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An Optimal Inventory Policy for Machining Tools with Maximum Allowable Lifespan

Bhaba R. Sarker
Department of Mechanical & Industrial Engineering
Louisiana State University
Baton Rouge, LA 70803

Cun Rong Li
School of Mechanical & Electronics Engineering
Wuhan University of Technology
Wuhan City, P. R. China, 430070

Hui Zhi Yi
Department of Mechanical & Industrial Engineering
Louisiana State University
Baton Rouge, LA 70803

Abstract

For high-value added products, machining tools' lifespan significantly influences the quantity of procurement in machining process. The impact of the machining tool practical lifespan on production-inventory policy is investigated here, and an integrated lifespan related inventory model for machining tools is developed to meet the requirement of procurement and inventory. A numerical example is presented to illustrate the integrated model. The results show that the practical lifespan adoption of machining tools has significant impact on the whole quantity of procurement, and eventually influences the coordinating economic decision-making. The integration model of procurement and manufacturing process determine an optimal procurement policy for varying machining tools life.

Key words: Machine tool usable lifespan assessment, procurement policy, and tool lot sizing.

1. Introduction

The lifespan of machine tools has a great impact on their procurement and inventory. Machining tools have expected lifespan around its mean value, and lifespan is a function of several cost-sensitive properties such as tool materials, workpiece materials, machine and machining process, coolants, tool types and design, and other associated properties including environment. If fewer tools are kept in the crib, there might be a shortage of tools while the production is going on, resulting in loss of production (which is an opportunity loss). On the other hand, having too many tools in the crib incurs more monetary investment in tool inventory which is not acceptable either. So, finding an optimal order size of the tools can minimize the overall cost of the production system. Thus, this paper constructs a general inventory model which considers the tool lifespan distribution to design *tool procurement policy* (TPP) for storing optimal number of tools and shows its applications with several different typical tool lifespan distributions.

Majority of machining tools can run with few minimal disturbances (resetting, tightening, readjustment, etc.) and can meet the expected lifespan with certain confidence level. Fewer tools have longer lifespan due to their individual variety and material properties; however, it is hazardous for both an operator and the work piece itself for failure of a tool, because the work piece might be damaged while the tool is broken or splinters of tool or the work piece could be harmful to the operator and/or other surrounding workers. On the other hand, shortening of machining time to avoid tool failure may decrease the failure loss, however, a new tool is then needed to replace the one currently in use, but that will incur an extra tool cost. So, under this circumstance, finding an optimal working time for a tool can minimize the total cost that incurs from "high possibility of tool failure" and "waste of tool lifespan.

1.1 Tool lifespan-related procurement policy

The lifespan of cutting tools could be defined as the time from the beginning of its first using to its blunt and noted as T (Shaw 2005). The well known *F. W. Taylor's* formula $V = A/Tm$ describes relations between lifespan of cutting tools and its cutting parameters, where V is the cutting speed, T indicates the lifespan of the cutting tool, m means the influence of cutting speed impose on the lifespan and A means a coefficient related to the cutting condition; however, when economic penalty of tool breakdown is taken into account, tool lifespan adoption transformed into another issue.

Research on lifespan of machining tools is traditionally concentrated on the materials performance. On the aspect of lifespan prediction, Li and Zhang (2012) made a contribution at time-variant reliability assessment and sensitivity analysis for cutting tool under six cases. ElWardany and Elbestawi (1997) worked on the prediction of tool failure rate and presented a stochastic model; however, this model is complicated and thus difficult to be adopted in supply chain policy. Hirvikorpi *et al.* (2007) studied job scheduling with the assumption that the tool wearing is stochastic, and they paid more attention on the job scheduling other than the effects on tools procurement scheduling. Stubbe and Rose (2011) presented novel model and simulation in optimizing replacement of batch tools with mini-batch which is mainly applied in semiconductor manufacturing industry. Jeang (2012) proposed an integrated model that enables process parameters, production lot size and cycle time to be determined concurrently, but it is weak in discussing the practical lifespan of the manufacturing process. Li and Sarker (2013) posed an evaluation on how the parameters influence the lifespan; however, the inventory policy was not included in it.

There are very fewer researches concentrated on the lifespan distribution of machine tool products in supply chain. In fact, the lifespan have great impact on the procurement and inventory. At the same time, the economics of tool quantity to be stored, that can minimize the tool inventory costs, also lacks investigation. Machining tools have expected lifespan around its mean value, and lifespan is a function of several cost-sensitive properties such as tool materials, workpiece materials, machine and machining process, coolants, tool types and design, and other associated properties including environment. If fewer tools are kept in the crib, there might be a shortage of tools while the production is going on, resulting in loss of production (which is an opportunity loss). On the other hand, having too many tools in the crib incurs more monetary investment in tool inventory which is not acceptable either. So, finding an optimal order size of the tools can minimize the overall cost of the production system. Thus, this paper constructs a general inventory model which considers the tool lifespan distribution to design an economic tool crib policy for storing optimal number of tools and shows its applications with several different typical tool lifespan distributions.

2. Model Formulation

Lifespan and order size of machining tools have significant impacts on the minimization of procurement and inventory total cost. In this section, an attempt is made to formulate the objective function (total cost) that needs to be minimized to find the optimal lifespan and order size for the manufacturing system.

2.1 Assumptions and notations

As the procurement issue of machining tools is quite complex, for the purposes of this paper, several assumptions are taken into account during the formulation of cost-minimization process.

The following assumptions are necessary to model this paper:

1. A failure of a machining tool causes potential damage of work piece, thus results in a penalty cost.
2. Only one type of machining tool is considered for model formulation.
3. Tool vendors are located nearby resulting in negligible tool supplying time.
4. Consumption of tools per period is approximately steady.
5. Total working time in a period is fixed.

2.2 Effects on lifespan with different machining parameters

Expanded *Taylor's* formula shows the relationship of tool lifespan with cutting speed (*V*), feed (*f*) and machining depth of cut (*d*). The lifespan of a michining tool is discribed as *k = VfadbTn* where *V* is the cutting speed, *k* is a constant related to the cutting condition. *a, b* and *n* are coefficients attached on *f, d* and *T*, respectively. Then the lifespan *T* can be written as

$$T = \sqrt[n]{(kV^{-1}f^{-a}d^{-b})}\ . \tag{1}$$

2.3 Lifespan-dependent penalty cost estimation

In practical application, cutting speed (*V*), feed (*f*) and cutting depth (*d*) are determined from the actual work piece processing. Normally it is feasible and economical to avoid applying machining limits for every machining parameter so that the machining tools can work in a regular part of its upper and lower bound. As a result, cutting speed, feed and cutting depth are practically applied with optimal parameter values. In this paper it is assumed that the lifespan of machining tools, *T*, follows a generic distribution function of *f(T)*. The assumption of generic distribution for lifespan makes the solution developed in this study applicable to any lifespan distribution pattern.

Assume the machining tools have an expected lifespan, *E(T)* which is depicted in Figure 1. Majority of machining tools can run with a few minimal disturbances (resetting, tightening, readjustment, etc.) and can meet the expected lifespan with certain confidence level. Fewer tools have longer lifespan due to their individual variety and material properties. However, it is hazardous for both an operator and the work piece itself for failure of a tool, because the work piece might be damaged when the tool is broken or splinters of tool or the work piece could be harmful to the operator and/or other surrounding workers. Hence, because the yearly total working time is fixed, longer working time for a machining tool can decrease total quantity of machining tools to be ordered. As shown in Figure 1, prolonged usable time *Tm* incurs lower holding cost and purchasing cost, but it results potentially higher penalty cost. On the other hand, shortening of machining time to avoid tool failure may decrease the failure loss, but a new tool is then needed to replace the one currently being used, and that will incur an extra tool cost. As a result, shorter usable time of *Tm* will potentially increase the holding cost and purchasing cost for higher order quantity, however, that will decrease the penalty cost. This see-saw problem demands an optimal strategy to follow for operating the tool crib. So, under these circumstances, finding an optimal working (usable) time for tools to minimize the total cost is necessary for this natural tool failure and tool pre-emption problem.

Let us assume that a product has demand rate of D_p products/year. Given the average unit processing time T_u per product (time-unit/product), the total yearly manufacturing work time T_w required for the product can be computed easily as $T_w = T_u D_p$ time-unit/year where the time-units could be days, hours, minutes, etc. For an expected lifespan (in time-units/tool) of a machining tool, *E(T)*, the total yearly demand of machining tools, D_T (tools/year), is given by $D_T = T_u D_p / E(T)$, where the tool lifespan T follows a generic distribution *f(t)*.

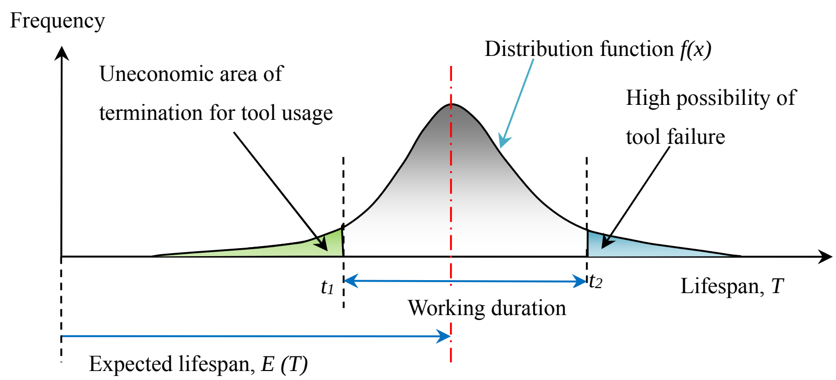

Figure 1. Different effects of possible cost depending on lifespan

Let's assume that the *maximum allowable usage-time* of machining tools is T_m. The maximum allowable usage time could be also termed as *stopping time* since the starting time of all tool lifespan is assumed to be zero. If T_m is the maximum allowable usage time for a machining tool, then the expected lifespan for the tool populations can be divided into two portion: one portion with their actual lifespan $0 \le T \le T_m$ and the other portion can be expressed as $T_m < T \le \infty$. The potential penalty cost, C_P, due to a tool failure is calculated as

$$C_P = c_p F(T_m) = c_p \int_{-\infty}^{T_m} f(T)dT \; . \qquad (2)$$

2.4 Expected lifespan-dependent demand

In machining *n* tools, assume that tool lifespan T_i, $i = 1,2,..,n$, follows a generic distribution. If a stopping policy is implemented, the earlier distribution, $f(T)$ with $-\infty \le T \le \infty$ is revised to $f(T)$ with $-\infty \le T \le T_m$. So, obviously the tools that lasted T_m time units will populate by increasing the frequency of the last class-interval of the revised distribution. For the portion with $T \le T_m$, marked with hatched area, A, as shown in Figure 2, we *define* the expected lifespan of all tools in the range $T \le T_m$, as

$$E(T)\big|_{T=T_m} = \int_{0}^{T_m} Tf(T)dT \; . \qquad (3)$$

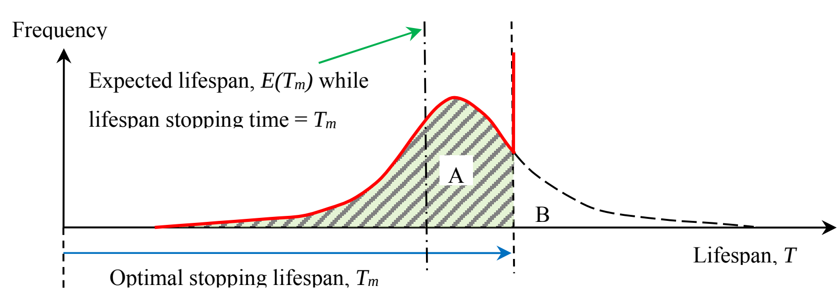

Figure 2. Depiction of expected lifespan, $E(T_m)$ and tool stopping time, T_m

For the other portion (tool pre-empting) marked as area B in Figure 2, the lifespan of the tools exceeds the maximum allowable usage time, i.e., $T > T_m$; thus the lifespan of all these tools are practically T_m. So, the expected lifespan for these pre-empted tools (in area *B*) is *defined* as

$$E(T_m) \;=\; T_m \int_{T_m}^{\infty} f(T)dT \;=\; T_m\left[1 - F(T_m)\right] \tag{4}$$

where $f(T)$ follows the same generic distribution.

Since the total population of the tools is comprised of two groups, *A* and *B* as explained above, each group of tools has different *weighted usable* expected lifespan as defined in equations (3) and (4), respectively. We specifically mentioned 'weighted' to emphasize that the life span of a group is weighted by its population proportion and the word 'usable' indicates the actual or usable life length of a tool. For example, in group *A*, the life length of all tools is $T < T_m$ and that in group *B* (that is, when each individual tool life is more than T_m) the usable life length of all tools is T_m. We now define the total expected lifespan of both groups as

$$E(T)_{A+B} = E(T)\big|_{T=T_m} + T_m\left[1 - F(T_m)\right]. \tag{5}$$

This result indicates that if the tools do not fail (say, due to high quality tool materials with respect to the easily workable piece); the population in group B will be less and as the maximum allowable usable time, T_m tends to be higher. When no tools fail, all tools will fall in group A resulting in the expected lifespan of $E(T)$ which is the highest possible value. The total yearly demand can be expressed as

$$D_T \;=\; \frac{T_u D_p}{E(T)_{T=T_m} + T_m[1 - F(T_m)]} \tag{6}$$

2.5 TPP model construction for machining tools

In this paper, the total machining time required is fixed, and once the tool lifespan T_m is determined, the lifespan-dependent tool quantity demand transformed into a static demand. As a result, the problem can be deemed as a deterministic single-item model. For each cycle, the total cost includes fixed cost of a replenishment order C_f, holding cost TC_I, purchasing cost TC_{PC} and penalty cost TC_{PT}. Then the total cost for a purchasing cycle, TC_c can be expressed as

$$TC_c = C_f + TC_I + TC_{PC} + TC_{PT}. \tag{7}$$

Here the ordering policy is such that the order quantity is expected to meet the demand of each cycle as defined above. Therefore, the average inventory holding cost TC_I in equation (7) is a geometry-based value obtained as $\bar{I} = T_c Q/2 = Q^2/(2D_T)$, thus, the holding inventory cost TC_I in one cycle can be calculated as

$$TC_I = c_h \bar{I} = \frac{c_h Q^2}{2D_T}. \tag{8}$$

The purchasing cost $TC_{PC} = c_u Q$ and total penalty cost for tool failure TC_{PT} per cycle can be obtained by using equation (2) as $TC_{PT} = Qc_p F(T_m)$. Therefore, collecting all these segmental cost, we can express the total cost per cycle, TC_c as

$$TC_c = C_f + \frac{c_h Q^2}{2D_T} + c_u Q + Qc_p F(T_m). \tag{9}$$

Therefore, the average annual cost, TC for D_T/Q cycles per year is obtained as

$$TC(Q,T_m) = \frac{C_f D_T}{Q} + \frac{c_h Q}{2} + c_u D_T + D_T c_p F(T_m) . \qquad (10)$$

Combined with equation (6), equation (10) can be rewritten as

$$TC(Q,T_m) = \frac{C_f T_u D_p / Q + [c_u + c_p F(T_m)] T_u D_p}{E(T)\big|_{T=T_m} + T_m[1 - F(T_m)]} + \frac{c_h Q}{2} , \qquad (11)$$

where $F(T_m)$ is the cumulative probability of lifespan T when $T \le T_m$.

3. Solution Methodology and Computational Results

In the total cost function $TC(Q,T_m)$ in Equation (11) for the lifespan-related procurement system, T_u, D_p, C_f, c_u, c_p and c_h are the system characteristic parameters. So, $TC(Q,T_m)$ is a function of only two decision variables Q (procurement quantity of machining tools per cycle) and T_m (optimal stopping time of machining tools) required to be solved to satisfy the minimum total cost. When the tools are not pre-empted, $T_m \to \infty$ and this leads to following property:

Property 1: If Q_{T_m} and Q_∞ are the order quantities under preemptive and non-preemptive machining processes, respectively, then $Q_{T_m} \ge Q_\infty$.

3.1 Algorithm for TPP

With different initiative values of parameters C_f, c_p, c_h, c_u, T_u, D_p and the distribution of lifespan for T, corresponding results can be computed out by running TPP Algorithm.

Step 1: Initialize C_f, c_p, c_h, c_u, T_u, D_p and distribution type of T. Specify the boundaries of T and Q. Specify the characteristic parametric values for distribution of T, $f(T)$.

Step 2: Initialize objective value TC^*, Q^* and T^*.

Step 3: For each value $T \in [0,3E(T)]$, calculate cumulative distribution probability $F(T)$, compute expected lifespan $E(T)_{A+B}$ with stopping time is T using Equation (5).

Step 4: For each value of Q from 1 to a reasonably arbitrary high value (at a step of 1), compute $TC(Q,T)$ by using Equation (11).

If $TC < TC^*$, set $TC^* = TC$, $T_m^* = T$, $Q^* = Q$.

Step 5: Repeat Steps 3 and 4 until both upper boundaries are reached.

Step 6: Stop and current value of T_m^* and Q^* is the best solution and TC^* is the minimum total cost. □

3.2 Numerical analysis

The following examples illustrate the theoretical results obtained from the algorithm for TPP. Two different types of lifespan distributions are used here to demonstrate the generic solution methodology that can be applied for any type of demand distributions.

(a) Uniformly distributed lifespan:

Under some conditions, machining tools are manufactured with uniform distributed parameters including machine, operator, material, and measurement. As a result, the lifespan of machining tools will follow uniform distribute. The cumulative distribution probability is expressed as follows:

$$F(T_m; a, b) = \frac{T_m - a}{b - a} \tag{12}$$

The lifespan of certain cutter is usually distributed uniformly from 4 to 6 hours in general due to actual conditions with a = 4 hours, b = 6 hours, for fixed purchasing cost Cf = \$20.00/order, c_p = \$3.00/tool, c_h = \$8.00/tool, c_u = \$15.00/tool, T_u = 0.2 hours/product, D_p = 10,000 products/year. The objective is to minimize the total cost of the tool by determine the optimal value of Q and T.

Table 1. Computational results of total cost TC for uniformly distributed tool lifespan

Order size Q	Lifespan T_m (Hours)					
	4.00	4.50	5.00	**5.20***	5.50	6.00
20	8,080.00	7,629.30	7,448.42	7,435.37	7,472.41	7,680.00
30	7,953.33	7,519.06	7,348.07	7,337.63	7,377.38	7,586.67
40	7,910.00	7,483.94	7,317.89	7,308.76	7,349.87	7,560.00
45*	7,902.22	7,478.90	7,314.50	**7,305.80**	7,347.37	7,557.78
50	7,900.00	7,478.87	7,315.79	7,307.44	7,349.37	7,560.00
60	7,906.67	7,488.83	7,327.72	7,319.89	7,362.36	7,573.33
70	7,922.86	7,507.36	7,347.67	7,340.21	7,383.07	7,594.29

* Optimal Values

When T follows uniform distribution, the computational results by running the programmed algorithm for TPP are shown in Table 1. The approximate optimal results are: Q^* = 45, T_m^* = 5.20 hours, and the minimum total cost TC^* = \$7,305.80. So for U (4,6) with T_m = 5.2 and $F(T_m)$ = 0.6, $E(T)\big|_{T=T_m}$ = $\frac{T_m^2 - a^2}{2(b-a)}$ = 2.76, and $T_m[1 - F(T_m)]$ = 2.08. Thus, $E(T)_{A+B}$ = 2.76 + 2.08 = 4.84 hours. So the optimal procurement cycle time, T_{cyc}^* = Q^*/D_T $= Q^* E(T)_{A+B} / T_u D_p \approx 0.1089$ year = 40 days.

It is illustrated that too smaller values of lifespan and order size will dramatically lead to a higher total cost from Table 1. Reasonable choice of T and Q values can minimize the total cost. The TPP model can works when the lifespan of machining tools follows a uniform distribution.

(b) Normally distributed lifespan:

Lifespan of machining tools follows normal distribution for kind of conditions (see Li and Sarker 2013). The cumulative distribution function for a normal distribution can be expressed as follows:

$$F(T_m; \mu_T, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \int_0^{T_m} \exp\left(-(x-\mu_T)^2 / 2\sigma^2\right) dx\,, \tag{13}$$

where μ_T represents the mean value of lifespan and σ is the standard deviation of the lifespan.

For milling cutters, the lifespan follows normal distribution with mean μ_T = 4 hours and standard deviation of σ = 0.2. If the fixed purchasing cost C_f = \$20.00/order, c_p = \$1.00/tool, c_h = \$8.00/tool.

c_u = \$15.00/tool, T_u = 0.2 hours/product, D_p = 10,000 products/year. The objective is to minimize the total cost *TC* of the tool by determine the optimal value of *Q* and T .

The simplified computational results by running the programmed algorithm for *TPP* are shown in Table 2. The data shows every exact values of TC corresponding to values of Q and T . The approximate optimal results are: Q^* = 50 tools/order, T_m^* = 4 hours, the corresponding expected lifespan is 3.92 hours, and the optimal total cost TC^* = \$8,311.83.

Table 2. Computational result of total cost TC for normally distributed lifespan

Order size *Q*	Lifespan T_m (hours)				
	3.00	3.50	4.00	4.50	5.00
20	10,746.67	9,227.53	8,497.93	8,577.65	8,579.99
30	10,564.45	9,077.04	8,367.87	8,450.97	8,453.33
40	10,493.34	9,021.79	8,322.84	8,407.63	8,409.99
50	10,466.67	9,004.64	**8,311.83**	8,397.62	8,399.99
60	10,462.23	9,006.54	8,317.81	8,404.28	8,406.66
70	10,470.48	9,019.32	8,333.52	8,420.47	8,422.85

Here, as defined in equation (3), $E(T)\big|_{T=T_m} = \int_0^{T_m} Tf(T)dT = \int_0^{4.0} Tf(T)dT$ = 1.9202, $T_m[1-F(T_m)]$ = 4.0 (1 - 0.5) = 2.0. Thus $E(T)_{A+B}$ = 3.9202 hours and the procurement cycle time T_{cyc}^* = Q^*/D_T = $Q^*E(T)_{A+B}/T_uD_p$ = 50(3.9202)/2000 ≈ 0.0980 year = 36 days.

Small order size and short practical lifespan result in higher purchasing cost, finally increase the total cost. Otherwise, big order size and longer practical lifespan induce higher holding cost and penalty cost, and also eventually add up to total cost. As a result, proper values of Q and T can minimize the total cost.

From the two examples with uniform and normal distributions, the TPP model shows its robustness with different distributions. For symmetrical distributions, the examples suggested the same results of optimal Q and T which lead to the economic total cost, and because of the central tendency for normal distribution, the total cost TC is lower than the total cost when lifespan follows uniform distribution.

4. Sensitivity Analysis

In this section, c_p, c_h, are analyzed for their sensitive impact on T^*, Q^*, T_{cyc}^* and TC^*. In order to simplify the analysis process, only normal distribution is are discussed for intensive exploration.

4.1 Impact of c_p

The unit penalty cost c_p is penalty amount if a machining tool fails usually along with work piece damage or broken. In practice, c_p has an impact on TC, T_{cyc}^* when the optimal value of T^* and Q^* are decided.

According to different value of c_p, the optimal practical value of T_m^*, Q^*, T_{cyc}^* and TC^* vary as shown in Table 3. The data in Table 3 show that the penalty cost c_p has an impact on the total cost, TC, and the mainly influences the adoption of decision variable T_m. On the contrary, if value of T_m^* and Q^* are not decided to be the optimal value, total cost TC^* fluctuates dramatically with the fluctuation of c_p. However, there is little influence on the time of ordering cycle.

Table 3. Sensitivity comparison of T according to different value of c_p

Unit penalty cost c_p	T_m^* (Hours)	Q^* (Tools)	TC^* ($)	T_{cyc}^* (Days)
0.30	4.55	50	8,049.60	36
0.50	4.20	50	8,143.40	36
1.00	4.00	50	8,311.83	36
1.20	3.95	50	8,359.70	36

4.2 Impact of c_h

The unit holding cost c_h has impact on the total cost TC whenever there is inventory of tools in stock. Table 4 shows fluctuation of c_h resulting in the change of T_m^*, Q^*, T_{cyc}^* and TC^*. The smaller for c_h, the bigger for order size, Q^*, and this can minimize the total cost TC^*. Compared with the decrease of c_h, increase of c_h incurs bigger order size and results in raising of TC^*. The change of c_h also has significant impact on the time of ordering cycle along with the change of Q^*.

Table 4. Sensitivity comparison of T according to different value of c_h

Unit penalty cost c_h	T_m^* (Hours)	Q^* (Tools)	TC^* ($)	T_{cyc}^* (Days)
3.00	4.00	85	8,155.30	61
5.00	4.00	65	8,227.20	47
8.00	4.00	50	8,311.83	36

5. Conclusions

The allowable stopping time *T* for a machining tool is investigated in this paper, and a lifespan TPP model is proposed to control the accurate procurement of machining tools. An iterative search procedure is developed to find the approximate optimal solution of the TPP model under a practical circumstance. Two examples of uniform distribution and normal distribution are implemented that show the robustness of the model to cope with different distribution for *T*. For sensitivity analysis, the variation of unit penalty cost , c_p, and tool unit holding cost, c_h, are illustrated to show how it influences the total cost TC in simulation process. In this paper, the TPP model is considered to meet the basic requirement for procurement of inventory of machining tools. It is found that there exists feasible solution applicable to the tool procurement policy with maximum allowable lifespan in manufacturing industry. Research dealing with multiple types of tools needs to be explored. While we consider the variability in tool lifespan, demand uncertainty of the products will alter the total work time of the tools, eventually affecting the demand of the machining tools; so such an effort may me undertaken to investigate end results of the study.

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Biography

Bhaba Sarker is the Elton G. Yates Distinguished Professor of Engineering at the Louisiana State University. Before joining LSU, he worked with several organizations and taught at UT-Austin and Texas A&M University. Professor Sarker published more than 125 papers in refereed journals, and more than 75 papers in conference proceedings. He is a Fellow of IIE. He won of the *Best Dissertation Awards* from IIE, DSI and POMS, and 2006 *David F. Baker Distinguished Research Award* from IIE for his outstanding research in Industrial Engineering. He is currently on the editorial boards of *American J. OR, Intl. J. Prod. Econ., Intl. J. Pure and Appd Math Sc., Intl. J. Logistics and Transp. Res, Intl. J. of SCOM, and PPC.* Dr. Sarker is a member of ASEE, DSI, IIE, and INFORMS, and his research was funded by NSF, ONR, USAE and NASA. He is currently working in the general area of supply chain logistics and lean production systems, military logistics and large convoy movement.

Cun Rong Li is an Associate Professor at the School of Mechanical & Electronics Engineering at Wuhan University of Technology (China). He published technical papers in refereed journals including *IJAMT, Industry Eng. and Mgt., J. of Mechanics: Manufacturing, J. of Mechanics: Design and Manufacture Eng., J. of*

CAD/CAM, and conference proceedings. He is now a visiting scholar at Louisiana State University, and is supported by China Scholarship Council. He is currently working in the area of supply chain, reliability and manufacturing automation.

Huizhi Yi obtained his MS and PhD degree in Industrial Engineering from Louisiana State University. He has published papers in refereed journals including, *Computers and Operations Research, Intl. J. Production Research* and *Applied Soft Computing* and conference proceedings. He is currently working in the area of supply chain logistics, lean production systems, meta-heuristics and homeland security problems.