An Economic Production Quantity Model for Smart and Connected Product with Upstream and Downstream Trade Credit

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Abstract

This study investigates an inventory model considering the effect of smart and connected product. The advanced development of technology, such as the Internet of Things (IoT), has transformed traditional physical products into smart and connected products equipped with sensors, artificial intelligence (AI), and information technology. This transformation adds new product capabilities, including the ability to monitor surroundings, product functions control, and performance enhancement based on the level of technology embedded in the product. In this study, a manufacturer produces a smart and connected product, where demand increase as the selling price decreases and the number of sensors embedded in the product increases. Moreover, in practice, the manufacturer often receives a permissible delay in payment, also called trade credit, from the supplier while also offering it to the customer to attract more sales. Hence, this paper aims to determine the optimal selling price, the number of embedded sensors, and lot size in a single product to maximize the manufacturer's profit under the upstream and downstream trade credit. An economic production quantity (EPQ) model is developed and the conditions of the optimal solution are derived. A numerical example is solved to illustrate the theoretical results and solution approach.

Keywords
EPQ inventory model, Smart and connected products, Pricing, Lot-sizing, and Trade credit.

1. Introduction
By the year 2025, it is predicted that more than 41.6 billion connected devices will be available worldwide (World Economic Forum, 2020). This phenomenon is enabled by the advanced development of technology, such as the Internet of Things (IoT), which connects objects, machines, and people, and Artificial Intelligence (AI) to make highly

informed decisions. The emergence of IoT underlies the rise of smart and connected products (SCP) (Porter and Heppelmann, 2014). These SCPs are composed of physical, smart, i.e., the sensors, microprocessors, and connectivity components, i.e., the ports, antennae, and protocols (Porter and Heppelmann, 2014). SCP markets have been growing quite rapidly. For instance, in 2020, around 801.5 million smart home products have been delivered and were forecasted to surpass 1.4 billion by 2025 (IDC, 2021). Companies increasingly recognize the need to create value beyond the traditional product to improve customer relationships and remain competitive. SCP can offer various new values through enhanced capabilities and performances, including the ability to monitor surroundings, product functions control, and performance enhancement based on the level of technology embedded in the product.

The more functionality a product has would undoubtedly increase the selling price, which may not be followed by an increase in sales as customers view the product as unaffordable. Moreover, price is one of the main purchase barriers and negatively influence customer's decision to purchase SCP (Nikou, 2019). Contrarily, the product's perceived usefulness drives customers to buy SCP (Gao et al. 2016, Shin et al. 2018). Hence, in this paper, the SCP's demand is assumed to increase when the selling price decreases and the number of sensors increases. Increasing the number of sensors embedded in SCP is a way for the manufacturer of SCP to improve the product capabilities and thus perceived usefulness. An economic production quantity (EPQ) model is developed to determine the optimal selling price, the number of sensors, and the production lot size that would simultaneously maximize the manufacturer's profit.

In the traditional EPQ model, the buyer is assumed to pay the seller the entire payment of the ordered items when receiving them. However, in real life, the seller often offers buyers a credit period where the buyer receives the items ordered without paying until sometime later. During this credit period, the buyer can retain interest revenues by saving the revenues in an interest-bearing account. When the credit period ends, the buyer must pay according to the purchase amount and finance all items not paid by customers. Trade credit is ubiquitous in business transactions (Wilson and Summers, 2002) and is particularly suited for SCP in helping to reduce the perceived price barrier.

There has been extensive research addressing the situation where the seller offers trade credit. Goyal (1985) first explored a single item economic order quantity (EOQ) model where the supplier provides permissible delay for his customer. Teng (2002) expanded Goyal's model to differentiate unit price and unit cost and found that it is economically reasonable for some customers to order less to gain trade credit benefit more frequently. Chung and Huang (2003) extended to the case that all items are replenished at a finite rate, following the EPQ model. Huang (2003) further developed the model where the retailer receives the trade credit period from the supplier and offers it to the customer, also called the two-level trade credit. A detailed review of trade credit can be seen in Seifert et al. (2013).

Selling price is one of the critical factors affecting the products' demand. Teng et al. (2005) expanded the case for deteriorating items where demand is a function of price and supplier gives the buyer a permissible delay in payment. Liao (2007) amended Goyal's model using a finite rate and considered the difference in selling price and selling cost. The case was extended to where inventory is reduced due to demand and a constant deterioration rate. Mahata (2012) developed the EPQ model under trade credit where the items are deteriorating at a steady pace. The retailer receives full trade credit from the supplier but instead gives a partial downstream trade credit to the customer to gain the most benefit. Giri and Maiti (2013) develop a model where demand is sensitive to selling price and trade credit under a profit-sharing contract. Chen et al. (2014) developed an EPQ model closely related to Mahata (2012), but calculated the interest earned and interest payable differently by including the fact that the seller offers customers permissible delay of N, hence receives revenues from N to $T+N$, not from 0 to T. Wu et al. (2016) study an EOQ model where the retailer gets an upstream full trade credit from the supplier and offers downstream partial trade credit to credit-risk customers for perishable items with maximum lifetime. The research related to pricing and trade credits is summarized in Table 1.

To the best of the authors' knowledge, there is yet research that specifically considers SCP, i.e., the number of sensors in SCP as a decision variable and a factor that influences products demand. Thus, to summarize, this research contributes through the following: (1) propose an EPQ model that considers the selling price, the number of sensors, and production cycle time as decision variables for SCP under the upstream and downstream trade credit, (2) consider the demand of SCP as the combined effect of selling price and number of sensors, and (3) provide a numerical example.

The rest of this paper is organized as follows. In Section 2, we present the mathematical models for the different cases of trade credit. Then, we derive the results and optimal solutions in Section 3. In Section 4, we provide a numerical example and solve it to illustrate the mathematical models. Finally, the conclusions and suggestions for future research direction are discussed in Section 5.

Table 1. A comparison of our model with previous works

References	Demand function	Trade Credit	Decision Variable
Min et al. (2012)	Constant	Upstream	Lot-sizing
Wu et al. (2014)	Price & stock	Upstream	Lot-sizing & ending inventory level
Wu and Chan (2014)	Constant	Two-level	Lot-sizing
Feng et al. (2013)	Constant	Two-level	Lot-sizing
Feng et al. (2017)	Price & time	No	Lot-sizing, pricing & ending stock
Tiwari et al. (2018)	Price	Two-level	Lot-sizing, pricing & time for inventory to reach zero
Feng and Chan (2019)	Price	Two-level	Lot-sizing & pricing
This paper	Price & number of sensors	Two-level	Lot-sizing, pricing & number of sensors

2. Model Formulation

The followings are the notation and assumptions used.

Decision Variables:

T^*	the manufacturer's optimal production cycle time	(years)
S^*	the manufacturer's optimal number of sensors	(number/product)
P^*	the manufacturer's optimal selling price	(\$/product)
Parameters:		
a	price coefficient on demand	
b	number of sensors coefficient on demand	
c	product component cost	(\$/product)
c_s	cost of sensors	(\$/sensor level)
d	the manufacturer's downstream credit period to customers	(years)
u	the manufacturer's upstream credit period from the supplier	(years)
h	the inventory holding cost excluding interest charge	(\$/unit/year)
p	the annual production rate that is larger than the annual demand rate	(units)
X_e	the interest rate earned	(\$/year)
X_c	the interest rate charged	(\$/year)
K	the maximum number of potential customers with $p \geq K$	
o	set-up cost	(\$/production run)
Functions		
$D(P,S)$	the annual demand rate as a function of unit selling price P and number of sensors S	(units)
Q	the manufacturer's production lot size $Q = D(P,S)T$	(units)
$\Pi(P,S,T)$	the manufacturer's profit function	(\$/year)

The product's demand is depicted as:

$$D(P,S) = Ke^{-aP}S^b, \tag{1}$$

where $K, a, b > 0$. $D(P,S)$ and D is used interchangeably. Increasing number of sensors is an effort to raise a level in product intelligence or capabilities. The cost of sensor is then assumed to be the same for any type of sensor. Moreover, we consider the replenishment by the supplier to be instant, lead time negligible, and shortages not allowed. Therefore, there are neither backorders nor lost sales.

We consider a supply chain consists of supplier, manufacturer, and customer. The manufacturer produces smart and connected products, orders the product's component and sensors from the supplier, and sells the finished product to the customers. The supplier provides an upstream trade credit period to the manufacturer while the manufacturer provides a downstream trade credit period to the customers. The manufacturer must determine the optimal selling price *P*, production lot size *Q,* and number of sensors *S* of a single smart and connected product simultaneously to maximize the yearly profit $\Pi(P,S,T)$. Based on the production cycle time and trade credit period, the cases can be categorized as: (1) case 1: $u \geq d$ and $u \leq T+d$, in which the manufacturer save sales revenue from d (where customers start to pay as the downstream period ends) in an interest-bearing account and gain revenues interest until the upstream period ends at *u*. He then must finance all items sold after $u-d$ with interest charged until $T+d$ (the last payment made by customers), (2) case 2: $u \geq d$ and $u \geq T+d$, in which the manufacturer start to receive revenue at *d* and save it to gain interest revenues until $T+d$, where customer last pay for the products. Hence, there is no more increases in revenues earned until *u*, when manufacturer pay back the purchase fees to the supplier without interest charged, and (3) case 3: $u \leq d$, where the manufacturer has not received revenues even at time *u*, and he must finance the purchase fees to the supplier at *u* to *d*, and start paying off the loan and interest charged from time d (when customers start to pay) until $T+d$ (last payment made by customers). The annual manufacturer's profit is then formulated as follows:

$\Pi(P,S,T) =$ Sales revenue (SR) − product cost (PC) − set-up cost (SC) − holding cost (HC) − interest charged (IC) − interest earned (IE)

Hence, for case 1, 2 and 3, the followings are the annual manufacturer's profit, respectively. Notice that for case 2 only has interest earned, while case 3 only has interest charged.

$$\Pi_1(P,S,T) = PD - (c+c_sS)D - \frac{o}{T} - \frac{hDT}{2}\left(1-\frac{D}{p}\right) - \frac{1}{2T}(c+c_sS)DX_c(T+d-u)^2 + \frac{1}{2T}PDX_e(u-d)^2 \tag{2}$$

$$\Pi_2(P,S,T) = PD - (c+c_sS)D - \frac{o}{T} - \frac{hDT}{2}\left(1-\frac{D}{p}\right) + PDX_e\left(u-d-\frac{T}{2}\right) \tag{3}$$

$$\Pi_3(P,S,T) = PD - (c+c_sS)D - \frac{o}{T} - \frac{hDT}{2}\left(1-\frac{D}{p}\right) - (c+c_sS)DX_c\left(d-u+\frac{T}{2}\right) \tag{4}$$

3. Results

To solve the model, the necessary and sufficient condition for each of the cases' concavity are proven to obtain the unique optimal decision variables' solution that would maximize the manufacturer's annual profit. The necessary condition is established by taking the first-order partial derivative of the profit with respect to the decision variable. The sufficient condition is fulfilled if the second-order partial derivative is less than zero. For any given unit selling price *P* and number of sensors *S*, the first and second-order partial derivative of $\Pi_1(P,S,T)$ with respect to *T* are:

$$\frac{\partial \Pi_1(P,S,T)}{\partial T} = -\frac{1}{2}D(h(1-\frac{D}{p}) + X_c(c+c_sS)) - (-\frac{1}{2T^2})[2o + D(u-d)^2(X_c(c+c_sS) - PX_e)] \tag{5}$$

and

$$\frac{\partial^2 \Pi_1(P,S,T)}{\partial T^2} = -\frac{1}{T^3}\left[2o - D(u-d)^2\left(PX_e - X_c(c+c_sS)\right)\right] < 0 \tag{6}$$

Hence, $\Pi_1(P,S,T)$ is a strictly concave function on T if $2o - D(u-d)^2(PX_e - (c+c_sS)X_c) > 0$. The optimal production cycle time for the case of $u \geq d$ and $u \leq T+d$ is thus:

$$T_1 = \sqrt{\frac{2o - D(u-d)^2[PX_e - (c+c_sS)X_c]}{D[(c+c_sS)X_c + h(1-\frac{D}{p})]}}, \text{ if } 2o - D(u-d)^2[PX_e - (c+c_sS)X_c] > 0 \tag{7}$$

For any given unit selling price *P* and number of sensors *S*, $\Pi_2(P,S,T)$ and $\Pi_3(P,S,T)$ is a strictly concave function in T. Similarly, the derivation into the second-order results:

$$\frac{\partial^2 \Pi_2(P,S,T)}{\partial T^2} = -\frac{2o}{T^3} < 0 \tag{8}$$

The same result is obtained for $\Pi_3(P,S,T)$. Hence, both derivatives are less than 0. The optimal production cycle times for case 2 and 3 then are listed as follow:

$$T_2 = \sqrt{\frac{2o}{D[PX_e + h(1-\frac{D}{p})]}} \tag{9}$$

(10)

$$T_3 = \sqrt{\frac{2o}{D[X_c(c+c_sS)+h(1-\frac{D}{p})]}}$$

Hence, the optimal production lot size for all cases can be attained by $Q = D(P,S)T$.

For any given unit selling price *P* and production cycle time *T*, the first and second-order partial derivative of $\Pi_1(P,S,T)$ with respect to S is:

$$\frac{\partial\Pi_1(P,S,T)}{\partial S} = \frac{bDP}{S} - \frac{D}{S}(c_sS + b(c+c_sS)) + \frac{bDhT}{S}(\frac{D}{p}-\frac{1}{2}) - (c_sS + b(c+c_sS))\frac{D(d+T-u)^2X_c}{2TS} + \frac{bD(-d+u)^2X_e}{2TS} \tag{11}$$

$$\frac{\partial^2\Pi_1(P,S,T)}{\partial S^2} = -\frac{bDP}{S^2}(1-b) - \frac{bD}{S^2}(c_sS + b(c+c_sS)-c) + \frac{bDhT}{S^2}\left(\frac{D(2b-1)}{p}+\frac{1}{2}(1-b)\right) - \frac{bD(d+T-u)^2X_c}{2TS^2}(c_sS+b(c+c_sS)-c) - \frac{bDP(u-d)^2X_e}{2TS^2}(1-b) \tag{12}$$

The first three terms in (12) are associated to sales revenue, product cost, and holding cost. Meanwhile, the remaining two terms are related to interest charged and interest earned. Thus, the only positive term is holding cost, which is generally smaller than sales revenue and production cost. Accordingly, $\frac{\partial^2\Pi(P,S,T)}{\partial S^2} \le 0$ if $1 \ge b$ and $c_sS + b(c+c_sS) \ge c$. Case 2 and case 3 result in similar terms such as in case 1, with the only differences are in the interest earned and charged. Hence with the same analogous argument, $\Pi_1(P,S,T)$, $\Pi_2(P,S,T)$ and $\Pi_3(P,S,T)$ are concave in S.

For any given number of sensors *S* and production cycle time *T,* the first and second-order partial derivative of $\Pi_1(P,S,T)$ with respect to *P* is:

$$\frac{\partial\Pi_1(P,S,T)}{\partial P} = D(1-aP) + aD(c+c_sS) - aDhT(\frac{D}{p}-\frac{1}{2}) + \frac{aD(d+T-u)^2(c+c_sS)X_c}{2T} + \frac{D(-d+u)^2X_e}{2T}(1-aP) \tag{13}$$

$$\frac{\partial^2\Pi_1(P,S,T)}{\partial P^2} = -aD(2-aP) - a^2D(c+c_sS) + a^2DhT\left(\frac{2D}{p}-\frac{1}{2}\right) - \frac{aD(u-d)^2X_e}{2T}(2-aP) - \frac{a^2D(d+T-u)^2X_c(c+c_sS)}{2T} \tag{14}$$

Similarly, the only positive terms in (14) are from holding cost, which is generally smaller than the sales revenue and production cost. Accordingly, $\frac{\partial^2\Pi(P,S,T)}{\partial P^2} \le 0$ if $2 \ge aP$. Case 2 and case 3 for the case of *P* also result in similar terms such as in case 1, with the exception in the interest earned and interest charged, hence with the same analogous argument, it is proven that $\Pi_1(P,S,T)$, $\Pi_2(P,S,T)$ and $\Pi_3(P,S,T)$ is a strictly concave function in *P*. This proves the existence of optimal *T, S,* and *P* that would maximize the manufacturer's total annual profit.

There are two possible solutions between the first and second case ($u \ge d$), either T_1^* or T_2^*. To locate the optimal solution T^*, a discrimination term $\Delta(T)$ is defined to be the first-order partial derivative of (2) or (3) with respect to *T*, as follow:

$$\Delta(T) = \frac{o}{T^2} - \frac{D(P,S)}{2}\left[PX_e + h\left(1-\frac{D(P,S)}{p}\right)\right] \tag{15}$$

The following theoretical results can be drawn by combining the results of the previous derivation and applying (15). For any given unit selling price *P,* the number of sensors *S*, and $u \ge d$.

(a) if $\Delta(u-d) < 0$, then the manufacturer's optimal cycle time is $T^* = T_2$.
(b) if $\Delta(u-d) = 0$, then the manufacturer's optimal cycle time is $T^* = u - d$.
(c) if $\Delta(u-d) > 0$, then the manufacturer's optimal cycle time is $T^* = T_1$.

As $\Pi_2(T)$ is strictly concave in T and from (15), it can be determined that,

$$\lim_{T\to 0} \Delta(T) = \infty, \tag{16}$$

If $\Delta(u-d) < 0$, then by (16) and applying the Mean-value Theorem, there exists a unique $T_2^* \in (0, u-d)$ such that $\Delta(T_2^*) = 0$. Hence, $\Pi_2(T)$ is maximized at the unique point T_2^*, which implies:

$$\Pi_2(T_2^*) \geq \Pi_2(T_2) \text{ for all } T_2 \leq u-d, \text{ and hence } \Pi_2(T_2^*) \geq \Pi_2(u-d). \tag{17}$$

Similarly, $\Pi_1(T)$ is strictly concave in T, and,

$$\lim_{T\to\infty} \Delta(T) = -\frac{D}{2}\left[P X_e + h\left(1-\frac{D}{p}\right)\right] < 0. \tag{18}$$

If $\Delta(u-d) < 0$, by (18) it is known that the first-order derivative of (2) with respect to T is $\Delta(T) < 0$ for all $T \geq u-d$. Thus, $\Pi_1(T)$ is decreasing and maximized at $u-d$.

Hence,

$$\Pi_1(u-d) \geq \Pi_1(T_1), \text{ for all } T_1 \geq u-d. \tag{19}$$

If $\Delta(u-d) < 0$ then,

$$\Pi_2(T_2^*) \geq \Pi_2(u-d) = \Pi_1(u-d) \geq \Pi_1(T_1), \text{ for all } T_1 \geq u-d. \tag{20}$$

By using a similar argument, one can prove for $\Delta(u-d) = 0$ and $\Delta(u-d) > 0$.

Due to the complexity of the problem, we cannot find the jointly concave or pseudo-concave function of $\Pi(P, S, T)$ with respect to P, S, and T. Hence, a search algorithm is built based on the theoretical results and conditions derived to find the value S, P, and T that would jointly maximize the manufacturer's annual profit.

4. Numerical Example

To illustrate the mathematical model formulated, a numerical example is provided for the case of $u \geq d$. The following parameters are assumed in manufacturing an SCP: component cost $c = \$35$ per unit, cost of sensor $c_s = \$20$, downstream trade credit period $d = 0.08$ years, upstream trade credit period $u = 0.25$ years, inventory holding cost $h = \$10$ per unit per year, production rate $p = 5000$ units, set-up cost $o = \$20$ per order, interest earned $X_e = 0.03$ per year, interest charged $X_c = 0.05$ per year, and demand rate $D(P,S) = 3000e^{-0.005P}S^{0.75}$ units per year.

By using the search algorithm and MATHEMATICA 7.0, the unique optimal solution for the case of $u \geq d$ can be obtained as follows: $P_1 = \$400$, $S_1 = 10$, $T_1 = 0.17$, $Q_1 = 388.134$, $D_1 = 2283.14$, $\Delta_1 = -19{,}209.762$ and $\Pi_1 = \$377{,}874.53$. The Δ_1 calculated with $T = u-d$, is less than zero. This shows that the function Π_1 is decreasing and maximized at $u-d$. Hence, the optimal solution for T is in T_2. The solution for the case of $u \geq T+d$ is attained as follow.
$P_2 = P^* = 394.14$, $S_2 = S^* = 8$, $T_2 = T^* = 0.03357$, $Q_2 = Q^* = 66.76$, $D_2 = D^* = 1988.70$, $\Delta_2 = -17{,}054.016$ and $\Pi_2 = \Pi^* = \$398{,}840.64$.

It can be seen that the profit in case 2 is also higher, hence the optimal solution is located in case 2 where $u \geq d$ and $u \geq T+d$.

From the result, we can see that the value of price coefficient $a = 0.005$ set the maximum $P = \$400$ (based on $2 \geq aP$). Hence, sensors could only be increased if the price coefficient lowers, which in practice is obtained from historical sales data. Consequently, it is reasonable to consider the maximum price, $P = \$400$, as the price threshold still regarded as attractive and affordable to customers for a given number of sensor. This result could help companies deal with the trade-off between selling price and number of sensors as a way to increase product capabilities.

5. Conclusion

An EPQ mathematical model was developed to reflect: (a) the increases in demand for smart and connected products when the selling price decreases and the number of sensors increases, (b) the influence of selling price, number of sensors, and trade credit decision in manufacturer's lot size, and (c) the case where manufacturer receives an upstream trade credit period from the supplier while gives a downstream trade credit period to the customer. The necessary and sufficient conditions to obtain the optimal solution have been proven, and the explicit closed-form solution to optimal production cycle time was obtained. We have also confirmed that the total profit is concave under certain conditions. Furthermore, which one from the cases is optimal can be identified under certain conditions. The pricing, inventory, and product intelligence policy can also be obtained, as demonstrated in the numerical example. This result could be used as a consideration for the manufacturer of SCP to decide the best approach to maximize his profit.

In real life, demand for SCP does not only depend on the selling price and the number of sensors. It could be extended as a dynamic function of advertisement, downstream credit, quality, and so on. Many SCPs offer a monthly subscription plan for enhanced functionalities which could also be incorporated in future research.

References

Chen, S., Teng, J., and Skouri, K., Economic production quantity models for deteriorating items with up-stream full trade credit and down-stream partial trade credit, *International. Journal of Production Economics*, vol. 155, pp. 302–309, 2014.

Chung, K. J., and Huang, Y. F., The optimal cycle time for EPQ inventory model under permissible delay in payments, *International Journal of Production Economics*, vol. 84, no. 3, pp. 307–18, 2003.

Feng, H., Li, J., and Zhao, D., Retailer's optimal replenishment and payment policies in the EPQ model under cash discount and two-level trade credit policy, *Applied Mathematical Modelling*, vol. 37, no. 5, pp. 3322–3339, 2013.

Feng, L., and Chan, Y. L., Joint pricing and production decisions for new products with learning curve effects under upstream and downstream trade credits, *European Journal of Operational Research*, vol. 272, no. 3, pp. 905–913, 2019.

Feng, L., Chan, Y. L., and Cárdenas-Barrón, L. E., Pricing and lot-sizing polices for perishable goods when the demand depends on selling price, displayed stocks, and expiration date, *International Journal of Production Economics*, vol. 185, pp. 11–20, 2017.

Gao, S., Zhang, X., and Peng, S., Understanding the adoption of smart wearable devices to assist healthcare in China, *Social Media: The Good, the Bad, and the Ugly*, vol. 1, pp. 280–91, 2016.

Giri, B. C., and Maiti, T., Supply chain model with price- and trade credit- sensitive demand under two-level permissible delay in payments, *International Journal of Systems Science*, vol. 44, no. 5, pp. 937–948, 2013.

Goyal, S. K., Economic order quantity under conditions of permissible delay in payments, *The Journal of the Operational Research Society*, May 1985, vol. 36, no. 4, pp. 335–338, 1985.

Huang, Y.-F., Optimal retailer's ordering policies in the EOQ model under trade credit financing, *Journal of the Operational Research Society*, vol. 54, no. 9, pp. 1011-1015, 2003.

IDC. (2021). IDC Forecasts Double-Digit Growth for Smart Home Devices as Consumers Embrace Home Automation and Ambient Computing. Available: https://www.idc.com/getdoc.jsp?containerId=prUS47567221, Accessed Day: May 13, 2021.

Liao, J., On an EPQ model for deteriorating items under permissible delay in payments, *Applied Mathematical Modelling*, vol. 31, pp. 393–403, 2007.

Mahata, G. C., An EPQ-based inventory model for exponentially deteriorating items under retailer partial trade credit policy in supply chain. *Expert Systems With Applications*, vol. 39, no. 3, pp. 3537–3550, 2012.

Min, J., Zhou, Y., Liu, G., and Wang, S., An EPQ model for deteriorating items with inventory- level-dependent demand and permissible delay in payments, *International Journal of Systems Science*, vol. 43, no. 6, pp. 1039-1053, 2012.

Nikou, S., Factors driving the adoption of smart home technology: An empirical assessment, *Telematics and Informatic*s, vol. 45, 101283, 2019.

Porter, M. E., and Heppelmann, J. E., How smart, connected products are transforming competition, *Harvard Business Review*, vol. 92, no. 11, pp. 64–88, 2014.

Seifert, D., Seifert, R. W., and Protopappa-sieke, M., A review of trade credit literature: Opportunities for research in operations, *European Journal of Operational Research*, vol. 231, no. 2, pp. 245–256, 2013.

Shin, J., Park, Y., and Lee, D., Who will be smart home users? An analysis of adoption and diffusion of smart homes, *Technological Forecasting & Social Change*, vol. 134, pp. 246-253, 2018.

Teng, J.-T., On the economic order quantity under conditions of permissible delay in payments, *Journal of the Operational Research Society*, vol. 53, no. 8, pp. 915–918, 2002.

Teng, J., Chang, C., and Goyal, S. K., Optimal pricing and ordering policy under permissible delay in payments, *International Journal of Production Economics*, vol. 97, pp. 121–129, 2005.

Tiwari, S., Cárdenas-Barrón, L. E., Goh, M., and Shaikh, A. A., Joint pricing and inventory model for deteriorating items with expiration dates and partial backlogging under two-level partial trade credits in supply chain, *International Journal of Production Economics*, vol. 200, pp. 16–36, 2018.

Wilson, N., and Summers, B., Trade credit terms offered by small firms: Survey evidence and empirical analysis, *Journal of Business Finance & Accounting*, vol. 29, no. 3-4, pp. 317-351, 2002.

World Economic Forum., State of the Connected World 2020 Edition, Available: http://www3.weforum.org/docs/WEF_The_State_of_the_Connected_World_2020.pdf, December, 2020.

Wu, J., Al-khateeb, F. B., Teng, J., and Cárdenas-barrón, L. E., Inventory models for deteriorating items with maximum lifetime under downstream partial trade credits to credit-risk customers by discounted cash- flow analysis, *International Journal of Production Economics*, vol. 171, pp. 105–115, 2016.

Wu, J., and Chan, Y., Lot-sizing polishincies for deteriorating items with expiration dates and partial trade credit to credit-risk customers, *International Journal of Production Economics*, vol. 155, pp. 292–301, 2014.

Wu, J., Skouri, K., Teng, J., and Ouyang, L., A note on "optimal replenishment policies for non-instantaneous deteriorating items with price and stock sensitive demand under permissible delay in payment", *International Journal of Production Economics*, vol. 155, pp. 324–329, 2014.

Biographies

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