Learning-Curve Applications for Emerging Products and Services

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Abstract

A learning curve is a powerful tool for companies producing large lots or cutting-edge products, enabling them to negotiate cost savings. New products and services are crucial for the growth of any business, particularly in the technology sector. However, they also come with inherent risks. One of these challenges is the learning curve associated with new offerings. Companies can assess the cost savings of acquiring new skills by applying the learning curve. A common mistake is to price new products solely based on their initial manufacturing costs. However, if businesses utilize the learning curve effectively, it can be a valuable tool for estimating costs, improving productivity, and achieving long-term profitability. Understanding and implementing the learning curve empowers companies to make informed pricing, resource allocation, and project management decisions. It allows them to optimize their processes and identify opportunities for cost reduction and improved performance. The study aims to determine the learning rate for emerging or exceptionally large-scale products where traditional learning curve theory may not readily apply. This research will show how large corporations and defense organizations can effectively use the learning curve to manage extensive projects involving emerging products and services.

Keywords
Learning curve, Learning rate, Emerging products.

1. Introduction
The learning curve holds significant relevance in the business context, finding various applications. One such application involves its utility in estimating the actual cost of a project. The learning curve illustrates that as time progresses, productivity increases, albeit at a diminishing rate as production levels rise. It signifies the enhancement of efficiency or productivity through repetitive task execution. According to Investopedia, the learning curve is defined as "a concept that visually represents the relationship between cost and output over a specific time period." In this study, we explore how applying the learning curve can assist in estimating the learning curve of emerging products. By leveraging the learning curve, a company can determine the rate at which acquiring new skills translates into cost savings. A steeper slope on the learning curve implies higher cost savings per unit of output. As employees gain proficiency, tasks demand less time and resources, leading to improved performance. A common misconception arises when pricing a new or emerging product solely based on the initial manufacturing cost. This approach makes it unlikely to achieve the long-term cost objective. Initial units are unlikely to attract significant purchases, preventing the accumulation of quantities necessary for cost reduction and long-term profitability. Pricing a product should be based on its market value while considering the learning curve estimation, enabling early profitability.

The foundation of the learning curve concept rests on the premise that a process improves over time through learning and increased proficiency. As the process is repeated and mastered, tasks require less time and resources, resulting in enhanced performance. This study provides further elaboration on these concepts, accompanied by relevant examples. Its demonstration aims to benefit students, new employees, and professionals working across various industries, including defense companies like Raytheon Technologies (Raytheon, Collins, Pratt & Whitney) and General Dynamics (Electric Boat). While many individuals comprehend the applications of the learning curve in terms of knowledge acquisition, skill development, and productivity enhancement through repetitive tasks, it is worth noting that successful implementation of the learning curve offers advantages beyond cost savings for both producers and buyers. It can also serve as a negotiating tool for future projects. Large corporations and defense organizations extensively engage in managing large-scale projects (Ghanmi et al., 2014). The learning curve can be applied to both emerging markets and extremely large products, such as single military ships or specialized vehicles. In the case of emerging products, businesses may initially target niche segments that are less cost-sensitive before expanding to the general marketplace. For example, Tesla introduced its first vehicle, the Roadster, at a high price point targeting the affluent market segment and gradually reduced prices over time. Finally, as industry 4.0, modelling and simulation, and big data analysis become prevalent in today's industries, some experts are finding learning curve to be a natural extension of these technologies (Tamás & Koltai, 2020), (Tortorella et al., 2022).

The rest of the paper is organized as follows. Section 2 introduces the learning curve concept. Section 3 presents the learning-Curve for emerging products. The Learning Curve Model for Emerging Products is discussed in Section 4 Results and Discussion is in Section 5. Final Section 6 is reserved for conclusion and future works.

1.1 Objectives

The learning curve serves as a valuable tool for businesses, providing insights into cost savings, productivity improvement, and long-term profitability. By embracing the learning curve, companies can navigate the challenges associated with new offerings and make strategic decisions that drive success The objective of this study is to determine the learning rate for emerging products or exceptionally large-scale products (e.g., individually produced submarines or military ships), where the traditional learning curve theory may not readily apply.

2. The Learning Curve Concepts

In literature, there are several formulations of the learning curve applications. The learning curve model is based on the principle that as workers gain experience, their productivity increases, leading to cost reductions. Wright's (1936) model is the most used because of its simplicity and generality of applications. The model assumes that the time required to produce each unit decreases by a consistent percentage with each doubling of cumulative production quantity. The learning curve concept has many other applications, including lot sizing (Jaber et al., 2009), implementation of ERP (Plaza et al., 2010), everyday electric home appliances such as washing machines, laundry dryers, and dishwashers (Weiss et al., 2010), production planning (Glock et al., 2012), human resources assignment (Attia et al., 2014), inventory management (Teng et al., 2014), construction (Srour et al., 2015), and recently in machine scheduling (Ji et al. 2016) and construction costs of nuclear power reactors (Lovering et al., 2016). Several authors featured learning curve attributes, such as Uzumeri (2000), depending on aggregated or individual models. Wright (1936) discovered that, in aircraft manufacturing, a 20 percent productivity improvement is achieved each time the production quantity is doubled. While in the construction industry, the learning rate is between 85-95%. The Learning-Curve effect can help businesses make informed decisions about pricing, resource allocation, and project management. A business can effectively utilize the Learning-Curve Effect to negotiate better deals and maximize the potential of your emerging product. By estimating the cost savings associated with acquiring new skills, companies can achieve long-term profitability while improving productivity.

Numerous factors can influence how fast, far, and well a worker learns within a specified horizon. A learning curve can assess the project's cost by identifying how quickly a task can be performed over time as the employees gain proficiency. A company can use this information to plan financial forecasts, price goods, and anticipate whether it will meet customer demand. The learning curve model can be expressed using the following formula:

$$T_n = T_1 n^b \tag{1}$$

where,

T_n = The average time or cost per unit
T_1 = Time taken to produce initial quantity, the first unit
n = Cumulative units of production or the cumulative number of batches
b = Slope or learning curve index, (Log of the learning curve / Log 2), typically a value between 0 and 1.

The steeper slope of the learning curve indicates the high cost of the first unit while higher cost savings per unit of output. A deeper understanding of the learning curve (LC) can help a project manager or an industry leader to use this as an essential negotiation tool to benefit all parties in their supply chain.

The learning curve is significant in determining production costs and costs per unit. Consider a new employee working in a production line who understands the task attributes to improve the product and expertise relationship in their field. They can produce more products in less time. For example, a 90% learning curve indicates that performance improves by 10% each time repetitions are doubled. Using an example of 90% of the learning rate, if a job is hundred hours, a repetition of that is ninety hours in the second completion and 84.62 hours in the fourth completion if the working conditions are similar. Over time, a business may use this data to estimate its financial performance, set product prices, and determine if it can satisfy client demand. Figure 1 shows a learning curve with 90% learning rate.

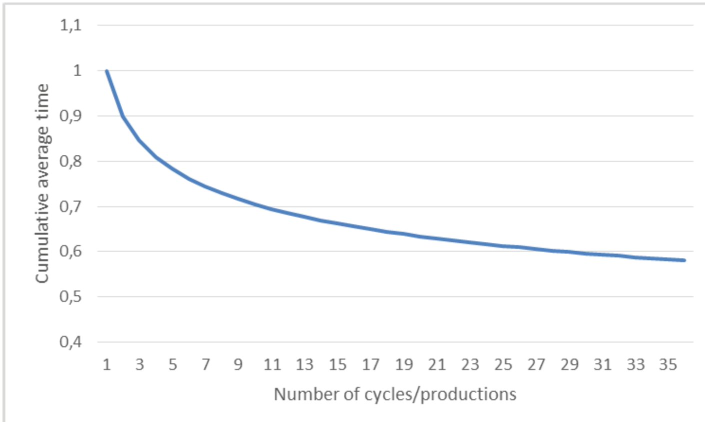

Figure 1. Learning curve with 90% learning rate

The learning curve, also known as production efficiency, is significant in assessing cost risk factors in defense acquisition projects, particularly in the military shipbuilding sector. The risk associated with production efficiency, or the learning curve, is that shipbuilders may need to achieve the anticipated efficiency level during the production process. This can result in increased costs and budget overruns. An example is an emerging technology company with a contract to produce eight workstations. The learning curve can be applied to this problem to predict the required labor hours, profits, and costs. This method will help the work progress in a timelier manner and efficiently. The learning curve effect does not always apply, of course. Identifying the learning curves of an emerging product can be tricky, especially when there is no actual data collection. The learning curve applied to emerging markets, or a significant product of one unit, determines the average time of the cumulative value of units produced.

3. **Learning-Curve for Emerging Products**

The Learning-Curve is a powerful tool for businesses producing large lots or cutting-edge products to negotiate cost savings and achieve success in emerging markets. A business can use the Learning-Curve for negotiating favorable deals for emerging products. Here are the steps to follow when utilizing the Learning-Curve Effect in the context of emerging products:

- *Understand the Learning Curve*: Familiarize yourself with the concept of the Learning Curve Effect and its applications. Gain knowledge of how the learning curve can impact productivity, cost savings, and performance improvement over time.

- *Identify Key Parameters*: Determine the relevant parameters for your specific emerging product. This may include factors such as initial production quantity, time taken for the first unit, and the learning curve index.

- *Gather Data*: Collect relevant data points, if available, to understand the learning curve's progression. This can include production data, performance metrics, and any other information that reflects the learning curve's impact on the product.

- *Estimate Learning Rate*: Use the data and parameters to estimate the learning rate for your emerging product. This will provide insights into how productivity and costs are expected to improve as production increases.

- *Analyze Cost Savings*: Evaluate the cost savings potential based on the learning curve. Consider how increased productivity and efficiency can lead to reduced costs per unit and overall profitability.

- *Use as a Negotiation Tool*: Leverage the insights gained from the Learning-Curve Effect as a negotiation tool. Present the potential cost savings and performance improvements that can be achieved over time to negotiate better deals with suppliers, partners, or customers.

- *Communicate the Value Proposition*: Clearly communicate the value proposition of the Learning-Curve Effect to relevant stakeholders. Explain how the learning curve can drive down costs, improve product quality, and create long-term profitability, ultimately benefiting all parties involved.

- *Monitor and Refine*: Continuously monitor the actual performance and progress of the learning curve for your emerging product. Adjust your strategies and forecasts as needed to ensure alignment with the observed learning curve trends.

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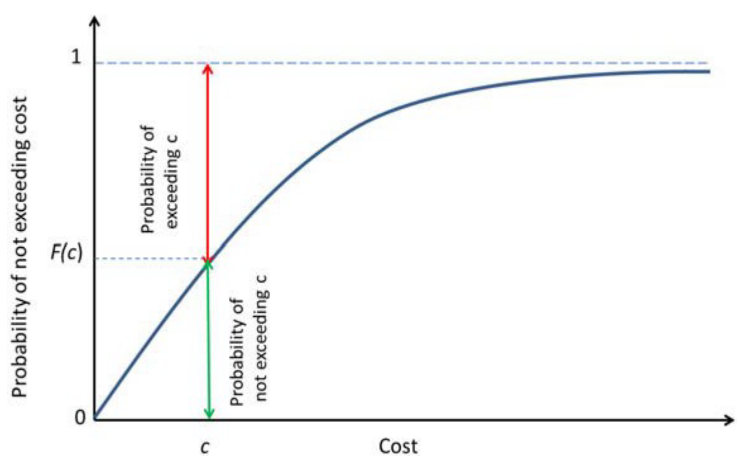

Figure 1. Cost risk cumulative distribution (Sokri & Ghanmi, 2017)

Many cost risk factors are generally identified in defense acquisition projects. Here are some key points to consider regarding cost risk factors related to the learning curve in military shipbuilding:

- *Experience and Skill Level*: The learning curve assumes that as workers gain experience and familiarity with a particular task or production process, their productivity improves. However, if the shipbuilding workforce lacks experience or the required skills, it can impact production efficiency. Inadequate training programs or a shortage of skilled workers may hinder the expected learning curve benefits, leading to increased costs.

- *Technology Readiness*: The integration of advanced technologies and systems into military ships can introduce complexity and potential challenges. If the shipbuilders are not adequately prepared to handle these technologies or if the technologies themselves face developmental or operational issues, it can affect production efficiency. Delays or difficulties in implementing new technologies can lead to cost escalations.

- *Supply Chain and Dependencies*: Military shipbuilding involves complex supply chains with various dependencies on subcontractors, suppliers, and other stakeholders. If any of these external entities encounter difficulties or delays in delivering their components or services, it can disrupt the production process and impact the learning curve. Supply chain disruptions can result in increased costs and schedule delays.

- *Changes in Design or Requirements*: Modifications or changes in ship design or project requirements can introduce uncertainty and affect production efficiency. If design changes are implemented during the production process, it can disrupt workflow, require rework, or lead to delays. Changes in requirements can also impact the learning curve assumptions and affect cost projections.

- *Schedule and Time Constraints*: The learning curve assumes a consistent production rate over time, but schedule delays or time constraints can disrupt this assumption. If the project faces unexpected delays or if there is pressure to accelerate production, it can strain resources and impact the learning curve. Rushed production can lead to inefficiencies, errors, and increased costs.

- *Foreign Exchange and Inflation*: Cost risk factors such as foreign exchange rates and inflation can impact the procurement of raw materials, equipment, and labor costs. Fluctuations in exchange rates or high inflation rates can lead to increased expenses, affecting the overall cost of shipbuilding projects. These external factors can influence the expected learning curve benefits.

- *Material and Equipment Availability*: Availability and accessibility of required materials and equipment can influence production efficiency. If there are shortages or delays in procuring necessary materials or equipment, it can disrupt the learning curve assumptions. Additional time and costs may be required to overcome these challenges.

It's important to note that the specific cost risk factors associated with the learning curve in military shipbuilding can vary based on the project, region, and other contextual factors. Proper risk management, contingency planning, and effective coordination among stakeholders can help mitigate these risks and improve cost control in defense acquisition projects.

4. Learning Curve Model for Emerging Products

The learning curve can be applied to emerging markets or an extremely large product of one unit, in addition to determining the average time of the cumulative value of units produced. A business may decide to introduce the initial models to niche segments that are less cost-sensitive than the general marketplace. For example, Tesla targeted its first vehicle, the Roadster, to the high-end affluent market segment with a price tag of around $100,000. Over time, Tesla prices went down. Similarly, in the military shipbuilding industry, ships are frequently acquired as single units rather than in lots, and pricing information is supplied by units (Sokri, 2015). To depict the learning curve of a single unit, Younossi et al., (2007) stated the learning curve of a single unit model as the following.

Deriving a Cost Risk Profile: To derive a cost risk profile using the learning curve model, historical production data is analyzed to determine the learning curve exponent (b) and the initial unit cost (a). This data is used to fit the learning curve equation to the observed production data. By extrapolating the learning curve equation beyond the observed data, a cost risk profile can be developed. This profile provides an estimate of the expected unit costs for future production quantities. The cost risk profile considers the inherent uncertainties associated with the learning curve and provides a range of potential costs based on different confidence levels. Let $M_i(b)$ denote the midpoint of the i^{th} lot and $T_{(n)i}$ is the lot average cost. The marginal cost of the lot midpoint is equal to the lot's average cost. The formula is given below.

$$T_{(n)i} = T_1[M_i(b)]^b \times r_i^c \tag{2}$$

Where r_i is the production rate of lot i. As in Eq. (1), T_1 represents the cost of the first unit, b is the learning (or improvement) index and c is the production (or procurement) index. For a large single product unit, Sokri & Ghanmi (2017) expressed that the production rate r_i is equal to one, i.e., $r_i^c \to 1$.

Determining Cost Contingency:
Cost contingency is an important aspect of risk management in defense acquisition projects. It involves allocating additional funds to account for potential cost overruns or unexpected events. The learning curve model can inform the determination of cost contingency. Based on the cost risk profile derived from the learning curve analysis, the level of uncertainty and potential cost variations can be assessed. The cost contingency is then determined by considering

the acceptable level of risk and the desired confidence level in cost estimates. The lot midpoint *Mi*(*b*) is expressed as equivalent to the sequence of nth ship. Eq. 1 then reduced to

$$T_{(n)i} = T_1[n]^b \tag{3}$$

Which is equivalent ot Eq. 1. The logarithms on both sides Eq. (3) simply the equation as

$$Ln(T_n) = Ln(T_1) + b \times Ln(n) \tag{4}$$

Finding data on an emerging product or a large-scale product such as a containership regarding the learning curve is difficult. We used a publicly available dataset of building regular ships (to avoid issues with classified information) to demonstrate how to obtain the learning curve of an emerging product or a large product. We applied the ordinary least squares (OLS) regression method to identify the two parameters T_1 and b using a log-linear model. Data used here is collected from Sokri & Ghanmi (2017), converted to USD presented in Table 1. For selected data, the estimated parameter, b, obtained by a simple linear regression method will illustrate the learning rate by 2^b. This technique demonstrated an important concept of learning curve application using a conventional method.

Table 1: Shipbuilding Data converted to USD

Ship	Hours	Can ($000)	USD (000)
1	550,500	16,615.00	$12386
2	450,500	15,615.00	11636
3	400,500	12,115.00	9011
4	370,500	11,215.00	8336
5	341,000	10,330.00	7673

Literature suggests a higher level of cost contingency may be recommended if the project is associated with significant uncertainties, such as a steep learning curve, limited historical data, or high complexity. Conversely, a lower cost contingency may be appropriate if the project has a well-established learning curve, ample historical data, and low uncertainty. Table 2 shows the learning curve model fitness for the data.

Table 2. Learning Curve model fitness

Model Summary – Learning curve (shipbuilding)				
Model	**R**	**R^2**	**Adjusted R^2**	**RMSE**
H_0	0.000	0.000	0.000	2082.540
H_1	0.949	0.900	0.867	760.453

Determining cost contingency is a complex decision that involves considering multiple factors, including the organization's risk tolerance, the criticality of the project, and the available resources. It typically results from a thorough risk analysis process that incorporates inputs from various stakeholders and experts. Table 3 shows the coefficient of the model.

Table 3. Coefficient of the model

Model		**Unstandardized**	**Standard Error**	**Standardized**	**t**	**p**
H_0	(Intercept)	9808.400	931.340		10.531	< .001
H_1	(Intercept)	-354.216	1985.193		-0.178	0.870
	Hours	24.048	4.628	0.949	5.196	0.014

From the above equation, *Tn* is the time required to produce the *n*th ship. The natural logarithm of the time to have the first ship gives 10.53. The number -0.178 is the slope of the learning curve. For selected data, the estimated parameter, b, obtained by a simple linear regression method, will illustrate the learning rate by 2b. Using the above values, the range of the expected learning rate would be u = 2-0.178, approximately 88.4%. It's worth noting that the learning curve model provides a framework for understanding production efficiency improvements and estimating costs. However, it is essential to regularly monitor actual production performance and adjust cost estimates and contingency plans as the project progresses to ensure effective cost management and risk mitigation.

5. Results and Discussion

This example illustrates how the learning curve effect can be applied to estimate the cost of producing the next product unit based on the cumulative production volume. The regression analysis indicates that the natural logarithm of the time taken to make the nth ship decreases with the logarithm of n, and the slope of the learning curve is -0.178. This means that the time taken to produce each ship reduces by 17.8% every time the number of ships produced doubles. The learning rate is, therefore, 88.4%, which is within the range of the expected learning rates for shipbuilding projects (i.e., between 85% and 89%).

Businesses can use available data and regression analysis to estimate the learning curve parameters for emerging or large products. This information can inform decision-making and help achieve cost savings and improved efficiency over time. For example, a company planning to produce a new type of ship can use the learning curve to estimate the time and cost of production for the first few ships. This information can be used to set realistic expectations and make informed decisions about the project. The learning curve is a powerful tool that can be used to improve efficiency and productivity. By understanding how the learning curve works, businesses can make better product and process decisions.

6. Conclusion

The proposed model will improve the perception of the learning curve as the Effect of learning efficiency, cognitive learning, and productivity, as most people usually get better at repeated processes. The learning-Curve Effect as a negotiation tool requires careful analysis of data and a clear understanding of the efficiencies gained over time. By highlighting experience, a company can negotiate based on efficiency gains and negotiate better deals and agreements. Continued improvement could be used as a negotiation tool to estimate the project cost. This example illustrates how the learning curve effect can be applied to calculate the cost of producing the next product unit based on the cumulative production volume. The provided tables show an example of shipbuilding data and the results of the learning curve model. The R-squared value of 0.9 indicates a strong relationship between the hours and the shipping number, demonstrating the learning curve effect. The estimated parameter b, obtained from the linear regression, represents the learning rate. In this case, the expected learning rate falls within the typical range for shipbuilding projects (around 88.4%).

A human phenomenon is that an employee gets quickly in performing repetitive tasks and becomes proficient over time. The study showed that the learning curve could be used to predict the cost of production during large-scale production. This information was helpful to the company in making decisions about how to develop and launch large-scale emerging products such as a new containership or super tanker. A high learning curve indicates that the initial cost is high, but the tasks might be intensive to employee training. As the learning curve has many applications, a company can identify the significance of dedicated training for new procedures, allocating employees' time, or allocating costs across a new product or an extensive unit and use the information for negotiation. Future research direction is how a project manager or industry leader can use various learning curve applications to derive financial forecasts, estimate the budget, anticipate due dates, and meet customer demand.

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