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Manufacturer's printing forecast, reprinting decision, and contract design in the educational publishing industry

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A R T I C L E I N F O

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A B S T R A C T

An educational publishing industry generally builds lots of inventory for make-to-stock production; however, the frequent revision causes the obsolescence problem. This study proposes two models to address different but related problems, inventory scrap and contract design. The industry uses prediction modeling to forecast demand and manage inventory of diverse print products. The *printing decision module* is developed to improve the accuracy of the demand forecast and reduce the inventory scrap problem. In addition, there exists asymmetric information in a two-echelon supply chain and contract design favors educational publishing retailers; thus the profitability of the overall supply chain is not maximized and manufacturers' profits are limited. This study suggests a *contract design module* to encourage retailers to provide true information for improving profitability in the overall supply chain. An empirical study of Taiwan's leading educational publisher validates the proposed models. The results show that the proposed printing decision model improved forecast accuracy by 3.7%, reduced cost by 8.3%, and the contract design enhanced overall supply chain and manufacturer profitability by 0.5% and 2.7%, respectively.

1. Introduction

The global educational publishing industry has faced significant challenges in the past two decades such as unsalable books and other print products because of high return rates from retailers; short life cycles of publications that are frequently updated; fluctuating student headcounts because of lower birth rates; severe competition resulting from similar teaching materials, accessible online and print-on-demand texts, etc. Due to make-to-stock production, many firms build planning models (for printing decision, i.e., how many books the firm should print) with ad hoc demand forecasting technique such as moving average method (MA) for practical applications. MA, however, is insensitive to demand fluctuation; thus, manufacturers are saddled with high inventory scrap. In addition, the retailers generally more close to the customers in the supply chain show more market power than the manufacturer and design contract with the asymmetric information. Information asymmetry raises an imbalance of power in transactions where one party has more or better information than the other. Thus the manufacturer presents a relatively lower profit and the profitability of the overall supply chain is not maximized (Simchi-Levi, Kaminsky, & Simchi-Levi, 2009). This study addresses the two issues mentioned above by proposing the printing decision module and contract design module.

In fact, the first issue is indeed a capacity planning problem while the second issue is related to contract design. As a whole, both issues play important roles for smart production and industry 4.0 since a critical concern for manufacturing firms is the mismatch between supply and demand in supply chain (Yin, Stecke, & Li, 2017). Yin et al. (2017) only investigated the demand factor and claimed that (1) Industry 1.0, which brought human activities from agriculture to the industrial society, focused on *product volume* with a central idea that prices rise if supplies were smaller than demands, prices rise; otherwise prices fall if supplies were larger than demands; (2) Industry 2.0, which showed technological innovations on electronic and mechanical devices, and cars, focused on *volume and variety* in order to achieve economies of scale by using mass production and address various customer interests by developing the Toyota production system, respectively; (3) Industry 3.0, which built the product architecture from integral to modular and formed the supply chain, focused on *volume, variety and delivery time* and was characterized by volatile demand environment with a dramatic reduction in the product life cycle; (4) Industry 4.0 is an initiative with technology innovations such as internet of things (IoT), big data, 3D printing, cloud computing, artificial intelligence and cyber-physical systems; however, it lacks of an explicit definition and shows *unknown and uncertain* on demand dimension. In the current study, the educational publishing industry addresses the

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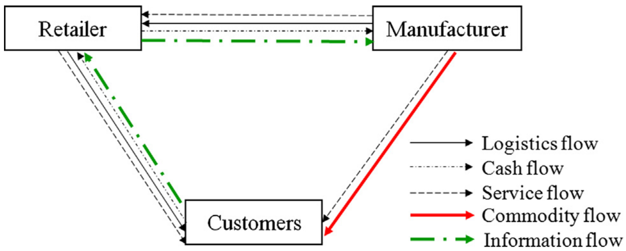

Fig. 1. Flows and relationship among customer, retailer and manufacturer.

variety of customer demand accompanied by the short life cycles of publications. The inaccurate prediction of the make-to-stock production causes a huge amount of inventory and scrap. The competitive pressure and technological innovation push the evolution of the industry from the Industry 3.0 to Industry 4.0.

Printing decision involves demand forecast and capacity planning. The demand forecast plays an important role which significantly affecting the capacity decision (Chen & Chien, 2018; Chien, Dou, & Fu, 2018; Chien, Wu, & Wu, 2013), particularly, in a make-to-stock production system like the educational publisher. Thiesing and Vornberger (1997) considered the prices, advertising campaigns, and holidays as input factors for sales prediction and demonstrated the neural network (NN) outperformed the moving average (MA). However, the NN cannot identify the cyclical effect well. Ramos, Santos, and Rebelo (2015) demonstrated retail sales forecasting by using error-trend-seasonality (ETS) model and autoregressive integrated moving average models (ARIMA) Ho & Xie, 1998 for cyclical panel data; however, the time series data didn't support the casual analysis, for example, how the marketing activities affect the sales by price reductions or promotions. For capacity planning, Chien et al. (2013) suggested a two-stage stochastic programming (SP) to fulfill new tap-out in the semiconductor manufacturing: the first stage considered forecast demand allocation among factories and the second stage developed capacity plan by suggesting capacity migration or backup for capacity reconfiguration. Lee and Chiang (2016) proposed a two-stage framework embedded with demand-forecast stage and capacity-decision stage in the TFT-LCD industry; in particular, the minimax regret (MMR) model and the SP model were developed to quantity the capacity regret for addressing the mismatch between capacity shortage and capacity surplus. Based on the literature, the current study proposes a two-stage printing decision model: using MA, NN and ARIMA techniques in the first stage for enhancing the demand forecasting, and then developing MMR and SP for optimizing the reprinting decision and reducing the inventory scrap in the second stage.

In addition, in practice, since manufacturers may not acquire the first-hand information about customer demand and then the inventory management issue are challenging to them. Fig. 1 illustrates a typical relationship among manufacturers, retailers, and customers, where the ownership of goods only transfers from the manufacturer to the customer. However, manufacturers suffer insufficient information about demand due to contacting customer indirectly. Therefore, manufacturers make inaccurate predictions in a make-to-stock production system.

In fact, if we can encourage retailers to provide detailed information (related to customers or end users) through contract design, then manufacturers can improve the predicting accuracy and reduce the inventory scrap, and thus finally achieve the profit maximization of overall supply chain (Wang, Guo, & Wang, 2017). To enhance the connection between manufacturer and retailers, Pasternack (2008) demonstrated that buy-back contracts can facilitate cooperation between suppliers and promote overall supply chain profitability, and Taylor and Xiao (2009) found that a win-win contract design can encourage retailers to share their forecasting information with manufacturers. Pan, Pavur, and Pohlen (2016) examined the impact of forecasting methods and investigated the value of information sharing in supply chain. They found that some advanced forecasting methods such as generalized autoregressive conditional heteroscedasticity (GARCH), neural network, and seasonal ARIMA significantly reduce costs under most scenarios examined. Therefore, the current study develops the new contracts according to the forecasting method and demonstrates the differences between price discount and buy-back contract in supply chain. The expert interview is conducted to address both practical and theoretical aspects further and the proposed contract motivates retailers to share their information and promote overall profitability of the supply chain.

Fig. 2 illustrates the proposed framework embedded with two modules—printing decision module and contract design module. The printing decision module includes printing forecast of preliminary edition (demand forecast) before the book production and reprinting quantity decision (capacity planning) after the new semester starts. The statistical data mining techniques such as MA, NN, and ARIMA are used to predict the printing quantity while optimization methods such as MMR and SP are suggested to decide the reprinting quantity with a minimal batch size. The contract design module includes design of screening contract and comprehensive interview for contract design. In particular, the screening mechanism is used to acquire information from retailers in order to enhance profit capability of both manufacturer and retailers in the supply chain. That is, screening refers to a strategy of combating adverse selection by the manufacturer with less information (Spence, 1973). An empirical study of Taiwan's leading educational publisher is conducted to validate the proposed models and provide insights into improving the practice. This empirical study focuses on highly-volatile products, i.e. learning-aid materials, provided by junior high schools to teachers, students, and parents.

Note that two proposed modules complement each other. Good forecast and capacity decision can excavate the missing information in the manufacturers for supporting contract design while good contract design improves the quality of information sharing in the supply chain to enhance the forecast accuracy. In the framework, the reason why the printing decision module is investigated first is that it emphasizes on the manufacturers and improves the decision quality directly. Then we extend to retailers in a supply chain and obtain first-hand demand

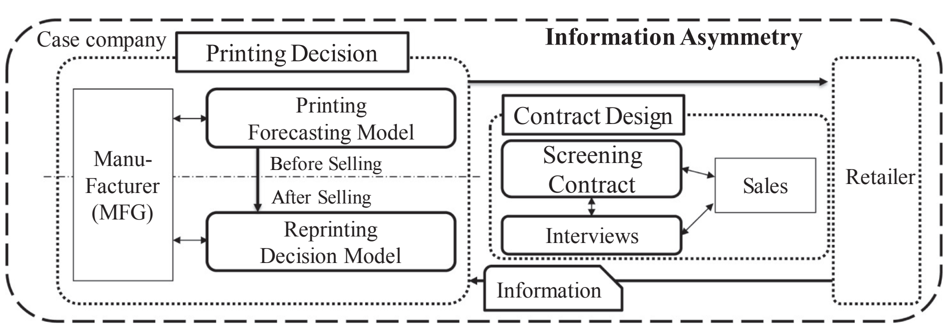

Fig. 2. The proposed framework with two modules.

information through contract design to improve the overall profits step by step.

2. Printing forecasting model

The printing decision module is a two-stage framework including a printing forecasting model of preliminary edition before the book production and reprinting decision model after the new semester starts. This section discusses the printing forecasting model and next section discusses the reprinting quantity decision. Fig. 3 describes the entire printing decision module.

The printing forecasting model includes data preparation, data preprocessing, forecasting, data postprocessing, and the decision for final prediction on print quantity of preliminary printing (i.e., preliminary edition). In data preparation, sales data are collected and key factors (i.e. number of students) that affect sales quantity are investigated. In data preprocessing, data quality are improved by removing the effects of the number of students, to improve accuracy of the predictive model. Prediction models are developed based on the features and underlying assumption of different methods. In data postprocessing, the predictive values are corrected by the number of students, and a weighting mechanism is used to integrate the pros and cons of various predicting methods in order to obtain a robust prediction of the preliminary printing decision. We illustrates the details of each process as follows.

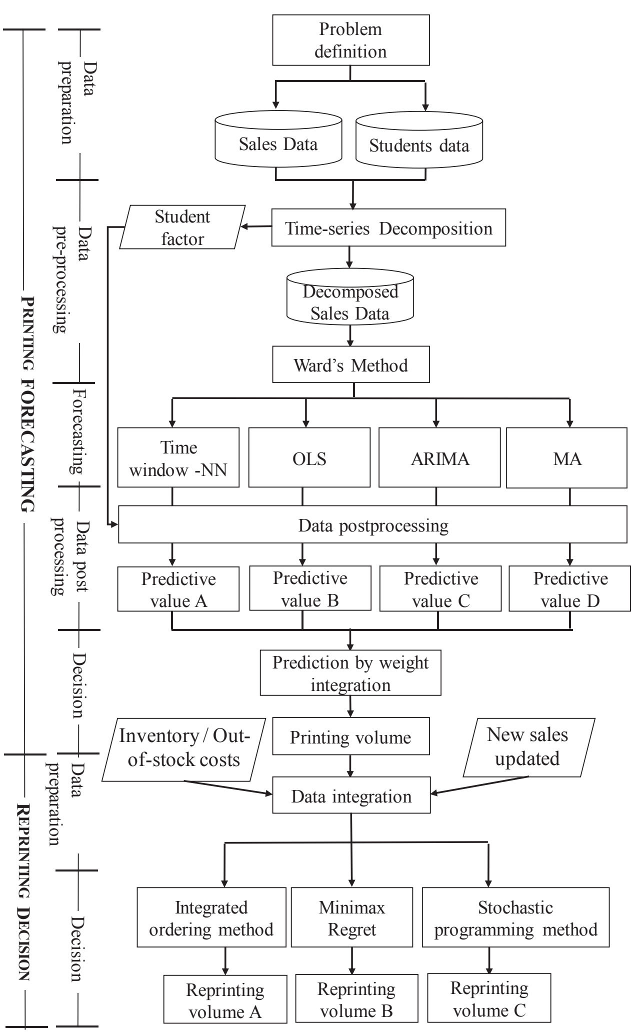

Fig. 3. Printing decision module.

2.1. Data preparation

The monthly sales data of the learning-aid materials is collected from the manufacturer. Student data includes the number of students in different educational stages and is yearly collected from the Ministry of Education.

2.2. Data preprocessing

Since number of students significantly affects sales variability, time series decomposition is used to remove the student effect from the sales pattern. Next, a prediction model is constructed to forecast the long-term trend. Note the data clustering technique of Ward's method (Ward, 1963) is applied to build a divide-and-conquer strategy to address the similar sales pattern of diverse products in the same cluster and improve the accuracy of the prediction model (Khashei, Bijari, & Ardal, 2012).

2.3. Forecasting

The sales data feature the downtrend, periodic and the nonlinear time series pattern with small-sized samples, the relevant predictive methods are proposed according to characteristics of the issues. Note that we predict the sales without student effect. The four prediction models suggested in this study are ordinary least squares (OLS), ARIMA, MA, and backward propagation neural network (NN) Fausett, 1994, for capturing the characteristics of trend, periodicity, smoothness, and nonlinearity, respectively. OLS can obtain the main trend of sales quantity; ARIMA involves autocorrelation of historical data to address the cyclic patterns; and MA, which provides a smooth forecast pattern is used as a baseline in the case company. We use NN with time-window to handle the nonlinear sales pattern and increase the data samples for model training.

2.4. Data postprocessing

Based on the four prediction methods, we obtain four predictive values of sales. We correct the values by the significant factor of student effect (i.e., the number of students) through data postprocessing.

2.5. Weight integration and decision

Since the four predictive values will differ in importance, the weight of each model is extracted using Markov transition probability. The predicting errors calculated show the gap between the predictive value and the realized sales last year. For the prediction method i, the initial weights P_i (initial probability) for the starting year are calculated by the mean-square-error (MSE) acquired last year as

$$P_i = \frac{1}{MSE_i} \Big/ \sum_i \frac{1}{MSE_i}. \tag{1}$$

The transition probability T_{ij} is the probability from the prediction method i (the best one in the last year) to method j (the best one this year) between two consecutive years. For example, in our four prediction models, T_{13} refers to the prediction model 1 which shows the best performance (i.e., the lowest MSE) in the prior year, whereas prediction model 3 shows the best performance in the latter (see Fig. 4).

Let T_{ij}^{∞} be the steady-state probability (i.e. n-step transition probability with $n \to \infty$) calculated by T_{ij} (assume irreducible ergodic Markov chain), the probability of steady state W_j acquired by Eq. (2) is used to integrate the importance of the four prediction models with trend, periodicity, nonlinearity, and smoothness. Thus, a robust forecast demand is obtained for the preliminary printing quantity.

$$W_j = \sum_i P_i \times T_{ij}^{\infty} \tag{2}$$

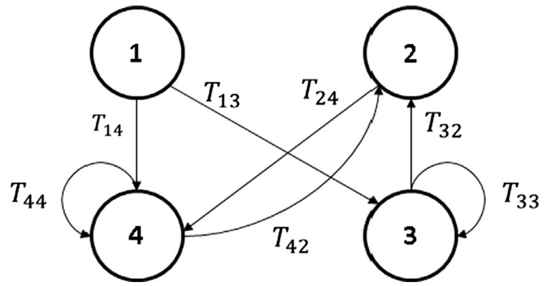

Fig. 4. An example of Markov transition diagram.

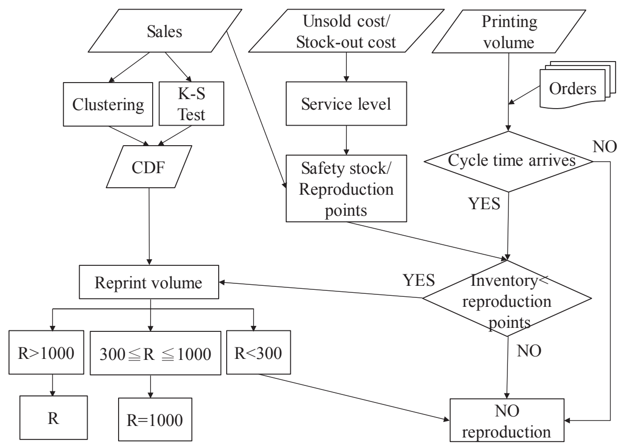

Fig. 5. Integrated ordering method.

3. Reprinting decision model

The reprinting decision occurs when the preliminary printing does not fulfill customer demand. It focuses on the timing and quantity of reprint. After new semester starts, the new sales and inventory levels are updated immediately. The costs of unsold goods (i.e., capacity surplus) and stock-out (i.e., capacity shortage) are calculated to justify the reprinting quantity decision. In particular, the reprint decision model is constructed with the integrated ordering method, minimax regret method, and stochastic programming method, respectively.

3.1. Integrated ordering method

The integrated ordering method provides a mechanism for inventory and procurement management. The method is shown in Fig. 5. Two sub-functions are developed. First, to address *when-to-reprint*, the method decides the service level according to the balance between the cost of unsold goods and the cost of stock out. Service level is determined by the ratio of cost of out-of-stock over the total cost, where the total cost is equal to the out-of-stock cost plus inventory cost plus reprinting cost. Service level multiplied by standard deviation of pre-demand is the safety stock to meet demand for production lead time (LT). Reproduction point is equal to safety stock plus expectation demand of lead time. Second, to address *how-many-to-reprint*, Cumulative Distribution Function (CDF) of the historical sales data is used to estimate reordering quantity and its max limit. For the batch-sized production, the rule of thumb suggests (1) the reprint quantity is larger than 1000, then the quantity is for production; (2) if the reprint quantity is between 300 and 1000, then the 1000 is for production; (3) otherwise, do not reprint for this specific product.

3.2. Minimax regret (MMR) method

For the MMR and SP methods, two linear programming models consider the costs of unsold goods and stock out to provide a cost minimization for optimizing the reprinting decision. In addition, the forecast techniques are used to predict the *time-rolling reprinting demand* (Huang, Hsieh, & Farn, 2011; Lee & Chiang, 2016); in particular, NN is replaced by CDF for the reprinting decision. In each sales year, since the front-end of sales provides data with larger variability, it causes the unstable result by NN; whereas since the annual demand distribution in this industry is similar, CDF is more robust. Fig. 6 shows the MMR and SP methods.

<u>Sets:</u>
S: Set of all demand scenarios
<u>Indexes:</u>
s: Demand scenario, $s \in S$
<u>Decision variables:</u>
c: Total cost (i. e. regret) under all scenarios
c_S: Total cost under scenario set s
q_s^+: Quantity of inventory under scenario set s
q_s^-: Quantity of shortage under scenario set s
q_r: Quantity of reprint
z: A binary variable which is 1 if quantity of reprint $\geqslant$ 1000; otherwise 0
<u>Data and parameters:</u>
p^+: Cost of recycling (i.e. unsold costs, indicating capacity surplus case and the cost includes production costs, materials, manpower, promotion, etc.)
p^-: Cost of shortage (i.e. stock-out costs, indicating capacity shortage)
I: Quantity of initial inventory
M: A large positive number
d_s: Sum of the last four periods of demand under scenario set s.

To describe the MMR and SP, some notations are defined as follows. MMR, which aims to minimize the maximal regret (i.e., risk caused by either unsold goods or cost of stock) and generally provides a conservative or pessimistic solution (Savage, 1951), considers the extreme demand scenario and avoids the maximal loss. The MMR model is formulated as follows to solve the q_r quantity of reprint.

$$\text{Min c} \tag{3}$$

$$c \geqslant p^+ \times q_s^+ + p^- \times q_s^- \quad \forall\, s \in S \tag{4}$$

$$q_s^+ - q_s^- = q_r - d_s + I \quad \forall\, s \in S \tag{5}$$

$$q_r \geqslant 1000 - M \times (1 - z) \tag{6}$$

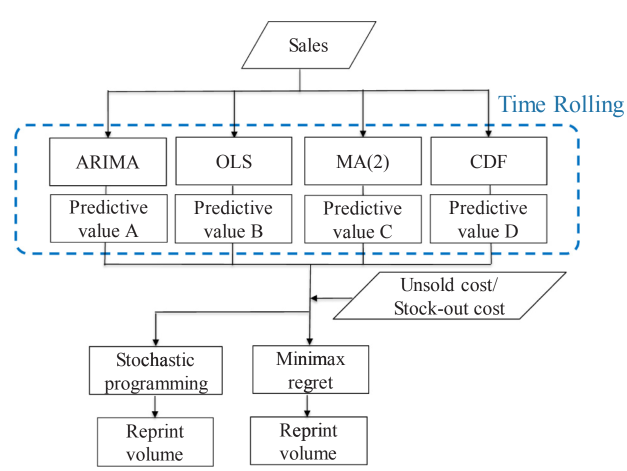

Fig. 6. Minimax regret and stochastic programming.

$$q_r \leqslant M \times z \tag{7}$$

$$z \in \{0, 1\} \tag{8}$$

$$q_r,\ q_s^+,\ q_s^- \geqslant 0. \tag{9}$$

Eq. (3) is the objective function of minimax regret used to obtain the best reprinting decision. Constraint (4) is the total cost calculated by cost of unsold goods and the cost of stock out. Constraint (5) is the demand fulfillment and the material balance constraint including inventory level, surplus, or shortage after the reprinting decision. Constraints (6) and (7) are the conjunctive constraints indicating batch size limit at 1000 quantity. Constraint (8) defines the binary variable z. When z equals to 1, reprint will be possible; otherwise no reprint. Constraint (9) is a non-negativity constraint.

3.3. Stochastic programming (SP) method

SP aims to minimize the expected total cost under different uncertain demand scenarios with probability distribution and generally provides a robust solution (Birge & Louveaux, 2011; Lee & Chien, 2014). The SP model is similar to MMR models with an objective function and the first constraint replaced by the following equations.

$$\mathrm{Min} \frac{1}{|S|} \times \sum_{s \in S} c_s \tag{10}$$

$$c_s = p^+ \times q_s^+ + p^- \times q_s^- \quad \forall\, s \in S \tag{11}$$

where the objective function (10) calculates the expected total cost under several scenarios to obtain the best reprinting decision. The remaining constraints are similar to the MMR models for interpretation.

4. Contract design

To address the issue of information asymmetry between manufacturer and retailer, the contract design is constructed based on the newsvendor problem. Taking the manufacturer's side, we develop a contract to optimize the whole profit of the two parties in the supply chain. A mathematical model is used to investigate the current contract as the validation reference for the contract design. A single contract analysis is developed and its solution determines the order quantity from retailers as the theoretical value for the screening contract; that is, the screening contract is based on the result of the single contract analysis. We assume the retailers are divided into groups with high/low demand for screening. Thus, the manufacturer provides two types of contracts designed with different parameters to motivate the groups to choose the contract consistent with their demand scenario and to acquire part of the information. The demand forecasting developed in the printing decision module is used for generating the demand scenarios of contract design. A comparison between the current contract and the screening contract is provided to validate the profitability of supply chain and manufacturer. Finally, expert interviews are conducted to assess the feasibility of the contract design. Fig. 7 depicts the process.

4.1. Problem and environment description

This study is based on the two-echelon supply chain, which employs quantity discount and return contract as shown in Fig. 8. This study considers one manufacture and one retailer in the supply chain according to an empirical study.

To clarify profitability in the supply chain, the price structure of the educational product is investigated as shown in Fig. 9. The production cost of the educational products is 20% of the selling price and the high/low limits of the discounts are 30% and 50% of the selling price, respectively.

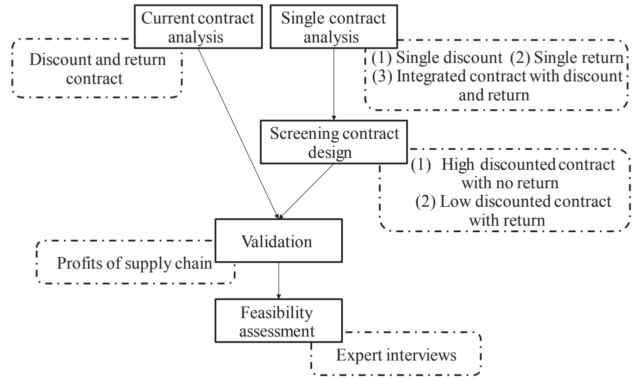

Fig. 7. Contract design module.

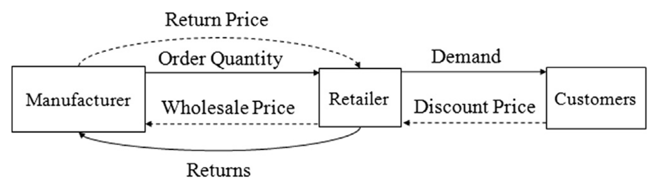

Fig. 8. Two-echelon supply chain.

4.2. Assumptions and limitations

For the contract design, the assumptions and limitations are as follows:

(1) Manufacturer is the contract designer, even though it has less and unreliable information to assess ordering quantity of retailer and market conditions.
(2) Retailer possesses much information and can predict the high/low demand (with a high accuracy) and formulate the probability distribution of the demand to determine the optimal ordering quantity from manufacturer. Retailers have more market power in the supply chain.
(3) Probability distribution of demand in the market follows normal distribution, and decision on printing quantity indicates mean of distribution. Standard deviation (SD) is calculated by four demand forecast techniques (i.e., four scenarios).
(4) One-to-one supply chain environment.
(5) Retailer only orders once within one school year.
(6) Manufacturer can satisfy any number of retailer orders without

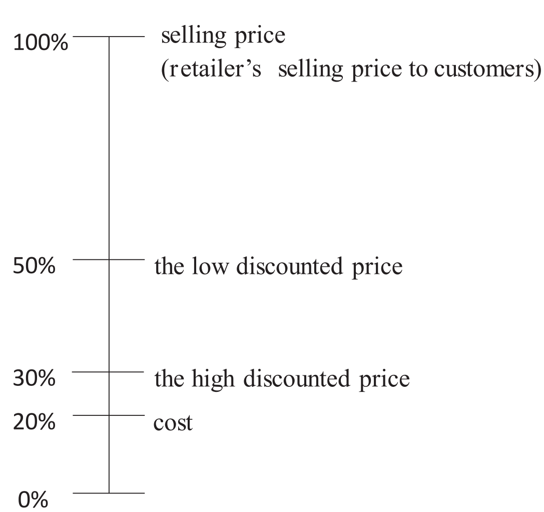

Fig. 9. Product price structure.

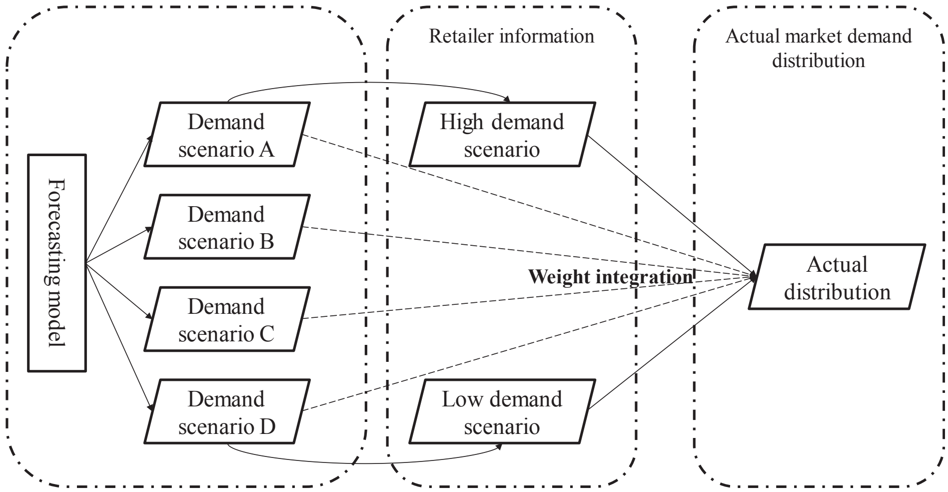

Fig. 10. Demand scenario and information flow.

capacity constraints.
(7) Retailer has no level of stock before sales period.

Based on assumptions (1)-(3), the information flow is shown in Fig. 10.

4.3. Current contract analysis

Optimal ordering quantity and profit of retailers are obtained based on three types of single contracts: (1) Single Discount, (2) Single Return and (3) Integrated Contract with Discount and Return (ICDR). Here, we only focus on the ICDR contract since the current contract is developed with ICDR in our empirical study. The contract design refers to a newsvendor problem and describes the mathematical relationships in ICDR, and then provides the benchmark for designing the screening contract.

Some notations are defined as follows.

π^M: Manufacturer profits
π^R: Retailer profits
π^T: Profits of the total supply chain
w': Wholesale price under the discount contract
q: Order quantity
q^*: Optimal order quantity
r: Return price
P: Retailer's selling price to customers
Q: Threshold for manufacturer identifying high/low retailer
x: Demand
f_N: Normal probability distribution function of market demand
F_N: Normal cumulative distribution function of market demand
π_H^R: Retailer profits under the high discounted contract
π_L^R: Retailer profits under the low discounted contract
w_H: Wholesale price under the high discounted contract
w_L: Wholesale price under the low discounted contract
q_H: Order quantity under the high discounted contract
q_L: Order quantity under the low discounted contract
q_H^*: Optimal order quantity under the high discounted contract
q_L^*: Optimal order quantity under the low discounted contract
f_H: Normal probability distribution function in high demand
F_H: Normal cumulative distribution function in high demand
f_L: Normal probability distribution function in low demand
F_L: Normal cumulative distribution function in low demand

For the ICDR, retailer's expected profit $E[\pi^R(q)]$ is formulated as follows.

$$E[\pi^R(q)] = -w' \times q + r\int_0^q (q-X)f_N(x)dx + P\left[\int_0^q xf_N(x)dx + \int_q^\infty qf_N(x)dx\right] \tag{12}$$

The first- and second-order conditions of q are

$$\frac{d}{d(q)}(E[\pi^R]) = -w' + r + (P-r) \times (1-F_N(q)) \tag{13}$$

$$\frac{d^2}{d(q)^2}(E[\pi^R]) = -(P-r)f_N(q). \tag{14}$$

The second-order condition is derived to present a concave function, thus ensuring an optimal solution maximizing the expected profit.

$$-w' + r + (P-r) \times (1-F_N(q^*)) = 0 \tag{15}$$

$$F_N(q^*) = \frac{-w' + P}{P-r} \tag{16}$$

$$q^* = F_N^{-1}\left(\frac{-w' + P}{P-r}\right) \tag{17}$$

Note that, based on Eq. (17), when the wholesale price equals the return price, optimal ordering quantity increases infinitely as Eq. (18), but this case never occurs in practice. Therefore, two constraints are used to limit the optimal ordering quantity: r is set as 0.99 and maximal ordering quantity is set as no more than 1.12 times the mean of demand distribution in order to ensure a full refund based on the current contract.

$$q^* = F_N^{-1}\left(\frac{-w' + P}{P-r}\right) = F_N^{-1}(1) \tag{18}$$

4.4. Screening contract design

In the screening contract, two kinds of contract are designed: (1) High Discounted Contract with No Return and (2) Low Discounted Contract with Return. In this study, the difference between high discount and low discount is the selling price and it is irrelevant to the contract of quantity discount.

Screening contract design has following notes:

(1) Manufacturer provides two types of contracts.
(2) Retailer chooses one of the two contracts- High Discount Contract with high-demand distribution $F_H(x)$ (i.e. larger order quantity) and Low Discount Contract with low-demand distribution $F_L(x)$ (i.e. less order quantity).

(3) Both parties fulfill the contractual obligation.

For the High Discounted Contract (with no return), retailer's expected $E[\pi^R(q)]$ is formulated as follows.

$$E[\pi_H^R(q_H)] = -w_H \times q_H + P\left[\int_0^{q_H} xf_H(x)dx + \int_{q_H}^{\infty} qf_H(x)dx\right] \tag{19}$$

The first- and second-order differential conditions of q are.

$$\frac{d}{d(q_H)}(E[\pi_H^R(q_H)]) = -w_H + P(1-F_H(q_H)) \tag{20}$$

$$\frac{d^2}{d(q)^2}(E[\pi_H^R]) = -Pf_H(q_H) \tag{21}$$

The second-order condition is derived as a concave function for ensuring a global optimum.

$$-w_H + P(1-F_H(q_H^*)) = 0 \tag{22}$$

$$F_H(q_H^*) = \frac{-w_H + P}{P} \tag{23}$$

$$q_H^* = F_H^{-1}\left(\frac{-w_H + P}{P}\right) \tag{24}$$

In low discounted contract with return, retailer's expected profit $E[\pi^R(q)]$ is formulated as

$$E[\pi_L^R(q_L)] = -w_L \times q_L + r\int_0^{q_L}(q_L-x)f_L(x)dx + P\left[\int_0^{q_L} xf_L(x)dx + \int_{q_L}^{\infty} qf_L(x)dx\right] \tag{25}$$

The first- and second-order differential conditions of q are

$$\frac{d}{d(q_L)}(E[\pi_L^R(q_L)]) = -w_L + r + (P-r)(1-F_L(q_L)) \tag{26}$$

$$\frac{d^2}{d(q_L)^2}(E[\pi_L^R]) = -(P-r)f_L(q_L). \tag{27}$$

Similarly, the second-order condition is derived as a concave function for ensuring a global optimum

$$-w_L + r + (P-r)(1-F_L(q_L^*)) = 0 \tag{28}$$

$$F_L(q_L^*) = \frac{-w_L + P}{P-r} \tag{29}$$

$$q_L^* = F_L^{-1}\left(\frac{-w_L + P}{P-r}\right) \tag{30}$$

4.5. Validation

To develop the screening contract, the four parameters are wholesale price of high discounted contract, wholesale price of low discounted contract, refund of low discounted contract, and threshold value Q defined by the manufacturer to distinguish between high-demand contract (with high discount and no return) and low-demand contract (with low discount and potential return). Note that the wholesale price is equal to the selling price minus the discount.

If the wholesale price is set too high, retailer will not sign the contract; thus, the whole supply chain may not earn any profit. To increase the feasibility, this study suggests promoting manufacturer's profit ratio (i.e., manufacturer's profit over the profit in the whole supply chain) according to the actual setting conditions obtained in expert interviews. The three wholesale price scenarios are listed in Table 1.

Table 1
Wholesale price scenarios.

Scenario	w_H	w_L
A	30	40
B	35	45
C	40	50

Since the manufacturer had no information about demand distribution, this study sets Q as the mean of the maximal forecast demand and the minimal forecast demand from the proposed four demand forecast techniques. The value of return price r is obtained by using the relation expressions of the screening contract, which sets the r value as the maximal value that differentiates high-demand retailer and low-demand retailer. Finally, the optimization model is formulated.

$$\max_r r \tag{31}$$

$$q_H^* = F_H^{-1}\left(\frac{-w_H + P}{P}\right) \geqslant Q \tag{32}$$

$$q_L^* = F_L^{-1}\left(\frac{-w_L + P}{P-r}\right) < Q \tag{33}$$

4.6. Expert interview

The interviews covered three aspects of contract design: (1) importance; (2) rationality, and (3) feasibility. The interviewees were managers with more than fifteen years of experience in customer service, marketing, and sales.

5. Empirical study

An empirical study of Taiwan's leading education publisher validated the proposed printing decision model and screening contract design. Thirteen learning-aid materials were selected for data collection, including monthly sales data of third-year junior high school students in Taiwan from May 2009 to April 2015. Without loss of generality, the data were transformed to protect proprietary information.

5.1. Demand forecasting for preliminary printing quantity

Regarding the prediction model of preliminary printing quantity for the starting semester, the MA method was used as the current policy. The proposed forecasting technique embedded with four methods aggregated by weights improves around 3.7% prediction accuracy of preliminary quantity. Table 2 gives a comparison of different methods by the predictive errors. The variance of error presented 0.013 in the current MA method and 0.007 in the proposed model. Thus, a higher

Table 2
Demand forecast errors.

Product	This study*	Current (MA)	NN	OLS	ARIMA
A	0.107	0.09	0.286	0.205	0.116
B	0.052	0.033	0.038	0.032	0.219
C	0.077	0.072	0.095	0.01	0.16
D	0.081	0.106	0.107	0.012	0.05
E	0.013	0.07	0.01	0.268	0.394
F	0.079	0.123	0.08	0.007	0.018
G	0.083	0.056	0.248	0.188	0.104
H	0.165	0.12	0.213	0.301	0.119
I	0.246	0.214	0.318	0.39	0.126
J	0.301	0.44	0.025	0.002	0.506
K	0.231	0.357	0.075	0.087	0.474
L	0.075	0.172	0.167	0.205	0.306
M	0.0255	0.157	0.265	0.28	0.208
Avg. error	0.118	0.155	0.148	0.153	0.215
Variance	0.007	0.013	0.011	0.017	0.023

* error = |predictive value−actual value|/actual value.

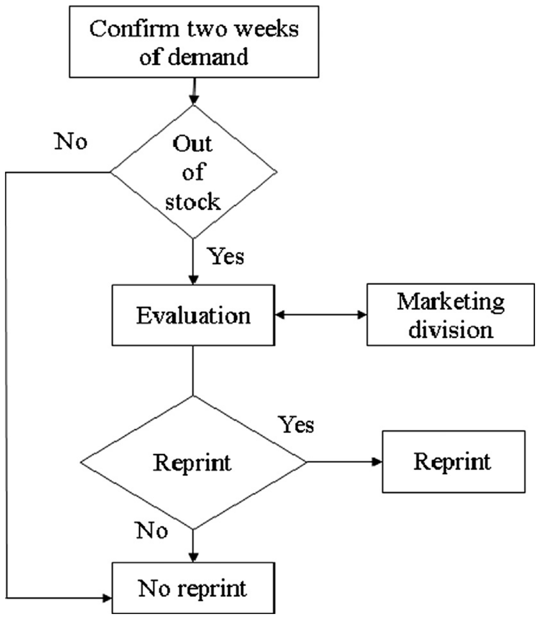

Fig. 11. Current reprinting decision method.

accuracy and lower variance of the proposed demand forecast provide an effective production of the preliminary printing decision.

5.2. Reprinting decision

For the reprinting decision, the current method was used to predict whether stock out will occur in the next two weeks. If the prediction indicated a shortage case, the manufacturer contacted the marketing division about market conditions and reevaluated the reprinting decision. The current policy was useful when the manufacturer had more information about demand and the market condition was clear. In fact, the current policy is highly dependent on experienced marketing agencies and the safe stock is the demand considered in the next two weeks. In practice, although it lacks a theoretical basis, the current method was still flexible to address a rapidly changing market. The current policy is shown in Fig. 11.

A comparison of the current method and the proposed reprinting models is presented in Table 3. Integrated ordering (IO) method obtained a satisfactory solution, but was highly dependent on the historical data due to CDF calculation. MMR was sensitive to outlier values and thus obtained a poor result because of severe demand fluctuation (Lee, 2016). SP obtained a robust solution addressing uncertainty due to providing a better balance between capacity surplus and capacity shortage (i.e. a tradeoff between cost of stock-out and cost of recycling), and improved 8.3% for cost reduction. It can also be found that the current method is superior to the three methods proposed in a few of products since the current method is more flexible and integrates expert's manual adjustment. This implies that the SP will get more benefits by introducing expert's flexible adjustment. Note that cost of stock-out and cost of recycling occurred when the sales period ended and the reprint cost was the total reprint cost during the sales period.

Note that a robust/conservative reprint decision generated by SP/MMR may reduce the level of inventory and stock-out, it may cause a significant reprint cost when demand dramatically increases. See the SP results of some products do not get low cost in Table 3. In other words, the number of reprinting times (with fixed cost) may decrease, but may induce a high level of inventory/stock-out.

Table 3
Cost comparison of capacity planning models.

Product	Current	IO	MMR	SP
A	166,538	162,394	61,486	91,285
B	54,634	148,406	259,511	129,479
C	66,732	83,734	74,140	162,597
D	132,468	165,215	159,824	75,385
E	42,693	88,919	64,636	64,584
F	99,453	123,256	132,219	132,219
G	170,076	109,639	115,190	88,380
H	153,055	84,467	140,491	110,214
I	185,347	139,965	152,653	148,723
J	107,684	60,678	111,012	115,571
K	103,968	45,579	52,486	44,263
L	72,661	64,152	107,539	58,311
M	39,530	47,253	61,566	58,049
Cost	1394 K	1313 K	1492 K	1279 K
Variance	49 K	46 K	55 K	36 K
Improve	–	5.82%	−7.02%	8.30%

Table 4
T-test of the current contract and three types of screening contracts.

Type	Contract Parameters	p-value
I	w_H= 30, w_L= 40, r = 0.78	0.430
II	w_H= 35, w_L= 45, r = 0.82	0.057
III	w_H= 40, w_L= 50, r = 0.85	0.000005

5.3. Contract design

Since the full buy-back price was adopted in the current policy, retailers aimed to order large amounts of products to satisfy demand and the manufacturer bore the dead stock when a large amount of product returns after the end of the sales period. This study suggests screening contract to address the issue; that is, the manufacturer acquires part of demand information and can negotiate the retailer's ordering quantity and buy-back price to reduce the dead stock. Three types of screening contracts were designed as shown in Tables 4 and 5 with the related parameters. The contract parameters are determined by experts' opinions to present three feasible contracts. The results show that it was likely that total sales quantity of retailers decreased slightly; however, since manufacturer's inventory cost decreased significantly, supply chain's total profit increased as shown in Table 5. For example, retailer's profit is decreased by 624 K, but the manufacturer

Table 5
Manufacturer's profit ratio relative to the two-echelon supply chain.

Product	Current	Contract I	Contract II	Contract III
A	0.198	0.248	0.311	0.374
B	0.163	0.248	0.311	0.374
C	0.215	0.246	0.309	0.372
D	0.190	0.149	0.221	0.291
E	0.308	0.158	0.233	0.305
F	0.187	0.248	0.311	0.374
G	0.110	0.249	0.311	0.374
H	0.208	0.156	0.231	0.303
I	0.158	0.136	0.203	0.268
J	0.325	0.246	0.309	0.372
K	0.327	0.247	0.310	0.372
L	0.263	0.237	0.300	0.364
M	0.320	0.151	0.224	0.295
Avg	0.229	0.209	0.276	0.341
W-Avg[a]	0.186	0.213	0.279	0.344
π^M	5071 K	5832 K	7635 K	9424 K
π^R	22,244 K	21,620 K	19,836	18,058 K
π^T	27,315 K	27,452 K	27,471 K	27,482 K
Improve π^M		↑0.150	↑0.506	↑0.858
Improve π^T		↑0.005	↑0.0057	↑0.0061

[a] W-Avg. indicates the weighted average by sales quantity.

Table 6
Interview summaries.

Importance	
Interview	(1) Retailer operates locally and possess much customer information (2) Manufacturer prefers to surrender a large part of its profit to encourage retailer's purchases and promote total sales quantity
Conclusion	(1) Information asymmetry in two-echelon supply chain (2) Manufacturer is relatively less profitable
Rationality	
Interview	(1) In the worst case, manufacturer provides the prices of most products with discount less than 60% (2) Demand and ordering quantity affect retailer's decisions on high-demand contract or low-demand contract
Conclusion	(1) Assumptions of the screening contract are justified
Feasibility	
Interview	(1) Feasible. Most products are provided with a discount of less than 60%. Retailer still gains considerable profits whether discount is below 60% or 70% (2) Partly feasible. Manufacturer has some difficulties implementing new contract because of traditional practices (3) Sometimes full refund predominates in the industry (4) Retailer may be reluctant to sign contract if manufacturer does not have high market share, or products lack brand specificity
Conclusion	(1) Feasibilities may vary by product type (2) Use direct sales for potentially unique products

can increase 761 K in the contract A. It means the overall profits increase and then the manufacturer and retailer can share the extra profits to create a win-win situation.

A *t*-test of the current contract and the three types of screening contracts was conducted to check the significant differences of profitability. Let π^{M} be the profit of manufacturer and π^{T} be the total profit of the supply chain (including the manufacturer and the retailer). Tables 4 and 5 indicate that the screening contracts are better than the current contract, although only Contract III statistically shows a significant difference. Note that the results are consistent with why we recommend a conservative solution (suggest Contract I with profit improvement 0.5%, then go to Contract II step-by-step) for defining the wholesale price since, in practice, it is not necessary to pursue a too high profitability, which could result in retailer's reluctance to sign Contract C.

To validate the proposed contract design module, expert interviews were conducted. Most responses agreed with that the information asymmetry caused the manufacturer's lower profitability in the two-echelon supply chain. Interviewees acknowledged the importance and rationality of the proposed contract design, but gave different opinions about feasibility of the screening contract. The interviews are summarized in Table 6.

Two important managerial insights into product development and marketing strategies were obtained: (1) only products with brand specificity could survive price-cutting competition, and (2) direct sales by manufacturer of potentially unique products could amass more information and enable identifying customers' needs.

Table 7
Contribution of this study.

Printing decision	
Operational efficiency	(1) Demand forecasting increases 3.7% (2) Cost of the capacity planning saves 8.3%
Operational strategy	(1) Tradeoff between republished times and out-of-stock quantity. In the later period of sale, decrease republished times and can be out of stock
Contract design	
Operational efficiency	(1) Profit of the whole supply chain improves 0.5% in a win-win situation (2) Assumptions of the screening contract are justified and feasible
Operational strategy	(1) Product positioning and marketing strategies: feasibility of direct selling. Direct selling can be implemented to some specific products and customers, decreasing the loss caused by the dealer

6. Conclusion

This study addresses two most radical issues at present in view of printing decision and contract design in the educational publishing industry, and the proposed two modules reduce manufacturer's inventory scrap and address the information asymmetry for profitability improvement. An empirical case study of an educational publisher shows that accuracy of the demand forecasting increases 3.7%, the cost of the capacity planning saves 8.3%, and the profit of the whole supply chain improves 0.5%. Finally, expert interviews justifies the contract designs and explain the results from the aspects of importance, rationality, and feasibility.

Fig. 12 and Table 7 summarize the contribution of this study. In particular, Fig. 12 illustrates the improvement from current policy to the two proposed modules: (1) scrap and cost reduction in the manufacturer by the printing decision module; (2) increase of overall profit in a supply chain by the contract design module.

The study is limited to the one-to-one (one manufacturer and one retailer) supply chain and future research could expand to address competition among multiple manufacturers or multiple retailers. This study found that direct selling strategy without retailers as intermediate party may be applicable and useful to some specific products and customers. How to identify these products and customers is also interesting. In addition, sales/marketing behaviors is another interesting issue and relevant factors could be extracted to investigate how the sales activities affect the demand fluctuation to enhance the forecasting accuracy.

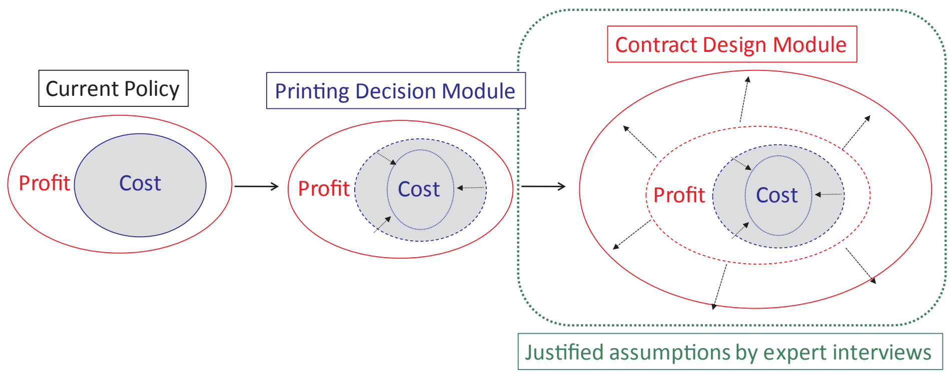

Fig. 12. Profit concept of this study.

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References

Birge, J. R., & Louveaux, F. (2011). *Introduction to stochastic programming* (2nd ed.). New York: Springer Verlag.

Chen, Y.-J., & Chien, C.-F. (2018). An empirical study of demand forecasting of non-volatile memory for smart production of semiconductor manufacturing. *International Journal of Production Research*. http://dx.doi.org/10.1080/00207543.2017.1421783 (in press).

Chien, C.-F., Dou, R., & Fu, W. (2018). Strategic capacity planning for smart production: Decision modeling under demand uncertainty. *Applied Soft Computing, 68*, 900–909.

Chien, C. F., Wu, J. Z., & Wu, C. C. (2013). A two-stage stochastic programming approach for new tape-out allocation decisions for demand fulfillment planning in semiconductor manufacturing. *Flexible Services and Manufacturing Journal, 25*(3), 286–309.

Fausett, L. (1994). *Fundamentals of neural networks; architectures algorithms and applications.* Prentice-Hall Inc.

Ho, S. L., & Xie, M. (1998). The use of ARIMA models for reliability forecasting and analysis. *Computers & Industrial Engineering, 35*, 213–216.

Huang, L. T., Hsieh, I. C., & Farn, C. K. (2011). On ordering adjustment policy under rolling forecast in supply chain planning. *Computers & Industrial Engineering, 60*, 397–410.

Khashei, M., Bijari, M., & Ardal, G. A. R. (2012). Hybridization of autoregressive integrated moving average (ARIMA) with probabilistic neural networks. *Computers and Industrial Engineering, 63*, 37–45.

Lee, C. Y. (2016). Most productive scale size versus demand fulfillment: A solution to the capacity dilemma. *European Journal of Operational Research, 248*(3), 954–962.

Lee, C. Y., & Chiang, M. C. (2016). Aggregate demand forecast with small data and robust capacity decision in TFT-LCD manufacturing. *Computers & Industrial Engineering, 99*, 415–422.

Lee, C.-Y., & Chien, C.-F. (2014). Stochastic Programming for Vendor Portfolio Selection and Order Allocation under Delivery Uncertainty. *OR Spectrum, 36*(3), 761–797.

Pan, Y., Pavur, R., & Pohlen, T. (2016). Revisiting the effects of forecasting method selection and information sharing under volatile demand in SCM applications. *IEEE Transactions on Engineering Management, 63*(4), 377–389.

Pasternack, B. A. (2008). Optimal pricing and return policies for perishable commodities. *Marketing Science, 27*(1), 133–140.

Ramos, P., Santos, N., & Rebelo, R. (2015). Performance of state space and ARIMA models for consumer retail sales forecasting. *Robotics and Computer-Integrated Manufacturing, 34*, 151–163.

Savage, L. J. (1951). The theory of statistical decision. *Journal of the American Statistical Association, 46*, 55–67.

Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2009). *Designing and managing the supply chain: Concepts, strategies, and case studies* (3rd ed.). McGraw-Hill Education.

Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics, 87*(3), 355–374.

Taylor, T. A., & Xiao, W. (2009). Incentives for retailer forecasting: Rebates vs. returns. *Management Science, 55*(10), 1654–1669.

Thiesing, F. M. and Vornberger, O. (1997). Sales forecasting using neural networks. In *IEEE international conference on neural networks, Houston, USA* (pp. 2125–2128).

Wang, Z. H., Guo, H. M., & Wang, X. Y. (2017). Supply chain contract mechanism under bilateral information asymmetry. *Computers & Industrial Engineering, 113*, 356–368.

Ward, J. H., Jr. (1963). Hierarchical grouping to optimize an objective function. *Journal of the American Statistical Association, 58*, 236–244.

Yin, Y., Stecke, K. E., & Li, D. (2017). The evolution of production systems from Industry 2.0 through Industry 4.0. *International Journal of Production Research, 56*(1–2), 848–861.