

A Service of

ZBW

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

Chiua, Singa Wang; Liang, Gang-Ming; Chiub, Yuan-Shyi Peter; Chiu, Tiffany

#### Article

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

**Operations Research Perspectives** 

Provided in Cooperation with:

Elsevier

*Suggested Citation:* Chiua, Singa Wang; Liang, Gang-Ming; Chiub, Yuan-Shyi Peter; Chiu, Tiffany (2019) : Production planning incorporating issues of reliability and backlogging with service level constraint, Operations Research Perspectives, ISSN 2214-7160, Elsevier, Amsterdam, Vol. 6, pp. 1-10,

https://doi.org/10.1016/j.orp.2018.100090

This Version is available at: https://hdl.handle.net/10419/246380

#### Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

#### Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



ND https://creativecommons.org/licenses/by-nc-nd/4.0







Contents lists available at ScienceDirect

**Operations Research Perspectives** 



### Operations Research Perspectives

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



Singa Wang Chiu<sup>a</sup>, Gang-Ming Liang<sup>b</sup>, Yuan-Shyi Peter Chiu<sup>b,\*</sup>, Tiffany Chiu<sup>c</sup>

<sup>a</sup> Dept. of Business Administration, Chaoyang University of Technology, Taichung 413, Taiwan

<sup>b</sup> Dept. of Industrial Engineering & Management, Chaoyang University of Technology, Taichung 413, Taiwan

<sup>c</sup> Anisfield School of Business, Ramapo College of New Jersey, Mahwah, NJ 07430, USA

#### ARTICLE INFO

Keywords: Production planning Runtime decision Stochastic breakdown Backlogging Scrap Service level constraints

#### 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

https://doi.org/10.1016/j.orp.2018.100090

Received 10 October 2018; Received in revised form 9 December 2018; Accepted 9 December 2018 Available online 11 December 2018 2214-7160/ © 2018 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license

2214-7160/ © 2018 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/BY-NC-ND/4.0/).

<sup>\*</sup> Corresponding author.

E-mail address: ypchiu@cyut.edu.tw (Y.-S.P. Chiu).

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  $\lambda$  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,
- $C_{\rm S}$  = disposal cost per item,
- $C_1$  = unit cost of safety stock,
- $C_{\rm T}$  = 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,
- $\beta$  = 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 backlogging stage.

#### 2.2. Case 1: when machine breakdowns in the backlogging 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 backlogging 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 backlogging 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 backlogging 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.

$$TC_{1}(T_{1}) = K + CQ + C_{S}xQ + M + \left[h_{3}(\lambda t_{r})\left(t + \frac{t_{r}}{2}\right) + C_{1}(\lambda t_{r})\right] + h\left[\frac{H}{2}(t_{1}') + \frac{H}{2}(t_{2}') + (dt)t_{r} + \frac{d(T_{1})}{2}(T_{1})\right] + C_{T}\left[(1 - x)Q + (\lambda t_{r})\right] + b\frac{B}{2}(t_{3}' + t_{4}') + b(H_{0})t_{r}$$
(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

$$E[TC_{1}(T_{1})] = K + CT_{1}P + T_{1}PC_{S}E[x] + M + \left[h_{3}(\lambda t_{r})\left(t + \frac{t_{r}}{2}\right) + C_{1}(\lambda t_{r})\right] + h\left[-\frac{B(1-E[x])T_{1}P}{\lambda} + \frac{(1-E[x])^{2}T_{1}^{2}P^{2}}{2\lambda} - \frac{(1-2E[x])T_{1}^{2}P}{2}\right] + bt_{r}(B - Pt + \lambda t) + (h + b)\left[\frac{B^{2}}{2(P - PE[x] - \lambda)} + \frac{B^{2}}{2\lambda} + P_{1}E[x]tt_{r}\right] + C_{T}[(1 - E[x])T_{1}P + (\lambda t_{r})]$$
(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:

$$H_1 = (P - d - \lambda) \cdot (t - t_4') \tag{3}$$

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

$$TC_{2}(T_{1}) = K + CQ + C_{S}XQ + M + \left[h_{3}(\lambda t_{r})\left(t + \frac{t_{r}}{2}\right) + C_{1}(\lambda t_{r})\right] + h\left[\frac{H_{1}}{2}(t - t_{4}') + \frac{(H_{1} + H)}{2}(T_{1} - t) + \frac{H}{2}(t_{2}') + (H_{1} + dt)t_{r} + \frac{dT_{1}}{2}(T_{1})\right] + C_{T}\left[(1 - x)Q + (\lambda t_{r})\right] + b\frac{B}{2}(t_{3}' + t_{4}')$$
(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

$$E[TC_{2}(T_{i})] = K + CT_{i}P + T_{i}PC_{S}E[x] + M + \left[h_{3}(\lambda t_{r})\left(t + \frac{t_{r}}{2}\right) + C_{1}(\lambda t_{r})\right] + h\left[-\frac{B(1 - E[x])T_{i}P}{\lambda} + \frac{T_{i}^{2}P^{2}(1 - E[x])^{2}}{2\lambda} - \frac{T_{i}^{2}P(1 - 2E[x])}{2}\right] + htt_{r}(P - \lambda) + (h + b)\left[\frac{B^{2}}{2(P - PE[x] - \lambda)} + \frac{B^{2}}{2\lambda}\right] + C_{T}[T_{i}P(1 - E[x]) + (\lambda t_{r})] - hBt_{r}$$
(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:

$$TC_{3}(T_{1}) = K + CQ + C_{S}xQ + [h_{3}(\lambda t_{r})T + C_{1}(\lambda t_{r})] + h\left[\frac{H}{2}(t_{1}) + \frac{H}{2}(t_{2}) + \frac{d(T_{1})}{2}(T_{1})\right] + C_{T}(1 - x)Q + b\frac{B}{2}(t_{4} + t_{5})$$
(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

$$E[TC_{3}(T_{1})] = K + CT_{1}P + T_{1}PC_{5}E[x] + M + \left\lfloor h_{3}(\lambda t_{r})\left(t + \frac{t_{r}}{2}\right) + C_{1}(\lambda t_{r})\right\rfloor + h\left[-\frac{B(1-E[x])T_{1}P}{\lambda} + \frac{(1-E[x])^{2}T_{1}^{2}P^{2}}{2\lambda} - \frac{(1-2E[x])T_{1}^{2}P}{2}\right] + (h+b)\left[\frac{B^{2}}{2(P-PE[x]-\lambda)} + \frac{B^{2}}{2\lambda}\right] + C_{T}[(1-E[x])T_{1}P]$$
(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  $\alpha$  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

$$E[TCU(T_{1})] = \frac{\left\{ \int_{0}^{t_{5}^{t}} E[TC_{1}(T_{1})]f(t)dt + \int_{t_{5}}^{T_{1}} E[TC_{2}(T_{1})]f(t)dt + \int_{T_{1}}^{\infty} E[TC_{3}(T_{1})]f(t)dt \right\}}{E[T]}$$
(9)

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:

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

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

$$E[TCU(T_{1})] = \frac{\lambda}{(1-E[x])} \left\{ \frac{z_{1}}{T_{1}} + T_{1} \left[ \frac{\frac{v^{2}(h+b)}{2P\lambda} + \frac{v^{2}(h+b)}{2P^{2}} - \frac{h}{2} + E[x]}{1 - E[x] - \frac{\lambda}{p}} \right] - \frac{h}{2} + E[x] \right\} + \frac{\lambda}{(1-E[x])} \left\{ + C - C_{S}E[x] + \frac{vg}{p}(b-h) + C_{T}[1-E[x]] - hv \right\} \right\} + \frac{\lambda}{(1-E[x])} \left\{ + \frac{w_{1}}{T_{1}} + w_{2}e^{-\beta T_{1}} + \frac{w_{3}e^{-\beta T_{1}}}{T_{1}} + \frac{w_{4}e^{-\beta T_{1}s}}{T_{1}} + w_{5}[e^{-\beta T_{1}(1-s)} + e^{-\beta T_{1}s}] \right\}$$

$$(11)$$

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

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

$$Y_1 = \frac{\nu T_1}{P - PE[x] - \lambda} = sT_1; s = \frac{\nu}{P - PE[x] - \lambda}$$
(13)

$$w_{1} = \left[\frac{M}{P} + \frac{h_{3}\lambda g^{2}}{2P} + \frac{h_{3}\lambda g}{\beta P} + \frac{C_{T}\lambda g}{P} + \frac{hE[x]g}{\beta} - \frac{bg(P - PE[x] - \lambda)}{\beta P}\right]$$
(14)

$$w_{2} = \left[ -\frac{h_{3}\lambda g}{P} - hg + \frac{h\lambda g}{P} \right]; w_{3} = \left[ -\frac{M}{P} - \frac{h_{3}\lambda g^{2}}{2P} - \frac{h_{3}\lambda g}{\beta P} - \frac{C_{T}\lambda g}{P} - \frac{hg}{\beta} + \frac{h\lambda g}{\beta P} \right]$$
(15)

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

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

Table 1Results 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 $T_{\rm 1U}$ and $T_{\rm 1L}$	$E[TCU(T_{1U})]$	$E[TCU(T_{1L})]$	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	<b>0.4264</b>	0.8080	<b>0.4264</b>	0.0000	<b>\$10,454.92</b>	<b>\$10,454.92</b>	\$0.00



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

$$\frac{dE[TCU(T_{1})]}{dT_{1}} = \frac{\lambda}{(1-E[x])} \left\{ -\frac{z_{1}}{T_{1}^{2}} + \begin{bmatrix} \frac{\nu^{2}(h+b)}{2P\lambda} + \frac{\nu^{2}(h+b)}{2P^{2}\left[1-E[x]-\frac{\lambda}{P}\right]} - \frac{h}{2} + E[x] \\ + \frac{(1-E[x])}{\lambda} \begin{bmatrix} \frac{hP(1-E[x])}{2} - hv \end{bmatrix} \end{bmatrix} \right\} \\ + \frac{\lambda}{(1-E[x])} \left\{ -\frac{w_{1}}{T_{1}^{2}} - \beta w_{2}e^{-\beta T_{1}} - \frac{\beta w_{3}e^{-\beta T_{1}}}{T_{1}} - \frac{w_{3}e^{-\beta T_{1}}}{T_{1}^{2}} - \frac{\beta sw_{4}e^{-\beta T_{1}s}}{T_{1}} \\ - \frac{w_{4}e^{-\beta T_{1}s}}{T_{1}^{2}} \\ -\beta w_{5}e^{-\beta T_{1}}(e^{-\beta T_{1}s})^{-1} + \beta sw_{5}e^{-\beta T_{1}}(e^{-\beta T_{1}s})^{-1} - \beta sw_{5}e^{-\beta T_{1}s} \\ \end{bmatrix}$$
(17)

$$\frac{d^{2}E\left[TCU\left(T_{1}^{i}\right)\right]}{dT_{1}^{2}} = \frac{\lambda}{\left(1-E\left[x\right]\right)} \begin{cases} \frac{2z_{1}}{T_{1}^{3}} + \frac{2w_{1}}{T_{1}^{3}} + \beta^{2}w_{2}e^{-\beta T_{1}} + \frac{\beta^{2}w_{3}e^{-\beta T_{1}}}{T_{1}} + \frac{2\beta w_{3}e^{-\beta T_{1}}}{T_{1}^{2}} \\ + \frac{2w_{3}e^{-\beta T_{1}}}{T_{1}^{3}} + \frac{\beta^{2}s^{2}w_{4}e^{-\beta T_{1}s}}{T_{1}} + \frac{2\beta w_{4}e^{-\beta T_{1}s}}{T_{1}^{2}} + \frac{2w_{4}e^{-\beta T_{1}s}}{T_{1}^{3}} \\ + \beta^{2}w_{5}e^{-\beta T_{1}}(e^{-\beta T_{1}s})^{-1}(1-2s+s^{2}) + \beta^{2}s^{2}w_{5}e^{-\beta T_{1}s} \end{cases} \end{cases}$$
(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:



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:

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

where  $\pi_{\alpha}$ ,  $\pi_b$ , and  $\pi_c$  stand for the following:

$$\pi_{a} = \begin{cases} \frac{\nu^{2}(h+b)}{P_{\lambda}} + \frac{\nu^{2}(h+b)}{P^{2}\left[1-E[x] - \frac{\lambda}{P}\right]} - h + 2E[x] \\ + \frac{(1-E[x])h}{\lambda} [P(1-E[x]) - 2\nu] \\ - 2\beta w_{2}e^{-\beta T_{1}} - 2\beta w_{5}e^{-\beta T_{1}}(e^{-\beta T_{1}s})^{-1} + 2\beta s w_{5}e^{-\beta T_{1}}(e^{-\beta T_{1}s})^{-1} \\ - 2\beta s w_{5}e^{-\beta T_{1}s} \end{cases}$$
(21)

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



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

- 11

Table 2							
Analytical	results of effect	ts of variation	s in service	levels on	different	system	parameters.

(1–α)%	В	Н	Annual expected backordering cost	Annual expected holding cost	$T_1^*$	E[TCU(T <sub>1</sub> *)]	Increase of cost due to a raise in $(1-\alpha)\%$	% of cost increase due to a raise in $(1-\alpha)$ %
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	-	-

(23)

$$\pi_{c} = \left(-2z_{1} - 2w_{1} - 2w_{3}e^{-\beta T_{1}} - 2w_{4}e^{-\beta T_{1}s}\right)$$

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

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

Since  $e^{-\beta T}$  is the complement of  $F(T_1)$  (i.e.,  $(1 - e^{-\beta T})$ ), and we know that  $0 \leq F(T_1) \leq 1$ , hence,  $0 \leq e^{-\beta T} \leq 1$ . By using Eqs. (20) and (24), we propose a recursive algorithm based on the existence of bounds for  $e^{-\beta T}$  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.,  $T_{11}$ ). Step 2: substitute  $T_{111}$  and  $T_{11}$  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  $T_{111}$  and lower bound  $T_{11}$ . 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:

C =\$2 (which includes unit screening cost).

h =\$0.80. M =\$500.  $C_{\rm S} =$ 

\$0.30, unit disposal cost, \$0.01, unit delivery cost,

 $C_{\rm T} =$ \$2, unit cost of safety stock,  $C_1 =$ 

 $h_{3} =$ \$0.60, holding cost per safety stock per year,

g = 0.018 year, fixed repairing time (i.e.,  $t_r$ ),

h =\$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  $e^{-\beta T}$  (Eq. (24)) and their associated runtimes (Eq. (20)), we obtain  $T_{1\rm U} = 0.6009 < \delta(T_{1\rm U}) = 2.5055$  and  $T_{1\rm L} = 0.3698 < \delta(T_{1\rm L}) = 2.1646$ (Additional results of the effect of variations in mean breakdown rate  $\beta$ 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  $T_{1\rm U}$  = 0.6009 and lower bound  $T_{1\rm L}$  = 0.3698. Substituting  $T_{1\rm U}$  and  $T_{1\rm L}$ 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 backordering 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 meantime-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:

$T_1 = (t'_4 + t'_1) = \frac{Q}{P}$	(A-1)
$H_0 = B - (P - d - \lambda) \cdot t$	(A-2)
$H = (P - d - \lambda) \cdot t_1'$	(A-3)
$t_1' = \frac{Q}{P} - t_4'$	(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

#### Acknowledgement

This work was sponsored by the Ministry of Science and Technology of Taiwan (under grant no. MOST 103-2410-H-324-006-MY2).

$$t'_{2} = \frac{H}{\lambda}$$

$$t'_{3} = \frac{B}{\lambda}$$
(A-5)
(A-6)

$$t'_{4} = \frac{B}{(P - d - \lambda)}$$

$$T' = \left(\sum_{i=1}^{4} t'_{i}\right) + t_{r}$$
(A-7)
(A-8)

#### Appendix B

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

$$T_1 = (t_4 + t_1) = \frac{Q}{P}$$

$$H = (P - d - \lambda) \cdot t_1$$
(B-1)
(B-2)
(B-2)

$$t_2 = \frac{H}{\lambda}$$
(B-3)  
$$t_1 = \frac{B}{\lambda}$$

$$t_{4} = \frac{B}{(P-d-\lambda)}$$
(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  $\beta$  on  $T_{1\rm U}$ ,  $\delta(T_{1\rm U})$ ,  $T_{1\rm L}$ , and  $\delta(T_{1\rm L})$ .

β	$1/\beta$	$T_{1U}$	$\delta(T_{1\mathrm{U}})$	$T_{1\mathrm{L}}$	$\delta(T_{\rm 1L})$
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

## $\frac{e^{-\beta t_1^*}(\beta t_1^*)^x}{x!}$

Table D1

The probabilities of Poisson distributed breakdown rates.

β	$t_1^*$	$e^{-\beta t_1^*}$	$\beta t_1^*$	P(x=0)	P(x=1)	$P(x \le 1)$	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%

(D-1)

- [1] Taft EW. The most economical production lot. Iron Age 1918;101:1410–2.
- [2] Nahmias S. Production & operations analysis. New York: McGraw-Hill Inc.; 2009.[3] Aucamp DC, Fogarty DW. EOQ with limited backorder delays. Comput Oper Res
- 1984;11(3):333–5. [4] de Kok AG. Approximation for a lost-sales production/inventory control model with
- service level constraints. Manage Sci 1985;31(6):729–37. [5] Aucamp DC. Aggregate backorder exchange curves. IIE Trans 1990;22(3):281–7.
- [6] Boyaci T, Gallego G. Minimizing holding and ordering costs subject to a bound on backorders is as easy as solving a single backorder cost model. Oper Res Lett 2001;29(4):187–92.
- [7] Chiu Y-SP. The effect of service level constraint on EPQ model with random defective rate. Math Probl Eng 2006;2006:98502.
- [8] Jaggi CK, Khanna A. Nidhi. Effects of inflation and time value of money on an inventory system with deteriorating items and partially backlogged shortages. Int J Ind Eng Comput 2016;7(2):267–82.
- [9] Rakyta M, Fusko M, Herčko J, Závodská L, Zrnić N. Proactive approach to smart maintenance and logistics as a auxiliary and service processes in a company. J Appl Eng Sci 2016;14(4):433–42.
- [10] Salemi H. A hybrid algorithm for stochastic single-source capacitated facility location problem with service level requirements. Int J Ind Eng Comput 2016;7(2):295–308.
- [11] Jindal P, Solanki A. Integrated supply chain inventory model with quality improvement involving controllable lead time and backorder price discount. Int J Ind Eng Comput 2016;7(3):463–80.
- [12] Chiu SW, Liu C-J, Chen Y-R, Chiu Y-SP. Finite production rate model with backlogging, service level constraint, rework, and random breakdown. Int J Eng Model 2017;30(1–4):63–80.
- [13] Oblak L, Kuzman MK, Grošelj P. A fuzzy logic-based model for analysis and evaluation of services in a manufacturing company. J Appl Eng Sci 2017;15(3):258–71.
- [14] Mak KL. Inventory control of defective products when the demand is partially captive. Int J Prod Res 1985;23(3):533–42.
- [15] Widmer M, Solot P. Do not forget the breakdowns and the maintenance operations in FMS design problems. Int J Prod Res 1990;28(2):421–30.
- [16] Groenevelt H, Pintelon L, Seidmann A. Production lot sizing with machine breakdowns. Manage Sci 1992;38(1):104–23.
- [17] Widyadana GA, Wee H-M. An economic production quantity model for deteriorating items with preventive maintenance policy and random machine breakdown. Int J Syst Sci 2012;43(10):1870–82.
- [18] Chiu SW, Chou C-L, Wu W-K. Optimizing replenishment policy in an EPQ-based inventory model with nonconforming items and breakdown. Econ Model 2013;35:330–7.
- [19] Porteus EL. Optimal lot sizing, process quality improvement and setup cost reduction. Oper Res 1986;34:137–44.
- [20] Makis V. Optimal lot sizing and inspection policy for an EMQ model with imperfect

inspections. Naval Res Log 1998;45(2):165-86.

- [21] Wee H-M, Yu J, Chen MC. Optimal inventory model for items with imperfect quality and shortage back ordering. Omega 2007;35:7–11.
- [22] Lin GC, Gong D-C, Chang C-C. On an economic production quantity model with two unreliable key components subject to random failures. J Sci Ind Res India 2014;73(3):149–52.
- [23] Yeh T-M, Pai F-Y, Liao C-W. Using a hybrid MCDM methodology to identify critical factors in new product development. Neural Comput Appl 2014;24(3):957–71.
- [24] Jawla P, Singh SR. Multi-item economic production quantity model for imperfect items with multiple production setups and rework under the effect of preservation technology and learning environment. Int J Ind Eng Comput 2016;7(4):703–16.
- [25] Zhang D, Zhang Y, Yu M. A machining process oriented modeling approach for reliability optimization of failure-prone manufacturing systems. J Eng Res 2016;4(3):128–43.
- [26] Kaylani H, Almuhtady A, Atieh AM. Novel approach to enhance the performance of production systems using lean tools. Jordan J Mech Ind Eng 2016;10(3):215–29.
- [27] Aboumasoudi AS, Mirzamohammadi S, Makui A, Tamosaitiene J. Development of network-ranking model to create the best production line value chain: a case study in textile industry. Econ Comput Econ Cyber Stud Res 2016;50(1):215–34.
- [28] Majumder P, Mondal SP, Bera UK, Maiti M. Application of Generalized Hukuhara derivative approach in an economic production quantity model with partial trade credit policy under fuzzy environment. Oper Res Persp 2016;3:77–91.
- [29] Nazir M, Khan AQ, Mustafa G, Abid M. Robust fault detection for wind turbines using reference model-based approach. J King Saud Univ Eng Sci 2017;29(3):244–52.
- [30] Chiu Y-SP, Liu C-J, Hwang M-H. Optimal batch size considering partial outsourcing plan and rework. Jordan J Mech Ind Eng 2017;11(3):195–200.
- [31] Ghalme S, Mankar A, Bhalerao Y. Integrated Taguchi-simulated annealing (SA) approach for analyzing wear behaviour of silicon nitride. J Appl Res Technol 2017;15(6):624–32.
- [32] Abubakar M, Basheer U, Ahmad N. Mesoporosity, thermochemical and probabilistic failure analysis of fired locally sourced kaolinitic clay. J Assoc Arab Univ Basic Appl Sci 2017;24:81–8.
- [33] Ashfaq H, Hussain I, Giri A. Comparative analysis of old, recycled and new PV modules. J King Saud Univ Eng Sci 2017;29(1):22–8.
- [34] Chiu SW, Liu C-J, Li Y-Y, Chou C-L. Manufacturing lot size and product distribution problem with rework, outsourcing and discontinuous inventory distribution policy. Int J Eng Model 2017;30(1–4):49–61.
- [35] Kazemi SM, Rabbani M, Tavakkoli-Moghaddam R, Shahreza FA. An exact solution for joint optimization of inventory and routing decisions in blood supply chains: a case study. Econ Comput Econ Cyber Stud Res 2017;51(4):315–33.
- [36] Settanni E, Harrington TS, Srai JS. Pharmaceutical supply chain models: a synthesis from a systems view of operations research. Oper Res Persp 2017;4:74–95.
- [37] Saari J, Odelius J. Detecting operation regimes using unsupervised clustering with infected group labelling to improve machine diagnostics and prognostics. Oper Res Persp 2018;5:232–44.