Organizational Structure and Process—An Analysis in Decision-Making

Dingyu Zhang

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By: **Mr. Dingyu Zhang**
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Dr. Shanling Li

______________________________ Examiner
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______________________________ Examiner
Dr. Gerard Gouw

______________________________ Examiner
Dr. Mingyuan Chen

______________________________ Supervisor
Dr. Nadia Bhuiyan

Approved by ______________________________
Martin D. Pugh, Chair
Department of Mechanical and Industrial Engineering

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Amir Asif, Dean
Faculty of Engineering and Computer Science

Abstract

Organizational Structure and Process—An Analysis in Decision-Making

Dingyu Zhang, Ph.D.

Concordia University, 2016

It is known that the performance of an organization is highly related to the process through which activities are organized. However, the dyadic relationship between organizational structure and process along with their influence on performance become complicated when faced with complex activities. We explore this relationship and its influence by following three lines of study.

First of all, in a setting of product development, we introduce a process model for organizing concurrent activities. We show how to determine an optimal schedule. The results demonstrate the variation of design performance, i.e., lead-time, rework, and total workload, under a set of different overlapping strategies. Although depending on the setting of case incidences, there generally exists no dominant strategy over all the performance measures. As a result, managers should select the strategy based on preference over the measures. Secondly, we address the question of how should an organization be structured in a static as well as dynamic process variation. Organizational form will be changed along two dimensions, i.e., departmentalization and assignment, whereas process evolves in terms of complexity. In addition to improving the alignment of organizational structure with a static process, we emphasize and study strategic guidelines of restructuring in the presence of a dynamic environment. The last line of study is geared towards evaluating a group of organizations which differ in preference. In the form of decision process, team specialty, and communication structure, we show the comparative performance between two stylized

decision processes, i.e., hierarchy and polyarchy, with or without communication between agents in an environment where each project must be determined by two features. [1]

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Chapter 1

Introduction

The behaviour of organizational process and structure has been an active area of study for decades (e.g., March & Simon, 1993; Thompson, 1967). Organizational performance is related to process arrangement whereby the flow of material and information is allocated (Galbraith, 1977). In a similar vein, organizational structure, as a more holistic entity, exerts great influence on the performance through the coordination of a combination of processes under limited recourse. Because processes are usually inherently complex and interdependent on one another (Simon, 1996), improving organizational performance is not an easy task since both the role of the organization and the process must be taken into account. In relation to organizational performance, we follow three lines of study in this thesis, which are (1) a process analysis in concurrent new product development (NPD) [chapter 2], (2) an organizational structure analysis in a static as well dynamic process environment [chapter 3], and (3) an organizational structure analysis in a decision making process [chapter 4]. While the spatial and temporal scales of these studies differ, the focal areas are also different. The first line of study takes a relatively more atomistic view of an organization by investigating the effect of various process strategies on performance, whereas the second appreciates the important role of organizational structure in response to process variation, and the third evaluates the performance through decision-making effectiveness.

These studies are organized to stand on their own where each research problem is motivated and accompanied by a focused literature review relevant to its topic. Although each study provides guidelines of strategic decision-making from different aspects in organizational structure and process, they complement one another in improving performance and jointly contribute to form a more comprehensive understanding of organizational behavior. Hence, we start with an overall literature review of the existing knowledge, followed by defining the scope and the objectives of the thesis, and finally we describe the organization of the thesis.

1.1 A Brief Review

1.1.1 Part One

In today's highly uncertain and competitive market environment, organizational activities like new product development (NPD) are crucial to the success of most industrial companies (Datar, Jordan, Kekre, Rajiv, & Srinivasan, 1997; Swink, Talluri, & Pandejpong, 2006; Ulrich & Eppinger, 2015). In addition to product quality, improving NPD processes through shortening the lead-time and reducing the cost has become the top priority of NPD managers for the past few decades (Ulrich & Eppinger, 2015). Various strategies have been investigated amongst which overlapping of NPD activities is in general a successful strategy for reducing time-to-market (Hossain & Chua, 2014; Krishnan, 1993; Lin, Qian, & Cui, 2012; Terwiesch & Loch, 1999; Yang, Lu, Yao, & Zhang, 2014a; Yang, Yao, Lu, & Zhang, 2014b). However, prediction of the performance such as rework (iteration), lead time, cost, and design quality under varying overlapping policies is not easy. Consequently, strategic decision-making in terms of the timing of overlap, the communication intensity, and other decision variables become difficult (Le, Wynn, & Clarkson, 2012).

For the analysis of overlapping strategy, Krishnan, Eppinger, & Whitney (1997) characterize NPD processes behaviour through capturing an evolutionary nature of process as well as a sensitivity measure between processes. Their work provides an insightful way of predicting rework which inspired a group of studies (e.g., Bhuiyan, Gerwin, & Thomson, 2004; Lin, Chai, Brombacher, & Wong, 2009; Lin et al., 2012; Lin, Qian, Cui, & Miao, 2010; Loch & Terwiesch, 1998). However, since the rework function does not easily relate to the downstream evolution behaviour under conditions of overlap (Lin et al., 2010), analytical models are mostly limited to only two sequentially dependent tasks (Cho & Eppinger, 2005); the exception is the simulation work in Bhuiyan et al. (2004) in which a full process is covered. On the other hand, coupled processes are analyzed through modelling. Smith & Eppinger (1997b) estimate the relative length of design cycle time by adopting a design structure matrix architecture through the reward Markov chain method. Their study serves as a basis for a group of others that focus on the effects of the sequence of coupled tasks on NPD performance (e.g., Liu, Ding, & Liu, 2010; Othman, Bhuiyan, & Kong, 2011; Smith & Eppinger, 1997a).

Although there has been much understanding and methods for prediction in relation to how the complex relationship among processes exerts its influence on the performance of overlapping, a rigorous reasoning and determination about the behaviour of up- and downstream dependence is unclear (Jun, Ahn, & Suh, 2005; Roemer & Ahmadi, 2004). Simplified assumptions have appeared to be the remedy. For example, while entailing inevitable errors in estimating the dependence, downstream rework is modelled through probability or an estimated degree of rework (e.g., Ahmad, Wynn, & Clarkson, 2013; Browning & Eppinger, 2002; Cho & Eppinger, 2005; Smith & Eppinger, 1997b). Or the downstream rework is considered as a function of upstream progress. Examples are Loch & Terwiesch (1998), Roemer, Ahmadi, & Wang (2000), Lin et al. (2009), and Lin et al. (2010), while what is missing is how the function is derived from practice (Jun et al., 2005). Clearly, a solid basis for the relationship between overlapping policy and its impact on process performance is inadequately studied. Missing such a link would impede the decision-making in choosing appropriate overlapping strategies. In this thesis, we build a framework with addressing this gap where process dependence is derived from the dependent nature between design specifications. We shall argue that this nature is a key element in the analysis of the effect of overlapping policies on process performance.

1.1.2 Part Two

An organizational process is not constant in that it may evolve continuously by responding to, for example, a potential market change, or a need for coordinating with another changing process. Since one of an organization's main function is to support everyday tasks in a varying process environment, its ability to adapt fluidly through this changeable process becomes more critical than ever before. It is clear that process performance is highly variable with organizational structure (Csaszar, 2012; Hsieh & Chen, 2011; Kong, Bhuiyan, & Thomson, 2008; Mihm, Loch, & Huchzermeier, 2003; Mihm, Loch, Wilkinson, & Huberman, 2010), but the difficulty is to value the extent to which an organizational structure fits in a varying process environment. A better understanding of how organizational structure evolves in order to respond to process variation becomes crucially important.

In the literature, the topic of organizational structure has long been one of the center themes. Bavelas (1948) studies the mathematical property of a group communication pattern and investigated its theoretical influence on group performance. His theoretical result is later confirmed by Leavitt (1951) and Guetzkow & Simon (1955). In addition to this pure structure effect, organizational structure as a whole has been argued from different perspectives. For example, it is studied based on its function of reducing information uncertainty and resolving information discrepancy (Galbraith, 1977), of generating ad hoc communication structures that support the implementation of everyday tasks (Mintzberg, 1979), and of shaping individual behaviour through the variation of communication structure and the rules of reporting (March & Simon, 1993).

With a similar focus on organizational structure, a more fine-grained treatment can be found in, for example, Marschak & Radner (1972), Gibson, Finnie, & Stuart (2015), Christensen & Knudsen (2010), and Csaszar (2012) and later in Csaszar (2013). However, the interactive as well as dynamic role of organizational process has largely been ignored. In today's highly uncertain and changing market environment, processes are continuously modified and improved. Thus, how an organizational structure that is relatively inert responds so as to better coordinate the changing processes becomes increasingly important to managers. We shall address this question with an organizational framework where a group of organizational models and assignments are studied in process variation.

1.1.3 Part Three

Simon (1976) delineates his boundedly rational administrative person who not only has insufficient information, but limited cognitive resource to make correct decisions. With emphasis on its roles of providing relevant knowledge to agents as well as aggregating individual decisions, organization has long been studied through the perspective of decision-making effectiveness. Individuals of different specialty are given information according to the position within the organization, their decisions are organized through certain decision structures where fallible individual decisions due to bounded rationality can be aggregated and, to some extent, rectified, see studies in Sah & Stiglitz (1985), Csaszar (2012) and Csaszar (2013).

Sah & Stiglitz (1986) start to investigate the influence of two stylized decision structures, i.e., hierarchy and polyarchy, in dichotomous choice situations where agents are asked to screen projects which are either accepted or rejected. This line of study is extended to the analysis of committees (e.g., Ben-Yashar & Nitzan, 1997; Ioannides, 2012;

Koh, 1994; Sah & Stiglitz, 1988), as well as to a set of more general decision structures (Christensen & Knudsen, 2010; Csaszar, 2013; Ioannides, 2012). On the other hand, decision effectiveness is also dependent on the knowledge of the agent. Few studies address the role of specialty in decision structure. For example, Prat (2002) links team homogeneity with error reduction. He shows that the relative merit of workforce homogeneity or inhomogeneity is contingent on the environment through the correlation among errors faced by agents.

Although the behaviour of the stylized decision structures have been well studied, only few studies consider the environment with more than one dimension. Practical decisions less frequently involve only a single factor under judgement. For example, a launch of a new product should collect both opinions from the marketing department for its marketability and from the production department for its productivity. Even fewer analytical studies are to take both roles of organizational structure into account; exceptions are Visser (2000) and Csaszar & Eggers (2013). On the other hand, decision-making not only depends on the agent's knowledge, but can be effectively affected by previous judgements to a similar situation. For example, an agent can be made aware of her predecessor's decision on the project. Then how this awareness would change the performance of the entire decision structure is an important question to managers who can subsequently be advised on how to design the organization. To the best of our knowledge, only a few studies emphasize the effect of historical decisions on the current decision-maker, such as herd-like behaviour in Swank & Visser (2008). In short, given the fact that knowledge, including previous judgement, is the basis of decision making, it would be natural to further the question of how the decision structures perform with different group compositions of specialty in a complicated environment. We shall address this important question in a project screening environment where managers are to construct the organization in the form of three structures, i.e., decision, information as well as communication.

1.2 Scope and Objectives

In response to the existing research gaps, our first line of study explores the behaviour of two sequentially dependent processes in the setting of NPD. We build on the previous results, as that in Krishnan et al. (1997), with a more fine-grained treatment on the product design specifications and the communication between the processes so as to understand how design dependencies affect downstream performance in overlapping. This study aims to provide managers of NPD with strategic guidelines in determining the timing of overlapping, namely, when overlapping should begin, as well as the selection of appropriate strategies accompanying the overlapping. These guidelines will be based on our model through the prediction of the effect of varying strategic variables on NPD lead-time, design quality, rework, and total work load (this line of study presented in Chapter 2)

The second line of study focuses on the interactive relationship between organizational structure and process. Static environment, on one hand, will be studied to show how organizational structure fits its process. We consider departmentalization and assignment as two key variables of the structure. The results will be tested with data from the NPD industry. On the other hand, equal emphasis will be placed on a dynamic environment. Specifically, one key question of the thesis is to find how organizational structure responds to process change which evolves along two particular dimensions, exploration and exploitation. We aim at summarizing a set of strategic guidelines for managers who face process improvements that are either incremental (exploitative), or radical (explorative) as their problem solving approaches over a short as well as a long period of time. These guidelines will be focused on the structural side where managers are able to adjust in terms of departmentalization and assignment. Also an alternative approach is taken into consideration in which managers keep the organizational structure unchanged by opportunity loss (this line of study presented in Chapter 3).

Finally, in the setting of project screening, we question the important role of organizational structures in the form of three parts: (1) decision process, (2) team specialty, and (3) communication structure. Especially with two stylized structures, which are hierarchy and polyarchy, we compare the relative performance with one another when the team specialty is an external variables. Conversely, determining the right team composition when the decision process is given is investigated. In addition to the omission and commission errors which have long been emphasized in the literature, this line of study explores how over and underestimation causes loss in different architecture of our model space. Furthermore, we shall also answer that when the communication structure should be so designed that the previous decision of accepting or rejecting projects is, or not, transmitted to the later decision-maker with respect to the comparative advantages over decision-making effectiveness (this line of study presented in Chapter 4).

1.3 Thesis Organization

This thesis is organized into six chapters. After having briefly introduced the research background and thesis objectives, the first line of the study on organizing overlapped NPD processes is presented in Chapter 2 [1]. A review of the existing methods is presented, followed by a modelling of the nature of design specifications through an information uncertainty approach which is linked to the process workload. Then, the effect of overlapping on lead-time, design quality, rework, and total workload are derived by taking overlapping strategies as strategic variables. The model is applied to a numerical example where a set of overlapping strategies are compared. An industrial application is also summarized in Appendix A.

[1] Chapter 2 is published as: Zhang, Dingyu, and Nadia Bhuiyan. "A study of the evolution of uncertainty in product development as a basis for overlapping." Engineering Management, IEEE Transactions on 62.1 (2015): 39-50.

Chapter 3 [2] reports the research results on the interactive role between organizational structure and process. It follows the same structure starting with a comprehensive review of the existing knowledge. Then, it provides a generic approach to the modelling of organizational structure and process along with a team solution method with which simplified limits are addressed. The model applied to the concurrent NPD activities is then compared to empirics in the literature. Finally the model is extended to investigate the static as well as dynamic fitness between the dyadic attributes, i.e., organizational structure and process, with respect to key variables such as organizational model and assignment in process variation.

The last line of study is presented in Chapter 4 [3]. It starts with reviewing the relevant knowledge. A general model consists of decision and information structure is then introduced. A single agent case is studied under a different information structure, i.e., specialty, before a decision-making team of two-agent is considered. On the one hand, stylized, or discrete, treatment of information structure is used for the purpose of producing the results more illustratively. Continuous information structure, on the other hand, is also analyzed to draw generalized managerial implications. Finally, the communication structure where decisions made by former agents are, or not, disclosed to the latter is studied under the assumption of herd-like behaviour. The last chapter, Chapter 5, concludes the thesis contribution by highlighting the managerial implications drawn from each line of the studies. Potential opportunities for future research are also summarized in this chapter.

[2]Chapter 3 is resubmitted to Organization Science: Zhang, Dingyu, Nadia Bhuiyan, and Linghua Kong. "An analysis of organizational structure in process variation."

[3]Chapter 4 is submitted to Organization Science: Zhang, Dingyu, Yaqiao Li, and Nadia Bhuiyan. "Design of team specialty for decision making structures."

Chapter 2

A Study of the Evolution of Uncertainty in Product Development as a Basis for Overlapping

2.1 Abstract

Overlapping new product design process is widely applied in industry. However, selections of appropriate overlapping strategies based on the prediction of process performance can be problematic due to insufficient understanding on the dependency between design processes and its effect on the performance. This paper introduces a new model for a product design organization that is based on the evolving nature of the design process, the dependency between up- and downstream design specifications, and the design technology being adopted. The model presents an evaluation method for quantifying the downstream

evolutionary behaviour. Through an industrial case study, it is applied to evaluate how the design performances vary under different overlapping strategies and how to determine an optimal overlapping; the results imply that the performance is contingent on the strategy, and no single strategy outperforms in overall performance measures. Furthermore, the model measures process dependency—a quantification of the downstream work that is indifferent to the change of the upstream. This quantification can be applied to determine the rework probability or rework function proposed by other studies. The model also addresses the rationale of how improving design technology efficiency can lead to an upgrading of design performances.

2.2 Introduction

Numerous empirical studies have confirmed that overlapping new product development (NPD) activities is in general a successful strategy for reducing time-to-market (e.g., Swink et al., 2006; Terwiesch & Loch, 1999). However, due to the inherently complex nature of the dependent behaviour of the overlapping processes (Simon, 1996), it is difficult to predict the design performances under varying overlapping policies, thus leading to an ineffective determination in terms of the timing of overlap, the communication intensity, and other decision variables (Le et al., 2012). This ineffectiveness usually result in higher cost due to increased rework (iteration) and communication (Lin et al., 2009; Loch & Terwiesch, 1998). Rework is a solution for coping with upstream changes when downstream starts with preliminary information from upstream (Hauptman & Hirji, 1996; Terwiesch, Loch, & Meyer, 2002); whereas communication is necessary in resolving information discrepancy between up- and downstream (Clark & Fujimoto, 1991). Thus, a better understanding of the dependent behaviour of NPD processes is vital to the decision making whereby the cost of rework and communication is determined. Although there have been extensive studies on the overlapping problem, this dependent behaviour of up- and downstream still lacks a rigorous link with the physical properties of the products that are designed.

In the extant literature, a number of models exist. Krishnan et al. (1997) characterized upstream behaviour as an evolution function of time, and downstream dependency as a rework function of upstream information change. Their framework can provide estimated completion time of two dependent tasks under varying overlapping strategies and suggests situations under which overlapping is most adaptive. In relation to the risk of rework, other analytical models consider communication as an influential factor and investigate how it may mitigate the impact of downstream rework resulting from uncertain initial information (e.g., Lin et al., 2010; Loch & Terwiesch, 1998; Tyagi, Yang, Tyagi, & Dwivedi, 2011).

As outlined by Roemer & Ahmadi (2004) and Jun et al. (2005), the question of how to rigorously determine the behaviour of up- and downstream dependency is unclear. Two common assumptions in NPD literature are (a) the downstream sensitivity is modelled as rework probability or degree of rework (Lin et al., 2009), which is estimated through interviews with experienced managers and/or through survey of historical design data (Ahmad et al., 2013; Bogus, Diekmann, Molenaar, Harper, Patil, & Lee, 2011; Bogus, Molenaar, & Diekmann, 2005; Browning & Eppinger, 2002; Cho & Eppinger, 2005; Jun et al., 2005; Smith & Eppinger, 1997b; Wang & Lin, 2009; Wang & Yan, 2005; Yang et al., 2014a). (b) It is modelled as a function of upstream progress where the assumption is that a longer intermediate review period causes more rework (Lin et al., 2010; Loch & Terwiesch, 1998; Roemer & Ahmadi, 2004; Roemer et al., 2000; Tyagi et al., 2011). It is suggested that while the former assumption is a simplification of the NPD process, it entails subjective errors in estimating the dependency; whereas the second assumption captures what is observed but does not directly address how to derive the function from engineering data (Jun et al., 2005).

More recent studies model the relationship through a more explicit functional form that links the dependency of information and the downstream progress. Lin et al. (2012) estimate the degree of rework in relation to the rate of design progress and the rate of upstream change. This line of study also extends to the result that the dependency is a multiplication of upstream variability with downstream sensitivity (Qian & Lin, 2014). Similarly, Yang, Zhang, & Yao (2012) and Yang et al. (2014b) propose a metric by combining the features of upstream evolution and downstream sensitivity in multiple development processes. The degree of rework is also modelled as a function of downstream progress and the value is decreasing return to the number of iterations (Lin, Chai, Wong, & Brombacher, 2008; Tyagi et al., 2011). Another line of study by Chua and Hossain consider the rework probability of each activity as a chance of rework caused by all its predecessors when the initial information are not confirmed (Chua & Hossain, 2011; Hossain & Chua, 2014).

The literature has shown that one key part in most of NPD analytical methods is the modelling of up- and downstream relationship. This modelling evolves from taking simple assumptions to establishing complex functions. However, it is believed that the rudimental causes for this up- and downstream dependency are the physical relationships among the product's parts that constraints the decision making in NPD. In the aforesaid literature, this knowledge regarding to how physical relationships alter the up- and downstream dependency is only indirectly addressed, and this knowledge is key to the nature of NPD per se. In this study, we propose a new model for overlapping activities in which the up- and downstream dependency is derived directly from the physical characteristics of the products. A method for estimating the magnitude of rework is presented, as well as the downstream evolutionary behaviour associated with this rework. Additionally, a measure that can be used by other studies as a quantification of rework function or rework probability is discussed. The remainder of this paper is organized as follows. Section 2.3 introduces the model. Section 2.4 presents an evaluation method for the model. Section 2.5 applies the model to the analysis of an industrial case study. Section 2.6 compares and contrasts the model to the literature and discusses applications of the up- and downstream dependency to the NPD organization. The paper ends with a conclusion in Section 2.7.

2.3 Model Constructs

We follow the information-based view in Alexander (1964) and treat each task in a design project as an information processing unit which receives information from the other units and produces a unique design specification. The evolving nature of each unit, up- or downstream, is captured by an evolution function of time whereby information, in terms of design specifications, shared with its downstream unit is determined. In addition, the evolving nature of the downstream unit depends on the content of upstream information and the timing of the overlap and hence, it is decisive to the performance of the design project. We begin with defining the concepts of the evolution function and the information, then model this dependency.

2.3.1 Evolution Function and Information

It has been confirmed that for a design task (i), the variation of the relative amount of the remaining expected work (U_i) with the time spent (t) can be estimated in practice (e.g., Krishnan, 1993). In particular, this relationship is modelled by an evolution function of time ($U_i(t)$). Throughout this study, this function is assumed to be; (1) continuous, (2) monotonically decreasing with time under sequential engineering (when task is implemented without overlapping), (3) reducing to 0 at the termination of the task.

In the literature, the information to be shared by a unit has been modelled via a probability distribution over some design scope of the specification (Krishnan, 1993; Krishnan et al., 1997; Levardy & Browning, 2009; Yang et al., 2014a). This design scope refers to a range wherein the ultimate value of the specification will finally lie, whereas the probability distribution conveys the likelihood of each value inside the scope being the ultimate value. In this study, the information for a design task (i) at time t is defined as a set, discrete or continuous, over which a probability function is assigned. Moreover, the probability distribution varies during the design period as the scope narrows—there will be fewer positively valued probabilities, and finally there will be only one value, or one interval in the continuous case, left with certainty ($p = 1$). As a matter of fact, a discrete design scope indicates that designers can definitely distinguish each value in the set from the others. For example, in airplane conceptual design, the configuration of empennage should be determined within a discrete set which usually includes the forms of conventional, T-tail, cruciform, H-tail, Triple-tail, V-tail, twin-tail, etc. In contrast, a continuous design scope indicates that designers cannot, at least within some intervals, distinguish each value from the others. For example, airplane engine propulsive efficiency is continuous and if its design precision is restricted at δ level, then a nominal value a could indicate that the values within the interval ($[a - \frac{1}{2}\delta, a + \frac{1}{2}\delta]$) are all acceptable specifications. However, it may be different when two intervals are compared, e.g., interval $[a - \frac{3}{2}\delta, a - \frac{1}{2}\delta]$ is different from $[a - \frac{1}{2}\delta, a + \frac{1}{2}\delta]$, since their nominal values, $a - \delta$ and a, are distinguishable at δ level. In the following sections, we introduce methods for modelling discrete and continuous information.

2.3.2 Information—Discrete Case

The discrete information shared to downstream, in other words, the discrete set with a probability mass function (PMF), represents the work progress of the unit, thus relating to the remaining expected work, or the evolution function. For the modelling of this relationship, a few requirements are considered. (1) The remaining expected work must increase with the size of the discrete set, ceteris paribus. This implies that the larger the number of candidates of the design specification, the more work remains. (2) The remaining expected work must decrease with the efficiency of the design technology being adapted (Hsieh &

Chen, 2011; Iansiti, 1995; Thomke, 1997). Here the technology implies the number of candidates that can be simultaneously processed, tested, or decided upon, by the information processing unit. When a more efficient design technology is applied, the capability of the unit in information processing increases, thus reducing the remaining expected work. (3) The remaining expected work, if it is measured by the required expected number of tests, should not exceed the size of the discrete set. In accordance with Simon (1996), designers are not to optimize by testing every design candidate in the set, but rather require a satisfactory one after a certain period of searching. Actually, only a small portion of this whole set is conducted during the NPD process. (4) At the end of a task, the remaining expected work reduces to zero while the PMF contains only one element with a positive probability, which is the ultimate design specification.

In this study, the simplest relationship is considered to be that the remaining expected work is quantified as the expectation of the number of tests needed. In relation to the information, as per Shannon & Weaver (1949), it is formulated as (time is measured from the beginning of each respective unit)

$$U_i(t) = -\sum_{j=1}^{n} p_j(t) \log_a p_j(t) \tag{2.3.1}$$

where n is the number of elements in the initial discrete set; $p(t)$ is the PMF over the elements; and a is a measure of the design technology being adapted. Mathematically, this quantification of $U_i(t)$ in (2.3.1) is an expectation of the number of trials required in searching for the right value given the information (PMF) (Abbas, 2006). It is variable with the technology (a) which quantifies the number of elements that can be processed in each trial. It can be easily shown that (2.3.1) satisfies the four requirements stated earlier. Moreover, Equation (2.3.1) is a well-known result as the definition of the information uncertainty, or information entropy (Jaynes, 1957; Shannon & Weaver, 1949); hence, the remaining expected work for a unit can be interpreted as the uncertainty about its information evolution. Throughout this article, the expected work and the information uncertainty are used interchangeably.

2.3.3 Information—Continuous Case

It is worth noting that the extent to which values are distinguishable differ from continuous information to discrete information. In discrete case, every value is distinct from any other. In continuous set, any design dimension is restricted to its fabrication precision which cannot be infinitesimal and due to errors, fabrication towards an exact value is unrealistic. Therefore, it is usually that more than one value may be considered as feasible design specifications, which implies that one method for discretizing the continuous set is through chopping the set into distinct intervals. In practice, this interval can refer to those values within upper and lower specification limits. Engineers define upper and lower specification limits and consider any value within the limits acceptable. Moreover, the limits also vary case by case. In order to model this feature, we introduce design precision (δ). Two common factors that alter design precision are, in relation to manufacturing precision, the engineering upper and lower limits of the specification, and the precision of the equipment when testing is performed. In the following model, design precision determines the size of the interval.

For a continuous set, we assume that for any small interval $[a, a+\delta]$, its nominal value is the median $(a+\frac{1}{2}\delta)$, and any design outcome lies within this small interval is equivalent to this median. Consider a continuous set $[a, b]$ in $\mathbf{R}$ with a probability density function (PDF), $f(x)$, the discretized set is defined as a combination of the nominal value of each small interval $\{a+\frac{1}{2}\delta i | i=1, ..., k\}$, where k is the number of intervals [1]. For each interval, the PMF derived from PDF is, $p(a+\frac{1}{2}\delta i) = F(a+\frac{1}{2}\delta i) - F(a+\frac{1}{2}\delta(i-1)), i = 1, ..., k,$

[1] For simplicity, we assume that the following relationship holds $\delta = \frac{b-a}{k}$, where k is chosen such that δ approximates true design precision requirement. The error becomes negligible when $\delta \ll (b-a)$.

where $F(x)$ is the cumulative distribution function for $f(x)$.

In addition to the design technology (a) in (2.3.1), which is an efficiency measure, the continuous information involves design precision (δ) which can be considered as an effectiveness measure. The relationships between this discretized information and the remaining expected work of the information precessing unit follow the same logic as shown in the preceding section and can be estimated by (2.3.1).

2.3.4 Rework Estimation and Information Dependency

The model elements defined in the preceding section are valid for all information processing units including those of the downstream. However, under overlapping, incomplete initial upstream information may lead to downstream rework that alters the evolution function. It is known that the degree of the rework is related to the information dependency between up- and downstream, and to the evolving nature of the downstream unit. In this study, this rework is defined through a standard process.

When an upstream unit (X) evolves at time t_1, it sends some information ($p_X(t_1)$) to a downstream unit (Y). The downstream starts with this initial information and generates its own information ($p_{Y|X}$). Since $p_X(t_1)$ is incomplete, it ensures that only partial work done by the downstream is effective. Hence, at the downstream time t, the discrepancy, if any, between this effective work and the actual downstream progress is the rework (R). Since the order of work done by the downstream affects the analysis, we assume that it remains the same as in sequential engineering and that it starts with the jobs that are dependent on the upstream information. Furthermore, we also assume there is no learning effect that the rework should be similar to the evolving nature as defined in the evolution function. Therefore, the rework can be modelled as

$$R(t) = U_Y(t') - U_Y(t) \qquad t' \leq t \leq t_c \tag{2.3.2}$$

where t' is the solution to $U_Y(t') = -\sum_{p' \in p_{Y|X}} p' \log_a p'$, and is the time until which the work ensured by the initial upstream information is completed. Therefore, $U_Y(t')$ implies the magnitude to which the initial information is going to decrease the uncertainty of the downstream processing unit. On the other hand, the second part ($U_Y(t)$) is the actual progress as measured by the remaining expected work at time t. Hence, Equation (2.3.2) quantifies the difference between the actual work and the effective work—a measure of rework. It should be noted that when $t < t'$ as in a period for implementing the effective work, we consider the discrepancy to be negligible ($R(t) = 0$). Furthermore, Equation (2.3.2) is restricted by an upper bound t_c which is defined as the time until which a final upstream information is going to decrease the uncertainty of the downstream processing unit; its magnitude corresponds to the up- and downstream information dependency and can be calculated by solving $U_Y(t_c) = -\sum_{p' \in A} p' \log_a p'$, where$A \in p_{Y|X_{final}}$.

In relation to the assumption made earlier on the order of work, t_c separates the entire downstream time frame into two parts: (1) work dependent on the upstream information ($t \leq t_c$) and (2) work independent of the upstream information (Figure 2.1). Therefore, the magnitude of t_c is reflective of the degree of up- and downstream dependency. Consider two extreme situations when the information sent from upstream is finalized. If the up- and the downstream design specifications are independent, the expected benefit from receiving the upstream information will be zero; and hence, $t_c = 0$, or there will be no rework generated by this information. On the other hand, if the relationship is functionally dependent, the downstream specification will be determined once the upstream information is complete $t_c = t_{final}^{downstream}$ (there will be no remaining independent work). Time t_c thus varies with the information dependency. In general, the greater the information dependency between up- and downstream, the larger is t_c. It will be later shown that both the magnitudes of t_c and $U(t_c)$ are closely related to the analysis of various design strategies; and $(t_c, U(t_c))$ is called the critical point in the later analysis (Figure 2.1).

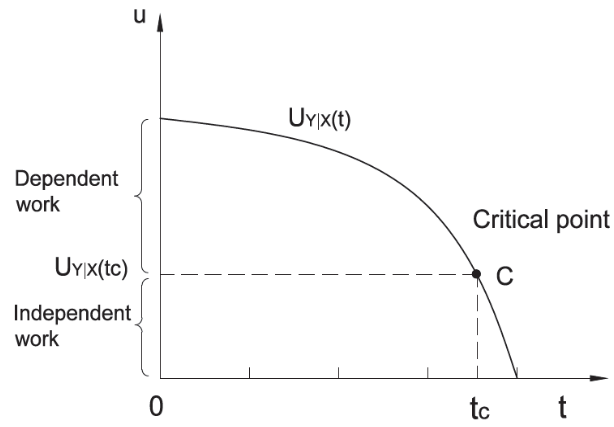


Figure 2.1: Downstream evolution function: critical point and critical time.

In conclusion, Equation (2.3.2) is one way to estimate rework through information dependency and the timing of overlap. Upon receiving the updated information from upstream, this rework leads to a rise in the remaining expected work for the downstream. In theory, the evolution nature of the downstream under overlapping can be predicted with some evaluation method of (2.3.2). Nevertheless, any evaluation method requires, ex-ante, the knowledge about how the information, that is the discrete set with a PMF or the continuous set with a PDF, of both up- and downstream units varies. Hence, the prediction of a downstream evolution function demands extra assumptions about the variation of this information. In this study, the method applied is based on the principle of maximum uncertainty (Jaynes, 1957).

2.4 Evaluation Method

This section develops an evaluation method that is applicable to NPD organizations in which the initial, individual or joint, discrete sets for the units can be determined. As drawn from the concept of set-based design, the joint discrete set (for units $i, j, ...$) follows the structure as:

$$\Omega_{i,j,\ldots} = \{(\text{specification i}, \text{specification j}, \ldots), \ldots\} = \{(\text{red}, \text{high}, \ldots), \ldots\}. \tag{2.4.1}$$

As will be shown later, this structure can also be alternatively represented by tabulating the specifications with their relationships. It contains the initial solution set of the design variables, which is a group of possible design combinations. This initial information is generally viable for the product where major design is an improvement of some older version, i.e., incremental innovation. As a result, the initial sets can be based on the historical development records, the engineer's experience, the manufacturing standards, and the functional demands (Chua & Hossain, 2011). Moreover, this information is an estimation of the dependency between up- and downstream, and its strict validation is considered as the task of NPD.

2.4.1 Probability Estimation

In order to estimate the distribution function for design information, we apply the principle of maximum uncertainty (Jaynes, 1957). The principle states that the least-biased probability distribution is the one with maximum uncertainty and it is the solution to the following problem.

$$\max \quad S_X = -\sum_{i=1}^{n} p(x_i) \log_a p(x_i) \tag{2.4.2}$$

$$\text{subject to:} \qquad \sum_{i=1}^{n} p(x_i) = 1 \tag{2.4.3}$$

$$f(p) \geq 0, f(p) = b \tag{2.4.4}$$

$$p(x_i) \in [0, 1] \quad \text{for all } i$$

where $X = \{x_1, ..., x_n\}$ is the design set, and p_X is the density function. Constraints (2.4.3) and (2.4.4) represent the ex-ante knowledge about X. This knowledge alters the density function under the principle of maximum uncertainty and in turn, it affects, by (2.3.1), the relationship between the remaining expected work and the information. Since an ex-ante knowledge about X is usually very limited, it is of our particular interest to first consider a general case in which the information processing units have no extra knowledge about the design specification.

Limited Knowledge—Simple Information Assumption

Consider the information processing units possess, at any time, no information except the remaining expected work (high vs low). This assumption is consistent with Krishnan et al. (1997) and follows from the reality that one cannot precisely predict the exact information about the discrete set, rather one can only estimate the scope of the design as related by the evolution function. In addition, the assumption removes the constraints (2.4.4) in the optimization problem. The remainder can be solved by introducing Lagrangian multiplier, and through the usual calculation we have $p(x_i) = \frac{1}{n}$, for all i. Suppose the discrete set at time t is X^t, then it follows easily from the result that the information at time t is $p_X^t(x_i) = \frac{1}{n(X^t)}$, where $n(\bullet)$ is a function measuring the size, or the cardinality, of the set X^t. Eventually, for any discrete set Ω_i at time t, by (2.3.1), the relationship between the remaining expected work and the information is

$$U_i(t) = \log_a n(\Omega_i^t) \tag{2.4.5}$$

The PMF in (2.4.5) follows uniform distribution. In the extant literature, both uniform and non-uniform distributions over the discrete set are suggested (e.g., Krishnan, 1993; Levardy & Browning, 2009). Hence, we now turn to the non-simple information assumption.

The Effect of Extra Knowledge

When constraints (2.4.4) convey extra knowledge about design specification, applying the principle of maximum uncertainty will yield a non-uniform distribution. To illustrate, consider an example in camera design, if engineers have an initial belief that a final camera resolution is more likely to be over 20 megapixels, the initial probability distribution ($p(0)$) would be non-uniform with this information being added. Furthermore, with extra information added would decrease the initial uncertainty of the design process (the overall expected work). This intuitive result follows from the fact that the uncertainty defined in (2.3.1) reaches maximum when the probability is uniformly distributed, and any non-uniform distribution adds certain degree of certainty, thus reducing the uncertainty. Hence, the overall expected work is smaller when more information is available than is the case with no extra information. However, in addition to the evolutionary behaviour of the information processing unit, the knowledge generated during the design process which changes the information ($p(t)$) is unobservable, ex-ante, because it is the job of NPD per se. In this article, the initial non-uniform distribution is considered as a result of adding extra knowledge, and the assumption of limited knowledge is made during the design process. Even though, by having some initial extra knowledge would linearly reduce the workload at any time t.

2.4.2 Downstream Rework

In order to evaluate downstream behaviour, the information shared from upstream is important. The first step is to determine the total expected work ($U(0)$). For non-uniform information, this value is given by (2.3.1), and uniform information by (2.4.5). Equation (2.4.5) also links the evolving nature of the unit (the evolution function) with the scope of the design. At any time, the amount of information that can be shared to downstream is determined by first referring to the remaining expected work ($U(t)$), and then solving the range ($n(\Omega_i^t)$) as a variable through (2.4.5). During the overlap, this information being sent determines, in part, the degree of effective work to which the downstream evolves. Since we assume the content of the discrete set is not known, ex-ante, the range of the downstream discrete set can only be inferred from the range of the exchanged information from the upstream. Hence we consider an expectation of range as the dependent measure of the information for the downstream discrete set.

This expectation measure is defined as:

$$n_j = E[n(\Omega_{j|i})|n(\Omega_i^t)] \tag{2.4.6}$$

To illustrate the calculation of this measure, consider an example which is an joint discrete set

$$\Omega_{X,Y} = \{\{\text{U1, D1}\}, \{\text{U1, D2}\}, \{\text{U2, D2}\}, \{\text{U2, D3}\}, \{\text{U2, D4}\}, \{\text{U3, D4}\}, \{\text{U4, D3}\}\}^{2} \tag{2.4.7}$$

If the upstream evolution function at time t predicts, through (2.4.5), the design process is evolved to the extent that the discrete set only has three elements left. Then, without knowing which three are left exactly, we should estimate and calculate the expected size of downstream discrete set. In this case, 3 different Us are drawn from the set (the information sent from upstream), there are $\binom{4}{3} = 4$ different combinations of the information. And for each combination (j), we calculate the number of different Ds (z_3^j)which satisfies the joint discrete set. They are $z_3^1 = z_3^2 = z_3^3 = 4, z_3^4 = 3$ [3].

[2]The joint set can be alternatively represented by a table form as will be shown in section 2.5.

[3] z_3^1 : {{U1, D1}, {U1, D2}, {U2, D2}, {U2, D3}, {U2, D4}, {U3, D4}},
z_3^2 : {{U1, D1}, {U1, D2}, {U2, D2}, {U2, D3}, {U2, D4}, {U4, D3}},
z_3^3 : {{U1, D1}, {U1, D2}, {U3, D4}, {U4, D3}},
z_3^4 : {{U2, D2}, {U2, D3}, {U2, D4}, {U3, D4}, {U4, D3}}

By (2.4.6), given $n(\Omega_X^t) = 3$, the dependent measure of the downstream information is

$$E[n(\Omega_{Y|X})|n(\Omega_X^t)] = E[n(\Omega_{Y|X})|3] = \frac{z_3^1 + z_3^2 + z_3^3 + z_3^4}{\binom{4}{3}} = 3.75. \tag{2.4.8}$$

Equation (2.4.6) is calculated through taking the weighted average over all possible sizes each of which satisfies the given upstream information and the joint design scope. Moreover, as a property, this expectation measure increases with the size of upstream information. In other words, it implies the practice that the more the upstream information evolves and shares, the more benefit the downstream has (the proof for this monotonicity is available from the authors).

Hence, by (2.4.5) and (2.4.6), the rework defined in (2.3.2) can be evaluated through:

$$R(t) = \log_a \frac{E[n(\Omega_{j|i})|n(\Omega_i^T)]}{n(\Omega_j^t)} \qquad t' \leq t \leq t_c \tag{2.4.9}$$

where T is the overlapping time, measured from the upstream unit (i), when the information is sent to the downstream unit (j), and t' and t_c are the solutions to the downstream evolution functions

$$U_j(t') = \log_a E[n(\Omega_{j|i})|n(\Omega_i^t)] \tag{2.4.10}$$

and

$$U_j(t_c) = \log_a E[n(\Omega_{j|i})|1] \tag{2.4.11}$$

respectively. It follows immediately that the hours of rework (H), is

$$H_j(t) = t - t' \qquad t' \leq t \leq t_c. \tag{2.4.12}$$

In the most general form, when a downstream unit (s) is dependent on multiple upstream units $(i, j, k, ...)$, Equation (2.4.9) extends to

$$R(t) = \log_a \frac{E[n(\Omega_{s|i,j,k,...})|n(\Omega_i^T), n(\Omega_j^T), n(\Omega_k^T), ...]}{n(\Omega_s^t)} \qquad t' \leq t \leq t_c. \tag{2.4.13}$$

As caused by overlapping product design processes, this modelling of the rework is decisive to the estimation of the downstream evolution function which in turn, enables the prediction of NPD performances—lead time, total work load, and design quality. While in a managerial situation, a number of overlapping strategies exists, this model may provide managers with an analysis on the NPD performances when different strategies are applied, thus improving the effectiveness of decision making in NPD.

2.5 Example and Numerical Experiments

In this section, we provide a case of an industrial NPD process. Through interview, the information provided by the engineers has revealed three key design specifications X,Y, and Z. Task X is the upstream since it determines the performance of the machine, whereas Y and Z are sequentially dependent on X. Based on prior data, engineers estimate the joint discrete sets for the design specifications (Figure 2.2). Furthermore, the evolving natures for X, Y, and Z are estimated and they are fast, slow, and fast, respectively (Figure 2.3).

Y (m²) \ X (kw)	1.3	1.6	1.8	2.0	2.2	2.5	3.0	3.6	4.0	4.5
1.0	•									
1.2	•	•	•							
1.5	•	•	•	•						
2.5			•	•	•	•				
2.8				•	•	•				
3.0						•	•			
3.2						•	•	•		
3.5								•		
4.4								•	•	•

Z (size) \ X (kw	1.3	1.6	1.8	2.0	2.2	2.5	3.0	3.6	4.0	4.5
Small 1	•	•	•							
Small 2	•	•	•	•						
Medium 1				•	•					
Meduim 2				•	•	•				
Medium 3						•	•	•		
Large 1							•	•		
Large 2									•	•

Figure 2.2: Left: Elements of joint discrete set for X-Y; right: Elements of joint discrete set for X-Z

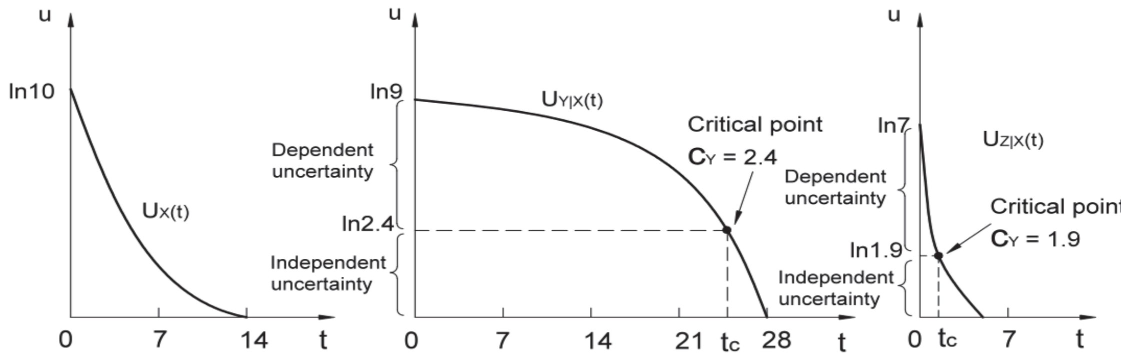


Figure 2.3: Evolution functions with time (days) for the design variables X, Y, and Z

It is obvious that 42 days are the total expected lead time of the NPD process under sequential engineering. But this time can be improved by overlapping the design tasks. Through the analysis of downstream evolutionary behaviour, the following analysis provides the engineers and the managers with the estimation of the NPD performance, in terms of lead time, rework, quality loss, and total work hours, under various overlapping strategies.

2.5.1 Model Input Determination

Throughout the analysis, the assumptions of simple information made in the preceding sections hold. In addition, for the ease of calculation, we shall first consider the quantification of the design technology (a) as fixed at $e = 2.718$. This is because taking it as a constant does not alter the analysis and the implication drawn from the model results. At the end, we treat a as an exogenous variable, and analyze its effect on the NPD performances.

To calculate the base value of the expected total work, by (2.4.5), we have $U_X(0) = \ln n(\Omega_X^0) = \ln 10$, $U_Y(0) = \ln n(\Omega_Y^0) = \ln 9$, $U_Z(0) = \ln n(\Omega_Z^0) = \ln 7$. These quantifications imply the magnitude of the number of tests or decisions (high vs. low) needed to determine the satisfied machine specifications within the design scope at the outset.

Given the complete information from X, by (2.4.6), the expected sizes for the dependent units (Y and Z) are $c_Y = 2.4$ and $c_Z = 1.9$, respectively. By (2.4.5), the critical time (t_c^Y and t_c^Z) for the dependent units (Y and Z) are the solutions to $U_Y(t_c^Y) = \ln c_Y$ and $U_Z(t_c^Z) = \ln c_Z$, respectively.

For downstream units Y and Z, the calculations yield two critical points that are $(25.2, \ln 2.4)$ and $(1.5, \ln 1.9)$, as shown in Figure 2.3. Each point separates the total downstream work into two parts: dependent work and independent work. The dependent part indicates an expected contribution on which the upstream design information may help decrease the downstream uncertainty. According to the monotonic property, Equation (2.4.6) implies that the more specific the upstream information that is shared with the downstream, the more the downstream work will be resolved. But this work will be bounded by the critical point; the lower point the more sensitive the relationship between the up- and downstream design variables.

2.5.2 Early Partial Information Sharing to Y—Effect on Lead Time

This section evaluates the effect of overlapping X and Y at day 7 on the NPD performance (Figure 2.4a). At time $t = 7$, the remaining expected work of the upstream is $\ln 2$, and by (2.4.5), the size of the discrete set is $n(\Omega_X^1) = 2$. Given this upstream information, by (2.4.5) and (2.4.6), the remaining expected downstream work is $U_{Y|X}(3) = \ln E[(n(\Omega_{Y|X}^{21})|n(\Omega_X^7)] = \ln 4.28$ where the time $t = 21$ is the solution to $U_{Y|X}(t) = \ln 4.28$ (point A in Figure 2.4a). The model shows that if the upstream shares information at day 7, the degree of the expected work through which the downstream may benefit is the subtraction of the remaining expected work from the total initial work, that is $\ln 9 - \ln 4.28 = 0.74$. In other words, partial information sharing at week 1 will help decrease the downstream uncertainty by 34%. The time for the downstream design evolution to reach this progress is, due to its evolving nature, about 21 days.

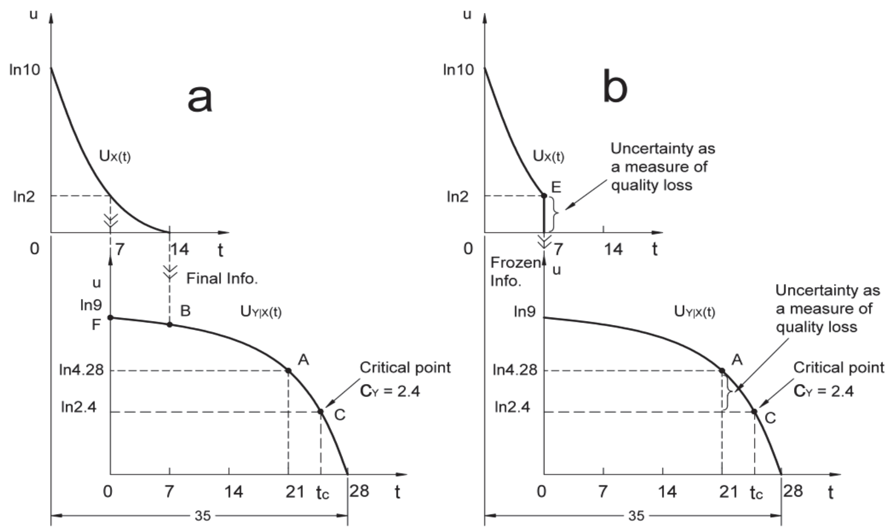


Figure 2.4: a. Sharing partial information b. sharing frozen information—to downstream unit Y at t=day 7

As the complete information from the upstream will be sent at day 14 while the downstream is still on the way to reach point A, the downstream effort will not be futile. And as expected the downstream will reach completion at the end of the fourth week. Thus, the total lead time under this strategy will be one week shorter than when under sequential organization. In conclusion, overlapping at day 7 could avoid rework for the downstream unit (since we assume during the course of implementing effective dependent work, rework is negligible). The model applied here implies that there exists, at least in theory, a managerial condition where rework can be effectively avoided. Additionally, the result drawn from the model suggests that this condition usually occurs when upstream evolves so quickly and downstream evolves slowly.

On the other hand, the model is in line with what many studies have shown that slow evolution and high uncertainty exacerbate the overlapping performances (Krishnan et al., 1997; Terwiesch & Loch, 1999). Consider the case where upstream evolves slowly such that by day 7, it can only provide limited information which does not help prompt the downstream work resolution. Hence, the downstream may overtake upstream progress (in this case, point A would move upward overtaking point B), and proceed upon the basis of unknown information. Rework as a price must be paid for such a walk in the dark. We shall explore this effect in detail in Section 2.5.4.

2.5.3 Early Frozen Information Sharing to Y—Effect on Quality Loss

Early frozen information may cause quality loss in product development (Krishnan et al., 1997). The relationship defined in (2.3.1) could play a role in measuring the quality loss by the monotonic property of the evaluation method and the belief that an earlier frozen time should result in a higher loss in quality. We shall evaluate the same design variables X and Y under the strategy that the information is frozen at week 1, and explore the quality losses in the up- and the downstream respectively.

If the upstream closes the information at $t = 7$ (Figure 2.4b), its remaining expected work remains at $\ln 2$, and in turn, the loss in quality is caused by the commensurate uncertainty $\ln 2$, which is about 30% of the total remaining expected work (the expected number of tests or decisions missed). Moreover, an earlier closed design corresponds to a greater uncertainty remaining, causing higher loss in its quality.

On the other hand, by (2.4.9), the loss in the downstream design caused by the unsophisticated upstream information is calculated as $\ln 4.28 - \ln 2.4 = 0.58$. This value equals the difference in the downstream uncertainty between points A and C (Figure 2.4b). It amounts to the rework as measured at time t_c, or $R(t_c)$. In other words, 0.58 out of $\ln 9$, or 26%, uncertainty will remain in designing Y which is not rectifiable, and recall that it is a part of the dependent uncertainty.

2.5.4 Ordinary Overlap—Early Partial Information Sharing to Z

This section studies the lead time of downstream with respect to overlapping. Suppose only preliminary information from upstream is available during overlapping. Then for the problem as shown in Fig 2.5 where information is shared at t_s, let t_e and t_d be the durations of up- and downstream processes, respectively, and denote t_o as the duration of overlap and $H(t_s)$ as rework. We consider an optimization model that minimizes lead time,

$$\min \quad T(t_s) = t_e + t_d - t_o + H(t_s) \tag{2.5.1}$$

$$\text{subject to:} \quad t_o = t_e - t_s \tag{2.5.2}$$

$$H(t_s) = t_c - t' \tag{2.5.3}$$

Eqs. (2.4.10), and (2.4.11)

$$0 \leq t_s \leq t_e \tag{2.5.4}$$

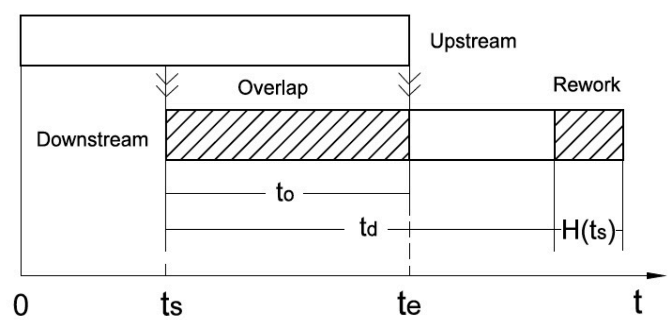


Figure 2.5: An ordinary overlapping model for two processes

The optimal timing of overlap ($\widetilde{t_s}$) can be approximately solved by the following one-dimensional search algorithm.

Initial step: Let δ be the search step length; initialize $t_s = \delta$.

Step 1) Given upstream evolution function, solve the upstream information ($n(\Omega_{up}^{t_s})$) by (2.4.5).

Step 2) Given the upstream information, solve the effective work to which the downstream evolves by (2.4.6). Through (2.4.10) and (2.4.11) and finally by (2.5.3), calculate the rework time ($H(t_s)$).

Step 3) Solve the total lead time ($T(t_s)$) by (2.5.1) and if it is the minimum so far, save

$T_{min} := T(t_s)$ and $\widetilde{t_s} := t_s$.

Step 4) If $t_s + \delta < t_e$, $t_s := t_s + \delta$, go step 1; otherwise stop.

Following this algorithm, we evaluate the performance of the overlapped information processing system (system X and Z with the search step length $\delta = 1$ day). As can be seen in Figure 2.6, the degree of rework increases with the degree of overlap, while the lead time first decreases and then increases as the degree of rework compensates the degree of overlap. The optimal overlapping is found at $\widetilde{t_s} = 9$ day and the lead time is $T_{min} = 14.3$ day. The result suggests that, as shown in Figure 2.7a, the downstream starts at day 9 and achieves the completion of the effective dependent work. The downstream receives the final information at $t = 14$ day; it decides to rectify a portion of the work where unknown information was used. In other words, it will rework l as sophisticated upstream information is now available. By (2.4.9), $l = R(t_c) = 0.56$.

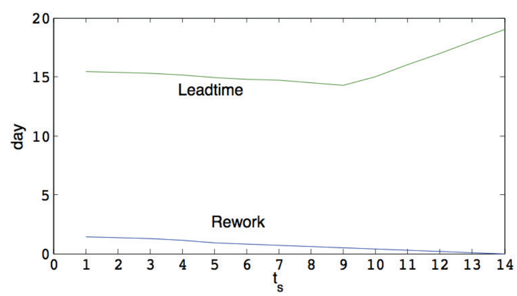


Figure 2.6: Overlapping timing vs. rework and lead time

On the other hand, the lead time (14.3 days) is shorter than under the sequential engineering (19 days). However, the total work hours for the downstream increases to $5 + H(t_c) = 5.94$ days, or by about 20%. This calculation is an approximation as we assume the effort made under uncertain information is completely futile. However there is a probability $\frac{1}{n(\Omega_X^t)}$ that the work done by downstream in the first iteration is consistent with the final upstream information. In other words, the downstream knows the final upstream information could be one of $n(\Omega_X^t)$, but does not exactly know which one it will be. Moreover, it has one in $n(\Omega_X^t)$ chance that the guess is correct and the rework is avoided. Thus, precisely deriving, the expected rework should be $(1 - \frac{1}{n(\Omega_X^t)})(t_c - t_d)$, which is less than l as derived by (2.4.9). But when $n(\Omega_X^t)$ is large, this effect can be negligible.

Aside from this ordinary overlap, strategies like functional interaction, starvation, and duplication are supplementary to the organizations of the overlapped tasks. Consistent with previous literature, (e.g. Bhuiyan et al., 2004; Lin et al., 2009; Loch & Terwiesch, 1998), we refer to functional interaction as a strategy for up- and downstream to reach a consensus at the beginning of the process, i.e., the degree to which downstream could proceed free of rework, given initial upstream information. In other words, functional interaction enables, regarding downstream units, the making of effective progress based on initial information. On the other hand, by Terwiesch et al. (2002), starvation refers to the process that the downstream decides to wait until the complete information is received; whereas duplication means, following functional interaction and initial information, the downstream enumerates every possible upstream results, and conducts multiple design tasks on each of them. All these strategies, as means for the rework elimination, are a kind of work load-lead time trade-off, and the analysis follows.

2.5.5 Functional Interaction with Starvation

In this analysis, one day is assumed for X and Z to discuss and calculate the degree to which an early information sent at day 9, which is the optimal solution under ordinary overlapping, is going to reduce the downstream uncertainty. Through this functional interaction, the evolution function of Z first remains at the initial level for functional interaction and then, by (2.4.6), it can at most proceed to point D, as shown in Figure 2.7b, without the penalty of rework (which corresponds to only a half-day, overdo will result in rework). In contrast to the ordinary overlap, Z decides to apply starvation till the final information from X is available (the horizontal line starts with D). This could be economic since such

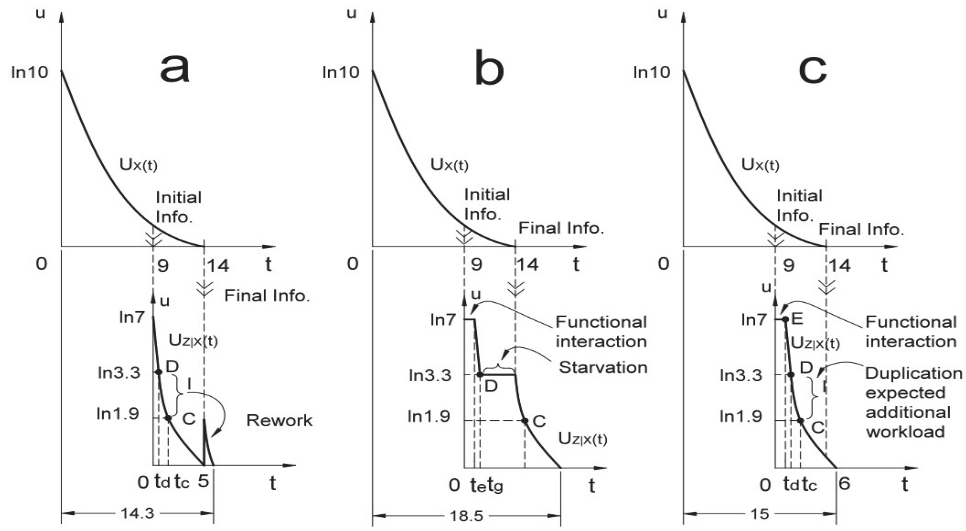


Figure 2.7: Sending partial information to downstream unit Z at t= 9 under a. normal b. starvation c. duplication strategies

waiting may save resources (McDaniel, 1996). As a result, the total lead time is 18.5 days, but the work hours for Z is 6 days including design and coordination. Although it does not give a sharp comparison between this overlapping strategy and the ordinary, starvation can be efficient when the cost per design hour is high and the functional interaction cost is low (sometimes a short meeting may serve the purpose).

2.5.6 Functional Interaction with Duplication

Followed by functional interaction, Z could alternatively apply the strategy of duplication for reducing the risk of rework. By (2.4.9), the measure of the rework $R(t_c)$, or curve DC as shown in Figure 2.7c, is subject to the upstream information change; and Z does not have such information yet. Therefore, unit Z must base its activities on each possible outcome of X, that is for each upstream possibility, Z performs the work indicated by DC. In the case where overlapping starts at day 9, the size of the information, or the discrete set, from X is 1.3, which suggests that Z pays $(n(\Omega_X^{week1}) - 1) \cdot R(t_c) = 0.3R(t_c)$ extra workload. As shown in Figure 2.7c, the bold line delineates the revolution behaviour for X and

Table 2.1: Model results summary: X-Z.

Organization strategy X-Z	Performance		
	Lead time (days)	Rework (Uncertainty)	Workload (Uncertainty)
Sequential Engineering (Non-overlap)	19	0*	1.95*
Ordinary Overlap (Optimal)	14.3*	0.55	2.5
Functional Interaction With Starvation	18.5	0*	1.95*
Function Interaction With Duplication	15	0*	2.12

*Best Strategy in each individual performance

Z. The duplication starts form point D and finishes when the final upstream information is ready. The lead time is 15 days.

In conclusion, ordinary overlapping yields the shortest lead time. Table 2.1 summarizes the NPD performances under different strategies for units X and Z. The best strategies in terms of each individual performance are marked. As can be seen, ordinary overlap has a moderate improvement in lead time with respect to sequential engineering at the costs of rework and total workload. On the other hand, no unique strategy outperforms the others in terms of overall three performance measures. This result implies that, in general, the individual performance is contingent on the strategy adapted, and managers and engineers should pay attention to which performance they value most, and choose overlapping strategies based on the model in relation to the targeted performance.

2.5.7 Performance Improvement by Efficient Design Technology

So far, we have restricted our interest in the managerial strategies, i.e. overlap, however, the design technology being adopted also plays a determining role in design performance (Hsieh & Chen, 2011; Iansiti, 1995; Krishnan & Loch, 2005; Thomke, 1997). More efficient design technology should result in a better performance; and the result of our model supports this.

As stated earlier, variable a in (2.4.5) is a measure of design efficiency. If it is 2, it corresponds to a "yes/no" judgment and each test or decision can at most rule out one element from the design set. On the other hand, if it is 100, the design technology is more efficient so that each test or decision could make a great leap. As stated in Loch, Terwiesch, & Thomke (2001), this phenomenon can be considered as what happened in the pharmaceutical industry where test techniques have vastly improved. Regarding the model, consider a company has invested in a new technology for NPD with higher design efficiency b $(b > a)$. In addition, it is assumed that the initial discrete set and the evolving nature of uncertainty remain unchanged. Because $\log_a n > \log_b n$, the new technology will push the evolution function towards the lower left. In terms of the decrease of total work load, the technology applied is at decreasing return to scale, reducing both lead time and work load (Figure 2.8). Since explicit exploration of the new evolution function under improved design technology demands its topological feature to be conserved, and this exceeds the scope of this study, we only use a linear evolution function as an example, as shown in Figure 2.8. Recall the case study, if more efficient design technologies are adopted for X Y and Z, all the evolution functions should be shrunk towards the lower left, and the overall performance is improved. On the other hand, if only one technology is upgraded for some units, the overlapping strategy should be re-explored to best adapt this improvement.

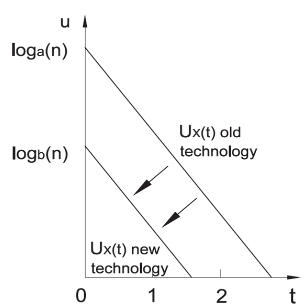


Figure 2.8: Design technology improvement pushes the evolution function towards the lower left

2.6 Discussion

In this study, the overlapping model non-linearly relates the evolution function with the size of the design scope. Its psychological implication is similar to the marginal utility effect in economics, and can be argued by the following experiment: ask some people to estimate the uncertainty of a choice question that has n options, then adding one more option and ask how they would feel regarding to the change in uncertainty. It is fair to estimate that the change in uncertainty would be much less if $n = 10$ than if $n = 3$. Non-linearity of this estimation is modelled by a logarithmic relationship, which is the most conservative estimation derived by the principle of maximum uncertainty. Furthermore, this uncertainty measures the number of guesses one needs to make in order to find the correct answer. In the literature, analogous result can be drawn to the choice reaction time experiment. In Hick (1952), the reaction time is found to be proportional to the logarithm of the degree of choice which manifests the same characteristic as the relationship between the evolution function and the discrete set (Equation (2.4.5)).

In addition, due to the fact that any downstream design, if it is not the final one, can be treated as an upstream process relative to its own downstream processes, this model can be used to evaluate a product development problem that involves multiple sequentially dependent design specifications when downstream starts no early than upstream and in each time, only one overlapping can occur during NPD implementation, i.e., Sashimi-style solution (Imai, Nonaka, & Takeuchi, 1985) [4]. For interdependent design tasks, or for completely new products, however, the evaluation method developed in this study may fail. In these cases, more assumption is needed for the method and we shall conclude this in section 2.7.

In relation to the ordinary DSM model (Smith & Eppinger, 1997b), the model in this

[4] We have applied the model to the overlapping processes in a design of snake robotic endoscope, the results are summarized in Appendix A.

study is sensitive to the degree of interdependency among design variables, and to the evolutionary nature of the design. On the other hand, this model is applicable in determining the degree of rework probability. Since it is virtually related to up- and downstream dependency (Roemer et al., 2000), the rework probability can be viewed as a function of the critical point $(t_c, U(t_c))$. As an example, one possible definition of rework probability, processing unit Y on information change of X, is $p_{Y|X} = \frac{U_{Y|X}(0) - U_{Y|X}(t_c)}{U_{Y|X}(0)}$, which is the ratio of dependent work to total work. This definition has an objective basis on the dependency between up- and downstream information. For studies that propose rework probability as a function of time, we also suggest that the critical point may play a role. One possible definition considers time as a variable such that the rework probability of Y on information change of X is $p_{Y|X}(t) = \frac{U_{Y|X}(0) - U_{Y|X}(t)}{U_{Y|X}(0)}$, $t \leq t_c$, which is the ratio of dependent work to total work as a function of time. Again this definition of the dynamic rework probability is based on the dependency between up- and downstream information, and monotonically increases with time which implies that a frequent review mitigates the magnitude of rework.

The concept of uncertainty in this study is modelled as the remaining expected work in relation to the scope of the design space. It differs from the one defined in Loch & Terwiesch (1998) where the uncertainty is characterized as the change rate in the upstream. Similarity, the sensitivity feature is modelled by the expected scope of downstream design variable given the upstream information. Dependency becomes a sensitivity measure that is closely related to the nature of physical constraint among design variables.

Aside from these emphases on analytical applications, this model is also an approximation of the process of cooperative problem solving. We refer to the process as a group of information processing units each of which can receive information from others, follow searching algorithms and pass the result on to the units where it is needed. The evolution function is a representation of the convergent behaviour of the searching algorithm.

Although current product design is indispensable to manpower, design by artificial intelligence could be a possible outcome in future, and the implications drawn from the model should be conserved.

Lastly, the model can be improved to provide a more accurate comparison in selecting the overlapping strategies if the cost coefficients of design processes are specified and applied, i.e., payment rate, the costs for functional interaction, and information sharing. Furthermore, since this micro-product design model is deterministic, it provides good estimates under situations where design processes do not present too many complex features such as when too many tasks are interrelated. However, if the design processes are complex, the decisions based on the single value without a measure of variation is dangerous. Hence, only treating the model elements probabilistically can yield meaningful results for complex design processes.

2.7 Conclusions

Understanding the dependency of up- and downstream processes is a basis for effective decision making in overlapping. Our model explicitly addresses this dependency in terms of the evolving nature of the process and the design technology. The model shows how the NPD performance, especially for downstream rework, can be varied under different overlapping strategies. An evaluation method is applied for cases involving incremental innovation and for an three-process sequential industrial example. Furthermore, the critical point of the dependent process derived in our model can serve as an argument in determining rework probability or rework function proposed by other studies.

Some refinements of the model are possible. (1) The model does not address how the rework can be estimated under coupled design activities; that is, the up- and downstream discrete sets are defined interdependently. Hence, future work on this aspect is needed. (2) Since most of NPD processes are more complex than the case we considered in this paper, our next step is to apply the model to a situation where the number of processes and the size of design spaces are both high.

Chapter 3

An Analysis of Organizational Structure in Process Variation

3.1 Abstract

In today's highly uncertain and changing market environment, the need for organizational structures to respond to persistent improvement in organizational processes becomes more critical than ever before. Current organizational studies mostly emphasize categorized processes and structures and lack development of continuity in temporal and spatial layers of environmental change. In this study, organizational structure varies along departmentalization and assignment, whereas process environment changes in the space of exploration and exploitation. We develop a systemic framework and the results are compared with industrial data from new product development. We then analyze the interplay between organizational structure and performance with coordination costs through a static as well as dynamic process environment, and find that organizations, including organizational models and assignments, are stable at certain level in continuous process change. The implications drawn from the results conclude a set of strategic guidelines in response

to the need for restructuring: (1) the need for restructuring is low in short term, moderate, explorative or exploitative process improvement; (2) a low level of tolerance (entailing opportunity loss) should be used when it takes explorative, or exploitative, or both efforts in long term, radical process improvement in order to avoid high costs of structural adjustments; (3) once major process changes are completed, the alignment should be restructured or at least improved without delay in order to avoid accumulative opportunity loss.

3.2 Introduction

The dyadic relationship between organizational process and structure has been a central theme for decades (Thompson, 1967). Organizational theories and studies provide explanations on the behaviour of organizational structure (e.g., Galbraith, 1977; Levinthal, 1997; March & Simon, 1993; Mintzberg, 1979). These studies emphasize that one of an organization's main function is to coordinate everyday tasks in a varying process environment, and study how organizational structure evolves in order to respond to process variation. It is clear that organizational structure is key in determining performance (Weber, 1947). However, due to simplified representations, results at the organizational level are mostly explanatory and applicable to categorized processes and structures, thus limiting direct implication in terms of continuity in temporal and spatial layers of environmental change. In today's complex and highly uncertain and changing market environment, the need for an organization to adapt fluidly from its structure through its processes is more critical than ever before. Developing mechanisms that apply broadly to any organization is of primordial concern to managers.

In this article, we provide a systematic framework that builds process and structure through an information dependence matrix and coordination matrix among agents, respectively. We allow the process representation to be variable in two dimensions, i.e., explorative improvement and exploitative improvement (March, 1991; Tushman & O'Reilly, 1996). Our results contribute to the current literature in two major ways. (1) For a static process environment, the model explores, and confirms with existing explanations, the interplay among the performance of organizational structure, the communication cost, and the organizational size. (2) For a dynamic process environment, in relation to the organizational model as well as agents assignment, we identify organizational stability in continuous process improvement and conclude with a set of strategic guidelines in response to the need for restructuring. We analyze the cost of restructuring and provide, from a process dynamic perspective, an economic explanation as to how the role of structural inertia exerts influence on old as well as young organizations with complex processes.

In the literature, Simon (1976) defines an organization as the pattern of communications and relations among a group of human beings, including the processes for making and implementing decisions. His view of organizations as information-processing units made up of boundedly rational individuals led to an extensive amount of research on the interaction between agents and organizational environment (Puranam, Stieglitz, Osman, & Pillutla, 2015). On the other hand, in the field of contingency theory, many authors study the effect of external environmental variables on organization design (Blau & Schoenherr, 1971; Hage, 1965; Lawrence & Lorsch, 1999; Perrow, 1967; Pugh, Hickson, Hinings, & Turner, 1968; Thompson, 1967). This approach does not consider an organization's ability to affect performance, in part by adapting to its environment. Miles, Snow, Meyer, & Coleman (1978) states that structure and the processes within an organization are closely linked, and that one cannot speak of one without the other. Bloisi, Cook, & Hunsaker (2007) define organizational structure as a bringing together people and tasks into units with the aim of improving coordination of communication, decision-making, and actions taken. Thus, one can design a more efficient organization through a better understanding of the processes therein.

In his pioneering work, Alexander (1964) studies the effect of intra-organizational dependence on a design task and found that the effectiveness of the task is dependent on the degree of information dependencies among the design variables. Galbraith (1977), from an information processing perspective, theorizes the organizational structure as a means for reducing information uncertainty and resolving information discrepancy. Likewise, Mintzberg (1979) demonstrates that organizations act as various ad hoc communication structures that support the implementation of everyday tasks and processes. March & Simon (1993) in contrast, analyze the behaviour of individuals in organizations, and study how it varies with the communication structure and the information dependence. Mount & Reiter (2002) treat organizations as combinations of calculation units of different functions, and studied the behaviour of computational efficiency with communication structure that links the units. Moreover, the possibility of whether any organizational structures and the processes within can be quantitatively represented in a uniform manner was explored (Mackenzie, 2013). However, the suggested framework lacks immediate applicability to analyze dynamic process environment such as new product development (NPD) with different level of concurrency.

Although there has been much concern over organizational structure in the literature, Gavetti, Levinthal, & Ocasio (2007) point out that the role and importance of specialized decision-making structures has been lost, further stating that it is risky for organizational studies to ignore these foundational constructs. Cyert & March (1992) also hold the view that an organization should be mainly described as a decision-making process. They further question how hierarchical groups make decisions. Christensen & Knudsen (2010) and Csaszar (2013) identify and investigate the effect of applying complex organizational structures on the errors in decision-making. Similarly, Ioannides (2012), through a pure mathematical approach, studies the organizational design in the case of project screening by modelling the features of organizational architecture. He proved that the performance of decision-making, in terms of error reduction, can be continuously improved in a convergent manner if the organization is structured properly. On the other hand, while Gibson et al. (2015) propose a hierarchical framework to analyze the dynamic evolutionary behaviour for a complete structure space, process is not modelled in a comparable level of detail. Bavelas (1948), Leavitt (1951), and Guetzkow & Simon (1955) show that simple process performance is highly variable with the change of group communication patterns. Marschak & Radner (1972) investigate organizational structure from a decision-making perspective such that a group of simple communication patterns can be characterized, e.g., decentralized and centralized organizational structure. Façanha & Resende (2010) further discuss how the hierarchical structure of an industrial firm could be determined through a group of pertinent organizational factors.

In relation to structural dynamics, Hannan & Freeman (1984) and Mens, Hannan, & Pólos (2015) find that the rate of change in organizational structure is inversely propositional to its size and age, whereas Baker & Cullen (1993) claim large size has more resource to conduct reorganizing. Haveman (1993) finds U-shaped relationship between organizational size and flexibility to change. These seemingly inconsistent results may have overlooked the role of process dynamics played in affecting the change of organizational structure. In this article, from another perspective, we explore this organizational ability to change in relation to the nature of process development.

The literature clearly demonstrates the close relationship that exists between organization structure and process, and consequently performance. The nature of the organizational structure has a major impact on the success of organizational projects and the processes executed to complete them. Although the literature shows that a wide variety of mechanisms have been adopted and studied in order to address this issue, more knowledge is required in order to answer how the coordinated efforts of various resources within an organization can contribute to the effective and successful execution of processes, especially in an environment where organizations need to adapt to process variation.

In this article, we model the effect of applying different organizational structures, in the form of coordination structure, on process performance. We take the team decision making approach (Marschak & Radner, 1972), which models decision processes of agents where information, as a basis of decision making, is interdependent and represented as process matrix. Modelling results are compared with data observed in the automotive industry and extended to the analysis of the variation of organizational structure in response to static as well as dynamic process environment with varying communication costs. We study organizational structure and process in general, and conclude with a set of strategies on how to react with process changes in specific.

3.3 Modelling Method and Solutions in Special Process and Structure space

3.3.1 Process, Structure, and Agent

An organizational task can be considered as a process of team decision making. Agents, or organizational members, make decisions based on the information regarding the task. Consider a task x of n members. We denote $R = \{r_{ij}\}$ as the interpersonal information dependence matrix regarding the task, also called process structure. A non-zero value r_{ij} indicates the relative dependence of member i's information on j's. In a short time period, we assume the process is static. This representation can be easily extended in a dynamic setting where at each time period there is a corresponding R representing the process status.

We shall clarify that R is not necessarily the same as the interdependence among tasks; if the latter is exogenously given, the former is mostly subject to the implementation of the tasks. As a result, the same task may have different R. Puranam, Raveendran, & Knudsen

(2012) provide an example where the actions of two agents, i.e., one making pin heads and another pin tails, do not depend on the information of one another if they are rewarded based on the individual, not collective, performance. Hence, the tasks interdependence of making a pin do not imply the interpersonal information dependence, rather the reward plan does in this example. Moreover, it is the interpersonal information dependence serves the basis of decision making for implementing the tasks. Another example is sequential and concurrent engineering, which are two structures widely applied in the NPD industry. The inter-department information dependence can vary with respect to the degree of concurrency whereas the dependence among tasks is stable. Starting with sequential engineering where one's information is most likely dependent on its immediate predecessor and successor, more dependent relations are to be expected as the level of concurrency rises. We shall explore this effect in section 3.3.3.

Another key attribute is organizational structure. We focus on one of its major functions that is to facilitate the coordination of individual actions so as to balance the need for intensive interactions among those who are intimately connected by the process with the need for alleviating the coordination burden. We denote $\{q_{ij}\} \in [0,1]$ as the interaction intensity matrix, or coordination structure, that is supported by the organization.

Let us now consider the behaviour of agent (i) that implements task processes through a decision process α_i, i.e., choosing appropriate actions (a_i) based on information (ξ_i). For the modelling of the utility function, in the literature, it is usually assumed to be concave (or sub modular in discrete cases) (e.g., Milgrom, 1990); that is, the behaviour of the utility growth generally follows from the law of decreasing return to scale. We adapt a quadratic utility function of actions and the state of the task (a, x), that is:

$$\omega(x, a) = \mu_0 + 2a'\mu(x) - a'Qa, \tag{3.3.1}$$

where a is a vector of action variables and $\mu(x)$ is a vector-valued functions of the state of the process on which each member's action a_i is dependent. Moreover, Q is the $n \times n$ interaction matrix, or coordination structure.

In addition to the concavity (we assume Q is positive definite before exploring a general case), Equation (3.3.1) is a reasonable way to mimic life (Kong, Bhuiyan, & Thomson, 2009): the payoff is better off when more effort is put in (increasing a within some scope), but worse off when overdone—an effect of decreasing return to scale. The optimal payoff is, though hard to achieve in reality, believed to exist and located on a moderate exercise of decisions, i.e. neither too low nor too high. Qualifying these basic conditions as a quadratic form, Equation (3.3.1) is chosen to be the utility function in our analysis.

3.3.2 Assessment Method

An organizational structure, a set of decision rules, and information determine at least in part, the utility of an organization. Let $\omega(\alpha, Q, R)$ be the utility of coordination structure Q for a process that is executed through R. Comparisons of various Q and R can then be based on some evaluation methods of ω, which is called the value of organizational structure. In this article, we adapt the method suggested in Marschak & Radner (1972), that is to calculate the maximum expected utility

$$\Omega(Q, R) = \max_{\alpha} E[\omega(R, \alpha_1(\xi_1), ..., \alpha_n(\xi_n), Q)], \tag{3.3.2}$$

where $E(\bullet)$ is the expectation function.

The maximum expected utility method provides a relatively fair basis in comparing among different process and organizational structures. Although for any given R and Q, the utility could be variable with different decision rules, equation (3.3.2) states that the utility is evaluated to the organization on the exercise of the *best* decision rule such that it maximizes the expected utility function. Without this criterion, comparisons may lead to results of unfairness.

The best decision rule maximizes the expectation of the utility function (3.3.1) given the information ξ, process R, and structure Q. Referring to the person-by-person satisfaction theorem (Marschak & Radner, 1972), this decision rule is located at the stationary point and calculated through a set of linear equations derived from taking the first partial derivative on each decision variables given the available information: each member is searching for the best decision based on the conditional expectations about actions that might be taken by others and on the estimation about the state of the design. Without loss of generality, the unconditional expectation $(E(\mu_i), i = 0, ..., n)$ is set to be zero as relative values (high vs low), rather than absolute, of the organizational structures are our concern. This also means that the value of the organizational structure is measured from zero, or the value of null-information. As a result, the best decision rule $(\widehat{\alpha})$ is the solution to the following set of linear equations:

$$q_{ii}\alpha_i + \sum_{j \neq i} q_{ij} E(\alpha_j|\xi_i) = E(\mu_i|\xi_i) \qquad i = 1, ..., n. \tag{3.3.3}$$

The value of the organizational structure is calculated as the deviation from the null-information, and since $E\mu = 0$ and $E\alpha' Q\alpha = E\mu'\alpha$, it reduces to:

$$V(\eta) = E\widehat{\alpha}\mu - (E\alpha)(E\mu) = E\widehat{\alpha}\mu. \tag{3.3.4}$$

We shall then study R with increased links of information dependence under identical interaction.

3.3.3 The Value of Organizational Structure in NPD Process

In this section, we study a set of R that represents the processes of NPD. As stated earlier, the process structure R depends on the level of concurrency. Consider three design elements in car development, i.e., 1. engine size, 2. overall shape, and 3. drawing of dies for car outer panels. An interpersonal information dependence at a low level of concurrency could be realized as $r_{ij} = 0$ for all $i \neq j$ except $r_{1,2}, r_{2,1}, r_{2,3}$, and $r_{3,2}$, i.e., the information of 1 and 2, and 2 and 3 are interdependent, respectively. However, parallel development changes process structure which increases the breadth of information dependence. Die drawing development may need to estimate the overall shape through the information of engine size, creating information dependence between 1 and 3.

We assume for simplicity that the number of agents on which one's information is dependent is identical, and denoted by $m \in [1, n-1]$, and correspond to the degree of concurrency to coefficient $d = \frac{m}{n-1}$. Before exploring a more general process and structure space, let us consider R is symmetric and with the degree of concurrency d. In addition, the following assumptions hold: (1) μ_x is normally distributed; (2) self-interaction intensities (q_{ii}) are unified to be 1, whereas interpersonal interaction intensities are assumed to be the same ($q_{ij} = q$); (3) process is implemented based on adequate communication, and equivalently information is the best decision rule for each agent $\xi = \beta_i$, where β_i is normally distributed with zero mean; (4) the covariance matrix of the information is $R = cov(\xi) = \{r_{ij}\}$, where $r_{ii} = \sigma^2$ for all i, and $r_{ij} = r \geq 0$ for all interdependent i and $j \neq i$. These assumptions will not change the implications drawn from the mathematical models since the overall differences (q, d, r) are compared.

The value of the organizational structure is (Appendix B has a detailed calculation):

$$V = \sum_{i=1}^{n} E(\beta_i \sum_{j=1}^{n} q_{ij}\beta_j). \tag{3.3.5}$$

And by applying the foregoing assumptions, we have:

$$V = n(\sigma^2 + d(n-1)rq). \tag{3.3.6}$$

Equation (3.3.6) implies that, for each member, the value of the organizational structure corresponds to a summation of two parts: (1) a reduction of uncertainty as measured by each individual's own information variance (σ^2); (2) a reduction of uncertainty about peers' information as measured by the covariance between information. Since each member interacts with $d(n-1)$ members, this second part is scaled at interaction intensity q. Summing over n members yields the total value. As a result, the value is increasing with the breadth of information dependence in R through the degree of concurrency d. Furthermore, the more rapidly the state of the design changes (the higher the variances and covariances), the more value the organizational structure is worth. We shall extend the implication drawn from the results to non-unified interaction intensity q and general process dependence r in section 3.5.

3.4 Industrial Observations and Model Predictions

In connection to two NPD practices, i.e., sequential and concurrent engineering, this section compares the model results with industrial observations. As summarized by Kong et al. (2009), concurrency can be empirically evaluated as level of specialization. Sequential engineering requires low information dependence that one's decisions can be made without an estimation of the others' following actions (high specialization); however, concurrent engineering leads the information of each team member to be dependent since, in order to coordinate concurrently, they must estimate peers' actions and at the same time, make their own decisions (low specialization). Hence, the first comparison is made between the following two relationships (Figure 3.1): (1) the value of the organizational structure (V) given in Equation (3.3.6) with respect to the degree of concurrency (d); and (2) the NPD performance (lead time) with respect to the degree of specialization, or concurrency, as reported by Fujimoto (2000).

Figure 3.1 demonstrates two trends that show the reduction of lead time in comparison

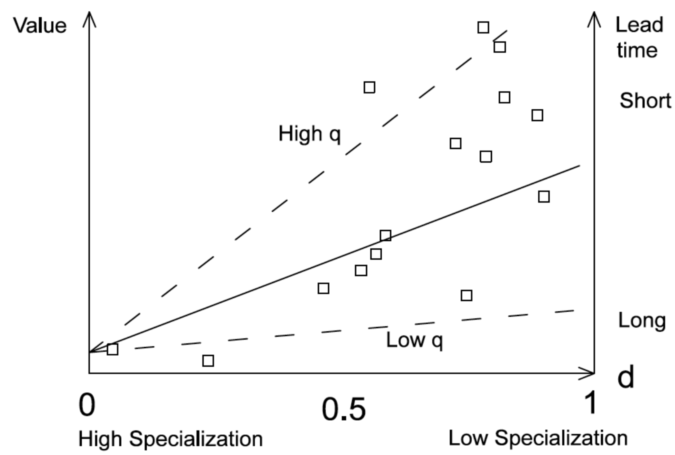


Figure 3.1: Comparison between (1) model results as Eq. (3.3.6) horizontal axis: degree of concurrency; vertical axis: the value of organizational structure (solid line: moderate q, and dashed lines: higher and lower qs) and (2) data reported by Fujimoto (2000) (□), horizontal axis: specialization; vertical axis: adjusted lead time.

with the increase of the value of the organization. The NPD lead time will be shortened when more concurrency is applied and that in turn, demands higher level of information dependence. Our model predicts that the value will increase as d and can even be enhanced with greater interaction intensity (q). That means higher interaction intensity, or better coordination, increases the effectiveness of concurrency.

The second comparison is made between the effect of interaction intensity (q) on the organizational value and the effect of internal integration on lead time as observed by Clark & Fujimoto (1991). In their study, internal integration is defined as the degree of interaction among team members in an NPD process, which corresponds to the interaction intensity in our model. Figure 3.2 shows the comparisons of the empirical data and the model results. The value linearly increases with the interaction intensity. The three lines indicate conditions under which levels of concurrency (d) are high, moderate, and low, respectively. On average, the companies in area 1, mostly Japanese companies, exercise a higher extent of concurrency than that of area 2, i.e., companies from Europe and the U.S.

As a matter of fact, the observed data shows that the NPD performance is positively

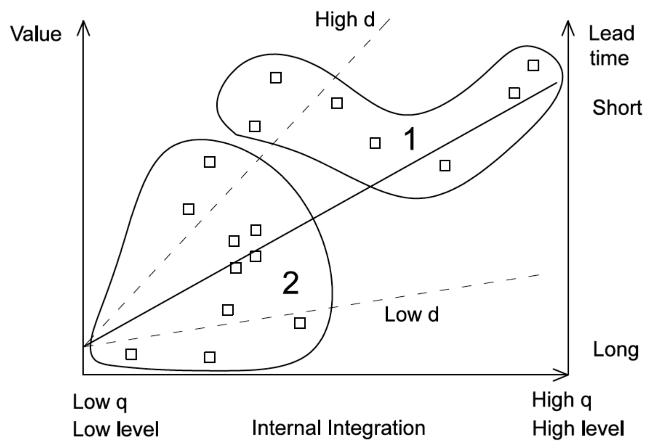


Figure 3.2: Comparison between (1) model results as Eq. (3.3.6) horizontal axis: interaction intensity; vertical axis: the value of organizational structure (solid line: moderate d, and dashed lines: higher and lower ds) and (2) data reported by Fujimoto (2000) (□), horizontal axis: level of integration; vertical axis: adjusted lead time. Companies in area one, mostly Japanese, have higher average concurrency than that of area two.

related to the degree of internal integration and concurrency. The modelling results further suggest that the two factors are complementary. According to Theorem 2 in Milgrom (1990), higher breadth of information dependence (higher concurrency) makes each additional interaction (higher internal integration) more effective in making better decisions (shorter lead time), and vice versa (this can be verified with $\partial V^2/\partial d \partial q \geq 0$). In other words, high concurrency without an appropriate internal integration would impede the process performance.

3.5 General Organizational Structure and Process Dependence in Static and Dynamic Environment

This section extends the major implications drawn from Equation (3.3.5) to the analysis of the influence of departmentalization on process performance in static and dynamic environment.

The previous sections have shown that the value of the organizational structure increases with interaction intensity (q), and information dependence (r) through concurrency (d). But in reality, coefficient q differs among members and it is highly dependent on the department structure. Consider that between every member i and j there is q_{ij} as a measure of their interaction intensity. This q is not required to be the same for every different i and j. Intra-department interaction is usually more intensive than inter-department interaction. On the other hand, high interaction intensity incurs more cost, such as communication cost. Hence, an organization can be viewed as a coordination system with capacity Q at the cost C.

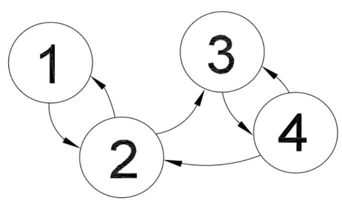
In addition, an organization solves problems through executing processes that tie organizational members in another manner. The strength of the ties, as a nature of the process, is the interpersonal information dependence among members (R). Likewise, depending on the process, r_{ij} usually differs for different members i and j. Given R, the process dependence, and C, the coordination cost, an organizational design problem is to find an appropriate organizational structure Q that facilitates process R. Hence, we have:

$$\begin{aligned} \max \qquad & V(q) = \sum_{i=1}^{n} \sum_{j \in \{1,\ldots n\}/i} r_{ij} q_{ij} - c(q) \\ \text{subject to} \quad & 0 \leq q_{ij} \leq 1, \text{ for all } i \neq j. \end{aligned} \tag{3.5.1}$$

In the objective function the positive part is a variation of the value of the organizational structure in Equation (3.3.6). It is derived from ignoring the parts that are independent on q and breaking the rest down to the summation of all individual parts ($r_{ij}q_{ij}$). In effect, Equation (3.3.6) can be viewed as an average formulation with its information dependence r to be interpreted as the average degree of dependence ($n(n-1)rq = \sum_{i=1}^{n} \sum_{j \in \{1,\ldots n\}/i} r_{ij} q$). Before analyzing how process (R) and cost (C) affect the value of organizational structure (Q), we describe the spaces in which process R and organizational structure Q vary.

3.5.1 Process Variation—Exploration and Exploitation

Exploration and exploitation are two approaches in organizational learning (March, 1991). The former often refers to a global search in problem solving whereas the latter local search (e.g., Baum, Li, & Usher, 2000; Tushman & Romanelli, 1985). We interpret process structure R as solutions to organizational tasks, or problems. Like Zhou (2013) and Levinthal (1997), we define the complexity of an NPD process as the total number of non-zero entries in R, except diagonal entries ($\sum_{i \neq j} s_{ij}, s_{ij} = 1$ if and only if $r_{ij} \neq 0$). Figure 3.3 shows a process R with complexity six.



$$
\begin{array}{c|cccc|}
 & 1 & 2 & 3 & 4 \\
\hline
1 & \bullet & r_{12} & 0 & 0 \\
2 & r_{21} & \bullet & 0 & r_{24} \\
3 & 0 & r_{32} & \bullet & r_{34} \\
4 & 0 & 0 & r_{43} & \bullet \\
\hline
\end{array}
$$

Figure 3.3: A process of six dependence links (complexity six); left: process flow diagram; right: process dependence matrix

Process structure R varies along two dimensions. The first dimension is an exploration process through which R takes a series of transition states. At each time period, similar to the mutation process in the NK model (Levinthal, 1997; Levinthal & Warglien, 1999), there is, randomly selected, d_1 pairs of interpersonal information dependencies to be swapped, also called rate of change. For example, one period of explorative improvement with $d_1 = 1$ swaps the interdependent pairs between 3 and 4 with 1 and 3 (see Figure 3.4a). Hence, a persistent improvement along exploration renders process structure R memoryless in the long run. The structure is eventually capable of escaping from the local optimum. Organizational adaptation of this approach may be a result of, for example, rapid change of product family, employment of a new operation process or manufacturing layout, among other types of explorative efforts.

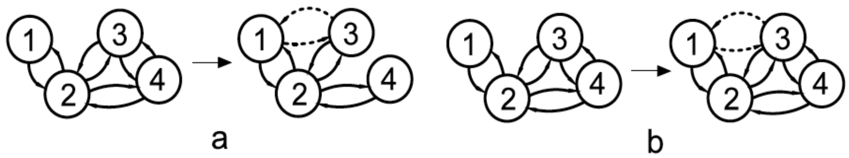


Figure 3.4: Examples of one period process variation: a. explorative b. exploitative

Along another dimension, R can respond to the challenge of organizational tasks through an exploitation process. Different from that of exploration, new process structure inherits, or memorizes, the complete process structure from old ones. At each time period there is d_2 new interpersonal information dependencies to be added in a random manner. For example, shown in Figure 3.4b, one period of exploitative improvement with $d_2 = 1$ increases the process complexity by adding interdependent pairs between 1 and 3. Hence, a persistent improvement along exploitation means a series of local improvement where new solution is based on an old one, the past information of process structure is preserved in the current. Evolution of R in this manner may refer to, for example, incremental innovation in NPD where the development is based on an existing product, refinement of an operation process, etc.

As per our definition, process variation along exploration discovers new structure with conserved complexity whereas problem solving by exploitation improves existing solution with increased complexity. To summarize, we have delineated a two-dimension process variation space, see Figure 3.5. It is worth noting that we adapt a dynamic representation. Any point in the space indicates the rate of process change along exploration and exploitation, and the origin is the static state.

3.5.2 Coordination Structure Variation—Departmentalization

The coordination structure Q, represents the relative interaction intensity of an organization. In this article, we pay particular attention to the variation of the structure in relation

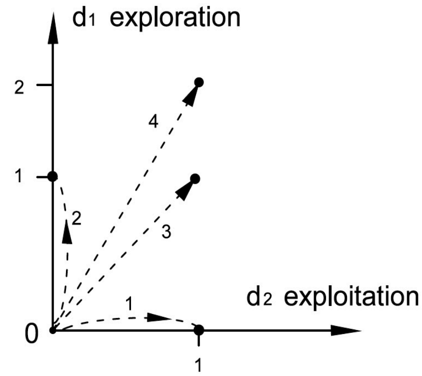
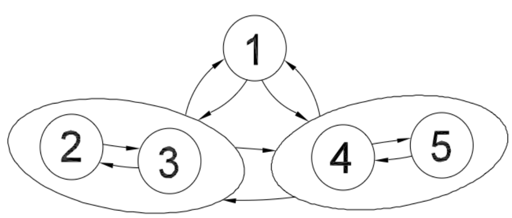


Figure 3.5: Dynamic space in exploration and exploitation process variation

to the number of departments. As illustrated in Figure 3.6, Q is a structure where five units are organized into three departments, i.e., Q_1, Q_2, and Q_3. Each unit has intra-department interaction intensity q_1, and inter-department interaction intensity q_2. More agents are able to freely coordinate with one another in less divisionalized, or more integrated structure, and vice versa. Hence, fewer departments correspond to a more organic, integrated model, whereas more departments correspond to a more hierarchical, differentiated model. It is worth noting that the organizational structure of our consideration involves two parts, the number of the departments and the assignment of organizational members to the departments. As a matter of fact, organizational structures may have the same organizational model, though different assignments.



	1	2	3	4	5
1	●	q_2	q_2	q_2	q_2
2	q_2	●	q_1	q_2	q_2
3	q_2	q_1	●	q_2	q_2
4	q_2	q_2	q_2	●	q_1
5	q_2	q_2	q_2	q_1	●

Figure 3.6: A structure of three department; left: organizational diagram; right: interaction intensity matrix

The foregoing framework provides a basis for the analysis of the interplay among organizational structure Q, process R. Before investigating organization dynamics, we first study the static condition.

3.5.3 Comparative Performance in Static Environment

We shall construct a set of processes $\{R_i\}$, where i is the complexity of the process. In static and dynamic environments, an exploitative process of seven units (R_{12}) is set as our base process. The relative process dependencies are uniformly distributed random numbers $(U(0, 1))$. New processes with higher complexity are generated by randomly adding more dependencies among units. Hence, as shown in Figure 3.7, a complete set contains sixteen processes of different complexity which spans from 12 to 42. Appendix C has complete process structures R. We further assume that any organizational structure that supports the processes has intra-department interaction intensity q_1, inter-department interaction intensity q_2, $q_1 = 2q_2 = 1$; the cost of the former is c_1, the latter c_2. Hence the value of an organizational structure $Q = \{Q_1, Q_2, ..., Q_m\}$ for a static process R is:

$$V(Q, R) = \sum_{i=1}^{n} \sum_{j \neq i} r_{ij} q_{ij} - c_1 \sum_{k=1}^{m} \sum_{i,j \in Q_k} h_{ij} - c_2 \sum_{k \neq l} \sum_{i \in Q_k, j \in Q_l} h_{ij} \tag{3.5.2}$$

where $h_{ij} = 1$ if the process dependence $r_{ij} > 0$.

Comparisons of Structures

The value of an organizational structure varies with the organizational model, or the number of departments. Figure 3.8 shows the comparisons of structures of this variation in three static processes. The comparison is among the best structures with respect to the value. It takes account of the number of the departments and the assignment of organizational members to the departments, though the specific assignments are not shown. In the

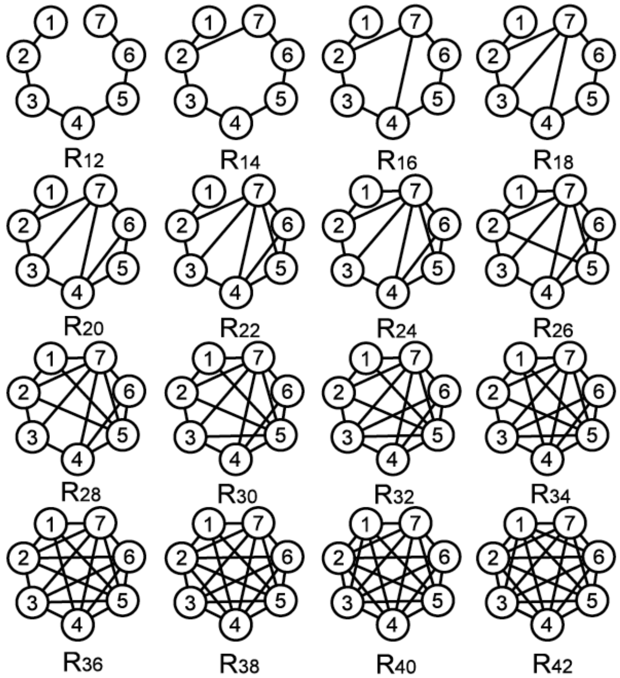


Figure 3.7: Seven units processes with different complexity from 12 to 42, Appendix C has complete process dependence

setting of moderate costs where $c_1 = 0.4, c_2/c_1 = 0.25$, $V(Q, R)$ is first increasing then decreasing with the number of departments. We have studied that for all processes in the given R, this relationship holds irrespective of the complexity. In effect, departmentalization resolves a partial complexity of the process by assigning relatively lower interaction intensity among organizational members of different departments. The loss of the value due to that lower intensity trades off the opportunity cost of coordination that would have incurred by high interaction intensity within the department. On the other hand, this loss finally overtakes the opportunity cost and hence, the value of the organizational structure decreases as more departments are formed. In short, the size of the organization, or the number of departments, follows a convex behaviour with the value. However, the optimal size depends on the coordination costs. In the next section, we study how the number of departments changes with c_1 and c_2/c_1.

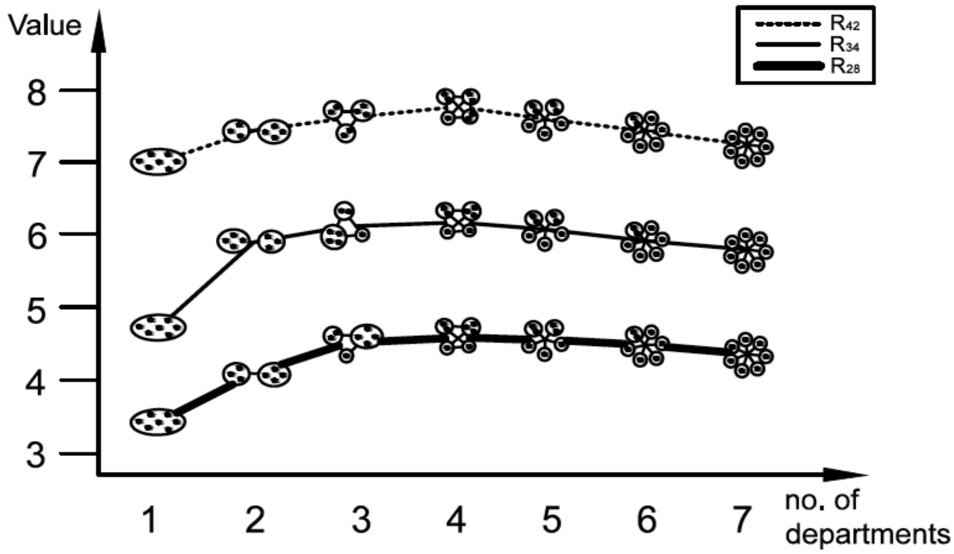


Figure 3.8: Comparison of the optimal structures with the number of departments in three processes, R_{28}, R_{34}, R_{42}.

Effectiveness of Organizational Structure and the Costs of Coordination

The best organizational structure balances the gain from reducing communication complexity and the opportunity cost. Its formation depends on this gain and loss through the exercises of coordination structure. Hence, it is necessary to study how the intra-department coordination cost (c_1) and inter-department coordination cost (c_2) impact the formation of the best structure. Based on process R_{42}, Figure 3.9 illustrates the comparisons of the optimal organizational structures with c_1, ratio c_2/c_1, and value of organizational structure V. As can be seen, the value corresponding to each optimal structure decreases with the costs, c_1 and c_2, respectively. The number of the departments increases with c_1 as it gradually divisionalizes the structure so as to resolve the growing intra-department coordination complication. On the other hand, this number decreases, ceteris paribus, with c_2, or ratio c_2/c_1, which is due to the fact that the increasing inter-department coordination cost limits the divisionalization of the organization, i.e., more departments entail higher inter-department cost as c_2 raises. Furthermore, simple structures, i.e., less divisionalized, are preferable to high c_2/c_1; complex structures, i.e., more divisionalized, in contrast, are preferable to low c_2/c_1. It is also worth noting that non-divisionalized structure are the best for small c_1. This usually occurs when the complexity of the process can be resolved by an efficient coordination method. The very group of the organizational members coordinates according to the nature of the process, i.e., $q_{ij} = 1$ if $r_{ij} \neq 0$. Summarizing the above results, we have shown how the processes' behaviour, when supported by the optimal organizational structure, changes as the coordination costs vary. In the cases of different complexity, the results also hold.

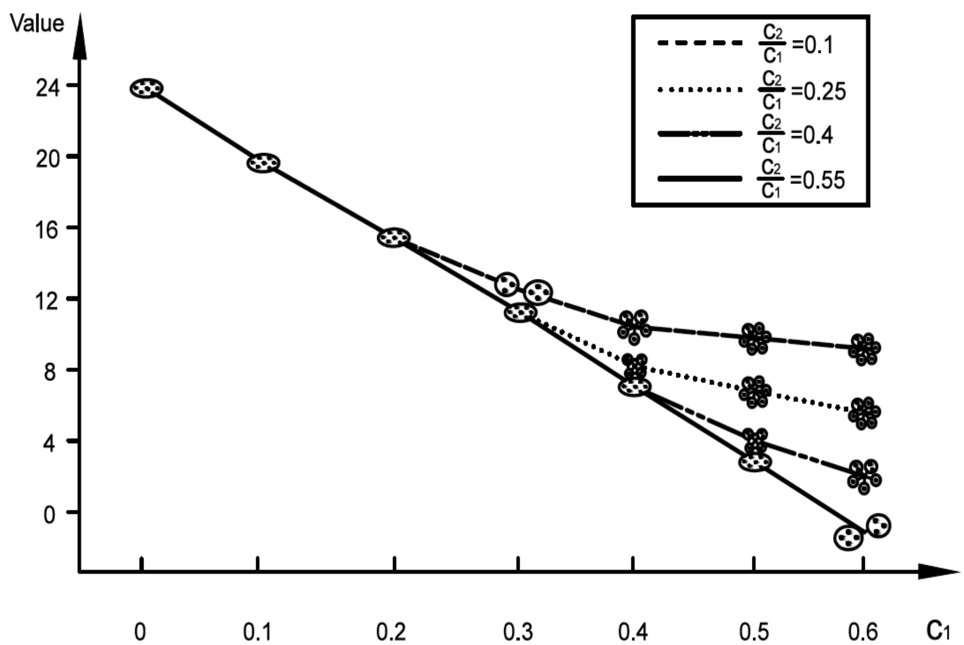


Figure 3.9: Comparisons of the optimal structures with coordination costs on process R_{42}.

Summarizing Results in Static Process Space

We have analyzed the static behaviour of a set of processes under different organizational structures. The results are intuitive and mostly in line with previous studies pertinent to organization size or the degree of divisionalization and coordination burden (e.g., Galbraith, 1977; Gibson et al., 2015; Lawrence & Lorsch, 1999; Zhou, 2013). To illustrate major implications, we apply the results to a set of NPD processes of different concurrency. It should be noted that the results hold for general organizational process and structure. As can be seen in figure 3.10, since a concurrent process demands a higher level of dependency among members than sequential process, it changes the process structure and intensifies coordination. As the level of concurrency increases, the process becomes more complex and the costs of interaction raises. We conclude that, for an NPD process with a low level of concurrency, coordination demand is relatively simple and direct. Process iteration usually involves fewer organizational members. In this case, simple organizational structure is preferable. When a higher level of concurrency is introduced, coordination demand is complex and indirect. Process iteration involves more organizational members. The organization then needs a divisionalized organizational structure to separate those groups who are loosely dependent on one another. We also found that, in order to avoid value loss due to this separation, efficient coordination can be introduced for a high level of concurrency and as a result, the structure remains stable.

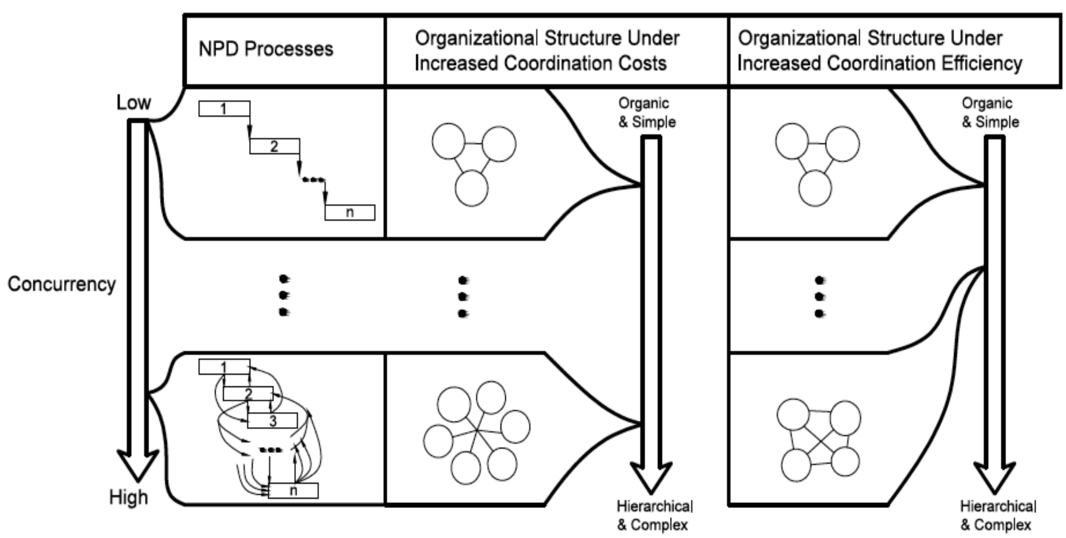


Figure 3.10: Fits between organizational structures and NDP processes as concurrency and coordination costs change.

3.5.4 Comparative Performance in Dynamic Environment

This section studies how organizational structure responds to internal change, or continuous process variation, and to what extent it is stable. We investigate and compare the behaviour of structures in three special dynamic conditions, i.e., process evolves in exploitation, in exploration, and in both dimensions. Next, we analyze the opportunity cost for stabilizing structures in a dynamic environment in relation to organization inertia.

Comparison of the Best Structures with Respect to Exploitative and Explorative Processes

Organizational processes are usually developed and continuously improved. The fitness between organizational structure and the processes is key to the performance. We start with analyzing processes that corresponds to curve 1 in Figure 3.5. Figure 3.11a, and b illustrate the best structures of two exploitative processes, where 'a' is calculated through our base processes R_{12} to R_{48} and 'b' is based on another randomly generated processes that shares the same initial process with R ($R_{12} = R'_{12}$). Both a and b have the rate of change equal to one along exploitation, meaning one pair of interpersonal information dependence is added for each period. As indicated, the change of the best structure appears to be relatively sensitive to great process exploitation, insensitive to small process exploitation. It further implies that, although the process performance is mostly contingent on the organizational structure, structures can have certain degrees of stability. The same structure could fit multiple processes of similarity. Stated differently, modification of industrial processes in an incremental manner does not necessarily alter the effectiveness of the applied organizational structure. When there is a change in the structural level, the new optimal structures are continuous improvements of the old ones by transferring members to other departments. We can see multiple fits as the process complexity rises.

Additionally, even more stable is the number of the departments, or the model of organization. Under exploitative dynamics of 16 periods, the organizational model for R remains unchanged, whereas for R' it changes only twice through simple movements, i.e., splitting one department into two, and merging two departments, respectively. We define the extend to which organizational model varies as the maximum difference in the number of departments between each pair of organizational structure. Thus, it is zero in R, and one in R' because the structure has experienced maximum reduction, or increase, of departments from four to three.

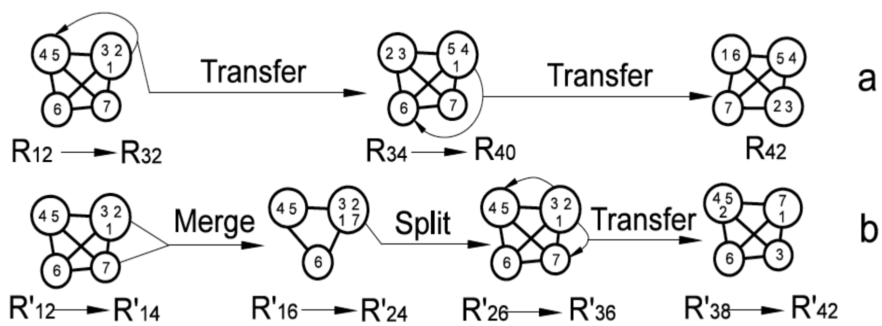


Figure 3.11: Variation of the optimal structures in two randomly generated exploitative processes with rate of change $d_2 = 1$.

Let us now consider an explorative process that corresponds to curve 2 in the dynamic space (see Figure 3.5). The question that immediately follows is that whether the same behaviour holds when the process changes in a radical manner for the exploration in a more complete process space. We study a set of randomly generated explorative processes with moderate complexity in 16 successive periods (the initial process matrix is R_{26}). Figure 3.12a shows a simplified representation of the variation in optimal structure. While the structures still have a certain degree of stability, as indicated by the period under the circle, the specific assignment changes seem to be more sensitive to continuous process exploration than exploitation. On the other hand, as indicated by the solid circle, the organizational model changes three times in 16 periods, which is still stable.

Similar results can be obtained when the process varies jointly along exploration and exploitation dimensions with identical rate of change equal to one, see Figure 3.12b (this corresponds to curve 3 in Figure 3.5). However, increasing in the rate of change in exploration would (curve 4 in Figure 3.5) render the stability property vastly absent, as shown in Figure 3.12c. Drastic process change destabilizes organizational structure with respect to maintaining effective fitness. As discussed in the preceding section, one solution is to increase coordination efficiency. The optimal organizational model would then be simpler so as to reduce the space in which organizational structure varies. One can imagine the occurrence of an assignment change will be less frequent in response to process variation under less rather than more divisionalized structure. As will be discussed in the next section, if the coordination efficiency is hard to improve, then the optimal organizational structure is unstable and one has to choose between maintaining old structure while, perhaps, having suboptimal performance, and maintaining optimal structure while entailing restructuring cost.

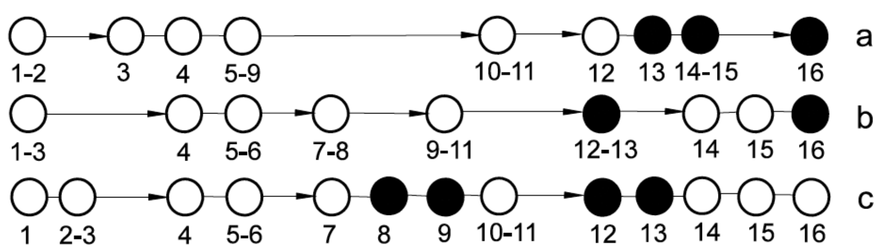


Figure 3.12: Variation of the optimal structures in a. explorative process with $d_1 = 1$; b. process jointly varies with identical rate of change, $d_1 = d_2 = 1$; c. process jointly varies with $d_1 = 2d_2 = 2$.

Thus far, the analysis is only based on a few scattered incidences in dynamic process space. However, it is important to further study to what extent the results are subject to the particular incidences, or if it is generally true. The normalized histograms shown in Figure 3.13 compares the stability in explorative as well as in exploitative process variation (with $d_1 = d_2 = 1$). Each analysis is based on 50 randomly generated incidences (having the same initial process with R_1 in exploitation and R_{26} in exploration). While stability is remarkable in terms of organizational model as well as assignment, structure in an explorative environment is found to be less stable than in an exploitative environment, note that the histograms for explorative processes are behind and filled with diagonal lines. On average, the optimal organizational structure varies 3.78 times with variance 2.95 in exploitation in contrast to 6.8 with variance 5.39 in exploration, whereas with comparable magnitude in variance, the organizational model changes 2.96 times in exploitation as compared to 4.6 in exploration. On the other hand, while we understand that the coordination efficiency is decisive to the form of the optimal organizational model, the analysis further indicates that process dynamics only fine-tunes the model within the adjacent variation space. Organizational structures have experienced on average 1.04 maximum departments addition or removal within 16 variation periods for the exploitative process, and 1.58 for the exploration process, among all the process incidences.

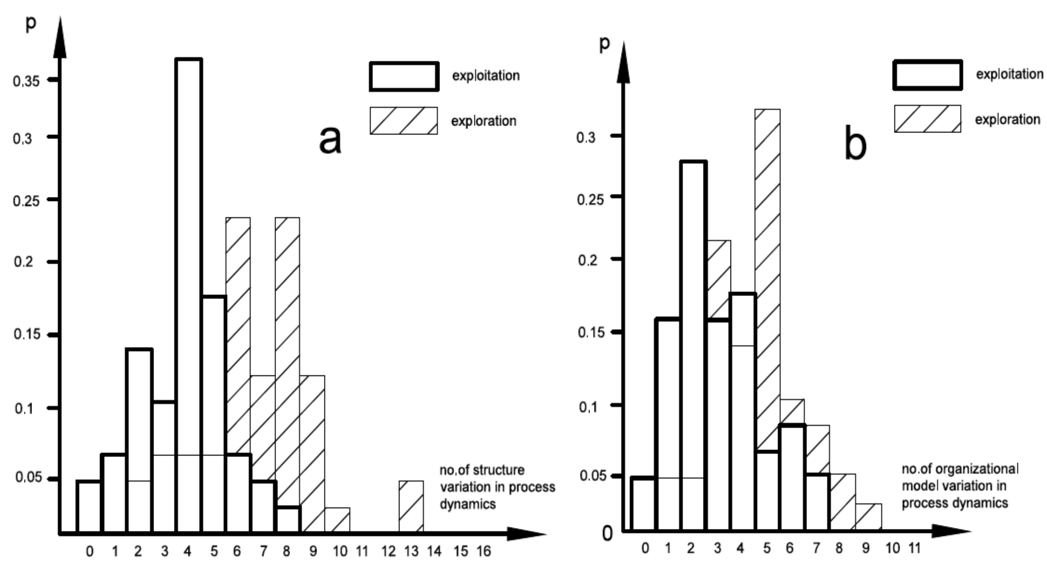


Figure 3.13: Comparisons of histograms between 50 exploitative and 50 explorative process incidences in a. number of structure variation in 16 periods; b. number of organizational model variation in 16 periods.

Cost Analysis

The cost for changing the organizational structure depends on the complexity of the process. Consider a simplified case of an n-department organization with a total of m agents. Suppose all departments are equal in size and the complexity of a process is s. Then, with transferring one agent between departments, it can be shown that in relation to the average level of the total impact to the coordination structure, the cost is $\frac{s}{m}(2 - \frac{1}{m} - \frac{1}{n})$. Here the cost is defined by the addition and removal of process dependencies among departments caused by such a transfer. As simple change in assignment would be more costly if the process is more complex, or the agent has more interdepartmental relations. By the calculation, the impact of simple assignment change roughly equals to $0.23s$ for a seven-person organization of four departments. It raises from 2.8 in R_{12} to 8.3 in R_{36}. Moreover, one would expect to have a higher cost in changing organizational model than adjustment of assignment. Hence in our model, structure with process varying along exploitation is relatively stable, but the cost for structural change increases with complexity. In other words, early change is more cost-effective than late change. On the other hand, structure with process varying along exploration is relatively unstable, but the cost for structural change remains constant as the complexity is conserved. In both directions, the impact is apparent and it is necessary to analyze an alternative strategy, that is to study the opportunity cost for maintaining current organizational structure in dynamic environment.

Figure 3.14a demonstrates the opportunity cost of 6 processes in terms of the percentage of average value at each time period. The deviation between the values when the processes are executed via a set of optimal structures (always update the structure with time) and when executed via only one static structure (the optimal structure at period one) is found, in most cases, to grow rapidly in first few periods, and then stabilize as time elapses. It finally converges within the level of about 7% to 15% of the average value. This behaviour is found in explorative as well as exploitative processes with comparable magnitude.

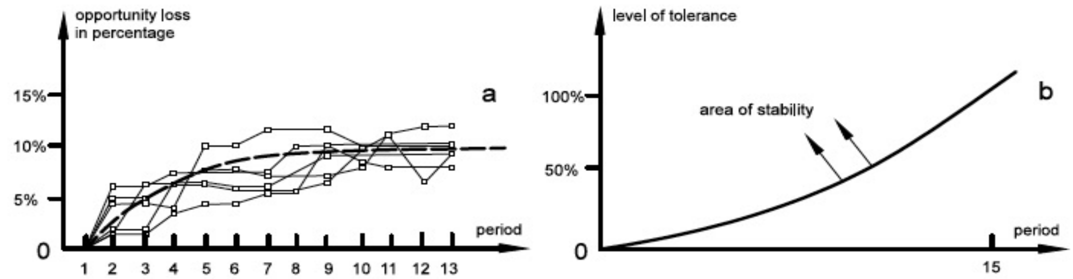


Figure 3.14: a. growth of opportunity cost with time—illustrated through six process incidences in exploration and exploitation; b. stylized area of stability with level of tolerance

If an organization may be willing to bear a certain percentage of this opportunity cost, also called the level of tolerance, then stability should be improved. Figure 3.14b offers a stylized depiction of this relationship based on the dashed curve in Figure 3.14a. We define stability improvement as the time periods during which the structure of the organization can remain unchanged while the total opportunity cost is capped at a certain level of tolerance. Note that this cost is an accumulative value over a time period in a dynamic environment. The level of tolerance is increasing with increasing increment with stability improvement. In other words, setting a low level of tolerance is more effective. A 50% tolerance level renders a stability improvement of about 8 periods. This is quite significant as it corresponds to roughly 35% of information difference in exploration, or 130% of complexity increase.

Summarizing Results in Dynamic Process Space

The analysis thus far provides a general picture regarding the structural stability and process dynamics. In short, with or without implementing structure change while an organization continuously improves its current process matrix depends on the trade-off between restructuring cost and opportunity cost. If we admit a monotonic relationship between organizational inertia and age, that older organizations are usually larger and more complex than younger ones (e.g., Hannan & Freeman, 1984; Péli, Pólos, & Hannan, 2000), and improvements are mostly incremental and therefore exploitative (Sørensen & Stuart, 2000), then the organizational structure is stable for certain periods of process improvement. An older organization, first of all, has a good reason to believe that its current structure has the potential to fit an improved process. Secondly, as the cost for restructuring is proportional to the complexity of process, it may not be economic for older organizations to invest in such an effort. They may, otherwise, choose to maintain their current structure. On the other hand, a younger organization usually has processes of low complexity, and is more willing to conduct process improvement in exploration (Sørensen & Stuart, 2000). The structure under this condition is less stable while the cost for restructuring is low and constant. As a result, younger organizations have more incentive to change their organizational structure than older ones.

An organization also needs to evaluate the opportunity cost. Even though this cost does not diverge with time periods, it endlessly accumulates until the structure is optimal. Hence, we can draw from the results that: (1) organizational structure can remain unchanged while short term, moderate, explorative or exploitative, or both approaches are taken; (2) low level of tolerance should be used when it takes explorative, or exploitative, or both efforts in long term and radical processes improvement in order to avoid high costs of structural adjustments; and (3) restructure without delay, or at least improve the alignment between process and structure, when major process improvement completes in order to avoid accumulative opportunity costs. We understand that a more fine-grained analysis requires additional assumptions in relation to the cost of restructuring; the framework in this section provides a basis for such study. We shall extend this as part of a future study.

3.6 Discussion and Conclusions

An organization implements everyday tasks through processes which are coordinated by organizational structure. We have used a rigorous model, i.e., the maximum expected payoff method, to study a set of special R and Q. In particular, we model R with varying level of concurrency in NPD and assume identical interaction intensity matrix. The results are then extended to R and Q with non-trivial structures, enabling a more practical analysis in static as well as dynamic environment. The definition of process complexity resembles the level of dependence in the NK model (Levinthal, 1997), and we relate it to the exploitative problem solving as the complexity increases with information preserved. On the other hand, similar to the mutation process in the NK model, R changes its interdependent relations while it conserves the complexity. We relate it to the explorative problem solving. The dynamic space for process variation is thus based on these two dimensions of improvement. Compared to configurationalism (Miller, 1986) that suggests few fits between process and structure, our results in the dynamic process environment demonstrate the existence of many fits, which supports cartesianism (Donaldson, 2001). Each structure has a certain degree of stability within a certain period of process changes, forming a pattern of punctuated equilibrium (Romanelli & Tushman, 1994). We have shown that, in particular with Figure 3.10, 3.11 and 3.12, organizational structures incrementally change with different assignments as processes vary. In addition to the degree of routinization (Donaldson, 2006), we argue that the coordination efficiency is also decisive to the formation of structure. Low coordination costs assist the formation of more organic structures, and high coordination costs tend to favour the formation of bureaucratic structures.

Although we have studied a set of process movements in the space, i.e., independent, and joint movements along exploration and exploitation, they represent only limited process improvement in practice and a set of others is important. For example, instead of a continuous additive effort, an organization may improve its current process via try-and-error iteration, which can be considered as oscillation in terms of complexity of a certain degree. An organization may also experience oscillation between exploration and exploitation through temporal separation (Gibson & Birkinshaw, 2004), or simultaneously explore and exploit through organizational structure separation (Adler, Goldoftas, & Levine, 1999; Raisch, Birkinshaw, Probst, & Tushman, 2009). On the other hand, while the defined explorative-exploitative space is illustrative, it is by no means complete. It actually restricts process variation in other possible directions such as decomposability (Zhou, 2013). We shall, in future work, continue exploring the space of process variation.

Supervisory and subordinative relations among organizational members are another important features. Different from the screening problem (e.g., Swank & Visser, 2008; Visser, 2000), the order of decision processes are not considered in our model. In contrast, by the nature of complex process where specialists coordinate for less routinized problems, such as NPD, we take the team approach where the right of decision making is decentralized among members. Hierarchy, in our model, is simplified as a group of decision makers who are divisionalized. On the other hand, limited information processing capability (Simon, 1976) and fallible decisions (Sah & Stiglitz, 1985) have impacts on the process performance. In future extensions, we shall incorporate these important features of organizational attributes for a more comprehensive analysis on the interplay between the structure and process.

Finally, at the model level, we have thus far explored only a partial set of organization design attributes whereas a more comprehensive inclusion to the model is possible. For example, although we assume complete communication, information could be misinterpreted and miscommunicated among people (e.g., Galbraith, 1977; Schilling & Fang, 2014; Sparrow, 1999). We can incorporate this feature by introducing a noise term (ε) to the information $\xi_i(x) = \beta_i + \varepsilon_i$. Assume for simplicity that the state of the process and the noise are independent of each other, and the noise is normally distributed with mean zero. Applying Equation (3.3.4), the value of organizational structure is

$$V' = \frac{V^2}{V + \sum_i \mathbf{var}(\varepsilon_i) + \sum_i \sum_{j \neq i} \mathbf{var}(\varepsilon_i, \varepsilon_j) q}, \tag{3.6.1}$$

where V is in equation (3.3.5) and $V = V'$ in errorless communication. Since the interplay amongst these error terms can be dependent on the structure of the organization (Schilling & Fang, 2014), Equation (3.6.1) proposes another line of study that allows analysis of different hypotheses in terms of how the communication error, in relation to organizational structure, impact the implementation of process.

Chapter 4

Team Specialty and Decision-Making Structures

4.1 Abstract

In the face of changing and uncertain environments, organizational structures are designed and continuously modified. Two important design attributes are decision structure and information structure. While the former refers to an institution of decision aggregation in organizational decision-making, the latter is an organizational assignment ensuring decisions meet with appropriate knowledge. We study how the two attributes interact with each other in a two-dimensional project screening environment where decisions must be made through evaluating two characteristics of the project. We further investigate the comparative performance of hierarchy and polyarchy in the presence of a set of discrete and continuous information structures, i.e., diverse team specialties. By endogenizing organizational preference over the two characteristics, the relative merit of hierarchy and polyarchy is not only dependent on the environment, but on the team composition as well as the organizational preference. Hierarchy can be better than polyarchy in a "good" environment if the agents are not equally specialized over the two factors, and vice versa. On the other hand,

since underestimating bad projects and overestimating good projects are common, increasing knowledge is not always preferable to the overall decision-making effectiveness. This usually occurs, for example, when the agent's knowledge on a less organizationally preferred factor is increased when the environment of a preferred factor is bad. Finally, the communication between agents should allow the sharing of decision-making in an uncertain environment if the agents exhibit propensity to follow historical decisions. However, sharing is not always advantageous and we have explored guidelines for the design of organization in communication channel.

4.2 Introduction

Amongst attributes to organizational success that have long been identified and investigated, one of the key factors is the information structure referring to the organizational capability of assigning right agents to appropriate positions. A good assignment means decisions meet with relevant knowledge ensuring effectiveness at a certain level (e.g., Galbraith, 1977; March & Simon, 1993). On the other hand, decision structures such as hierarchy and polyarchy also play a vital role. Individual decisions are organized through the structures where fallible decisions at an agent level can be aggregated and, to some extent, rectified at an organization (e.g., Csaszar, 2013; Sah & Stiglitz, 1985). In reality, decision and information structures are closely related to one another and consequently to organizational performance.

The two attributes complement one another serving as mechanisms for coordinating everyday organizational tasks. Although much attention has been paid to address the comparative performance of each structure within an uncertain environment, the interplay between them has not been adequately addressed; exceptions include Visser (2000) and Csaszar & Eggers (2013). Formal models mostly evaluate one without fully considering the interactive role of the other, thus limiting the results to be interpreted in a more general context, or possibly, incurring the chance of misinterpretation. In this article, we explore the design of organizational structure by recognizing the fact that agents judge based on multifaceted information and organizations differ in preference. Specifically, we study information and decision structures in a two-dimensional project screening environment, and the results contribute to the existing work with addressing basic problems in areas of organizational design.

It has been well-known that organizations play a vital role in ensuring that important decisions are made based on appropriate information (Burton, Obel, & DeSanctis, 2011; Simon, 1976). But in today's competitive market environment, decisions usually involve multiple characteristics that a board of directors has to fully evaluate. For example, a university hiring committee may decide to select a new hire based on a candidate's research and teaching abilities. Likewise, the success of new product development can rely on its marketability as well as the difficulty in production. Then the decision on whether or not to develop the product requires both knowledge from, most likely, marketing analysts and process engineers. This important role of organization in aligning specific decisions with relevant information has long been emphasized. Galbraith (1977) studies organizations as a coordination mechanism for reducing environmental uncertainty and resolving discrepancy. Bavelas (1948), Leavitt (1951), and Guetzkow & Simon (1955) show the relationship between the performance of a small group and the influence of various communication patterns. Marschak & Radner (1972) formally state the problem as designing information structures. They treat agents who can make decisions that maximize the utility given limited information, and compare a set of simplified schemes such as centralized versus decentralized structures.

Simon (1976) views organizations as information processing systems including patterns of communication and rules for making and implementing decisions. He puts forward the view of bounded rationality that decision-makers not only have insufficient information, but limited cognitive resources to make correct decisions. As a result, fallible decisions are inevitable and one way to compensate is through organized decision structures (Sah & Stiglitz, 1985). For example, the role and importance of hierarchy has long been recognized. The structure serves as a mechanism that facilitates decision-making processes through aggregating relevant information as well as reducing process complexity (e.g., Cyert & March, 1992; Radner, 1992; Reitzig & Maciejovsky, 2015; Simon, 1996).

On the other hand, a properly organized decision process improves decision-making effectiveness with respect to omission (rejecting a superior alternative) and commission (accepting an inferior alternative) errors. Sah & Stiglitz (1986) begin to question the influence of the process in dichotomous choice situations in a project selection environment. The contingent nature to the uncertain environment is then studied through different decision processes. For example, hierarchy outperforms polyarchy in a relatively bad environment, and vice versa (Sah & Stiglitz, 1986). Koh (1992) extends the problem in an incentive environment and then, to a sequential decision-making structure where he argues the fragility of hierarchy and polyarchy (Koh, 2005). Committee, by sharing the advantages of both hierarchy and polyarchy, manifests superiority in reducing both omission and commission errors (Ioannides, 2012; Sah & Stiglitz, 1988). Koh (1994) and Ben-Yashar & Nitzan (1997) further question the optimal decision rule of a fixed-size committee. Csaszar (2014) studies the size of committee in which agents have non-homogeneous preferences and different accuracies in decision-making. On top of these stylized structures, more general ones are recently explored (e.g., Christensen & Knudsen, 2010; Csaszar, 2013; Ioannides, 2012). Ioannides (2012), by simply composing hierarchy with polyarchy or vice versa, shows one way to approach a decision structure that is free of omission and commission errors.

Examples such as the processes of new product selection and job recruitment, the environment on which the decision structures are contingent has multiple dimensions, thus requiring the organization to be capable of processing heterogeneous information. A few studies address this issue. Knudsen & Levinthal (2007) explore the nature of collective decision-making behaviour through project screening on a rugged landscape. Agents are exposed and able to process multi-dimensional information. Prat (2002) shows the relationship between the team homogeneity and error reduction. Visser (2000) models a two dimension-environment in which heterogeneous agents act through hierarchy and polyarchy. Csaszar & Eggers (2013) question how decision policies, as they examining patterns like delegation, unanimity, and averaging, compensates for the cognitive weakness of specialists facing multiple environmental factors as contrast to generalists.

The literature clearly shows the close relationship that exists among decision processes, a multi-factor environment faced by the organization, specialties of the team of directors, and consequently decision-making effectiveness. Yet more knowledge is required to address how information structure interacts with the decision process. Furthermore, the effect of communication between agents on decision-making has been over simplified. Although it is often assumed that the information transferred is either ”accept” or ”reject”, only few studies emphasize the effect of historical decisions on the current decision-maker, such as herd-like behaviour in Swank & Visser (2008). In this study, we compare two types of communication structures in which an organizer opts to give former decisions to agents and the latter decision-maker has a tendency to follow the former. In relation to the behaviour model appearing in Simon (1976), we model boundedly rational agents who have limited knowledge (like Marschak & Radner (1972)) and insufficient cognitive abilities in their decision-making (like Sah & Stiglitz (1986)). To keep the analysis tractable, we consider a problem where the organization faces an environment that varies along two dimensions. The agents have knowledge about the environment. The every day decision-making is modelled by a screening process. The performance of the screening is affected by the information structure, or the specialty of each agent, and the decision processes, namely hierarchy and polyarchy. Furthermore, along with the agent's specialty, the nature of over and underestimation to a good as well as bad project is analyzed. We pay special attention to the comparison of information structures when good projects are overestimated, and bad projects are underestimated.

4.3 Basic Model

The decision structure of an organization exerts influence on the collective organizational behaviour through an individual's decision-making process. We adopt for this process a project screening task where agents make a dichotomous choice on whether to accept or reject projects. Agents have bounded rationality with respect to information and calculation, resulting in fallible decision-making. Limited information about projects as a result of insufficient knowledge, and erroneous calculation in decision-making as a result of cognitive and environment limits that all contribute to an inaccurate evaluation of projects. Moreover, communication also shapes this decision-making process. Whether the agent knows the decisions from previous evaluations affects her decision-making propensity, such as herd-like behaviour. In the following, we shall start with modelling three key units of the processes, i.e., the project, the organization, and the evaluator. We then introduce the decision-making process and finally the communication.

4.3.1 Modelling Attributes—the Project, the Organization, and the Agent

To describe a typical project screening environment, there are three parties that need to be characterized, i.e., the project, the organization, and the agent. Suppose a project X has n factors to be evaluated. It is described by a vector $X = (x_1, x_2, \ldots, x_n)$ specifying its intrinsic true value on each factor. Organizations may have distinct preferences over these n factors of a project. An organization W is described by a vector $W = (w_1, w_2, \ldots, w_n)$

specifying its weight on each factor. Here we require $\sum_{i=1}^{n} w_i = 1$ and $0 \le w_i \le 1$ for all $i = 1, \ldots, n$. We model that an organization W obtains value $V := V(W, X) = \sum_{i=1}^{n} w_i x_i$ if it accepts the project X, and 0 otherwise. Naturally we assume all evaluators know the preference W. Throughout this article, the terms value and utility are interchangeable.

The evaluators differ in terms of the knowledge regarding X, and the ability to make reasonable decisions given the knowledge as we call screening abilities. We characterize an evaluator E as her knowledge or specialties on n factors $(\epsilon_1, \ldots, \epsilon_n)$ where $0 \le \epsilon_i \le 1$ for every $i = 1, \ldots, n$. In Marschak & Radner (1972), a collection of ϵ_i for all agents is known as the information structure of an organization. The screening ability of an agent is linearly modelled by coefficients a and b. We now explain the meaning of ϵ, a, and b.

4.3.2 Specialties and Decision-Making Process

Consider a set of projects available for evaluation, let $X = (X_1, X_2, \ldots, X_n)$ denote a random project, where X_i is the random variable representing the value of the i-th factor of project X, the expected value of factor i is $\mathbb{E}X_i$. We assume the probability distribution of the value on each factor about the projects is common knowledge among all evaluators. Hence, given a project $X = (x_1, x_2, \ldots, x_n)$, the partial description revealed by an agent $(\epsilon_1, \ldots, \epsilon_n)$ is

$$y_i = \mathbb{E}X_i + \epsilon_i(x_i - \mathbb{E}X_i), \qquad i = 1, ..., n, \tag{4.3.1}$$

again ϵ_i measures the knowledge or the specialty, representing the extent to which the evaluator is able to approach the true information of the project. It is also the extent to which the evaluator is able to identify the project from the average, or to resolve the uncertainty of the information regarding the true value. Null information on factor i, that is $\epsilon_i = 0$, results in $y_i = \mathbb{E}X_i$, which implies that a factor is deemed as an average to any evaluator who has no knowledge on it. This definition allows agents to have basic, or average, knowledge over projects if $\epsilon = 0$. On the contrary, $\epsilon_i = 1$ corresponds to an evaluator of full knowledge on i, meaning the evaluator is exposed to the complete information of X on factor i. Any intermediate ϵ_i derives only partial description about the project on i. In the following analysis, we call an evaluator E a specialist if she has $\epsilon_i \to 1$ for some, not all, factors, whereas a generalist if $\epsilon_i \neq 0$ for all factors.

Now suppose a project X is received by an organization W, an agent E chooses to accept or reject based on the value

$$V_E = \sum_{i=1}^{n} w_i y_i. \tag{4.3.2}$$

In an ideal situation, evaluators accept a project if $V_E > 0$, reject otherwise. However, perfect evaluation is hard to achieve. Thus we use a screening function as the probability of accepting a project $p : \mathbb{R} \to [0, 1]$. We consider linear screening behaviour $p(V_E, a, b) = aV_E + b$, where $a \geq 0$ meaning the screening is informative. It also represents the discriminating capability in Sah & Stiglitz (1986), which measures the effectiveness of the decision-making. The evaluator accepts more good projects and rejects more bad projects, or makes less omission and commission errors, if a is greater. And also the evaluator is more likely to accept a high utility project than a low one. On the other hand, intercept $0 \leq b \leq 1$ is the probability that the evaluator accepts a project when the revealed utility is zero, or the bias of the agent's error (Knudsen & Levinthal, 2007). Higher b also corresponds to low conservative that agents accept more good as well as bad projects. To sum up, a single evaluator E working for organization W will accept a project X with probability p, and reject it with $1 - p$.

4.3.3 Decision Structure

When two agents are available for an organization, it is important to study the decision structure or the sequence of decision-making. The decision structure determines among three options, whether the organization should accept the project, reject the project, or pass the project to other evaluators to repeat the screening process. In this article we focus on hierarchy and polyarchy. A hierarchical structure (H) accepts a project if all evaluators reach unanimous consent, rejects otherwise, whereas a polyarchy (P) accepts a project if any one of the two evaluators accepts, rejects if all reject.

4.3.4 Communication Structure

In the literature, a widely assumed communication structure is that the agent has only the information of projects, or decisions are made independently. We call this the first communication structure. Although many studies, like Sah & Stiglitz (1986), claim communication comprises dichotomous signals of whether a project is accepted or rejected, they essentially assume independent decision-making where the previous decisions or the signals have no effect on the current ones. In effect, under this communication structure agents are not informed with the decision structure. A double-blind peer review process is an example of this structure. Reviewers receive manuscripts from editors without knowing prior review decisions. Following some decision structure, only editors make a collective judgement based on individual independent decisions. Figure 4.1a depicts a stylized hierarchical process for this communication structure. Initially, the organization passes a project to its first agent, and waits for the decision. Evaluator one replies with acceptance or rejection. Then the organization chooses to repeat the process for the second evaluator if evaluator one accepts, and evaluator two receives the same information as that of one. Following this structure, screening behaviour is independent of the previous decision. The case of polyarchy under this communication structure is similar and thus omitted.

Another structure which we call it the second communication structure where in addition to the projects, the second agent has the information about the prior decision. In other words, she knows the decision structure. The screening process under this structure is that

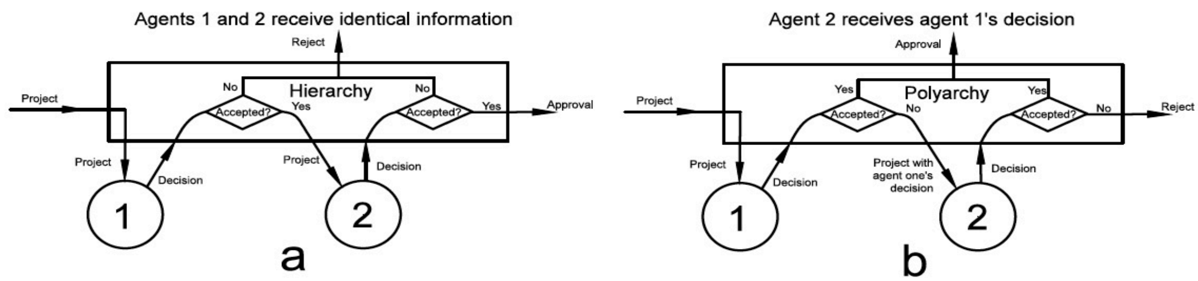


Figure 4.1: Communication structure: a. independent decision-making hierarchy; b. dependent decision-making polyarchy

after the first round of screening, agent two receives extra information about the decision of agent one (see Figure 4.1b for a polyarchy). The case of hierarchy under this communication structure is similar and thus omitted. This extra information exerts effects on the screening ability. In this article, we mainly consider the effect of herd-like behaviour, and we have an increasing (decreasing) screening probability if the project is previously accepted (rejected), which implies that the second agent tends to follow the decision of the first, i.e., past decision of accepting (rejecting) increases the likelihood of being accepted (rejected). In the following sections, we shall first analyze the comparative performance of an organizational structure under the first communication structure, and then extend our analysis to the second.

4.4 Single Person—Specialist and Generalist

This section discusses the case when an organization dedicates one decision maker to evaluate projects. The results serve as a basis for subsequent analysis to the two-person case. We assume that the projects have two factors and the information regarding the two is distinct and independent. For ease of understanding, we introduce the problem in the setting of university recruitment where a hiring committee is formed. Consider that a university is to plan for a new bachelor's programme. Both research and teaching value are important; and professors for this programme will be responsible for lecturing classes as well as supervising students' research projects. In order to evaluate applications, a hiring committee should include professors who are specialists in the area of specialization of the programme, in teaching and/or research. Now, the university needs to determine based on its needs in research and teaching (or preference) about who should be the independent professors to be selected in the committee, how their decisions are aggregated, and whether or not they communicate the results against each other.

Consider a group of candidates who submit job applications to universities. Each candidate demonstrates her ability in terms of two factors, i.e., research (r) and teaching (t), and suppose the true values are $X = (x_r, x_t)$. We further assume that any candidate can be good or bad at teaching and research, respectively. If she is good at $i = \{r, t\}$, then $x_i = 1$, otherwise $x_i = -1$. Furthermore, the portfolio of the applications, or the environment, is $\alpha = \mathrm{Prob}[x_r = 1]$, i.e., the probability that the candidate is a good researcher ($1 - \alpha = \mathrm{Prob}[x_r = -1]$ a bad researcher). Likewise, $\beta = \mathrm{Prob}[x_t = 1]$ is the probability that the candidate is a good teacher ($1 - \beta = \mathrm{Prob}[x_t = -1]$ a bad teacher). The variance $\mathrm{Var}\, x_r = \alpha(1 - \alpha)$ characterizes the level of *information uncertainty* for x_r, we see the information uncertainty is small when α is close to either 0 or 1, on the contrary it is large when α is close to $\frac{1}{2}$. Similarly $\mathrm{Var}\, x_t = \beta(1 - \beta)$ is the information uncertainty for x_t. We call an environment *neutral* if $\alpha = \beta = \frac{1}{2}$, which corresponds to the environment having largest information uncertainties. Moreover, universities have preference over research and teaching (w_r, w_t). We can consider $w_r >> (<<)\frac{1}{2}$ as a research (teaching) oriented university and $w_r \approx \frac{1}{2}$ as a comprehensive university.

The application is sent to an agent, in our example it refers to an external evaluator, who has the specialties (ϵ_r, ϵ_t). We call a research specialist (R) if $\epsilon_r > 0$, and $\epsilon_t = 0$, a teaching specialist (T) if $\epsilon_r = 0$ and $\epsilon_t > 0$, and finally a generalist (G) if $\epsilon_r > 0$ and $\epsilon_t > 0$. The specialties imply in the example that an experienced professors who can better judge a candidate's value in research and/or teaching to the new programme. Agents then accept the candidate with probability $p(V_E)$ based on the value according to her specialties, or by definition, $V_E = w_r y_r + w_t y_t$, where y_i is in (4.3.1).

We can now conclude that a university of type (w_r, w_t) chooses an evaluator whose information structure is (ϵ_r, ϵ_t) and whose screening function is $p_{x_r,x_t} = p(V_E(x_r, x_t), a, b)$, will gain expected utility

$$U = \alpha\beta p_{1,1} + (1-\alpha)\beta(-w_r + w_t)p_{-1,1} + \alpha(1-\beta)(w_r - w_t)p_{1,-1} + (1-\alpha)(1-\beta)(-1)p_{-1,-1}. \tag{4.4.1}$$

It can be simplified as a summation of two parts, i.e., the expected utility with and without information,

$$U = V_I + V_0, \tag{4.4.2}$$

where

$$V_I(\epsilon_r, \epsilon_t) = 4a\epsilon_r w_r^2 \alpha(1-\alpha) + 4a\epsilon_t w_t^2 \beta(1-\beta), \tag{4.4.3}$$

and

$$V_0 = a(2w_r\alpha + 2w_t\beta - 1)^2 + b(2w_r\alpha + 2w_t\beta - 1). \tag{4.4.4}$$

As per Marschak & Radner (1972), V_I is called the value of information structure as compared with null information structure. Let U_R, U_T and U_G denote the expected utility when an evaluator of type R, T and G is chosen, respectively. The properties of U is summarized in the following proposition.

Proposition 4.4.1. [1] *Part A. The expected utility is increasing with ϵ_r and ϵ_t ($\frac{\partial U}{\partial \epsilon_i} \geq 0, i = r, t$); it is increasing in a ($\frac{\partial U}{\partial a} \geq 0$). The value of information structure is increasing with the information uncertainty ($\frac{\partial V_I}{\partial \operatorname{Var} x_i} \geq 0, i = r, t$).*

Part B. There exists a positive number $w^0 = \frac{\sqrt{\epsilon_t \operatorname{Var} x_t}}{\sqrt{\epsilon_r \operatorname{Var} x_r} + \sqrt{\epsilon_t \operatorname{Var} x_t}}$, such that $U_R > U_T$ if

[1] All proofs, except for obvious ones, are in Appendix D

and only if $w_r > w^0$; $\frac{\partial w^0}{\partial \operatorname{Var} x_t} \geq 0$ *and* $\frac{\partial w^0}{\partial \operatorname{Var} x_r} \leq 0$.

Part C. Consider the cost for agent $E \in \{R, T, G\}$ *is* C_E. *In a neutral environment, if either one of the following conditions is satisfied, (1)* $\epsilon_r, \epsilon_t, a$ *are the same for* R, T, *and* G, *and* $C_R + \frac{a\epsilon_r\epsilon_t}{(\sqrt{\epsilon_r}+\sqrt{\epsilon_t})^2} > C_G > C_R = C_T$; *(2)* $a\epsilon_r$ *and* $a\epsilon_t$ *are greater in* R, T *than is in* G *with the magnitude less than* $\frac{a\epsilon_r\epsilon_t}{(\sqrt{\epsilon_r}+\sqrt{\epsilon_t})^2}$, *and* $C_G = C_R = C_T$, *ceteris paribus; then there exists two positive numbers,* $1 > w^+ > w^- > 0$, *such that the agent that maximizes the utility is* R *if* $w_r > w^+$, G *if* $w^+ > w_r > w^-$, *and* T *if* $w_r < w^-$.

If $\epsilon_r, \epsilon_t, a, b$ *and* C *are the same for* R, T *and* G, *then* $U_G \geq U_T$ *and* $U_G \geq U_R$ *for all* w_r.

Proposition 4.4.1 is intuitive and it implies that a university usually benefits more from dedicating an evaluator with more knowledge (ϵ) and better judgement (a). Complementarily, the benefit of knowledge is evaluated in the presence of uncertain environment ($\operatorname{Var} x$). In this single-agent decision process, uncertainty renders knowledgable agents with good judgement more valuable to the university. And between two specialists R and T, the more uncertain the environment, the higher the need for the university to dedicate a specialist who can observe the environment (Part B).

It is also intuitive that the generalist outperforms, regardless of the types of the university, over the two specialists when she is as good as the specialists and does not cost more (see G' in Fig 4.2). However, it is of practical importance to study condition (1) and (2) in proposition 4.4.1 in which the generalist costs more to have more specialties, or the generalist is less knowledgable than the specialists with the same cost. In either condition, all types of the universities are divided into three categories where the comparative performance is very obvious (see the thick line in Fig 4.2).

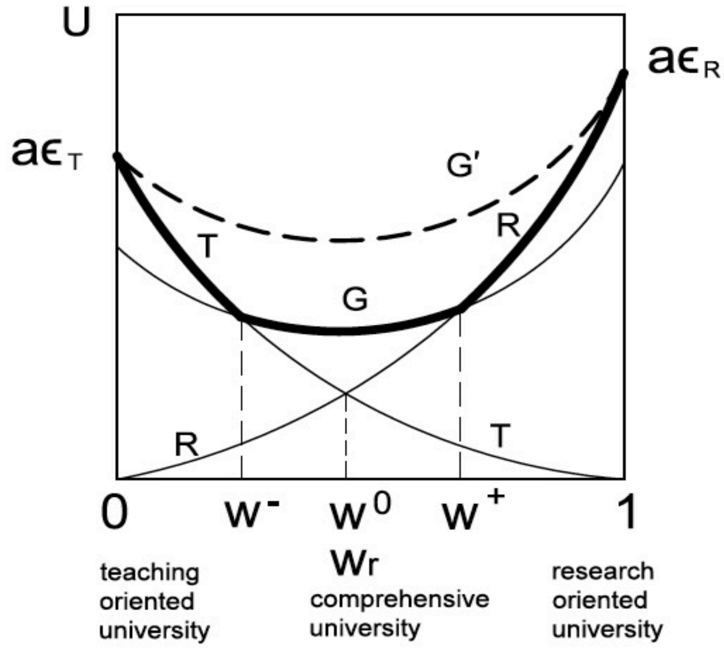


Figure 4.2: Comparative performance with university type and evaluator.

4.5 Team Structures

We extend the single person screening problem to the case when an organization dedicates a team. In this section, a two-person team is considered and the decision structures are hierarchy and polyarchy. We shall study the comparative performance of organizational structures, and then analyze the behaviour of the decision-making process. For conciseness, we denote a two-person information structure by $E_1 - E_2$ where $E \in \{R, T, G\}$.

4.5.1 The Value of Organizational Structures

Let us first consider a university of type $W = (w_r, w_t)$ dedicating a hierarchical team with information structure $(\epsilon_{r_i}, \epsilon_{t_i})$ and screening function $p_i(V_i, a_i, b_i)$, $i = 1, 2$. Following the assumptions made in the preceding section, the expected utility under environment (α, β) is the summation of two parts, i.e., the expected utility with and without knowledge,

$$U^H = V_I^H + V_0^H, \tag{4.5.1}$$

where

$$\begin{aligned} V_I^H = {} & 4a_1\epsilon_{r_1}\alpha(1-\alpha)w_r^2(a_2(2\alpha w_r + 2\beta w_t - 1) + b_2) \\ & +4a_2\epsilon_{r_2}\alpha(1-\alpha)w_r^2(a_1(2\alpha w_r + 2\beta w_t - 1) + b_1) \\ & +4a_1\epsilon_{t_1}\beta(1-\beta)w_t^2(a_2(2\alpha w_r + 2\beta w_t - 1) + b_2) \\ & +4a_2\epsilon_{t_2}\beta(1-\beta)w_t^2(a_1(2\alpha w_r + 2\beta w_t - 1) + b_1) \\ & +4a_1a_2\epsilon_{r_1}\epsilon_{r_2}w_r^2\alpha(1-\alpha)(w_r - w_t - \alpha + \beta + (w_t - w_r)(\alpha+\beta)) \\ & +4a_1a_2\epsilon_{t_1}\epsilon_{t_2}w_t^2\beta(1-\beta)(w_t - w_r - \beta + \alpha + (w_r - w_t)(\alpha+\beta)), \end{aligned} \tag{4.5.2}$$

and

$$V_0^H = (a_1(2w_r\alpha+2w_t\beta-1)+b_1)(a_2(2w_r\alpha+2w_t\beta-1)+b_2)(2w_r\alpha+2w_t\beta-1). \tag{4.5.3}$$

Similarly, the utility under polyarchy is

$$U^P = V_I^P + V_0^P, \tag{4.5.4}$$

where

$$
\begin{aligned}
V_I^P = 4a_1\epsilon_{r_1}\alpha(1-\alpha)w_r^2(a_2(-2\alpha w_r - 2\beta w_t + 1) + 1 - b_2) \\
+4a_2\epsilon_{r_2}\alpha(1-\alpha)w_r^2(a_1(-2\alpha w_r - 2\beta w_t + 1) + 1 - b_1) \\
+4a_1\epsilon_{t_1}\beta(1-\beta)w_t^2(a_2(-2\alpha w_r - 2\beta w_t + 1) + 1 - b_2) \\
+4a_2\epsilon_{t_2}\beta(1-\beta)w_t^2(a_1(-2\alpha w_r - 2\beta w_t + 1) + 1 - b_1) \\
+4a_1a_2\epsilon_{r_1}\epsilon_{r_2}\alpha(1-\alpha)w_r^2(-w_r + w_t + \alpha - \beta + (-w_t + w_r)(\alpha + \beta)) \\
+4a_1a_2\epsilon_{t_1}\epsilon_{t_2}\beta(1-\beta)w_t^2(-w_t + w_r + \beta - \alpha + (-w_r + w_t)(\alpha + \beta)),
\end{aligned}
\tag{4.5.5}
$$

and

$$
V_0^P = (1-(1-(a_1(2w_r\alpha+2w_t\beta-1)+b_1))(1-(a_2(2w_r\alpha+2w_t\beta-1)+b_2)))(2w_r\alpha+2w_t\beta-1).
\tag{4.5.6}
$$

4.5.2 Behaviour of Hierarchy and Polyarchy Under Neutral Environment

It is of particular interest to first consider the neutral environment (or equivalently the environment with maximum uncertainty). Let us assume identical screening ability ($p_1 = p_2 = p(a, b)$). Then the utility for decision structures $j \in \{H, P\}$ is

$$
U^j = ab^j(\epsilon_{r_1}w_r^2 + \epsilon_{r_2}w_r^2 + \epsilon_{t_1}w_t^2 + \epsilon_{t_2}w_t^2),
\tag{4.5.7}
$$

where

$$
b^j = \begin{cases} b, & \text{if } j = H, \\ 1-b, & \text{if } j = P. \end{cases}
\tag{4.5.8}
$$

Note that $V_0^j = 0$ and proposition 4.5.1 states the properties of U^j when agents (ϵ) and preference W are fixed.

Proposition 4.5.1. *$U^H = U^P$ if $b = \frac{1}{2}$, $U^H > (<) U^P$ if $b > (<) \frac{1}{2}$.*

In a neutral environment, a hierarchy is equivalent to a polyarchy if the evaluator is equally likely to accept and reject candidates with zero value. In other words, the screening property has moderate slack, or risk-neutral ($b = \frac{1}{2}$). Recall Sah & Stiglitz (1986), under this special condition, hierarchy is as good as polyarchy, and the decision structures are indifferent to the final screening result. Although it is known that hierarchy rejects more good projects (makes more omission errors) and polyarchy accepts more bad projects (makes more commission errors), the negative impacts due to the two types of errors cancels out for each structures. Proposition 4.5.1 also identifies the conditions under which one structure outperforms the other. The results are intuitive. If the screening behaviour of the evaluator is globally more slack, i.e., $b > \frac{1}{2}$, meaning one at the same time accepts more good and bad projects which compensates the weakness of hierarchy, then it is better to organize the team as hierarchy. Conversely, if the evaluator is less slack, i.e., $b < \frac{1}{2}$, polyarchy is better.

Consider the effect of information structure on the screening behaviour. We further assume the total specialties $\sum_{i=1,2}(\epsilon_{r_i} + \epsilon_{t_i})$ are the same in teams of specialists, i.e., $R-R$, $T-T$, and $R-T$. We use superscript to indicate the information structure. For example, $\{\epsilon_{r_i}^{R-G}, \epsilon_{t_i}^{R-G}\}_{i=1,2}$ is the knowledge representation for a team formed with a research specialist and a generalist. Proposition 4.5.2 below summarizes the comparison made amongst information structures.

Proposition 4.5.2. *Part A. If the following condition is satisfied, (1) $\{\epsilon_{r_i}\}_{i=1,2}$ and $\{\epsilon_{t_i}\}_{i=1,2}$ in $G-G$ are the same as in $R-R$ and $T-T$, respectively, and $C_{R-R} + \frac{ab(\epsilon_{t_1}+\epsilon_{t_2})}{4} > C_{G-G} > c_{R-R} = C_{T-T}$; or (2) $C_{G-G} = C_{R-R} = C_{T-T}$, but $(\epsilon_{r_1} + \epsilon_{r_2})$ is less in $G-G$ than in $R-R$, and $(\epsilon_{t_1} + \epsilon_{t_2})$ is less in $G-G$ than in $T-T$, then there exists two positive* *numbers,* $1 > w^+ > w^- > 0$*, such that the structure that maximizes the utility is* $R-R$ *if* $w_r > w^+$*,* $G-G$ *if* $w^+ > w_r > w^-$*, and* $T-T$ *if* $w_r < w^-$*.*

Part B. If the following condition is satisfied, (1) generalist is as knowledgable as specialists in terms of research and teaching, and $C_{G-G} - C_{T-G} > C_{T-G} - C_{T-T}$*,* $C_{G-G} - C_{R-G} > C_{R-G} - C_{R-R}$*; or (2) the costs for all structures are equal, but*

$$\frac{(\epsilon_{t_1}^{T-G} + \epsilon_{t_2}^{T-G}) - (\epsilon_{t_1}^{G-G} + \epsilon_{t_2}^{G-G})}{(\epsilon_{r_1}^{G-G} + \epsilon_{r_2}^{G-G}) - \epsilon_{r_2}^{T-G}} > \frac{(\epsilon_{t_1}^{T-T} + \epsilon_{t_2}^{T-T}) - (\epsilon_{t_1}^{T-G} + \epsilon_{t_2}^{T-G})}{\epsilon_{r_2}^{T-G}} \tag{4.5.9}$$

and

$$\frac{(\epsilon_{t_1}^{G-G} + \epsilon_{t_2}^{G-G}) - \epsilon_{t_2}^{R-G}}{(\epsilon_{r_1}^{R-G} + \epsilon_{r_2}^{R-G}) - (\epsilon_{r_1}^{G-G} + \epsilon_{r_2}^{G-G})} < \frac{\epsilon_{t_2}^{R-G}}{(\epsilon_{r_1}^{R-R} + \epsilon_{r_2}^{R-R}) - (\epsilon_{r_1}^{R-G} + \epsilon_{r_2}^{R-G})} \tag{4.5.10}$$

then there exists four positive numbers, $1 > w^4 > w^3 > \frac{1}{2} > w^2 > w^1 > 0$*, such that the structure that maximizes the utility is* $T-G$ *if* $w^1 < w_r < w^2$*,* $R-G$ *if* $w^3 < w_r < w^4$ *(Figure 4.3).*

It is not surprising that in the neutral environment, agents' specialties should fit to organizational preference. Homogeneous team of specialists, like $R-R$ or $T-T$, is better off for non-comprehensive university that has a strong preference in research or teaching. As the weights tends to be balanced, non-homogeneous team, like $G-T$, $G-R$, or sometimes $G-G$ depending on the relative costs, outpaces and responds to different level of needs in uncertainty resolution, see Figure 4.3 for a stylized depiction.

4.5.3 Hierarchy or Polyarchy—Given Information Structure with General Environment

This section discusses the relative merits of the two decision structures when the information structure of the organization is given. It is well-known that hierarchy has advantages

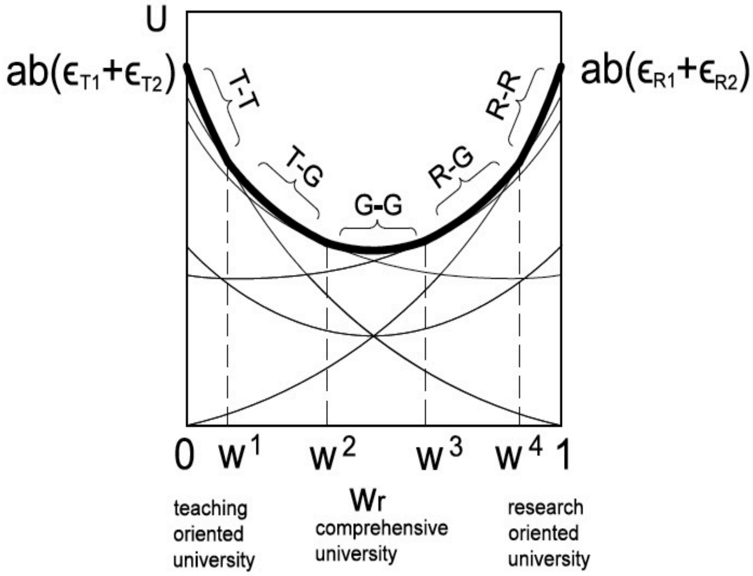


Figure 4.3: Comparisons of information structures in a neutral environment

in a bad environment whereas polyarchy in good (bad environment is defined as the probability that the project is good is less than $\frac{1}{2}$). We shall show, when the environment has two dimensions, it is subject to the organizational preference and the composition of the decision-making team.

Consider the case when a university is limited to using existing agents, i.e., the information structure is given as $\eta \in E \times E$, and it is viable to change the decision structure, then the utility difference of the two structures is

$$\Delta = (U^H - U^p)|_{\eta, w_r, \alpha, \beta}. \tag{4.5.11}$$

The sign of Δ implies the relative severity of making the two types of errors in hierarchy versus polyarchy, when agents (E_1 and E_2), environment (α and β), and type of the university (w_r and w_t) are given. A line on which $\Delta = 0$ is called indifference line.

Let $E_1 - E_2$ be an information structure, we call this structure *symmetric* if $\epsilon_{r_1} + \epsilon_{r_2} = \epsilon_{t_1} + \epsilon_{t_2}$, that is, knowledge in research and teaching are balanced. Assume for simplicity identical screening ability and $a = b = \frac{1}{2}$. The results for symmetric information structures are summarized in Figure 4.4a. Horizontal line $\{l_1 : \beta = 0.5\}$ on which $\Delta = 0$ for a pure teaching university ($w_r = 0$) divides the environment space into two parts. Because the research ability adds no value to the university, the sign of Δ is independent on α. As a result, when there are less good teachers ($\beta < 0.5$), hierarchy is better, otherwise polayarchy is better. The indifference line changes as w_r increases, or w_t decreases, see line l_2 in Figure 4.4a. The university in this scenario starts to have preference in the research ability of the candidates which renders l_2 dependent on α. We find that hierarchy turns out to be better than polyarchy in area ABO, which is inside the region of good teaching and bad research environment, i.e., rectangle AOEC. Furthermore, this area grows as the university weighs more heavily on the research ability of the candidates. Hierarchy becomes more effective when the bad research environment has increasing importance to the university. On the other hand, when good environment ($\alpha > 0.5$) has increasing importance ($w_r \uparrow$) to the university, polyarchy becomes more effective, see area GIO. Diagonal line $\{l_3 : \beta = 1 - \alpha\}$ is the solution to $\Delta = 0$ at $w_r = 0.5$. The university in this scenario has equal preference in research and teaching, and should choose hierarchy if $\alpha + \beta < 1$, polyarchy if $\alpha + \beta > 1$. As the importance on research (teaching) continuously increases (decreases), area CDO is taken by hierarchy, and area JKO by polyarchy. Eventually when $w_r = 1$, or a pure research university, we see the whole area ACEO is under hierarchy and GJLO under polyarchy.

We observe similar behaviour as w_r increases for non-symmetric information structures, namely, $\epsilon_{r_1} + \epsilon_{r_2} \neq \epsilon_{t_1} + \epsilon_{t_2}$ in $R - R, T - T, R - G$, and $T - G$. As can be seen in Figure 4.4b, hierarchy is better than polyarchy for a pure teaching university in rectangle AGIM ($\beta < 0.5$). As w_r increases from 0 to 1, the area for hierarchy changes to rectangle BELM ($\alpha < 0.5$). Solid curve BDOKI and dashed curve BCOJI are two indifference lines at $w_r = 0.5$. The former characterizes the behaviour of a research rich structure

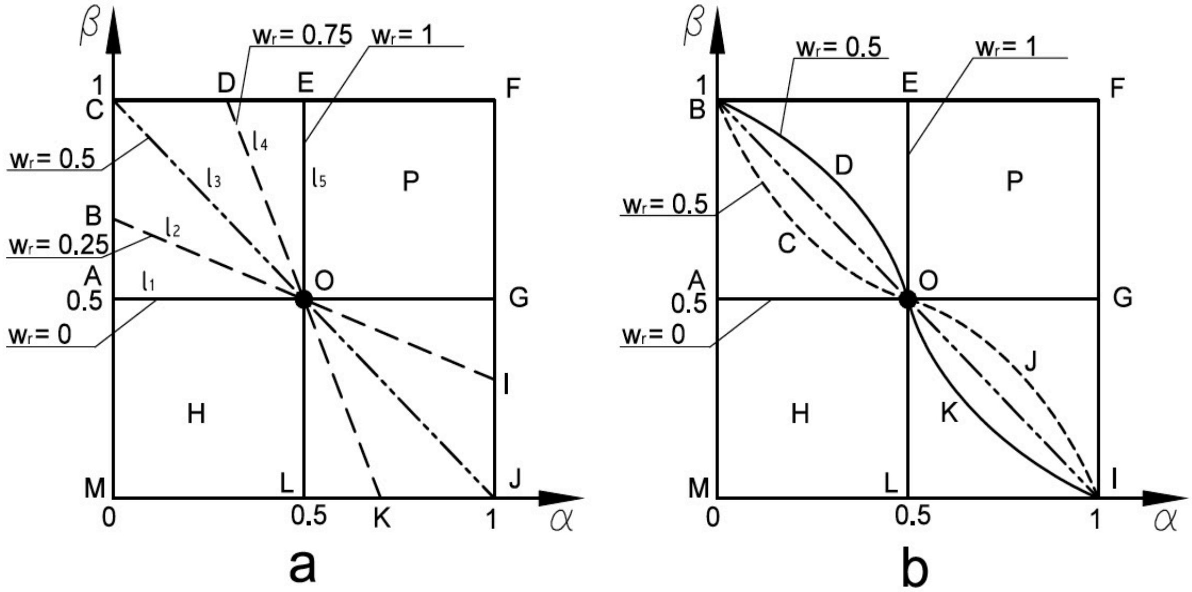


Figure 4.4: Relative merits of hierarchy versus polyarchy in two-dimensional environment with various organizational preference

$(R-R, R-G)$, the latter a teaching rich structure $(T-T, T-G)$. In contrast to the symmetric information structures where the indifference line is BI, area BDO has a higher value in a good teaching environment (β). However, a research rich structure has less knowledge in teaching. Therefore, in the bad research environment, the slight improvement in teaching environment does not sufficiently compensate the loss due to commission errors caused by polyarchy, nor does it ultimately let polyarchy outperform hierarchy. Likewise, in a good research environment, a slight decrease in research environment does not let hierarchy outperform polyarchy, see area IKO. As a result, a sigmoid indifference curve is so formed. On the opposite side, the same reasoning follows for the teaching rich structures, see area BCO and IJO.

In general, hierarchy should be chosen if the environment in which the type of the university depend is relatively bad, otherwise polyarchy is more effective. Furthermore, insufficient knowledge would render hierarchy to dominate polyarchy even if the environment is slightly better than the threshold to which structure of polyarchy would have been better under symmetric information structures. On the other hand, it would render polyarchy to dominate hierarchy when the environment is slightly worse than the threshold. For example, line BI is the threshold at $w_r = 0.5$ in symmetric case.

4.5.4 Information Structures—Given Decision Structure with General Environment

If one considers the state or the economic systems of a country or the decision structure of a mature company, these are sometimes tremendously difficult to change. Therefore, changing the information structure becomes an important solution for performance improvement in the face of a changeable environment. This section starts with exploring the effect of team homogeneity on the screening performance through a continuous representation of the information structure, and then it compares a set of discrete information structures of interest.

Continuous Information Structures

The proposition below summarizes the behaviour of a continuous information structure in a general environment. We assume identical agents $E_1 = E_2$ and $a = b = 0.5$.

Proposition 4.5.3. *Part A. The first-order derivatives of the utility* $s_1 := \frac{\partial U}{\partial \epsilon_r}$ *and* $s_2 := \frac{\partial U}{\partial \epsilon_t}$ *have the following properties.*

(1) In a hierarchy, if $\epsilon_r \geq \frac{2\beta}{1-2\beta}$ *and* $\beta \leq \frac{1}{4}$*, then there exists* $w' \geq \frac{1}{2}$ *such that* $s_1 \leq 0$ *if and only if* $w_t \geq w'$*. And symmetrically, if* $\epsilon_t \geq \frac{2\alpha}{1-2\alpha}$ *and* $\alpha \leq \frac{1}{4}$*, then there exists* $w' \geq \frac{1}{2}$ *such that* $s_2 \leq 0$ *if and only if* $w_r \geq w'$*.*

(2) In polyarchy, if $\epsilon_r \geq \frac{2\beta-2}{1-2\beta}$ *and* $\beta \geq \frac{3}{4}$*, then there exists* $w' \geq \frac{1}{2}$ *such that* $s_1 \leq 0$ *if and only if* $w_t \geq w'$*. And symmetrically,* $\epsilon_t \geq \frac{2\alpha-2}{1-2\alpha}$ *and* $\alpha \geq \frac{3}{4}$*, then there exists* $w' \geq \frac{1}{2}$ *such that* $s_2 \leq 0$ *if and only if* $w_r \geq w'$*.*

(3) In both hierarchy and polyarhcy, if $w_r \geq (\leq)\frac{1}{2}$*, then* $s_1 \geq 0$ $(s_2 \geq 0)$*.*

(4) If $\beta = 0$ or 1, $\alpha \in (0,1)$ and $w_r \in (0,1)$, then $s_1 > s_2$ in H as well as in P. Symmetrically, if $\alpha = 0$ or 1, $\beta \in (0,1)$ and $w_r \in (0,1)$, then $s_1 < s_2$ in H as well as in P.

Part B. The second-order derivative of the utility $s_3 : \frac{\partial U^2}{\partial \epsilon_r \partial \alpha}$ ($s_4 : \frac{\partial U^2}{\partial \epsilon_t \partial \beta}$) is a concave function of α (β) in hierarchy, convex in polyarchy. For both hierarchy and polyarchy, definite integral $\int_0^1 s_3 \, \mathrm{d}\alpha = 0$ ($\int_0^1 s_4 \, \mathrm{d}\beta = 0$), and if $w_r \geq (\leq) \frac{1}{2}$, $s_3|_{\alpha=0} \geq 0, s_3|_{\alpha=1} \leq 0$ ($s_4|_{\beta=0} \geq 0, s_4|_{\beta=1} \leq 0$).

Part C. The second-order derivative of the utility $s_5 : \frac{\partial U^2}{\partial \epsilon_t \partial \alpha}$ and $s_6 : \frac{\partial U^2}{\partial \epsilon_r \partial \beta}$ have the following properties.

(1) s_5 and s_6 are positive in hierarchy, negative in polyarchy.

(2) s_5 (s_6) is proportional to the information variance in teaching (research).

(3) For $w_r \geq \frac{1}{2}$ ($w_t \geq \frac{1}{2}$), s_5 (s_6) is decreasing with w_r (w_t) in hierarchy, increasing in polyarchy.

Part D. For $w_r \geq (\leq)\frac{1}{2}$, if $\epsilon_r \geq (\leq)\epsilon_t$, then $s_3 - s_5$ ($s_4 - s_6$) is positive in bad research (teaching) environment, negative in good.

We have verified that an increase in specialties improves the utility in a single-person setting (proposition 4.4.1). However, a rather non-intuitive result is that in a two-person team, there exists conditions in which the decision structures negates this effect. Proposition 4.5.3 part A implies that in a *teaching* oriented university where the *teaching* environment is bad (good), improving research knowledge does not guarantee a globally improved hierarchy (polyarchy) performance. Here for conciseness, we do not restate the implication regarding the symmetric factor, i.e., *research*. This nonintuitive result is attributed to the fact that if the decision made by agents is a right one, accepting a good project or rejecting a bad project, or a wrong one, accepting a bad project or rejecting a good project, incomplete knowledge brings about imperfect evaluation that deviates from the true value from two directions, i.e., overestimating and underestimating the project. And a project is more likely to be accepted if it is over rather than underestimated. Hence, more knowledge would change the global utility through a net effect. It brings benefit if a bad project was overestimated, or a good project was underestimated before knowledge increase, and it causes loss if a bad project was underestimated, or a good project was overestimated. Although in single agent, or single factor environment, this net effect is always positive, meaning more knowledge is better to the organization, it can be negative in a multi-factor environment as we show in proposition 4.4.1 part A. The decision structure, organizational preference, and the projects portfolio determine the conditions in which knowledge impedes performance. We use a numerical example to illustrate the conditions in hierarchy and conditions of polyarchy are symmetric in terms of organizational preference as well as projects portfolio.

A research oriented university, $w_r = 0.9, w_t = 0.1$, selects candidates from a portfolio $\alpha = 0.1, \beta = 0.5$; we study the utility difference when a hierarchically organized team with identical agents $a = b = 0.5$ changes its individual teaching knowledge from 0.5 to 1, while the research knowledge equals 1 and remains unchanged. The impact of this knowledge improvement breaking down to each type of candidates is summarized in Table 4.1. We use G and B to mean good and bad, respectively. The estimation and the accepting probability at agent level vary in a conserved manner, i.e., the difference before and after knowledge improvement adds up to zero. As we know from proposition 4.4.1, the utility is always increasing with knowledge in the single agent case. However, individual changes give rise to nonlinear changes in hierarchy. The probability that a candidate is accepted equals q^2, or the rate of change is proportional to p and a higher p brings about more impacts. In the example, the selected condition led the negative effect to dominate and finally the utility decreases.

Part A also implies that a university should dedicate an agent with more knowledge to which it is preferred. In a research (teaching) oriented university, evaluators with high

Table 4.1: Utility calculation breakdown: comparison between before and after knowledge improvement.

Candidate type	Portfolio	Before knowledge improvement (difference after improvement)			
		Agent Estimation	Agent Prob.	Hierarchy Prob.	Utility
Gr Gt	0.05	$0.95(+0.05)$ Under.	$0.975(+0.025)$	$0.951(+0.049)$	$0.047(+2.47\text{E}-3)$
Gr Bt	0.05	$0.85(-0.05)$ Over.	$0.925(-0.025)$	$0.856(-0.046)$	$0.034(-1.82\text{E}-3)$
Br Gt	0.45	$-0.85(+0.05)$ Under.	$0.075(+0.025)$	$0.006(+0.004)$	$-2.03\text{E}-3(-1.57\text{E}-3)$
Br Bt	0.45	$-0.95(-0.05)$ Over.	$0.025(-0.025)$	$6.25\text{E}-4(-6.25\text{E}-4)$	$-2.81\text{E}-4(+2.81\text{E}-4)$
				Sum	$0.079(-6.5\text{E}-4)$

research (teaching) knowledge is always helpful. In addition, when organizations face limited resources, we find, in hierarchy, that increasing teaching (research) knowledge is more efficient for a university in a certain research (teaching) environment, either good or bad. Hence in short, regardless of the decision structure, one should increase the knowledge in one dimension if the opposite one is stable.

Parts B, C, and D consider a dynamic environment in which the information α and β vary with time. When the environment in research (teaching) gets better, the marginal utility of a research (teaching) oriented university is first increasing then decreasing in research (teaching) knowledge. This behaviour is due to the change of environment uncertainty. As a result, increases in knowledge becomes more (less) efficient when the environment uncertainty increase (decrease).

On the other hand, part C summarizes, regarding the behaviour of interactive terms α with ϵ_t and β with ϵ_r, that the marginal utility of a hierarchy is increasing in research (teaching) knowledge as the teaching (research) environment gets better, whereas the marginal utility of a polyarchy is decreasing in research (teaching) as the teaching (research) environment gets better. In other words, when the teaching (research) environment gets better, it is more efficient to increase research (teaching) knowledge in hierarchy than polyarchy. Under the same condition, part C also implies that it is more preferable, in hierarchy than polyarchy, to increase research (teaching) knowledge under high than low research (teaching) uncertainty, and in comprehensive than specialized university.

Finally, part D compares the marginal utility in research and teaching as the environment varies and the result is intuitive. It suggests that if $\epsilon_r \geq (\leq)\epsilon_t$, then in dynamic environment a research (teaching) oriented university should always prefer to increase research (teaching) knowledge in bad research (teaching) environment, and increase teaching (research) knowledge in good. This holds for both hierarchy and polyarchy.

Discrete Information Structures

This section analyzes discrete information structures η. By equation (4.5.1) and (4.5.4), the information structure that maximizes the utility is

$$\bar{\eta}^i = \arg\max_{\eta}\{U^i_{\eta}|\eta \in E \times E\}_{w_r,\alpha,\beta}, \qquad i = H, P. \tag{4.5.12}$$

We further assume that all information structures have the same costs, while specialists have equal knowledge in research or teaching ($\epsilon = 0.8$). Generalists have equal, but less than that of specialists, knowledge in research and teaching ($\epsilon = 0.5$).

Figure 4.5 summarizes the numerical results in hierarchy and polyarchy. As can be seen, the performance of the information structures mainly depends on the type of university and the uncertainty of the environment. In a comprehensive university, the team of centralized generalists $(G - G)$ is, among all the information structures, the best in the environment where the uncertainty of both research and teaching are moderate to high. If the university has preference in research, a team of centralized research specialists $(R - R)$ is the best in the environment where the uncertainty of research is moderate to high. Likewise, team of centralized teaching specialists $(T - T)$ is the best for a teaching oriented university in the environment where the uncertainty of teaching is moderate to high. Moreover, regardless of the type and the decision structure, university exposed to low uncertainty in one factor demands less knowledge requirement to the agents while the uncertainty in the other factor starts to play a part. For example, in addition to teaching knowledge, for a teaching oriented university under hierarchy, information structures with research knowledge component like $R-T, G-G, T-G$ become the best team when the environment of teaching is bad, and structures like $G-G, R-G, R-R$ becomes the best when the environment of teaching is good (see Figure 4.5 a1). Furthermore, as α increases, the knowledge of research in the best team first increases then decreases, which is a similar result comparing to the continuous case (proposition 4.5.3 Part B). On the other hand, the teams generally have higher research knowledge in a good teaching environment than bad in hierarchy. The opposite is true in polyarchy, see the continuous case in proposition 4.5.3 Part C. The implications for a research oriented university are symmetric (see a3 and b3 in Figure 4.5), and we do not restate.

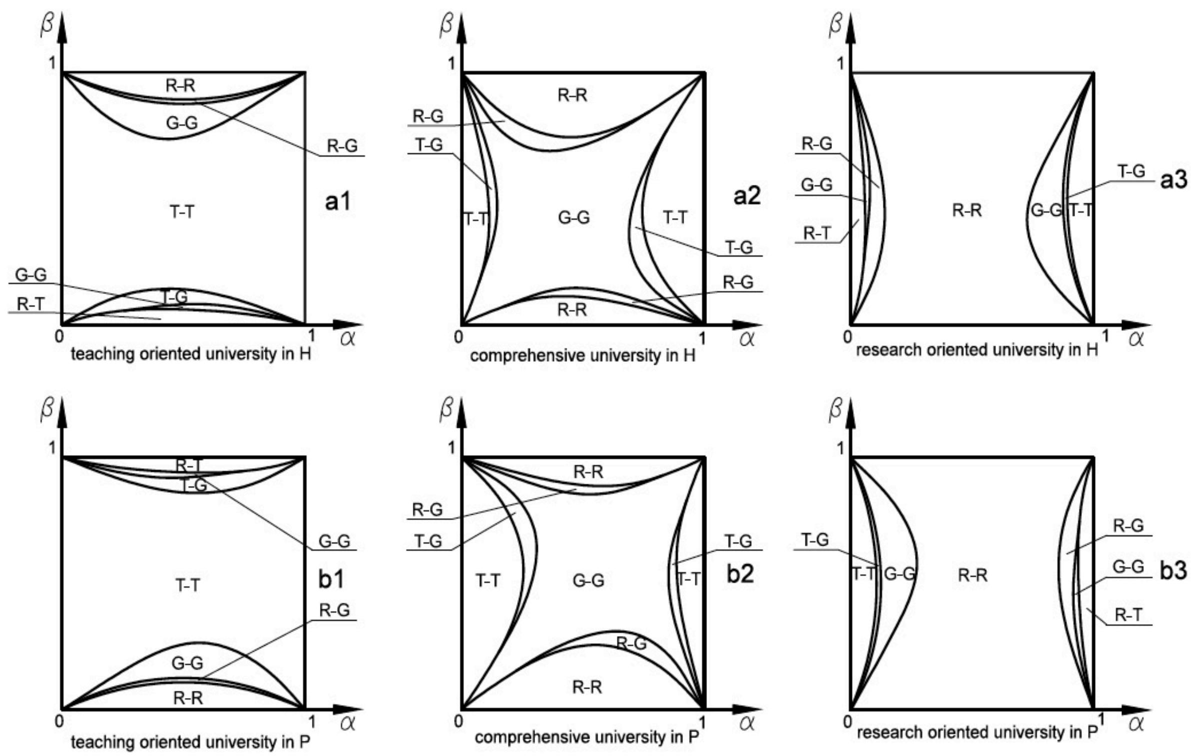


Figure 4.5: Comparison of information structures in a general environment

4.5.5 Summarizing Results

In the most general case, the variable space of an organizational structure, denoted ζ, includes both information structure and decision structure. The best ζ that maximizes the utility is

$$\bar{\zeta} = \arg\max_{\zeta}\{U^i_{\zeta} | \zeta \in \{E \times E\} \times \{H, P\}\}_{w_r,\alpha,\beta}. \tag{4.5.13}$$

This equation can be considered as the superposition of the results derived in the preceding two sections. In Figure 4.6, hierarchy and polyarchy are equally separated by dashed indifference lines that depend on the type of the university (equation (4.5.11)). In general, polyarchy is more preferable than hierarchy when the environment is better, i.e., to the right of the line, and vice versa. Like the effectiveness of decision structure relays on the environment quality, that of information structure is more sensitive to the environment uncertainty. The results in section 4.5.3 and proposition 4.5.3 provide a general guideline on how to structure a decision-making team by considering the interactive relationship of decision process and information structure. Mainly, the decision process serves as an important means to reduce omission and commission errors while the basis of decision-making is the specialties of the agents. We have shown that the important influence an asymmetric information structure exerts on the performance of hierarchy and polyarchy. On the other hand, there exist inevitable errors that are due to over and underestimating a project, further complicating the decision-making nature. We have identified conditions under which an appropriate level of specialty complements decision structures in a changeable environment.

4.6 The Alternative Communication Structure

Finally, we consider the second communication structure that the evaluator knows the previous decision about the candidate. Assuming the second evaluator is prone to follow the

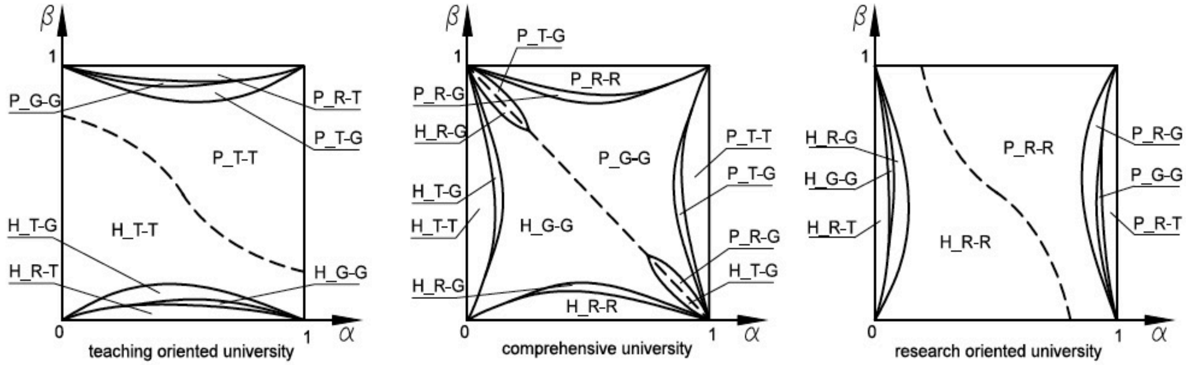


Figure 4.6: Comparison of discrete organizational structures in general environment

decision received, we shall analyze the comparative performance of the two communication structures. Formally, we have the screening behaviour for the second evaluator

$$p_2 = p(V_E, a, b) + z \tag{4.6.1}$$

where $z = \mu > 0$ if the project is accepted, $-\mu$ otherwise. We also assume identical agents, $\epsilon = \epsilon_r = \epsilon_t$ and $a < 0.5$, $b = 0.5$.

Proposition 4.6.1. *Part A. There exists*

$$\frac{1}{2} \geq c = \frac{4a - 4\epsilon a - 1 + \sqrt{16\epsilon^2 a^2 - 16\epsilon a^2 + 1}}{8a - 8\epsilon a}, \tag{4.6.2}$$

such that for pure research university, if $\alpha < (\geq) c$, then $\frac{\partial U^H}{\partial z} < (\geq) 0$, and if $\alpha < (\geq) 1 - c$, then $\frac{\partial U^P}{\partial z} > (\leq) 0$. For pure teaching university, if $\beta < (\geq) c$, then $\frac{\partial U^H}{\partial z} < (\geq) 0$, and if $\beta < (\geq) 1 - c$, then $\frac{\partial U^P}{\partial z} > (\leq) 0$.

Part B. For comprehensive university ($w_r = 0.5$), there exists c^H, c^P, such that if $\beta < (\geq) c^H$, then $\frac{\partial U^H}{\partial z} < (\geq) 0$. And if $\beta < (\geq) c^P$, then $\frac{\partial U^P}{\partial z} > (\leq) 0$. Along the diagonal ($\beta = 1 - \alpha$),

$$\frac{\partial U^H}{\partial z} = \frac{\partial U^P}{\partial z} = 2a\epsilon\alpha(1 - \alpha) \geq 0. \tag{4.6.3}$$

Part C. c, $-(1 - c)$, c^H, and $-c^P$ is decreasing with ϵ.

The second agent is informed with an acceptance in hierarchy and rejection in polyarchy. Essentially, the second communication structure led the later agent to more slack in hierarchy and less slack in polyarchy, an offset for the downsides of the decision structures. It renders hierarchy more risk-seeking while polyarchy more risk-averse. Firgure 4.7 depicts a stylized comparison in which the second communication structure is better, indicated by the arrows. Results of pure teaching and research universities are symmetric: pure teaching university values only the teaching quality about the candidate. Hence, hierarchy exposed to a moderate to good teaching environment and polyarchy to a moderate to bad teaching environment benefits more from using the second communication structure (part A). When the university starts to have preference in research, the condition changes following similar pattern as that of indifference line in (4.5.11). For example, polyarchy dominates hierarchy above diagonal line AB in a comprehensive university ($w_r = 0.5$). The university could even benefit more in area ABC when decisions are shared.

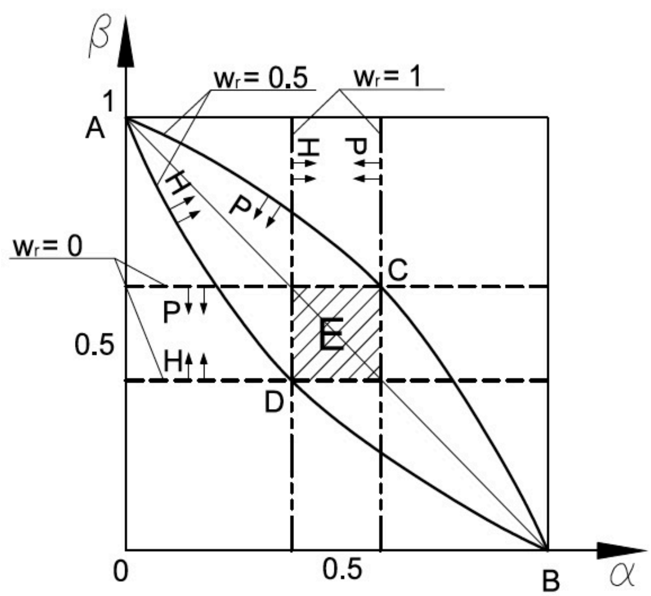


Figure 4.7: Relative merits of the first and second communication structures in pure research, pure teaching, and comprehensive university; the arrows indicate areas in which the second communication structure is better.

We can also interpret the results as an extension to (4.5.11) (Figure 4.4). Knowledge

$\epsilon > 0$ and herd-like behaviour cause the original indifference line splitting into two, thus generating areas in which the second communication structure is always beneficial, like $ACBD$. This effect can be generalized. Regardless of the preference, high uncertainty in both research and teaching environments encourages the sharing of decisions, see area E. In short, the second communication structure is always advantageous in an uncertain environment if the decision shared is not pure guessing. However, when agents have no knowledge $\epsilon = 0$, the conditions degrades to that of indifference lines in (4.5.11).

4.7 Discussion and Conclusion

The state of a project environment that comprises of two characteristics has been the primary determinant to the performance of organizational decision structures. Our study shows that this is not sufficient. By merely taking account of the environment might result in achieving sub-optimal performance. The team specialties, or the information structure, matter. We have investigated the relationship between decision and information structures in a two-dimensional environment where organizations differ in preference. The results confirm with the existing literature the essential role of the two attributes in general, and identify conditions under which one structure interacts with another affecting the decision-making effectiveness, specifically.

Hierarchy and polyarchy exhibit relative merits over one another subject to the organizational preference over the state of the two-dimensional environment. Furthermore, a team of unbalanced knowledge would impact the effectiveness of decision structure. For example, even the research environment is not good enough to let polyarchy outperform hierarchy, a team with more research knowledge than teaching would compensate the deficiency of polyarchy in making commission errors and consequently, one should consider adopting polyarchy for that team. In addition, we have studied how to form a team while the decision structure is predetermined. Because overestimating a good project and underestimating a bad could be beneficial, performance is not simply improvable by knowledge increase. We identify conditions under which knowing less is better. This especially occurs, for instance, when a hierarchy (polyarchy) increases its specialty in, say research, while what is preferred to the organization is teaching and more than half of the candidates in the portfolio are (not) bad at teaching. Finally, we extend our basic model to incorporate extra information about historical decisions, i.e., the second communication structure. We question if one should let the decision-makers be informed with the decision structure, hierarchy or polyarchy, or should the screening results be communicated. On top of a set of explicit conditions, we conclude that sharing decisions between agents is always beneficial when information uncertainty in both environmental dimensions are high, and agents exhibit herd-like behaviour.

Although the analysis has been based on an example in university recruitment for launching a new specialized programme, the results could directly apply to firms in the following situation. An organization is to select good projects which have two important features, say A and B. Not everyone has a good knowledge on both A and B. Hence in order to select, the organization needs to put right person in a screening process. At the same time, due to the fundamentally limited resource and organizational diversity, it is common that different organizations who face the same group of projects differ in preference. For example, organization 1 could favor feature A whereas organization 2's sale relies more on its strength in feature B. Our results imply the directions for improvement in decision-making effectiveness through organizational changes in decision structure, team specialties, and communication structure.

At least three lines of immediate extensions are possible. The first one is along a deeper exploration of the behaviour of the agent. Puranam et al. (2015) summarizes that besides the important role of a decision process in aggregating individual decisions that are imperfect because of bounded rationality, decision-making effectiveness can be improved with experience, see Csaszar (2014) for such a model. We shall incorporate this nature of individual learning in analyzing the comparative utility between decision structures. The second is along an extension of decision structures by including a general set of structures (Christensen & Knudsen, 2002). Hierarchy and polyarchy are simple and special cases in project screening; a more comprehensive view with respect to how information structure interacts with decision structures is needed in practice. General structures have been summarized and studied, (e.g., Csaszar, 2013; Ioannides, 2012); but these are not complete. For example, structures like ones that involve decision loops are practically important while inadequately studied. Hence, we shall extend our current study in exploring a more general decision structure space. Lastly, the assumptions regarding the information conveyed between decision-makers can be further modified to study the manner in which a communication structure influences the decision-making effectiveness. Projects can be evaluated beyond the dichotomous choice that we have explored. For example, a percentage scale is usually adopted in practice. Agents would now face, instead of a straightforward decision from previous agents, such as an acceptance or rejection, a rate which is a continuous variable. Hence, we will extend the model by considering the effect of transmitting continuous information about the projects on the performance of the decision-making structures.

Chapter 5

Conclusions, Contributions and Future Work

5.1 Summary of Conclusions

Organizational problems confronted by managers who need to strategically make decisions, involve analyzing complex environments. The decisions can span, for example, from a lower level of determining the start time of a process to a higher level of evaluating the present fitness between organizational structure and processes. We have devoted much of our attention to three specific levels of organizational research. The overlapping NPD processes analysis provides a framework for estimating the lead time through the dependence between up and downstream processes, and in turn, supporting managers on choosing among a set of strategies. Under the conditions of incremental innovation, this dependency is linked to the evolutionary behaviour of downstream so that the magnitude of rework can be evaluated. Based on that, decision-making for the managers on the selection of overlapping strategies can be improved. When different overlapping strategies are applied, the model provides information on how the performance varies in terms of lead time, total workload, and rework, and how an optimal overlapping strategy is determined. On the other hand, determining the right organizational structure is critical. We allow organizational structure to be varied along departmentalization and assignment, and process structure to be changed along dimensions of exploration and exploitation. In this model framework, we investigate the manner in which organizational model exhibits the property of stability in response to process variation when prefect alignment is retained. We next turn to question the important role of organizational structure in decision-making. The attributes considered in this line of study include the decision process, i.e., hierarchy and polyarchy, information structure, or team specialties, and two types of communication structures. We show how the comparative performance of each combination of these attribute can be impacted with one another, furthering the design of organizational structure. In addition to these highlights, a set of important managerial implications drawn from these studies are summarized as main contributions of this thesis.

5.2 Contributions

Managers face overlapped NPD processes usually consider lead time, rework, and total workload as key performance measures. However, each measure is most likely to be contingent on the overlapping strategy adapted. Clearly, comparing among a set of strategies, sequential engineering would yield the least workload and rework while entailing the longest lead time. Ordinary overlap and functional interaction with duplication are two strategies most potential for achieving shortest lead time. However, the former faces the inevitable risk of rework whereas the latter may, most likely, entail huge amount of workload. On the other hand, functional interaction with starvation performs well in terms of reducing the total workload. The drawback is its relatively longer lead time. In short, the strategies have demonstrated diverse effectiveness in terms of lead time, rework, and total workload, thus selection of an appropriate strategy for organizing sequentially dependent

NPD processes is subject to the measure which managers value the most.

While organizational process changes, managers who respond by altering the organizational model and assignment should evaluate the need for restructuring. In short term and moderate process improvement along exploration and/or exploitation dimension, fitness in terms of alignment may be retained as organizational structures are stable in this dynamic environment. Since the level of tolerance is convex to the opportunity loss, a low tolerance level is preferable when long term radical and continuous process improvement occurs. This strategy uses low tolerance to retain organizational structure stable while entailing a net cost of restructuring, which is usually high, with the relatively lower opportunity loss. The study also implies that restructuring is necessary at the completion of process improvement. Otherwise, opportunity loss cumulates as time elapses which would ultimately render the organization less competitive.

Finally, managing organizations by decision structures becomes complicated when team specialty is introduced as a variable in a project screening environment where each project is characterized by two factors. On the one hand, our analysis on a group of organizations has shown that the relative merit of hierarchy and polyarchy is not only dependent on the environment, but on the specialty of agents as well as the organizational preference over the two factors. Only the knowledge that agents possess is equally balanced over the two factors can the decision structures be solely compared with respect to the environment. Otherwise, there is less clear-cut difference between hierarchy and polyarchy. For example, hierarchy may still be better than polyarchy in "good" environment of the one factor when the team knowledge on this factor is less than the other. On the other hand, determining the right team composition is also important. The results imply that when an organization prefers one factor more than another, and the corresponding environment to that factor is bad, increasing the team specialty on the other factor is not preferable to the increase of total utility. Attention should be paid to the net effect of over and underestimation, which are inevitable during everyday decision-making, on the overall decision process. Lastly, the comparison between the two types of communication structures yields the conclusion that sharing between two agents the decision results is always preferable when the environment is uncertain as opposed to independent decision making. The communication structure should be so designed as to make the agents aware of the previous decisions. But note that this implication is based on the assumption that agents tend to follow the historical decisions on the same event. That is, if the project is previously accepted, she is more likely to accept it, and vice versa.

5.3 Future Research

The possible extensions of this thesis have been separately discussed in each chapter. A set of key future development is concluded here. First of all, in addition to the case study summarized in Appendix B which is based on the processes of an instrument company, we shall apply the process model to a different industry. More investigation is needed to understand how design strategies affect the NPD performance when the design specification and the process evolution are changed. On the other hand, coupled activities are common in NPD. Different from sequential engineering, its interdependent nature forces simultaneous development. Uncertain information becomes inevitable for both up and downstream processes. Overlapping strategies not only affect downstream process, but impact the progress of upstream. We shall extend our model to address this effect for coupled-activities and ultimately study the comparative performance under different strategies. Secondly, much emphasis on the design of organizational structure studied in Chapter 3 is through the investigation in a dynamic space where processes change incrementally and/or radically. As stated earlier, it is of practical interest to further understand the behaviour of organizational structure when processes evolve through an approach other than direct exploration and exploitation. For example, processes can change locally and globally with respect to agents, and discretely and continuously with respect to time. Hence, the process variation space immediately extends with the inclusion of these two important factors, suggesting a direction of future study that we shall follow. Lastly, as a study on the classical problem in decision structure, we shall further extend the work present in Chapter 4 by applying the model to more general, but practically sound, decision structures, such as committee with more than two agents. We shall question to what extent the implications drawn from our simplified model hold in a more general setting. In particular, we would like to move the thesis forward to study the manner in which a continuous evaluation operation, instead of dichotomous decisions, impacts the decision-making behaviour, and consequently affects the performance of the organization.

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Appendix A

This contains additional information about Chapter 2.

[Dingyu Zhang, and Nadia Bhuiyan. "Designing Snake Robotic Endoscope by Overlapping Processes." Proceedings of the 2016 Industrial and Systems Engineering Research Conference]

We have investigated the comparative performance of different overlapping strategies for the development of a snake robotic endoscope. By using the model concerning information exchange and evolution, we evaluate the magnitude of rework, lead-time, and total workload based on the dependence of up-stream process, i.e., actuator power, and down-stream process, i.e., nominal dimension. The results show that when the up-stream evolves slowly whereas down-stream quickly, ordinary overlapping has moderate performance, and function interaction with duplication is the best strategy in reducing lead-time.

Appendix B

Through Equation (3.3.3), the best decision rule is a solution to the following system,

$$q_{ii}\alpha_i + \sum_{j\neq i} q_{ij} E(\alpha_j|\xi_i) = E(\mu_i|\xi_i) \qquad i = 1, ..., n. \tag{B.0.1}$$

It can be solved by introducing new co-ordinates $b_1, ..., b_n$, and by Marschak & Radner (1972)

$$\alpha_i = b_i \xi_i \qquad i = 1, ..., n. \tag{B.0.2}$$

In addition, it follows from the assumptions made in section 3.3.3 that

$$E(\xi_j|\xi_i) = \frac{r_{ij}}{\sigma^2}\xi_i, \tag{B.0.3}$$

and

$$E(\beta_j|\xi_i) = \frac{E(\beta_j|\beta_i)}{\sigma^2}\xi_i. \tag{B.0.4}$$

Equation (B.0.1) also gives the relationship between the best decision function under the complete communication (β) and μ

$$\mu_i = \sum_{j=1}^{n} q_{ij}\beta_j. \tag{B.0.5}$$

By substituting Equation (B.0.2)–(B.0.5), Equation (B.0.1) reduces to

$$\sigma^2 q_{ii} b_i + \sum_{j \neq i} q_{ij} b_j r_i j = \sigma^2 + \sum_{j \neq i} q_{ij} r_i j \qquad i = 1, ..., n. \tag{B.0.6}$$

Under identical interaction, that is $q_{ii} = 1$, $q_{ij} = q$, we have $b_i = 1$ for all i. As a result, the best decision rule under information ξ is $\widehat{\alpha} = \xi$. That is, every team member follows the instruction. By Equation (3.3.4), the value for η_1 is

$$V = E\widehat{\alpha}\mu = \sum_{i=1}^{n} E(\beta_i \sum_{j=1}^{n} q_{ij} \beta_j) = n(\sigma^2 + d(n-1)qr). \tag{B.0.7}$$

Appendix C

Initial process R_{12} is generated by structuring a sequential process whose dependences are uniformly distributed random numbers ($U(0,1)$), see the tabulated representation summarized in Figure C.1, R_{12}. Each new process of higher complexity is generated by adding one random bilateral link over its neighbour process. For example, R_{14} is generated by adding a dependent link between units two and seven, the degrees of dependence are random numbers, i.e., $r_{27} = 0.45$, $r_{72} = 0.61$. This procedure continues until the most complex process (R_{42}) is generated, see Figure C.1, R_{42}. We adopt a convention that a process R_n is generated by adding dependences based on R_{n-2}. All intermediate complexities are shown in table C.1.

Table C.1: Process dependence structures

R14	r27=0.45 r72=0.61	R16	r47=0.38 r74=0.75	R18	r37=0.13 r73=0.91
R20	r46=0.10 r64=0.63	R22	r57=0.96 r75=0.16	R24	r17=0.96 r71=0.34
R26	r25=0.22 r52=0.75	R28	r15=0.51 r51=0.70	R30	r35=0.91 r53=0.13
R32	r36=0.63 r63=0.10	R34	r14=0.55 r41=0.96	R36	r26=0.16 r62=0.97
R38	r24=0.49 r42=0.80	R40	r13=0.42 r31=0.92	R42	r16=0.79 r61=0.96

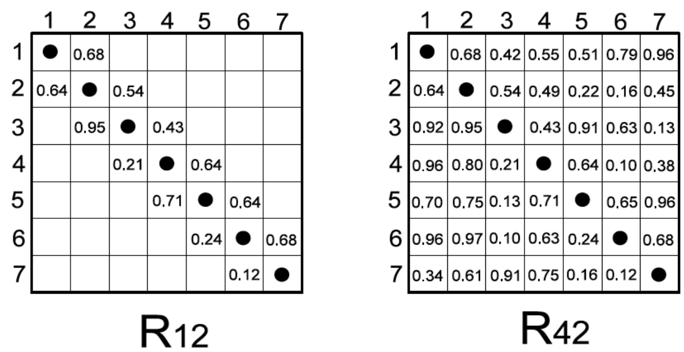

Figure C.1: Process dependence structures R_{12} and R_{42}

Appendix D

Proof of proposition 4.5.3.

Part A. The first-order derivatives of the utility s_1 are

$$s_1^H = \frac{\partial U^H}{\partial \epsilon_r} = -2Aw_r^2(Bw_r + C), \tag{D.0.8}$$

and

$$s_1^P = \frac{\partial U^P}{\partial \epsilon_r} = 2Aw_r^2(Bw_r + C + 2), \tag{D.0.9}$$

where $A = \alpha(1-\alpha)$, $B = -2\epsilon_r - 2\alpha + 2\beta + 2\epsilon_r\alpha + 2\epsilon_r\beta$, and $C = \epsilon_r - 2\beta - 2\epsilon_r\beta$. Due to symmetry, replacing $(\epsilon_r, \alpha, \beta, w_r)$ with $(\epsilon_t, \beta, \alpha, w_t)$ gives s_2^H and s_2^P.

Let us consider s_1^H as a function of w_r, which is $1-w_t$. We have $s_1^H|_{w_r=1} = 2A(2\alpha(1-\epsilon_r)+\epsilon_r) \geq 0$ and $s_1^H|_{w_r=\frac{1}{2}} = \frac{1}{2}A(\alpha(1-\epsilon_r)+\beta(1+\epsilon_r)) \geq 0$. Besides, $s_1^H = 0$ has three roots, among which $w_r = 0$ is a repeated root of order two, another root is $w_r = \frac{-C}{B}$. Observe that $B = -C - \epsilon_r - 2\alpha(1-\epsilon_r) \leq -C$. Let $w' := \frac{-C}{B}$, a simple analysis shows,

	$C < 0$	$C \geq 0$ and $0 \leq w_r \leq w'$	$C \geq 0$ and $w' \leq w_r \leq 1$
s_1^H	≥ 0	≤ 0	≥ 0

Note that the condition $C \geq 0$ is equivalent to $\beta \leq \frac{1}{4}$ and $\epsilon_r \geq \frac{2\beta}{1-2\beta}$, and it is not hard to see that in this case $0 \leq w' \leq \frac{1}{2}$. The cases for s_2^H, s_1^P and s_2^P are similar.

Suppose $\frac{1}{2} \leq w_r < 1, 0 < \beta < 1$, then

$$(s_1^H - s_2^H)|_{\alpha=1} = \beta(1-\beta)(1-w_r)^2(\epsilon_t(4\beta - 4\beta w_r - 2) - 4\beta - 4w_r + 4\beta w_r) < 0.$$

By continuity of $s_1^H - s_2^H$ with respect to α, we know $s_1^H - s_2^H < 0$ when α is close but not equal to 1. Similar calculation gives the following table which is equivalent to part A (4).

	$\frac{1}{2} \leq w_r < 1$		$\frac{1}{2} \leq w_t < 1$	
	$\alpha = 1, 0 < \beta < 1$	$\beta = 0, 0 < \alpha < 1$	$\alpha = 0, 0 < \beta < 1$	$\beta = 1, 0 < \alpha < 1$
$s_1^H - s_2^H$	< 0	> 0	< 0	> 0
	$\alpha = 0, 0 < \beta < 1$	$\beta = 1, 0 < \alpha < 1$	$\alpha = 1, 0 < \beta < 1$	$\beta = 0, 0 < \alpha < 1$
$s_1^P - s_2^P$	< 0	> 0	< 0	> 0

Part B. Applying the second-order condition, we have $\frac{\partial {s_3^H}^2}{\partial \alpha^2} = -\frac{\partial {s_3^P}^2}{\partial \alpha^2} = -24w_r^3(1 - \epsilon_r) \leq 0$. And by noting $\frac{\partial U^2}{\partial \alpha} = 0$ at $\alpha = \{0, 1\}$, s_3 is conserved over α. Consider extreme environment in hierarchy, we have

$$s_3^H|_{\alpha=0} = -w_r^2(w_r(-4\epsilon_r + 4\beta + 4\epsilon_r\beta) + 2\epsilon_r - 4\beta - 4\epsilon_r\beta), \quad \text{(D.0.10)}$$

$$s_3^H|_{\alpha=1} = w_r^2(w_r(-4 + 4\beta + 4\epsilon_r\beta) + 2\epsilon_r - 4\beta - 4\epsilon_r\beta). \quad \text{(D.0.11)}$$

For general and research oriented university, we have $s_3^H|_{\alpha=0, w_r=\frac{1}{2}} = \frac{\beta}{2}(\epsilon_r + 1) \geq 0$, $s_3^H|_{\alpha=0, w_r=1} = 2\epsilon_r \geq 0$, $s_3^H|_{\alpha=1, w_r=\frac{1}{2}} = \frac{1}{2}(\epsilon_r - 1 - \beta(\epsilon_r + 1)) \leq 0$, and $s_3^H|_{\alpha=1, w_r=1} = 2\epsilon_r - 4 < 0$. Again, since $s_3 = 0$ has three roots, among which $w_r = 0$ is a repeated root of order two, we can derive from these conditions that $s_3^H|_{\alpha=0, w_r \geq \frac{1}{2}} \geq 0$, and $s_3^H|_{\alpha=1, w_r \geq \frac{1}{2}} \leq 0$. Applying the same logic for polyarchy, we have

$$s_3^P|_{\alpha=0} = w_r^2(w_r(-4\epsilon_r + 4\beta + 4\epsilon_r\beta) + 2\epsilon_r - 4\beta - 4\epsilon_r\beta + 4), \quad \text{(D.0.12)}$$

$$s_3^P|_{\alpha=1} = -w_r^2(w_r(-4 + 4\beta + 4\epsilon_r\beta) + 2\epsilon_r - 4\beta - 4\epsilon_r\beta + 4). \quad \text{(D.0.13)}$$

And for polyarchy, we have $s_3^P|_{\alpha=0,w_r=\frac{1}{2}} = \frac{1}{2}(2-\beta-\epsilon_r\beta) \geq 0$, $s_3^P|_{\alpha=0,w_r=1} = 4-2\epsilon_r > 0$, $s_3^P|_{\alpha=1,w_r=\frac{1}{2}} = -\frac{1}{2}(2\epsilon_r + 1 - \beta - \epsilon_r\beta) \leq 0$, and $s_3^P|_{\alpha=1,w_r=1} = -2\epsilon_r \leq 0$. As a result, $s_3^P|_{\alpha=0,w_r\geq\frac{1}{2}} \geq 0$, and $s_3^P|_{\alpha=1,w_r\geq\frac{1}{2}} \leq 0$. Finally, if $w_r \geq (\leq)\frac{1}{2}$, then $s_3|_{\alpha=0} \geq 0, s_3|_{\alpha=1} \leq 0$ as desired. Proof regarding s_4 is symmetric.

Part C. The results follow immediately by noting

$$s_5^H = -s_5^P = 4\sigma_\beta^2(\epsilon_t + 1)w_r(w_r - 1)^2, \tag{D.0.14}$$

where σ_β^2 is the variance of information β. Again, s_6 is symmetric, thus omitted.

Part D. Note that s_5 is independent of α, positive in hierarchy, and negative in polyarchy. Furthermore, s_3 is non-negative in bad research environment and non-positive in good. Hence, in order to prove part D, it is sufficient to consider the sign of $s_3 - s_5$ at $\alpha = 0$ in hierarchy, and $\alpha = 1$ in polyarchy. Let us consider hierarchy first. If $\arg\min_{w_r} s_3^H|_{\alpha=0} = 1$, then

$$(s_3^H - s_5^H)|_{\alpha=0} \geq 2A - \frac{\epsilon_t + 1}{8}. \tag{D.0.15}$$

On the other hand, if $\arg\min_{w_r} s_3^H|_{\alpha=0} = \frac{1}{2}$, then

$$(s_3^H - s_5^H)|_{\alpha=0} \geq \frac{\beta}{2}(\epsilon_r - \epsilon_t + \beta(\epsilon_t + 1)). \tag{D.0.16}$$

Now consider polyarchy, if $\arg\max_{w_r} s_3^P|_{\alpha=1} = 0.5$, then

$$(s_3^P - s_5^P)|_{\alpha=1} \leq -(s_3^P - s_5^P)|_{\alpha=1,\beta=1} = -\frac{1}{2}\epsilon_r. \tag{D.0.17}$$

On the other hand, if $\arg\max_{w_r} s_3^P|_{\alpha=1} = 1$, then

$$(s_3^P - s_5^P)|_{\alpha=1} \leq \frac{1}{8}(\epsilon_t + 1) + 2\epsilon_r. \tag{D.0.18}$$

Let (D.0.15) and (D.0.16) be positive, (D.0.17) and (D.0.18) be negative, we have $(s_3^H - s_5^H)|_{\alpha=1} \geq 0$ and $(s_3^P - s_5^P)|_{\alpha=1} \leq 0$ if $\epsilon_r \geq \epsilon_t$. The symmetric case regarding teaching is omitted.

Proof of proposition 4.6.1.

Part A. Consider a pure teaching university, we have

$$s^H(\beta) = \frac{\partial U^H}{\partial z} = 4a(1-\epsilon)\beta^2 + (1 - 4a + 4\epsilon a)\beta - 0.5, \tag{D.0.19}$$

$$s^P(\beta) = \frac{\partial U^P}{\partial z} = 4a(1-\epsilon)\beta^2 + (-1 - 4a + 4\epsilon a)\beta + a + 0.5, \tag{D.0.20}$$

which are convex in β, $s|_{\beta=0} < 0$, and $s|_{\beta=1} > 0$ in hierarchy, and $s|_{\beta=0} > 0$, and $s|_{\beta=1} < 0$ in polyarchy. It follows immediately that $s = 0$ has one solution $\beta = c$ in hierarchy, and $\beta = 1 - c$ in polyarchy, refer to equation (4.6.2). Hence, we have, in hierarchy, $s \leq 0$ if and only if $\beta \leq c$, and in polyarchy, $s \leq 0$ if and only if $\beta \geq 1 - c$. On the other hand, a pure research university has exactly the same results with β replaced by α.

Part B. Consider a general university ($w_r = \frac{1}{2}$), we have

$$s^H(\alpha, \beta) = \frac{\partial U^H}{\partial z} = (0.5 + a\epsilon - 2a)(\alpha + \beta) + (a - a\epsilon)(\alpha^2 + \beta^2) + 2\alpha\beta a + a + 0.5, \tag{D.0.21}$$

$$s^P(\alpha, \beta) = \frac{\partial U^P}{\partial z} = (-0.5 + a\epsilon - 2a)(\alpha + \beta) + (a - a\epsilon)(\alpha^2 + \beta^2) + 2\alpha\beta a - 0.5, \tag{D.0.22}$$

which are convex in α and β, and $s|_{\alpha=0} \leq 0$, $s|_{\alpha=1} \geq 0$ in hierarchy, and $s|_{\alpha=0} \geq 0$, $s|_{\alpha=1} \leq 0$ in polyarchy. Again, the solution to $s = 0$ is

$$\beta = c^H = \frac{4a - 2\epsilon a - 4\alpha a - 1 + 2A}{4a(1-\epsilon))}, \tag{D.0.23}$$

$$\beta = c^P = \frac{4a - 2\epsilon a - 4\alpha a + 1 - 2B}{4a(1-\epsilon))}, \tag{D.0.24}$$

where $A = \sqrt{-4\epsilon^2\alpha^2 a^2 + 4\epsilon^2\alpha a^2 + \epsilon^2 a^2 + 8\epsilon\alpha^2 a^2 - 8\epsilon\alpha a^2 + 2\epsilon\alpha a - \epsilon a + 0.25}$,

$B = \sqrt{-4\epsilon^2\alpha^2a^2 + 4\epsilon^2\alpha a^2 + \epsilon^2a^2 + 8\epsilon\alpha^2a^2 - 8\epsilon\alpha a^2 - 2\epsilon\alpha a + \epsilon a + 0.25}$. Finally, in hierarchy, $s \leq 0$ if and only if $\beta \leq c^H$, and in polyarchy, $s \leq 0$ if and only if $\beta \geq c^P$, as desired.

Part C. It is straightforward by verifying that $\frac{\partial c}{\partial \epsilon} \leq 0$, $\frac{\partial c^H}{\partial \epsilon} \leq 0$, and $\frac{\partial c^P}{\partial \epsilon} \leq 0$.