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TOKYO INSTITUTE OF TECHNOLOGY

DOCTORAL THESIS

Study on Organizational Behaviors of Post-acquisition Integration Using Agent-Based Simulation

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Abstract

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Study on Organizational Behaviors of Post-acquisition Integration Using Agent-Based Simulation

Mergers and acquisitions (M&A) are popular means for the development of modern corporations. However, there is a high rate of failure after M&A. Post-merger/post-acquisition integration was found to have great effects on the success of the M&A, and hence, there is a growing interest in the post-merger/post-acquisition integration in the literature. Nonetheless, most of the studies are empirical works applying case study, meta-analysis, and/or other methodologies. Theoretical research on post-acquisition integration is quite few.

The behavioral theory of the firm conceptualizes large firms as unions of bounded rational individuals who are conducting decision-making. It can help researchers to model the large firms from both the internal structures and external environment. Besides, agent-based modeling and simulation (ABM & ABS) is an effective tool to model and simulate the actions and interactions of the individuals in an organization. Thus, it can help researchers to observe how agents affect the system and explore the explanatory insight of the collective behaviors of the individuals.

This thesis studies the post-acquisition integration from the perspective of the behavioral theory of the firm by using agent-based modeling and simulation. Specifically, it focuses on two topics: 1) Human integration strategies during the post-acquisition integration phase; 2) Knowledge learning during the post-acquisition integration phase. Specifically, the first research focuses

on the internal features of the system including personnel allocation strategies and vertical decision-making structures of the organization after M&A. Particularly, the post-acquisition integration is modeled from the aspects of strategy and structure based on the NK model, and a three-level hierarchical decision-making process is proposed to simulate the companies' search process. Then, the organization's behaviors and the personnel allocation strategies are discussed according to the experimental results.

According to the simulation result, information feedback manners of managers, employees' communication frequency, and personnel allocation methods are found to be influential to the organization's search performance. Managers' feedback manner has a dominant effect on the organizational performance in the post-acquisition integration stage. Excessive feedback from managers may make the company quickly be trapped in the local optima, and thus prevent the company from achieving high performance. In the absence of managers' feedback, the effects of low-level employees' communication behaviors become evident. Frequent communications may do harm to the search performance. Regarding the personnel allocation, assigning the core employees who take charge of important tasks in the target company to the central department in the acquiring company could help the organization get high performance during the post-acquisition integration.

The second research focuses on the interactions between the organization and the external environment. Considering the bounded rationality, the companies are assumed to have limited knowledge about each other, and hence about the new environment after the acquisition. The new environment is modeled based on NK landscapes. Then, the incomplete knowledge of both companies are defined, and a coupled learning model with a collaborative search process is proposed. Finally, the learning and search behaviors of the organization during the post-acquisition integration are discussed according to the experimental results.

According to the simulation result, companies' initial knowledge and perception about each other and the unknown environment is quite influential for the organization's learning and search performance. Correct knowledge and perception help the organization achieving high performance after M&A,

whereas incorrect knowledge and perception lead to a performance that even worse than the case of no perception. The sensitivity of the performance feedback in updating companies' perception during the learning process could have an opposite impact on the organization's learning performance when companies have different initial perceptions. A high sensitivity of feedback may weaken the impact of the initial perceptions, whereas lower sensitivity could reinforce the impact of the initial perceptions. Besides, frequent learning can accelerate learning progress and intensify the learning efficiency. In addition, organization's exploration in both the learning and search process is found to be helpful to the organization's performance even with an incorrect perception of the environment. Therefore, the organization can obtain a high performance by exploring to complement the effect resulted from the lack of knowledge in the post-acquisition integration stage.

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Chapter 1

Introduction

1.1 Motivations and objectives of this research

Mergers and acquisitions (M&A) can be defined as transactions in which the corporations, other types of business organizations or their units transfer or combine their possession with other entities (*Mergers and acquisitions (Wiki)*). They become popular means for the development of modern corporations, because they allow companies to obtain quick access to new markets, products, technologies and source to grow. However, there is a high rate of failure after mergers and acquisitions (Christensen et al., 2011; Dauber, 2012). As long as the development of research on M&A, there is an increasing interest in the post-merger/post-acquisition integration in the literatures. It was found that post-merger/post-acquisition integration has great effects on the success of the M&A (Haspeslagh and Jemison, 1991; Uzelac et al., 2016). However, many of the studies are empirical works applying case study, meta-analysis, and/or other methodologies. Theoretical research on post-acquisition integration are very few.

Empirical research is a method of acquiring knowledge through direct and/or indirect experience or observation (*Empirical Research (Wiki)*). It depends on the empirical evidence such as periodical reports, surveys, etc. Thus, the results of the empirical works are highly dependent on the exact data and the periods of the data that provided by these “evidence”. It could be difficult to track and observe the process with continuous time line. Moreover, since real cases are often highly complex with numerous types of data and multiple factors that has complicated interdependencies between each other, it could be difficult to recognize or to control the interrelationships in the whole system. Therefore, sometimes, it could be able to explain only “what happened there” but hardly “why it happened” by empirical methods.

The behavioral theory of the firm (Cyert and March, 1963) conceptualizes large firms as unions of individuals or groups which include workers, managers, stockholders, etc. These groups or individuals set goals and make economic decisions for the firms. It argues that the firms suffer from the internal resource allocation problems resulted from the complex interrelationships between the individuals or the groups. It also argues that the decision-making behaviors of a firm are dependent on not only the organizational structure, resource allocations, and other internal features, but also the external environment which is determined by the competitors, the suppliers, the customers, etc. Therefore, the behavioral theory of the firm can help researchers to model the large firms from both the perspectives of internal structures and external environments, and also to study the decision-making behaviors of the firms.

Agent-based modeling (ABM) can be defined as modeling systems as a collection of self-governing entities (i.e. agents) which can make decisions based on a serious of rules (Bonabeau, 2002). An agent-based model generally consists of five elements (*Agent-based model*): (1) agents of different scales; (2) decision-making approaches; (3) adaptation rules or processes; (4) a structure of agents’ interactions; and (5) an environment. Researchers can observe how agents affect the system with different actions or interactions, and thus, can explore the explanatory insight of the agents’ individual or collective behaviors in the systems through agent-based modeling and simulation (ABM & ABS). Consequently, ABM and ABS are widely used in the domains of biology, ecology, as well as social science such as economics, social networks, organization theories, etc.

According to the need for studying post-acquisition integration and the advantages of behavioral theory and ABS, this thesis studies the post-acquisition integration from the perspective of the behavioral theory of the firm by using agent-based modeling and simulation. Especially, it focuses on two topics: 1) Human integration strategies during the post-acquisition integration phase;

2) Knowledge learning during the post-acquisition integration phase. Particularly, the first topic focuses on the internal features of the system including personnel allocation strategies and vertical decision-making structures of the organization after M&A. The second topic focuses on the interactions between the organization and the external environment.

1.2 Challenges of this research

Many existing M&A research are empirical works, meanwhile, very few theoretical research on organizations studied the M&A problems. Therefore, there is lack of consistency between the research in these two domains in the aspects of definitions, concepts, concerns, and topics. For instance, the existing research on post-acquisition integrations may focus on the synergies of the companies (Lubatkin, 1983), the strategic and organizational fit after M&A (Jemison and Sitkin, 1986a), however, these concepts or definitions are rarely found in the theoretical research of organizations. Therefore, one of the big challenges of this study is to constitute a reasonable model for companies' post-acquisition integration from the perspective of the behavioral theory of the firm. Also, it is difficult to analyze and explain the simulation results from the empirical perspective and to compare the results of this study to the empirical works. In addition, it is difficult to find the applicable data to validate the model of this study from the real cases. Consequently, it is very crucial to ensure the reasonableness of the models proposed in this research. Since the behavioral theory of the firm has been validated by the empirical studies, this work proposes the model of each topic with the references of the existing research on this theory as well as sufficient consideration of the objective cases.

1.3 Major contributions of this research

The major contributions of this research are listed as follows:

- In the context of M&A, this work studies the human integration problem and knowledge learning problem during the post-acquisition integration phase from the perspective of the of the behavioral theory of the firm and using agent-based simulation.
- In the context of the academic studies of the organizations, this work proposes two agent-based models to describe companies' post-acquisition integration problem. One model is to study the impact of organization's changed internal structure on the organizational performance in the post-acquisition integration phase. The other is to study the interactions between the organization and the changed external environment in the post-acquisition integration phase.
- In the context of methodology, this work originally proposes a learning model that applying at the level of interaction matrix of NK landscapes (Kauffman and Weinberger, 1989).

1.4 Outline of the thesis

The overall structure of the thesis is shown as Figure 1.1 and organized as follows:

Chapter 1 - Introduction. This chapter presents an overview of this thesis by introducing the motivations, objectives, the challenges, and the contributions of this research.

Chapter 2 - Backgrounds. This chapter presents several concepts and the related works in the fields that relevant to this research, in order to give readers explicit views of each problem. In particular, some basic concepts of M&A is introduced first, following by the related works of post-acquisition integration. Then, the existing studies of the behavioral theory of the firm and NK model are reviewed.

Chapter 3 - Human integration strategies during the post-acquisition integration phase. This chapter contains four sections: overview, model description, simulations and results, and summary. This chapter focuses on the internal features of the system including personnel allocation strategies and vertical decision-making structures of the organization after M&A. Particularly, the post-acquisition integration is modeled from the aspects of strategy and structure based on NK model, and a three-level of hierarchical decision-making process is proposed to simulate the companies' search process. Then, the organization's behaviors and the personnel allocation strategies are discussed according to the experimental results.

Chapter 4 - Knowledge learning during the post-acquisition integration phase. This chapter focuses on the interactions between the organization and the external environment. It also contains four sections that is same as Chapter 3. In particular, agents are modeled in the company level rather than the individual level. The companies are assumed to have limited knowledge about each other, and hence about the new environment after the acquisition. The new environment is modeled based on NK landscapes. Then, the incomplete knowledge of both companies are defined, and a coupled learning model with a collaborative search process is proposed. Finally, the learning and search behaviors of the organization during the post-acquisition integration are discussed according to the experimental results.

Chapter 5 - Conclusions. This chapter summarizes the key points of this research and gives some propositions for the future improvements.

The relationship of the research in Chapter 3 and Chapter 4 is shown in Figure 1.2. Both of the two research study on the influential factors which would affect the success of M&A during the post-acquisition integration phase. However, from the perspective of behavioral theory of the firm, the research in Chapter 3 focuses on the internal features of the organization, whereas the research in Chapter 4 focuses on the interaction between the organization and the external environment.

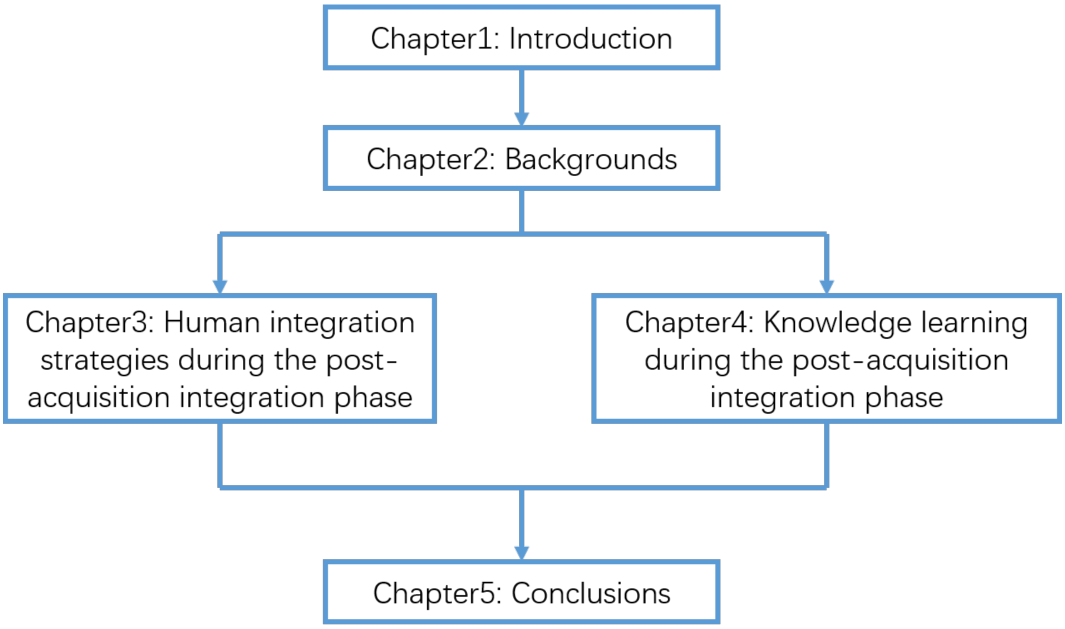

FIGURE 1.1: Structure of this thesis

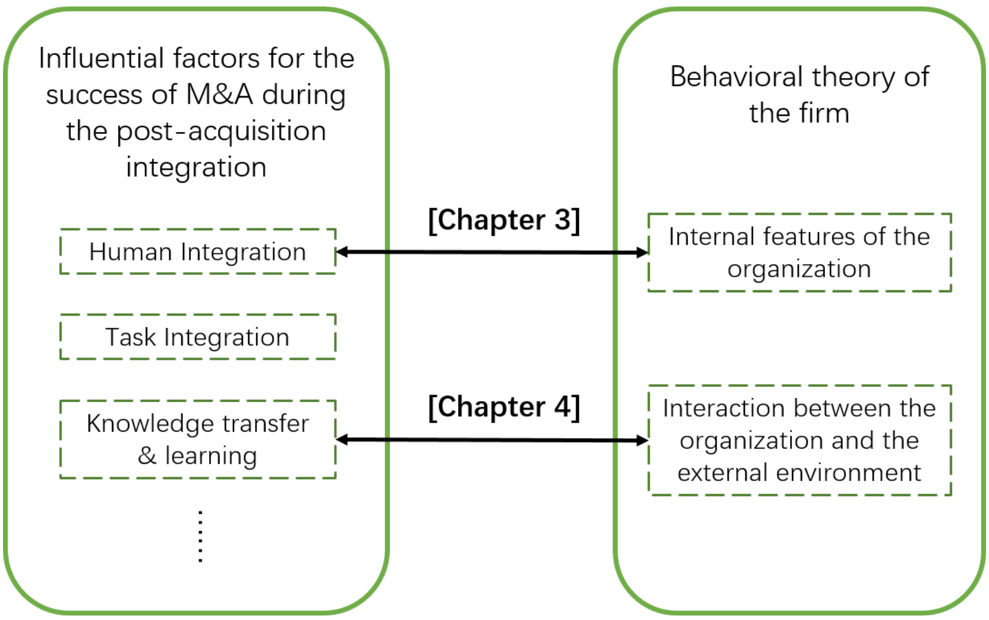

FIGURE 1.2: The relationship of the research in Chapter 3 and Chapter 4

Chapter 2

Backgrounds

2.1 Post-acquisition integration

2.1.1 Mergers and acquisitions

Mergers and acquisitions (M&A) are generally concerns the combination of two companies or their properties. There are different types of transactions of M&A, such as mergers, acquisitions, consolidations, tender offers, etc. (*Mergers and Acquisitions - M&A*). In addition, mergers and acquisitions have also been classified into five categories by the United States Federal Trade Commission (FTC) according to the primary economic relationships between the acquiring company and the target company (Walsh, 1988).

- **Horizontal** - In a horizontal acquisition, the two companies manufacture the same or related products in the same geographic market.
- **Vertical** - In a vertical acquisition, the target company is typically one of the suppliers of the acquiring company before the acquisition.
- **Product extension** - In a product extension type of acquisition, the production and/or distribution of the two companies are functionally related, however, the products of companies do not directly compete with one another. For instance, a soap producer acquiring a bleach producer would be the case of product extension.
- **Market extension** - In a market extension type of acquisition, the two companies produce the same products, yet sell them in different geographic markets.

- **Unrelated** - This type of M&A involves the consolidation of two companies which are essentially unrelated with one another.

2.1.2 Related works of the post-acquisition integration

According to Birkinshaw et al. (2000) and Haspeslagh and Jemison (1991), the academic research of M&A can be categorized as four schools: 1) Financial economics (Jensen, 1987; Manne, 1965), which concerns about the wealth creation for shareholders and economic objectives; 2) Strategic management (Lubatkin, 1983), which focuses on the impact of synergies to the performance of the acquiring and/or acquired firms; 3) Organizational behavior (Nahavandi and Malekzadeh, 1988), which studies the impact of acquisition on individuals and organization culture; and 4) Process perspective (Cyert and March, 1963; Jemison and Sitkin, 1986a,b), which concerns about the value creation after acquisition, especially the significance of the actions of management and the process of integration after M&A.

Specifically, the school of *Organizational behavior* argues that the human side of M&A is frequently neglected by managers, however, it is quite essential to the success. For instance, it was argued that the successful communication as well as the sensitivity to the desires and concerns of employees on both the two firms were determinant for achieving the long-term success (Birkinshaw et al., 2000; Buono and Bowditch, 1989). In the stream of *Process perspective* research, strategic fit and organizational fit are believed to be conductive to the synergies of the involved companies, and both of them depend on the capability of effectively managing the post-acquisition integration process (Jemison and Sitkin, 1986a,b). For instance, Jemison and Sitkin (1986a,b) identified three impediments, those were activity segmentations, increasing momentum and ambiguity of expectations, inherent in the process of post-acquisition integration, which could affect the success of M&A and give several suggestions to the corresponding impediments.

In addition, Birkinshaw et al. (2000) distinguished the post-acquisition integration between task integration and human integration. The research of human integration concerns creating employees' satisfaction and shared identity, whereas the research of task integration focuses on the value creation and operational synergies. Certain research of task integration argued the level of integration could be effective to the value creation or company's performance (Larsson and Finkelstein, 1999; Zaheer et al., 2013), whereas certain other research studied on the influence of integration speed (Uzelac et al., 2016). In addition to the research that focused on the task integration and human integration, knowledge learning, sharing and transfer during the integration process was also found be one of the influential factors to the success of acquisitions (Bresman et al., 1999; Gammelgaard et al., 2004; Gomes et al., 2013; Ranft, 2006). Nevertheless, most works that have been focused on the study of post-acquisition integration are empirical works, and the emphasis has been placed on the procedures of the integration. There are very few theoretical research works in which the post-acquisition integration has been discussed by applying ABM and ABS.

2.2 Related theoretical works of the organizations

According to behavioral theory of the firm (Cyert and March, 1963), the business goal of a company can be conceptualized as a search for good strategies to obtain high economic payoffs, where a strategy can be conceptualized as a series of choices, e.g., whether to expand its market, develop a new product, make a personnel change, etc. The operations of the company can be conceptualized as bounded rational people conducting the search through decision-making processes. As fitness landscapes have been adopted to model human organizations, the operation of a company can be modeled as a search on a fitness landscape. In certain academic research, the company was modeled as a unitary actor who conducted search over a landscape (Levinthal, 1997), whereas in certain other researches, the company was modeled as a hierarchical structure of managers and employees who conducted search through a co-operative decision-making process (Mihm et al., 2010; Rivkin and Siggelkow, 2002, 2003). In these studies, interdependencies between the choices were found to be influential to the search performance. More interdependencies led to a more complex system, and hence would prevent the organization from achieving high search performance (Rivkin and Siggelkow, 2007).

Typically, large companies can be seen as complex systems since it needs to solve problems with complex interdependencies among one another. Therefore, NK model[1] proposed to build fitness landscapes by Kauffman and Weinberger (1989) becomes a popular tool which is widely used in organization studies, since it allows researchers or modelers maintain control over the interactions among the elements of the system. For instance, in certain research, NK model was used for modeling the organizational structures (Rivkin and Siggelkow, 2002, 2007), whereas in certain other research, it was used for modeling the external environment of the organizations (Claussen et al., 2015; Levinthal and Marino, 2015; Siggelkow and Rivkin, 2005; Uotila, 2017; Yi et al., 2016).

In addition to the research that studied the behaviors of one organization, there are a few other research which focused on two organizations' alliance or collaboration with a cooperative search process. For instance, Aggarwal et al. (2011) built a model of inter-firm decision making based on NK landscape to discuss different types of alliance between two companies. Claussen et al. (2015) built a two-components system which could represent the collaboration between either two companies or two departments in a single company, to discuss the adaptation of the organizations in the environmental turbulence. However, very few theoretical research has been found to discuss the decision-making behaviors of the organization during the M&A process.

Bounded rationality (Simon, 1955) indicates the limited rationality of individuals (or agents) in decision making owing to the limited knowledge and information, cognitive limitations, and available time to make the decision. As one of the central concepts of the behavioral theory of the firm, it is often considered by the modelers from various perspectives in the search process. Aggarwal et al. (2011) and Claussen et al. (2015) considered the bounded rationality of the limited authority of each company (department) in conducting search within the collaboration (i.e. to search only on its own subcomponent). Csaszar and Eggers (2013) and Knudsen and Levinthal (2007) modeled

[1] An introduction of NK model in details is in Appendix A.

the bounded rationality as the ability of the decision makers to evaluate or screen the alternatives owing to the effect of different domains of expertise. Mihm et al. (2010) implemented their search model, in which they introduced the bounded rationality of the search authorities of the decision makers, as well as the frequency of communications through which the decision makers could obtain the necessary information to make proper choices. Nonetheless, very few researchers consider the bounded rationality in recognizing the environmental changes, despite the fact that it is a crucial factor that could affect the search performance of the organization.

Chapter 3

Human integration strategies during the post-acquisition integration phase

3.1 Overview of this research[1]

Since the human integration has been found as an important factor which would affect the success of the post-acquisition integration (Birkinshaw et al., 2000), the first topic of this study is designed to discuss the human integration strategies from the perspective of organizational decision-making. In this chapter, the model is built for the case of a core company acquiring a peripheral company, the business and the structures of which would merge together with interrelationships between each other. This type of acquisition may happen when a core company wants to explore some new functions on its products or to combine its own business to some other business, yet it has little knowledge in the exact fields. Then it may cover these shortages through acquiring a peripheral company that is professional in those fields. In particular, the two companies' original decision-making process are conceptualized as finding good strategies on two NK landscapes[2]. After the acquisition, their strategies and the environmental landscapes get merged and become correlated to each other. Also, the structure of the acquiring company would be

[1] The research in this chapter has been published in a paper by Lecture Notes in Computer Science, Springer. See details in Appendix A.

[2] An introduction of NK model in details is in Appendix B.

re-arranged with new comers from the target company. Then, a multi-level search (decision-making) process with vertical decision-making and horizontal information exchange is proposed. Finally, several simulation scenarios are designed to discuss how the personnel allocation strategies and search behaviors will affect the company's performance in the post-acquisition integration phase. The model is described in detail in Section 3.2, followed by the simulation result in Section 3.3 and summary in Section 3.4.

3.2 Model description

In this section, the core company is modeled as the acquirer with a three-level hierarchical structure. There are N front-line workers as the lowest level that equally distributed in D number of departments being managed by one CEO. The peripheral company with a flat structure of M workers and a CEO is modeled as the target company.

3.2.1 Original development of two companies

In reality, company's goal is to find good strategies with high payoff. A strategy can be seen as a series of binary decisions about how to configure different activities. For instance, the company has to decide whether to develop a new product, whether to extend its market, and so forth. Thus, it can be defined as a binary string with N elements, each of which representing a decision of company's activities. This N-digit string is denoted as $\mathbf{d} = \{d_1 d_2 ... d_N\}$, where d_i equals 0 or 1. Each strategy, that is, each configuration of the string can be evaluated by a fitness function. The value of fitness can be seen as the payoff of that strategy in the reality, while it also can be used to measure the overall company's performance in the model.

Specifically, each decision has a contribution to the fitness of strategy. The efficacy of each decision is affected not only by the choice of that decision, but also by the choices regarding other relevant decisions. Each decision i makes a contribution C_i to the fitness, and C_i depends on not only d_i but also some other decisions of $\{d_j\}$, which can be denoted by $C_i = C_i(d_i; \{d_j\})$.

The exact set of $\{d_j\}$ for each d_i is determined by the relationships of the decisions. These relationships can be denoted by an matrix which is termed as "interaction matrix" for each company.

In acquiring company, the strategy is divided into N decisions and equally assigned to D number of departments. The decisions within each department could be highly relevant to each other, and have many interactions. However, those decisions that belong to different departments are less likely to be relevant, and have less interactions. Nonetheless, considering some of the departments may be more important than others, the decisions assigned to these departments could be more relevant to the ones of other departments. As an instance, the interaction matrix for a company with $N = 10$ decisions and $D = 2$ departments is shown in Figure 3.1. According to the matrix, No.1-5 represent the decisions belong to department 1 and No.6-10 represent those belong to department 2. Mark "Y" represents the focal decision and mark "x" represents the interaction between the exact decision and the focal one. Consider decision No. 6, it has three interactions with decisions No.7,8,9 from the same department as well as two interactions with decisions No.2,4 from the other department. Thus, the contribution of decision No.6 is $C_6 = C_6(d_6; \{d_7 d_8 d_9 d_2 d_4\})$. The yellow area shows that some of the decisions of department 1 are relevant to the ones of department 2, and the former could affect the contribution of the latter. However, as shown by blank cells in matrix for columns 6-10 and rows 1-5 (i.e. the upper right of matrix area), none of decisions No.6-10 in department 2 affect the decisions of department 1. Therefore, department 1 with more important decisions can be seen as a central department of the acquiring company.

Unlike the acquiring company, the target company has a flat structure without department. But considering there could also be some decisions which are more influential than others, an interaction matrix similar to the one of acquiring company is designed in this research, which is shown in Figure 3.2. Particularly, the target company's strategy contains six binary decisions. No.1,2,3 are more influential, and they could affect the contributions of the other three decisions.

		Department 1					Department 2				
		1	2	3	4	5	6	7	8	9	10
Department 1	1	**Y**	x		x	x					
	2	x	**Y**	x	x						
	3	x	x	**Y**		x					
	4	x		x	**Y**	x					
	5		x	x	x	**Y**					
Department 2	6		x		x		**Y**	x	x	x	
	7	x		x			x	**Y**	x		x
	8	x				x		x	**Y**	x	x
	9			x		x	x		x	**Y**	x
	10	x		x			x	x	x		**Y**

FIGURE 3.1: An example of interaction matrix of acquiring company ($N = 10, D = 2$)

With the interaction matrix, the contribution of each decision can be determined. In particular, for each decision d_i, each configuration of $(d_i; \{d_j\})$ has an independent contribution value $C_i(d_i; \{d_j\})$, which is drawn at random from a uniform $U[0,1]$ distribution. Hence, changing the state of either d_i or any relevant decision d_j could result in a different contribution value C_i. Then, the overall fitness associated with a configuration of all the decisions is the average of the N (M for target company) contributions, which is shown in Equation (3.1). Since the contributions are stochastic in the range of $[0,1]$, the fitness value $F(\mathbf{d})$ for each configuration is also between 0 and 1. Higher fitness value indicates better configuration of strategy. With 2^N (2^M for target company) possible strategy configurations and corresponding fitness values, the original landscapes of two companies' performance can be generated. This generating procedure is adapted from Kauffman's NK model.

$$F(\mathbf{d}) = \frac{1}{N} \sum_{i=1}^{N} C_i(d_i; \{d_j\}) \tag{3.1}$$

3.2.2 Post-acquisition integration

As the previous section defined the original development of two companies, this section describes their integration process after M&A, especially from the

	1	2	3	4	5	6
1	**Y**		x			
2	x	**Y**				
3		x	**Y**			
4	x	x		**Y**		x
5		x	x	x	**Y**	
6	x		x		x	**Y**

FIGURE 3.2: An example of interaction matrix of target company ($M = 6$)

aspects of strategy integration and structural integration.

Strategy Integration.

As the business merge together, the strategies of two firms, and their performance landscapes become interdependent, too. To simplify the problem, the new strategy after the acquisition is defined as the simple combination of the two original ones. However, these two strategies will no longer be independent as before. Instead, they become interdependent to each other with some new interactions emerged among decisions.

The new interaction matrix is modeled by following the work of Claussen et al. (2015) in combining two interdependent ones. Specifically, two strategies are integrated into a $(N + M)$-digit string with N digits from the acquiring company and M digits from the target. To simplify the problem, the original decision interactions within each company are assumed to remain unchanged while some new interactions emerge among the decisions from different companies. Figure 3.3 shows an example of new interaction matrix after acquisition referring to the examples in Figure 3.1 and Figure 3.2.

In Figure 3.3, decisions No.1-10 are the original ones from the acquiring company while No.11-16 are from the target company. Thus, the interaction pattern of upper left and lower right areas, which represent the interactions among decisions within two companies respectively, are the same as before. The upper right and lower left areas represent new interactions emerged

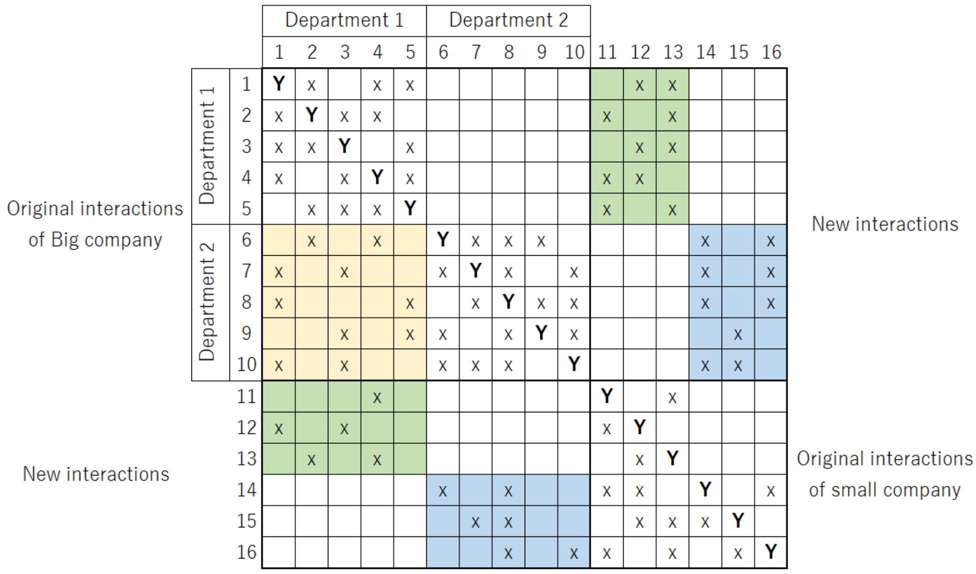

FIGURE 3.3: Example of a new interaction matrix after acquisition (Referring to Figure 3.1 and Figure 3.2)

among decisions from different companies.

Generally, the pattern of new interactions between companies is unknown and it is likely to have particular pattern, rather than random. Nonetheless, to study how the new interactions affect company's performance after M&A, an extreme case with a special type of pattern is considered as shown in Figure 3.3. Specifically, more influential decisions of target company would become correlated with the ones in the central department of the acquiring company, while the less influential decisions of target company and the ones in less important department could have some interactions with each other after merging together. These new interactions are shown as the green and blue areas in the matrix.

As interaction matrix changed, the contribution of each decision to the fitness of strategy would change, too. However, the performance landscapes of both companies would not totally change. New landscape should be correlated to both of the two original ones. This correlation can be reflected by the correlations between each decision's new contributions and the original ones.

Particularly, the concept of Adner et al. (2014) on the correlation between contributions is adapted in this model. Specifically, a correlation coefficient, denoted by $\rho \in [0,1]$, is defined to represent the correlation degree of the new contributions with the original ones. For each decision i, its new contribution $C_i^{'}$ could be the same as the original one C_i with probability of ρ, or could be independent from C_i, hence generated randomly following an uniform distribution with probability of $(1-\rho)$. This process can be written as Equation (3.2). For instance, the original contribution of decision No.6 is $C_6 = C_6(d_6; \{d_7d_8d_9d_2d_4\})$ according to Figure 3.1 and it becomes $C_6^{'} = C_6^{'}(d_6; \{d_7d_8d_9d_2d_4; d_{14}d_{16}\})$ after M&A according to Figure 3.3. Thus, each configuration of $(d_6; \{d_7d_8d_9d_2d_4\})$ will derive four new configurations due to d_6's new interactions with d_{14} and d_{16}. The new contribution of each new configuration will be generated according to the original contribution value and Equation (3.2).

With new interaction matrix and new contributions, the fitness of new strategies can be evaluated and a new landscape of company's performance can be obtained.

$$C_i^{'} = \begin{cases} C_i, & if\, \rho \\ c \sim U[0,1], & if\, 1-\rho \end{cases} \tag{3.2}$$

Structural Integration: Personnel Allocation.

Although the decisions in the strategy are highly interdependent with each other, the company has to assign them to different teams or employees, because no single individual can solve all the relevant problems. In this model, lowest-level employees, that is front-line workers of each company take charge of making choices on the decisions, and each worker is assigned with one particular decision. After the acquisition, workers from the target company are allocated to different departments of the acquiring company. Assume these new comers will still work on their original tasks after allocation, then, the allocation of workers also can be seen as the allocation of decisions. Considering the complex interactions between decisions and company's search process (introduced in the next section), personnel allocation method may affect company's search performance.

Generally, the managers in either company do not know the new interactions among decisions after M&A, and they could allocate new comers in many different ways. In this research, two simple allocation methods are designed as follows to study how personnel allocation affects company's performance with the influence of new interactions.

Allocation Method 1. The first method is to allocate employees who take charge of influential decisions to the central departments and other employees to the less central departments. Consider the case in Figure 3.3, employees who take charge of decisions No.11, 12, 13 will be allocated to department 1 and the other three employees will be allocated to department 2.

Allocation Method 2. On the contrary, the second method is to allocate employees who take charge of influential decisions to the less central departments and allocate others to the central department. That is, to allocate employees who take charge of decisions No.11,12,13 to department 2 and others to department 1 for the case of Figure 3.3.

Figure 3.4 shows the decision interaction patterns after personnel allocation. Note that these two patterns are only the examples to show the interactions among the decisions, but do not change the performance landscape. According to Figure 3.4, allocation method 1 made highly relevant decisions centralized, while allocation method 2 made them decentralized. Specially, the highly relevant decisions are allocated into the same department when method 1 is practiced, while they are allocated into different department when method 2 is practiced.

3.2.3 Search process

In reality, company's goal is to find good strategies to get high payoff. According to the behavior theory of the firm, this process is conceptualized as search process. It also can be seen as company climbing on the landscape from the perspective of NK model. Nonetheless, employees and managers in company have no idea of the whole landscape and no one can finish this

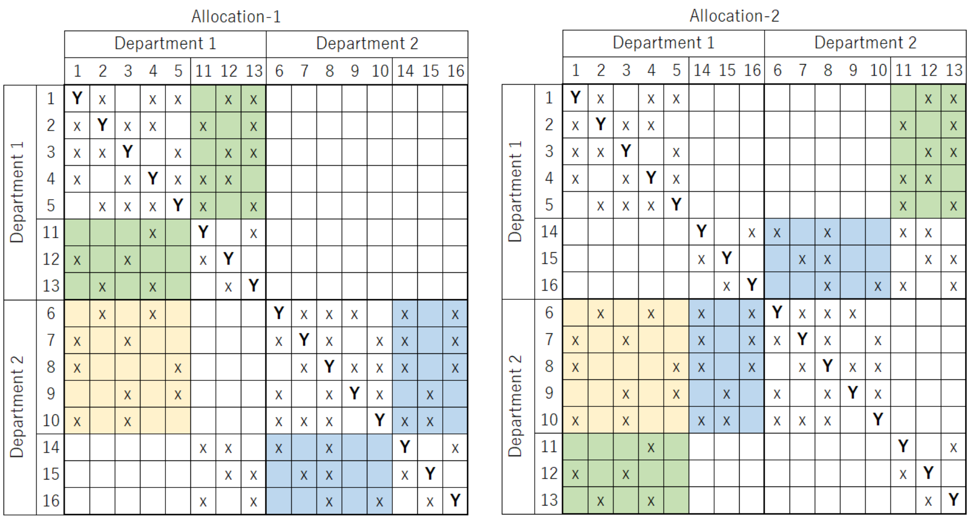

FIGURE 3.4: Example of interaction patterns after personnel allocation (According to Figure 3.3)

task by himself. Thus, a three-level vertical search process is proposed in this research. Note that the personnel allocation after the acquisition do not change the vertical structure of acquiring company and thus has no influence of search process, workers from two companies will not be distinguished in this section.

Figure 3.5 shows an example of the three-level hierarchical structure of the acquiring company. Specially, there are N workers and D departments managed by CEO, and workers are equally distributed in each department. The detailed process is described in the following subsections.

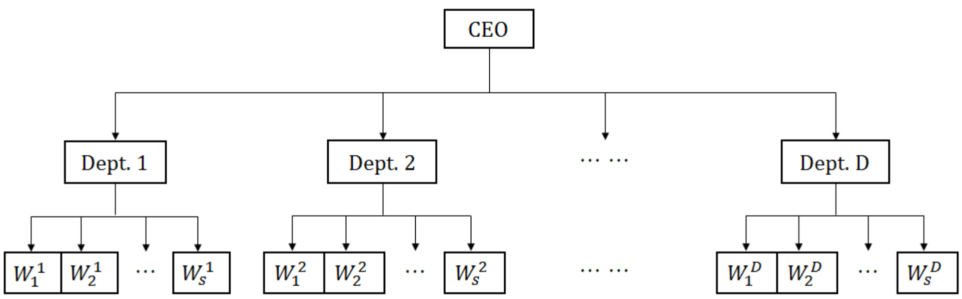

FIGURE 3.5: Hierarchical structure of the acquiring company

Front-Line Workers' Local Search.

As mentioned in the previous section, each front-line worker is assigned with one particular decision of the strategy, and he can make choices (choosing 1 or 0) only on that decision. However, he has information of other decisions either through a guidance from high levels or through an information exchange with his colleagues (introduced in the later subsections). Each worker has to make a proper choice on his own decision with his information of other decisions to make the whole strategy get a higher fitness.

For instance, worker i in department 1 is denoted by W_i^1. He has a set of information on other decisions, denoted by $\{\overline{d_1} \ldots \overline{d_{i-1}}, \overline{d_{i+1}} \ldots \overline{d_N}\}$. Hence, he has two alternative configurations of the whole strategy with that information set and his own decision d_i as 1 or 0. Then, he evaluates these two alternatives by their fitness according to Equation (3.1), and chooses a better one with a higher fitness value. This process of making a choice can be written as

$$d_i^* = arg\ max\ F(d_i, \{\overline{d_j}\}), \text{where } j \in [1, N], j \neq i \tag{3.3}$$

In Equation (3.3), $F(\cdot)$ indicates the fitness of the strategy configuration according to Equation (3.1), and $\overline{d_j}$ indicates the information of the state on decision d_j that worker W_i^1 has.

Periodically, that is every T_W time periods in this research, workers submit their proposals to their department managers (Rivkin and Siggelkow, 2003; Siggelkow and Rivkin, 2005). Considering worker's observation is bounded, each worker is assumed to submit a proposal containing only the information of decisions within his own department. For instance, worker W_i^1 of department 1 in Figure 3.5 can submit a proposal with s digits information of $\{\overline{d_1}...\overline{d_{i-1}}, d_i, \overline{d_{i+1}}...\overline{d_s}\}$. In this proposal, d_i indicates the choice of W_i^1's own decision, and $\overline{d_j}$ ($j \in [1, s], j \neq i$) indicates the information of his colleagues' decisions within department 1.

Department Managers' Decision-Making.

Every T_W time periods, department managers gather the proposals submitted by their subordinates. Similar to workers, each manager has not only the s-digit information submitted by the workers, but also $(N-s)$-digit information on other decisions through the guidance from high level or the information exchange with his colleagues. Then he combines each proposal to the other $(N-s)$-digit information as different options. After evaluating all of the options by their fitness values, the manager compares those with his previous proposal, and then chooses the best one with the highest fitness value as his new proposal. Different from workers, department managers submit their proposals every T_D time periods, and they can only compare the options rather than changing the state of any digit. Furthermore, since department managers have more holistic observation than the front-line workers, each manager is assumed to submit a proposal containing full information of the N-digit strategy string.

Meeting Colleagues and Exchanging Information.

During the search process, workers and department managers may have chances to meet their colleagues (of the same level) by either regular meetings or "random" encounters. Through these meetings, workers or department managers can exchange and update their own information sets. Consider worker W_i and W_j, each of them has a set of information about the states of all other decisions besides his own one, denoted by $I_i = \{\overline{d_k}\}$, $(k \in [1, N], k \neq i)$ and $I_j = \{\overline{d_l}\}$, $(l \in [1, N], l \neq j)$ respectively. When they meet each other, they exchange the information of their own decisions and update their information sets, which become $I_i' = \{\overline{d_j}', \{\overline{d_k}\}\}$, $(k \in [1, N], k \neq i, j)$ and $I_j' = \{\overline{d_i}', \{\overline{d_l}\}\}$, $(l \in [1, N], l \neq j, i)$. In the equations, $\overline{d_j}'$ and $\overline{d_i}'$ represent the up-to-date information that worker W_i and W_j obtained. With these updated information, workers can do the local search again according to Equation (3.3). Similar to workers, department managers can also meet each other. But instead of exchanging the information of a particular digit, they exchange all information of decisions within their departments.

It is assumed that each worker or department manager meets his colleagues following a Poisson Process (Mihm et al., 2003, 2010), including the cases of company's regular meetings and the "random" encounters. Hence, the time interval of two employees' meeting follows an exponential distribution with a scale parameter as the mean of meeting time interval. It is also plausible to assume that workers who are working in the same department meet more frequently than workers from different departments do. Thus, $scale_w$ is denoted as the average time interval that two workers within the same department meeting each other. $scale_b$ is denoted as the average time interval that two workers from different departments meeting each other, and the average time interval two department managers meeting each other. Besides, each employee's meeting process is independent process.

CEO's Decision-Making and Feedback.

Every T_D time periods, CEO gathers the proposals that contain N-digit information from department managers. Then she compares these proposals besides company's previous strategy (her last choice) by evaluating their fitness values according to Equation (3.1), and chooses the best one as company's new strategy. The fitness value of this strategy can be seen as the measurement of company's performance. This procedure represents CEO's decision making process. In addition, in some cases, CEO may give her choice of the best strategy back to the lower levels as a developing guidance, and three types of information feedback process are designed as follows.

Full Information Feedback. In this case, CEO always gives back her choice of the best strategy to the department managers every time after she making a decision. Then the department managers give this feedback that contains full information to the workers. Thus, everyone can update his own information set and do his local search with this new information in the next time period.

Partial Information Feedback. Similar to the full information feedback case, CEO always gives back her choice to the department managers. However, in this case, each department manager only cares about the decisions of his own department. Thus, instead of the full feedback that he obtained, each manager picks a particular part of it which contains only the information of his own department and give this partial feedback to the workers. Therefore, the department managers can update their whole information sets, while the workers can get only part of their information sets updated.

No Feedback. In this case, CEO do not give back her choice as the developing guidance at all. Department managers and workers can update their information only through meeting their colleagues.

3.3 Simulation and results

In this section, the organization's behavior after M&A are discussed from two aspects: (i) the company's search behavior, and, (ii) the influence of post-acquisition integration with particular integrated performance landscape and personnel allocation methods. Specifically, the influence of different types of information feedback, different sets of employees' meeting frequency, different personnel allocation methods, and different complexity of landscapes are examined.

To simplify the problem, the acquiring company is designed to have $N = 10$ workers who are equally assigned to $D = 2$ departments, and the target company has $M = 6$ workers. Hence, the scale of strategies of two companies can also be determined as the same. The original landscapes of two companies as well as the new landscape are generated according to the process previously described in the model section with the correlation coefficient $\rho = 0.6$. Regarding the search process, a total simulation time is set to be $T = 3000$ time steps. In addition, workers submit their proposals every $T_W = 5$ steps and department managers submit theirs every $T_D = 23$ steps. In each time step, each person can only focus on one activity, that is, either (i) conducting search, (ii) submitting proposals (gathering submissions), or (iii) meeting with one colleague.

To study company's behavior, 90 simulation scenarios with 3 types of information feedback (details in model section), 5 sets of meeting frequency, 2 personnel allocation methods (details in model section), as well as 3 levels of landscape complexity are designed. As introduced in the model section, the scale parameter of exponential distribution can be used to measure employees' meeting frequency. Specially, $scale_w = \{4, 6, 8, 10, 12\}$ and $scale_b = 4 \cdot scale_w$ are set, where smaller values represent that employees meet each other more frequently. Moreover, the complexity of NK landscape is measured as K/N in this research, where N represents the number of decisions, and K represents that each decision d_i has in average K number of relevant decisions $\{d_j\}$ which have impact on d_i's contributions. Due to the special pattern of interaction matrix, the maximum complexity of the landscape could be around 0.5. Thus, 0.16, 0.35, and 0.49 are set as low, medium and high level respectively. For each complexity level, 100 different landscapes are generated and simulation runs 5 times on each landscape. Due to the limited space, only the results of low complexity and high complexity are shown in this research. The results of medium complexity are similar to the high level ones.

Figure 3.6–3.9 show the simulation results of different scenarios by box plots. Figure 3.6 and 3.7 show the results of simulations with low level complexity, while figure 3.8 and 3.9 show the results of high level complexity. The three panels of each figure shows the results of three types of information feedback. In each panel, x-axis shows different value of $scale_w$ which represents different meeting frequencies, and y-axis shows either the normalized performance or the convergence time of search. For each value of $scale_w$, there is a blue box showing the simulation results of personnel allocation method 1 and a red box illustrating the results of allocation method 2. The red mark in each box represents the statistical average of the exact set of data.

3.3.1 Influence of different types of feedback.

In the low complexity case in Figure 3.6 and Figure 3.7, the landscape is very smooth with less local peaks, and it is easy for company to get high performance via the search process. Thus, different scenarios show similar results. Figure 3.8 and 3.9 that represent the results of high complexity scenarios show the obvious difference between different types of feedback. In full feedback

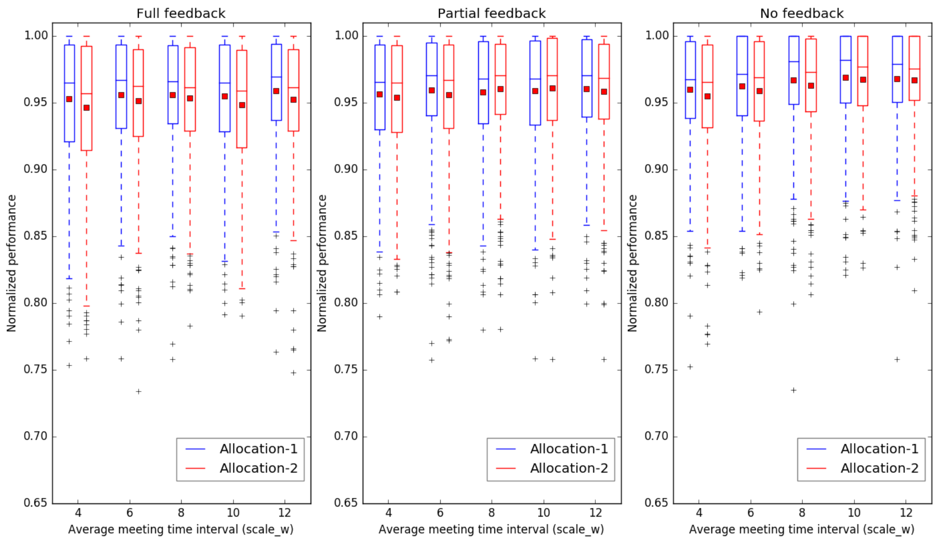

FIGURE 3.6: Search performance of different simulation scenarios with complexity $= 0.16$

case, everyone gets a feedback from CEO periodically, and then conducts the search with the information of this feedback. Since the feedback was chosen as the best strategy among all the options in the mean time, it could lead everyone quickly reach to a higher position on the landscape. Hence, this type of feedback process may accelerate the search process and make it converge in a very short time. Nonetheless, it also makes everyone's configuration same, hence will cause everyone getting stuck once the feedback reaches to a local optimum.

On the contrary, in no feedback case, CEO has no influence to the lower levels' search process. Everyone updates his information through meeting colleagues. Hence, company's search process could be much slower than those in the feedback cases. However, search without feedback somehow keeps the strategy options highly diverse, so the company could have opportunities to jump out of a local optimum and find better strategies. The partial feedback is the case between the other two. Periodical feedback reduces the search time while partial feedback from department managers retains some of the diversity of the strategy options. Therefore, no feedback case takes the longest time to converge but obtains the highest performance, while the full

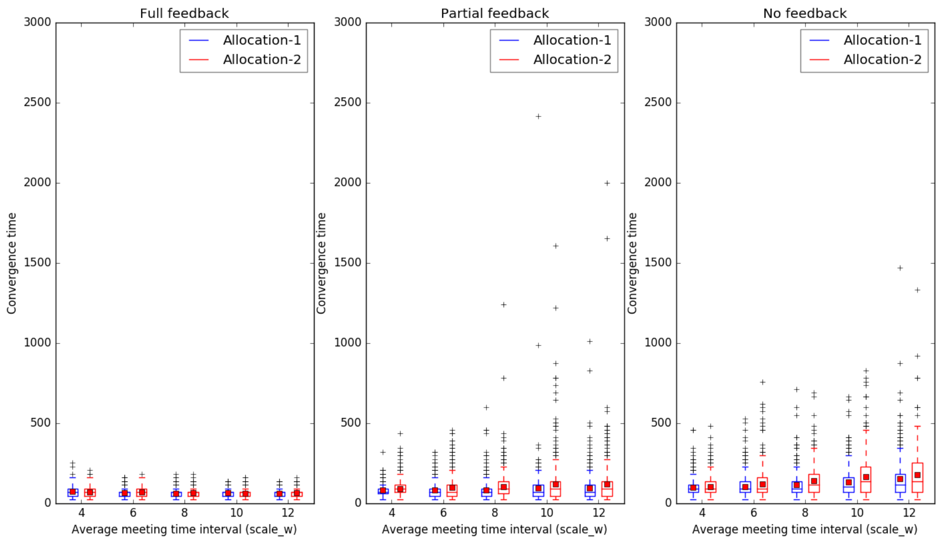

FIGURE 3.7: Convergence time of different simulation scenarios with complexity = 0.16

feedback case shows the other way around.

3.3.2 Influence of different meeting frequencies.

The high complexity simulation results shows the difference between different meeting frequencies especially in the partial feedback and no feedback cases. In full feedback case, periodical feedback coming from high levels affects the search process more than employees' meeting does. Thus, there is little difference between the results of different meeting frequencies. However, in partial feedback and no feedback cases, both the search performance and convergence time increase when employees' meeting frequency decreases. When $scale_w$ gets smaller, employees meet each other and hence get their information updated more frequently. Consequently, employees' configurations become the same quickly, which could cause everyone rapidly getting stuck at the same point. In addition, spending lots of time to meet colleagues would occupy the search time. Therefore, too much meeting may lead to a lower performance but less convergence time.

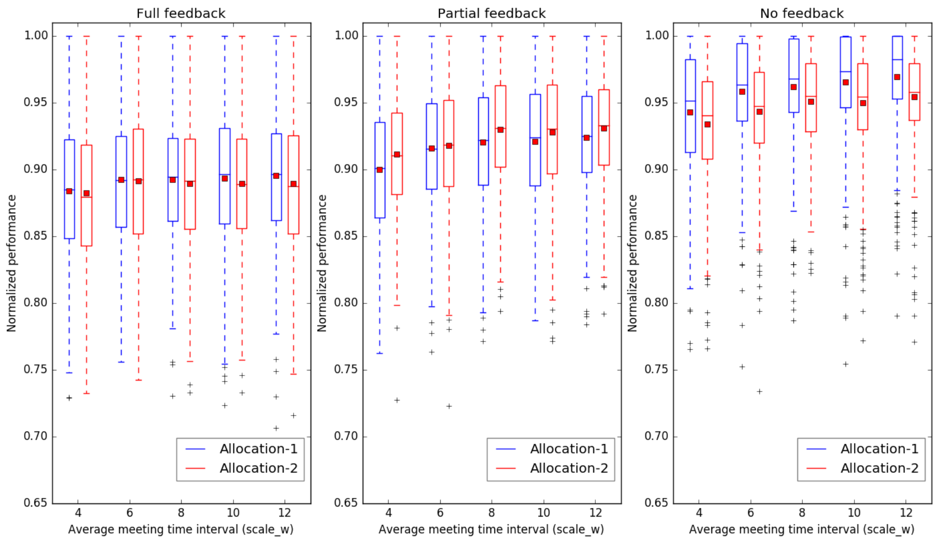

FIGURE 3.8: Search performance of different simulation scenarios with complexity = 0.49

3.3.3 Influence of different personnel allocation methods.

In partial feedback and no feedback cases of Figure 3.8 and Figure 3.9, the difference between red boxes and the blue ones appears to be significant, which represent the different personnel allocation methods would affect the performance and convergence time of the search. Allocation method 1 and 2 perform similar in the full feedback and partial feedback cases, yet method 1 performs better than method 2 in the no feedback case. However, method 2 always takes longer time to converge than method 1.

In no feedback case, workers and department managers update informations only through meeting colleagues. Workers in the same department meet each other more frequently than the ones from different departments. Department managers meet each other infrequently as well. As a result, everyone focuses on the decisions in his own department, yet, to some extent, ignore the ones of the other department. As for the case of allocation method 1, highly relevant decisions are in the same department, thus workers can promptly obtain the up-to-date information of these decisions and make a proper choice.

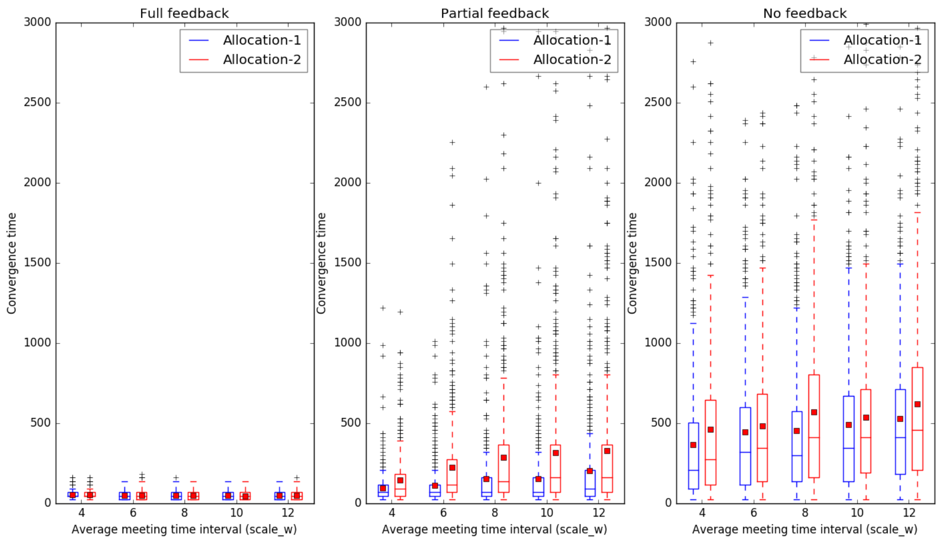

FIGURE 3.9: Convergence time of different simulation scenarios with complexity = 0.49

However, with allocation method 2, workers cannot promptly obtain the up-to-date information which is highly relevant to their own decisions. Thus, allocation method 1 performs better than method 2, and takes shorter time to converge.

Partial feedback and full feedback cases are quite different from no feedback case. As mentioned in the previous sections, the feedback from high levels rather than the meetings among the employees dominates the information update. Employees can obtain the up-to-date information of the other department from this feedback. Thus, there is little difference between the two allocation methods. Specially, in the partial feedback case, workers cannot promptly update the information of the other department because of the partial feedback from their managers. Thus, it may take longer time to converge when allocation method 2 put into practice.

3.4 Summary

In this chapter, the impact of human integration strategies as well as some search behaviors on the organizational performance in the post-acquisition integration phase are discussed. In particular, the two companies' original environments are defined as two NK landscapes. Their strategies and the environmental landscapes merge together after the acquisition, and the acquirer's structure also gets merged by allocating the new personnel from the target company. Then, a multi-level search process with vertical decision-making and horizontal information exchange is proposed for the simulation.

According to the simulation result, when problem complexity is low, that is, decisions of company's strategy are less interdependent to each other, it is easy for employees to find superior strategies with high performance even after mergers and acquisitions. However, when the complexity becoming high, that is, decisions of strategy become highly interdependent with each other, it becomes difficult for employees to find superior strategies with high performance. Many factors could influence the search process. Specially, excessive feedback from high levels may help the company quickly find some good strategies, but it may restrict employees' and managers' cognition to search for other possible strategies. Thus, it could easily make company's search get stuck with low performance. Without feedback, company's search process is dominated by low level employees' cooperation. In this case, frequent meetings among the employees may do harm to the search performance by occupying employees' search time as well as make their cognition quickly converge. As for re-arranging employees after mergers or acquisitions, employees who take charge of highly relevant tasks working together could help the company get high performance, especially when there is no information feedback from high levels.

Chapter 4

Knowledge learning during the post-acquisition integration phase

4.1 Overview of the research[1]

The second topic of this study is to discuss the knowledge learning and sharing, which is another influential factor of the success of the post-acquisition integration (Ranft, 2006). In this chapter, the "knowledge" is modeled as the companies' recognition/perceptions of the changed environment resulted from the acquisition. Specifically, the external environment of the two companies is assumed to change during the acquisition. However, considering the bounded rationality (Simon, 1955), both companies may have limited knowledge about how the environment has changed. The limited knowledge could probably affect the companies' evaluation about their strategies and hence could have impact on their decision-making. Therefore, the companies would learn the knowledge about the new environment from their experience in order to make appropriate decisions to obtain high payoffs. Similar to the last chapter, the model in this chapter is also built for the case of a core company acquiring a peripheral company. However, since this topic focuses on the interaction between the companies and the external environment, the agents are defined as two companies rather than the individuals. Particularly, after defining the environmental change and the companies' limited knowledge

[1]The research in this chapter has been accepted to be published in a paper by the Journal of Advanced Computational Intelligence and Intelligent Informatics. See details in Appendix A.

about the new environment, a collaborative search (decision-making) process and a coupled learning process over the NK landscape[2] are proposed. Then, the simulations are implemented to study the effect of learning and search behaviors to the organizational performance. The model is described in detail in Section 4.2, followed by the simulation result in Section 4.3 and summary in Section 4.4.

4.2 Model description

In this chapter, two companies are defined as two agents and to conduct search over their original environment. After the acquisition, two companies merge together and become two subsystems of the whole organization. Accordingly, their strategies become correlated to each other and thus their environment would change. Considering the bounded rationality, both of the two companies could probably be unfamiliar with the new environment due to their limited knowledge about each other (e.g. business, techniques, etc.). However, the two companies could adapt to the new environment by a collaborative search behavior and a coupled learning behavior. It should be noted that we discuss the system's behavior in focusing on the adaptation process after the environmental change rather than through the environmental change. The details of the model are described from four aspects: the environmental changes in post-acquisition integration phase, companies' limited knowledge about the new environment, collaborative search process, and coupled learning process.

4.2.1 Environmental changes in the post-acquisition integration phase

Original task environments of two companies.

Similar to the previous research, the company's operational strategy is modeled as an n-digit string of $\mathbf{d} = \{d_1 d_2 ... d_N\}$. Element d_i equals 0 or 1 and

[2] An introduction of NK model in details is in Appendix B.

indicates the decision of an activity (i.e. whether to approve a project or not). Each configuration of strategy can be evaluated by a fitness function. The value of fitness can be seen as the payoff of that strategy in the reality, and it can be used to measure the overall company's performance.

According to the NK model, each decision (each element of the string) has a contribution to the fitness of the strategy. This contribution is affected not only by the choice (value) of that decision, but also by the choices of other relevant decisions. Specifically, each decision i makes a contribution C_i to the fitness, and C_i depends on not only d_i but also K number of other decisions which are relevant to d_i and denoted by $\{d_j\}$. Hence this contribution can be denoted by $C_i = C_i(d_i; \{d_j\})$. The exact set of $\{d_j\}$ for each d_i is determined by the interactions between the decisions. These interactions of the decisions can be represented by an interaction matrix. To simplify the model without loss of generality, a random pattern for each company is adopted in this research. Figure 4.1 shows an example of interaction matrices of two companies, where mark "Y" indicates the focal decision and mark "x" indicates the interaction between the exact decision and the focal one. Changing the value of either d_i or any relevant decision d_j could result in a different contribution value C_i. These contributions are independently drawn at random from a uniform $U[0, 1]$ distribution.

Finally, the overall fitness associated with a configuration of the decisions can be evaluated as the average of their contributions, which is shown in Equation (4.1). Higher fitness value indicates better configuration of strategy. With all possible strategy configurations and corresponding fitness values, the original landscapes of two companies' performance can be determined.

$$F(\mathbf{d}) = \frac{1}{N} \sum_{i=1}^{N} C_i(d_i; \{d_j\}) \tag{4.1}$$

Environmental Change After the Acquisition

Environmental changes can be commonly defined as changes in how strategic actions impact the performance outcomes (Stieglitz et al., 2016). Thus, it can be defined as the change of the mapping between the strategies and

	Acquiring Company									
	1	2	3	4	5	6	7	8	9	10
1	Y	x		x	x		x			
2	x	Y		x		x		x		
3	x	x	Y		x				x	
4			x	Y	x		x		x	
5		x		x	Y	x		x		
6		x		x		Y	x		x	
7	x		x			x	Y			x
8	x				x			Y	x	x
9			x		x			x	Y	x
10	x		x				x	x		Y

(A) Acquring company (N=10,K=4)

	Target Company					
	1	2	3	4	5	6
1	Y		x	x		x
2	x	Y		x	x	
3		x	Y		x	x
4	x		x	Y		x
5	x	x		x	Y	
6	x		x		x	Y

(B) Target company (N=6,K=3)

FIGURE 4.1: Interaction matrices of two companies before the acquisition

their fitness values (i.e. the change of landscapes). In this research, we consider the acquisition case that the business of two companies combine with each other and become interdependent[3]. To make the description clear, we literally use the term "organization" to specify the entire company after the acquisition, the terms "the acquiring company" (or "the acquirer") and "the target company" (or "the target") to specify the subsystems of the former acquiring company and the former target company in the following sections of this chapter.

As the business getting merged, some of the decisions of two companies' strategies may become correlated by the form of emerged interactions between each other. Consequently, the contribution of each decision, and hence the performance landscape, could change, too. The work of Claussen et al. (2015) is employed to model the new interaction matrix after the acquisition in our research. Figure 4.2 shows an example of new interaction matrix after

[3]This type of acquisition may occur when a core company wishes to explore certain new functions on its products or to combine its own business with other businesses, yet it has little knowledge of the exact fields. Then, the core company may cover these shortages by acquiring a peripheral company that has expertise in these fields.

		Acquiring Company										Target Company					
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Acquiring Company	1	**Y**	x		x	x		x					x			x	
	2	x	**Y**		x		x		x			x			x		
	3	x	x	**Y**		x				x			x	x			
	4			x	**Y**	x		x		x			x				x
	5		x		x	**Y**	x		x			x		x			
	6		x		x		**Y**	x		x					x		x
	7	x		x			x	**Y**			x		x	x			
	8	x				x			**Y**	x	x				x		x
	9			x		x			x	**Y**	x			x		x	
	10	x		x				x	x		**Y**				x	x	
Target Company	11				x			x				**Y**		x	x		x
	12	x		x								x	**Y**		x	x	
	13		x					x					x	**Y**		x	x
	14			x			x					x		x	**Y**		x
	15							x	x			x	x		x	**Y**	
	16					x					x	x		x		x	**Y**

FIGURE 4.2: Interaction matrix of the organization after the acquisition (N_A = 10, K_A = 4, N_T = 6, K_T = 3, K_B = 2)

the acquisition referring to the examples in Figure 4.1. The integrated strategy of the organization contains $(N_A + N_T)$ decisions with $N_A = 10$ decisions coming from the former acquirer and $N_T = 6$ decisions coming from the former target. For each decision, it is assumed that the original interactions coming from its own company would remain unchanged during the acquisition, while $K_B = 2$ number of new interactions with the other company's decisions would emerge. Therefore, the intra-firm interaction patterns in the upper left area and lower right area are consistent to the patterns in Figure 4.1(A) and 4.1(B) respectively, while the inter-firm interaction emerge in the upper right area and lower left area.

As interaction matrix changed, the contribution of each decision to the fitness of strategy would change, too. However, the new performance landscape should be correlated to both of the two original ones. This can be reflected by the correlations between the original and new contributions of each decision. Specifically, for each decision d_i, the new contribution is denoted by $C_i^{'} = C_i^{'}(d_i; \{d_j\}, \{d_l\})$ while the original one is denoted by $C_i = C_i(d_i; \{d_j\})$, where $\{d_j\}$ indicates the original interactions and $\{d_l\}$ indicates the new interactions. Then, $C_i^{'}$ is drawn at random from a triangular distribution $Tr(0, C_i, 1)$, where 0 is lower limit, 1 is upper limit, and C_i is the mode. For instance, the original contribution of decision No.6 is $C_6 = C_6(d_6; \{d_2 d_4 d_7 d_9\})$ according to Figure 4.1(A), then it becomes $C_6^{'} = C_6^{'}(d_6; \{d_2 d_4 d_7 d_9; d_{14} d_{16}\})$ according to Figure 4.2. Therefore, each configuration of $(d_6; \{d_2 d_4 d_7 d_9\})$ will derive four new configurations due to d_6's new interactions with d_{14} and d_{16}. The new contribution of each new configuration will be generated following the distribution of $Tr(0, C_6, 1)$.

With new interaction matrix and new contributions, the fitness of new strategies can be evaluated and a new landscape of the organization's environment can be obtained. This landscape that represents the objective environment of the organization is identified as "true environment" in this research.

4.2.2 Companies' limited knowledge about new task environment

Considering the bounded rationality, each company could have limited knowledge about how the other company's decisions, activities, and/or business could affect its own ones even after the knowledge transfer, because some "tacit knowledge" is difficult to transfer during the acquisition (Bresman et al., 1999; Ranft, 2006). These limited knowledge can be represented by the partial correct interactions between the decisions of the strategy in our model. It is assumed that each company has a perceived interaction matrix with partial correct interactions comparing to the "true landscape". Furthermore, this perceived interaction matrix could affect company's evaluation about the contributions of the decisions, and hence, the evaluation about the fitness of the strategy. Therefore, the organization's decision making could probably be affected by the companies' perceptions of the landscape. The perceived landscape of each company will be introduced from the aspects of interaction matrix and the contributions of the decisions in the following paragraphs.

Perceived Interaction Matrix.

In this model, each company's perceived interaction matrix is determined by the knowledge of its own subsystem and the knowledge about the other subsystem shared from the other company. As the two subsystems are symmetric in the organization, only the acquiring company is taken to introduce the details in this section.

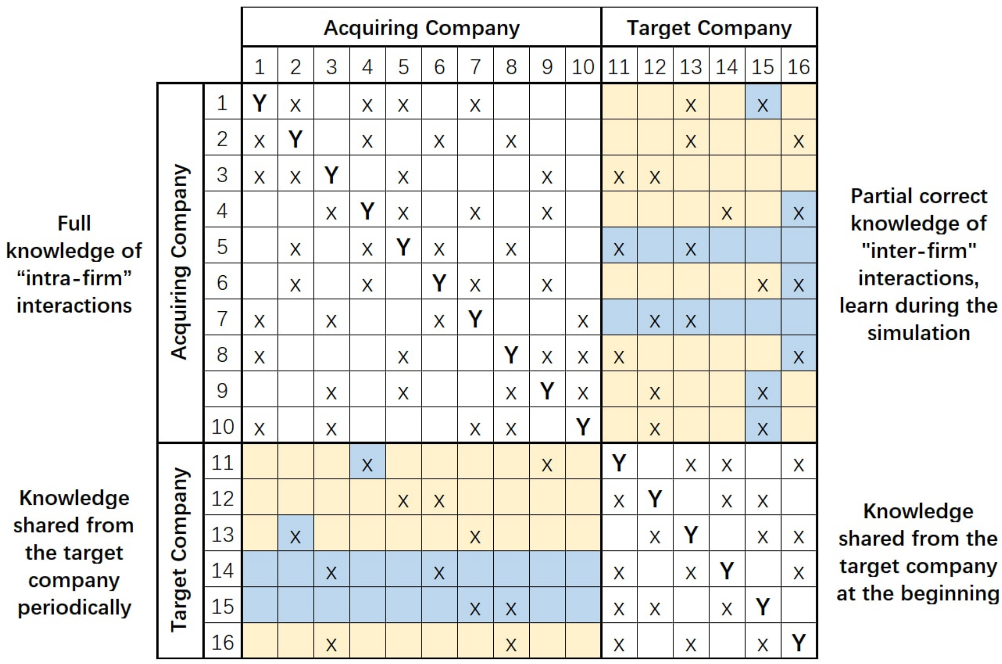

FIGURE 4.3: The acquiring company's perceived interaction matrix[4]

Figure 4.3 shows an example of the acquiring company's perceived interaction matrix. The upper left and upper right areas show the knowledge

[4]The "partially correct knowledge" of the inter-firm interactions has been indicated at the lower left area and the upper right area of the graph in the same manner. However, the knowledge and the authority of learning over the lower left area belong to the target company. For the acquiring company, all inter-firm interactions in this area will be shared by the target company during the learning process.

about its own subsystem which contains the decisions No.1-10. Specially, it is assumed that the acquiring company has full knowledge about the intra-firm interactions, and hence, the pattern in the upper left area is consistent to the "true interaction matrix" shown in Figure 4.2. For the inter-firm interactions (the upper right area), the company is assumed to have X (percentage) of the correct knowledge which are denoted as the blue cells in the figure. Then, the rest $1 - X$ of interactions are determined from the yellow cells. These X of interactions are randomly determined at the beginning of the simulation.

Specifically, the company knows that there are K_B number of inter-firm interactions for each decision i. It also has correct knowledge of K_k^i number of interactions. Then, for decision i, the company has to determine the other $K_B - K_k^i$ number of interactions from the $N_T - K_k^i$ number of candidates. For instance, for decision No.1, the company has to determine one interaction from the candidates No.11,12,13,14,16 (i.e. $K_B = 2, K_k^1 = 1$), whereas, for decision No.2, it has to determine two interactions from the candidates No.11-16 (i.e. $K_B = 2, K_k^2 = 0$). However, the company does not have to determine any interaction for decision No.5 because it has full knowledge about this decision's interactions (i.e. $K_B = 2, K_k^5 = 2$).

Although the company does not know some of the interactions for the focal decision, it may have a perception about which candidate(s) is (are) likely to be the interaction(s). This perception is modeled as a set of expected payoffs and term it as a "belief". For instance, regarding decision No.1 in Figure 4.3, the company has a belief about the expected payoffs for interaction candidates No.11,12,13,14,16, which are denoted as $\{w_{11}^1, w_{12}^1, w_{13}^1, w_{14}^1, w_{16}^1\}$. Then, the company can determine the interaction for decision No.1 based on these expected payoffs.

Generally, for decision i, the company has a belief of the expected payoffs $\{w_{m_1}^i, w_{m_2}^i, \ldots, w_{m_s}^i\}$ concerning to the corresponding s number of the interaction candidates, where $m_1 \sim m_s$ denote the candidates' ID. Then the probability of selecting any candidate is relevant to these expected payoffs with the softmax function which is widely used in the reinforcement learning process (Jafari Songhori et al., 2017; Puranam and Swamy, 2016). In particular, the probability of selecting candidate m_j is

$$p^i_{m_j} = \frac{e^{w^i_{m_j}/\tau}}{\sum_{r=1}^{s} e^{w^i_{m_r}/\tau}} \tag{4.2}$$

In Equation (4.2), $w^i_{m_j}$ indicates the expected payoff of candidate m_j for decision i. The parameter τ controls the exploration level of search process (Puranam and Swamy, 2016; Sutton and Barto, 1998). High values of τ result in the equal likelihood for selecting any of candidates, whereas, low values of τ result in higher probability of selecting the candidates with higher expected payoffs. Lastly, the determination of selecting any candidate is conducted by using the roulette wheel mechanism with the probabilities derived from Equation (4.2).

The lower left and lower right areas in Figure 4.3 show the knowledge shared from the target company, which contains the interactions of decision No.11-16. Considering two companies would share the knowledge about their business, technologies, policies to each other during the acquisition, it is assumed the target company will share the knowledge of its intra-firm interactions to the acquirer at the beginning of simulation (the lower right area in Figure 4.3). It is also assumed that the target company will share the knowledge about the inter-firm interactions of its own subsystem to the acquirer after each time of the determination (the lower left area).

Consequently, the acquiring company can obtained a perceived interaction matrix with its original knowledge of intra-firm interactions, the inter-firm interaction determined according to the belief of expected payoffs, and the knowledge shared from the target company. Similar to the acquirer, the target company has a perceived interaction matrix of the landscape containing its own knowledge and the knowledge shared from the acquirer.

Evaluation of Contributions Based on Perceived Interaction Matrix.

With the perceived interaction matrix, the companies can evaluate the contributions of each decision and then the fitness of the strategy string. We assume each company evaluates the contributions and fitness independently. For each decision, the company is able to evaluate its contribution properly (i.e. equal to the real contribution of the new environment) if all of its interactions are correctly perceived (i.e. consistent with the real interaction matrix of the new environment). If the perceived interactions are not consistent with the true ones, the company cannot evaluate the contributions properly.

Figure 4.4 shows the mechanism of the contribution evaluation in our model. For example, decision No.i has real interactions with decision No.3 and No.10, yet the company has a perception of the interactions with decision No.3 and No.7. Then the company's evaluation of the contribution will be affected by this incorrectness of the interactions. Specifically, the possible configurations of decision $(d_i; \{d_3 d_{10}\})$ and the corresponding contributions are shown in the left box of Figure 4.4 as the real contributions with the real interactions of decision d_i. As each decision can take two values (0 or 1), there are eight possible configurations of $(d_i; \{d_3 d_{10}\})$ which are shown in the first column of the left box. Since the company mistakenly perceived one of the interactions as d_7 rather than d_{10}, the evaluation of d_i's contributions will be affected by this incorrectness. We define the evaluated contribution (shown in the right box of Figure 4.4) as the contribution with correctly perceived interactions (shown in the middle box of Figure 4.4) plus a noise denoted by $\widetilde{n}$. For instance, when the perceived $(d_i; \{d_3 d_7\})$ takes the values (the configuration) of (000) or (001), the evaluated contribution will be $C\_1 + \widetilde{n}$ where C_1 is the average contribution when $(d_i; \{d_3\})$ takes the values as (00). This average contribution $C\_1 = (C1 + C2)/2$ can be derived from the real contributions $C1$ and $C2$ when $(d_i; \{d_3 d_{10}\})$ takes the values of (000) and (001).

The noise $\widetilde{n}$ is generated independently for each configuration of the decisions, and follows a normal distribution with a standard deviation which is correlated to the incorrect rate of the perceived interactions. In the example of Figure 4.4, the incorrect rate is 0.5 (one error among the two interactions), thus the standard deviation is defined as $\sigma = 0.1 * 0.5 = 0.05$. The parameter 0.1 is set to adjust the magnitude. Therefore, more accurate contributions are obtained with less incorrect perceived interactions. Besides, the contributions of each decision are time invariant with the same interaction pattern.

With the perceived interaction matrix and the corresponding evaluated contributions, each company can evaluate the fitness of strategies to obtain a

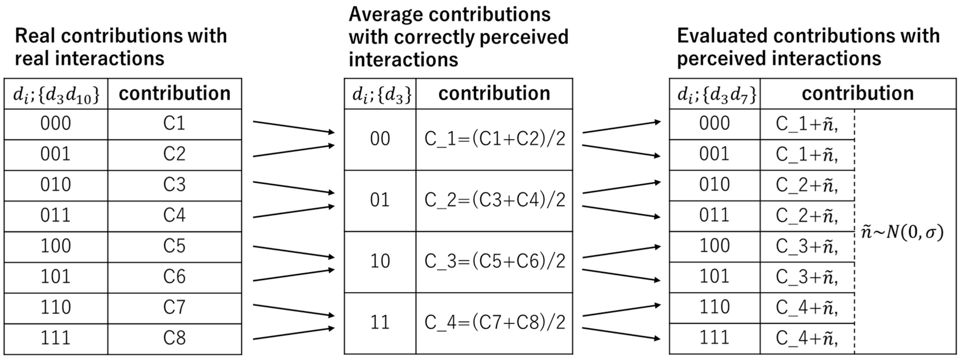

FIGURE 4.4: Mechanism of generating contribution with perceived interactions

perceived environment landscape.

4.2.3 Collaborative search process

In this research, two companies are defined as two agents, and each of them is a decision maker. The acquiring company has the authority over the decision No.1-10, while the target company has the authority over the decision No.11-16. Organization's search process is carried out by the two agents' collaboration.

At the start of each single simulation, the organization will be placed at a random point on the landscape. That is, the organization will conduct search from a random state. In each subsequent time period, the two companies (agents) conduct local search by making a choice regarding whether to alter the value of the decision elements of the strategy string (i.e. to change a decision from 0 to 1, or vice versa.) In particular, each company can randomly select one of the decisions in its subsystem and alter its value (0 or 1) based on the current strategy to obtain an alternative. Then it will evaluate the fitness of the alternative and approve it as a proposal if the fitness is higher than the one of the current strategy. On the contrary, the company will propose the current strategy if the fitness of that alternative is lower. It should be noted that each company evaluates the fitness based on its own perceived interaction matrix and corresponding contributions which are derived by the mechanism described in the last section.

Specially, three collaboration type with different decision-making order (Aggarwal et al., 2011) are adopted in this model: (I) the acquiring company search first; (II) the target company search first; (III) the two company search simultaneously. Collaboration type I indicates the case that the acquiring company has a high priority to make decisions. In each time period, the acquiring company conducts its local search based on the current strategy. Then, the target company conducts its local search based on the proposal of the acquiring company. Finally, the new strategy proposed by the target company will be implemented. Collaboration type II indicates the case that the acquiring company has the authority to make final decision before the strategy being approved. The process is opposite to collaboration type I. Collaboration type III indicates the case that the two companies are relatively independent on decision making. In each time period, two companies conduct local search based on the current strategy simultaneously and give their proposals. Then, the strategy being put into implementation will be the combination of the corresponding sub-components of the two companies' proposals (Sub-component with decision No.1-10 coming from the acquirer's proposal and sub-component with decision No.11-16 coming from the target's proposal).

4.2.4 Coupled learning process

Since both companies have incomplete knowledge about the inter-firm interactions, they may explore the possible interactions through a "try and learn" process. It is assumed the organization conducts one trial every T_L time periods and randomly select n_L number of decisions to execute a reinforcement learning process. Parameter n_L represents the incentive of the exploration, where a small n_L indicates a cautious organization while a large n_L indicates an adventurous organization.

In each trial, there are n_L^A number of decisions belong to the acquirer's subsystem while n_L^T number belong to the target's subsystem, hence, $n_L^A, n_L^T \in [0, n_L], n_L^A + n_L^T = n_L$. For each of the n_L^A (n_L^T) decisions, the acquiring (target) company determines the perceived interactions based on the "beliefs" of their expected payoffs and keeps the interactions of other decisions unchanged. Then the two companies exchange the information of determined interactions and update their perceived interaction matrices. In the following $T_L - 1$ time periods, the companies conduct search process by evaluating the fitness of strategies with their new interaction matrices. Ultimately, the companies update the expected payoffs of the determined interactions for each selected decisions according to the following rule:

$$w^i_{j,t} = w^i_{j,t-T_L} + \phi(\overline{F(\mathbf{d})} - w^i_{j,t-T_L}) \tag{4.3}$$

In Equation (4.3), $w^i_{j,t}$ indicates the updated expected payoff of the interaction No.j for decision No.i, and $w^i_{j,t-T_L}$ indicates the previous expected payoff. $\overline{F(\mathbf{d})}$, which can be obtained by Equation (4.4), indicates the average performance feedback (i.e. real performance comes from the real task environment) of the organization with strategy string $\mathbf{d}$ arisen from the search behavior in each of these $T_L - 1$ time periods.

$$\overline{F(\mathbf{d})} = \frac{1}{T_L - 1} \sum_{m=1}^{T_L - 1} F(\mathbf{d})_{t-T_L+m} \tag{4.4}$$

Parameter $\phi \in [0, 1]$, as the key parameter in this reinforcement learning process, represents the rate at which the expected payoffs are rewarded (or penalized) with the performance feedback. A high ϕ may indicate that the agent (the company) is sensitive to recognize and adapt to the feedback. This updating rule captures the two central features reinforcement learning models: (i) the reward (penalty) of the expected payoff via ϕ captures the tendency ot repeat actions that perform well while not repeating actions that perform not well; (ii) the former expected payoff $w^i_{j,t-T_L}$ implicitly represents an aspiration level of performance that depends on the history of past performance (Denrell and March, 2001; Puranam and Swamy, 2016).

Although the two companies conduct reinforcement learning within its own subsystem (the upper right and lower left areas respectively), their learning process will probably affect each other via the collaborative search result since the decision elements of the two subsystems are highly correlated to each other. Therefore, this learning process is termed as coupled learning process.

4.3 Simulation and results

In this research, two series of experiments are designed to study about organization's learning and search behavior during the post-acquisition integration. In this section, the basic settings of NK landscapes and the simulation are introduced firstly, followed by the description of the experiments setups and results. Specifically, the acquiring company's strategy contains $N_A = 10$ decisions, each of which has interactions with $K_A = 4$ other decisions. Target company's strategy is composed of $N_T = 6$ decisions, each of which has interactions with $K_T = 3$ other decisions. There are $K_B = 2$ number of inter-firm interactions emerge for each decision element of the organization during the acquisition process. Therefore, the organization's post-acquisition performance landscape can be obtained according to the process previously described in the model section. All of the simulation results are the average of 200 runnings over 50 different landscapes (4 runs times over each landscape). In each single run, the simulation time is set as $T = 1600$ time periods. Specially, different scenarios with different parameter settings are designed in the following experiments. However, only representative results of several scenarios with some particular parameter values will be shown in the main body of this chapter. Other results which are found to be similar will not be shown in this research but are available from the appendix.

4.3.1 Learning behaviors' impact on the performance

The first experiment is to discuss how the organization's learning behavior will affect its performance. The relevant parameters can be divided into 2 categories according to their implications: (i) Agents' initial knowledge about the interactions among the decisions; (ii) Agents' learning behaviors. Initial knowledge contains two parameters: proportion of the prior knowledge about the inter-firm interactions, denoted as X, and the initial belief about interaction candidates' expected payoffs, denoted as $\{w^i_{m_j}\}, \forall i \in [1, N_A + N_T]$.

Specially, two levels of X are set as $X = 80\%$ and $X = 20\%$, to represent the case that agents have good or poor knowledge about the correlations between two companies (or in other words the inter-firm interactions). As the beliefs about interaction candidates' expect payoffs are quite crucial to determine the perceived interaction matrix for each agent, three types of initial belief are designed to indicate three different initial conditions. Take decision No.2 as an example. It is firstly assumed that the summation of the expected payoffs for each decision to be unit. Thus, $\sum_m w_m^2 = 1, m \in [11, 12, 13, 14, 15, 16]$ is set for decision No.2 according to Figure 4.2 and Figure 4.3. The first type of initial belief is to set high expected payoffs to the candidate(s) which is (are) consistent to the "true interaction matrix", while to set low expected payoffs to other candidates. In particular, the summation of the high expected payoffs is set as 0.8 while the summation of low expected payoffs is set as 0.2. Since the "true interactions" are decision No.11 and No.14 for decision No.2, the initial expected payoffs of these two candidates are $w_{11}^2 = w_{14}^2 = 0.8/2$, and the initial expected payoffs of other candidates are $w_{12}^2 = w_{13}^2 = w_{15}^2 = w_{16}^2 = 0.2/4$. This type of initial belief represents the case that the agent has a preference about selecting interaction candidates and this preference is consistent to the "true landscape", and hence, this type is termed as "Correct initial belief".

The second type of initial belief is opposite to the first one, which indicates the case that the agent has a wrong perception of the interaction candidates. For instance, the agent may have a perception that decision No.12 and No.13, rather than No.11 and No.14, are likely to be the interactions of decision No.2. Thus, we assign high expected payoffs to the candidates No.12 and No.13, while low expected payoffs to other candidates. That is, $w_{12}^2 = w_{13}^2 = 0.8/2$ and $w_{11}^2 = w_{14}^2 = w_{15}^2 = w_{16}^2 = 0.2/4$ are set. In the simulation, the preferred interactions (No.12 and No.13 in this example) are randomly chosen. This wrong perception may result in a wrong perceived interaction matrix that is quite different from the real environment. Hence, we term this type as "Incorrect initial belief".

Considering the agent may not have any perception about the possible interactions, the third type of initial belief is designed, where every interaction candidates have the same expected payoffs, i.e. $w_m^2 = 1/6, m \in [11, 12, 13, 14, 15, 16]$. This type is termed as "Fair initial belief". Besides, it should be noted that only one type will be chosen to implement over all the decisions in a single simulation.

In this experiment, 18 scenarios are drawn with two levels of parameter X, three types of initial beliefs, in addition to three types of collaborative search that are described in section 4.3. In each scenario, three parameters of agents' learning behavior are selected in the following ranges, respectively: reinforcement learning parameters $\phi \in [0.1, 0.8]$, $n_L \in [1, 3]$, $\tau = 0.1$, and learning frequency parameter $T_L \in [5, 50]$. Figure 4.5 and Figure 4.6 show the representative results about how the reinforcement learning parameter ϕ and n_L affect the organizational performance with different initial knowledge. Specifically, these results are based on the parameter $X = 20\%$, $T_L = 5$, and search collaboration type III.

Figure 4.5 shows the organization's learning performance at each learning time period. The learning performance is measured by the correctness of the perceived inter-firm interactions (the y-axis in each graph). Specifically, this correctness is defined as the percentage of the correct interactions among the perceived inter-firm interactions (i.e. in the yellow area of the interaction matrix). According to the results in three panels, the "initial beliefs" are found to be quite influential to the learning performance. The organization obtains a high (over 0.9) learning performance when agents' have "correct initial beliefs", yet obtains a very low performance (less than 0.05) when agents' have "incorrect initial beliefs". However, learning performance in the case of "Fair initial beliefs" is found to be robust at a medium level (around 0.2-0.3). Parameter ϕ, which indicates the sensitivity of the performance feedback in updating the expected payoffs of interaction candidates, is found to have opposite effect to the learning performance in cases of "correct initial beliefs" and "incorrect initial beliefs". Small ϕ improves the performance when initial beliefs are correct, yet deteriorates the performance when initial beliefs are incorrect. On the contrary, large ϕ has an opposite influence. Parameter n_L, which indicates the number of decisions that are chosen to execute learning at each time, is found to have the same impact in most cases: large n_L can intensify the improvement or the decline of the performance.

Figure 4.6 shows the organization's search performance at each search

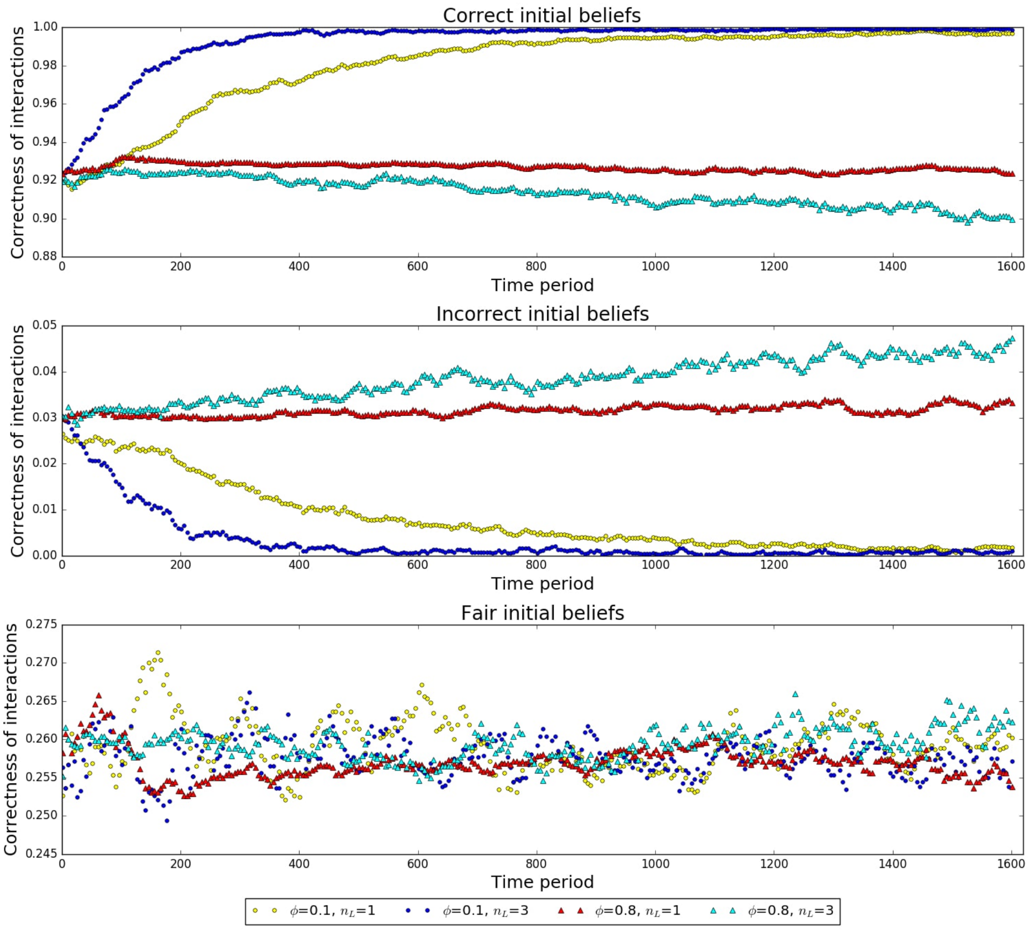

FIGURE 4.5: Organization's learning performance with different ϕ and n_L ($X = 20\%$, $T_L = 5$, search collaboration type III)

time period. The search performance is measured by the fitness value (according to the "true landscape") of the organization's proposed strategy. Comparing the results in three panels, agents' "initial beliefs" about inter-firm interactions are found to have similar effects to organization's search performance and learning performance. "Correct initial beliefs" could result in high learning and search performance, yet "incorrect initial beliefs" leads to low learning and search performance. Lower ϕ is found to have positive effect to the search performance in most cases and larger n_L could intensify this effect. According to the NK model, interactions between decisions are essential factors in evaluating the fitness of the strategy. More correct perceived interactions

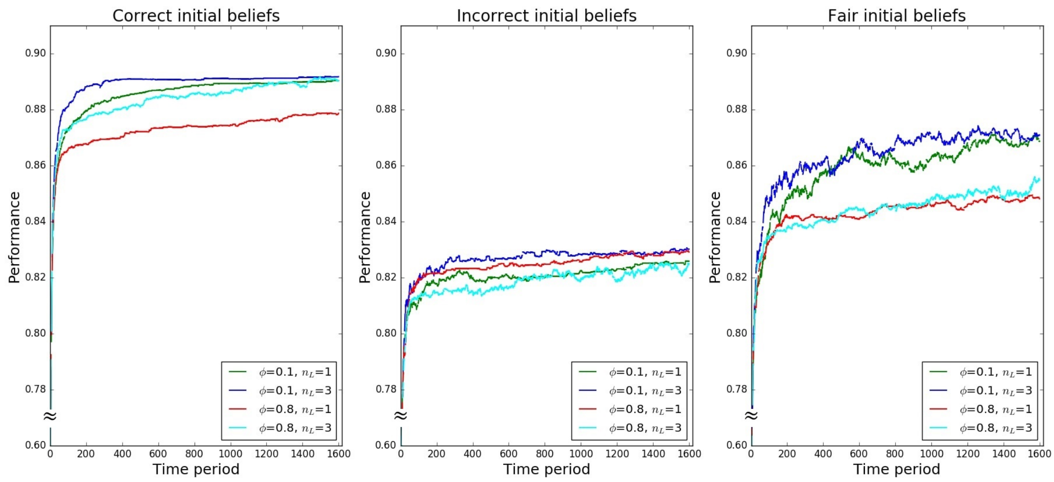

FIGURE 4.6: Organization's search performance with different ϕ and n_L ($X = 20\%$, $T_L = 5$, search collaboration type III)

could help agents evaluate the fitness more properly. Thus, the results of organization's learning performance and search performance are generally consistent.

Figure 4.7 and Figure 4.8 present the representative results about the impact of learning frequency parameter T_L to the organizational performance with different initial knowledge. Specifically, these results are based on the parameter $X = 20\%$, $\phi = 0.1$, $n_L = 1$ and search collaboration type III. According to Figure 4.7, large T_L, which indicates large learning time interval or low learning frequency, could weaken the learning efficiency unless agents' have "fair initial beliefs" about inter-firm interactions. In particular, large T_L could prevent the organization from getting high performance when agents' have "correct initial beliefs", while protect the organization against low performance when agents have "incorrect initial beliefs". This feature is suitable for both levels of X. According to Figure 4.8, organization's search performance with the impact of different "initial beliefs" are found to be similar to Figure 4.6 in the case of $X = 20\%$. Moreover, frequent learning (small T_L) is found to have positive influence to the search performance in the case of "Correct initial beliefs" and "Fair initial beliefs". However, in the case of $X = 80\%$, organization's search performance in different scenarios are almost

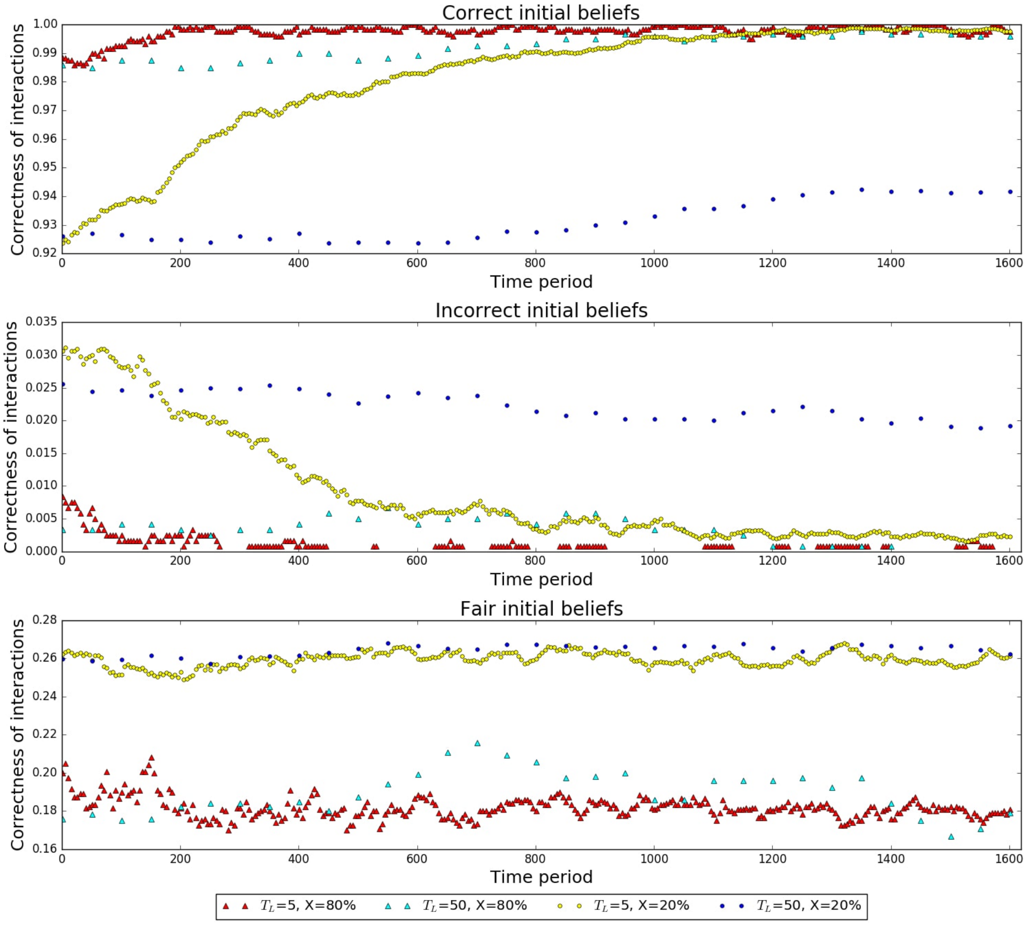

FIGURE 4.7: Organization's learning performance with different T_L and X ($\phi = 0.1$, $n_L = 1$, search collaboration type III)

at the same level. The probable reason is that the percentage of the total correct inter-firm interactions are quite high (as a minimum of 80%) with three types of "initial beliefs", although the percentage of the correct perceived interactions are different. The correctness of interactions are in the range of [80%, 100%]. Thus, the search performance are almost at the same level.

Consequently, companies' "initial beliefs" about inter-firm interactions are quite influential for the organization's learning and search performance. Generally, the organization in which the agents have "fair initial beliefs" about the interactions is likely to perform steadily at a medium level being robust to other learning behaviors. However, organization's performance is found

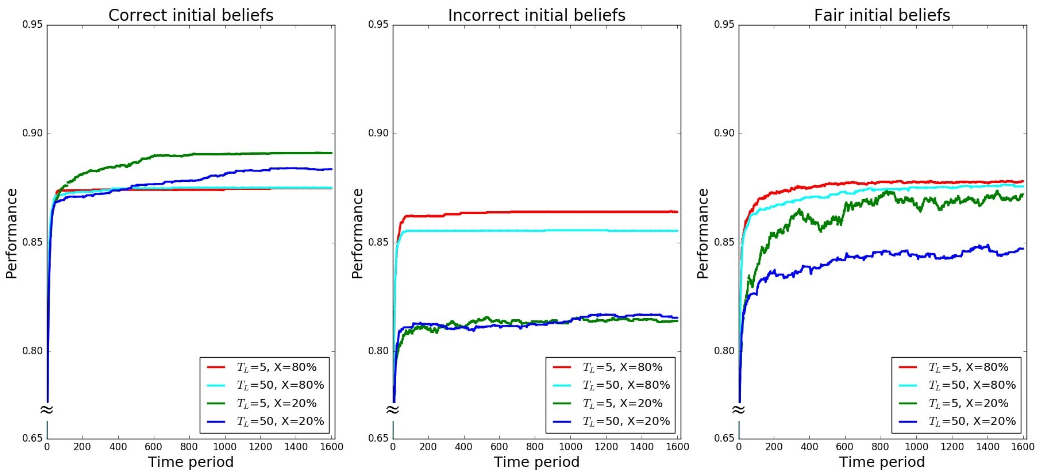

FIGURE 4.8: Organization's search performance with different T_L and X ($\phi = 0.1$, $n_L = 1$, search collaboration type III)

to be sensitive to other learning behaviors when the agents' have "correct initial beliefs" or "incorrect initial beliefs". Specifically, reinforcement learning parameter ϕ, which represents the sensitivity of performance feedback in updating "beliefs" about interactions, could have opposite impact to organization's learning performance when agents have different "initial beliefs". However, small ϕ may help organization achieve high search performance in most cases. Larger n_L, which indicates that organization chooses more decisions to conduct learning process at each time, could accelerate the learning progress and intensify the learning results. Besides, large T_L could slow down the learning progress and weaken the learning efficiency, and hence, do harm to the organization's search performance.

4.3.2 Search behaviors' impact on the performance

The second experiments is to discuss how the organization's search behavior impact its performance. In this experiment, scenarios are also designed with two levels of X, three types of agents' "initial beliefs" and three types of collaborative search process. Whereas, one of the search behavior which is termed as "search radius (parameter SR)" (Aggarwal et al., 2011) will be released. Specifically, search radius is defined as the number of decisions can be changed in each time of search. As a base case described in section 4.3

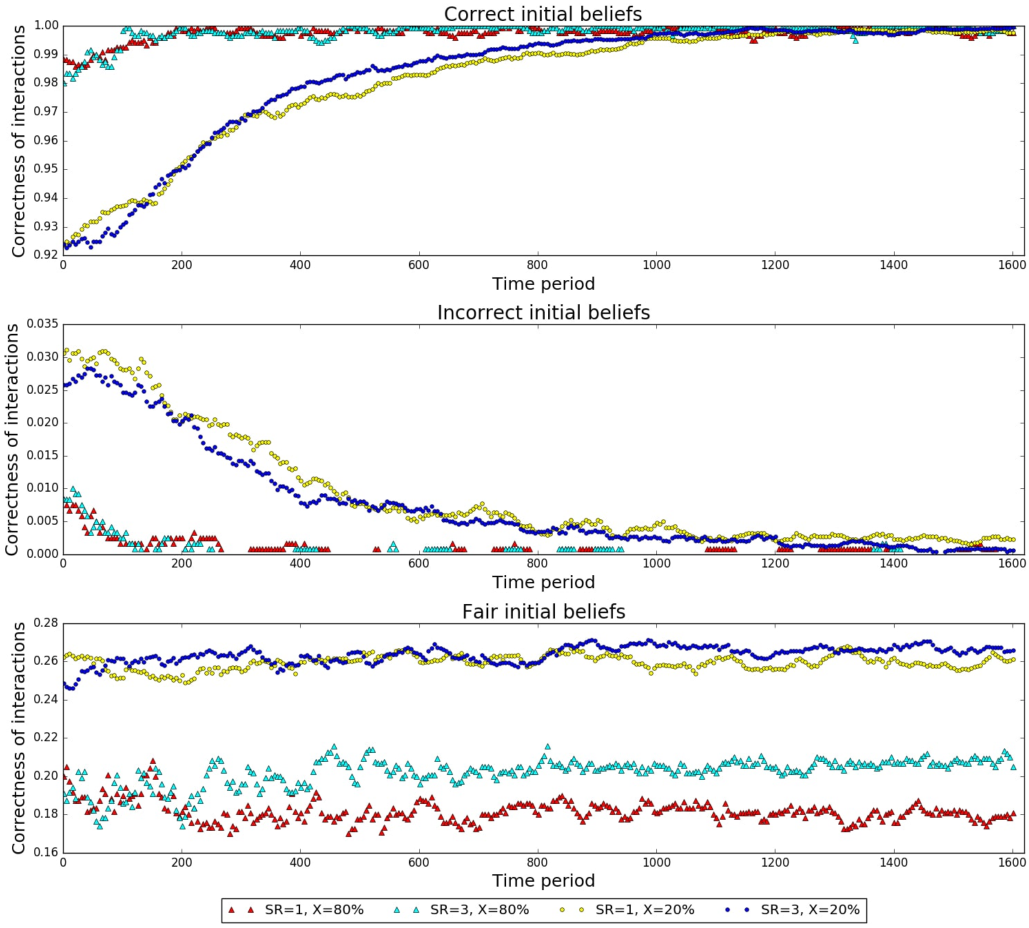

FIGURE 4.9: Organization's learning performance with different SR and X ($\phi = 0.1$, $n_L = 1$, $T_L = 5$, search collaboration type III)

in which agents can change the value of only a single decision in each time of search (SR=1) was executed in the previous experiments, a more complex case in which agents can change the values of three decisions simultaneously (SR=3) will be executed in this experiment. To focus on the search behaviors, learning behavior parameters are set to be fixed, particularly: $\phi = 0.1$, $n_L = 1$, and $T_L = 5$.

Figure 4.9 and Figure 4.10 show the representative results of the effect arisen from different SR and X. Same as previous experiments, the results of search collaboration type III are chosen for discussion. According to Figure 4.9, the organization's learning performance is basically consistent to the result of previous experiment, and search radius shows little impact to the

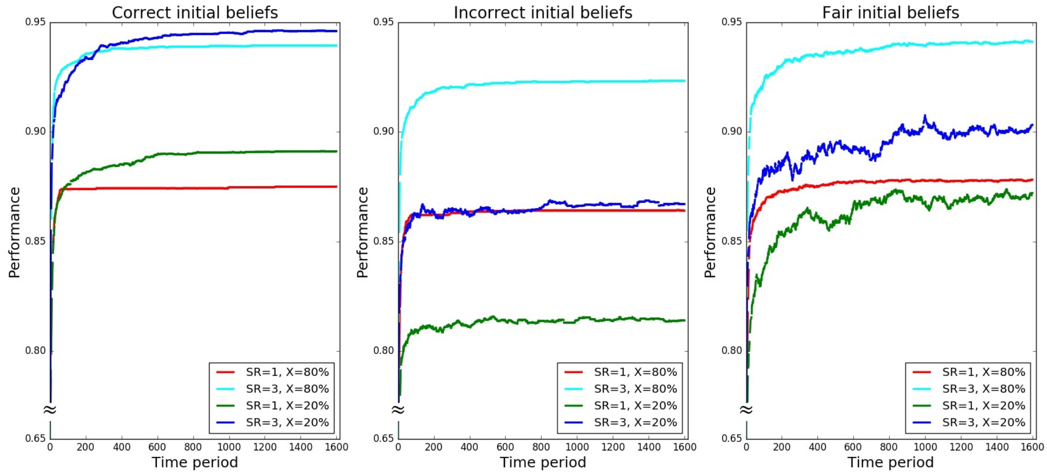

FIGURE 4.10: Organization's search performance with different SR and X ($\phi = 0.1$, $n_L = 1$, $T_L = 5$, search collaboration type III)

learning performance in most cases. Nonetheless, organization's search performance is found to be quite sensitive to the SR according to Figure 4.10. Large search radius can significantly enhance organization's search performance in all cases. Since complex interdependencies exist between decisions, the landscape could be rugged with many local peaks. Agents could easily get stuck on the local peaks during search process. However, an increase in the search radius could reduce the chances that agents being trapped in theses local peaks (Aggarwal et al., 2011).

4.4 Summary

This chapter proposes an agent-based model to study companies' knowledge learning behavior during post-acquisition integration phase. Especially, the "knowledge" is modeled as the companies'recognition/perceptions of the changed environment resulted from the acquisition. As the companies merge together, their external environment could change. However, both companies may have limited knowledge about the new environment due to the lack of knowledge about each other. Then, a collaborative search process and a coupled learning method over the NK landscapes are proposed to study the organizational behaviors in the knowledge learning process. Then, simulations are designed to study the effect of learning and search behaviors to the organizational performance during the post-acquisition integration phase.

According to the simulation result, companies' "initial beliefs" about inter-firm interactions are quite influential for the organization's learning and search performance. Generally, the organization can obtain high performance if the acquirer and target have "correct initial beliefs" about the unknown knowledge, whereas it may get much lower performance if they have "incorrect initial beliefs". The organization performs steadily at a moderate level when the the acquirer and target have a "fair initial beliefs" with no bias to the unknown knowledge. Since this "initial belief" represents each company's perception about the correlations between two companies, it can reflect the company's perception or knowledge about the other company to some extent. Therefore, proper knowledge and correct perception about the partner can benefit the companies' performance after acquisition, however, an improper perception or misunderstanding about the partner, rather than lack of knowledge, could hinder the organization from getting high performance after acquisition.

Moreover, reinforcement learning parameter ϕ, which represents the sensitivity of performance feedback in updating companies' perception about the inter-firm interactions, could have opposite impact to organization's learning performance when companies have different "initial beliefs". Basically, higher sensitivity of performance feedback (large ϕ) may help organization "revise" the impact of the "initial beliefs", while lower sensitivity of feedback could reinforce the impact of the "initial beliefs". Furthermore, frequent learning (small T_L) can accelerate learning progress and intensify learning efficiency, whereas infrequent learning will weaken the learning efficiency and do harm to the organizational performance. Besides, organization's search behaviors such as different search radius and decisions making order are found to have no impact to organization's learning performance. However, search radius is found to be quite influential to the organization's search behavior. In short term, organization can obtain a high performance by increasing search radius to complement the effect resulted from the lack of knowledge.

Chapter 5

Conclusions

5.1 Conclusions of this work

Mergers and acquisitions (M&A) become popular means for the development of modern corporations, but there is a high rate of failure after M&A. As long as the development of research on M&A, there is a growing interest to the post-merger/post-acquisition integration in the literatures. It is found that post-merger/post-acquisition integration has great effects on the success of the M&A. However, most of the studies are empirical researches that apply case study, meta-analysis, and/or other methodologies, and studies of post-acquisition integration from the perspective of organizational behaviors are few.

Since the behavioral theory of the firm and agent-based simulation (ABS) can help researchers to model companies with various scales, different interaction topologies, diverse decision-making heuristics, various learning or adaptive rules, as well as different environment, they are widely used in the context of organizational studies to discuss different factors that could affect the company's performance such as structure design, behaviors of individuals' in decision-making, and so forth. Thus, this research aims to study the post-acquisition integration from the perspective of behavioral theory of the firm by using agent-based modeling and simulation. Especially, this research is composed by two topics: 1) Human integration strategies during the post-acquisition integration phase; and 2) Knowledge learning during the post-acquisition integration.

Chapter 3 presents the first topic, in which a multi-level agent-based model is proposed to study the effect of post-acquisition integration. In particular, the two companies' original developments are defined as two NK landscapes, and the post-acquisition integration process on both the landscapes and the structures of two companies are modeled. Then a multi-level hierarchical search process is elaborated to simulate the organization's behavior in finding good strategies.

According to the simulation results, top manager's feedback is found to have essential impact to the organization's search performance. Excessive feedback from high levels may help the company quickly find some good strategies, but it may restrict employees' and managers' cognition to search for other possible strategies. Thus, it could easily make company's search get stuck with low performance. Without feedback, company's search process is dominated by low level employees' cooperation, and can usually obtain good strategies with high performance. Also, frequent meetings among the employees may do harm to the search performance by occupying employees' search time as well as make their cognition quickly converge. Moreover, for the case that the acquiring company has to allocate employees from target company after the acquisition, arrange employees who take charge of highly relevant tasks to work together (rather then assign the new comers together) could help the company get high performance.

Chapter 4 presents the second topic, in which a company-level agent-based model is proposed to study organization's learning behavior during post-acquisition integration. Specifically, the post-acquisition integration is modeled as the two companies merging together and conducting collaborative search on an integrated landscape. The companies are assumed to have limited knowledge about each other, and hence about the new environment after the acquisition. Then, the incomplete knowledge of both companies are defined, and a coupled learning model with a collaborative search process is proposed. Finally, simulations are implemented to study the effect of learning and search behaviors to the organizational performance.

According to the simulation result, companies' "initial perception" about the new environment are quite influential for the organization's learning and search performance. Generally, the organization can obtain high performance if the acquirer and target have correct perceptions, whereas it may get much lower performance if they have incorrect perceptions. The organization performs steadily at a moderate level when the the acquirer and target have no (biases in the) initial perception of the new environment. The sensitivity of performance feedback in updating companies' perception about the environment, could have opposite impact to organization's learning performance when companies have different "initial perceptions". Basically, higher sensitivity of performance feedback may help organization "revise" the impact (both positive and negative) of the "initial perceptions", while lower sensitivity of feedback could reinforce the impact (both positive and negative) of the "initial perceptions". Furthermore, frequent learning can accelerate learning progress and intensify learning efficiency, whereas infrequent learning will weaken the learning efficiency and do harm to the organizational performance. Besides, large search radius can help organization quickly obtain high performance even with incomplete or incorrect knowledge.

5.2 Limitations and the future works

Technically, some definitions and assumptions proposed in the model of post-acquisition integration are very simple with particular design. For instance, in the first topic, the landscapes of two companies' original development is defined by special interaction patterns of decisions, and the post-acquisition interaction pattern is designed in a particular way. In the second topic, the companies' limited knowledge is applied only over the inter-firm interactions (i.e. particular areas in the matrix). These restrictions can be released in the future works.

In the context of methodology, a coupled learning method over the NK landscape is proposed in this research and it is found to be feasible according to our simulation results. However, the new environment of the companies after M&A has a relatively special interaction matrix with a four-quadrant pattern according to to the definition. This restrictions of interaction pattern can be released with many other research problems or scenarios in the future works. As NK landscape is widely used to model the complex interactions within or between the system(s), the model proposed in this work can be modified and applied in many research problems for learning the systems' complex interactions.

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Appendix A

Major Publications

1. Su, J., Jafari Songhori, M., Kikuchi, T., Toriyama, M., and Terano, T. (2017). **An Agent-Based Model for Evaluating Post-Acquisition Integration Strategies.** *New Frontiers in Artificial Intelligence. JSAI-isAI 2016. Lecture Notes in Computer Science*, vol. 10247, pp. 188-203. *Springer, Cham.*

2. Su, J., Jafari Songhori, M., and Terano, T.. **Study on the Adaptation with Learning about the Environment: The Case of Post-Acquisition Integration.** *Journal of Advanced Computational Intelligence and Intelligent Informatics.* Accepted on Jun. 8, 2018, scheduled to be published (Vol.22, No.5).

Appendix B

Introduction of the NK model

The NK model proposed by Kauffman Kauffman and Weinberger (1989) conceives the target problem in terms of a high-dimensional fitness landscape. Each component of the system constitutes a horizontal dimension, and the fitness outcome of the system constitutes the vertical dimension, thus creating a landscape function (Gavetti et al., 2005).

Unlike many fitness landscapes, the mapping from the horizontal dimensions to the fitness outcome is controlled by the interactions and the fitness contributions of the horizontal dimensions, rather than by a particular mathematical function. Parameter N of the "NK" controls the number of the system components (i.e., the number of horizontal dimensions); parameter K of the "NK" controls the number of interactions that each component has with other components.

Specifically, the target problem can be defined as an N-digit string of $\mathbf{s} = \{s_1 s_2 ... s_N\}$, where each element s_i denotes a component of the target problem. Each component makes a contribution C_i to the fitness of the entire string, and C_i depends on the value of s_i, as well as the values of K other components that have interactions with s_i, which are denoted as $\{s_j^i\} = \{s_1^i, s_2^i, ..., s_j^i, ..., s_K^i\}$. Hence, this contribution can be denoted as $C_i = C_i(s_i; \{s_j^i\})$. Then, the overall fitness of the string can be evaluated as the average of the contributions of the components, and can be expressed as Equation (B.1).

$$F(\mathbf{s}) = \frac{1}{N} \sum_{i=1}^{N} C_i(s_i; \{s_j^i\}) \tag{B.1}$$

An NK landscape can be generated by the following process.

Figure B.1 shows an example of a target problem with $N = 6$. Assume that each component s_i has interactions with $K = 2$ other components. An example of these interactions can be summarized in the form of an interaction matrix which is shown in Figure B.2. To simplify the example without loss of generality, the pattern of the interactions in Figure B.2 is generated randomly. However, it can be replaced by other types of patterns according to the exact relationships between the components of the target problem.

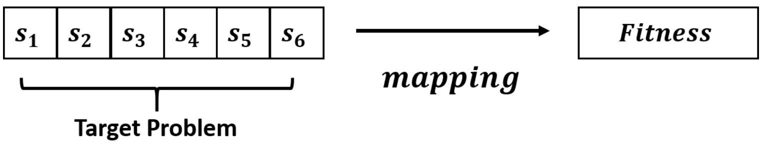

FIGURE B.1: An example of target problem with six horizontal dimensions ($N = 6$).

	Target Problem					
	1	2	3	4	5	6
1	Y		x			x
2	x	Y		x		
3		x	Y			x
4	x			Y		x
5		x		x	Y	
6	x		x			Y

FIGURE B.2: An example of the interactions between the components ($N = 6$, $K = 2$).

In Figure B.2, six numbers denotes the six components of the target problem (i.e. s_1–s_6). Mark "Y" denotes the focal component and mark "x" denotes the interactions between the exact component and the focal component. Therefore, the fitness contribution of each component can be denoted and summarized in the table of Figure B.3.

Component s_i	**Contribution C_i**
s_1	$C_1(s_1; s_3s_6)$
s_2	$C_2(s_2; s_1s_4)$
s_3	$C_3(s_3; s_2s_6)$
s_4	$C_4(s_4; s_1s_6)$
s_5	$C_5(s_5; s_2s_4)$
s_6	$C_6(s_6; s_1s_3)$

FIGURE B.3: The fitness contributions of each component of the target problem according to Figure B.2.

Since the fitness contribution of each component $C_i = C_i(s_i; \{s_j^i\})$ depends on the value of s_i as well as the values of $\{s_j^i\}$, each component has a set of fitness contribution values with different configurations of $(s_i; \{s_j^i\})$. According to the mechanism of basic NK model, this set of fitness contribution values are generated randomly following a uniform distribution $U[0,1]$. For instance, assume each component s_i can receive two values: 0 or 1. Since component s_1 has the interactions with components s_3 and s_6, its fitness contribution set can be shown as the table in Figure B.4.

Values of $(s_1; s_3s_6)$	**Contribution $C_1(s_1; s_3s_6)$**	**Contribution values**	
000	$C_1(0;00)$	$V^{s1}_{(000)}$	$V^{s1}_{(xxx)} \sim U[0,1]$
001	$C_1(0;01)$	$V^{s1}_{(001)}$	
010	$C_1(0;10)$	$V^{s1}_{(010)}$	
011	$C_1(0;11)$	$V^{s1}_{(011)}$	
100	$C_1(1;00)$	$V^{s1}_{(100)}$	
101	$C_1(1;01)$	$V^{s1}_{(101)}$	
110	$C_1(1;10)$	$V^{s1}_{(110)}$	
111	$C_1(1;11)$	$V^{s1}_{(111)}$	

FIGURE B.4: The set of fitness contributions of Component s_1.

In Figure B.4, the first column from the left side denotes all the possible configurations of the values of components s_1, s_3, and s_6, and the seconde column denotes the specific functions of the fitness contribution of component s_1. Then, the third column denotes the exact contribution values generated for each configurations of the three components following a uniform distribution.

Thus, six sets of fitness contribution values of the six components can be obtained by the similar generation process (Figures omitted). With the sets of fitness contribution values of all the components, the fitness value of each configuration of the string can be calculated. For instance, Figure B.5 shows an example of the configuration of the string ($s = 011001$). Then, the fitness contribution value of each component s_i can be illustrated with Figure B.6.

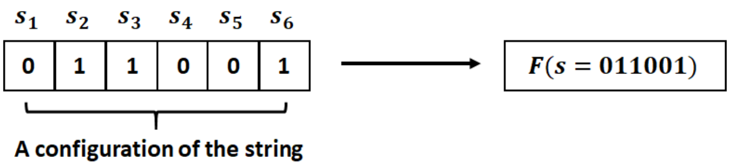

FIGURE B.5: An example of the configuration of the string.

Component s_i	Contribution C_i	Contribution with the values of components	Contribution values
s_1	$C_1(s_1; s_3 s_6)$	$C_1(0; 11)$	$V^{s1}_{(011)}$
s_2	$C_2(s_2; s_1 s_4)$	$C_2(1; 00)$	$V^{s2}_{(100)}$
s_3	$C_3(s_3; s_2 s_6)$	$C_3(1; 11)$	$V^{s3}_{(111)}$
s_4	$C_4(s_4; s_1 s_6)$	$C_4(0; 01)$	$V^{s4}_{(001)}$
s_5	$C_5(s_5; s_2 s_4)$	$C_5(0; 10)$	$V^{s5}_{(010)}$
s_6	$C_6(s_6; s_1 s_3)$	$C_6(1; 01)$	$V^{s6}_{(101)}$

FIGURE B.6: The fitness contribution value of each component with the example in Figure B.5.

In Figure B.6, the first column from the left side shows the six components, and the second column shows the function of the fitness contribution of each component according to the interaction matrix in Figure B.2. Then, according to the example in Figure B.5, the specific function of each contribution with particular values of the components can be obtained in the third column. Finally, the exact value of each function of the contribution can be obtained according to the sets of fitness contributions of the six components. For instance, for component s_1, the exact value of $C_1(0;11)$ is $V^{s1}_{(011)}$ according to Figure B.4. The contribution values of other components can be obtained by the similar means.

Finally, the fitness value of the string $s = 011001$ can be obtained by Equation (B.2).

$$F(\mathbf{s} = 011001) = \frac{1}{6}(V^{s1}_{(011)} + V^{s2}_{(100)} + V^{s3}_{(111)} + V^{s4}_{(001)} + V^{s5}_{(010)} + V^{s6}_{(101)}) \quad \text{(B.2)}$$

Summary

The process mentioned above for generating an NK landscape can be summarized as follows:

- **Step 1** - Determine the numbers of the components of the target problem (i.e. parameter N), and the values that each component can receive.
- **Step 2** - Determine the number and the pattern of the interactions among the components (i.e. parameter K and the "interaction matrix").
- **Step 3** - Generate the set of fitness contributions for each component.
- **Step 4** - Calculate the fitness value for each configuration of the N-digit string based on the "interaction matrix" and the sets of their fitness contributions.

Consequently, the shape of an NK landscape can be controlled by the interactions and the fitness contributions of the components. The complexity of the problem and the ruggedness of the landscape can be determined by the two parameters N and K.