A Dynamic Approach to Manufacturing Improvement from Learning and Decision-theoretic Perspectives

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Abstract

In this article, we develop a 'dynamic' approach to manufacturing improvement, based on perspectives of manufacturing learning and decision theory. First, we present an alternative definition of production system consistent with a decision-theoretic perspective: the system consists of structural, infra-structural, and decision making constructs. A primary proposition is that learning capability possessed by a manufacturing system be prerequisite for the system to improve its manufacturing performance through optimal controlling of the three constructs. To support the proposition, we elaborate on a mathematical representation of "learning" as defined in an applied setting. We show how the learning capability acts as an integrating force ameliorating the trade-off between two key manufacturing capabilities, i.e., process controllability and process flexibility.

1. Introduction

Manufacturing firms must be able to develop production technology for operations optimization. Production process control is an essential part of production technology, which has evolved over time. Jaikumar (1990) suggested an evolutionary model of process control technology, encompassing from periods prior to Taylor's scientific management to the present of computer-integrated manufacturing environment. For the purpose of this article, we consider more recent three epochs rather than six originally postulated, each of which had emphasized particular process objectives such as process stability during 'quality-focused (1950-75),' adaptability during 'systems-focused (1975-85),' and versatility during 'knowledge-focused (since 1985)' period. Process stability relates to basic process capability, e.g., basic controllability, while process adaptability to process flexibility as well as controllability at the system level. Finally, process versatility requires knowledge-based control of production process which we propose needs to be supported by the learning capability possessed by production systems. In line with Jaikumar's conceptualization, therefore, we can infer that a normal evolutionary path manufacturing firms might take follows a sequence, e.g., basic controllability → process controllability and flexibility →learning capability.

In order to optimally perform, a manufacturing system must be able to capitalize on its capability in both process controllability and flexibility at the same time. As we show later, however, there exists a distinct trade-off between controllability and flexibility: improvement in controllability might deteriorate the flexibility. We propose that the learning capability can mitigate the trade-off.

In this article, we first elaborate on an alternative definition of production system consistent with the learning capability perspective. A mathematical modeling, then, will be presented to prove the trade-off existing between controllability and flexibility, and the role of integrating force by the learning capability.

2. An Alternative Definition of Production System

Researchers in economics and operations management have suggested various definitions of a production system. A common feature of these definitions is that most of them view the production system as consisting of operations activities which transform 'input' into 'output,' which then is distributed through downstream channels (Buffa1983, Chase and Aquilano 1985).

In this article, we present an alternative perspective on production systems. We propose that production systems comprise structural construct and infra-structural construct (Figure 1). Constructing a physical environment of manufacturing systems, the structural construct includes such constituents as physical facilities, machinery, equipment, buildings, and other hardware structures. The infra-structural construct relates to manufacturing systems' infrastructure encompassing information systems, communication systems, logistics-related systems, and other software aspects. Although these two constructs have been well recognized and incorporated into the modeling in traditional theories, the interaction between the two has not been explicitly taken into account: the active role played by decision makers has not been considered properly. For instance, a question like "Who or What links the activities in structural and infra-structural constructs?" has seldom been raised. In our model, we explicitly includes the role of decision making entity which connects the structural and infra-structural activities. A spectrum of decision making entity includes all the participants in manufacturing improvement from top managers, engineers and R&D scientists, middle managers, foremen and supervisors, to field workers and operators. Each decision making entity has a unique set of expertise and knowledge specific to the actual problems in point. Thus, "Who is the most effective decision maker?" can not be properly answered until what kinds of expertise and knowledge the technology project in question requires is well analyzed.

One of the most important functions assumed by the decision makers is the 'learning' activity. Learning can be said to have happened when manufacturing firms realized productivity increase without involving 'additional' physical investment in structural and infra-structural constructs: the learning capability is a facilitating force between structural and infra-structural constructs. That is, the learning capability must be developed through the conscious efforts by the decision making entity, not solely by capital investment. Most of the learning phenomena economists had observed in structural and infra-structural constructs, in fact, resulted from the learning efforts by the decision making entity, which the economists had largely unrecognized.

The alternative definition is different from more traditional ones in several aspects: (i) the role of decision making entity is explicitly incorporated into the modeling process, (ii) it is emphasized that the system evolution in structure and infra-structure can be managed and controlled by the decision making entity, and (iii) 'learning capability' possessed by the decision making entity is a driving force underlying the 'dynamic interaction' between structural and infra-structural evolution.

3. Learning Capability as Integrating Force for Controllability and Flexibility

Consistent with the alternative definition of production system, we formally define the concepts of controllability, flexibility, and manufacturing learning. Suppose a manufacturing firm produces *m* products, utilizing *n* processes. Let *i* be product index, *i*=1, 2,..., *m*, and *j* be process index, *j*=1, 2,..., *n*. The firm adopts two measures of performance for each (*i*, *j*): $x_{ij}(t)$ is the intended (or, planned) level of operation, and $y_{ij}(t)$ is the actual (or, realized) level of operation. '*t*' represents time, and is added to highlight the dynamic nature of improvement process.

3.1 Manufacturing Learning

Since Arrow (1962 and 1969) stylized the concept of 'learning by doing,' extensive research has been carried on in manufacturing learning theory (Yelle 1979). A group of researchers has focused on an analytical formalization of learning, incorporating into the analysis the uncertain nature in the learning process (Roberts 1983, Muth 1986). Assuming that the learning effect is reflected in the productivity increase without involving additional resources allocated to structural and infra-structural constructs, we underline the role of decision making entity in the learning process and the procedural nature of the learning capability.

In line with the logic drawn above, we propose that the learning capability can be measured by the firm's ability to match the realized level of operation with the 'intended' level of operation: in a statistical term, the learning capability at each process is measured with the 'covariance' between intended and realized levels of operations, calculated across products for the process, i.e., how much closely the actual operation matches with the intended (or, planned) one. A composite measure for the production system as a whole can be obtained by averaging such covariance across processes.

Let λ be the composite measure of learning capability and K_l be a scalar constant associated with the learning measure, then $\lambda \equiv K_l E_j Cov(x_j(t), y_j(t))$,where $Cov(x_j(t), y_j(t)) \equiv E_i\{(x_{ij}(t)-\bar{x}_j(t))\,(y_{ij}(t)-\bar{y}_j(t))\}$ and $\bar{x}_j(t) \equiv E_i(x_{ij}(t))$, $\bar{y}_j(t) \equiv E_i(y_{ij}(t))$. Therefore, the larger λ in the positive direction, the larger the learning capability.

3.2 Process Controllability

The most immediate goal of process control is to make manufacturing process operate in complete conformance with the desired level of specification. Most of the research on process controllability has been carried on in the context of statistical process control (Duncan 1956 and 1971, Chiu 1976, Jaikumar 1988) and/or quality control (Fine 1986, Fine and Porteus 1989).

In this article, we distinguish 'process controllability' from 'process stability,' which, we assume, can be regarded as elementary controllability and relates to 'average behavior' of production process rather than at an individual and separate level. We can compare the elementary controllability to the stability during 'quality-focused' period as in Introduction, and the process controllability to that encompassing adaptability and versatility during the latter two periods.

Let η_h and η represent process stability and process controllability, respectively. $1/\eta_h \equiv K_{\eta h} E_j (\bar{x}_j(t) - \bar{y}_j(t))^2$, where $K_{\eta h}$ is a scalar constant of the stability measure, and $1/\eta \equiv K_\eta E_i E_j (x_{ij}(t) - y_{ij}(t))^2 \equiv K_\eta E_{ij} (x_{ij}(t) - y_{ij}(t))^2$, where K_η is a scalar constant of the controllability.

Since the process stability is regarded as a prerequisite for controllability and we focus more on the process controllability than basic stability, we assume $E_j (\bar{x}_j(t) - \bar{y}_j(t))^2 = 0$ when investigating the relation between controllability and flexibility.

3.3 Process Flexibility

Process flexibility is the measure of how much diverse activity the production process can accommodate: it can be defined as capability for concurrent or intermittent production of multiple products (product dimensions) in a steady state operating mode (Carter 1986, Graves and Jordan 1991). Here we focus on the range of process operation as a criterion. On average, we can measure the level of 'flexibility' with 'operational range in relation to a mean value.'

In the model we develop here, we distinguish 'realized flexibility,' i.e., $\chi_r \equiv K_r E_j E_i (y_{ij}(t) - \bar{y}_j(t))^2 = K_r E_{ij} (y_{ij}(t) - \bar{y}_j(t))^2$, from 'potential (intended) flexibility,' i.e., $\chi_p \equiv K_p E_j E_i (x_{ij}(t) - \bar{x}_j(t))^2 = K_p E_{ij} (x_{ij}(t) - \bar{x}_j(t))^2$, where K_r and K_p are relevant scalar constants. We assume that manufacturing firms try to maximize the value of flexibility in some form of linear combination of χ_r and χ_p.

3.4 Fundamental Relationship among Controllability, Flexibility, and Learning

Based on the algebraic definitions of controllability, flexibility, and learning, we show how they are related with each other, and how the learning capability can perform as an integrating force that ameliorate the trade-off between controllability and flexibility.

Proposition 1. A fundamental relationship among controllability, flexibility, and learning capability is: $E_{ij} (x_{ij}(t) - y_{ij}(t))^2 = E_{ij} (y_{ij}(t) - \bar{y}_j(t))^2 + E_{ij} (x_{ij}(t) - \bar{x}_j(t))^2 - 2\, E_j Cov(x_j(t), y_j(t))$, given $E_j (\bar{x}_j(t) - \bar{y}_j(t))^2 = 0$. **Proof.** In Appendix 1.

Thus, $\frac{1}{(K_\eta)\eta} = \left(\frac{1}{K_r}\right)\chi_r + \left(\frac{1}{K_p}\right)\chi_p - \left(\frac{2}{K_l}\right)\lambda$.

For simplification, we can also express $1/\eta \approx \chi - \lambda$, where χ is a weighted measure of flexibility, i.e., a linear combination of two flexibility measures, χ_r and χ_p. This relationship proves our proposition that (a) there exists a trade-off between controllability and flexibility, $1/\eta \approx \chi$, when they are not managed with learning capability, and (b) the learning capability, λ, can ameliorate the trade-off.

4. Inference and Implication

We have started this article with proposing an alternative definition of production system in which the role of decision making entity for learning capability is explicitly incorporated into the analysis. Consistent with the alternative model, we have premised that in order to develop manufacturing capability effectively, firms must manage process controllability and process flexibility. There exists, however, a distinct trade-off between the two: that is, firms can not improve in controllability and flexibility without facing some form of compromise between them. Utilizing a mathematical model, Proposition 1 has proved that there indeed exists a sharp trade-off between controllability and flexibility, and that the learning capability can act as an integrating force that can ultimately mitigate the trade-off. Figure 2 depicts the role of manufacturing learning as an integrating agency: when there is no learning effect, the firm achieves F_1 level of flexibility given C_1 level of controllability; but, with the increased learning capability, the firm now can achieve F_2 level of flexibility given C_1.

The primary conclusion we can draw from this research is that manufacturing firms must capitalize on their learning capability in order to effectively manage process controllability and flexibility for operations optimization. In a related paper (Kim 1996), we have reported on how the firms can actually facilitate the process to generate learning capability, and conditions ideal for effective learning activities.

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Figure 1. A Dynamic Architecture of Production Systems

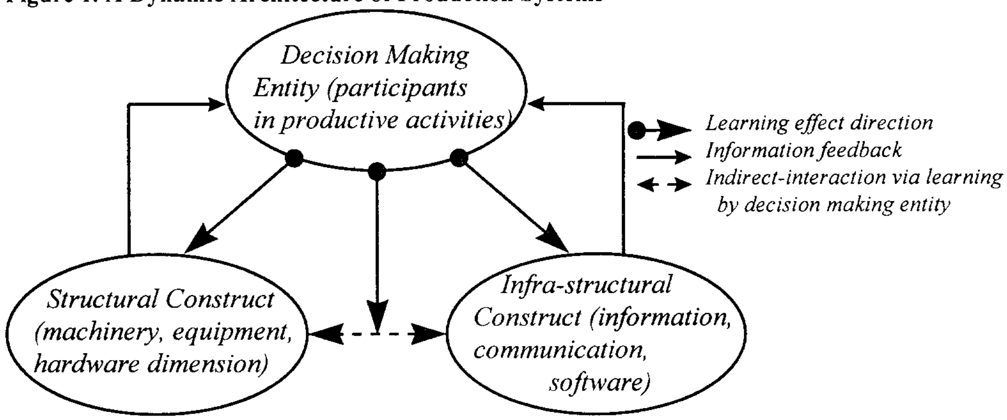
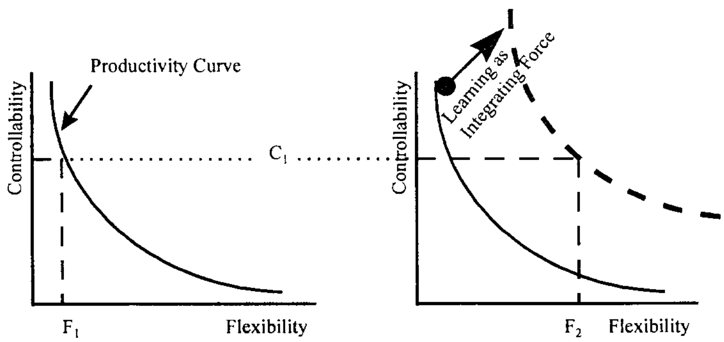


Figure 2. Learning Capability as an Integrating Force



(a) Trade-off between Controllability and Flexibility

(b) Learning Capability as Integrating Force to mitigate the trade-off

Appendix 1. Derivation of Proposition 1 ('(t)' omitted)

(a) $E_{ij}(x_{ij}-y_{ij})^2 = \frac{1}{mn}\sum_{i,j}(x_{ij}-y_{ij})^2 = \frac{1}{mn}\{\sum_{i,j}(x_{ij}-\bar{x}_j)^2+\sum_{i,j}(y_{ij}-\bar{x}_j)^2 - 2\sum_{i,j}(x_{ij}-\bar{x}_j)(y_{ij}-\bar{x}_j)\}$

(b) $\sum_{i,j}(y_{ij}-\bar{x}_j)^2=\sum_{i,j}(y_{ij}-\bar{y}_j)^2+\sum_{i,j}(\bar{y}_j-\bar{x}_j)^2$,(c) $\sum_{i,j}(x_{ij}-\bar{x}_j)(y_{ij}-\bar{x}_j)=\sum_{i,j}(x_{ij}y_{ij})-m\sum_{j}(\bar{y}_j\bar{x}_j)$.

Put (b) and (c) into (a),

(d) $E_{ij}(x_{ij}-y_{ij})^2 = E_{ij}(x_{ij}-\bar{x}_j)^2+E_{ij}(y_{ij}-\bar{y}_j)^2+E_j(\bar{x}_j-\bar{y}_j)^2+2\{E_j(\bar{x}_j\bar{y}_j)-E_{ij}(x_{ij}y_{ij})\}$, where we can show $E_j(\bar{x}_j\bar{y}_j)-E_{ij}(x_{ij}y_{ij}) = -E_{ij}(x_{ij}-\bar{x}_j)(y_{ij}-\bar{y}_j) = -E_jCov(x_{.j},y_{.j})$ $\therefore$ Proposition 1 is proved.