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COMPENSATING FOR PRODUCTION DISRUPTIONS CONSIDERING DYNAMIC DEMAND LEARNING

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Abstract. *After production disruptions, market demand becomes highly unpredictable, and changes to countermeasures enterprises adopt. This study aims to develop an optimal compensation strategy based on dynamic demand forecasting. To achieve this, we design a differential model to predict dynamic demand after disruption. On the basis of the prediction, we model the impact caused by random disruptions, and explore an optimal compensation mitigation strategy. The insights into the important roles of disruption length and uncertainty, and the factors impacting on customers' behavior are also numerically generated. The analysis reveals that disruption uncertainty affects the optimal compensation level for short and long disruptions with different ways, and the compensation strategy fails to cope with sufficiently long disruptions. As for the factors related to customers' behavior, the optimal compensation level shows significant change to competition intensity, mostly decrease to customers' brand loyalty, and keep steady to high customers' sensitivities.*
Keywords: Compensation strategy, Demand learning, Demand forecasting, Customer behavior, Production disruption

1. **Introduction.** A minor incident in supply chain systems can cause disruptions of major economic consequence [1]. In recent years, with trends such as global purchases, noncore business outsourcing, and single source supply, the probability of supply chain disruption increases [2]. Many approaches have been proposed by academics and practitioners to hedge against them [3]. One of the most common utilized mitigation strategies is compensation strategy. Various forms of compensation strategies are widely used in traditional and online retailing to control customers' reactions to disruptions [4,5].

While examining mitigation strategies, both deterministic and nondeterministic demands are studied [6], and a few recent researches start to concern forecasting demand. Many methods have been proposed to predict uncertain demands, such as, fuzzy tools, regression models, moving average (MA), weighted moving average (WMA), exponential smoothing (ES) [7], grey prediction method (GPM) [8], and machine learning algorithm [9]. In the extant literature, few studies reached to the prediction of dynamic market demand during mitigation strategies design. [10] used regression models to forecast demand when they plan safety stocks to cope with disruptions. [11] developed a fuzzy inference system (FIS) tool to predict the changes in future demand, and proposed a predictive mitigation planning approach for managing predictive demand changes.

To the best of our knowledge, no study has incorporated customers' changing behaviours into demand prediction while mitigates disruptions. Only a few studies have considered customer behaviours (response to disruptions) into demand dynamics [12,13]. However, during these studies, neither the change nor the prediction of customers' behaviors has been studied. As pointed out by [14], customer's behavior at disruption hitting could change under some circumstances. In reality, customers' responses to disruptions could be fast-changing to countermeasures the enterprise adopts. The forecasting method which uses few parameters to describe the demand distribution cannot possibly capture such changes [9].

Therefore, in this study, to capture customers' changing behaviours, we establish a differential model for demand learning to forecast the market demand after disruption. In the model, three factors related to customer behavior are taken into account. As revealed by [15], customer reactions are mainly impacted by loyalty and the presence of product alternatives. Hence, we consider competition intensity among alternative products, customers' sensitivities to disruption duration, and customers' brand loyalty. On the basis of the prediction, an optimal compensation strategy is established by minimizing the impact caused by the random disruption. Through numerical analysis, we further investigate how to change different compensation levels to the factors referring to disruption itself and customer behaviors.

We contribute to the literature of supply disruption management as follows. This study develops a new method to predict the market demand after disruption taking customers' changing behavior on countermeasures into consideration. It confirms demand dynamics cannot be specifically described by a demand function as given in most of the extant research work. Our results show there may be two scenarios, depending on the complicated relationship between the factors impacting on customers' behavior. An optimal compensation strategy is proposed to mitigate random disruptions. Several important managerial insights are offered to cope with disruptions with different length and uncertainty, facing different competition intensity, customers' sensitivity, and brand loyalty.

The paper is organized as follows. In Section 2, we establish a differential model including demand learning to forecast the market demand after disruption. In Section 3, the impact caused by disruptions is measured and an optimal compensation strategy is proposed. Numerical analysis and managerial implications are presented in Section 4. Finally, Section 5 concludes this paper.

2. Forecasting Market Demand after Disruption.

In this section, based on the observation of the competition intensity among alternative products, customers' sensitivities to disruption duration, and customers' brand loyalty, a differential model is formulated to forecast how the market demand will change after disruption.

After a disruption happens, some customers choose to leave while others stay waiting if no countermeasure is implemented. In this study, we suppose that k_0 of the customers leave immediately for alternative products. In other words, there are $1 - k_0$ of the customers left in the market, backordering their purchase. Comprehensibly, we let $1 - k_0$ reflect the mean brand loyalty of customers to the product. Higher loyalty results in more customers staying. Observing the customers' reactions, in order to keep more of them waiting for the delayed product, the manufacturer offers $c(a)$ compensation to make the customers sense a level of utility (we call it compensation level a in the paper). Therefore, at the initial time when the compensation is offered, y_0 of the customers accept the compensation and place backorder, i.e., $y_0 = k_0 + (1 - k_0)a$. In other words, the maximum compensation level "one" will stimulate all the customers to wait. However, the utility of the same amount of compensation is decreasing in the waiting time, $\theta(t) = a - bt$, $0 \le \theta(t) \le 1$, where, b is the sensitivity of customers to the disruption duration t $(0 \le b \le 1)$. Clearly, the customers sense zero utility from the compensation when the disruption lasts longer than $t_\theta = a/b$. On the other hand, because of the competition, the customers who choose to leave for alternative products gain utility λ. Clearly, λ reflects the competition intensity among the substitutable products. Letting

$y(t)$ denote the rate of customers who place backorder at t time, we have the following differential model, similar to [16].

$$\begin{cases} dy(t)/dt = y(t)(u_l - \bar{u}); \\ y(t)|_{t=0} = y_0, \end{cases} \tag{1}$$

where u_l is the customers' utility of the decision "to back order the purchase for the compensation", i.e., $\theta(t)$. $\bar{u}$ is the mean utility of the customers, which is $y(t)\theta(t) + (1 - y(t))\lambda$. Substituting u_l and $\bar{u}$ into the above differential equation, and solving the model, we have:

$$y(t) = \begin{cases} y_1(t) = 1 - 1/\left[1 + ce^{\left(a-\lambda-\frac{1}{2}bt\right)t}\right], & 0 \le t < a/b; \\ y_2(t) = 1 - 1/\left[1 + ce^{-\lambda t}\right], & t \ge a/b, \end{cases} \tag{2}$$

where $c = y_0/(1 - y_0)$. According to Equation (2), $y(t)$ is decreasing to t when $t \ge a/b$. As for $0 \le t < a/b$, $y(t)$ shows that: if $a \le \lambda$, $y(t)$ is decreasing; if $a > \lambda$, $y(t)$ is increasing when $t < t_1 = (a - \lambda)/b$, and decreasing when $t < t_1$. The manufacturer loses the whole market when no customer chooses to backorder, that is, the time when $y(t) = 0$, denoted by t_2. Based on $y(t)$, we see: t_2 could be achieved before and after a/b. To specifically determine t_2 and explore how the market demand changes after disruption, we discuss the dynamic processes of market demand from the following two scenarios.

Scenario 1. $t_2 > a/b$.

In this scenario, the market demand will be completely lost after a/b. In other words, there are still some customers remaining in the market at a/b time. That is, $y(a/b) > \varepsilon$, where $\varepsilon \approx 0$ is the calculation error here. According to $y_2(t)$ in Equation (2), we see all the market demand is lost when $ce^{-\lambda t} = \varepsilon$. Therefore, t_2 is determined in this scenario, which is, $t_2 = t_{2a} = (1/\lambda)\ln(c/\varepsilon)$. The whole process of market demand after disruption can be illustrated by Figure 1 (D is the market share of the manufacturer before disruption).

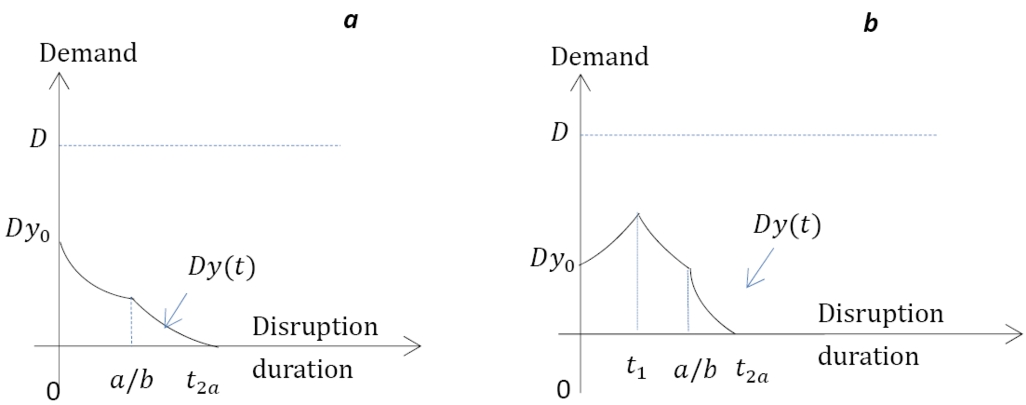

Figure 1. The demand process with compensation in Scenario 1 if $a < \lambda$ (Figure a) and $a > \lambda$ (Figure b)

Scenario 2. $t_2 \le a/b$. In this scenario, the market demand will be completely lost before a/b. According to Equation (2), we know the market demand will be completely lost when $y_1(t) = \varepsilon$. Solving the equation, we have $t = \left[a - \lambda \pm \sqrt{(a-\lambda)^2 - 2b\ln(\varepsilon/c)}\right]/b$. However, $\left[a - \lambda - \sqrt{(a-\lambda)^2 - 2b\ln(\varepsilon/c)}\right]/b$ is negative when $a < \lambda$, and is smaller than $t_1 = (a - \lambda)/b$ when $a > \lambda$. Hence, we can conclude that t_2 cannot be achieved at $\left[a - \lambda - \sqrt{(a-\lambda)^2 - 2b\ln(\varepsilon/c)}\right]/b$. That is, all the customers will be lost at $t_2 = t_{2b} = \left[a - \lambda + \sqrt{(a-\lambda)^2 - 2b\ln(\varepsilon/c)}\right]/b$ if $t_2 \le a/b$. The whole process can be similarly gained, as Figure 2.

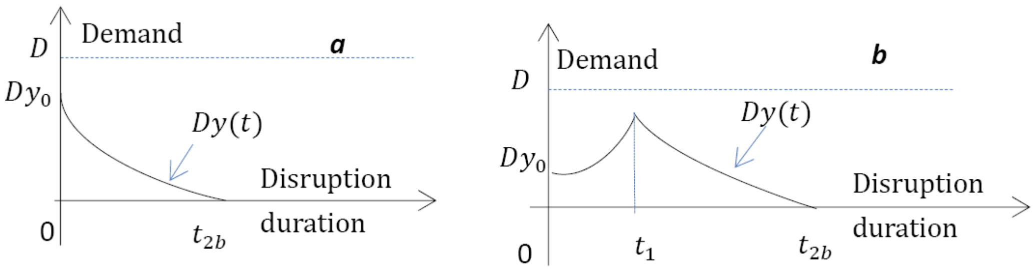

FIGURE 2. The demand process with compensation in Scenario 2 if $a < \lambda$ (Figure a) and $a > \lambda$ (Figure b)

3. **The Impact within Compensation Strategy.** In this section, we explore the impact caused by random disruptions on the basis of the demand prediction, and develop an optimal compensation strategy to minimize the disruption impact. To do so, the disruption duration is supposed to be a stochastic variable, denoted by T_d, and the density function is $f(x)$. The impacted caused by the random disruption can be described in the following two scenarios. Here, t_2 is the time when all the customers are lost. That is, $t_2 = t_{2a}$ in Scenario 1, and $t_2 = t_{2b}$ in Scenario 2.

3.1. $\boldsymbol{T_d > t_2}$**.** The demand process with compensation is stated as foregoing. The market demand is completely lost even with compensation adopted if the disruption will last longer than t_2. Hence, the compensation strategy is not very effective for mitigating the disruptions which are longer than t_2. If the manufacturer adopts the compensation strategy, the demand process is as Figure 3 (left).

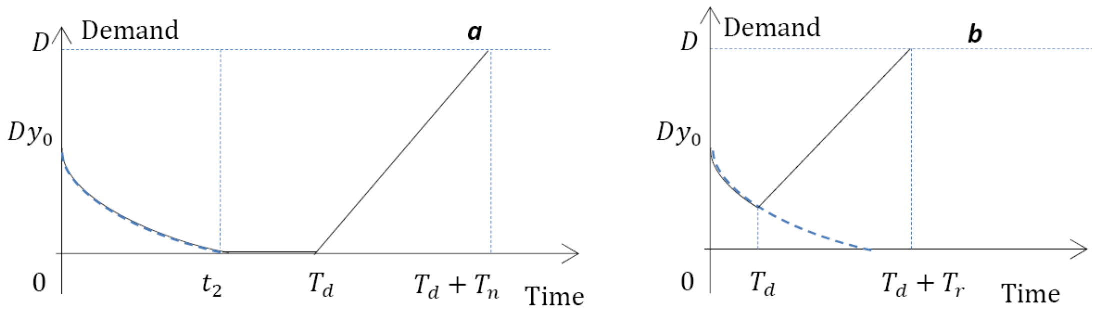

FIGURE 3. The demand process during the whole impacted period

In Figure 3, D is the market share of the manufacturer before disruption, and T_n is the time required to renew the lost market share, $T_n = t_n D$. The period impacted by the disruption is $(0, T_d + T_n)$. Specifically, the period for compensation is $(0, t_2)$, the period for renewing the lost market demand is $(T_d, T_d + T_n)$, and the period for production is $(T_d, T_d + T_n)$. Hence, during the impacted period, the total compensation cost is $c(a) \int_0^{t_2} Dy(t)dt$; the recovery cost (for renewing the lost market) is $c_n D$; the production cost is $0.5 c_p D T_n$; the lost-sales cost is $c_l[DT_d + 0.5DT_n]$, where $c(a) = c_m a$, c_m is the unit cost for compensation level a. The recovery time (for renewing the lost market) is $T_n = t_n D$. The total cost without disruption during the period is $c_p D(T_d + T_n)$. Therefore, the impact caused by the disruption is the additional cost:

$$C_1 = c(a) \int_0^{t_2} Dy(t)dt + c_n D + c_p \frac{1}{2} DT_n + c_l \left[DT_d + \frac{1}{2} DT_n \right] - c_p D(T_d + T_n). \quad (3)$$

3.2. $\boldsymbol{T_d \leq t_2}$**.** For those disruptions which are shorter than t_2, we can consider the compensation for mitigation, and then recover the lost market after the disruption restored. The process of the demand changing is as Figure 3 (right). The period impacted by the disruption is $(T_d, T_d + T_r)$. The period for compensation is $(0, T_d)$, the period for market recovery is $(T_d, T_d + T_r)$, and the period for production is $(T_d, T_d + T_r)$. Therefore, the impact caused by the disruption is the additional cost:

$$\begin{aligned} C_2 = c(a)\left[\int_0^{T_d} Dy(t)dt\right] + c_r D(1 - y(T_d)) + c_p\left[\frac{1}{2}(Dy(T_d) + D)T_r\right] \\ + c_l\left[DT_d + \frac{1}{2}(D - Dy(T_d))T_r\right] - c_p D(T_d + T_r). \end{aligned} \tag{4}$$

Synthesizing the above statements, the expectation of the impact caused by the disruption is

$$E(C) = \int_{t_2}^{+\infty} f(x)C_1 dx + \int_0^{t_2} f(x)C_2 dx, \tag{5}$$

where $t_2 = t_{2a}$ if $a/b < t_{2a}$, and $t_2 = t_{2b}$ if $a/b >= t_{2a}$. Minimizing $E(C)$, the optimal compensation level a^* to customers can be achieved, and an optimal compensation strategy is directly proposed.

4. **Numerical Analysis.** To examine the effects of the factors related to customers' behaviors and disruptions on the optimal compensation strategy, we conduct numerical analysis in this section. Suppose disruption duration T_d obeys a normal distribution $N(\mu, \sigma)$ and fix the relative parameters as an instance: $\mu = 10$, $\sigma = 0.3$, $c_l = 10$, $c_n = 20$, $c_m = 4$, $c_p = 5$, $c_r = 12$, $t_r = 1$, $t_n = 2$, $\lambda = 0.5$, $b = 0.3$, $D = 0.5$, $k_0 = 0.2$, $e = 0.001$. Minimizing $E(C)$ through algorithms, the optimal compensation level a^* to customers can be determined. Varying the relative factors $(\mu, \sigma, \lambda, b, k_0)$ while keeping other parameters the same, the variation trends of a^* to the factors are achieved as given in Figure 4 (we also testify there is similar pattern of the trends for most instances). Based on the numerical analysis, we further generate insights into the important role of disruption length and uncertainty, competition intensity (λ), customers' sensitivity (b), and customers' brand loyalty (k_0).

As can be seen in Figure 4 (top), it requires no compensation ($a^* = 0$) facing sufficiently longer disruptions, as compensation strategy is not effective to mitigate long disruptions. About the disruption uncertainty σ, we observe that the disruption with the same length and high σ requires high a^* until the highest ($a^* = 1$); for the short disruptions ($\mu \leq 13$), a^* stays the highest level once σ is sufficiently high; for the long disruptions, the compensation strategy fails to cope with those disruptions with high σ.

In Figure 4 (bottom), the x-axis respectively represents the parameters λ, b, k_0. Clearly, a^* stay the same for different b when $b >= 0.5$. On the contrary, low sensitivities dramatically influence a^*. The trend to the competition intensity λ reflects an interesting fact: enterprises should not compensate to customers if λ is very high or very low; and a^* should change to λ when λ is mediate. In reality, market demand vanishes fast if λ is extremely high that compensation strategy is not effective to mitigate the disruption. If λ is low, the market demand drops slowly, and the compensation is not necessary. a^* is decreasing in k_0, except when k_0 is sufficiently large (> 0.8). In other words, it will cost the enterprises less if customers are with higher brand loyalty. However, abnormally large k_0 corresponds to another fact in reality: the minority customers who choose to leave are extremely hard to be kept by compensation, and their reactions strongly affect others' intended behaviors as the disruption continues. Hence, high k_0 interestingly requires high a^* in some cases.

5. **Conclusions.** In this paper, we consider a manufacturer confronting a random production disruption, and there are substitutable products in the market. An optimal compensation strategy based on forecasting dynamic demand as a random disruption mitigation measure is explored.

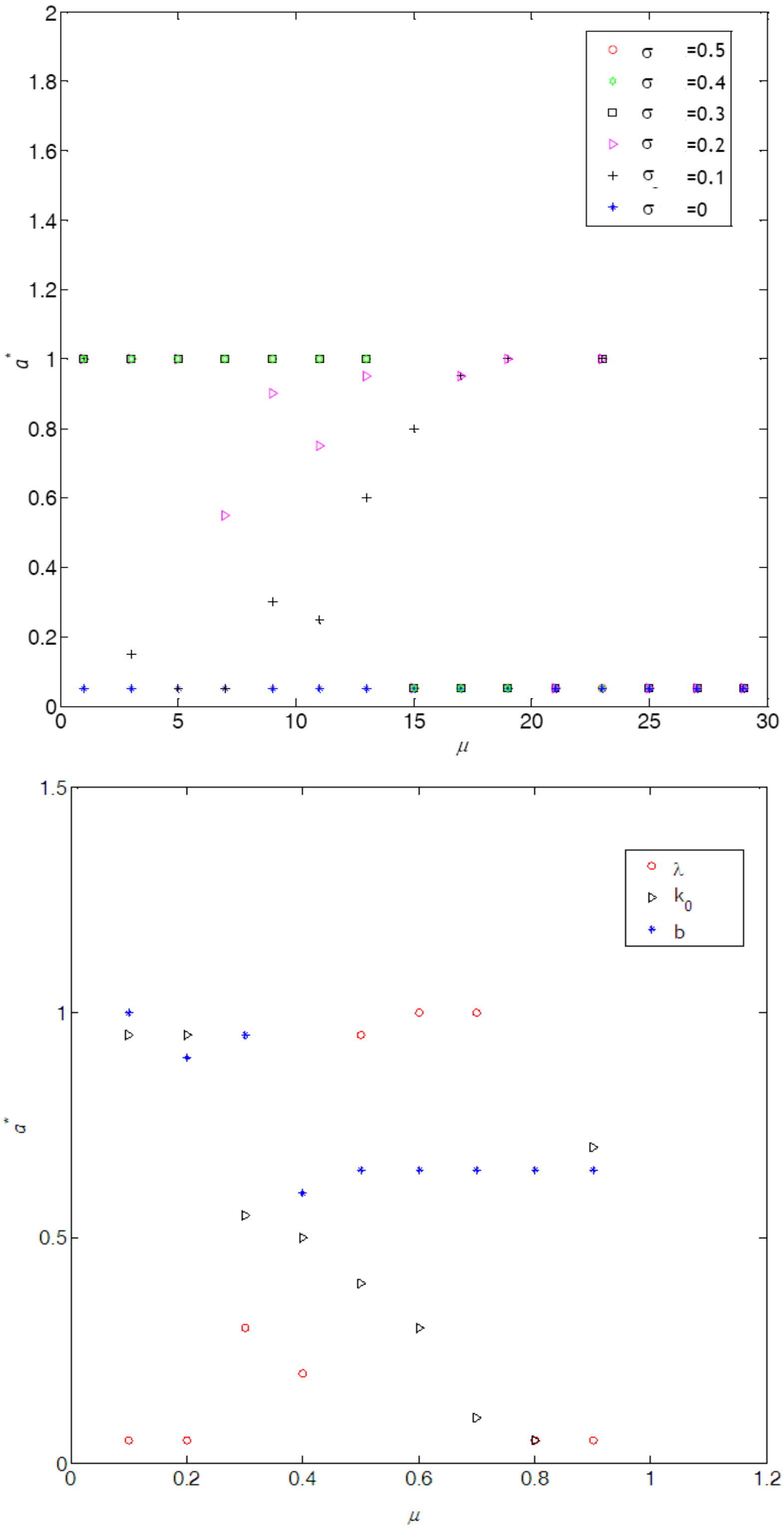

FIGURE 4. The variation trend of a^* to μ, σ, and to λ, b, k_0

To precisely predict how the market demand will change dynamically after disruption occurs and the manufacture implements mitigation strategy, we develop a differential model considering demand learning between customers. The model also captures three major factors impacting on customer reactions to the disruption: competition intensity among alternative products, customers' sensitivities to disruption duration, and customers' brand loyalty. Our analysis presents the dynamic processes of market demand after disruption considering all the potential scenarios of relative factors. Based on the prediction, we model the impact caused by the random disruption during the whole disruption impacted period, which covers both the periods of disruption duration and disruption recovering. An optimal compensation strategy is established by minimizing the impact.

We numerically analyze how the optimal compensation strategy should be changed to the relative factors, and show that in deciding compensation level, both the factors of disruption itself (disruption length and uncertainty) and the factors of customer behavior play important roles. Several important managerial insights are established: disruption uncertainty affects the optimal compensation level with different ways for short and long disruptions, and the compensation strategy fails to cope with sufficiently long disruptions. On the other hand, the optimal compensation level shows significantly change to competition intensity, mostly decrease to customers' brand loyalty, and barely keep the same for high customers' sensitivities.

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