



รายงานวิจัยฉบับสมบูรณ์

โครงการ การหาเวลาที่เหมาะสมในการเริ่มพัฒนาและอัตราการผลิตผลิตภัณฑ์ใหม่ภายใต้
ภาวะความไม่แน่นอนทางการตลาดและคุณภาพผลิตภัณฑ์

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สัญญาเลขที่ MRG5380235

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ชื่อโครงการ: การหาเวลาที่เหมาะสมในการเริ่มพัฒนาและอัตราการผลิตผลิตภัณฑ์ใหม่ภายใต้ภาวะความไม่แน่นอนทางการตลาดและคุณภาพผลิตภัณฑ์

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บทคัดย่อ: รายงานฉบับนี้นำเสนอผลงานวิจัยว่าด้วยความสัมพันธ์ระหว่างอัตราการผลิต อัตราผลผลิต การพัฒนาของระบบและความไม่แน่นอนของตลาดและคุณภาพสินค้าในช่วงการเริ่มผลิตสินค้า ในการนี้ ผู้วิจัยได้พัฒนาแบบจำลองทางคณิตศาสตร์ของระบบการผลิตเพื่อวิเคราะห์หากำไรอันจะเกิดขึ้นจากการเลือกผลิตสินค้าที่อัตราต่างๆเพื่อใช้ในการหาอัตราที่เหมาะสม โดยการวิเคราะห์นี้ได้รวบรวมเอาความไม่แน่นอนทั้งทางด้านของตลาดและคุณภาพของผลิตภัณฑ์เข้าไปด้วย ผู้วิจัยได้ทำการวิเคราะห์เชิงตัวเลขซึ่งผลแสดงให้เห็นว่าการวิเคราะห์โดยคิดความไม่แน่นอนให้ผลที่ดีขึ้นเมื่อตลาดมีความผันแปรสูง สินค้าที่ผลิตมีอัตรากำไรต่ำ หรือเมื่อระบบการผลิตมีอัตราการพัฒนาที่ช้า

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Abstract

Project Code: MRG5380235

Project Title: Optimizing Product Launch Decisions under Product Quality and Demand Uncertainty

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Abstract: This report explores the interactions among the decision of production speed, yield, learning, and demand uncertainty during production ramp-up. A dynamic net revenue model for production ramp-up coupled with learning and demand uncertainty is built to identify optimal ramp-ups under various contexts. Various numerical simulations are explored to determine the robustness of the optimal production ramp-ups under demand uncertainty. Results demonstrate that, in general, slower production ramp-ups are more profitable under increasing demand and product quality uncertainty. However, in high profit margin products, optimal production ramp-ups are much less sensitive to demand uncertainty.

Keywords: Demand Uncertainty, Production Ramp-up, Net Revenue Model, Learning

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1. Executive Summary

Increasing global competition forces manufacturing firms to release new products, or product launches, at a faster rate than ever. For any firm to survive, it must be capable of planning profitable product launches, which involves introducing the new products into a manufacturing facility and scheduling operation times from the beginning until production reaches full capacity (a set of operation times from the beginning of launch until full capacity production is called a ramp-up). Product quality during production ramp-up can be difficult to control as workers are learning new processes or learning to make new components. Piling on more pressure are economic volatility and constantly shifting customer demand, making sale forecast a very difficult task. With both product quality and demand uncertain, the problem of finding an optimal ramp-up can be challenging. Simply planning with the assumption of deterministic product quality and demand can lead to suboptimal results.

In this report, a net revenue model of production ramp-up is constructed. Production ramp-up is divided into small, quasi steady-state periods of operation. The model can evaluate the net revenue of a firm based on its ramp-up and parameters like process improvement rate (learning) and demand. The magnitude of demand uncertainty is modeled by its standard deviation.

For performance comparison, there are two objective functions—the total net revenue for the deterministic demand cases and the expected value of total net revenue for the uncertain demand cases. These two objective functions are used to search for optimal ramp-ups for their respective cases. The value of considering uncertainty is simply the difference in the expected values of the total net revenue of the two ramp-ups. Based on analysis, it is found that considering uncertainty leads to different ramp-ups when product profit margin is small or learning rate is low. Incidentally, under these manufacturing contexts, the ramp-ups under uncertain demand are always slower than that of their deterministic counterparts.

Managerial implications of this study are that for manufacturing firms whose productions have low learning rate (mostly matured or automatic processes) or have low profit margins (such as automotive, electronics, and agricultural industries) can benefit significantly from

incorporating product quality and demand uncertainties into planning and scheduling production ramp-up.

2. วัตถุประสงค์ของโครงการ

Increasing global competition means that customers are always looking for the latest model products on the market. Product lifecycles are becoming shorter while new product introduction rates have been steadily increasing. Hence, product introduction has become an increasingly larger part to the operation of a manufacturing firm. To survive, it must succeed financially at releasing new products. However, releasing new product is not a simple act of making announcement and putting the new products on store shelves. Before a new product can be introduced into the market, it must be introduced into a manufacturing facility. At first, the time it takes to make each new product, or operation time, is slow. The facility then progressively speeds up manufacturing by reducing the operation time until it reaches full manufacturing capacity. This progressive increase in production rate is called production ramp-up.

At the center of a production ramp-up is the learning effect, which in this report refers to the improvement in yield as workers cumulative output increases as opposed to the traditional meaning of the reduction in unit cost. By gaining experiences, workers become familiarized with the processes involved in manufacturing the new products and are less prone to making mistakes, allowing the manager to increase the production rate. It is evident that firms in various manufacturing industries, from semiconductor to automotive manufacture, have exhibited significant yield improvements from the learning effect during production ramp-up.

The key decision of operation time during production ramp-up directly affects productivity and, thus, profitability of the firm. If the facility is operated excessively fast, it can lead to defective parts as workers may not have sufficient operation time to properly process or are not yet sufficiently familiar with manufacturing the parts. On the other hand, overly slow production incurred the opportunity cost from wasted capacity. However, from a learning standpoint, operating the facility rapidly has high workers will be generating higher cumulative output, leading to faster improvement. This creates an “intertemporal trade-off between the short-term opportunity cost of capacity and long-term value of learning.”

Another significant factor that can affect profitability of the firm during production ramp-up is demand uncertainty. This adds a stochastic dimension to the tradeoff between the opportunity cost and value of learning. Regardless of the amount of marketing research going

into the product design, a firm may not be able to perfectly foresee the demand for its new products. When demand is underestimated, there is additional opportunity cost of underproduction; and when it is overestimated, capacity is wasted and the manufacturing facility incurred additional manufacturing costs without generating revenue. To accurately evaluate the effect of demand uncertainty to the net revenue stream of production ramp-up, these additional costs should be incorporated.

This report investigates the interaction between the decision variable of operation time throughout the production ramp-up, yield, yield improvement or learning, and the effect of demand uncertainty. A dynamic net revenue model of production ramp-up which allows for the flexibility of periodic changes in operation time is constructed. The model uses net revenue to find the optimal set of operation times from the introduction of the new product until full capacity production. Numerical illustrations are used to demonstrate such effect under various manufacturing contexts.

3. วิธีทำการทดลอง

In this section, the calculations and assumptions involved in modeling production ramp-up and evaluating its economic performance is detailed. The decision variables in this model are the operation times, which are allowed to change at different stage of production ramp-up. The economic performance is measured by the net revenue at the end of ramp-up. The model is subsequently utilized along with an optimal search algorithm to determine the set of operation times (a ramp-up) that maximizes net revenue. In this work, it is assumed that there is no experimentation effort to induce learning, i.e., yield improvement is only a result of autonomous learning.

3.1. Dynamic Production Ramp-up Model

A production ramp-up, as mentioned previously, is the duration since the new product is introduced into the manufacturing facility until the facility reaches full production capacity. Throughout the duration, the operation time is gradually reduced to speed up production rate. To evaluate the net revenue during production ramp-up, which consists of multiple periods of operation with different operation times, the production ramp-up must be divided into a number of periods of quasi-steady state operation. Let that number be n .

In each period i where $1 \leq i \leq n$, assume that there is a total available time of T , and that the minimum possible operation time for the process is $t_{\min}$. This minimum operation time is related to process's physical limit such as maximum speed of cutting tools or cooling time of a material. The operation time choice t_p is a decision variable in each period, and a set of operation times $\mathbf{T} = [t_1, t_2, \dots, t_n]$ is referred to as a ramp-up. The number of product starts with the available time is thus T/t_p . Therefore, the cumulative product starts into manufacturing up to period i is

$$v_i = \sum_{j=1}^i \frac{T}{t_j} \quad (1)$$

Define yield y_i as the fraction of nondefective products out of all that are started into manufacturing. It is modeled as a function of operation time and manufacturing learning parameter a_p , which is the reduction in defect rate due to accumulated experience. To simplify

the analysis, a specific functional form among defect rate, operation time, and manufacturing learning is defined according to Terwiesch and Bohn [1] as

$$y_i = y_0 \left(1 - a_i \frac{t_{\min}}{t_i} \right) \quad (2)$$

where $t_{\min}$ is the minimum operation time below which the operation is physically impossible. The parameter y_0 captures the base yield which is independent of the operation time and cannot be improved, while the parameter a represents the benefit of learning on the reduction of defective product rate. a is modeled using a truncated form of the log-linear relationship developed by Nadeau et al. [13]

$$a_i = \min(a_{\max}, \max(a_{\min}, bv_{i-1}^{-q})) \quad (3)$$

where $a_{\max}$ and $a_{\min}$ are the maximum and minimum observable values for a . The parameter b is the chance of first product being defective, v is the cumulative output, and q is the learning rate.

This functional form is consistent with the assumptions in [1] that yield should improve with increasing operation time but with diminishing returns; and that yield should also improve with increasing process capability, a quantity that is captured by a . It is different, however, in the way learning is modeled. According to [1], learning is modeled as a function of experimentation effort and cumulative time the facility has been processing the new product, which is independent to operation time choices. In this report, however, it is assumed that the facility is dedicated to production where learning occurs autonomously, leaving no capacity for experimentation. Furthermore, many previous works have shown the relationship between yield improvement and cumulative output. Therefore, learning is modeled after cumulative output which is a function of the operation times of all preceding periods.

The number of nondefective products in period i can then be expressed as

$$N_i = \frac{T}{t_i} y_0 \left(1 - a_i \frac{t_{\min}}{t_i} \right) \quad (4)$$

3.2. Deterministic Net Revenue Model

It is assumed that pricing is the decision of the manufacturing firm so the selling price p is fixed. Early in production ramp-up demand for the product is high, but this will decrease over

time as the product gradually loses its ‘new’ appeal. Therefore, it is assumed that the starting demand is d , and it decays at a rate of δ per period. As this report focuses on the dynamics inside the plant, it is viewed that the demand and its decay rate are exogenous to the model. If demand in a period is higher than the number of nondefective products, it is assumed that customers will not wait for products at a later period as there can be many other similar products available. Only the amount of products made to meet demand in each period is sold; unmet demand is irrecoverable. Surplus products, S_p , are stored for later sale. The number of products sold, s_p , in period i is

$$s_i = \min(d\delta^{i-1}, N_i + S_i) \quad (5)$$

where the first term is the demand in period i . The second term is the number of products available for sale in the same period, which is equal to the number of nondefective products in the period plus the number of surplus products from all preceding weeks. The number of surplus products at any period can be recursively defined as

$$S_i = \begin{cases} 0 & ; i = 0 \\ S_{i-1} + N_i - s_i & ; 0 < i \leq n \end{cases} \quad (6)$$

A variable cost per product start is c . Therefore, the deterministic net revenue generated in each period is

$$\pi_i = ps_i - c \frac{T}{t_i} \quad (7)$$

Based on Eq. (7), it would seem straightforward to derive the operation time that maximizes the number of nondefective products in a period. However, as learning is dependent on the cumulative output and thus the operation time, all subsequent period operation time decisions are dependent on the current period decision. The optimal operation time for a period is not necessarily the one that maximizes the net revenue in this period. In fact, it may be an operation time that generates more learning so that future periods may benefit.

The added complexity of considering demand is that the number of products sold is no longer singly dependent on the operation time decision. Equation (5)-(7) shows that while operation time directly translates to production ramp-up cost, it is not always directly related to revenue. When manufacturing is constrained by demand, decreasing operation time increases

the revenue up until production volume exceeds demand. Beyond this point, faster operation time only leads to product surplus which needs to be stored for sale later.

The deterministic total net revenue is the discounted net revenue streams over production ramp-up periods. Taking r as the discount rate, the deterministic total net revenue is

$$\Pi_d(\tau) = \sum_{i=1}^n \frac{\pi_i}{(1+r)^i} \quad (8)$$

The operation time choice in a given period affects its net revenue in two ways. First, the choice affects the revenue as it depends on the nondefective output. For the operation time choice to maximize the revenue, it must maximize the number of nondefective output. Second, the choice also affects the costs in subsequent periods as they depend on learning and thus the cumulative output.

However, if demand is lower than the capacity, then the revenue depends on the operation time choice up until the nondefective output reaches the demand. Beyond this point, reducing the operation time does not generate additional revenue, but the additional output would still enhance the future value of learning.

3.3. Incorporating Demand Uncertainty

To incorporate demand uncertainty into consideration, it is assumed that starting demand is no longer a deterministic value d but instead a randomly distributed number with an average of d and standard deviation of σ . Instead of evaluating a ramp-up's performance by the total net revenue based on Eq. (8), the objective function is now an expected value of total net revenue based on the distribution of demand. The magnitude of uncertainty in demand is captured by its standard deviation. The expected net revenue in period i is the revenue from expected sale minus the cost.

$$E[\pi_i] = pE[s_i] - c \frac{T}{t_i} \quad (9)$$

The objective function to be used to search for optimal production ramp-up is the discounted expected net revenue stream over the launch period. Taking r as the discount rate, the objective function becomes

$$\Pi_u(\tau) = \sum_{i=1}^n \frac{E[\pi_i]}{(1+r)^i} \quad (10)$$

3.4. Optimizing Production Ramp-ups

Due to the way learning is modeled as a function of cumulative output, each successive operation time choice influences learning and enhances production capacity of the systems to a varying degree, the problem of expected net revenue maximization becomes path-dependent, and optimization algorithms such as dynamic programming or do not guarantee global optimum. In this report, optimal ramp-ups are determined using a combination of excel and crystal ball, an excel add-on which provides means to search for an optimal set of solutions using OptQuest module.

In this report, the objective function for the deterministic demand case is the total net revenue defined in Eq. (8), while for the uncertain demand case it is the expected total net revenue defined in Eq. (10). The constraints on the operation times are that they are non-increasing, i.e. the operation time of current week is smaller than or equal to that of the preceding period. This condition is imposed to imitate a typical production ramp-up that gradually improves production rate. The second condition is that the operation times are integers. In reality, the operation time can be any real number; this constraint was added simply to reduce the optimization time. For each scenario, the simulation is repeated at least 100000 times to ensure that the confidence intervals are sufficiently small and the differences in expected net revenues between cases are statically significant.

3.5. Value of Demand Uncertainty Consideration

The benefit of incorporating demand uncertainty to help identify optimal production ramp-ups can be evaluated by comparing the expected net revenue difference of ramp-up optimized from deterministic demand (Eq. (8)) and those optimized from uncertain demand (Eq. (10)). With this value, manufacturing contexts that are more vulnerable to demand uncertainty can be identified and characterized. If τ_d is the optimal ramp-up for deterministic demand and τ_u is the optimal ramp-up for uncertain demand. The value of demand uncertainty consideration, V , is simply

$$V = \Pi_u(\tau_u) - \Pi_u(\tau_d) \quad (11)$$

When considering demand uncertainty, it is possible to show the asymmetry between the values of increased net revenue from improved yield and those of learning. If under a given

manufacturing context, T_d is faster than T_u , it signifies that the future value of learning is worth more than the increased net revenue from increased nondefective products in the current period, and vice versa.

4. ผลการทดลอง

A number of numerical examples are solved in this section in order to provide better understanding to the optimal ramp-up in various manufacturing contexts. Consider a typical automotive underbody manufacturing facility. The discount rate is 0.3% per period (week). The cost per start is \$500. The available manufacturing time T is 80 hour per period. The minimum possible operation time $t_{\min}$ is 60 s, which means the maximum production capacity is 4,800 vehicles per period. Without the loss of generality, the starting demand is assumed normally distributed with an average of 4500 vehicles per period with $\bar{\delta} = 0.95$, and the magnitude of demand uncertainty is modeled by its standard deviation. According to the available data from manufacturing experts, there are minimal yield loss during steady state operation ($y_0 = 1$) and learning parameter $b = 0.8$ and $q = 0.32$.

4.1. A Typical Optimal Ramp-up

By setting the standard deviation of demand to 400, the optimal ramp-up and resulting weekly yield during production ramp-up are shown in Fig. 1.

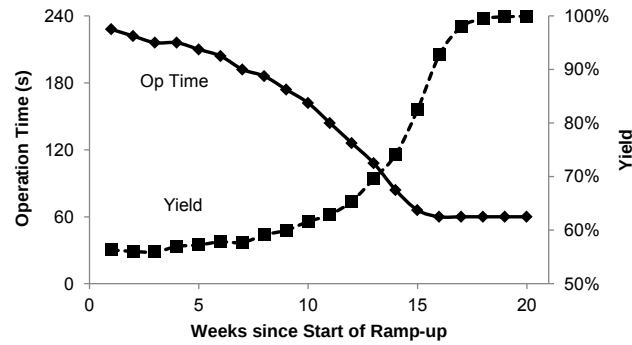


Fig. 1 An optimal production ramp-up and resulting yields for the example case with standard deviation of demand = 400.

Fig. 1 illustrates a typical suggested production ramp-up and resultant yields. The operation time in the first week steadily decreases as yields improve due to manufacturing learning. The operation time reaches a minimum possible operating time of 60 s and yield reaches 100% in week 16.

While the goal of this report is to present the effect of demand uncertainty on the optimal ramp-ups, it is difficult to show all of the optimal operation times in a ramp-up versus varying

demand uncertainty in a single diagram without some clarity loss. To remedy this issue, the author feels that presenting the optimal ramp-ups as 20-week average operation times allows for more effective figures.

4.2. Capacity Utilization

Here, the report will investigate whether demand-constrained system and capacity-constrained system are affected differently by demand uncertainty. First, consider a system that is operating at near maximum capacity—where the average starting demand (4500) is close to the maximum capacity (4800).

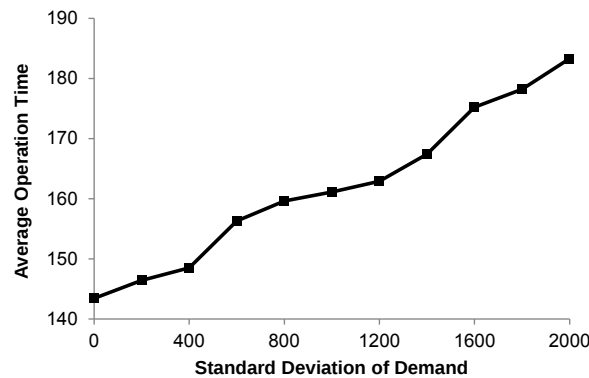


Fig. 2: Average operation times under varying demand uncertainty for a capacity-constrained production (average demand = 4500).

Under increasing demand uncertainty, the model suggests slower optimal production ramp-ups, as illustrated in Fig. 2. This is because the disadvantages resulting from excessive speed are twofold: 1) excessive speed leads to low yield and 2) even though lower yields lead to more learning and improved capacity in later period, there is an increased risk of unsold products. The disadvantage from a slower production ramp-up, on the other hand, is only the opportunity cost.

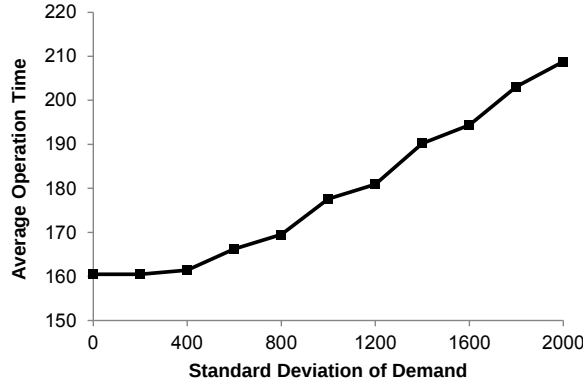


Fig. 3: Average operation times under varying demand uncertainty for a demand-constrained production (average demand = 2400).

Consider now a case where the average demand is much lower than the maximum capacity (2400 vs 4800). Similar to the capacity-constrained case, increasing demand uncertainty also leads to slower optimal production ramp-ups, as shown in Fig. 3. The increases in average operation times from the deterministic to the most uncertain demands are also comparable (28% vs 30%), exhibiting that the level of demand- or capacity-constrained of manufacturing system has very little effect on the robustness of optimal ramp-ups under demand uncertainty.

4.3. Product Profit Margin

Product profit margin refers to the difference between the selling price and the production cost of the product. Even with a fixed price, profit margin during production ramp-up can vary because yield changes. For clarity and simplicity, product profit margin refers to the ratio between the selling price and cost per start.

To understand how product profit margin affect robustness of the optimal ramp-up, consider the case for a production ramp-up of a low profit margin product—where the ratio of selling price to cost per start is low ($p/c = 1.5$). Fig. 4 shows that the model suggests slower ramp-ups as demand uncertainty increases. When profit margin is low and selling price is comparable to cost per start, opportunity cost is worth as much as unsold finished products. Thus, there is no incentive to hasten or slow production based on revenue. On the other hand, increasing the operation time guarantees cost reduction through increased yield and reduced

number of products started—a deterministic cost saving. Therefore, as demand uncertainty increases, the suggested optimal ramp-ups become slower.

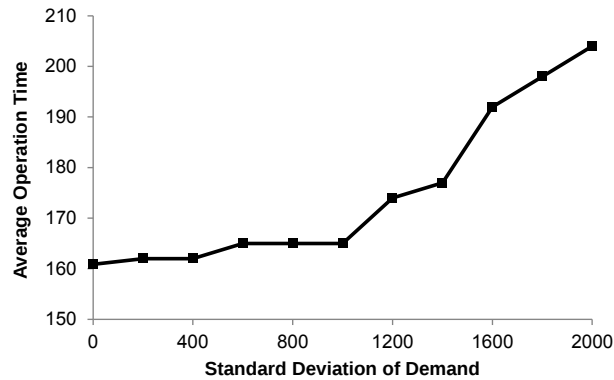


Fig. 4 Average operation times under varying demand uncertainty for a low profit margin product ($p/c = 1.5$).

Consider now a case for a high profit margin product ($p/c = 5$). As shown in Fig. 5, the most contrasting aspect of the result compared to low profit margin case is the insensitivity of the optimal ramp-ups to demand uncertainty. This is because the selling price is high, loss of sale is worth much more than unsold finished product; maximizing expected net revenue becomes a simple matter of maximizing the number of finished products. Therefore, increasing demand uncertainty does not affect the robustness of the optimal ramp-ups of high profit margin products.

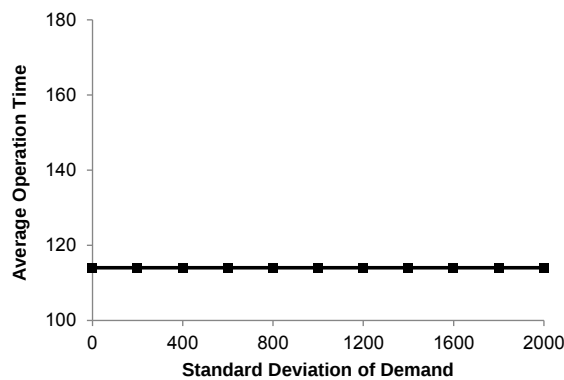


Fig. 5 Average operation times under varying demand uncertainty for a high profit margin product ($p/c = 5$).

The difference in behavior of low and high profit margin products clearly exhibits strength of the effect that a profit margin has on the robustness of optimal ramp-ups under demand uncertainty.

4.4. Manufacturing Learning Rate

For a manufacturing firm with fast learning ($q = 0.5$), i.e. where the production process is still immature or mostly labor-based, the production capability improvement is rapid and therefore the average operation times are faster. The model suggests that the optimal ramp-up should slow down as the magnitude of demand uncertainty increases. In fact, the suggested average operation time during ramp-up for when the standard deviation of demand is 2000 increases by 28% compared to deterministic demand (i.e. when standard deviation is 0.)

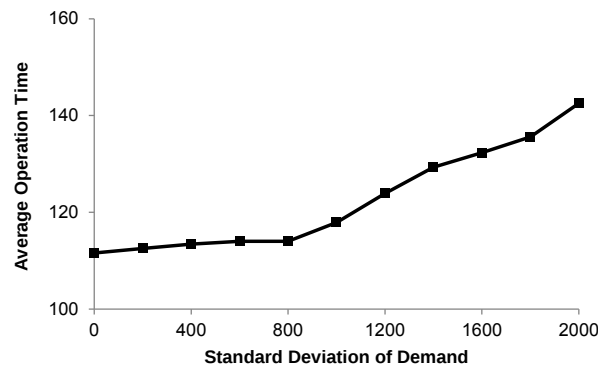


Fig. 6 Average operation times under varying demand uncertainty for a fast manufacturing learning system

Consider a firm with slow learning ($q = 0.15$), i.e. where the production process is mature or mostly mechanical, the capability improvement is slow, leading to slower production ramp-ups and thus longer average operation times. When standard deviation of demand is 2000, the suggested average operation time increases by 12%. Comparing to the case of fast manufacturing learning, the optimal ramp-up is less sensitive to demand uncertainty. The ramp-up was already slow to begin with and it cannot slow down much further since it still needs to satisfy the demand.

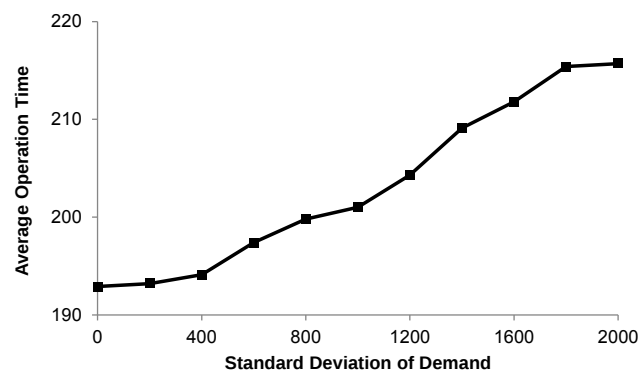


Fig. 7 Average operation times under varying demand uncertainty for a slow manufacturing learning system.

5. สรุปผลการทดลอง

The report presents the findings on the effect demand uncertainty has on optimal production ramp-ups under various manufacturing contexts. By developing a dynamic net revenue model of production ramp-up with manufacturing learning and coupled with uncertain demand, optimal production ramp-ups can be identified through maximization of expected net revenues. The findings shed light on the robustness of suggested optimal ramp-ups under the effects of varying profit margins and manufacturing learning rates.

Numerical illustrations demonstrate that, in certain manufacturing contexts, explicit consideration of the stochastic nature of demand can be crucial to the financial performance of production ramp-up. This is especially true for production of low profit margin products with slow learning rates.

The constraint on production, whether it is capacity or demand, has no effect on the changes in optimal ramp-ups under demand uncertainty. Net revenue changes due to capacity utilization is unaffected by demand, resulting in similar changes in optimal ramp-ups regardless of the constraints.

Product profit margin is crucial to the robustness of the optimal production ramp-ups under demand uncertainty. For low profit margin products, managers should consider slowing down the ramp-up as demand becomes increasingly uncertain. For such a case, cost saving is the way to increase expected net revenue. On the contrary, optimal production ramp-ups for high profit margin products are virtually insensitive to demand uncertainty; generating net revenue is easily achieved by producing more products to satisfy demand since the cost per start is inexpensive.

Manufacturing learning rates do not have as equally significant an impact as profit margin. A fast learning system is more affected than a slow learning system. A fast learning system tends to ramp up operation time faster, so there is more room to slow down the system, save on cost, and still be able to satisfy demand.

The report has investigated in details the robustness of optimal production ramp-up due to demand uncertainty, which affects revenue. Future research should address uncertainty in

factors that affect cost structure of production. It may also be interesting to explore uncertainties that affect cost and revenue simultaneously, and to investigate the interaction among them.

6. Output จากโครงการวิจัยที่ได้รับทุนจาก สกว.

1. ผลงานตีพิมพ์ในวารสารวิชาการนานาชาติ (ระบุชื่อผู้แต่ง ชื่อเรื่อง ชื่อวารสาร ปี เล่มที่ เลขที่ และหน้า) หรือผลงานตามที่คาดไว้ในสัญญาโครงการ
 - กำลังอยู่ในระหว่างรอผลการพิจารณาจากวารสารวิชาการ
2. การนำผลงานวิจัยไปใช้ประโยชน์
 - ในเชิงพาณิชย์ นักวิจัยได้นำความรู้ส่วนนี้ไปเผยแพร่ให้กับด้านอุตสาหกรรม โดยเฉพาะอย่างยิ่งอุตสาหกรรมผลิตยานยนต์ ซึ่งได้นำผลการวิจัยไปประยุกต์ใช้กับการวางแผนกระบวนการผลิตได้ผลเป็นที่น่าพอใจ ช่วยลดต้นทุนและลดความซับซ้อนในการจัดการวางแผนลงเป็นอย่างมาก
 - ในเชิงวิชาการ นักวิจัยได้นำองค์ความรู้ใหม่ซึ่งได้รับจากการทำวิจัยนี้มารวบรวมไว้ในเนื้อหาวิชาสอนและได้เตรียมการรับนักศึกษาปริญญาโทเพื่อดำเนินการวิจัยต่อไป