeking methods to design and optimize a manufacturing system. The integration between Taguchi method, which uses robust design concept to reduce the output variation, and the Response Surface Methodology (RSM), which is a combination of mathematical and statistical techniques, is introduced to optimize systems with multiple process characteristics.

KEYWORDS: multi-criteria optimization, Taguchi Method, response surface methodology.

INTRODUCTION

Various approaches, such as mathematical programming, queueing networks, artificial intelligence, have been proposed for the design and control of manufacturing systems. The usefulness of these tools depends on the nature of the problem. With the complexity of real systems, it is difficult to study the systems through an analytical approach. Therefore, simulation is widely used to study the manufacturing system's performance.[1] Pros and Cons of using simulation can be found in Law and Kelton.[2] Nevertheless, one major drawback of using simulation is that it does not prescribe the optimal system parameter setting. In this study, Taguchi method and Response Surface Methodology (RSM) are used to uncover the optimal combination of system parameters that maximize the outputs of manufacturing systems.

Taguchi method has proven to be successful for the improvement of process performance. Its objective of parameter design (also known as robust design) is to determine the best settings of the process parameters, which make the process functional performance insensitive to various sources of variation. In order to accomplish this objective, Taguchi advocates the use of Statistical Design of Experiments (SDOE).[3] Many successful applications of Taguchi method have been reported over the last fifteen years.[4] Taguchi parameter design is very useful if the problem involves uncontrollable factors such as time between machine failures and it is valuable when the decision variables are qualitative or discrete. However, when the input factors are quantitative and continuous, the RSM is better suited.[1] RSM studies the local geography of the response surface near the optimal value through the response function. It is also useful for modeling and analyzing applications where a response of interest is influenced by several variables.[5]

However, both methods can be used to supplement each other. The Taguchi method can be used to optimize qualitative variables, while RSM fine-tunes the quantitative results derived from the Taguchi method and strives for better solution. Shang and Tadikamalla[6,7] and Shang[1] have employed this approach by combining the Taguchi and RSM to study the multi-criteria performances of manufacturing systems. This study has followed their hybrid approach but also been modified to use the process costing method (especially the opportunity cost) as a means for normalization. This hybrid approach will reveal an interesting outcome, highlighting the importance of hybrid requirement towards multiple process characteristic problems.

OPTIMIZATION OF MULTIPLE PROCESS CHARACTERISTICS

Most Taguchi and RSM experiments are concerned with the optimization of a single characteristic and little attention has been given to optimization of multi-process characteristics in manufacturing systems[4]. With such complex multiple process characteristic problems, the target value is unknown. As a result, typical goal programming approach and the multi-attribute value function method, which are normally used in operations research for multi-objective optimization, are not applicable.

Referring to the system under study, we address the impact of various operational decisions or controllable factors (*ie*, set-up time, batch or magazine size and part inter-arrival time) and system parameters or uncontrollable factors (*ie*, mean time between machine failures and mean time to repair machines) on multiple system performance measures (*ie*, mean flow time, part waiting time in the system and system utilization). The decision to be made is to determine the impact of setting these parameters in order to yield maximum performance. Since the selected performance measures could be conflicting among one another. For instance, throughput can be maximized at the expense of high WIP. In addition, some variation of parameter settings could cause different effects to each performance measure. For instance, an increase in magazine size may result in longer mean flow time and part waiting time but lower system utilization. As a result, the importance of each measure needs to be given in order to combine different responses into a common response function, which may be used to represent system's outputs as a whole.

The performance measures used in this study have normally been used to evaluate system performances in past researches and they also represent inefficiency of poorly functional systems. Mean flow time is used to measure the time that a system can respond to a customer order (the time that a part spends in the system). Part waiting time is to measure the amount of time that parts spent in queues waiting to be processed (WIP level) and finally the system utilization is to measure how well the resources are effectively utilized. Given the presence of the selected system performance measures, we try to balance the different aspects of the shop performance and come up with an indicator for costs that are lost and foregone from the system inefficiency.

Manufacturing System Characteristics and Simulation Modeling: A Case Study

A case study of a printed circuit board (PCB) manufacturing plant was performed to demonstrate the methodology proposed. This automated plant has five processing workstations with one raw material store and one finished product warehouse. In each workstation, there are 10-20 machines depending on the capacity requirement by avoiding a serious bottlenecked station. The plant configuration is shown in Fig 1 and the type of circuit board plus their processing routes and operating time are shown in

Fig 1. System configuration.

Table 1. Processing route.

Board type	Processing route	Mean processing time (minute)*
1	Station 1-Station 2-Station 4	1 – 3 – 4
2	Station 1-Station 3	1 – 0.25
3	Station 2-Station 3-Station 5	7 – 0.25 – 4
4	Station 3-Station 4-Station 5	0.25 – 7 – 3

* Normally distributed with 10% of the mean as its standard deviation.

Table 1. Between workstations, PCBs need to be stacked in magazines for transporting by small vehicles (10 vehicles). Each magazine contains one batch of PCB and its size is varied according to the set parameter. The speed of the vehicles is set at 55 meters/minute and the nearest idle vehicle to the calling station is selected when one is called for service.

Raw materials are allowed to enter the system with equal probability among each board type. When parts arrive in the system, they enter workstations in a sequential order as indicated in Table 1. If all machines in the workstation are busy, they have to wait in a queue in front of that workstation until a machine in that workstation becomes available. When a machine is available, it can select a part to process according to one of the rules imposed from the parameter setting. Then, parts follow each stage till the last workstation. Machines can also be interrupted by failure. Mean time between machine failures and mean time to repair are considered as uncontrollable factors (noise). In addition, when a different board type is to be processed on a machine, a machine set-up is required. This set-up time is also an experimental factor.

Owing to the complexity of this manufacturing system, simulation is employed as a tool for analysis. All experimental models for the above manufacturing environment were developed using SIMAN simulation language.[8] For each experimental condition, the model is run with 10 independently-seeded replications of 15,000 minutes each. The first 3,000 minutes is truncated to eliminate initialization bias. Three key performance measures are then collected to represent the system performance.

Parameter Setting

There are four operational decisions or controllable factors, which are machine dispatching rule, set-up time, batch (magazine) size and part inter-arrival time. Two system parameters or noise factors include mean time between machine failures (MTBF) and mean time to repair (MTTR). Table 2 shows associated levels of each factor. The dispatching rule is the rule for machines to select a job when it becomes idle. The SPT (shortest processing time) gives the priority to the job with the shortest operating time from the current station. TPT (total processing time) gives the priority to the job that has the shortest total operating time (total operating time of the job from the first to the last process). The operating time x TPT rule dispatches the job that has the smallest value of operating time of the current station multiplied by the total operating time of the job.

The above are rules that are generally related with the processing time and well-known in the part scheduling research[9]. All times stated in Table 2 are in minutes and they are exponentially distributed with the means shown in the table. Each of the controllable factors is to be tested over three levels. The noise factors are uncontrollable during normal operations, and they are varied over two levels. Due to four noise combinations and 81 controllable factorial combinations, 324 experimental conditions result.

The Hybrid Sequential Approach

The sequential integration between the Taguchi method and RSM is introduced to compensate for any

Table 2. Factors and their associated levels.

Controllable factors	**Level**		
	1	2	3
Dispatching rule	TPT*	Operating time x TPT+	SPT#
Set-up time	45	60	75
Magazine size (units)	15	25	35
Part inter-arrival time	180	200	220
Uncontrollable factors	Level		
	1	2	
Mean time between failures	500	700	
Mean time to repair	30	50	

* Give higher priority to the part that has the shortest total processing time.
\+ Give higher priority to the part that has the smallest multiplication value of the current workstation operating time and total operating time of the part.
\# Give higher priority to the part that has the shortest processing time at the current workstation. All times are in minutes and exponentially distributed with the mean stated in the table.

drawback that may exist in each method alone. The Taguchi method has advantages of reducing time and cost necessary for experiments and incorporating robustness into the process while RSM is brought in to locate the optimum.

Taguchi Method

Apart from identifying controllable and uncontrollable factors, there are four more steps in performing Taguchi method.

Step 1. Normalization

Since each performance measure has different measuring units (*ie*, minutes and machine utilization in percentage), all measures need to be normalized to the same cost unit for uniformity purposes. In this study, the conversion process is carried out by converting existing units to opportunity costs. These costs are considered as potential economic benefits that are lost or sacrificed when the choice of action requires the giving up of an alternative course of action.[10] For example, if a system was only 80% utilized rather than fully 100% utilized, it would mean 20% of the system time, which could have been used to produce more products, was lost. This opportunity cost does not represent actual money and cannot be registered in the accounting system but it plays a significant role in the improvement of system performance and waste elimination.

a. Conversion of mean flow time into the opportunity cost due to having the flow time (if the flow time is zero, products can be shipped to the customer immediately and there will be no loss incurred)

Flow time's opportunity cost = Mean flow time x Number of finished jobs x Part unit cost x Cost of capital per unit time

b. Conversion of waiting time into the opportunity cost due to holding WIP (if there is no inventory, no waiting time will occur and hence there is no holding cost)

Waiting time's opportunity cost = Part waiting time in the system x Holding cost per unit time

c. Conversion of system utilization into the opportunity cost due to having machine idle time (if machines are fully utilized, there will be no loss from under utilizing machines)

System utilization's opportunity cost = System idle time x Efficiency x Depreciation cost x Cost of capital per unit time

It should be noted that the cost of capital is the expected cost incurred from time loss through pursuing one activity and giving up the others. It depends on each situation when charged. If there is demand, the cost may be considered as lost profit since opportunities of making and selling more products are foregone. However, if no demand, the loss may only be considered as a capital tied up since finished products are just being kept inside and no profit is generated. For normalizing processes in this study, the following cost structure is assumed.

- Part unit cost = 1,500 Baht
- Machine depreciation rate = 10% of machine investment cost per year
- Machine cost = 100,000 Baht per machine
- Machine efficiency = 80%
- Cost of capital » 2% per each replication length
- Holding cost » 10% per each replication length

Step 2. Evaluating performance statistic. (average loss)

In the Taguchi method, average loss is used to identify the optimal parameter setting in which the loss is minimum at the optimal point. Since, a robust design requires the reduction of variability, the loss function due to variability is defined as $L(y) = c(y-T)^2$. In this case, it is desirable to have the lowest loss and thus the ideal target (T) value is 0. Since characteristics of minimizing the opportunity cost belongs to this category, the loss function for this case is $L(y) = cy^2$. In the case that the largest value is preferred, such as profit maximization, the loss function would be $L(y) = c(1/y^2)$. In the equation, we can ignore c, since it is a constant and has no effect on the optimization procedure. The average loss on performance measure k due to controllable factor setting i is defined as:

$$L_{ik} = \frac{\sum_{j=1}^{n}\sum_{l=1}^{n} Y_{ijkl}^2}{n \times p} \qquad (1)$$

where:

L_{ik} = average loss on the performance k at controllable factor i
Y = performance measure
i = controllable factor (*1*= dispatching rule, *2*= set-up time, *3*= magazine size, *4*= part inter-arrival time)
j = noise factor
k^{th} = k^{th} criterion (*1*= mean flow time, *2* = part waiting time, *3*= system utilization)
l^{th} = (1^{st} to 10^{th}) replication
n(=4) = total number of outer array (noise combination)
p(=10) = total number of replications under each experimental condition, (i,j)

For example, L_{13} is the summation of squares of system utilization at factor *1* (dispatching rule) of every noise combination from replication 1 to 10 and divided by n x p (=40).

Step 3. Performance measures' weight assignment.

In multi-criteria optimization, one may see the importance of each performance measure differently. One company may give more importance to the throughput than their machine utilization while others may prefer to keep their inventory low by sacrificing lower production throughput. Thus, the importance needs to be given to each criterion according to that circumstance. The importance in terms of subjective weights is then established for prioritizing key performance measures that are in line with the circumstance and the company plan.

Weighting determination is not a small issue. There are a number of past researches trying to develop methods for this weighting decision. Saaty[11] developed the Analytic Hierarchy Process (AHP), which employs the pairwise comparison method as a ranking tool. Liang and Wang[12] employed a fuzzy multiple criteria decision-making method to select the best facility site. Larichev *et al.*[13] introduced ZAPROS, which is a method to support rank ordering task using ordinal input from decision makers.

Weighting assignment can have a significant effect to the final results. Thus, accuracy in weighting assignment is very important and plays a major role in obtaining the good system design. However, as this case study is intended to demonstrate the developed methodology, an equal weight to each performance measure is assumed. In more complex cases, the above-mentioned methods can easily be applied to assist in this decision process.

Having assigned proper weights to each of the three performance measures, the weighted performance measure (total loss), WPM_i, for controllable factor setting i, may be defined as:

$$WPM_i = \sum_k w_k \times L_{ik} \quad (2)$$

where w_k is the weight for performance measure k and the WPM_i is used as the response variable in the RSM. Thus, the weighted performance measure may be expressed as:

$$\textit{Weighted performance measure (WPM) or the total loss of controllable factor setting } i = 0.33L_{i1} + 0.33L_{i2} + 0.33L_{i3} \quad (3)$$

Step 4. Computation and plotting of total loss versus controllable setting level.

Since the Taguchi method emphasizes minimizing the total loss, Fig 2 leads us to choose the factor of dispatching rule at level 2 (Operating time x TPT), set-up time at level 1 (45 minutes), magazine size at level 1 (15 units) and part inter-arrival time at level 3 (220 minutes). However, it should be noted that there is no guarantee that choosing these points will lead to minimizing total loss since it may be at a saddle point.

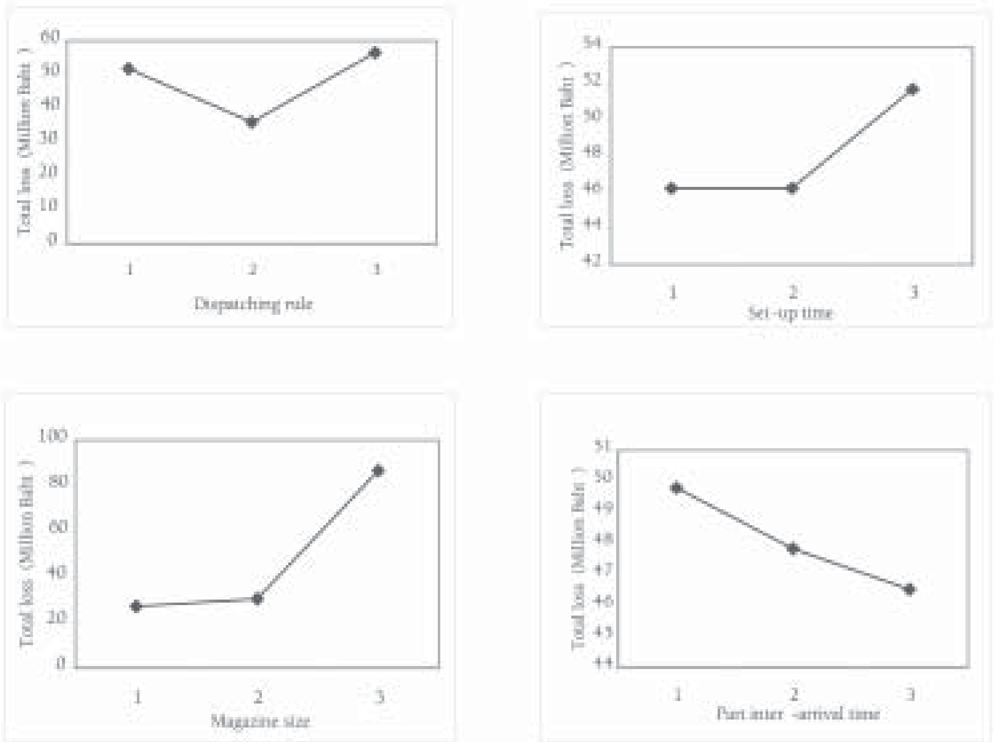

Fig 2. Total loss versus controllable factors.

Response Surface Methodology (RSM)

Factor levels recommended by the Taguchi method are used in this section as the initial setting. Since RSM cannot accommodate qualitative factors, the dispatching rule will not be included as a decision variable. Based on the weighted performance measure, the best rule, Operating time x TPT, is then used in the following experiments. Four sequential phases of RSM may be performed as:

Phase I: First-order Analysis

The first-order analysis is used to estimate a true functional relationship between the dependent variable and the set of independent variables.

Step 1. Range Determination of Each Factor

The optimum point suggested from the Taguchi method is used as a center of the range. The region of exploration for fitting the model is: set-up time of (40,50) minutes, magazine size of (10,20) units and part inter-arrival time of (215,225) minutes

Step 2. Code independent Variables in a (-1,1) Interval

This is done to simplify the calculations. The levels of the coded variables are defined as:

X_i = *(the ith factor's natural value – present value) / half the range of the variable* (4)

The coded values are X_1 = *(set-up time – 45) / 5*, X_2 = *(magazine size – 15) / 5*, X_3 = *(part inter-arrival time – 220) / 5* where X_1, X_2, X_3 are coded variables of set-up time, magazine size and part inter-arrival time respectively.

Step 3. Data Collection

2^k *(k=3)* full factorial design is used and augmented by four central points. Repeat observations at the center are used to estimate the experimental error and to allow for checking the adequacy of the first-order model. Since each design is simulated and averaged under four different noise settings, there are 48 experimental conditions in all. Under each experimental condition, we make further 10 replications with the length of 15,000 minutes each.

Step 4. First-order Model Fitting

By using the least square method, we obtain the following model in the coded variables:

$$Y = 15,700,300 + 267,835.72\, X_1 + 6,330,771.60\, X_2 - 220,744.66\, X_3 \quad (5)$$

The response, Y, is the total loss while X_1, X_2 and X_3 are coded variables, representing set-up time, magazine size and part inter-arrival time respectively.

Step 5. First-order Model's Adequacy Check

The first-order equation gives F-value of 25.422. Under 95% confidence level, the analysis of variance (ANOVA) indicates the fitted model is adequate ($F_{0.05,3,44}$ = 2.8) and it sufficiently shows a good estimation of functional relationship between the total loss and the set of independent coded variables.

Step 6. Method of Steepest Descent

Since we are to minimize the objective function (the total loss), the steepest descent procedure is chosen otherwise the steepest ascent is used for the maximization problems. The path of steepest descent is the direction in which the response decreases most rapidly. Therefore, the variable that has the largest absolute regression coefficient in the model, *ie* X_2 (magazine size) with β_2 = 6,330,771.6, is chosen. We allow a step size of 0.2 in coded units for X_2, and calculate the coded step size for other variables as ($\Delta X_i = \beta_i/\beta_2$) for *i=1,2,3*. The coded ΔX_i is then converted to the natural variable, DS_i. This is done by multiplying ΔX_i with the actual step size (S_i). The actual step sizes are selected based on the experimenter's knowledge of the process. In this study, we choose S_1, S_2, S_3 equal to 0.2. Therefore, the steps along the steepest descent path for ΔX_1 = (267,835.72/6,330,771.6) x 0.2 = 0.00846 and for ΔX_3 = (-220,744.66/6,330,771.6) x 0.2 = -0.00697. Thereafter, we determine the values of each point along the path of the steepest decent and observe the yields at these points until an increase in response is noticed. In Table 3 and Fig 3, the response has decreased through the tenth step and all steps beyond this point result in an increase in the total loss. In addition, we have tried to fit the first-order model at around the lowest total loss point. However, the first-order model does not fit. A second-order design is therefore in place.

Phase II: Second-order analysis

This procedure is similar to the procedure of the first-order model fitting. Central composite design is used for the second-order polynomial approximation. The optimum point recommended from the first-order model is used as the starting point. The design is composed of 2^k (k=3) factorial runs augmented with one center point and 6 axial runs (*2k*); ($\pm\alpha$,0,0), (0,$\pm\alpha$,0), (0,0,$\pm\alpha$). The value of α is defined as (number of treatments)$^{1/4}$, which is $(2^3)^{1/4}$= 1.6818. Each design is also simulated under four different noise settings so there are 60 experimental conditions in all. The least square method is also used to fit the second-order model. It is found that the model may be expressed in the following coded variables:

Table 3. Steepest descent experiment.

	Steps	Coded Variables			Natural Variables			Response
		X1	X2	X3	NT1 (minutes)	NT2 (units)	NT3 (minutes)	Y (Baht)
	Origin	0	0	0	45	15	220	
Step number	△	0.00846	0.2	-0.00697	0.0423	1	-0.0349	
1	Origin-1 △	-0.00846	-0.2	0.00697	44.9577	14	220.0349	20,165,034.85
2	Origin-2 △	-0.01692	-0.4	0.01394	44.9154	13	220.0698	19,684,116.46
3	Origin-3 △	-0.02538	-0.6	0.02091	44.8731	12	220.1047	16,011,254.75
4	Origin-4 △	-0.03384	-0.8	0.02788	44.8308	11	220.1396	17,274,306.47
5	Origin-5 △	-0.0423	-1	0.03485	44.7885	10	220.1745	12,451,712.80
6	Origin-6 △	-0.05076	-1.2	0.04182	44.7462	9	220.2094	13,091,168.95
7	Origin-7 △	-0.05922	-1.4	0.04879	44.7039	8	220.2443	13,446,944.76
8	Origin-8 △	-0.06768	-1.6	0.05576	44.6616	7	220.2792	12,369,454.84
9	Origin-9 △	-0.07614	-1.8	0.06273	44.6193	6	220.3141	10,276,376.50
10	Origin-10 △	-0.0846	-2	0.0697	44.577	5	220.349	8,539,343.57
11	Origin-11 △	-0.09306	-2.2	0.07667	44.5347	4	220.3839	10,280,337.99
12	Origin-12 △	-0.10152	-2.4	0.08364	44.4924	3	220.4188	11,852,967.87
13	Origin-13 △	-0.10998	-2.6	0.09061	44.4501	2	220.4537	12,087,544.79
14	Origin-14 △	-0.11844	-2.8	0.09758	44.4078	1	220.4886	14,565,412.19
15	Origin-15 △	-0.1269	-3	0.10455	44.3655	1	220.5235	15,018,428.24
16	Origin-16 △	-0.13536	-3.2	0.11152	44.3232	1	220.5584	16,248,718.17

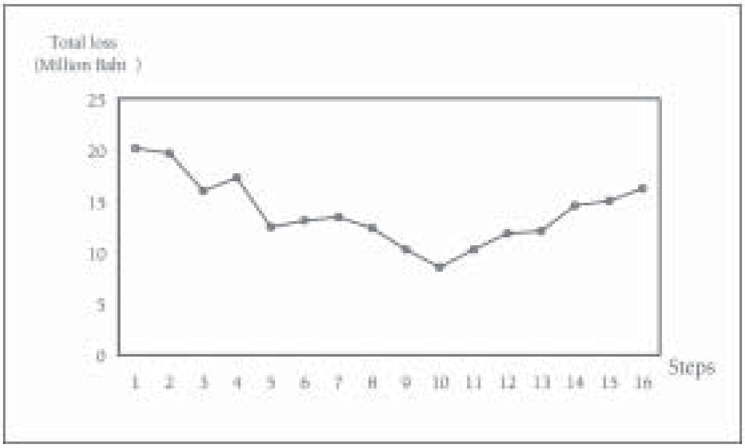

Fig 3. Steepest descent experiment on the total loss.

$$Y = 8,619,683.3 + 107,807.95X_1 + 255,752.23X_2 + 7,749.9X_3 + 301,103.204X^2_1 + 577,471.395X^2_2 + 284,833.47X^2_3 \quad (6)$$

Then, the analysis of variance is carried out for model adequacy checking. It finds the model is significant and fits appropriately in which the fitted model gives F-value of 1,278.11 higher than $F_{0.05,7,53}$ which yields the F-value of 2.17. That is the second-order model adequately approximates the true surface.

Phase III: Optimum Solution of the Weighted Performance Measure

To find the optimum value that minimizes response, partial derivation of all variables is carried out and the outcomes are set to 0.

$$\partial Y/\partial X_1 = 107,807.95 + 602,206.408\, X_1 = 0 \quad (7)$$

$$\partial Y/\partial X_2 = 255,752.23 + 1,154,942.79\, X_2 = 0 \quad (8)$$

$$\partial Y/\partial X_3 = 7,749.9 + 569,666.94\, X_3 = 0 \quad (9)$$

After conversion of these stationary points to their natural values, the levels of input variables that generate the near optimal solution are at set-up time = 44.2188 minutes, magazine size = 5 units and part inter-arrival time = 220.3218 minutes. In addition, the total loss of 8,505,600.97 Baht is found by substituting the values of the stationary points to the second-order model.

Phase IV: Result Verification

To ensure that the result is not arbitrary, we verify it again by running another set of 30 independently seeded replications at the suggested point. This set of data shows the total loss of 8,505,264.65 Baht with the standard deviation of 419,523. As a result, our previous estimation of the total loss (8,505,600.97 Baht) is very close and well within a 95% confidence interval in relation to the result obtained from the verified simulation runs.

Comparison Between Single and Multiple Criteria Performance Optimization

This hybrid sequential approach has also been put to a test under a single criteria problem and its results have been compared with the results obtained from the multiple criteria optimization approach. Mean flow time, part waiting time in the system and system utilization are individually selected as a sole performance measure. The results presented in Table 4 suggest different levels of the controllable factors from each individual criterion selected. Results from the multi-criteria approach clearly shows the lowest loss when compared to other single criterion approaches. This strongly indicates benefits from performing multi-criteria optimizing approach in relation to a single criterion optimizing approach where other criteria may consequently get worse as a result of optimizing one interested criterion in particular. It should also be noted that the amount of improvement is highly dependent on each set of data and each situation. However, the multi-criteria approach is proven to be suitable for the case where companies with multiple characteristics are interested to have an optimal result of their overall interested performances, rather than a piece by piece information.

Table 4. Comparison of parameter settings between single and multi-criteria optimization.

Single criteria optimization				Multicriteria optimization: Minimizing total loss
Controllable factors	Minimizing mean flow time's loss	Minimizing part waiting time's loss	Minimizing system utilization's loss	
Dispatching rule	Operating time x TPT	Operating time x TPT	Operating time x TPT	Operating time x TPT
Set-up time (min.)	58.4	24.153	82.198	44.219
Magazine size (units)	9	14	5	5
Part inter-arrival time (min.)	179.5415	227.27	170.815	220.3218
Total loss (Baht)	14,772,466.2	19,118,021.2	14,089,615.3	8,505,264.65

Conclusion

A methodology has been proposed in this study to improve manufacturing system design. We extended the approach considered in Shang and Tadikamalla[7] to include the opportunity costs. These are opportunity losses in efficiency, information and unnecessary expenses during production. The estimates of loss measures determine the optimal factor settings from the fitted response model. The methodology sequentially employed two methods, *ie* Taguchi method and Response Surface Methodology. Results obtained from the proposed hybrid sequential approach have shown a significant improvement from the results, which consider each criterian separately.

However, there are some drawbacks in the approach that need to be remarked. As poor inputs lead to poor results, weighting decision to each performance measure and accuracy of the applied cost structure will play a major role in obtaining good results. Future work will look into the impact of different relative weightings of each loss on the multiple performance measures. Although the approach attempts to optimize manufacturing system design and determine a region of the factor space in which operating specifications are satisfied, the generated outcome may fall into a local optimum only. However, if the experiment is well planned and the factor space is well defined, the true optimum can be achieved.

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