

Kinked Experience Curve

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INTRODUCTION

How much productivity improvement or cost reduction would be possible when the number of semiconductor chips fabricated increased from one million to two million? How many more wind farms or photovoltaic farms needed to be installed before their unit cost of producing electricity can become parity with unit cost from the fossil power plant? Can the child mortality rate in the world be reduced by two-thirds between 1990 and 2015? Or, can the prevalence rate from tuberculosis be reduced by 50% between 1990 and 2015? Can experience curve (EC) models provide answers to these questions? We present an extended EC approach known as kinked EC models which are capable of predicting the long-term future performance measures such as accident rate, mortality rate, energy efficiency index, etc. in the context of large learning systems such as nation, region, or even the world.

BACKGROUND

Initially discovered in 1936 (Wright, 1936), the functional relationship between performance measures such as cost, price, or efficiency index and accumulated experience has been shown to exist in nearly every fields of activities. For example, it has been recently reported (Weiss, Junginger, Patel, & Blok, 2010A) that the existence of EC relationship was verified by 207 energy-related studies as well as by 124 studies from manufacturing industries with an average learning rate of about

18%. Under EC, that indicates that performance measures such as price, cost, or index will improve 18% upon each doubling of cumulative experience. In other words, the simple concept of “practice makes it perfect” or “learning by doing” has been transformed into a mathematical relation between performance and accumulated experience. More specifically, it is defined as double log linear relationship between performance and cumulative experience. Thus, a fixed 100 percentage change of cumulative experience is correlated to another constant percentage change like 18 percentages in performance.

Theories about why such relationship exists are still not fully developed. However, we can begin with a simple black box of static learning system which converts input into output, as shown in Figure 1. The conversion rate of input into output is fixed in this system. Therefore performance measure which shows the ratio of input over output will also remain constant.

If learning system were to follow the concept of EC, then we will have a dynamic learning system where the same input will never produce the same output. Following cybernetic theory (Ashby, 1964; IEA, 2000; Wene, 2011), this dynamic learning system will generate continuously changing conversion ratio between input and output as a function of cumulative experience. Therefore, the resulting performance measure will also change (improve) continuously.

As shown in Figure 2, dynamic learning system has two types of information feedback loops dealing with performance measures and deployment (or volume) rate. Due to performance information

Figure 1. A simple static learning system

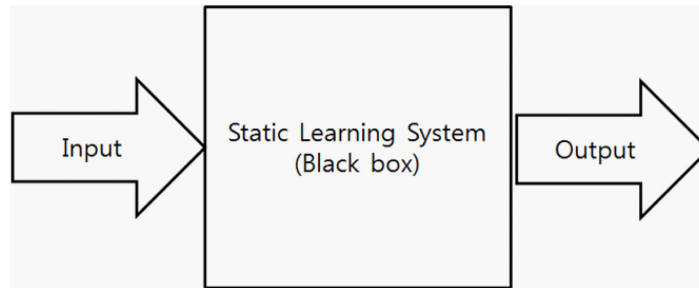
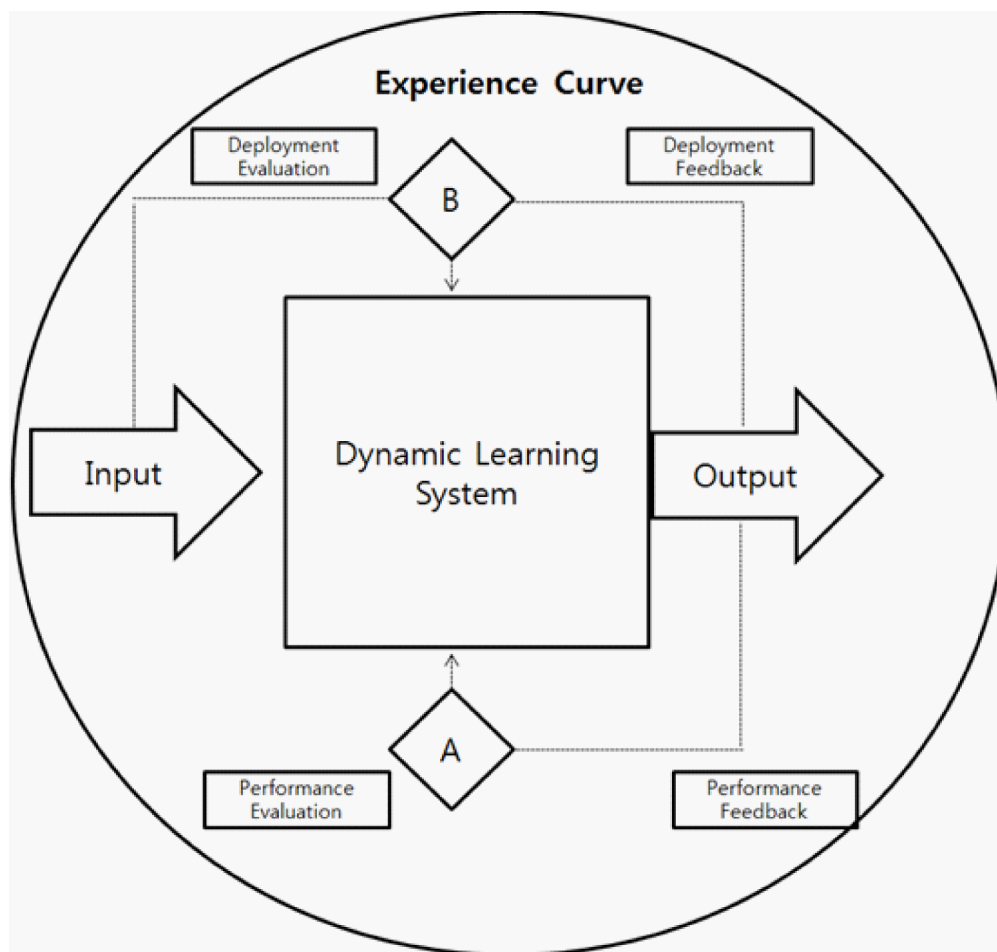


Figure 2. Dynamic learning system under experience curve



feedback, dynamic learning system will continue to improve its inner working so that performance measures can improve according to its learning rate. Similarly, deployment (or volume) information feedback will continue to adjust its deployment rate to match the requirement from environment like market or public demand.

MAIN FOCUS

One of the basic assumptions of dynamic learning system under EC is that learning rate will remain constant throughout the period. However, as early as 2000, a theory of kinked EC has been proposed (IEA, 2000) as shown in Figure 3. The

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