



Received: 05 January 2019  
Accepted: 26 March 2019  
First Published: 29 March 2019

\*Corresponding author: Hoedi Prasetyo, Mechatronics Study Program, Politeknik ATMI Surakarta, Surakarta, Indonesia; Master Study Program of Industrial Engineering, Faculty of Engineering, Universitas Sebelas Maret, Surakarta, Indonesia  
E-mail: [hoedi.prasetyo@gmail.com](mailto:hoedi.prasetyo@gmail.com)

Reviewing editor:  
Tao Peng, Zhejiang University,  
Hangzhou, China

Additional information is available at  
the end of the article

## PRODUCTION & MANUFACTURING | RESEARCH ARTICLE

# On optimizing the number of repetition in an operation skill training program based on cost of quality and learning curve

Hoedi Prasetyo<sup>12\*</sup>, Cucuk Nur Rosyidi<sup>2</sup> and Eko Pujiyanto<sup>2</sup>

**Abstract:** An operation skill training is useful to enhance the skill of the workers in a shop floor. The number of repetition is a prominent factor in the training and has to be determined in such a way so that the training can be performed cost-effectively. In this research, a novel model is developed to determine the optimal number of repetition in an operation skill training program by integrating learning curves into cost of quality. A real case study in a twist drill manual-sharpening training program is given to show the implementation of the model. A sensitivity analysis is performed to show the effect of the model's parameters to the decision variable and the objective function. Based on the optimization result, the optimal number of repetitions in the case study is found to be 26. It is also found that the developed model can be used to estimate the training cost, and to determine the training's target.

**Subjects:** Mathematical Modeling; General Engineering Education; Operations Research

**Keywords:** operation skill training; optimal number of repetition; optimization model; cost of quality



Hoedi Prasetyo

### ABOUT THE AUTHORS

Hoedi Prasetyo is a vocational instructor and trainer at Mechatronics Study Program, Politeknik ATMI Surakarta, Indonesia. When writing this article, he was in the process of completing his master degree in Industrial Engineering Master Study Program at Universitas Sebelas Maret, Indonesia.

Cucuk Nur Rosyidi is a lecturer in Master Program of Industrial Engineering at Universitas Sebelas Maret, Surakarta, Indonesia. His doctoral degree was obtained from Institut Teknologi Bandung, Indonesia in the field of manufacturing systems in 2010. He currently serves as the chief of Center for Research in Manufacturing Systems (CRIMS). His research interests include product design and development, quality engineering, and system modeling.

Eko Pujiyanto is an active lecturer at Industrial Engineering Master Study Program, Universitas Sebelas Maret, Indonesia. He completed his doctoral degree in 2012 at Universitas Gadjah Mada, Indonesia. His research interest is quality improvement.

### PUBLIC INTEREST STATEMENT

Operation skills such as welding, grinding, and assembling are very important for manufacturing employees. Those skills can be acquired through a training program. In the training, a trainee has to repeat a certain operation in order to master the skill. The question is how many repetitions that a trainee should do in the training. There are several methods to answer that question. Most of the methods are based on the skill-proficiency perspective. However, a training needs to be seen as an investment for the future, so the cost incurred in the training must be considered into the determination of the number of repetition. This research proposes a mathematical model to determine the number of repetitions based on the cost-effectiveness aspect. A real case study in a twist drill manual-sharpening training program was conducted and the optimal number of repetition for the training program was successfully determined.

## 1. Introduction

Operation skills require precision, proper timing, and well coordinated sequence of body movements (Du & Xu, 2012). The skills are needed in many professions, namely athletes, paramedics, military, and craftsmen. In manufacturing fields, the skills are mainly performed by the workers on the shop floor. Several examples of such skills in manufacturing fields are welding, grinding, and assembling. The operation skills are important to maintain company competitiveness and sustainability, especially for small, medium, and micro enterprises (McCoy, 2017; Noe, Clarke, & Klein, 2014; Urban & Naidoo, 2012).

An operation skill can be gained or enhanced through a training (Cheng, Niu, & Wei, 2011). In the training, the mastery of skill requires a series of learning stages. The series of learning stages consists of observing, imitating action based on instruction, taking action without assistance, and repetition of actions (Mavrikios, Papakostas, Mourtzis, & Chryssolouris, 2013). The repetition stage plays a major role in the training which will affect the automatization of skill, which means that the trainee is able to automatically perform a skill without any instruction and assistance (Spruit, Band, Hamming, & Ridderinkhof, 2014). Small number of repetitions lead to failure of skill mastery, while large number of repetitions result in a longer duration of training which will lead to unnecessary high cost. Therefore, the number of repetition in a training needs to be determined properly by considering both the skill proficiency and the training cost.

Most research in the field of training used learning curve and plateau analysis was done to determine the optimal number of repetition. A learning curve generally follows a power law, which shows a pattern of rapid improvement followed by ever diminishing further improvements with practice (Ritter & Schooler, 2001). This implies that the curve continues to follow a plateau pattern. The starting point of the plateau is determined as the optimal point, since the additional repetition is no longer effective to improve the trainee's skill. The analysis was done by finding the learning curve's asymptotes (Newell & Rosenbloom, 1981), which can be determined merely by visual observation on the curves, though this method suffers lack of accuracy (Hamade, Artail, & Jaber, 2005; Uribe S, Ralph Jr, Glaser, & Fried, 2004). The accuracy to find the asymptotes can be improved by analytical method (Papachristofi, Jenkins, & Sharples, 2016). The plateau of the learning curve can be analyzed by utilizing the cumulative sum control (CUSUM) chart (Ahlawat et al., 2018; Colli et al., 2018; Kang et al., 2015; Mathur & Lin, 2016; Serrano et al., 2017). The CUSUM chart is a method to detect out-of-control signals and to determine a certain performance level. If the number of data to build the learning curve is large, the analysis can be done by statistical tests such as Friedman test (Grantcharov, Bardram, Funch-Jensen, & Rosenberg, 2003), semiparametric and parametric mixed-effects models (Alli et al., 2016) or KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test (Suguita et al., 2017). If the number of data is small, a different approach is used by identifying certain period along the curve where the variability of improvement has slowed to a predetermined level. The predetermined variability level can be less than 5% (Moghadam et al., 2015) or, if better accuracy is required, it can be less than 2.5% for at least five consecutive trials (Champney, Milham, Carroll, Stanney, & Cohn, 2006).

Those mentioned research attempted to determine the optimal number of repetitions from the perspective of skill proficiency. The training must stop at the point where there are no improvements in the proficiency. The goal of the optimization was only to achieve the maximum level of skills. However, a training should not only focus on the skill proficiency, but also be cost-effective (Offir & Katz, 1990). From the perspective of economy, a training is an investment for the future (Basarab, 1990). Each unit of cost incurs in a training must be able to return the value of benefits. Hence, the cost and the benefit of the training need to be analyzed (Bazzoli et al., 2017; Gabbett, Windt, & Gabbett, 2016; Maloney & Haines, 2016; Saeed, Bury, Bonsall, & Riahi, 2016; Williams et al., 2016). Johnson (1980) developed a model to determine the optimal duration of a training by integrating cost and learning curve. The research found the optimal point by balancing the training

benefit (in monetary unit) and the training cost. However, the model's parameters were not clearly described and there is no real application of the model.

Ever since, it is very hard to find a research with cost consideration to find the optimal number of training repetitions. Most of the research only considered the skill proficiency without taking into consideration the cost aspect. In this research, we develop an optimization model to determine the number of repetitions in an operation skill training by taking into consideration not only the skill proficiency but also the cost. The optimization also integrates a learning curve into the model. A real case study is given to show the implementation of the model. Hence, this research contributes practically to help the training stakeholders in determining the optimal number of repetitions in their operation skill training program.

### 2. Model notations

The notations used in this research are shown in Table 1.

### 3. Model development

Learning curve is firstly introduced by Theodore Paul Wright in 1936 to examine the phenomenon of cost reduction in an aircraft product assembly (Grosse, Glock, & Müller, 2015). In a repetitive task, a worker tends to perform faster in every repetition due to the learning effects. Equation (1) shows the change of performance of a worker in a repetitive task.

$$y = y_1 r^n \tag{1}$$

Notation  $r$  is the number of repetition,  $y$  is the time needed for the  $r^{\text{th}}$  repetition of the task,  $y_1$  is the time required for the first repetition, and  $n$  is the slope of the learning curve (learning exponent), with  $(-1 < n < 0)$ .

In this research, the learning curve is used to model the training achievements in term of operation time ( $T$ ), training material consumptions ( $M$ ), and standard deviation of operation time ( $\sigma$ ). Based on Equation (1), the training achievements are then transformed into learning

**Table 1. The list of notations**

$r$	Number of repetition	$l_2$	Training provider's cost to recover reputation
$T$	Operation time	$l_3$	Customer's lost benefit of savings
$M$	Material consumption	$l_4$	Customer's opportunity loss for profit
$\sigma$	Standard deviation of operation time	$T_{max}$	The upper limit of operation time
$T_1$	operation time for the first repetition	$T_{tar}$	The target of operation time
$M_1$	Material consumption for the first repetition	$C$	The training cost
$\sigma_1$	Standard deviation for the first repetition	$F$	The training fixed cost
$a$	Learning exponent of operation time	$c_1$	Trainee salary rate
$b$	Learning exponent of material consumption	$c_2$	Trainer rate
$d$	Learning exponent of standard deviation	$c_3$	Facility rate
$L$	The training loss	$c_t$	Time-dependent rate
$L_{max}$	The maximum loss at the upper limit of operation time	$c_m$	Material consumption rate
$l_1$	Training provider's opportunity loss for profit	$Q$	Total cost

curves expressed as the function of the number of repetition ( $r$ ). The mathematical expressions of the functions are shown in Equations (2), (3), and (4).

$$T(r) = T_1 r^{-a} \quad (2)$$

$$M(r) = M_1 r^{-b} \quad (3)$$

$$\sigma(r) = \sigma_1 r^{-d} \quad (4)$$

The functions are then integrated into cost of quality, which consists of conformance and non-conformance costs (Schiffauerova & Thomson, 2006). Conformance costs are all costs to ensure that a product or service conforms to the specifications, while non-conformance costs deal with poor quality of product or service. In a quality management system, the optimal quality level can be determined by minimizing the total cost of quality. In term of training, the quality level means the level of skill. Hence, the training cost represents the conformance cost. The training cost consists of two components, namely fixed cost and variable cost. The fixed cost is any cost in training which is independent to the number of repetition, such as administration cost. The variable cost is any cost in training which depends on the number of repetitions. In this research, two types of variable cost are introduced, namely time-dependent cost and material cost.

Variable cost can be modelled mathematically by the concept of effective quality capital (Kim & Nakhai, 2008), which is defined as the result of investment accumulation in a quality improvement with a diminishing effect for each period. Each additional repetition in training requires additional variable cost and it will accumulate until the end of the training. Due to the learning effects, there will be a diminishing effect of skill improvement for each additional cost. The original diminishing effect is determined by a coefficient ( $\alpha$ ). In this research, the diminishing effect coefficient is substituted by the learning curve functions. Thus, the training cost can be expressed mathematically as in Equation (5).

$$C(r) = F + \sum_{i=1}^r [c_t(T_1)i^{-a} + c_m(M_1)i^{-b}] \quad (5)$$

$C(r)$  denotes the training cost as a function of repetition.  $F$ ,  $c_t$ , and  $c_m$  denote the fixed cost, the time-dependent rate, and the material consumption rate respectively. The time-dependent rate can be determined from the sum of trainee salary rate, trainer rate, and facility rate (Basarab, 1990).  $T_1$  and  $M_1$  are the learning curve's parameters from Equations (2) and (3). The learning curve functions in Equation (5) express the total length of the training time and the total consumption of training materials from repetition  $i$  to  $r$ .

Non-conformance cost is represented by the loss due to the poor quality of the training results. The loss arises from both the customer and the provider of the training. From the customer perspective, the loss may come from the lost opportunity to gain the benefits of training, which includes savings in wage/salaries, better service, penalty avoidance, and profit opportunity (Basarab, 1990). From the training provider perspective, the loss mainly comes from dissatisfied customers in the form of opportunity loss and cost to recover the reputation (Snieska, Daunoriene, & Zekeviciene, 2013). The better the skill achievement, the greater the opportunity for the customer and the provider to gain the benefits of training. It means any improvement of skill will reduce the loss.

Training loss can be quantified using Taguchi loss function, which is widely used to measure customer dissatisfaction cost and the effects of continuous improvement (Schvaneveldt & Enkawa, 1992). In this research, the quality characteristic is represented by the operation time performed by the trainee. Based on the original smaller the better Taguchi loss function, there will be no loss if the quality characteristic is at zero point, which is almost impossible to achieve in operation time

characteristic. Li (2003) modified the smaller the better of Taguchi loss function so that the function is more suitable to measure the time-based quality characteristics.

This research adopts Taguchi’s EQL (Expected Quality Loss) formula in Li (2003). The formula uses two parameters (mean and standard deviation) of operation time. Both of the parameters are assumed to be fixed. However, in training, the value of mean and standard deviation of operation time are influenced by the improvement effect and become subject of change. The value of those two parameters can be determined by the learning curve. Hence, the mean and the standard deviation of operation time in Li (2003) are substituted by the learning curve functions. Suppose that the trainee’s operation time is normally distributed with a mean is determined by  $T(r)$ , the standard deviation is determined by  $\sigma(r)$ , the target for the operation time is  $T_{tar}$ , the upper limit of the operation time is  $T_{max}$ , and the loss at the upper limit of operation time is  $L_{max}$ . Thus, the training loss as a function of repetition ( $L(r)$ ) can be expressed as:

$$L(r) = \frac{L_{max}}{T_{max}^2 - T_{tar}^2} \left[ \frac{\sigma(r)T(r)}{\sqrt{2\pi}} e^{\left(\frac{-(T(r))^2}{2(\sigma(r))^2}\right)} + (T(r))^2 + (\sigma(r))^2 \right] - \frac{L_{max}T_{tar}^2}{T_{max}^2 - T_{tar}^2} \tag{6}$$

According to Snieska et al. (2013), the value of  $L_{max}$  can be determined from four components, namely the training provider’s opportunity loss ( $l_1$ ), cost to recover the reputation ( $l_2$ ), customer’s opportunity loss ( $l_3$ ) and lost benefit of savings ( $l_4$ ). Thus,  $L_{max}$  is obtained by the following equation:

$$L_{max} = l_1 + l_2 + l_3 + l_4 \tag{7}$$

Since the training cost and the training loss are expressed as the function of the repetition number, then the total cost expression is also mathematically modelled as the function of the repetition number ( $Q(r)$ ) as in Equation (8).

$$Q(r) = C(r) + L(r) \tag{8}$$

The complete optimization model is shown in Equation (9).

$$\text{Min} \left\{ \begin{aligned} & Q(r) = \frac{L_{max}}{T_{max}^2 - T_{tar}^2} \left( \left[ \frac{\sigma(r)T(r)}{\sqrt{2\pi}} e^{\left(\frac{-(T(r))^2}{2(\sigma(r))^2}\right)} + (T(r))^2 \right] \right. \\ & \qquad \qquad \qquad \left. + (\sigma(r))^2 \right) \\ & \qquad \qquad \qquad + F \\ & \qquad \qquad \qquad + \sum_{i=1}^r [c_t T_1 i^{-a} + c_m M_1 i^{-b}] \\ & \qquad \qquad \qquad i, r \in Z, \quad i, r > 0 \end{aligned} \right\}, \tag{9}$$

#### 4. A real case study

A real case study is provided to show the model’s implementation. The case is about a twist drill manual-sharpening training program in a vocational higher education. This program aims to train employee or student to sharpen a twist drill. The sharpening skill is needed by a machine operator or a tool man. The task is quite difficult and requires particular skill. Failure in performing this task will result in poor quality of drilling, producing defect work piece or even damaging the twist drill itself. There are six quality attributes of geometry that must be checked when sharpening a twist drill (Headquarters Department of the Army, 1996). The training was conducted by two trainers with at least 5 years of experience.

Prior to the training, the trainers explain all the knowledge and give an example on how to do the task. The trainee practices to sharpen the twist drill repetitively until the result conforms to the predetermined standard. Two training achievements are measured, namely the operation time and the material consumption. The material consumption deals with the length of the twist drill

(in mm) consumed in the practice. There are two indicators used by the trainer as the guidance when to terminate the training. First is when the trainee finishes the task successfully within a predetermined target of time in at least two repetitions. Second is when the available time for the training is up.

In this research, 37 first-year students of Mechanical Diploma Program were involved. The participants consisted of 36 males and only 1 female. They had relatively same educational background: 20 participants were from general high school and 17 participants were from vocational high school. The participants aged between 17 and 19 years old. None of them ever joined the similar training program. An informal interview was conducted and it was concluded that there is no significant differences in the participant's past technical experiences. From a demographic perspective, the participants were found to have fairly homogenous background. To build the learning curves, each participant was requested to repeat the task 10 times. The target and the upper limit for the operation time were determined to be 15 min and 120 min respectively. The operation time and the material needed for each repetition were recorded on a monitoring sheet. The data parameters related to costs were collected based on the information from the trainee, the trainer, and the training manager.

## 5. Results and discussion

### 5.1. Model parameters

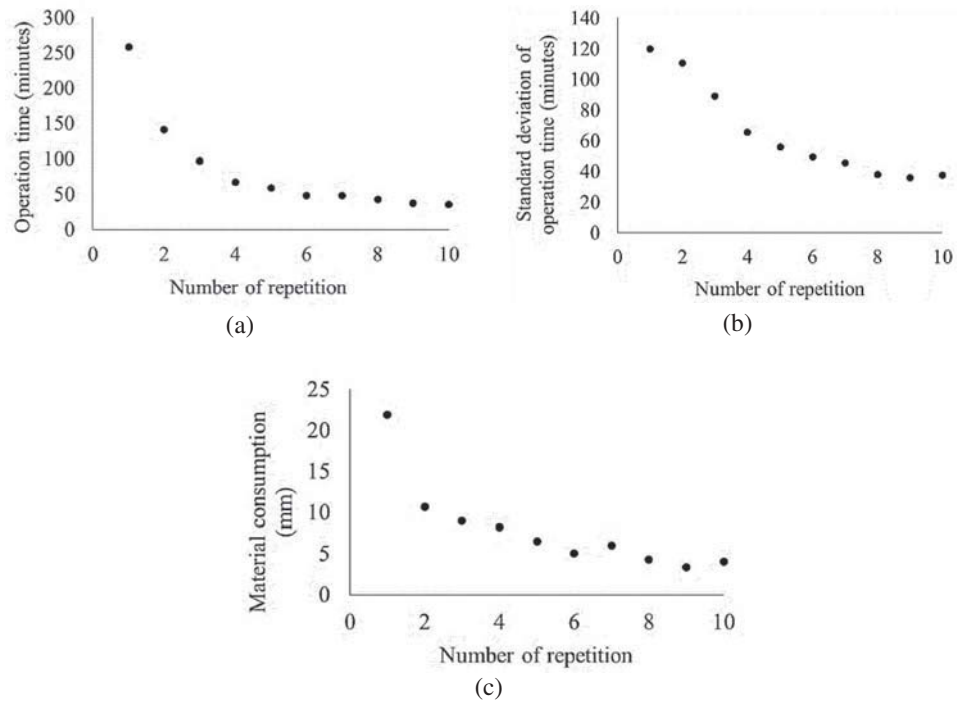
The raw data of the case study are given in Appendices A and B. Table 2 shows the mean and the standard deviation of operation time and material consumption. From Table 2, it can be seen that the average performance of the participants at the first repetition was very poor. They needed more than 3 h and more than 20 mm length of twist drill to finish the task. The standard deviation of operation time at the first repetition was also poor. It indicated that the variability of performance was high. However, there were skill improvements in each additional repetition. At the fifth repetition, the trainees needed approximately an hour and 6.5 mm length of twist drill to finish the task. At the 10<sup>th</sup> repetition, the trainees only needed 35 min with 4 mm length of twist drill. The improvement also occurred in the variability of performance. It is showed by the decrease in the standard deviation of operation time in each additional repetition.

Figure 1 shows the plot of the training data. In each plot, there is a rapid improvement in the beginning of the training followed by ever diminishing further improvements with practice. More repetitions in training make the operation time faster, less material consumption, and gap of performance among the trainees smaller.

**Table 2. The mean and standard deviation of training data**

Number of repetition	Mean of operation time (minute)	Mean of material consumption (mm)	Standard deviation of operation time (minute)
1	258.1	21.9	120.1
2	140.7	10.7	101.4
3	96.4	8.9	67.4
4	67.1	8.2	42.3
5	58.5	6.5	46.4
6	47.6	5.1	42.7
7	47.5	6.0	41.9
8	42.6	4.3	30.4
9	37.2	3.3	34.0
10	35.2	4.0	39.2

**Figure 1. The data plot of: (a) operation time, (b) standard deviation of operation time, and (c) material consumption.**



The parameters of the learning curves are found using regression technique. The coefficient of determination ( $R^2$ ) is used to assess the goodness of fit of the regression model. Equations (2), (3), and (4) are used as the basis model. The results of the learning curve parameters are shown in Equations (10), (11), and (12). The  $R^2$  values for those three equations are about 0.99 which means that 99% of the data can be explained appropriately by the model.

$$T(r) = 258r^{-0.904} \tag{10}$$

$$M(r) = 21r^{-0.768} \tag{11}$$

$$\sigma(r) = 126r^{-0.591} \tag{12}$$

The next parameters deal with the training cost model. The fixed cost is determined to be \$36, resulted from the sum of administration cost and trainee’s equipment cost. The time dependent rate is \$0.13 per minute. It is resulted from the summation of trainee salary rate at \$1.07 per hour, trainer rate at \$5.36 per hour, and facility rate at \$1.43 per hour. The material consumption rate is determined to be \$0.04/mm, which comes from the regular price of a twist drill divided by its effective length. Thus, based on Equation (5), the training cost can be rewrite as:

$$C(r) = 36 + \sum_{i=1}^r [(0.13)258i^{-0.904} + (0.04)21i^{-0.768}] \tag{13}$$

For the training loss, the upper limit of the loss is determined to be \$809. It is resulted from Equation (7) with the value of the training provider’s opportunity loss for profit and cost to recover reputation at \$176 and \$107 respectively, while the customer’s opportunity loss and lost benefit of savings at \$300 and \$225 respectively. Thus, based on Equation (6), the training loss can be rewrite as shown in Equation (14). A complete list of parameters value can be seen in Appendix C.



$$L(r) = \frac{809}{120^2 - 15^2} \left[ \frac{(126r^{-0.591})(258r^{-0.904})}{\sqrt[2]{(2\pi)}} e^{\left(\frac{-(258r^{-0.904})^2}{2(126r^{-0.591})^2}\right)} + (258.3r^{-0.904})^2 + (126r^{-0.591})^2 \right] - \frac{(809)(15^2)}{120^2 - 15^2} \tag{14}$$

### 5.2. Optimal solution

The optimal solution can be found by minimizing the training cost of quality. The training cost of quality is the summation of the training cost and the training loss (see Equation (8)). Thus, based on Equations (13) and (14), the model's objective function of the case study can be determined as shown in Equation (15).

$$\text{Min} \left\{ \begin{aligned} Q(r) &= \frac{809}{120^2 - 15^2} \left[ \frac{(126r^{-0.591})(258r^{-0.904})}{\sqrt[2]{(2\pi)}} e^{\left(\frac{-(258r^{-0.904})^2}{2(126r^{-0.591})^2}\right)} + (258r^{-0.904})^2 \right] \\ &\quad + (126r^{-0.591})^2 \\ &\quad - \frac{(809)(15^2)}{120^2 - 15^2} + 36 + \sum_{i=1}^r [(0.13)258i^{-0.904} + (0.04)21i^{-0.768}] \end{aligned} \right\} \tag{15}$$

$i, r \in \mathbb{Z}, \quad r > 0$

The optimal number of repetition ( $r^*$ ) can be determined when the first derivative of the objective function is equal to zero or  $Q'(r) = 0$ . The first derivative of the function can be expressed and simplified as follows:

$$Q'(r) = 798.62 \left[ \frac{17078e^{-\frac{2.1}{0.63}}}{r^{3.12}} - \frac{120628}{r^{2.81}} - \frac{19411e^{-\frac{2.1}{0.63}}}{r^{2.50}} - \frac{18765}{r^{2.18}} \right] + 8179 \left[ 1.93 - \sum_{i=1}^r i^{-1.77} \right] + 428011 \left[ 1.75 - \sum_{i=1}^r i^{-1.90} \right],$$

$i, r \in \mathbb{Z}, \quad r > 0$

It was very hard to find  $r^*$  by solving the equation  $Q'(r) = 0$  analytically. Therefore, we switch to numerical method by finding the root of  $Q'(r)$ . Utilizing Wolfram Mathematica, the optimal solution is achieved at  $r = 26.2$ . Because the number of repetition is discrete, we need to round the value of the optimal solution to the closest number of 26 repetitions.

### 5.3. Sensitivity analysis

Model parameters are uncertain and subject of changes in the future. Sensitivity analysis is required to investigate the influence of changes in the parameters (Pannell, 1997). In this research, there are four parameters to be analyzed:  $c_t$ ,  $L_{max}$ ,  $T_{tar}$ , and  $T_{max}$ . Those parameters are subject of change due to the management policy or inaccurate data. In the analysis, the selected parameters were varied from -50% to +50% and then the model's output (the optimal point and the total cost) variation were observed.

Table 3 shows the sensitivity index of the four selected parameters. A high index value means high sensitivity. The negative sign indicates the variation in output is in the opposite direction toward the parameter change. Based on the optimal point, parameter  $T_{max}$  has the highest value. It means the optimal point of the model is very sensitive to any change of  $T_{max}$ . Based on the total cost, parameter  $c_t$  has the highest value. It means the total cost of the model is moderately sensitive to any change of  $c_t$ . The other parameters ( $L_{max}$  and  $T_{tar}$ ) have relatively low value of sensitivity index, therefore these parameters are not so critical to be further analyzed.



**Table 3. The sensitivity index**

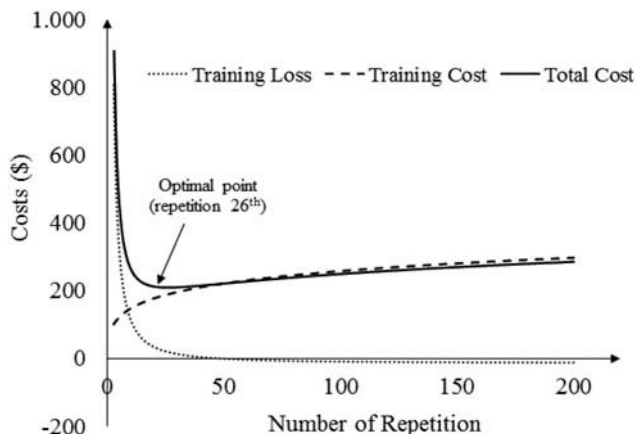
No	Parameters	Model's output being observed	
		Optimal point	Total cost
1	$T_{max}$	-1.58	-0.13
2	$c_t$	-0.81	0.54
3	$L_{max}$	0.5	0.11
4	$T_{tar}$	-0.04	-0.14

**5.4. Discussion**

Figure 2 shows the data plots of the costs. At the beginning of the training, the total cost is dominated by the loss. It means the performance of the trainee is very poor which results in the high value of the training loss. As the number of repetition increases, the loss decreases at a high rate. It means there is a rapid improvement during the early period of training. The training cost increases as it accumulates in every repetition. The decreasing loss which is accompanied by the increasing of the training cost indicates that each addition to the training cost will improve the trainee's skill. The improvement gives benefit to both the training provider and the training customer and hence contributes to the decreasing loss. After some repetitions, the improvement tends to slow and the total cost seems to be stable which means the diminishing effect occurs. The total cost still follows a decreasing trend but with a very small rate of improvement. This condition is in accordance with the phenomenon of plateau effect on the learning curve which states that the improvement effect provided by the training is getting smaller, until a certain period, the improvement effect is no longer significant. Eventually, at the 26<sup>th</sup> repetition, the total cost has reached its minimum value which means the optimal number of repetition has been achieved. By using Equations (10) and (11), the operation time at the optimal solution can be determined which is 14 min with 1.7 mm length of material consumption. By using Equation (13), we can also determine the training cost required for each participant at the optimal solution. In this case study, the training required a cost of \$264.

What if the optimal solution is compared with the result from plateau analysis? If the optimal point is analyzed based on 2.5%/5 trial rule-plateau method as suggested in Champney et al. (2006), the training should be stopped at 36<sup>th</sup> repetition. It differs 10 repetitions from this research solution due to the different perspective of optimization. If the optimal point is based on the skill-proficiency perspective, each participant requires a training cost of \$287. Optimization in this research is based on the cost-effectiveness, not the skill-proficiency. The optimal solution resulted from this research may not necessarily be on the learning curve plateau. Though the optimal point

**Figure 2. The curves of costs.**



is not located at the maximum level of skill, it has already given the maximum pay-off. After reaching the optimal point, the training is not economic to be continued.

What if the current practice of the training program is compared to the model's result? Admittedly, the model's optimization result cannot be compared directly to the real condition of the training program because there was no standard on how many repetitions that the trainee should make in the training program. However, the comparison can still be made by analyzing the average repetitions and average operation time from the past data of the training program. Table 4 shows a summary of comparison between the current practice and the model's result. Based on the past data, the average number of repetitions and the average of operation time was 11 repetitions and 26 min respectively. With only 11 repetitions, it can be assured that the average of the trainee was unable to meet the predefined target of operation time consistently. According to the model, the operation time performed by the trainee after 11 repetitions will be 30 min. The model's result differs only 4 min from the real condition.

The current practice of training has potential losses. Unfortunately, there were no available information about the training loss and the training cost from the current practice. The training program is actually a part of the Diploma curriculum and the only available information is the total cost for the whole curriculum. Therefore, the comparison is made between the model's result when  $r = 11$  and the model's optimal solution. Using Equation (14), the potential losses can be quantified. If the number of repetition is based on the current practice of training ( $r = 11$ ), the training loss will be \$103. But if the number of repetition is based on the optimal solution, then the training loss would be only \$21.

Table 3 shows that two parameters ( $T_{max}$  and  $c_t$ ) have a tendency to greatly change the optimal solution. Therefore, the allowable variation range for those two parameters need to be determined. Based on the case study, there are two rules that must be followed if the parameters are varied: the operation time cannot be more than 15 min (predefined target) and the total duration of the training cannot be more than 21 h (available time for training). Based on those two rules, the allowable variation range of parameter  $T_{max}$  and  $c_t$  are  $-20\%$  to  $+20\%$  and  $-30\%$  to  $+30\%$  respectively. If the parameter  $T_{max}$  vary to the limit of the allowable range, the total cost will vary at maximum 3% and this is relatively not significant. If the parameter  $c_t$  vary to the limit of the allowable range, the total cost will vary at maximum 21% which is relatively significant. However, the possibility for  $c_t$  to vary greatly is very low. The management policy naturally tries to minimize the extreme changes of  $c_t$  in order to avoid any negative risks. According to the result of sensitivity analysis, the model is reliable.

The parameter of  $T_{tar}$  has low sensitivity index. This condition actually can be exploited to help the trainer in designing the target. If the  $T_{tar}$  is loosened from 15 min to 30 min, the optimal solution only shifts from 26 to 25 with 14 min of operation time. If  $T_{tar}$  is tightened from 15 min to 10 min, the optimal solution only shifts to 27 with 13 min of operation time. The optimal solution and the operation time do not shift significantly even though  $T_{tar}$  vary greatly. This indicates that an inaccuracy in designing the target of training has only slight effect on the model's optimal solution.

**Table 4. Comparison between current practice and model's result**

Aspect of comparison	Current practice	Model's result ( $r = 11$ )	Model's optimal solution
Number of repetition	11	11	26
Operation time	26 min	30 min	14 min
Training loss	No information	\$103	\$21
Training cost	No information	\$151	\$189

## 6. Conclusion

This research proposed a novel model based on the cost-effectiveness perspective to determine the repetition number in operation skill trainings. The model was developed by integrating the learning curve into the cost of quality. A real case study in a twist drill manual-sharpening training program was carried out to show the model's implementation. Based on the optimization results, it was revealed that the training program in the case study has potential losses. The average number of repetition was too small and needs to be extended to 26 repetitions. The model is not only useful for optimization, but also useful to reveal the training's potential losses, to estimate the training cost, and to design the training's target. Among the model's parameters,  $c_t$  is identified as the most sensitive parameter. Therefore, it is suggested to be more careful in determining this parameter value. One of the limitations of this research was the small sample size which could have some consequences to the reliability and repeatability of the results. Hence, for further and more reliable research, the sample size must be larger. Another direction for further research is by including the dimensional-based quality characteristics such as the angles of the twist drill into the model. Despite the limitations, this research has successfully provided a foundation model based on the cost-effectiveness to determine the optimal number of repetition for operation skill trainings.

### Funding

The authors received no direct funding for this research.

### Author details

Hoedi Prasetyo<sup>1,2</sup>  
E-mail: [hoedi.prasetyo@gmail.com](mailto:hoedi.prasetyo@gmail.com)  
ORCID ID: <http://orcid.org/0000-0002-6279-7065>  
Cucuk Nur Rosyidi<sup>2</sup>  
E-mail: [cucuknur@staff.uns.ac.id](mailto:cucuknur@staff.uns.ac.id)  
Eko Pujiyanto<sup>2</sup>  
E-mail: [ekopujiyanto@ft.uns.ac.id](mailto:ekopujiyanto@ft.uns.ac.id)  
<sup>1</sup> Mechatronics Study Program, Politeknik ATMI Surakarta, Surakarta, Indonesia.  
<sup>2</sup> Master Study Program of Industrial Engineering, Faculty of Engineering, Universitas Sebelas Maret, Surakarta, Indonesia.

### Citation information

Cite this article as: On optimizing the number of repetition in an operation skill training program based on cost of quality and learning curve, Hoedi Prasetyo, Cucuk Nur Rosyidi & Eko Pujiyanto, *Cogent Engineering* (2019), 6: 1601053.

### References

- Ahlawat, R. K., Tugcu, V., Arora, S., Wong, P., Sood, A., Jeong, W., ... Menon, M. (2018). Learning curves and timing of surgical trials: Robotic kidney transplantation with regional hypothermia. *Journal of Endourology*, 32(12), 1160–1165. doi:10.1089/end.2017.0697
- Alli, O., Rihal, C. S., Suri, R. M., Greason, K. L., Waksman, R., Minha, S. A., ... Holmes, D. (2016). Learning curves for transfemoral transcatheter aortic valve replacement in the PARTNER-I trial: Technical performance. *Catheterization and Cardiovascular Interventions*, 87(1), 154–162. doi:10.1002/ccd.26120
- Basarab, D. J., Sr. (1990). Calculating the return on training investment. *Evaluation Practice*, 11(3), 177–185. doi:10.1177/109821409001100302
- Bazzoli, M., De Poli, S., Rettore, E., Schizzerotto, A., Piazzalunga, D., Azzolini, D., & Checchi, D. (2017). Are vocational training programmes worth their cost? Evidence from a cost-benefit analysis (No. 2017-04). Research Institute for the Evaluation of Public Policies (IRVAPP), Bruno Kessler Foundation. Retrieved from <https://www.rivisteweb.it/download/article/10.1429/92119>
- Champney, R., Milham, L., Carroll, M. B., Stanney, K. M., & Cohn, J. (2006). A method to determine optimal simulator training time: Examining performance improvement across the learning curve. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 50, No. 25, pp. 2654–2658). Sage CA: Los Angeles, CA: SAGE Publications. doi:10.1177/154193120605002510
- Cheng, Z., Niu, Z., & Wei, P. (2011, September). Operational skill training needs analysis for manufacturing industry. In *2011 International Conference of Information Technology, Computer Engineering and Management Sciences* (Vol. 3, pp. 394–397). Nanjing: IEEE. doi:10.1109/ICM.2011.99
- Colli, A., Bagozzi, L., Banchelli, F., Besola, L., Bizzotto, E., Pradegan, N., ... Gerosa, G. (2018). Learning curve analysis of transapical NeoChord mitral valve repair. *European Journal of Cardio-Thoracic Surgery*, 54(2), 273–280. doi:10.1093/ejcts/ezy046
- Du, Y. W., & Xu, X. L. (2012). Application research of personal learning curve in staff skill testing. In C. S. Zhang (Ed.), *Advanced materials research* (Vol. 433, pp. 3200–3205). Trans Tech Publications. doi:10.4028/www.scientific.net/AMR.433-440.3200
- Gabbett, H. T., Windt, J., & Gabbett, T. J. (2016). Cost-benefit analysis underlies training decisions in elite sport. *British Journal of Sports Medicine*, 50, 1291–1292. doi:10.1136/bjsports-2016-096079
- Grantcharov, T. P., Bardram, L., Funch-Jensen, P., & Rosenberg, J. (2003). Learning curves and impact of previous operative experience on performance on a virtual reality simulator to test laparoscopic surgical skills. *The American Journal of Surgery*, 185(2), 146–149. doi:10.1016/S0002-9610(02)01213-8
- Grosse, E. H., Glock, C. H., & Müller, S. (2015). Production economics and the learning curve: A meta-analysis. *International Journal of Production Economics*, 170, 401–412. doi:10.1016/j.ijpe.2015.06.021
- Hamade, R. F., Artail, H. A., & Jaber, M. Y. (2005). Learning theory as applied to mechanical CAD training of novices. *International Journal of Human-Computer Interaction*, 19(3), 305–322. doi:10.1207/s15327590ijhc1903\_2
- Headquarters Department of the Army. (1996). *Training circular no.9-524: Fundamentals of machine tools*. Washington, DC: US Department of the Army. Retrieved from [http://www.woodworkslibrary.com/repository/fundamentals\\_of\\_machine\\_tools.pdf](http://www.woodworkslibrary.com/repository/fundamentals_of_machine_tools.pdf)

- Johnson, S. L. (1980). A cost analysis method of establishing training criteria. *Ergonomics*, 23(12), 1137–1145. doi:10.1080/00140138008924820
- Kang, S. G., Ryu, B. J., Yang, K. S., Ko, Y. H., Cho, S., Kang, S. H., ... Cheon, J. (2015). An effective repetitive training schedule to achieve skill proficiency using a novel robotic virtual reality simulator. *Journal of Surgical Education*, 72(3), 369–376. doi:10.1016/j.jsurg.2014.06.023
- Kim, S., & Nakhai, B. (2008). The dynamics of quality costs in continuous improvement. *International Journal of Quality & Reliability Management*, 25(8), 842–859. doi:10.1016/j.jsurg.2014.06.023
- Li, M. H. (2003). Quality loss functions for the measurement of service quality. *The International Journal of Advanced Manufacturing Technology*, 21(1), 29–37. doi:10.1007/s001700300004
- Maloney, S., & Haines, T. (2016). Issues of cost-benefit and cost-effectiveness for simulation in health professions education. *Advances in Simulation*, 1(1), 13. doi:10.1186/s41077-016-0020-3
- Mathur, S., & Lin, S. Y. S. (2016). The learning curve for laparoscopic inguinal hernia repair: A newly qualified surgeon perspective. *Journal of Surgical Research*, 205(1), 246–251. doi:10.1016/j.jss.2016.06.041
- Mavrikios, D., Papakostas, N., Mourtzis, D., & Chryssolouris, G. (2013). On industrial learning and training for the factories of the future: A conceptual, cognitive and technology framework. *Journal of Intelligent Manufacturing*, 24(3), 473–485. doi:10.1007/s10845-011-0590-9
- McCoy, N. D. (2017). *The effect of high-skills shortage influence on Louisiana advanced manufacturing firms' competitiveness and sustainability* (Unpublished doctoral dissertation). Capella University, Minneapolis, US.
- Moghadam, Z. E., Zeydi, A. E., Mazlom, S. R., Abadi, F. S., Pour, P. M., Davoudi, M., & Banafsheh, E. (2015). How many repetitions of child care skills are required for health worker students to achieve proficiency? Learning curve patterns in child care skills acquisition. *Materia socio-medica*, 27(5), 323–327. doi:10.5455/msm.2015.27.323-327
- Newell, A., & Rosenbloom, P. S. (1981). Mechanisms of skill acquisition and the law of practice. In J. R. Anderson (Ed.), *Cognitive skills and their acquisition* (pp. 1–51). Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.
- Noe, R. A., Clarke, A. D., & Klein, H. J. (2014). Learning in the twenty-first-century workplace. *Annual Review of Organizational Psychology and Organizational Behaviour*, 1(1), 245–275. doi:10.1146/annurev-orgpsych-031413-091321
- Offir, B., & Katz, Y. J. (1990). The learning curve model for analysing the cost-effectiveness of a training system. *Education and Computing*, 6, 161–164. doi:10.1146/annurev-orgpsych-031413-091321
- Pannell, D. J. (1997). Sensitivity analysis: Strategies, methods, concepts, examples. *Agricultural Economics (Amsterdam, Netherlands)*, 16, 139–152. doi:10.1016/S0169-5150(96)01217-0
- Papachristofi, O., Jenkins, D., & Sharples, L. D. (2016). Assessment of learning curves in complex surgical interventions: A consecutive case-series study. *Trials*, 17(1), 266. doi:10.1186/s13063-016-1383-4
- Ritter, F. E., & Schooler, L. J. (2001). The learning curve. *International Encyclopedia of the Social and Behavioral Sciences*, 13, 8602–8605. <http://ritter.ist.psu.edu/papers/ritters01.pdf>
- Saeed, F., Bury, A., Bonsall, S., & Riahi, R. (2016). A cost benefit analysis approach to identify improvements in merchant navy deck officers' HELM (Human Element Leadership and Management) training. *TransNav: International Journal on Marine Navigation and Safety of Sea Transportation*, 10(4), 551–560. doi:10.12716/1001.10.04.02
- Schiffauerova, A., & Thomson, V. (2006). A review of research on cost of quality models and best practices. *International Journal of Quality & Reliability Management*, 23(6), 647–669. doi:10.1108/02656710610672470
- Schvaneveldt, S. J., & Enkawa, T. (1992). Variability and quality loss in services: Concepts and countermeasures. *Total Quality Management*, 3(3), 233–242. doi:10.1080/095441292000000031
- Serrano, O. K., Bangdiwala, A. S., Vock, D. M., Berglund, D., Dunn, T. B., Finger, E. B., ... Kandaswamy, R. (2017). Defining the tipping point in surgical performance for laparoscopic donor nephrectomy among transplant surgery fellows: A risk-adjusted cumulative summation learning curve analysis. *American Journal of Transplantation*, 17(7), 1868–1878. doi:10.1111/ajt.14187
- Snieska, V., Daunoriene, A., & Zekeviciene, A. (2013). Hidden costs in the evaluation of quality failure costs. *Inzinerine Ekonomika-Engineering Economics*, 24(3), 176–186. doi:10.5755/j01.ee.24.3.1186
- Spruit, E. N., Band, G. P., Hamming, J. F., & Ridderinkhof, K. R. (2014). Optimal training design for procedural motor skills: A review and application to laparoscopic surgery. *Psychological Research*, 78(6), 878–891. doi:10.1007/s00426-013-0525-5
- Suguita, F. Y., Essu, F. F., Oliveira, L. T., Iuamoto, L. R., Kato, J. M., Torsani, M. B., ... Andraus, W. (2017). Learning curve takes 65 repetitions of totally extra-peritoneal laparoscopy on inguinal hernias for reduction of operating time and complications. *Surgical Endoscopy*, 31(10), 3939–3945. doi:10.1007/s00464-017-5426-z
- Urban, B., & Naidoo, R. (2012). Business sustainability: Empirical evidence on operational skills in SMEs in South Africa. *Journal of Small Business and Enterprise Development*, 19(1), 146–163. doi:10.1108/14626001211196451
- Uribe S, J. I., Ralph, W. M., Jr, Glaser, A. Y., & Fried, M. P. (2004). Learning curves, acquisition, and retention of skills trained with the endoscopic sinus surgery simulator. *American Journal of Rhinology*, 18(2), 87–92. doi:10.1177/194589240401800204
- Williams, C., Bowles, K. A., Kiegaldie, D., Maloney, S., Nestel, D., Kaplonyi, J., & Haines, T. (2016). Establishing the effectiveness, cost-effectiveness and student experience of a Simulation-based education Training program On the Prevention of Falls (STOP-Falls) among hospitalised inpatients: A protocol for a randomised controlled trial. *BMJ open*, 6(6), e010192. doi:10.1136/bmjopen-2015-010192

## Appendices

Appendix A. Monitoring result of operation time (in minutes)										
Trainee	Number of repetition									
	1	2	3	4	5	6	7	8	9	10
1	780	150	190	45	30	120	60	30	15	82
2	415	30	160	24	26	18	69	45	12	73
3	390	120	75	60	95	105	110	30	61	100
4	310	215	47	30	23	103	23	5	72	13
5	335	155	202	66	158	95	15	78	111	15
6	255	85	211	120	39	12	12	102	90	217
7	206	336	26	115	40	6	55	32	50	15
8	330	113	197	33	48	18	98	72	65	33
9	260	260	85	80	140	37	83	94	20	51
10	360	210	100	36	25	15	7	18	21	5
11	303	11	88	84	74	18	178	53	15	44
12	195	365	218	115	24	6	29	25	14	76
13	180	265	30	36	14	25	86	56	4	10
14	309	55	101	202	40	85	142	17	39	29
15	185	120	120	52	17	10	40	48	22	50
16	350	100	162	65	120	155	31	149	7	18
17	220	53	100	40	32	90	27	27	20	14
18	198	37	31	38	51	65	27	4	27	53
19	270	35	235	52	95	73	15	28	56	13
20	110	100	45	55	188	39	38	55	6	14
21	228	115	205	38	9	13	61	39	16	9
22	317	275	75	90	105	2,5	12	28	27	18
23	263	77	25	127	38	27	8	17	15	15
24	343	66	37	127	31	34	19	24	61	60
25	195	91	77	20	160	61	40	89	13	11
26	120	54	20	118	51	6	40	24	20	12
27	206	116	33	39	55	43	41	39	10	4
28	70	150	130	33	14	113	5	25	169	5
29	120	240	90	135	16	34	134	50	85	2
30	140	375	40	63	40	25	57	19	20	33
31	205	130	99	19	37	61	5	12	62	74
32	182	114	42	47	22	11	11	53	35	35
33	335	315	15	17	119	155	25	74	15	18
34	255	46	85	107	28	16	30	6	33	28
35	135	8	11	5	87	22	13	35	30	12
36	255	192	10	60	40	35	96	20	10	25
37	220	26	149	89	34	6	17	55	29	17

**Appendix B. Monitoring result of material consumption (in millimeters)**

Trainee	Number of repetition									
	1	2	3	4	5	6	7	8	9	10
1	34.3	6	12	2	2	5	8	3	3	6
2	28	1.9	11	2.2	2.4	3	8.6	3.3	0.5	3.2
3	34.2	20.3	4.2	4	9.4	3.8	9.4	2.9	2	4.7
4	14.9	3	3	2	1.4	4.8	1.6	0.5	7	0.4
5	27.8	6	7.7	3.6	11.2	11	2.7	12.3	19	3
6	14.7	6.6	17	10	4.9	0.9	1.3	5.9	4.5	12.4
7	7.9	11.9	4.6	24.9	6.6	27.9	13.3	4	9	3.1
8	37.2	7.2	10.8	4.2	1.5	0.5	5.1	1.7	2.5	1.7
9	40.8	19.4	11	5.2	19.9	6	9.7	25.8	4	11
10	17.9	9.1	4.3	4.3	1.4	1	0.1	0.1	0.5	0.2
11	47.3	5.1	5.6	13.2	17	4.3	17.7	7.6	1.5	8
12	4.4	13.4	4.9	7.7	0.7	0.3	1.6	0.7	1.5	3.2
13	11	60	19	12.1	3.1	21.6	28.3	7	0.4	1.8
14	49.5	10.7	13.2	29.6	6.2	6.4	10.1	3.6	2	3.2
15	28.4	13.7	27.6	14.7	1.4	2.6	4.7	8.6	3.4	9.8
16	14.7	5.6	9.4	10.5	14.2	9.9	30	13	0.3	0.5
17	16.6	6.3	4.3	3.5	2.4	3.1	3	2.6	2.1	1.1
18	20.7	16.1	6.8	19.1	17	10.2	5.2	0.1	3.8	11
19	19	2	29.8	5.4	2.5	1.1	0.5	3.5	0.7	1.2
20	7.5	5.7	1.6	3	13	3.3	4.6	6.8	0.3	1.7
21	12.3	6.9	11	3.5	0.4	0.8	4	2	0.6	0.8
22	35.2	21.9	5	12.2	9.1	2.5	0.4	2.1	2	2.3
23	17.2	3.9	0.7	4	2.5	1.3	0.4	0.6	0.7	0.8
24	31.8	2.2	0.5	5.8	1.6	1	0.4	1.6	3.9	3.1
25	24.7	11.1	5.8	1.3	12.6	5.2	8	5.7	0.5	1.4
26	33.1	0.6	3.7	23.2	14.3	0.6	12.2	2.4	6.5	2.2
27	32.5	14.4	3.9	1.5	11.8	8.6	3	2.9	0.6	0.1
28	2.7	7.4	6.4	2.3	0.4	4	0.2	0.8	4.7	0.2
29	13.7	2	15.2	6.8	1.6	1.5	5.8	4.5	8.8	0.5
30	6.5	14.9	2.5	4.3	1.3	1.6	2.7	0.6	1.2	1.4
31	17.8	15.1	10.5	3.4	6.5	10.4	0.9	0.7	5	8.7
32	6	0.1	2.7	5.4	3.8	1.6	0.7	3.1	5.4	3.3
33	18.2	31.8	1.3	1.8	8.9	10.2	2.1	4.4	0.9	3.3
34	38.9	7.8	10.5	12.5	3.8	1.5	1.9	0.7	1.8	7
35	11.5	0.6	1.9	0.7	6.7	1.7	2.8	2	1.3	1.3
36	19.8	18.5	0.3	7.7	3.2	5.7	5.8	2.8	1	5
37	21.4	5.8	39.9	26	12.3	2.4	4.1	8.8	9.2	20.5

**Appendix C. List of parameters value**

<b>Notations and description</b>		<b>Value (based on case study)</b>	<b>Unit</b>
$T_1$	Operation time for first repetition	258	minute
$M_1$	Material consumption for first repetition	21	mm
$\sigma_1$	Standard deviation for the first repetition	126	minute
$a$	Operation time learning exponent	0.904	
$b$	Material consumption learning exponent	0.768	
$d$	Standard deviation learning exponent	0.591	
$L_{max}$	The maximum loss at the upper limit	809	\$
$l_1$	Training provider's opportunity loss for profit	176	\$
$l_2$	Training provider's cost to recover reputation	107	\$
$l_3$	Customer's lost benefit of savings	225	\$
$l_4$	Customer's opportunity loss for profit	300	\$
$T_{max}$	The upper limit of the operation time	120	minute
$T_{tar}$	The target of the operation time	15	minute
$F$	Training fixed cost	36	\$
$c_1$	Trainee salary rate	1.07	\$/hour
$c_2$	Trainer rate	5.36	\$/hour
$c_3$	Facility rate	1.43	\$/hour
$c_t$	Time-dependent rate	0.13	\$/minute
$c_m$	Material consumption rate	0.04	\$/mm





© 2019 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.

You are free to:

Share — copy and redistribute the material in any medium or format.

Adapt — remix, transform, and build upon the material for any purpose, even commercially.

The licensor cannot revoke these freedoms as long as you follow the license terms.

Under the following terms:

Attribution — You must give appropriate credit, provide a link to the license, and indicate if changes were made.

You may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use.

No additional restrictions

You may not apply legal terms or technological measures that legally restrict others from doing anything the license permits.

***Cogent Engineering* (ISSN: 2331-1916) is published by Cogent OA, part of Taylor & Francis Group.**

**Publishing with Cogent OA ensures:**

- Immediate, universal access to your article on publication
- High visibility and discoverability via the Cogent OA website as well as Taylor & Francis Online
- Download and citation statistics for your article
- Rapid online publication
- Input from, and dialog with, expert editors and editorial boards
- Retention of full copyright of your article
- Guaranteed legacy preservation of your article
- Discounts and waivers for authors in developing regions

**Submit your manuscript to a Cogent OA journal at [www.CogentOA.com](http://www.CogentOA.com)**

