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Article

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Production planning incorporating issues of reliability and backlogging with service level constraint

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ABSTRACT

To stay competitive in present-day turbulent business environment, managers of manufacturing firms must achieve crucial operational goals, such as maintaining product quality, reducing operating costs, and attaining customer satisfaction. In real manufacturing systems, allowing backordering sometimes can be an effective strategy to help smooth manufacturing schedules and lower operating costs. However, the consequence of excessive shortages is the undesirable service level which reduces customer satisfaction and goodwill. To cope with this unwanted result, a maximal permitted backlogging level is set as an operating constraint to achieve the minimum required service level. Also, production of scrap items and stochastic breakdown are both inevitable in the manufacturing processes. Motivated by addressing aforementioned issues and providing insight information to managers for supporting their operational decision makings, this paper investigates the optimal runtime for a fabrication system with backordering, service level constraint, stochastic breakdown, and scrap. Mathematical model was developed and optimization methods are used to decide the optimal runtime that minimizes total system costs. Various key insights relating to joint impacts of backlogging, service level, stochastic breakdown, and scrap on the optimal runtime decision are revealed through a numerical illustration along with sensitivity analyses.

1. Introduction

The present study investigates the optimal runtime for a fabrication system incorporating backlogging with service level constraints, scrap, and stochastic breakdown. Conventional economic production quantity (EPQ) model derived the most economic fabrication lot size for a production system without considering shortage/backordering, and it assumes that the manufacturing process is perfect [1–2]. However, in real-life fabrication systems, allowing backordering of shortages of certain portion of demand can sometimes be an effective strategy to help managers smooth production schedules and lower overall operating costs. But, the consequence of abusive shortages is the undesirable service level that reduces customer satisfaction and goodwill. To cope with this unwanted result, a maximal allowable shortage level is often set as an operating constraint to achieve minimum required service level. Aucamp and Fogarty [3] incorporated backordering strategy into conventional economic order quantity (EOQ) model, wherein no extra backlogging cost and a limited reasonable delay time were considered. de Kok [4] explored an inventory model with adjustable production

rate. The product demand is assumed to obey a compound Poisson process and the adjustable production rate was used to cope with fluctuations in demand. They considered that excess demands were lost and average number of lost-sales occurrences per unit time as the service measures. A two-critical-number control policy was used to derive approximations for the switch-over level so as to achieve the required service level. Aucamp [5] derived an exchange curve for managers to determine the backorder policy. Such an exchange curve illustrated the trade-off between aggregate inventory costs versus the costs for maximum allowed backorder delay. Boyaci and Gallego [6] investigated a stock refilling problem with the aim of minimizing ordering and holding costs subject to a constraint on the expected level of backorders. A algorithm was developed to compute an optimal policy, the imputed penalty cost rate, and the corresponding fill-rate. Chiu [7] analyzed the impact of service level on an EPQ model with random scrap. The expected system cost with backordering is proved to be less than that of the same model without backordering. Then, relationship between a so-called imputed backorder cost and maximum shortage level was derived, and a formula was proposed to compute the

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intangible backlogging expense for the case when desired service level is unattainable. Finally, applying the intangible backorder cost to the solution process, an update optimal batch size policy was determined. Other studies [8–13] also addressed diverse aspects of backordering with service level constraint.

Furthermore, in real world production environments, due to diverse uncontrollable factors, the production of scraps and the stochastic machine failure are both inevitable. Mak [14] studied a fabrication system featuring uncertain product quality in a production lot and demand is partially met. He assumed that an allowable fraction of the demand with known probability distribution can be backordered. A mathematical model was developed to help determine the optimal stock refilling policy and numerical example was used to verify his research result. Widmer and Solot [15] explored a machine failure and maintenance problem using the queuing network theory. They evaluated production rate, utilization, and other performances of a flexible manufacturing system, and used the simulation analyses and results to verify accuracy of their study. Groenevelt et al. [16] examined two separate production control policies that coped with random machine breakdown. The first policy considered that production of the interrupted lot will not be resumed after a machine failure occurrence (i.e., the NR policy). The second policy assumed that after a machine failure occurrence and if existing inventory level drops below a particular threshold point, then production of the interrupted lot will be resumed right away (this is called abort/resume (AR) policy). Machine fixing time is assumed to be insignificant, and impacts of machine failure occurrence and corrective maintenance on economic batch size decisions were explored accordingly. Widyadana and Wee [17] examined deteriorating items' EPQ models featuring preventive maintenance, stochastic breakdown and instant corrective action. The excessive demands are assumed lost. Two separate EPQ models were developed, one considered the distribution of corrective and maintenance times is uniform and the other one assumed exponential. Numerical examples with sensitivity analyses were provided to illustrate their models. They found that the corrective time variable for the exponential distribution model is most sensitive to the optimal total cost. Chiu et al. [18] decided the optimal runtime for an EPQ-based system with Poisson distributed machine failure rate and uniformly distributed scrap rate. After an occurrence of failure, the machine will be under repair at once and the fabrication of the interrupted lot resumes when the machine is repaired. They built a mathematical model and proposed a recursive algorithm to decide the optimal fabrication runtime. A numerical illustration was provided to demonstrate applicability and cost efficiency of their result as compared to a prior research that considered breakdown with NR policy. Other research that examined various aspects of imperfect fabrication systems such as breakdown, scrap, rework of defects, and other quality assurance matters, can also be found elsewhere [19–37].

Motivated by providing insight information to support managerial key operational decision makings, the present research extends prior studies [7,18] and investigates the optimal runtime for a manufacturing system with backordering, service level constraint, scrap, and random machine breakdown. Due to little attention has been drawn on exploration of joint impacts of backordering, service level constraint, scrap, and breakdown on the optimal runtime decision for such a particular fabrication system, we are intended to link the gap.

2. Materials and methods

2.1. The proposed problem

This study explores a manufacturing runtime problem with scrap, backordering, service level constraint, and random machine breakdown. Consider that the demand rate of a manufactured product is λ units per year, and this item can be fabricated at a rate of P units per year. The production process is imperfect, an x portion of scrap

products may be produced arbitrarily at rate d , yielding $d = Px$. To avoid stock-out situations, $P-d-\lambda > 0$ is assumed.

In the fabrication process, the production equipment is subject to a breakdown that obeys Poisson distribution. When an equipment failure happens, abort/resume (AR) control plan is implemented, and under the AR policy, machine repair initiates right away, and the disturbed batch resumed at once when the production facility is repaired. We assumed that the machine repair time is constant (however, if the actual repair time shall exceed this allowable time, then a rental machine will be used to avoid further delay in production). Shortage is allowed and backordered with an additional shortage cost b per product per unit time. To avoid an abusive backlogging situation [7], a minimum acceptable service level $(1-\alpha)\%$ is set as a predetermined policy. Additional notations include the following:

T_1	=	uptime, the decision variable,
K	=	setup cost,
C	=	unit fabrication cost (including unit screening cost),
M	=	equipment repair cost per breakdown,
C_S	=	disposal cost per item,
C_1	=	unit cost of safety stock,
C_T	=	unit delivery cost,
h	=	holding cost per product per year,
h_3	=	holding cost per item per unit time of safety stock,
Q	=	replenishment lot size per production cycle,
T'	=	cycle time in the case of breakdown occurring,
β	=	number of breakdowns per year—a Poisson distributed variable,
t	=	time to a breakdown occurs,
t_r	=	time needed to repair the machine,
t_1'	=	uptime when the stock piles up,
t_2'	=	time to consume all existing perfect quality items,
t_3'	=	time in which backlogging gradually accumulated,
t_4'	=	uptime in which backlogging being gradually satisfied,
$TC_1(T_1)$	=	total system cost per cycle in the case of breakdown occurs in backlogging stage,
$TC_2(T_1)$	=	total system costs per cycle in the case of breakdown occurs in stock pileup stage,
$E[TC_1(T_1)]$	=	expected total system cost per cycle when breakdown happens in backlogging stage,
$E[TC_2(T_1)]$	=	expected total system costs per cycle when breakdown happens in the stock pileup stage,
T	=	cycle length—in the case of no breakdown happening,
t_1	=	uptime when stock piles up—in the case of no breakdown happening,
t_2	=	time required to deplete all existing finished items—in the case of no breakdown happening,
t_3	=	time in which backlogging accumulated—in the case of no breakdown taking place,
t_4	=	uptime in which backlogging being satisfied—in the case of no breakdown happening,
$E[TC_3(T_1)]$	=	expected system costs per cycle in the case of no breakdown happening,
T	=	cycle time whether the machine breakdowns or not,
$TCU(T_1)$	=	total system cost per unit time whether a breakdown happening or not,
$E[TCU(T_1)]$	=	expected system cost per unit time whether a breakdown happening or not,
$I(t)$	=	perfect quality stock level at time t ,
$I_s(t)$	=	level of scrapped items at time t ,
g	=	time needed to repair the machine (i.e., t_r).

Because in the fabrication process, the machine is subject to a random failure (i.e., the time to a breakdown is random), so there are three possible cases of breakdown occurrence must be investigated:

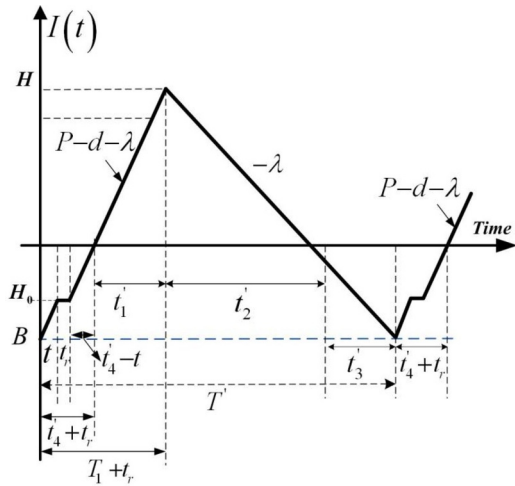


Fig. 1. The level of on-hand perfect quality items in the proposed manufacturing system when breakdown occurs in the backloging stage.

2.2. Case 1: when machine breakdowns in the backloging stage

In this situation, t is less than t_4' . The on-hand inventory status of perfect quality products is depicted in Fig. 1. It can be seen that when a breakdown occurs, the level of backloging is at H_0 , and under the AR policy, once the machine is fixed and restored, the production of the interrupted lot is immediately resumed. Hence, the level of backloging continues to reduce, and then changes to having positive stocks in t_1' . At the end of production uptime, the level of on-hand inventory reaches H . Then, all available products are consumed in t_2' , followed by a shortage in period t_3' until they accumulate to a permitted maximum level B (i.e., a predetermined level set by the minimum acceptable service level constraint). Subsequently, the uptime of the following replenishment cycle begins. Some basic formulas (see Appendix A) can be observed from Fig. 1.

Fig. 2 exhibits the on-hand stock status of scraps in the proposed system. It can be seen that at the end uptime, the maximal level of scrap products reaches dT_1 .

The total system costs $TC_1(T_1)$, in the case of breakdown in the backloging stage, comprise the manufacturing setup cost, variable production and disposal costs, fixed repairing cost of breakdown, holding and purchasing costs of safety stock, holding costs of perfect quality items and scrap items in t_1' and t_2' , variable shipping costs, and variable backordering costs. Hence, $TC_1(T_1)$ is as follows:

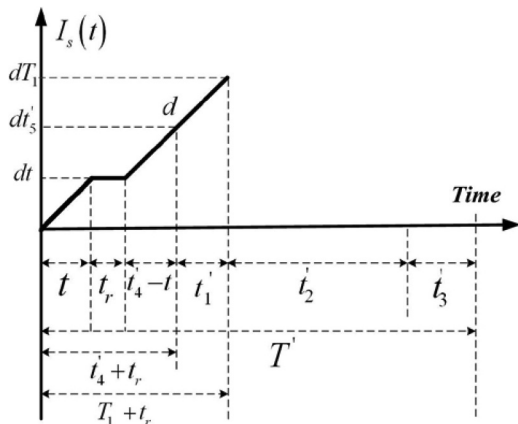


Fig. 2. The on-hand inventory status of scraps in the proposed system.

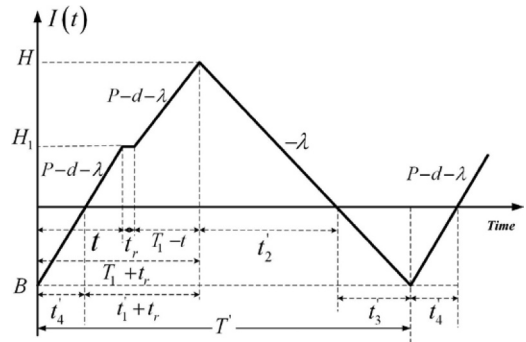


Fig. 3. The level of on-hand inventory of perfect quality products in the proposed manufacturing system when breakdown occurs in the stock pileup stage.

$$TC_1(T_1) = K + CQ + C_S xQ + M + \left[h_3(\lambda t_r) \left(t + \frac{t_r}{2} \right) + C_1(\lambda t_r) \right] + h \left[\frac{H}{2}(t_1') + \frac{H}{2}(t_2') + (dt)t_r + \frac{d(H)}{2}(T_1) \right] + C_T[(1-x)Q + (\lambda t_r)] + b \frac{B}{2}(t_3' + t_4') + b(H_0)t_r \quad (1)$$

Substituting Eqs. (A-1)–(A-8) in Eq. (1), and using the expected values of x to manage the scrap rate's randomness, and with extra computations, we obtain $E[TC_1(T_1)]$ as

$$E[TC_1(T_1)] = K + CT_1P + T_1PC_S E[x] + M + \left[h_3(\lambda t_r) \left(t + \frac{t_r}{2} \right) + C_1(\lambda t_r) \right] + h \left[-\frac{B(1-E[x])T_1P}{\lambda} + \frac{(1-E[x])^2 T_1^2 P^2}{2\lambda} - \frac{(1-2E[x])T_1^2 P}{2} \right] + bt_r(B - Pt + \lambda t) + (h + b) \left[\frac{B^2}{2(P - PE[x] - \lambda)} + \frac{B^2}{2\lambda} + P_1 E[x] t_r \right] + C_T[(1 - E[x])T_1P + (\lambda t_r)] \quad (2)$$

2.3. Case 2: when machine breakdowns in the stock pileup stage

In this case, the time to breakdown t falls within the range of $[t_5', T_1]$ (i.e., $t_5' < t < T_1$) (see Fig. 3). An additional Eq. (3) can be observed directly from Fig. 3 as follows:

$$H_1 = (P - d - \lambda) \cdot (t - t_4') \quad (3)$$

In this case, the total system costs $TC_2(T_1)$ comprise the manufacturing setup cost, variable fabrication and disposal costs, fixed repairing cost of breakdown, holding and purchasing costs of safety stock, holding costs of perfect quality items and scrap items, variable shipping costs, and variable backordering costs. Hence, $TC_2(T_1)$ is

$$TC_2(T_1) = K + CQ + C_S xQ + M + \left[h_3(\lambda t_r) \left(t + \frac{t_r}{2} \right) + C_1(\lambda t_r) \right] + h \left[\frac{H_1}{2}(t - t_4') + \frac{(H_1 + H)}{2}(T_1 - t) + \frac{H}{2}(t_2') + (H_1 + dt)t_r + \frac{d(H)}{2}(T_1) \right] + C_T[(1-x)Q + (\lambda t_r)] + b \frac{B}{2}(t_3' + t_4') \quad (4)$$

Substituting Eqs. (A-1)–(A-8), and Eq. (3) in Eq. (4), and using the expected values of x to cope with the random scrap rate, and with additional derivations, we obtain $E[TC_2(T_1)]$ as

$$E[TC_2(T_1)] = K + CT_1P + T_1PC_S E[x] + M + \left[h_3(\lambda t_r) \left(t + \frac{t_r}{2} \right) + C_1(\lambda t_r) \right] + h \left[-\frac{B(1-E[x])T_1P}{\lambda} + \frac{T_1^2 P^2 (1-E[x])^2}{2\lambda} - \frac{T_1^2 P (1-2E[x])}{2} \right] + ht_r(P - \lambda) + (h + b) \left[\frac{B^2}{2(P - PE[x] - \lambda)} + \frac{B^2}{2\lambda} \right] + C_T[T_1P(1 - E[x]) + (\lambda t_r)] - hBt_r \quad (5)$$

2.4. Case 3: no breakdown occurrence in uptime

In this situation, $t > = T_1$ (see Fig. 4). Observing Fig. 4, one can

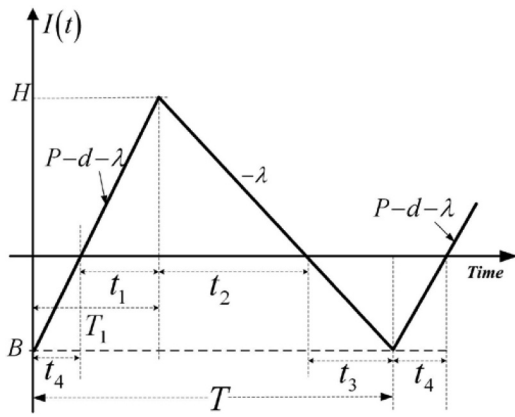


Fig. 4. The level of on-hand perfect quality items in the proposed manufacturing system when breakdown does not occur.

directly obtain basic formulas (as shown in Appendix B).

In this case, $TC_3(T_1)$ comprise the manufacturing setup cost, variable production and disposal costs, holding and purchasing costs of safety stock, holding costs of perfect quality and scrap products in t_1 and t_2 , variable shipping costs, and variable backordering costs. Therefore, $TC_3(T_1)$ is as follows:

$$TC_3(T_1) = K + CQ + C_S xQ + [h_3(\lambda t_r)T + C_1(\lambda t_r)] + h \left[\frac{H}{2}(t_1) + \frac{H}{2}(t_2) + \frac{d(T)}{2}(T_1) \right] + C_T(1-x)Q + b \frac{B}{2}(t_4 + t_5) \tag{6}$$

Replace Eqs. (B-1) to (B-6) in Eq. (6), and applying the expected values of x to cope with the randomness of scrap rate, and with extra derivations, we obtain $E[TC_3(T_1)]$ as

$$E[TC_3(T_1)] = K + C T_1 P + T_1 P C_S E[x] + M + \left[h_3(\lambda t_r) \left(t + \frac{t_r}{2} \right) + C_1(\lambda t_r) \right] + h \left[-\frac{B(1-E[x])T_1 P}{\lambda} + \frac{(1-E[x])^2 T_1^2 P^2}{2\lambda} - \frac{(1-2E[x])T_1^2 P}{2} \right] + (h+b) \left[\frac{B^2}{2(P-PE[x]-\lambda)} + \frac{B^2}{2\lambda} \right] + C_T [(1-E[x])T_1 P] \tag{7}$$

A predetermined desired minimum acceptable service level $(1-\alpha)\%$ is set by production planner to avoid the abusive backlogging situation. The following relationship between the maximum backlogging level and the service level indicator α can be obtained from a prior study [7] as follows:

$$B = \alpha \left(1 - E[x] - \frac{\lambda}{P} \right) T_1 P \tag{8}$$

3. Results

3.1. Integration of three possible cases

In this study, since Poisson distributed failure with mean $= \beta$ per year is assumed, thus, time to machine failure obeys exponential

Table 1
Results of iterations of our proposed recursive searching algorithm for T_1^* .

β	Iteration	$e^{-\beta T} 1U$	T_{1U}	$e^{-\beta T} 1L$	T_{1L}^*	Difference between T_{1U} and T_{1L}	$E[TCU(T_{1U})]$	$E[TCU(T_{1L})]$	Difference b/w $E[TCU(T_{1U})]$ and $E[TCU(T_{1L})]$
0.5	initial	0.0000	0.6009	1.0000	0.3698	0.2311	\$10,528.48	\$10,467.52	\$60.96
	2nd	0.7405	0.4453	0.8312	0.4198	0.0255	\$10,456.09	\$10,455.07	\$1.02
	3rd	0.8004	0.4286	0.8107	0.4257	0.0029	\$10,454.94	\$10,454.92	\$0.02
	4th	0.8071	0.4267	0.8083	0.4263	0.0004	\$10,454.92	\$10,454.92	\$0.00
	5th	0.8079	0.4264	0.8080	0.4264	0.0000	\$10,454.92	\$10,454.92	\$0.00

distribution with $f(t) = \beta e^{-\beta t}$ as density function and $F(t) = (1-e^{-\beta t})$ as the cumulative density function. Therefore, $E[TCU(T_1)]$ is as follows:

$$E[TCU(T_1)] = \frac{\int_0^{t_1^s} E[TC_1(T_1)]f(t)dt + \int_{t_1^s}^{T_1} E[TC_2(T_1)]f(t)dt + \int_{T_1}^{\infty} E[TC_3(T_1)]f(t)dt}{E[T]} \tag{9}$$

where the expected cycle time $E[T]$ is [18]

$$E[T] = \int_0^{T_1} E[T']f(t)dt + \int_{T_1}^{\infty} E[T]f(t)dt = \frac{P[1-E(x)]T_1}{\lambda} \tag{10}$$

By substituting three separate expected cost functions $E[TC_1(T_1)]$, $E[TC_2(T_1)]$, and $E[TC_3(T_1)]$, along with $f(t)$ and $E[T]$ into Eq. (9), and with additional derivations, we obtain $E[TCU(T_1)]$ as follows:

$$E[TCU(T_1)] = \frac{\lambda}{(1-E[x])} \left\{ \frac{z_1}{T_1} + T_1 \left[\frac{v^2(h+b)}{2P\lambda} + \frac{v^2(h+b)}{2P^2 \left[1 - E[x] - \frac{\lambda}{P} \right]} - \frac{h}{2} + E[x] \right] + \frac{(1-E[x])}{\lambda} \left[\frac{hP(1-E[x])}{2} - hv \right] \right\} + \frac{\lambda}{(1-E[x])} \left\{ C + C_S E[x] + \frac{v g}{P}(b-h) + C_T [1-E[x]] + h_3 g [1-E[x]] + \frac{w_1}{T_1} + w_2 e^{-\beta T_1} + \frac{w_3 e^{-\beta T_1}}{T_1} + \frac{w_4 e^{-\beta T_1} s}{T_1} + w_5 [e^{-\beta T_1(1-s)} + e^{-\beta T_1 s}] \right\} \tag{11}$$

where g , z_1 , v , Y_1 , s , w_1 , w_2 , w_3 , w_4 , and w_5 stand for the following:

$$g = t_r; z_1 = \left[\frac{K}{P} + \frac{C_1 \lambda g}{P} \right]; v = \alpha \left(1 - E[x] - \frac{\lambda}{P} \right) P \tag{12}$$

$$Y_1 = \frac{v T_1}{P - PE[x] - \lambda} = s T_1; s = \frac{v}{P - PE[x] - \lambda} \tag{13}$$

$$w_1 = \left[\frac{M}{P} + \frac{h_3 \lambda g^2}{2P} + \frac{h_3 \lambda g}{\beta P} + \frac{C_T \lambda g}{P} + \frac{hE[x]g}{\beta} - \frac{bg(P - PE[x] - \lambda)}{\beta P} \right] \tag{14}$$

$$w_2 = \left[-\frac{h_3 \lambda g}{P} - hg + \frac{h \lambda g}{P} \right]; w_3 = \left[-\frac{M}{P} - \frac{h_3 \lambda g^2}{2P} - \frac{h_3 \lambda g}{\beta P} - \frac{C_T \lambda g}{P} - \frac{hg}{\beta} + \frac{h \lambda g}{\beta P} \right] \tag{15}$$

$$w_4 = \frac{g \left(1 - E[x] - \frac{\lambda}{P} \right) (h+b)}{\beta}; w_5 = \left[\frac{hvg}{P} \right] \tag{16}$$

From Eq. (11), we obtain the first and second derivatives of $E[TCU(T_1)]$ as

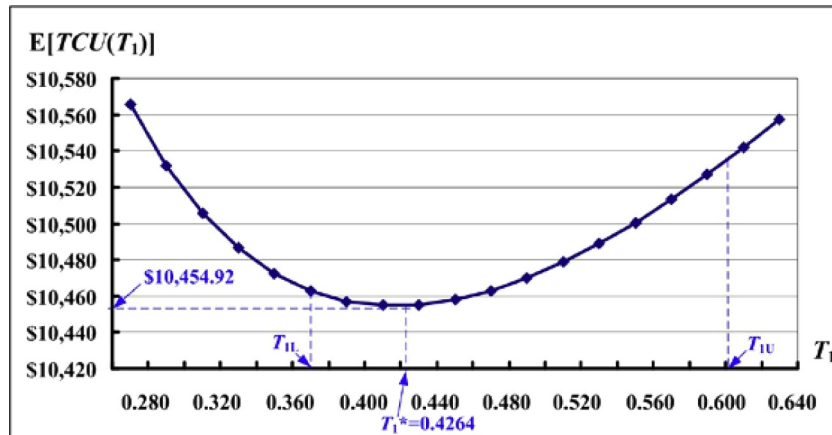


Fig. 5. The behavior of $E[TCU(T_1)]$ with respect to replenishment runtime T_1 .

$$\frac{dE[TCU(T_1)]}{dT_1} = \frac{\lambda}{(1-E[x])} \left\{ -\frac{z_1}{T_1^2} + \left[\frac{v^2(h+b)}{2P\lambda} + \frac{v^2(h+b)}{2P^2 \left[1 - E[x] - \frac{\lambda}{P} \right]} - \frac{h}{2} + E[x] \right] + \frac{(1-E[x]) \left[\frac{hP(1-E[x])}{2} - hv \right]}{\lambda} \right\} + \frac{\lambda}{(1-E[x])} \left\{ \begin{aligned} &-\frac{w_1}{T_1^2} - \beta w_2 e^{-\beta T_1} - \frac{\beta w_3 e^{-\beta T_1}}{T_1} - \frac{w_3 e^{-\beta T_1}}{T_1^2} - \frac{\beta s w_4 e^{-\beta T_1 s}}{T_1} \\ &-\frac{w_4 e^{-\beta T_1 s}}{T_1^2} \\ &-\beta w_5 e^{-\beta T_1} (e^{-\beta T_1 s})^{-1} + \beta s w_5 e^{-\beta T_1} (e^{-\beta T_1 s})^{-1} - \beta s w_5 e^{-\beta T_1 s} \end{aligned} \right\} \quad (17)$$

$$\frac{d^2E[TCU(T_1)]}{dT_1^2} = \frac{\lambda}{(1-E[x])} \left\{ \begin{aligned} &\frac{2z_1}{T_1^3} + \frac{2w_1}{T_1^3} + \beta^2 w_2 e^{-\beta T_1} + \frac{\beta^2 w_3 e^{-\beta T_1}}{T_1} + \frac{2\beta w_3 e^{-\beta T_1}}{T_1^2} \\ &+ \frac{2w_3 e^{-\beta T_1}}{T_1^3} + \frac{\beta^2 s^2 w_4 e^{-\beta T_1 s}}{T_1} + \frac{2\beta s w_4 e^{-\beta T_1 s}}{T_1^2} + \frac{2w_4 e^{-\beta T_1 s}}{T_1^3} \\ &+ \beta^2 w_5 e^{-\beta T_1} (e^{-\beta T_1 s})^{-1} (1 - 2s + s^2) + \beta^2 s^2 w_5 e^{-\beta T_1 s} \end{aligned} \right\} \quad (18)$$

If Eq. (18) > 0, then $E[TCU(T_1)]$ is convex. Because the first term on the right-hand side (RHS) of Eq. (18) $[\lambda / (1 - E[x])] > 0$, hence, if the second term on RHS of Eq. (18) > 0, then $E[TCU(T_1)]$ is convex. With further derivations, we know that under the following condition the convexity holds:

$$0 < T_1 < \frac{2z_1 + 2w_1 + 2w_3 e^{-\beta T_1} + 2w_4 e^{-\beta T_1 s}}{\left[\begin{aligned} &+ \beta^2 w_2 e^{-\beta T_1} T_1^2 + \beta^2 w_3 e^{-\beta T_1} T_1 + 2\beta w_3 e^{-\beta T_1} + \beta^2 s^2 w_4 e^{-\beta T_1 s} T_1 \\ &+ 2\beta s w_4 e^{-\beta T_1 s} \\ &+ \beta^2 w_5 e^{-\beta T_1} (e^{-\beta T_1 s})^{-1} (1 - 2s + s^2) T_1^2 + \beta^2 s^2 w_5 e^{-\beta T_1 s} T_1^2 \end{aligned} \right]} = \delta(T_1) \quad (19)$$

Once we confirm that $T_1 < \delta(T_1)$, then $E[TCU(T_1)]$ is convex, subsequently, we can seek T_1^* by setting the first derivative of $E[TCU(T_1)]$ (i.e., Eq. (17)) equal to 0. Applying the square root solution to Eq. (17), the following can be gained:

$$T_1^* = \frac{-\pi_b \pm \sqrt{(\pi_b)^2 - 4\pi_a \pi_c}}{2\pi_a} \quad (20)$$

where π_a , π_b , and π_c stand for the following:

$$\pi_a = \left\{ \begin{aligned} &\frac{v^2(h+b)}{P\lambda} + \frac{v^2(h+b)}{P^2 \left[1 - E[x] - \frac{\lambda}{P} \right]} - h + 2E[x] \\ &+ \frac{(1-E[x])h}{\lambda} [P(1-E[x]) - 2v] \\ &- 2\beta w_2 e^{-\beta T_1} - 2\beta w_5 e^{-\beta T_1} (e^{-\beta T_1 s})^{-1} + 2\beta s w_5 e^{-\beta T_1} (e^{-\beta T_1 s})^{-1} \\ &- 2\beta s w_5 e^{-\beta T_1 s} \end{aligned} \right\} \quad (21)$$

$$\pi_b = (-2\beta w_3 e^{-\beta T_1} - 2\beta s w_4 e^{-\beta T_1 s}) \quad (22)$$

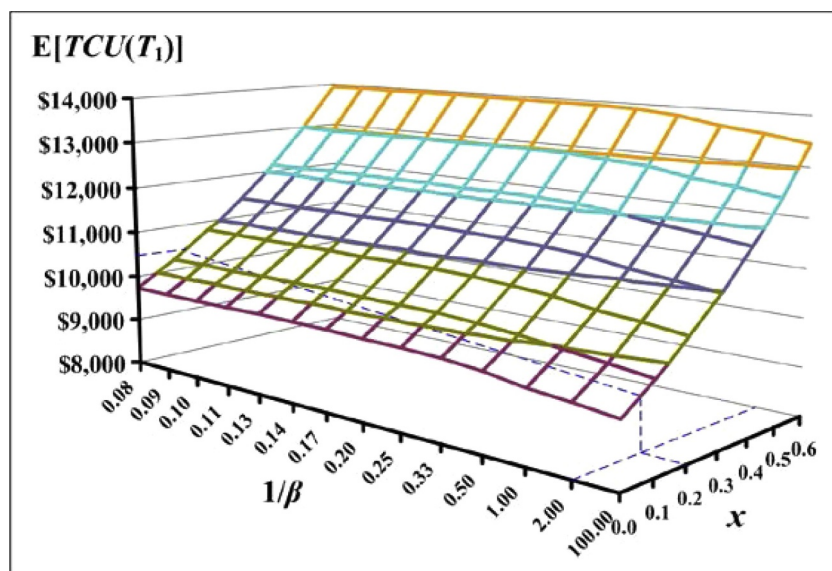


Fig. 6. Joint effects of time-to-breakdown $1/\beta$ and scrap rate x on the expected system costs $E[TCU(T_1)]$.

Table 2
Analytical results of effects of variations in service levels on different system parameters.

(1-α)%	B	H	Annual expected backordering cost	Annual expected holding cost	T ₁ [*]	E[TCU(T ₁ [*])]	Increase of cost due to a raise in (1-α)%	% of cost increase due to a raise in (1-α)%
100%	0	1746	\$0	\$764	0.3493	\$10,728.57	\$877.64	8.9%
90%	192	1730	\$1	\$694	0.3845	\$10,589.88	\$738.95	7.5%
80%	426	1706	\$4	\$624	0.4264	\$10,454.92	\$603.99	6.1%
70%	715	1667	\$11	\$554	0.4763	\$10,325.05	\$474.12	4.8%
60%	1071	1607	\$22	\$483	0.5356	\$10,202.30	\$351.37	3.6%
50%	1512	1512	\$38	\$411	0.6046	\$10,089.69	\$238.76	2.4%
40%	2043	1362	\$62	\$340	0.6810	\$9,991.65	\$140.72	1.4%
30%	2647	1134	\$93	\$271	0.7561	\$9,914.39	\$90.46	0.6%
20%	3252	813	\$131	\$210	0.8129	\$9,865.38	\$14.45	0.1%
11%	3699	457	\$165	\$169	0.8311	\$9,850.93	-	-

$$\pi_c = (-2z_1 - 2w_1 - 2w_3e^{-\beta T_1} - 2w_4e^{-\beta T_1^s}) \tag{23}$$

By rearranging Eq. (17), the following is gained:

$$e^{-\beta T_1} = \frac{-2z_1 - 2w_1 - 2w_4(e^{-\beta T_1})^s}{T_1^2\{2\beta w_2 + [2\beta w_5(e^{-\beta T_1})^{-1}]^s - [2\beta s w_5(e^{-\beta T_1})^{-1}]^s\} + T_1(2\beta w_3) + 2w_3} \tag{24}$$

Since $e^{-\beta T_1}$ is the complement of $F(T_1)$ (i.e., $(1 - e^{-\beta T_1})$), and we know that $0 \leq F(T_1) \leq 1$, hence, $0 \leq e^{-\beta T_1} \leq 1$. By using Eqs. (20) and (24), we propose a recursive algorithm based on the existence of bounds for $e^{-\beta T_1}$ and T_1^* to find the optimal replenishment runtime T_1^* as follows. Step 1: let $e^{-\beta T_1} = 0$ and $e^{-\beta T_1} = 1$; then applying Eq. (20) we can find the initial upper bound (i.e., T_{1U}) and the lower bound (i.e., T_{1L}). Step 2: substitute T_{1U} and T_{1L} in Eq. (24), respectively, to find the update values of $e^{-\beta T_1U}$ and $e^{-\beta T_1L}$. Step 3: back and forth, repeatedly computing Eqs. (20) and (24) until there is no significant difference between the upper bound T_{1U} and lower bound T_{1L} . Subsequently, T_1^* is derived.

4. Numerical example and discussion

Suppose a manufactured product has $\lambda = 4000$ units and $P = 10,000$ units per year. Shortage backordering is allowed with a predetermined eighty percent service rate (i.e., $(1-\alpha)\% = 80\%$) policy set as a minimum acceptable service level. In the manufacturing process, a uniform distributed random scrap items are produced over the range $[0, 0.2]$. All scraps are discarded in the end of each fabrication cycle. Moreover, during the process production equipment is subject to a Poisson distributed failure rate with mean $\beta = 0.5$ per year. We also assume the following values for other system variables:

$K =$ \$450,

- $C =$ \$2 (which includes unit screening cost),
- $h =$ \$0.80,
- $M =$ \$500,
- $C_S =$ \$0.30, unit disposal cost,
- $C_T =$ \$0.01, unit delivery cost,
- $C_1 =$ \$2, unit cost of safety stock,
- $h_3 =$ \$0.60, holding cost per safety stock per year,
- $g =$ 0.018 year, fixed repairing time (i.e., t_r),
- $b =$ \$0.10, unit backordering cost.

4.1. Convexity of $E[TCU(T_1)]$ and the optimal runtime

First, we verify whether or not $E[TCU(T_1)]$ is convex (Eq. (19)) at $\beta = 0.5$, by applying both upper and lower bounds of $e^{-\beta T_1}$ (Eq. (24)) and their associated runtimes (Eq. (20)), we obtain $T_{1U} = 0.6009 < \delta(T_{1U}) = 2.5055$ and $T_{1L} = 0.3698 < \delta(T_{1L}) = 2.1646$ (Additional results of the effect of variations in mean breakdown rate β on T_{1U} , $\delta(T_{1U})$, T_{1L} , and $\delta(T_{1L})$ are exhibited in Appendix C). Since Eq. (19) holds, we confirm that $E[TCU(T_1)]$ is convex. Subsequently, in order to determine the optimal runtime T_1^* , we first let $e^{-\beta T_1} = 0$ and $e^{-\beta T_1} = 1$, applying Eq. (20) to obtain the initial upper bound $T_{1U} = 0.6009$ and lower bound $T_{1L} = 0.3698$. Substituting T_{1U} and T_{1L} in Eq. (11), we obtain $E[TCU(0.6009)] = \$10,528.48$ and $E[TCU(0.3698)] = \$10,467.52$. By replacing initial values of T_{1U} and T_{1L} in Eq. (24) we have $e^{-\beta T_1U} = 0.7405$ and $e^{-\beta T_1L} = 0.8312$ as the starting exponential values for the second iteration. Following the same procedure, by repeatedly computing T_{1U} , T_{1L} , $e^{-\beta T_1U}$, and $e^{-\beta T_1L}$ back and forth until the difference between T_{1U} and T_{1L} is insignificant. Table 1 shows results of a few iterations of our recursive T_1^* searching algorithm for breakdown rate at $\beta = 0.5$ and the service level at 80%. It is noted from Table 1 that the optimal runtime $T_1^* = 0.4264$ and $E[TCU(T_1^*)] = \$10,454.92$. The behavior of $E[TCU(T_1)]$ with respect to

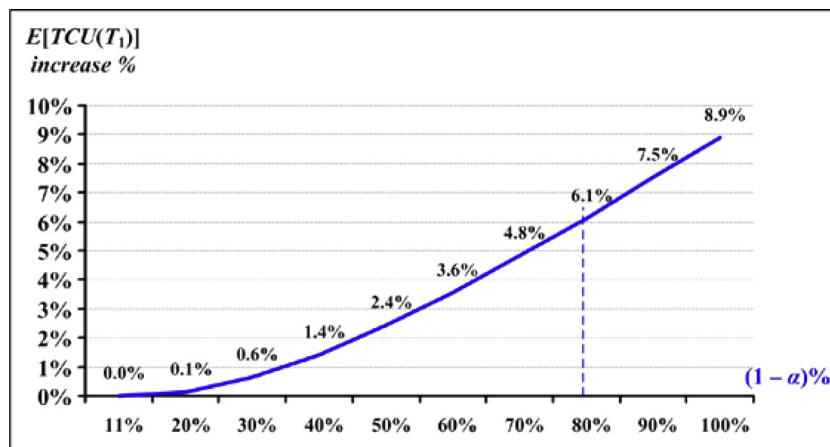


Fig. 7. Detailed increase percentages in $E[TCU(T_1)]$ with respect to various service level $(1-\alpha)\%$.

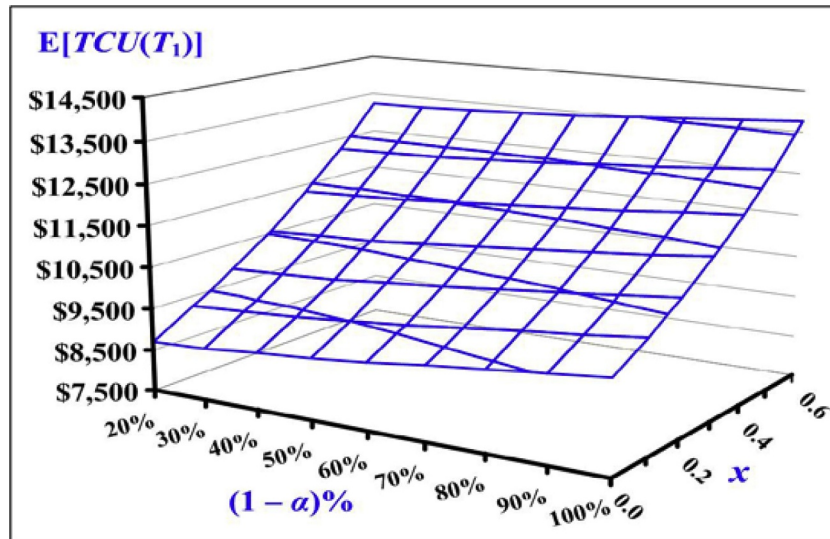


Fig. 8. The behavior of $E[TCU(T_1)]$ with respect to the service level $(1-\alpha)\%$ and the scrap rate x .

replenishment runtime T_1 is depicted in Fig. 5.

4.2. Joint effects of $1/\beta$ and x on the $E[TCU(T_1)]$

The joint effects of time-to-breakdown $1/\beta$ and the scrap rate x on $E[TCU(T_1)]$ is presented in Fig. 6. It indicated that as $1/\beta$ increases, $E[TCU(T_1)]$ declines slightly; but as x goes up, $E[TCU(T_1)]$ increases significantly.

4.3. Effects of service level $(1-\alpha)\%$ on the system parameters

Analytical results of the impacts of variations in service levels on different system parameters are exhibited in Table 2. It is noted that for the lowest systems cost, the service level falls on 11%, meaning that the system runs out of stock for 89% of the cycle time. However, such a low availability of on-hand inventories might not meet up with customer's satisfaction. Most of the firms often set a minimum acceptable service

level to maintain the customer's satisfaction, for instance, an 80% service level as we assumed in our numerical example.

The analytical result (refer to Table 2) specifies that there is a \$603.99 increase of cost due to a raise in service level from 11% to 80%, or 6.1% surge of $E[TCU(T_1)]$. Detailed increase percentages in $E[TCU(T_1)]$ with respect to various service level $(1-\alpha)\%$ is depicted in Fig. 7.

Detailed effects of service level $(1-\alpha)\%$ on the maximum back-ordering level B and its associated cost, maximum on-hand inventory level H and its related cost, the optimal runtime T_1^* , and its associated $E[TCU(T_1^*)]$ are revealed by the proposed model using this demonstrated example (Table 2).

Fig. 8 exhibits the behavior of $E[TCU(T_1)]$ relating to the service level $(1-\alpha)\%$ and the scrap rate x . It shows that as the service level $(1-\alpha)\%$ increases, $E[TCU(T_1)]$ goes slightly higher; but as x raises, $E[TCU(T_1^*)]$ increases significantly.

The joint effects of the service level $(1-\alpha)\%$ and x on optimal

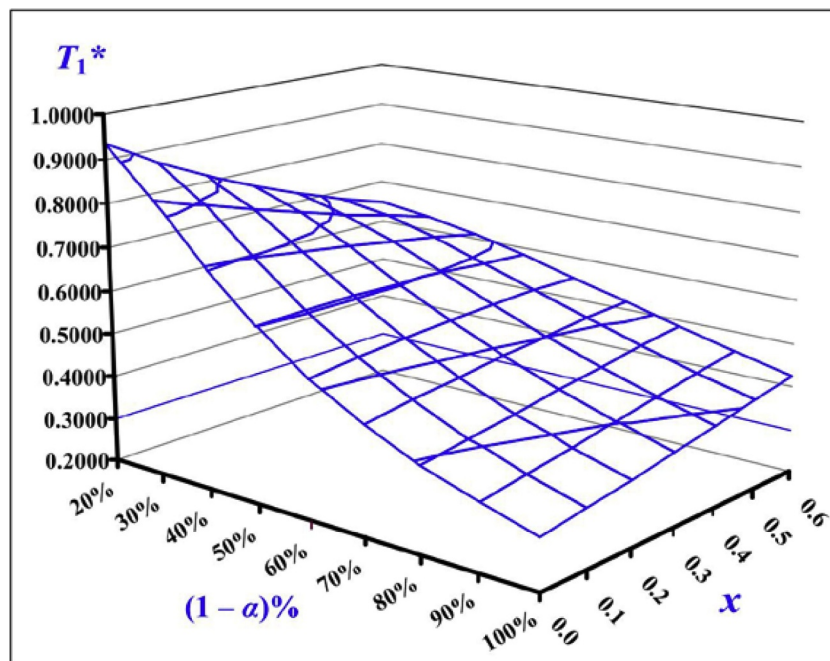


Fig. 9. Joint effects of the service level $(1-\alpha)\%$ and the scrap rate x on the optimal replenishment runtime T_1^* .

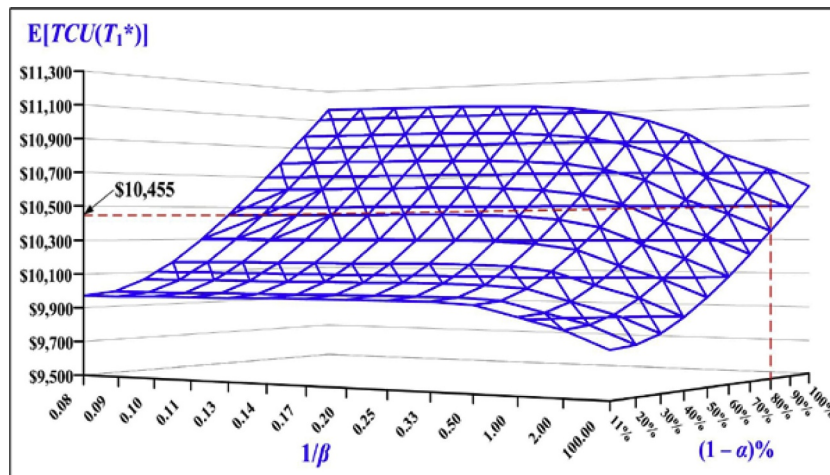


Fig. 10. The behavior of $E[TCU(T_1^*)]$ with respect to the mean-time-to-breakdown $1/\beta$ and the service level $(1 - \alpha)\%$.

runtime T_1^* is displayed in Fig. 9. It pointed out that as service level $(1-\alpha)\%$ raises, T_1^* declines significantly; and as x goes up, T_1^* increases slightly.

Fig. 10 shows the behavior of $E[TCU(T_1^*)]$ relating to the mean-time-to-breakdown $1/\beta$ and the service level $(1-\alpha)\%$. It is noted that as $1/\beta$ increases, $E[TCU(T_1^*)]$ declines; and as service level $(1-\alpha)\%$ raises, $E[TCU(T_1^*)]$ increases significantly. Suppose the mean-time-to-breakdown $1/\beta$ reaches infinite, the proposed system becomes the same as a fabrication system with scrap, backordering, and service level constraint [7]. If the service level $(1-\alpha)\%$ increases to 100%, the proposed system becomes the same as a production system with scrap and random machine breakdown [18].

4.4. Discussion and limitation

The present study constructed the production planning model based on a case where only one or no breakdowns occur during a production run. Table D1 (see Appendix D) presents the Poisson probabilities results for a machine with different mean breakdown rates per year. It indicates that for a piece of equipment in good condition, or with less than one breakdown occurrence per year, the present study is appropriate as there is over 92.88% chance that only one or no breakdowns will occur (refer to Table D1). In addition, for a machine in fair condition, or with less than or equal to two breakdown occurrences per year, our model indicates that there is over 76.27% chance of one or no breakdowns occurring (Table D1). However, to explore the production planning for a machine having a mean breakdown rate greater than three per year, a different model should be built for this specific condition.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.orp.2018.100090.

Appendix A

In Section 2.2., from Fig. 1, the following equations can be obtained:

$$T_1 = (t'_4 + t'_1) = \frac{Q}{P} \tag{A-1}$$

$$H_0 = B - (P - d - \lambda) \cdot t \tag{A-2}$$

$$H = (P - d - \lambda) \cdot t'_1 \tag{A-3}$$

$$t'_1 = \frac{Q}{P} - t'_4 \tag{A-4}$$

5. Conclusion

With the intention of offering insight information to backing managerial decision making on key operational goals, this research determines optimal runtime for a fabrication system with backordering, service level constraint, stochastic breakdown, and scrap. Consequently, a detailed solution process is presented to resolve the problem, it includes a mathematical model to portray the problem, derivation of system cost function by integrating three separate cost functions of sub-problems, a method to verify convexity of cost function, a recursive algorithm to search for the optimal fabrication runtime, a numerical illustration with sensitivity analyses to demonstrate applicability of our results.

As a result, with the in-depth exploration, various key insights relating to the joint impacts of the backlogging, service level, scrap, and random breakdown on the runtime decision are revealed (Figs. 5–10). An interesting direction for future research is to investigate the impact of a discontinuous stock issuing plan on optimal decision of the problem.

Conflicts of interest

The authors declare that they have no conflicts of interest

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$$t'_2 = \frac{H}{\lambda} \tag{A-5}$$

$$t'_3 = \frac{B}{\lambda} \tag{A-6}$$

$$t'_4 = \frac{B}{(P - d - \lambda)} \tag{A-7}$$

$$T' = \left(\sum_{i=1}^4 t'_i \right) + t_r \tag{A-8}$$

Appendix B

In Section 2.4., from Fig. 4, the following equations can be obtained:

$$T_1 = (t_4 + t_1) = \frac{Q}{P} \tag{B-1}$$

$$H = (P - d - \lambda) \cdot t_1 \tag{B-2}$$

$$t_2 = \frac{H}{\lambda} \tag{B-3}$$

$$t_3 = \frac{B}{\lambda} \tag{B-4}$$

$$t_4 = \frac{B}{(P - d - \lambda)} \tag{B-5}$$

$$T = \sum_{i=1}^4 t_i \tag{B-6}$$

Appendix C

Table C1

Table C1
The effect of variations in mean breakdown rate β on T_{1U} , $\delta(T_{1U})$, T_{1L} , and $\delta(T_{1L})$.

β	$1/\beta$	T_{1U}	$\delta(T_{1U})$	T_{1L}	$\delta(T_{1L})$
6.00	0.17	0.5780	3.9684	0.1583	0.5082
5.00	0.20	0.5784	2.9261	0.1792	0.5783
4.00	0.25	0.5790	2.2651	0.2055	0.6710
3.00	0.33	0.5801	1.8721	0.2388	0.8020
2.00	0.50	0.5822	1.7126	0.2815	1.0145
1.00	1.00	0.5885	1.9265	0.3366	1.4919
0.50	2.00	0.6009	2.5055	0.3698	2.1646
:	:	:	:	:	:
0.01	100.00	1.3428	6.3964	0.4065	5.4342

Appendix D

$$\frac{e^{-\beta t_1^*} (\beta t_1^*)^x}{x!} \tag{D-1}$$

Table D1
The probabilities of Poisson distributed breakdown rates.

β	t_1^*	$e^{-\beta t_1^*}$	βt_1^*	$P(x = 0)$	$P(x = 1)$	$P(x \leq 1)$	$P(x > 1)$
3	0.4966	0.2254	1.4898	22.54%	33.58%	56.12%	43.88%
2	0.4634	0.3959	0.9267	39.59%	36.68%	76.27%	23.73%
1.5	0.4488	0.5101	0.6732	51.01%	34.34%	85.35%	14.65%
1	0.4349	0.6473	0.4349	64.73%	28.15%	92.88%	7.12%
0.5	0.4264	0.8080	0.2132	80.80%	17.23%	98.03%	1.97%
0.01	0.4241	0.9958	0.0042	99.58%	0.42%	100.00%	0.00%

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