COMPUTATIONAL MATHEMATICS FOR COMPLEX SYSTEMS, TEAMS, AND LEADERSHIP WITH EMPIRICAL RESEARCH AT UTS, AUSTRALIA

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บทคัดย่อ

งานวิจัยฉบับนี้นำเสนอแบบจำลองเชิงคณิตศาสตร์เพื่อศึกษาระบบซับซ้อน โดยประยุกต์เข้ากับปัญหาการสร้างทีมเพื่อให้ได้ทีมที่มีประสิทธิผลสูงสุด การจำลองด้วยคอมพิวเตอร์เป็นเครื่องมือในการศึกษาปัญหาการหาค่าเหมาะสมที่สุดเชิงการจัดแบบ *NP*-complete นี้ ในตอนแรก ระบบซับซ้อนเชิงเดี่ยวและระบบพหุซับซ้อนจะได้รับการปรับปรุง เพื่อให้สอดคล้องกับสถานการณ์จริงและเหมาะสมกับปัญหาการสร้างทีมมากยิ่งขึ้น สำหรับระบบพหุซับซ้อน งานวิจัยนี้ได้นำเสนอวิธีใหม่ในการกำหนดตำแหน่งของการกระทบกันในทีม โดยนำไปใช้รวมกับขั้นตอนวิธีในการแทนที่สมาชิกในทีมที่หลากหลาย เพื่อให้ได้ระบบที่ดีสุด พร้อมกับการลดจำนวนครั้งในการแทนที่และจำนวนครั้งในการทดสอบด้วย ระเบียบวิธีการแทนที่ไม่มีผลกระทบต่อค่าประสิทธิผลของทีม แต่จะให้ค่าคาดหวังของจำนวนครั้งในการแทนที่และจำนวนครั้งในการทดสอบที่แตกต่างกัน

นอกจากนี้ งานวิจัยนี้จะนำเสนอแบบจำลองเชิงการคำนวณอีกชุดหนึ่งเพื่อศึกษาการสร้างทีมแบบมีผู้นำ สถานการณ์แรกคือการเปรียบเทียบระหว่างผู้นำที่มีส่วนร่วมแบบทางตรงและทางอ้อม แบบจำลองเชิงคณิตศาสตร์ที่พัฒนาขึ้น สะท้อนให้เห็นว่า ในแบบจำลองผู้นำทางตรง การมีผู้นำที่ถูกเลือกมาจากหลาย ๆ คนจะสามารถลดความหายนะของประสิทธิผลของทีม นอกจากนี้ทักษะและน้ำหนักของผู้นำจะสามารถทำให้ค่าประสิทธิผลของทีมสูงขึ้นด้วย

อีกสถานการณ์หนึ่งคือการศึกษาในเรื่องผู้นำแบบถาวรและผู้นำแบบหมุนเวียน ซึ่งจะได้ทำการทดสอบแบบจำลองของผู้นำแบบถาวรและผู้นำแบบหมุนเวียน กับงานวิจัยเชิงประจักษ์ที่กระทำที่มหาวิทยาลัยเทคโนโลยีซิดนีย์ ผลการทดลองหลักชิ้นหนึ่งที่ได้เสนอแนะว่า สำหรับช่วงระยะเวลาที่สั้น ประสิทธิผลของทีมที่มีผู้นำถาวรจะสูงกว่าทีมที่มีผู้นำแบบหมุนเหวียน

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ABSTRACT

This thesis proposes mathematical models for studying complex systems with a specific application in the team-building problem so as to obtain the expected performance of the best system. Computer simulations are tools for studying this kind of *NP*-complete combinatorial optimization problem. Single and multiple complex systems are first examined with an attempt of making them more realistic and more applicable to the team-building setting. As for the multiple complex systems, new methods for choosing interacting positions are given and experimented. These methods use various replacement algorithms to achieve the best system with smaller expected numbers of replacements and trials. Different replacement algorithms have no significant effects on the team performance but show different results on the expected number of replacements and trials.

In addition, this thesis proposes another collection of computational models for team building with leadership. The first situation is to compare between direct and indirect contribution leadership. The developed computational models reveal that in the direct leadership model, a choice of multiple leaders can help attenuate the interaction catastrophe. Moreover, the skill level and/or the weight of the leader in both indirect and direct models are additional factors for increasing the team performance.

Another situation arises in considering permanent and rotating leadership. An empirical study for testing the validity of the permanent and rotating models is also conducted at the University of Technology Sydney (UTS). One of the main results suggests that for a short period of time, the permanent-leader team seems to perform better than the rotating-leader team.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Statement and Significance of the Problem

Complex systems can be commonly found in almost everything around us. Among others, nervous systems, body functional cells, and even teamwork in an organization are such good examples. Complex systems are classified into single complex systems and multiple complex systems. In general, a *single* complex system is a system consisting of a finite number of parts. Each part can be filled with an interchangeable component available for that part. What complicates this is the interaction among the components that makes the system *complex* and difficult for its "effectiveness" or "performance" to be measured. This problem is a combinatorial optimization problem consisting of five factors which are data, feasible solution, building block, objective function and overall objective.

On another extent, a *multiple* complex system is defined as a system having at least two subsystems, each of which is a complex system itself. The word "complex systems" is often used as a broad term encompassing a research approach to problems ranged from Science to Management. Neuroscience, Meteorology, Chemistry, Physics, Mathematics, Computer Science, Psychology, Artificial Life, Evolutionary Computation, Economics and Organizational Behavior are such examples of the research areas that involve complex systems. In that regard, studying complex systems can be academically beneficial and applicable to several problems simultaneously.

A specific application of complex systems which is also the main focus of this thesis is about how to build an effective organizational team with an objective of accomplishing as highest performance as possible. Proposed ideas in trying to make the complex system models more realistic and more applicable to the team-building problem are presented. Moreover, the concept of adding different types of leaders such as direct and indirect leadership, as well as permanent and rotating leadership into the team are also mathematically modeled and computationally experimented. Apart from this, an empirical study carried out in graduate management classes at the University of Technology Sydney (UTS), Australia which will provide significant insights and robustness for the newly proposed computational models are discussed.

1.2 The Objectives

The main objectives of this thesis are the following:

1.2.1 To propose a new method for choosing interacting positions that affect team performance on multiple complex system models and to study how different replacement approaches affect the effectiveness of the system while keeping the replacement process as efficient as possible

1.2.2 To apply single complex system models to the team replacement problem so that it contains the concept of direct and indirect leadership

1.2.3 To develop computational models for examining permanent and rotating leadership

1.2.4 To test the proposed permanent and rotating leadership models with some real-world data by conducting an empirical study at UTS

1.3 Scope of the Research

In this thesis, there are assumptions and limitations of the proposed computational models and algorithms. They are presented here as follows.

1.3.1 A multiple complex system consists of only two single complex systems, each of which is a complex system itself and has an equal size.

1.3.2 Indirect contribution of a leader to overall team performance is achieved through ordinary leading roles such as motivation and cooperation.

1.3.3 Direct contribution occurs when the leader performs not only the usual leading roles but also the tasks undertaken by a typical team member. In other words, direct-contribution leaders perform additional work extra from their usual indirect leading roles.

1.3.4 Permanent leadership refers to the situation when the team has only one leader for the entire certain period of time.

1.3.5 Rotating leadership refers, in contrast, to the situation when each and every team member alternately assumes the leader position for an equal period of time.

1.3.6 An empirical study is carried out in six classes of the Managing People course at UTS.

1.4 Benefits

The benefits to achieve in this research include:

1.4.1 A new method for choosing interacting positions of multiple complex system models

1.4.2 Single complex system models that incorporate the concept of direct and indirect leadership

1.4.3 A brand new collection of computational models for examining the concept of permanent and rotating leadership

1.4.4 An empirical result at UTS that verifies the robustness of the proposed models for permanent and rotating leadership

1.5 Research Procedure and Schedule

Steps for doing this research are summarized here.

1.5.1 Study basic knowledge, related literature and applications about complex systems, organizational behaviors, teams and leadership

1.5.2 Develop more realistic models for multiple complex systems, especially on the aspects regarding how to choose the interacting positions

1.5.3 Implement the new method of choosing interacting positions with each of the replacement algorithms, using C^{++} programming

1.5.4 Compare and contrast the results of the above experiments on the expected performance of the overall system, the expected number of replacements, and the expected number of trials

1.5.5 Study the concept of indirect and direct contribution leadership so that it can be included in the models for single teams

1.5.6 Mathematically incorporate the indirect and direct contribution leadership into the single team models

1.5.7 Computationally implement the new direct contribution leadership model using C^{++} programming

1.5.8 Compare and contrast the results of these indirect and direct contribution leadership models on the expected performance of the team with variations on the weight of the leader's contribution and the skill of the leader

1.5.9 Study about leadership types or modes as well as questionnaire surveys related to team performance and leadership roles

1.5.10 Develop brand new mathematical models for teams with rotating and permanent leadership

1.5.11 Implement the rotating and permanent leadership models using Matlab

1.5.12 Prepare a questionnaire for studying the effects of rotating and permanent leadership on team performance

1.5.13 Conduct a questionnaire survey in graduate management classes at UTS.

1.5.14 Conclude all the work and write the thesis

The tentative time schedule for each corresponding step of the research procedure is planned and shown in Figure 1.1.

Research Procedure	Month											
	1	4	8	12	16	20	24	28	32	36	40	44
1.5.1	↔	↔	↔									
1.5.2		↔	↔									
1.5.3		↔	↔									
1.5.4			↔	↔								
1.5.5				↔	↔							
1.5.6					↔	↔						
1.5.7						↔	↔					
1.5.8							↔					
1.5.9						↔	↔					
1.5.10							↔	↔				
1.5.11								↔	↔			
1.5.12								↔				
1.5.13								↔	↔			
1.5.14				↔	↔	↔	↔	↔	↔	↔	↔	↔

Figure 1.1: Tentative Research Schedule

CHAPTER 2

LITERATURE REVIEWS

In this chapter, previous mathematical models for studying complex systems are presented. In addition, previous related works, algorithms and applications are reviewed and discussed. Beginning with the models for single complex systems, it is then followed by the models for multiple complex systems. A special application of complex systems, namely, the team building problem is examined along with the additional concept of leadership. As a complement to this technical literature reviews, another collection of research articles regarding teams and leadership from the Organizational Behavior (OB) point of view are also provided in the last section.

2.1 Single Complex System Models

Modeling complex systems is one of the popular interdisciplinary research areas that require knowledge from various fields such as mathematics, statistics, combinatorial optimization, biology, and computer simulation. Applications of complex systems with interacting components can be found in many different areas such as the study of chromosome evolution [1], the study of spin glasses [2], the process of organizational change [3], and the study of building a team for performing a task in an organization [4].

Basically, a complex system here refers to a system consisting of a finite numbers of parts, each of which can be filled by one of the interchangeable components available for that part. A measure of goodness of the system called effectiveness or performance is then determined. The objective is to achieve a highest level. One problem in doing so is the complex interaction among the components in the system which affects the system performance. To be able to understand the complex system problem deeper, a mathematical model is needed. A particular mathematical model called the *NK* model was introduced by Kauffman [1] for studying chromosome evolution and subsequently applied to explain behaviors of general complex systems [5]. The study of complex systems has been extended to the concept of multiple complex systems [6][7] which is to be explained in the next section.

In the *NK* model, a single complex system consists of parts where N is a positive integer. This model views a given system $\mathbf{x}$ as a binary N-vector, $\mathbf{x} = (x_1, x_2, \ldots, x_N)$ where $x_i = 0$ means that one of the two qualified components for part i is chosen and $x_i = 1$ means that the other component is chosen, based on the assumption used in most of the previous work that, there are only two available components for each part, namely, 0 and 1. The other parameter using in this model is the nonnegative integer K ranged from 0 up to $N-1$ representing the amount of interaction among components.

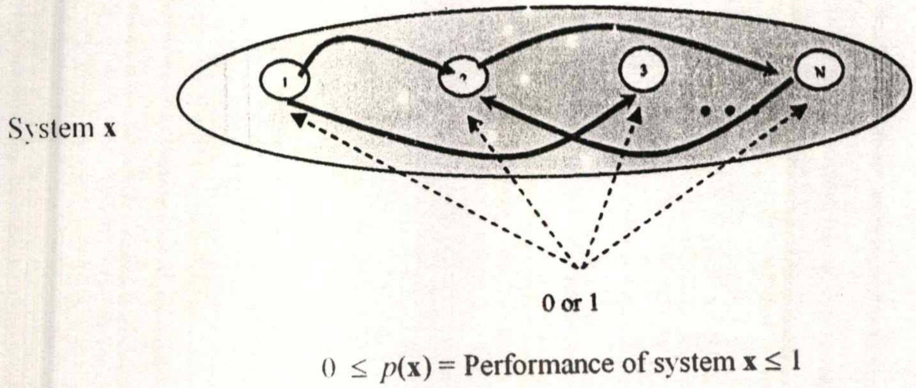


Figure 2.1: A System **x** as a Binary N –vector.

The contribution to performance of part i, namely, $p_i(\mathbf{x}_i^K)$, depends on the component in part i and also on the components in other K parts, wrapping around when necessary. Thus, $K = 0$ indicates that the contribution to performance of part i depends only on the component in part i. On the other hand, $K = N - 1$ indicates that the contribution to performance of part i depends on the component in part i and also on the components in all other $N - 1$ parts of the system. The value is chosen from one of the 2^{K+1} uniform random numbers that corresponds the combination of members in part i and the K other parts. Geometrically, each of the 2^N Binary N-vectors corresponds to a corner point of the N-dimensional unit cube, as shown in Figure 2.2 for $N = 3$.

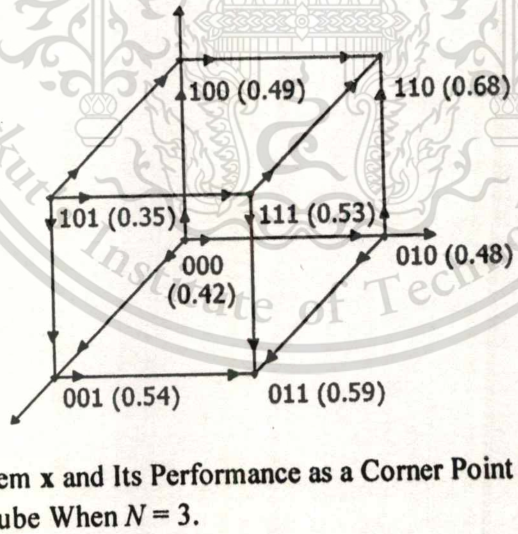


Figure 2.2: A System **x** and Its Performance as a Corner Point of the N-dimensional Unit Cube When $N = 3$.

In general, for part i, there are 2^{K+1} possible combinations of choices for the components at the K+1 parts that affect the contribution of the component in part i. So Kauffman [1] defines the value of $p_i(\mathbf{x}_i^K)$ to be one of 2^{K+1} uniform 0–1 random numbers. Specifically, it is the one that corresponds to the combination of components in part i and $K/2$ parts on either side of part i. The performance, $p(\mathbf{x})$, of system $\mathbf{x}$ is then an average of contributions:

$$p(\mathbf{x}) = \frac{\sum_{i=1}^{N} p_i(\mathbf{x}_i^K)}{N}$$

The list of all notations for use in the *NKC* model is summarized here.

- N = number of parts in a system
- $\mathbf{x}$ = a system $\mathbf{x} = (x_1, x_2, ..., x_N)$ where $x_i \in \{0,1\}$
- $x_i = 0$ means one of two qualified components for part i is chosen
- $x_i = 1$ means the other components for part i is chosen
- K = number of other components interacting with a component $(0 \le K \le N-1)$
- U[0,1] = uniform random from 0 to 1
- $p_i(x_i^K) \sim U[0,1]$ = individual performance of component x_i ,depending on x_i and K others
- $p(\mathbf{x})$ = the overall performance of system $\mathbf{x}$

Given values for N, K, and the N tables of 2^{K+1} uniform 0–1 random numbers, the collection of all 2^N binary N-vectors, together with their performance values, constitutes the *NK* model. The objective is to find a *global maximum*, that is, a system whose performance is better than the performances of all other systems. This *NK* problem has been proved [8] to be an *NP*-Complete problem. Therefore, one may need a heuristic algorithm in which a local maximum can be found. Kauffman [1] proposed a heuristic modified from mutation process in biology called the *one-replacement heuristic*. It obtains in a polynomial time a *local maximum*, that is, a system whose performance, though not necessarily optimal, is relatively good. The one-replacement heuristic involves searching all of the current system's one-replacement neighbors. A *one-replacement neighbor* of a system $\mathbf{x}$ is a system $\mathbf{x}'$ in which the component at exactly one part i of $\mathbf{x}'$ is different from the component in part i of $\mathbf{x}$, all other components being the same.

Kauffman uses computer simulations to determine the average performance of local maximum systems obtained from the *NK* model for different values of K (the amount of interaction K ranging from 0 to $N-1$). The result presented in Figure 2.3 compares the expected performance of a local maximum system in the *NK* model when $N = 20$. Figure 2.3 shows that when $K = 0$, the expected performance of a local maximum system is about 0.67; whereas, when $K = N-1$, the expected performance approaches 0.5. In addition, when the amount of interaction is small, the expected performance of a local maximum exceeds the performance of 0.67 associated with $K = 0$. Finally, as K increases, the expected performance of a local maximum decreases toward the performance of the system when $K = N-1$. This phenomenon —of decreasing performance associated with increasing interaction—is referred to as the *complexity catastrophe* or interchangeably, *interaction catastrophe* [9].

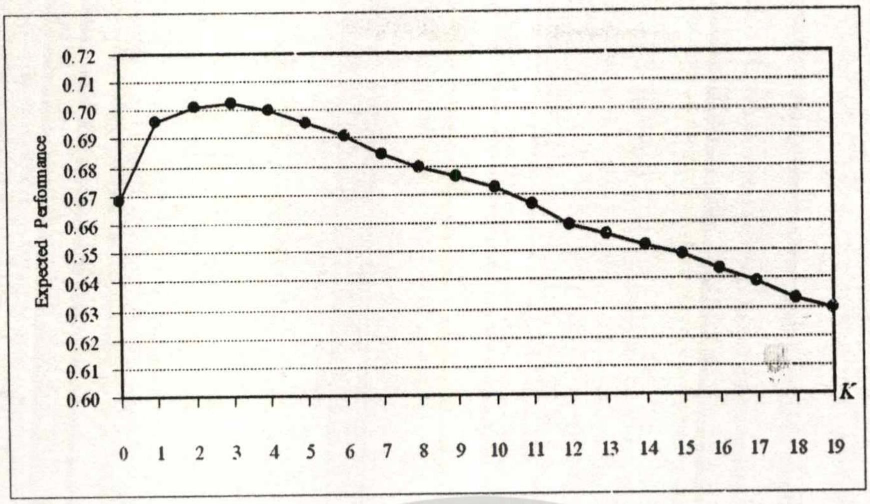


Figure 2.3: Expected Performance of a Local Maximum in the *NK* Model When N =20.

The *NK* model has been adopted by several research articles, for example, modeling the organization of innovative activity using the *NK* model [10], genetic algorithm their operators and the NK model [11], team replacement in the *NK* model [12], organizational sticking points on *NK* landscapes [13] and others on [14][15][16][17].

2.2 Multiple Complex System Models

Multiple complex systems are a generalized concept of single complex systems. They are essential due to the presence of their applications found in many areas as well. Some of them include having several departments within an organization [18][19] or coevolution of two species in an ecology system [20].

A multiple complex system is defined as a system having more than one subsystem, each of which is a complex system itself. The factors that affect the performance of the overall system become the interaction among the components both from within the same subsystem and from other subsystems. A mathematical model modified from the *NK* model for studying the multiple complex systems is called the *NKC* model where C refers to the amount of interacting components from the other subsystem. In this research, a multiple complex system is assumed to have only two subsystems and can be explained in details as follows.

The *NKC* model tries to find a multiple complex system that has the best overall performance. Feasible systems of each subsystem are binary N-vectors. Let (**x**,**y**) represent a multiple complex system where **x** is a feasible subsystem and **y** is the other feasible subsystem. In general, for part i of both systems **x** and **y**, there are 2^{K+C+1} possible combinations of choices for the components at the K+C+1 parts that affect the contribution of the component in part i. Figure 2.4 shows a combination of the components in subsystem 1. Moreover, an illustration of finding the overall performance of the *NKC* system is presented in Figure 2.5.

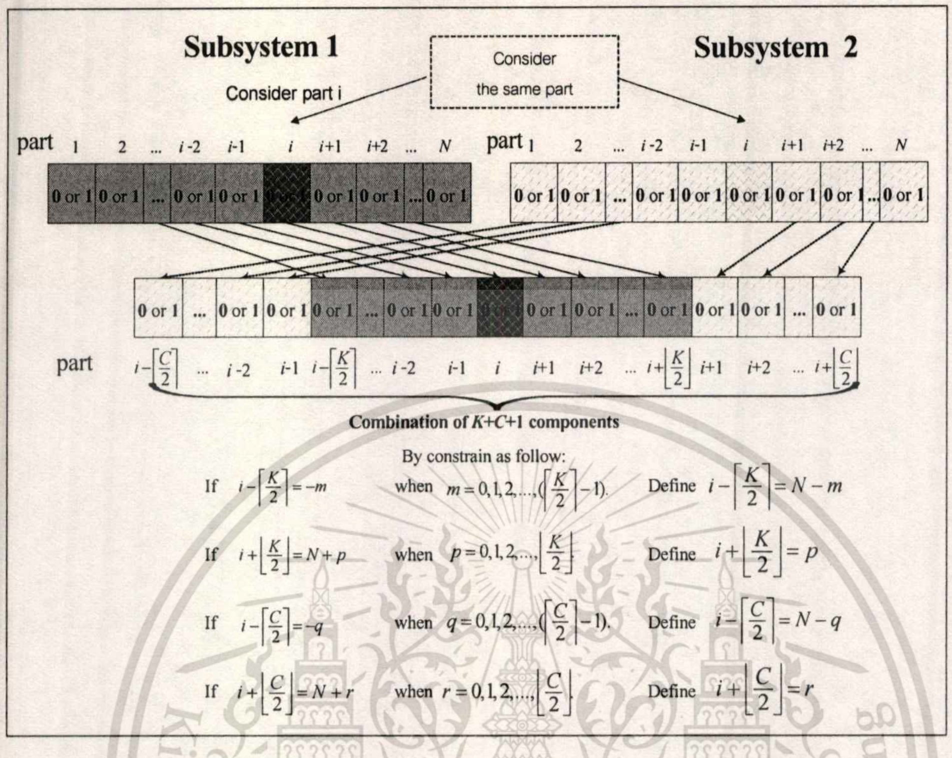


Figure 2.4: A Combination of *K*+*C*+1 Components in Subsystem 1.

So the value of contribution to performance of system **x**, $p_i = (\mathbf{x}_i^K, \mathbf{y}_i^C)$, and contribution to performance of system **y**, $p_i(\mathbf{y}_i^K, \mathbf{x}_i^C)$ is defined to be one of 2^{K+C+1} uniform 0–1 random numbers—the one that corresponds to the combination of components in part *i*, the *K*/2 parts on either side of part *i* in the same subsystem and *C*/2 parts on either side of part *i* in the other subsystem. The performance of subsystem x that is affected by subsystem **y**, $p(\mathbf{x}^K, \mathbf{y}^C)$, is then an average of these contributions:

$$p(\mathbf{x}^K, \mathbf{y}^C) = \frac{\sum_{i=1}^{N} p_i(\mathbf{x}_i^K, \mathbf{y}_i^C)}{N}.$$

Similarly, The performance of system **y** that is affected by system **x**, $p(\mathbf{y}^K, \mathbf{x}^C)$, is also an average of the corresponding contributions:

$$p(\mathbf{y}^K, \mathbf{x}^C) = \frac{\sum_{i=1}^{N} p_i(\mathbf{y}_i^K, \mathbf{x}_i^C)}{N}.$$

The overall performance, $p(\mathbf{x},\mathbf{y})$, of the multiple complex system $(\mathbf{x},\mathbf{y})$ is then an average of the average performances of the two subsystems, that is

$$p(\mathbf{x},\mathbf{y}) = \frac{p(\mathbf{x}^K,\mathbf{y}^C) + p(\mathbf{y}^K,\mathbf{x}^C)}{2}.$$

By reduction, it is shown that the *NKC* problem is also an *NP*-complete problem [7].

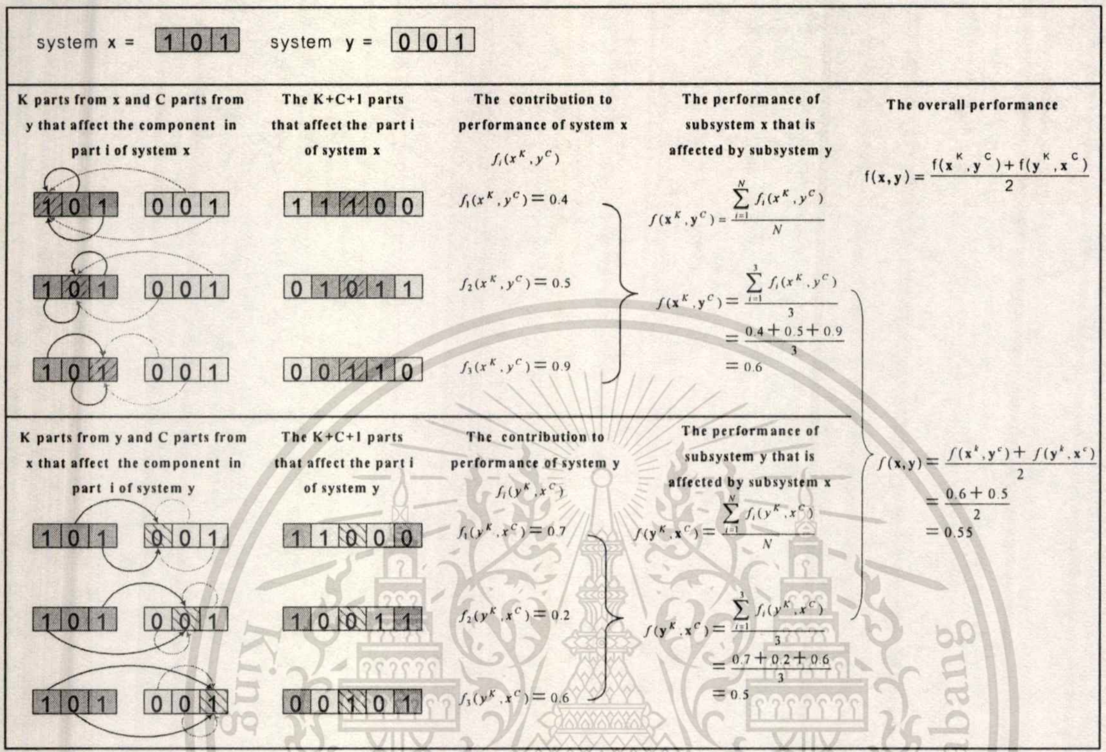


Figure 2.5: An Example of Determining Overall System Performance for *NKC* Model when $N = 3$, $K = 2$ and $C = 2$.

Computer experiments using C^{++} programming is also conducted [7] in order to study whether or not the effects of the interaction among the components are still present. The results presented in Figure 2.6 demonstrate that the complexity catastrophe still exists in the *NKC* model. Also, for any fixed amount of internal interaction *K*, small amount of external interaction *C* can increase the average overall performance of a local maximum. In turns, similar results can be drawn from the systems with a fixed *C* and different values of *K,* shown in Figure 2.7. These results suggest that, to obtain good system performance, both internal and external interactions should be kept low.

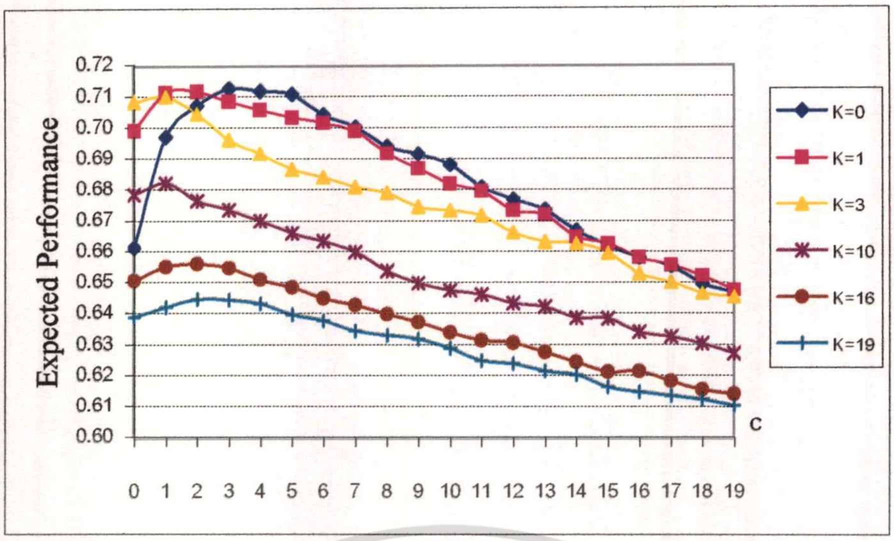


Figure 2.6: Expected Performance of a Local Maximum in the *NKC* Model as a Function of *C* for Different Values of *K* When $N = 20$.

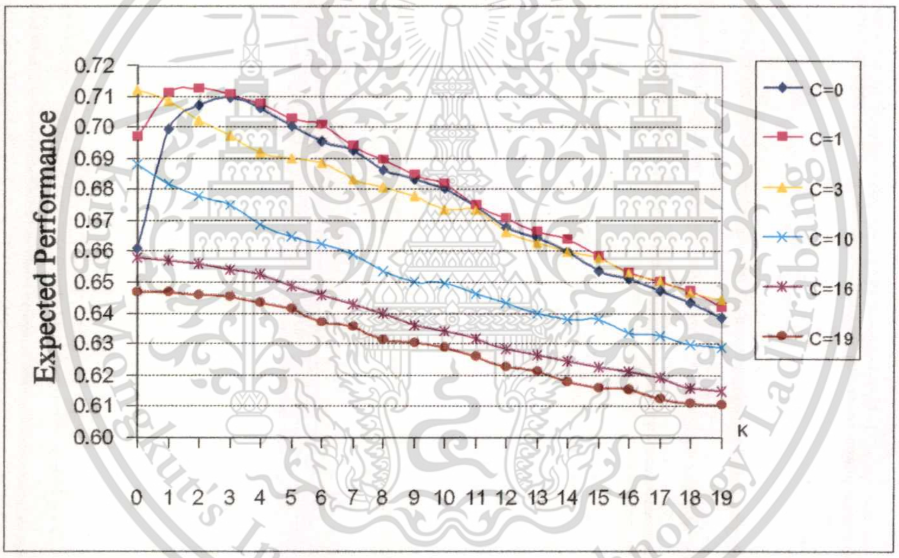


Figure 2.7: Expected Performance of a Local Maximum in the *NKC* Model as a Function of *K* for Different Values of *C* When $N = 20$.

Determining the order to consider replacing the components in the one-replacement process so as to achieve the best results at the least cost is challenging because it could consume time and effort in trying possible one-replacement neighbors before deciding to which neighbor the current system will actually move. A first step is to seek a myopic strategy that attempts to minimize the expected number of replacements needed to find a better system. Various replacement algorithms modified from [12] for using in the *NKC* model are presented here along with the explanation of general concept behind each algorithm [21][22][23].

2.2.1 Optimal Performance Policy (OPP)

In this replacement approach, the algorithm tries to obtain the best subsystem among the current subsystem and all of its corresponding neighbors. This approach considers every single component of the subsystem of interest and identifies the part to be replaced which results in highest performance for that subsystem. In particular, we first fix subsystem **y** and try replacing the component in each part of the current subsystem **x** to identify the subsystem **x′** with the best performance. If *p*(**x′**,**y**) is at least as good as *p*(**x**,**y**) for all **x** where **x** is the current subsystem and all of its neighbors, then the new system **(x′,y)** is retained and the process repeats for the subsystem **y** as well. Alternately apply this approach until a local maximum is reached.

The steps of the algorithm proceed as follows:

Step 1: Choose an arbitrary system **x** as subsystem 1 and another arbitrary system **y** as subsystem 2. Compute overall performance of this multiple complex system (**x**,**y**).

Step 2: Search all one-replacement neighbors of **x** in an attempt to find a new multiple complex system (**x′**,**y**) with better performance than (**x**,**y**). If there is no such neighbor **x′**, stop and go to Step 3. Otherwise, select the system (**x′**,**y**) whose performance is the highest and go to Step 4.

Step 3: Search all the one-replacement neighbors of **y** in an attempt to find a new multiple complex system (**x**,**y′**) with better performance than (**x**,**y**). If there is no such neighbor **y′**, stop, the current system (**x**,**y**) is a local maximum. Otherwise, set **y** = **y′** where **y′** gives highest performance among all possible systems (**x**,**y′**) and then go back to Step 2.

Step 4: Set **x** = **x′**. Then, search all one-replacement neighbors of **y** in an attempt to find a new multiple complex system (**x**,**y′**) with better performance than (**x**,**y**). If there is no such neighbor **y′**, stop and go back to Step 2. Otherwise, set **y** = **y′** where **y′** gives highest performance among all possible systems (**x**,**y′**) and then go back to Step 2.

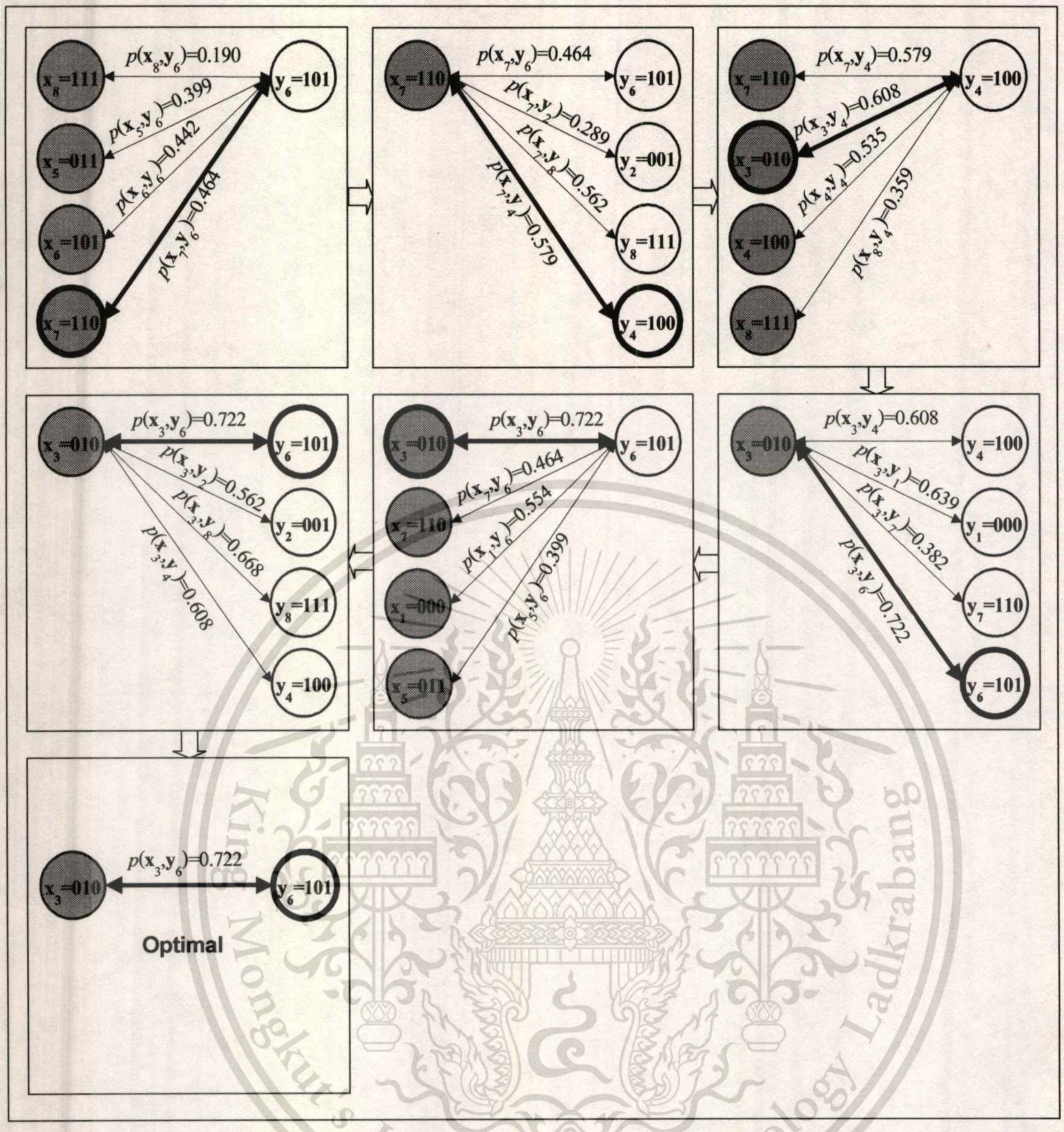


Figure 2.8: Illustration of the OPP on the Initial System (**x**,**y**) = (111,101).

2.2.2 First Come First Serve (FCFS)

This approach considers each component in the given order of the initial subsystem, the *first component* that causes a higher performance of the subsystem will be retained and the algorithm then moves to the other subsystem.

2.2.3 Random Improved-performance Policy (RIP)

This algorithm *randomly* obtains a new subsystem with better performance than the current subsystem.

2.2.4 Sorted First Come First Serve (S/FCFS)

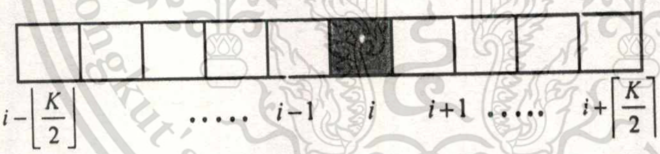
This approach is similar to FCFS except that the parts are re-sorted in increasing order according to their individual contributions. After that, the first-come first-serve rule is applied to the system.

2.2.5 Sorted First Come First Serve Based on *K* (SK/FCFS)

Similar to S/FCFS, this approach involves re-ordering the parts of the current subsystem in increasing order of $\overline{p_i}(\mathbf{x})$, the total contribution of the component in part i and all contributions of those components in the parts of the same subsystem that are affected by that component in part i. After that, apply the first-come first-serve rule to the system. In particular, we first fix subsystem $\mathbf{y}$ and sort the components of the current subsystem $\mathbf{x}$ in increasing order of total contributions $\overline{p_i}(\mathbf{x})$. Note that the parts of the parts in system $\mathbf{y}$ will change accordingly. Then, sequentially consider replacing based on this order in an attempt to find a first subsystem $\mathbf{x}'$ with $p(\mathbf{x}',\mathbf{y}) > p(\mathbf{x},\mathbf{y})$. Repeat the process for system $\mathbf{y}$ and continue in this manner until a local optimal system is reached.

For each part $i = 1, 2, \ldots, N$ of a given subsystem $\mathbf{x}$, let

$$\overline{p_i}(\mathbf{x}) = \begin{pmatrix} \text{The total contribution of the component in part} \\ i \text{ and all contributions of those components in the} \\ \text{parts of the same subsystem that are affected by} \\ \text{that component in part } i. \end{pmatrix} = \sum_{j=i-\left\lceil \frac{K}{2} \right\rceil}^{i+\left\lceil \frac{K}{2} \right\rceil} p_j\left(\mathbf{x}^K, \mathbf{y}^C\right)$$

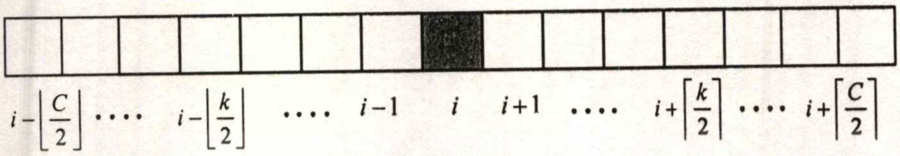


2.2.6 Sorted First Come First Serve Based on *K*, *C* (SKC/FCFS)

In this approach, the replacement still with re-ordering the parts of the current subsystem but the sorting includes the effects of external interaction form the other subsystem. In other words, all the parts are reshuffled in increasing order of $q_i(\mathbf{x})$, the total contribution of the component in part i and all contributions of those components in the parts of both the same and different subsystems that are affected by that component in part i. After words, apply the first-come first-serve rule to the system. To be more precise, the replacement algorithm starts with fixing subsystem $\mathbf{y}$ and then sorting the components of the current subsystem $\mathbf{x}$ in increasing order of the total contributions $q_i(\mathbf{x})$. Note that the parts of the parts in subsystem $\mathbf{y}$ will change according to these of $\mathbf{x}$. Then, sequentially consider replacing based on this order in an attempt to find a first subsystem $\mathbf{x}'$ with $p(\mathbf{x}',\mathbf{y}) > p(\mathbf{x},\mathbf{y})$. Repeat the process for subsystem $\mathbf{y}$ and continue in this manner until a local optimal system is reached.

For each part $i = 1, 2, \ldots, N$ of a given system $\mathbf{x}$, let

$$p^*_i(\mathbf{x}) = \begin{pmatrix} \text{The total contribution of the component in part } i \text{ and all} \\ \text{contributions of those components in the parts of both} \\ \text{the same and different subsystems that are affected by} \\ \text{that component in part } i. \end{pmatrix} = \sum_{j=i-\left\lfloor \frac{C}{2} \right\rfloor}^{i+\left\lceil \frac{C}{2} \right\rceil} \sum_{j=i-\left\lfloor \frac{K}{2} \right\rfloor}^{i+\left\lceil \frac{K}{2} \right\rceil} p_j\left(\mathbf{x}^K, \mathbf{y}^C\right)$$



2.3 Team Building and Leadership

In this section, previous models for studying single complex systems are applied to the team building problem both without and with the leadership concept. A collection of mathematical models are adapted from the *NK* model. A complex system is considered as a team having *N* job parts to be filled in with a qualified person. These people interact with each other according to the parameter *K* which refers to the amount of interaction among them.

Modification of the *NK* model concerning the team building problem that does not include leadership concept will first be examined. In the original *NK* model, there is a decrease in team performance due to the increase in the amount of interaction among team members in a large team or the interaction catastrophe. These modified models that try to attenuate the interaction catastrophe are briefly concluded here.

- Unlike the *NK* model, in the *NK/D* model [9], individual performances of team members are dependent. Particularly, this model is designed for the case when the replacement at part i results in an increased individual performance of team member i, then all individual team members' performances affected by team member i should also increase. The expression of this model when changing the team member at part i of team $\mathbf{x}$ results in the new team $\mathbf{x}'$ is shown below. More precisely, the individual performance of any team member j of team $\mathbf{x}'$ affected by team member i of team $\mathbf{x}$ is computed by.

$$p_j(\mathbf{x}') = p_j(\mathbf{x}) + \left(\frac{K-|i-j|}{K}\right)\left(\frac{Z-p_j(\mathbf{x})}{Z-p_i(\mathbf{x})}\right)(p_i(\mathbf{x}') - p_i(\mathbf{x}))$$

$$Z = \begin{cases} 1, & \text{if } p_i(\mathbf{x}') > p_i(\mathbf{x}) \\ 0, & \text{if } p_i(\mathbf{x}') \le p_i(\mathbf{x}) \end{cases}$$

- In the *NK* model, searching all *one*-replacement team members of team $\mathbf{x}$ is the heuristic that attempts to find a new better team. A modification that can naturally be tried is replacing more than one, say j where j =1,2,3,… team members at a time. With this j-replacement heuristic, it is shown that, when there is high interaction among the team members, the interaction catastrophe of the expected team performance can then be attenuated.

- *The NK/W model*: In the *NK* model [24], each team member contributes to team performance with an equal weight. This can intuitively mean that every member is equally significant. A natural modification would be to distinguish the team members so that everyone will contribute differently depending on their significance levels to the team. First, the formula for the team performance in the *NK* model could be written as:

$$p(\mathbf{x}) = \frac{\sum_{i=1}^{N} p_i(\mathbf{x}_i^K)}{N} = \frac{p_1(\mathbf{x}_1^K) + \ldots + p_N(\mathbf{x}_N^K)}{N} = \frac{1}{N} p_1(\mathbf{x}_1^K) + \ldots + \frac{1}{N} p_N(\mathbf{x}_N^K).$$

The equal weights now are $1/N$ which could be replaced by more general and different weights w_i, where $i = 1,2,\ldots,N$ and $w_1+\ldots+w_N = 1$. The formula becomes

$$p(\mathbf{x}) = w_1 p_1(\mathbf{x}_1^K) + \ldots + w_N p_N(\mathbf{x}_N^K)$$

and the weights can then be assigned individually.

Starting with the original *NK* model described in section 2.1, a leader is then added into the model so that the overall team performance now depends not only on the team members and their interaction but also on the relationship between the leader and the team members. However, in all of the previous leadership models to be explained in this section, the leader has only indirect contribution to team performance. In other words, the leader does not contribute directly to team performance but rather through the team members. Leadership roles are comprised of planning and organizing, communicating, motivating, and cooperating, just to name a few [25]. Some of these roles can be modeled mathematically but some cannot be. Apart from that, one of the following mathematical models presented here was not originally meant to include leadership explicitly but for some certain cases it can be thought of having an implicit leader.

- *The NK/W model*: This model could be seen as a leadership model as well, especially when one person has a weight larger than any other team members. This implies that the leader is the most important person in contributing to the overall team performance. In a special case, when one team member has a weight much higher than all other members, say $w_1 = w$ and so $w_j = (1-w)/(N-1)$, for $j = 2,\ldots, N$, the results show that this can attenuate the *interaction catastrophe* of decreasing performance as interaction increases, embedded in the original *NK* model. It is worth noting that this *NK/W* model is although not intended to embrace leadership explicitly, it demonstrates a subtle way of encapsulating direct contribution to team performance of the leader into the model.

Turning now to more leadership-oriented models that have been developed mathematically, two out of the various leadership roles, namely, motivation and cooperation, have been incorporated separately. Each of these skills is beneficial to enhancing the individual performance of the team members and thus the overall team performance as well. Starting with how to add a leader into the model followed by a way to reflect the motivational skill levels of the leader, the motivational leadership models [26] are summarized here.

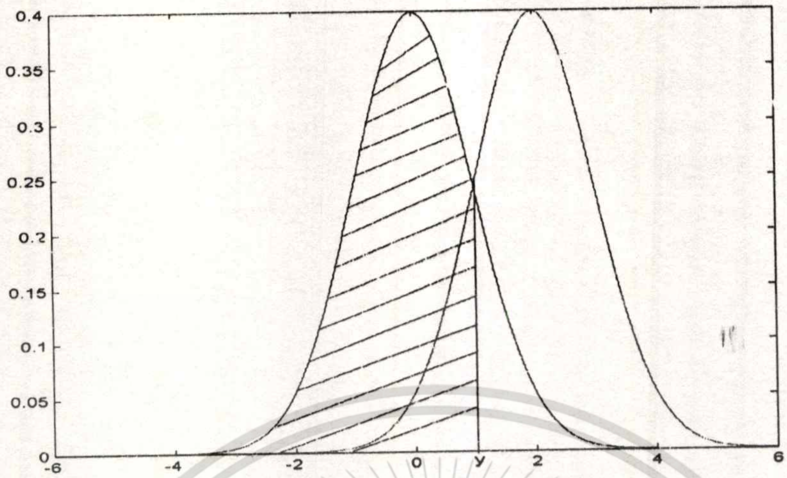
- *The NKL model*: In this model, the original *NK* model has been modified so that each team member's contribution is now not a random number between 0 and 1 but instead ranges from a lower bound $a_i(x_i)$ to an upper bound $b_i(x_i)$ where $a_i(x_i)$ and $b_i(x_i) \sim U[0,1]$ and $a_i(x_i) \leq b_i(x_i)$. The leader z then defines the contribution of member x_i through his/her relationship with that member, $r_i(x_i, z)$, as well as the following convex combination formula:

$$p_i\,(x_i,z) = (1 - r_i\,(x_i,z))\,a_i\,(x_i) + r_i(x_i,z)b_i\,(x_i)$$

  where $r_i(x_i,\ z) \sim U[0,1]$. Then the overall team performance is still the average of these individual contributions as usual. Consequently, the leader does not directly contribute to the team performance. The relationship parameter is the motivation the leader has on each team member, especially when r_i is closer to 1. However, there is no guarantee that r_i will be close to 1 and therefore the leader in this model is called a *random* leader, i.e., a leader who has no particular motivating skill. Note that there is no interaction among team members in this model. An interesting finding from computer simulation for this model shows that when having a choice of more than one leader, the performance of a local maximum team improves for small teams but starts to lose this benefit for larger teams.

- *The NKL(μ,σ) model*: In this generalized model, besides the interaction among team members, the motivational skill level of leader is also added to the *NKL* model. Two new parameters corresponding to the motivational skill of the leader, namely, μ representing the average skill and σ representing to the variability of the skill are created. The contribution range for each team member is also modified to include the interaction among team members and now becomes $a_i(x_i^K)$ and $b_i(x_i^K)$, all else being the same. In addition, $r_i(x_i,z)$ is generated from a *shifted normal distribution*, notationally, $r_i(x_i,z) \sim SN(\mu,\sigma)$. This is done by first generating a random number from Normal(μ,σ) then calculating the area to the left of that number under the Normal(0,1) curve. The main result of this model with the motivational skill level highlights that increasing the skill level of the leader helps improve the team performance despite the high level of interaction among team members. That means the skill of the leader can be more important than the amount of interaction.

Nevertheless, the leader portrayed in this model does not help reduce the interaction catastrophe.



$N(0,1)$ $N(2,1)$

Figure 2.9: An example $r_i(x_i,z) = \phi(y)$ when y is generated from $N(2,1)$

- *The NKLW(μ,σ) model*: This model is a combination of the $NKL(\mu,\sigma)$ model and the NK/W model. It is intended to take advantage of the NK/W in attenuating the interaction catastrophe particularly by assigning a weight W to the team member in part 1 of the the $NKL(\mu,\sigma)$ model much higher than all other members. The simulation results illustrate that for a fixed skill and variation of the leader, as the weight W of part 1 enlarges, the team performance improves no matter how much the interaction is. Furthermore, as W gets larger, the team performance is not inversely related to the amount of interaction and it can even be beneficial from an extremely large W.

As for the next leadership role, namely, seeking cooperation among the team members, three different models have been previously proposed [27]. Their underlying modeling ideas are presented here as follows:

- *The NKLC(μ,σ) Model*: This model is based on similar ideas used in the motivational leadership models. More precisely, in this model, it is assumed that each team member contributes to team performance within the range $[a_i(x_i), b_i(x_i)]$ and has a relationship variable $r_i\left(\mathbf{x}_i^K, z\right) \sim U[0,1]$. The difference is that the contribution range now depends only on that team member whereas the relationship variable depends also on the leader, that team member, and K other members so that it represents the cooperation level between the members the leader can achieve. Then, the individual contribution of a team member and the overall team performance are computed the same ways as in the $NKL(\mu,\sigma)$ model. Even though μ and σ are still used to represent the average skill level and the variability of the skill level of the leader, they refer to the cooperational skill, not motivational because of the change in the relationship variable. The simulation results show that a skillful leader can boost up the team performance as well as attenuate the interaction catastrophe because the high amount of interaction can still be managed by the leader who has high cooperational skill.

- *The NK(μ,σ) Model*: Applying the idea of the shifted normal distribution, the original *NK* model is simply modified by generating individual contributions from $SN(\mu,\sigma)$ rather than from $U[0,1]$. In the *NK* model, because each individual contribution already depends also on *K* other team members, it could be viewed that, without a cooperational leader, the team members already have some cooperation especially when they do not have to interact with many people. Depending on the skill level of the leader μ, switching from $U[0,1]$ to $SN(\mu,\sigma)$ provides a larger chance in obtaining a higher number and thus giving rise to a larger individual contribution. Subsequently, the simulation results reveal similar conclusions as those in the *NKLC* (μ,σ) model except that the expected team performance of skillful leader cases in this model approaches 1 as opposed to 0.8 in the $NKLC(\mu,\sigma)$ model due to the effects of the maximum contribution of each member being $b_i(x_i)$ in the $NKLC(\mu,\sigma)$ model which is less than 1 in the $NK(\mu,\sigma)$ model.

- *The NKLC(α) Model*: In this model, the idea of generating $p_i\left(\mathbf{x}_i^K\right)$ independently of each other in the original *NK* model is adjusted to include the dependency between the amounts of interaction *K*+1 and *K*. As a result, the individual contribution with *K*+1 interactions is a function of the contribution with *K* interactions and the cooperational skill of leader α being a number between 0 and 1, where 0 means the leader is skillless and 1 very skillful according to the following formula:

$$p_i\left(\mathbf{x}_i^{K+1}\right) \sim U[l_i^{K+1}(p_i\left(\mathbf{x}_i^K\right),\alpha), u_i^{K+1}(p_i\left(\mathbf{x}_i^K\right),\alpha)]$$

where $l_i^{K+1}(p_i\left(\mathbf{x}_i^K\right),\alpha) = \alpha p_i\left(\mathbf{x}_i^K\right)$ and $u_i^{K+1}(p_i\left(\mathbf{x}_i^K\right),\alpha) = (1-\alpha)[\frac{1+p_i\left(\mathbf{x}_i^K\right)}{2}] + \alpha$.

That is, the individual contribution is generated from a uniform distribution between a lower bound and an upper bound, each of which again is defined by $p_i\left(\mathbf{x}_i^K\right)$ and α in a way that when the leader has no skill, the contribution would be in the range between 0 and half way from $p_i\left(\mathbf{x}_i^K\right)$ to 1 while when the leader is very skillful, the contribution would be in the range between $p_i\left(\mathbf{x}_i^K\right)$ and 1. The simulation results indicate that the team performance with a skilless leader falls monotonically as the amount of interaction increases. In contrast, a more skillful leader can deal with higher amount of interaction leading to attenuating the interaction catastrophe as well.

With the exception of the *NK/W* model, all of the above leadership models can be called the indirect-contribution leadership models. In a later chapter, mathematical models that allow a motivational leader to perform the same tasks as an ordinary team member resulting in a direct contribution to team performance will be proposed. Similar concepts can also be applied to the cooperational leadership models with some proper modifications.

2.4 Other Work Related to Teams and Leadership

In this section, another collection of research papers concerning teams and leadership to be reviewed are presented. Organizational Behavior (OB) is the area that has long been studying about teams and leadership for quite a period of time. However, all of these research papers are different from those in the previous sections because most of them have no or little mathematical aspects in them. After all, for the completion of this thesis, these OB articles regarding teams and leadership are reviewed and discussed here.

In the following literature review, enormous amounts of papers mentioning factors that affect the performance of teams are presented. Individual learning such as experience, skill, and knowledge [28][29][30] is one of the key factors that help improve both individual and team performance. Team or organizational learning both internal and external learning is another key factor that also plays significant roles on team performance [31][32][33]. In contrast, some researchers also indicate that there are managerial problems which may adversely affect team performance. For example, some team members may become free riders or social loafers and often develop individual goals of their own, possibly different from those of the team. Therefore, every team member needs to broaden their skills and competencies in order to improve their own individual performance and thus team performance eventually.

Although individual team learning is beneficial to improving team performance [34][35], the overall performance is not the sum of performance of all individual team members, but rather only team members whose outcome are satisfied according to specific predetermined criteria. These team members interact with others so as to obtain cooperation throughout the team.

In reality, teams having no leaders are rarely found; therefore, one way or another, leaders will be placed into teams either as informal or formal leaders. In general, every team needs a person who guides and influences team members so as to obtain cooperation from them and hence the betterment of the entire team. Moreover, the leader can facilitate the team to achieve its goal and also help to improve team performance through their leadership roles which are examined in more details as follows.

In one of the initial scholarly journals focusing on the roles of leaders, Fayol [36] suggests that a leader is identified as a planner, organizer, chief, director and controller. Afterwards, according to Mintzberg [37], a leader is defined to have ten necessary managerial roles, namely, figurehead, monitor, leader, liaison, disseminator, speaker, organizer, disturbance handler, resource allocatur, and negotiator. The process for a leader in managing a team [37][38] is separated into four steps. Firstly, the leader improves and retains relationships with and among team members. Secondly, the leader obtains and provides information from and to every team member. Decision making is also one of the important steps. Finally, the leader tries to influence team members so that they can perform better on their jobs.

Additionally, the leader creates new directions and visions that motivate and communicate team members in order for them to understand new policies through words and actions and successfully achieve the goals of the organization[39][40]. Besides, the leader in an organisation that suffers from change needs to maintain the following five components, that is, self-awareness, emotional control, motivation, empathy, and social skills [41]. Indeed, the leader needs to be a person who provides knowledge and guidance to team members [42].

Besides the roles of the leader stated above, depending on by whom leadership is looked at, it can be classified into several types or modes. Mullen [43] considers different leadership modes and their productivities in a large organization. He characterizes leadership into 3 modes which are permissive or easy going leaders, recessive leaders, and authoritarian or hard-driving leaders. Moreover, Schwarzwald et al. [44] distinguish leadership modes into transactional leaderships and transformational leaderships. Apart from that according to the Makulis and Sashittal [45], leadership is divided into three modes, namely, emerging leaders, designated leaders and rotating leaders.

For the empirical study to be experimented in later chapters, small teams performing activities in a classroom also play significant roles in being a good demonstration of real-world team. Team activity has become one of the most important parts of classroom activity, especially for higher levels of education. Team activity not only appears in business programs [46] but also wide spreads into almost all other programs [47]. In addition, this practical activity in classroom [48][49][50][51] can also support students to become more accustomed to working in a real-world team.

This chapter has provided sufficient backgrounds of complex systems and their related work. Next, multiple complex systems will be examined in more details along with a proposed method for choosing interacting parts in the replacement process.

CHAPTER 3

CHOICES OF INTERACTING POSITIONS IN MULTIPLE COMPLEX SYSTEMS

In this chapter, to make the mathematical model for studying multiple complex systems more realistic, a new method for choosing the interacting positions is proposed. Computer simulation is used to show the effects of the way the interacting positions are chosen in the replacement process of multiple complex systems. More precisely, the new and existing methods are applied to the *NKC* model using also various replacement heuristic algorithms mentioned in the previous chapter for replacing a current team member with the other candidate for that position. Simulation results on the performance of the team, the expected number of replacements and the expected number of trials to a local maximum team are to be presented.

3.1 A Proposed Method for Choosing the Interacting Positions

In the *NKC* model, the current method of choosing the interacting positions is based on the neighboring positions of the concerned position. More specifically, the numbers of interacting positions both from within the same subteam (K) and from the other subteam (C) are split in half to the left and the right sides (rounded up to the left in case of odd numbers) of the considered position. For future references, this method will be called the Left-Right method (LR).

However, in a more realistic scenario, the interacting positions may be chosen from any other positions. The proposed method will employ this idea by randomly choosing the interacting positions, and hence be called the RANDOM method. In this method, the interacting positions within the same subteam can be any positions *other than* the concerned position whereas the interacting positions from the other subteam can be any arbitrary positions.

In RANDOM, some modifications on certain replacement algorithms, namely, SK/FCFS and SKC/FCFS will be needed because now the numbers of positions affected by each considered position may not be equal as they are in LR. Comparing the total contributions of all positions calculated by the summation of all associated positions would not be fair. The details of the modified SK/FCFS and SKC/FCFS algorithms are presented now.

3.1.1 SK/FCFS – An Average Approach (or SK/average)

This replacement approach is modified from SK/FCFS. It still involves reordering the positions of the current subteam but is in increasing order of $h_i(\mathbf{x})$, an average over contributions of the team member in position i and all contributions of those team members in the positions in the same subteam that are affected by that team member. Afterwards, the first-come first-serve rule can be applied to the team.

In particular, at first, the team members of the current subteam **x** are sorted in increasing order of their average contributions defined above. Note that all of the positions in subteam **y** will be reordered accordingly as well. Then, sequentially consider replacing the team members based on this order in an attempt to find a first subteam **x′** with $f(\mathbf{x}',\mathbf{y}) > f(\mathbf{x},\mathbf{y})$. Repeat the process for subteam **y** and continue in this manner until a local optimal team is reached.

For each position $i = 1, 2, \ldots, N$ in a given subteam **x**, let

$h_i(\mathbf{x}) = [f_i(x_i^K, y_i^C) + \Sigma f_j(x_j^K, y_j^C)]/[\text{Number of affected positions} + 1]$

where j = the positions in subteam **x**, affected by position i.

3.1.2 SKC/FCFS – An Average Approach (or SKC/average)

Similar to SK/average, this approach is modified from the original SKC/FCFS. The only change is similar to that change in SK/average, that is, the total contributions used in the reordering process are now the averages over the contributions of the affected positions both within the same subteam and in the other subteam. Note again that the positions in the other team will be reordered accordingly.

3.2 Computer Simulation Results and Discussions

Computer simulation has long been used to project the behavior of organizations too complex for analytical calculation [52]. Although increasingly important, modeling organization performance is more difficult than modeling individual performance because of the complexities and dynamics inherent in organization performance.

In this section, computer simulation results of the multiple-team assembly problem when the new method of choosing the interacting positions, namely, RANDOM, is used are presented. It is applied on each and every replacement algorithm previously stated. To observe the effectiveness and the efficiency of the problem, three characteristics resulted from each replacement approach will be investigated. They are the expected performance of a local maximum team, the expected number of replacements needed to reach a local maximum, and the expected number of trials needed for a local maximum.

These computer simulations are conducted using C^{++} programming. For a fixed team size $N = 40$, some fixed amount of internal interaction K, and the amount of external interaction C varying from 0 to N–1, 500 independent problems are generated randomly. Moreover, for a fixed team size $N = 40$, some fixed amount of external interaction C, and the amount of internal interaction K varying from 0 to N–1, another set of 500 independent problems are generated randomly. The computer simulation results are now presented with regard to each problem characteristic mentioned above.

3.2.1 The Expected Performance of a Local Maximum Team

When RANDOM is used in the multiple team setting for various replacement algorithms including the two modified ones, the expected performances of local maximum teams are shown in as a function of *C* when *K* is fixed at the value of 0. The results imply that, for a large team, the complexity catastrophe still exists in all of the replacement algorithms used here even though the SKC/FCFS, SK/average, and SKC/average curves show a slightly slower decrease in the expected performance as *C* increases.

In particular, when $K = 0$ and $C = 0$, the expected performance is approximately 0.67. As *C* increases toward $N-1$, the performance decreases, theoretically, to 0.5 in Figure 3.1 for a larger team. The patterns of the curves for other values of *N*, *K*, and *C* are comparable to Figure, although they are not shown in this paper. In addition, the conclusions drawn in this section are similar to those in when LR was the method for choosing the interacting positions instead. Other selection methods may be needed if the objective is to reduce the complexity catastrophe.

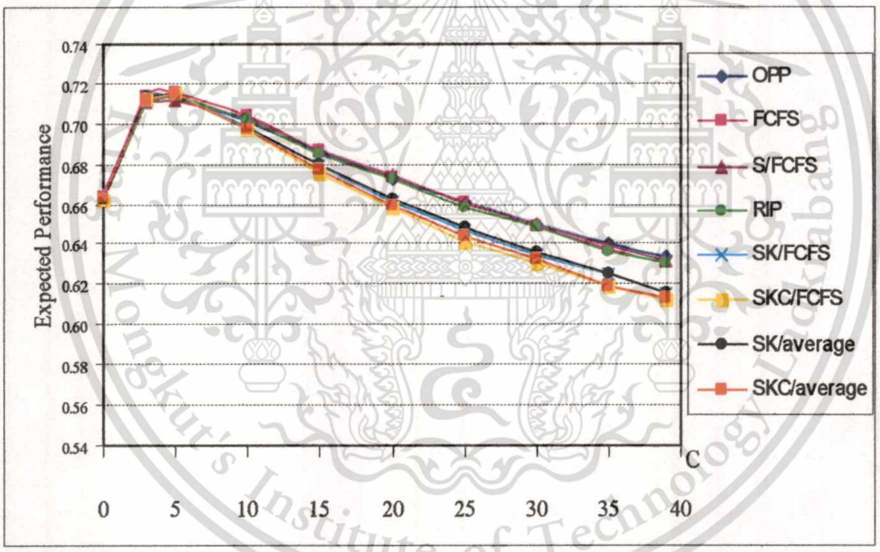


Figure 3.1: Expected Performance of a Local Maximum as a Function of *C* For Different Replacement Algorithms When $N = 40$, $K = 0$, and Random is Used.

3.2.2 The Expected Number of Replacements to a Local Maximum Team

In terms of the expected number of replacements to a local maximum, this value is shown in Figure 3.2 to Figure 3.4 as a function *C* or *K* for different replacement algorithms when RANDOM is used. Note that a qualified replacement is when a current subteam is replaced with one of its neighbors, keeping the other subteam unchanged. The process repeatedly alternates between the two subteams until a local optimum is reached. The lower this value gets, the more efficient the algorithm is.

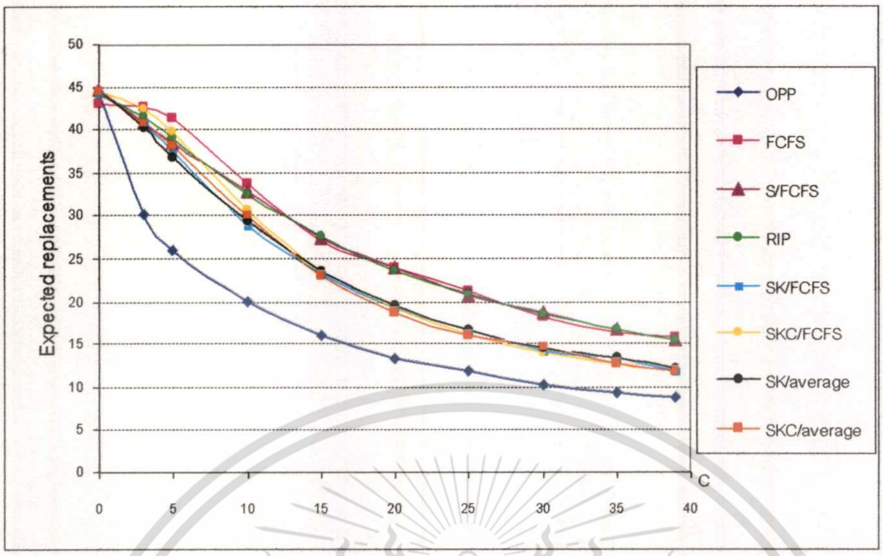


Figure 3.2: Expected Number of Replacements to a Local Maximum as a Function of *C* for Different Replacement Algorithms When *N* = 40, *K* = 0, and Random is Used.

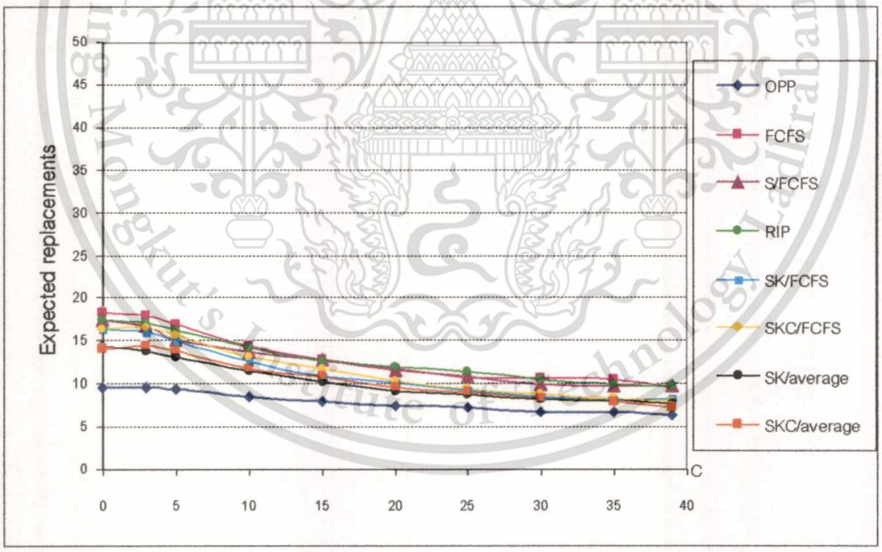


Figure 3.3: Expected Number of Replacements to a Local Maximum as a Function of *C* for Different Replacement Algorithms When *N* = 40, *K* = 20, and Random is Used.

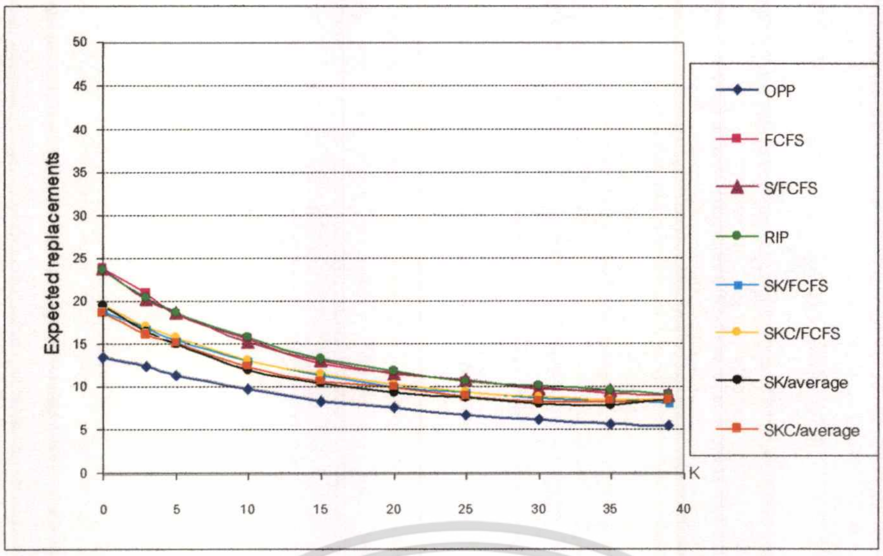


Figure 3.4: Expected Number of Replacements to a Local Maximum as a Function of *K* for Different Replacement Algorithms When $N = 40$, $C = 20$, and Random is Used.

Figure 3.2 indicates that when there is no interaction between the team members in the same subteam, OPP is the most preferred replacement algorithm. FCFS, S/FCFS, and RIP are among the least efficient algorithms. Though not most efficient, all the four interaction-based replacement algorithms are relatively good. Comparatively, when there is no external interaction, though the results are not shown in this paper, the curves are still declining. The only difference is that the SK/FCFS and SKC/FCFS curves are shifted up to the least efficient group.

Figure 3.3 and Figure 3.4 show the expected numbers of replacements to a local maximum as a function of *K* or *C*, either of which is fixed at a positive value. The two figures can lead to similar conclusions of the previous cases. In summary, according to the expected number of replacements, OPP is the most efficient algorithm because, at each iteration, it moves from a current subteam to one of its neighbors that gives the highest performance. On the contrary, all other replacement algorithms may not select the best next subteam from among all the current subteam's neighbors. As opposed to LR already examined in [23], RANDOM has only little effects on this efficiency indicator especially after some modification on the interaction-based replacement algorithms.

3.2.3 The Expected Number of Trials to a Local Maximum Team

As explained earlier in Section 1, this value is another efficiency indicator. It is counted when the algorithm considers replacing the team member in a position with the other candidate available for that position. When looked at the overall team, each and every *different* trial will be counted as one. Note that the values reported in this section are the expected values of the *total* numbers of trials needed for achieving a local maximum.

Figure 3.5 reports the expected total number of trials as a function of *C*, when *N* = 40, *K* = 0, and RANDOM is used in the process of choosing the interacting positions, for different replacement algorithms. It reveals that at the beginning when external interaction is low, the numbers of trials of OPP and RIP are relatively high compared to those of other algorithms. Nonetheless, as external interaction increases, these values seem to fall down faster. Similarly, for the case when there is no external interaction, results comparable to Figure 3.5 can be obtained for the expected number of trials as a function of *K*.

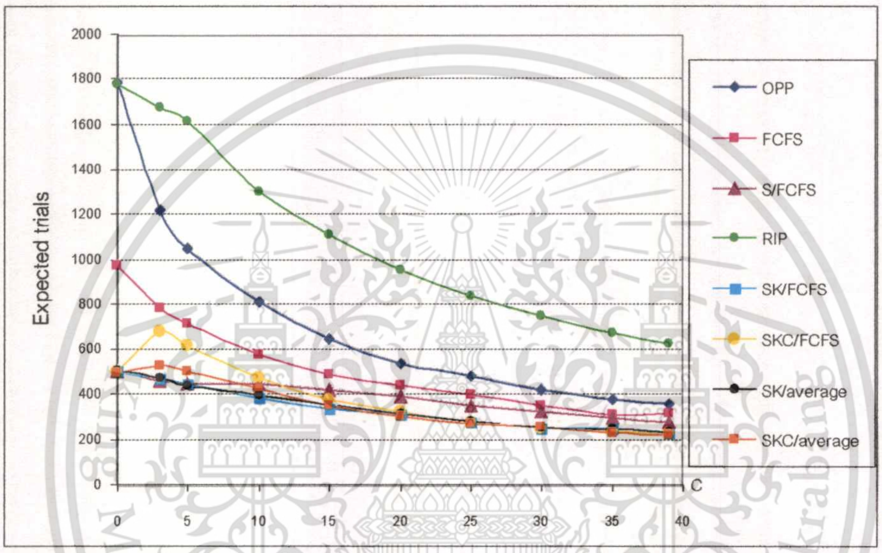


Figure 3.5: Expected Number of Trials to a Local Maximum as a Function of *C* for Different Replacement Algorithms When *N* = 40, *K* = 0, and Random is Used.

In Figure 3.6 and Figure 3.7, when both internal and external interactions are present, the patterns of the curves for all the replacement algorithms are similar to Figure 3.5 but it is clearer now that the two modified interaction-based algorithms, namely, SK/average and SKC/average outperform all other algorithms including their associated original ones.

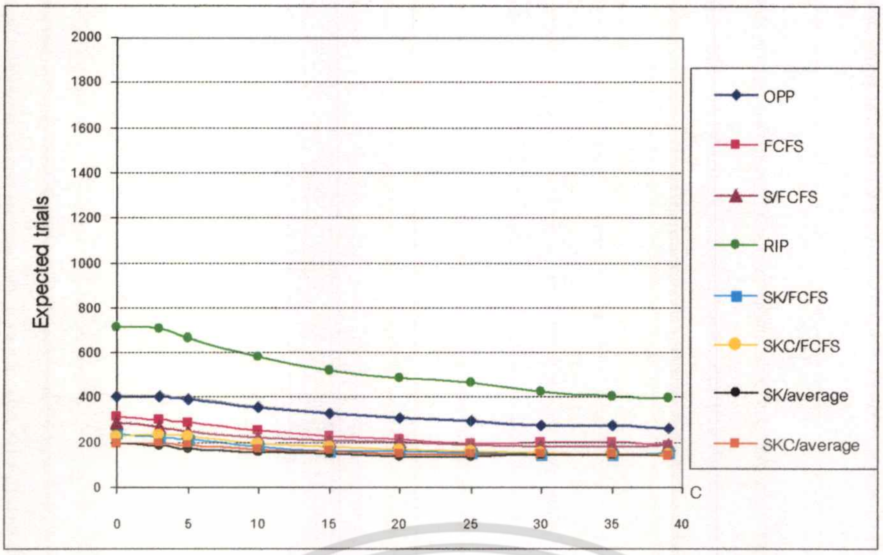


Figure 3.6: Expected Number of Trials to a Local Maximum as a Function of *C* for Different Replacement Algorithms When $N = 40$, $K = 20$, and Random is Used.

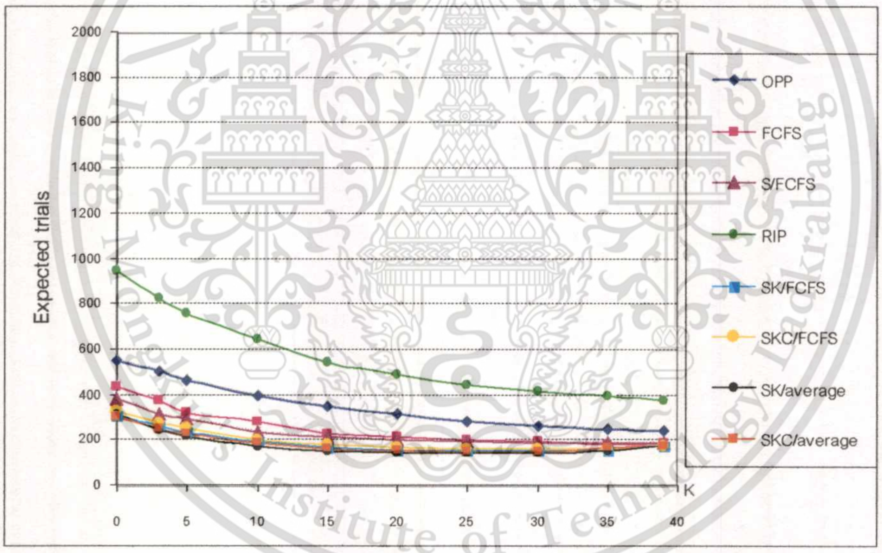


Figure 3.7: Expected Number of Trials to a Local Maximum as a Function of *K* for Different Replacement Algorithms When $N = 40$, $C = 20$, and Random is Used.

In summary, except OPP and RIP, the values of this expected number of trials for all algorithms indicate insignificant differences especially when the amount of interaction is high. The OPP and RIP curves being somewhat away from the others conform to the fact that OPP and RIP have to spend so much time checking every position before finally making the decision for a replacement.

In this chapter, the *NKC* model for studying multiple complex systems has been modified especially on how interacting positions are chosen in the replacement process.

As for the next chapter, a certain application of the *NK* model, namely, the team-replacement problem, will be presented in more details. New computational models for studying the value of direct contribution leadership will also be proposed and compared with the previous indirect contribution leadership models. Comparison of the simulation results between the direct and indirect contribution leadership models for the effects of having a choice of multiple leaders on team performance when there is no interaction among team members will be also considered.

CHAPTER 4
INDIRECT AND DIRECT CONTRIBUTION LEADERSHIP

The leader in each of the previous leadership models in chapter 2 contributes to team performance through his/her relationship with team members. Simply put, the leader does not directly contribute to team performance. Under several circumstances, in addition to traditional leading roles of leadership, the leader may have to perform the same tasks as an ordinary team member as well. Therefore, the leader has both direct and indirect contribution to team performance.

Of all the previous indirect-contribution leadership models, the motivational leadership models in chapter 2 will be modified so as to incorporate the direct contribution of the leader. Furthermore, another modification of the *NK* model using a weighted average for computing overall team performance is also considered and applied to the new direct-contribution leadership models. Compared with the simulation results from previous work, the effects of having a choice of multiple leaders in the new models on team performance when there is no interaction among team members are investigated. New simulation results of the motivational leadership models and the new models with the presence of interaction among team members are also generated and compared.

4.1 The Direct-Contribution Leadership Models

In this section, mathematical models for studying interacting teams with direct leadership are proposed. The general motivational leadership model, namely, the $NKL(\mu,\sigma)$ model, interchangeably referred to as *the indirect model* for simpler future references, will be modified to illustrate a situation such that the leader also performs, besides all the leadership roles, regular tasks as an ordinary team member. In other words, the leader takes part in contributing directly to the team performance as well.

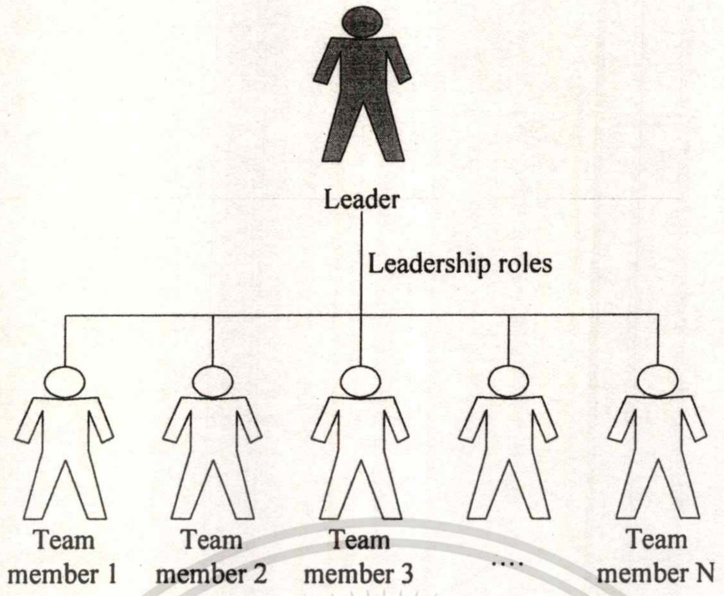


Figure 4.1: Indirect Contribution Leadership

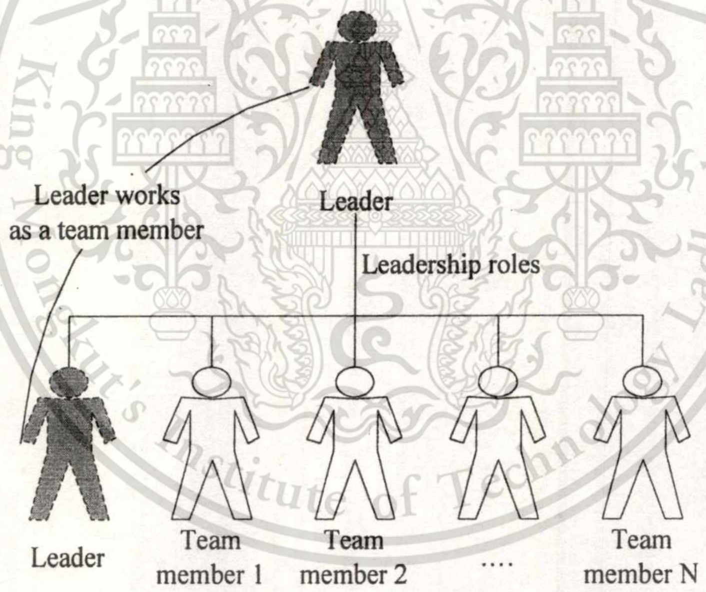


Figure 4.2: Direct Contribution Leadership

Furthermore, to increase the flexibility degree of the leader's direct contribution, the idea of using weights to differentiate each person's significance to the team will also be applied. Also, in the new models, the effects of having more than one candidate for the leader position will be examined with a comparison to the previous result from the indirect leadership model mentioned in Chapter 2. For completion, the set of all notations for later use in the proposed models is summarized here:

- N = number of positions in a team.
- K = number of other positions interacting with a team member.
- $(\mathbf{x}, z)$ = represents a team $\mathbf{x} = (x_1,\ldots, x_N)$ with leader z, where each $x_i = 0$ or 1.
- $[a_i(\mathbf{x}_i^K), b_i(\mathbf{x}_i^K)]$ = contribution range for team member x_i, depending on x_i and K others.
- $r_i(x_i,z) \sim U[0,1]$ = relationship between team member x_i and leader z.
- $p(z) \sim U[0,1]$ = direct contribution to team performance of leader z.
- $p_i(\mathbf{x}_i^K,z)$ = contribution to team performance of member x_i, depending on x_i, K others, and leader z.
- $p(\mathbf{x},z)$ = overall performance of team $\mathbf{x}$ with leader z.

In the $NKL(\mu,\sigma)$ model, it is assumed that the leader only perform his/her leading roles. In some more practical and realistic scenario, the leader may be the person who used to work as an ordinary team member and became competent in the tasks. After his/her promotion to the team leader, the leader may be required to do dual roles as both a team leader and a team member. Thus, the leader has an indirect contribution to team performance through the usual leading roles, and at the same time, a direct contribution through the tasks the leader performs as a team member. To include the direct contribution into the model, the formula for the team performance will be modified to

$$p(\mathbf{x}, z) = \frac{\sum_{i=1}^{N} p_i(\mathbf{x}_i^K, z) + p(z)}{N+1}$$

where the leader's direct contribution $p(z)$ is generated from $U(0,1)$ with the same interpretation for its values as usual. Other than this, the leader still also contributes indirectly through the motivation he/she has on the team members as reflected in the relationship parameter $r_i(x_i,z)$ and the following expression for each team member's contribution:

$$p_i(\mathbf{x}_i^K,z) = (1-r_i(x_i,z))\, a_i(\mathbf{x}_i^K) + r_i(x_i,z) b_i(\mathbf{x}_i^K)$$

This proposed model is then called *the NKL/D(μ,σ) model* or simply *the direct model* with D referring to the leader's direct contribution to team performance. For a special case when $(\mu,\sigma) = (0,1)$, this direct model is then said to have a *random leader* or the leader who does not have any particular motivating skill. Experimental results compared to those of the indirect model will be shown in Section 4.2 including the cases of multiple candidates for the leader position.

To make the model even more flexible, differentiating the significance levels of all the people including the leader accountable for undertaking the team's tasks would create a model adaptable to more situations. For example, it could happen that because the leader has to perform multiple tasks as a leader and a team member all at once, he will definitely have less time than an ordinary team member. Therefore, the contribution weight of the leader should not be equal to those of other ordinary members. On the other hand, it could be the case that, even though the leader has to do both leading and operating tasks, but because the leader is very skillful and very significant to the outcome of the team, the leader's weight then should be higher than all other team members. With these examples in mind, it would be wise to construct a model that could allow the weights of both the leader and each team member to fit every player's significance level to the team performance.

A generalization of the *NKL/D*(μ,σ) model on the weights of all the players in the team leads to a new model called *the NKLW/D*(μ,σ) *model*, interchangeably, *the weighted direct model*, in which the team performance is now not an average of everyone's contribution, instead it is the weighted average as follows:

$$p(\mathbf{x},z) = w_1 p_1(\mathbf{x}_1^K, z) + \ldots + w_N p_N(\mathbf{x}_N^K, z) + w_{N+1} p(z)$$

where $w_1 + \ldots + w_N + w_{N+1} = 1$. However, for a special case when the weights of all ordinary team members are equal and only the leader's weight is different, the team performance now becomes

$$p(\mathbf{x},z) = \frac{(1-W)}{N}\sum_{i=1}^{N} p_i(\mathbf{x}_i^K, z) + Wp(z)$$

where W is the weight of the leader. It is noted that the weights of all the members including the leader still sum up to 1 as shown here:

$$\sum_{i=1}^{N}\frac{(1-W)}{N} + W = N\frac{(1-W)}{N} + W = (1-W) + W = 1$$

This special case of the *NKLW/D*(μ,σ) model is very powerful in the sense that the leader's direct contribution to team performance could be experimented so as to appropriately fit any situation faced in practice. In the next section, along with other simulation experiments, different weights will be placed on the leader position using computer simulation to discover its effects on team performance.

4.2 Computer Simulation Results and Discussions

In this section, computer simulation results of the proposed models and new results of the indirect model together with their comparisons and discussions are presented. The simulations were conducted using C++ programming on an Intel Core 2 Duo T5450 1.6 GHz laptop computer with a 2 GB RAM. Starting with simulation results on the effects of having a choice of multiple random leaders, its effects on the team performance in the indirect and direct models are compared and contrasted for both situations when interaction among team members is present and when it is absent. Afterwards, the importance of the skill level of the leader and the changeable weight of the leader position towards the team performance will also be examined.

4.2.1 Choice of Multiple Leaders in the *NKL*(0,1) and the *NKL*/*D*(0,1) Models

In general, having a choice of something is always good. In this section, simulation results for studying the impact of having multiple candidates for the leader position on the team performance are presented and discussed.

First of all, with no interaction among team members, a choice of multiple random leaders is considered both in the indirect and direct models. Since this is the case when each team member does not have to interact with anyone else, obviously, the interaction parameter K and its associated effect, namely, the interaction catastrophe, will be out of the context here. Alternatively, an investigation will be placed on another important parameter of the model, that is, the team size N.

In Figure 4.3, the expected team performance as a function of N with a choice of 1, 2, 5, and 10 random leaders in the indirect and direct models when there is no interaction among team members is revealed. The results in both models show that for a small team, having a choice of multiple leaders helps improve the expected team performance. The more the number of candidates for the leader position is, the higher the team performance becomes, especially in the direct model when the leader can contribute to team performance both indirectly as usual and directly. On the other hand, when team size is large, in both Figure 4.3(a) and Figure 4.3(b), the performance starts to approach a certain level of 0.64 approximately. Thus, in general, having a choice of multiple leaders does not result in improved performance in large teams.

As for a special case when there is only one team leader, in the indirect model, the bottom curve of Figure 4.3(a) staying flat at approximately the algebraically-proven performance of 0.64 indicates that the team size does not affect the team performance at all.

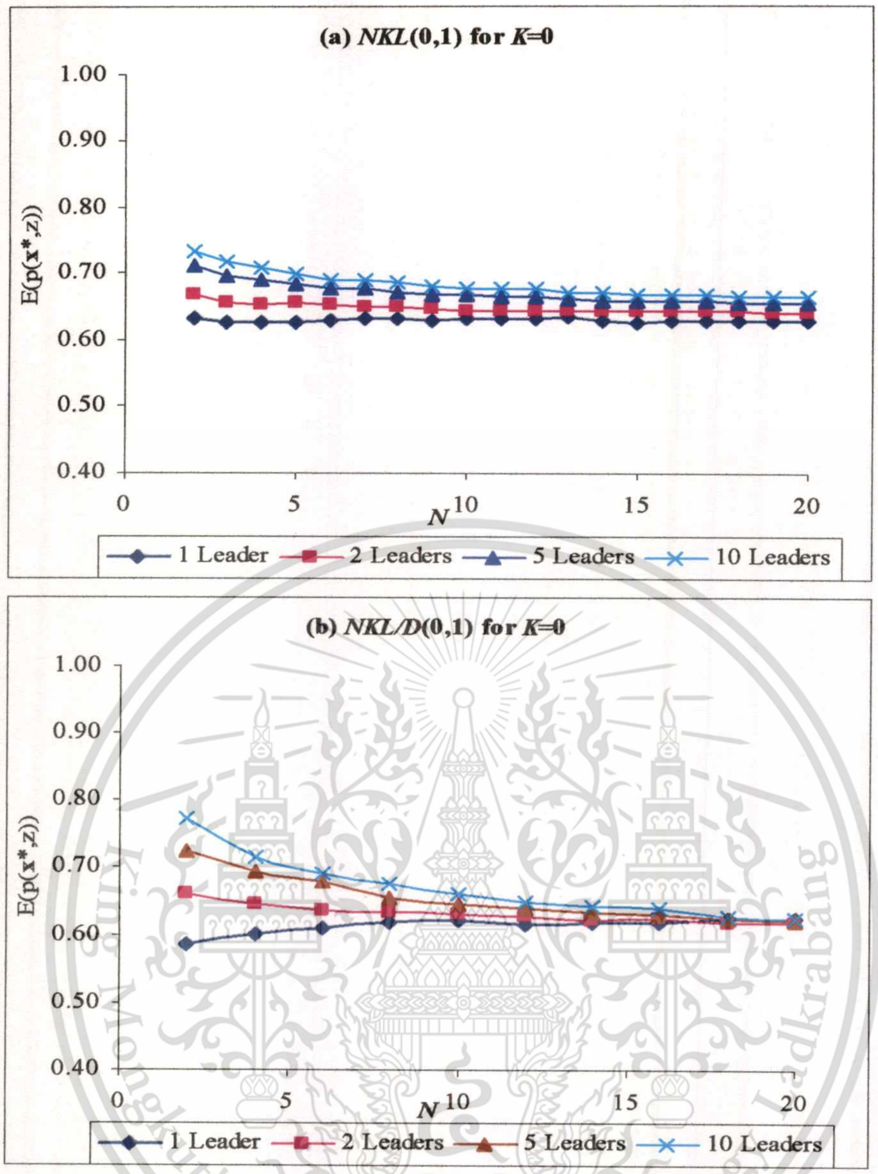


Figure 4.3: Expected Performance of a Local Maximum Team in the Indirect and Direct Models as a Function of *N* with a Choice of 1, 2, 5, and 10 Random Leaders When There is No Interaction among Team Members.

In contrast, in the direct model, the bottom curve of Figure 4.3(b) shows that the performance slightly increases as the team gets larger up to a certain size then starts levelling on towards the benchmark performance of 0.64 as in the cases mentioned previously. On average, the leader, as part of the working team, theoretically contributes 0.5 to overall team performance because his/her individual contribution is taken from a uniform distribution from 0 to 1 while a team member theoretically contributes 0.64. According to the team performance formula for the direct model mentioned in Section 3, the weight of the leader's contribution is equal to that of every other member's on the team. Hence, as the team grows larger, the leader's direct contribution to overall team performance will become smaller resulting in a convergence of team performance towards 0.64.

For a practical case in general, when the team is too small and only one random leader is available to directly participate in the team's tasks, neither the leader is skillful nor are there workforces sufficient enough to take care of all the workload for the team. Consequently, the team suffers as evidenced by the beginning of the bottom curve of Figure 4.3(b). By increasing the team size up to a certain point, the workload is shared more efficiently and hence the team performance increases.

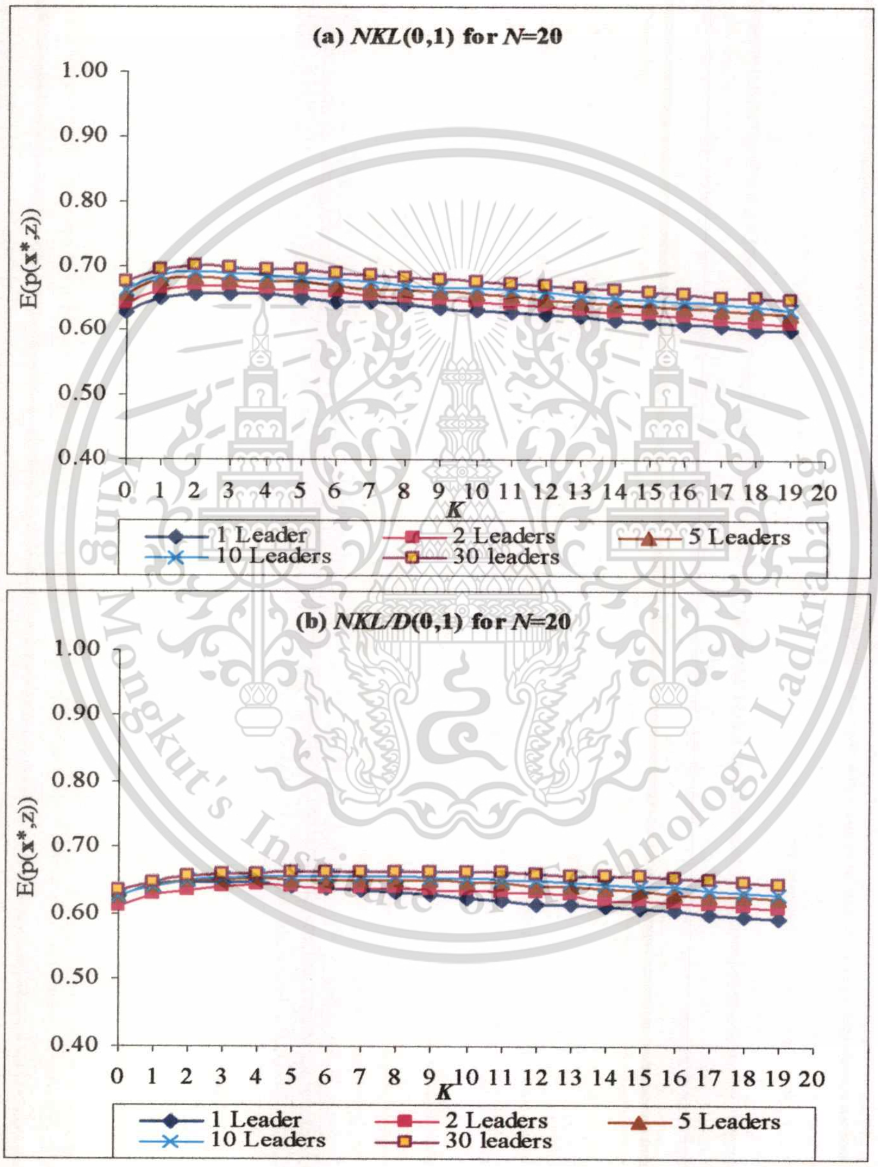


Figure 4.4: Expected Performance of a Local Maximum Team in the Indirect and Direct Models as a Function of K with a Choice of 1, 2, 5, 10, and 30 Random Leaders When $N = 20$.

In Figure 4.4, when interaction among team members is present, even though the leader has no particular motivating skill, having a choice of multiple leaders always improves the expected team performance both in the indirect and direct models regardless of the amount of interaction. Nevertheless, for the indirect model in Figure 4.4(a), the entire performance curve shifts up whereas for the direct model in Figure 4.4(b), the performance curve still shifts upward but its tails become flatter as K increases. Hence, having multiple candidates for the leader position can attenuate the detrimental effect on performance of increasing amounts of interaction among team members in the direct model but not in the indirect model.

4.2.2 Choice of Multiple Leaders in the *NKL*(μ,σ) and the *NKL/D*(μ,σ) Models

Having a choice of multiple random leaders already leads to better team performance as just described previously and can even attenuate the interaction catastrophe in the direct model. In this section, the skill level of the leader is taken into account both in the indirect and direct models to observe its effects on team performance.

Starting with the indirect model, computer simulation results in Figure 18 confirm a conclusion cited in Chapter 2 that the skill of the leader can be more important than the amount of interaction among team members when there is no choice of the leaders, i.e., only one leader with a certain skill level is assigned. This is evidenced by the bottom curves of both Figure 4.5(a) and Figure 4.5(b) because each entire curve moves up from when $\mu = 0$ to $\mu = 1$. More elaborately, the above conclusion also holds true for other cases when there is a choice of more than one leader. For another time, this is illustrated by the entire upward shifts of the corresponding curves from Figure 4.5(a) to Figure 4.5(b). In addition, besides the skill level of the leader, having multiple candidates for the leader position can improve the over team performance even more. Note that the interaction catastrophe is not, by any means, attenuated in this indirect model.

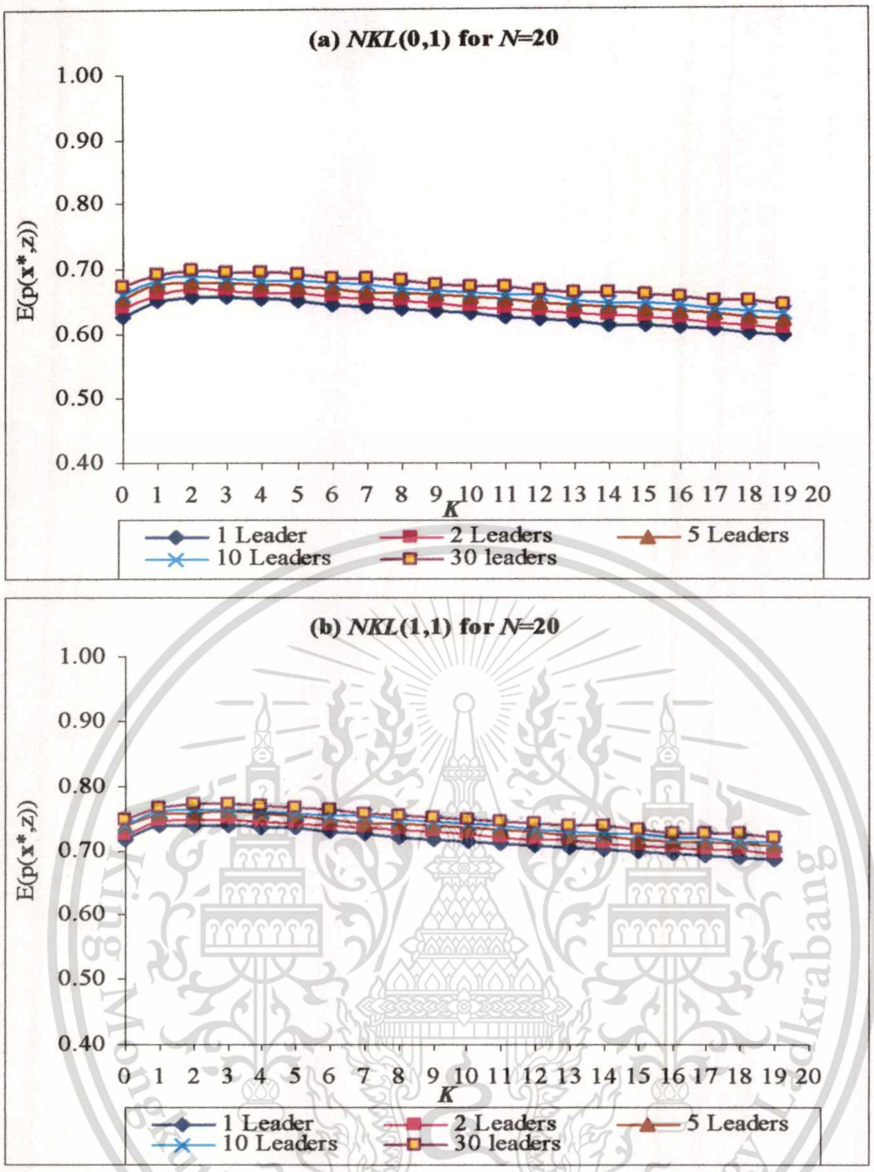


Figure 4.5: Expected Performance of a Local Maximum Team in the Indirect Model as a Function of K for $N = 20$ with a Choice of 1, 2, 5, 10, and 30 Leaders When $\mu = 0$ and 1, Respectively.

Comparable to Figure 4.5, similar simulation results for the direct model proposed in this article are produced and shown in Figure 19. Obviously, the skill level of the leader and having a choice of multiple leaders are still beneficial to team performance. However, unlike in the indirect model, for the case when the amount of interaction among team members is not large, having a choice of skillful multiple leaders does not facilitate the team performance to improve as exhibited in both Figure 4.6(a) and Figure 4.6(b) that all the curves lie on top of each other for several values of K before they divide apart. Another significant difference is that in this direct model, the interaction catastrophe diminishes because the tails of each curve becomes flatter as the number of leader candidates increases.

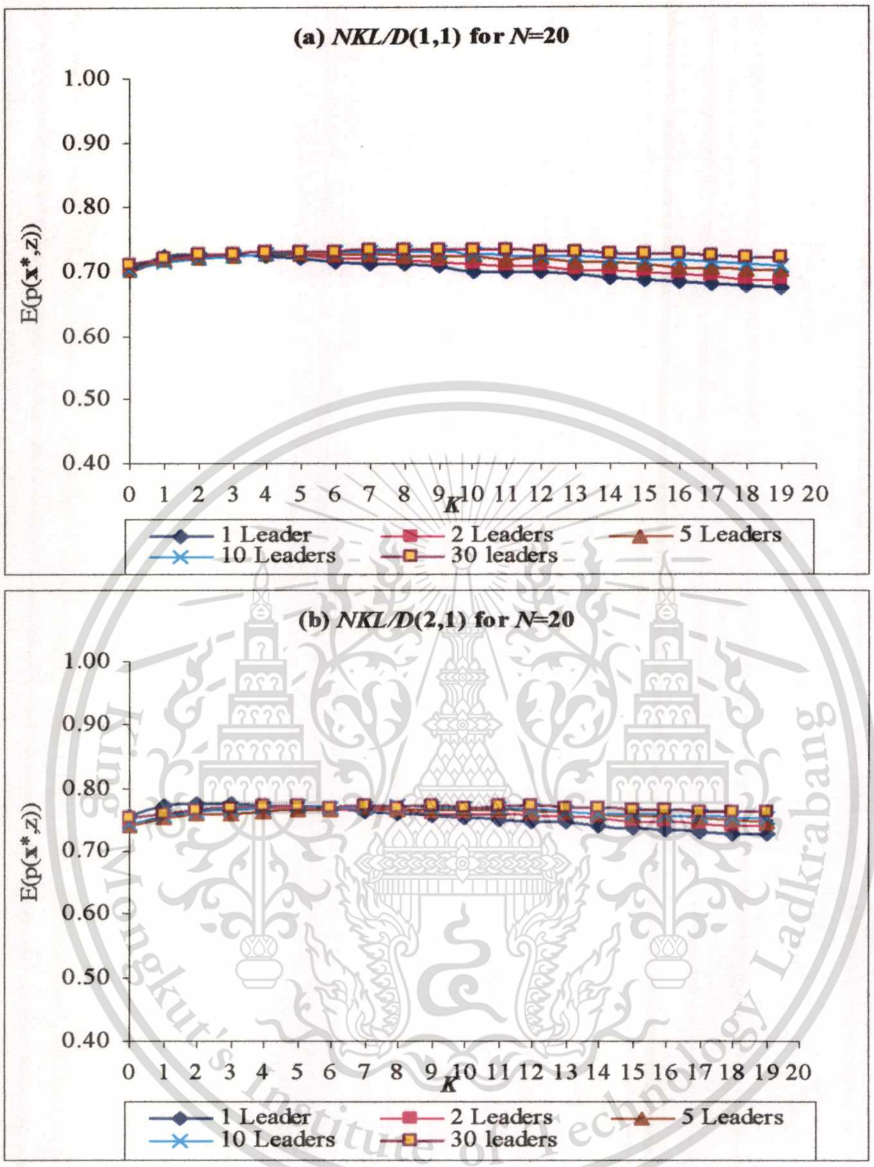


Figure 4.6: Expected Performance of a Local Maximum Team in the Direct Model as a Function of K for $N = 20$ with a Choice of 1, 2, 5, 10, and 30 Leaders When $\mu = 1$ and 2, Respectively.

4.2.3 The Weight and the Skill of the Leader in the *NKLW/D*(μ,σ) Model

In Figure 20, for a small weight of the leader's contribution to team performance such as W = 0.1 and 0.3 in Figure 4.7(a) and Figure 4.7(b), respectively, the interaction catastrophe is still present but it is lessen as the number of random leaders to choose from increases due to the fact that the tails of each curve in each of the two figures become flatter. On the contrary, when the weight is large such as W = 0.7 and 0.9 in Figure 4.7(c) and Figure 4.7(d), respectively, because all of the curves are almost flat, there seems to be no benefits for small amounts of interaction here and thus the interaction catastrophe is irrelevant.

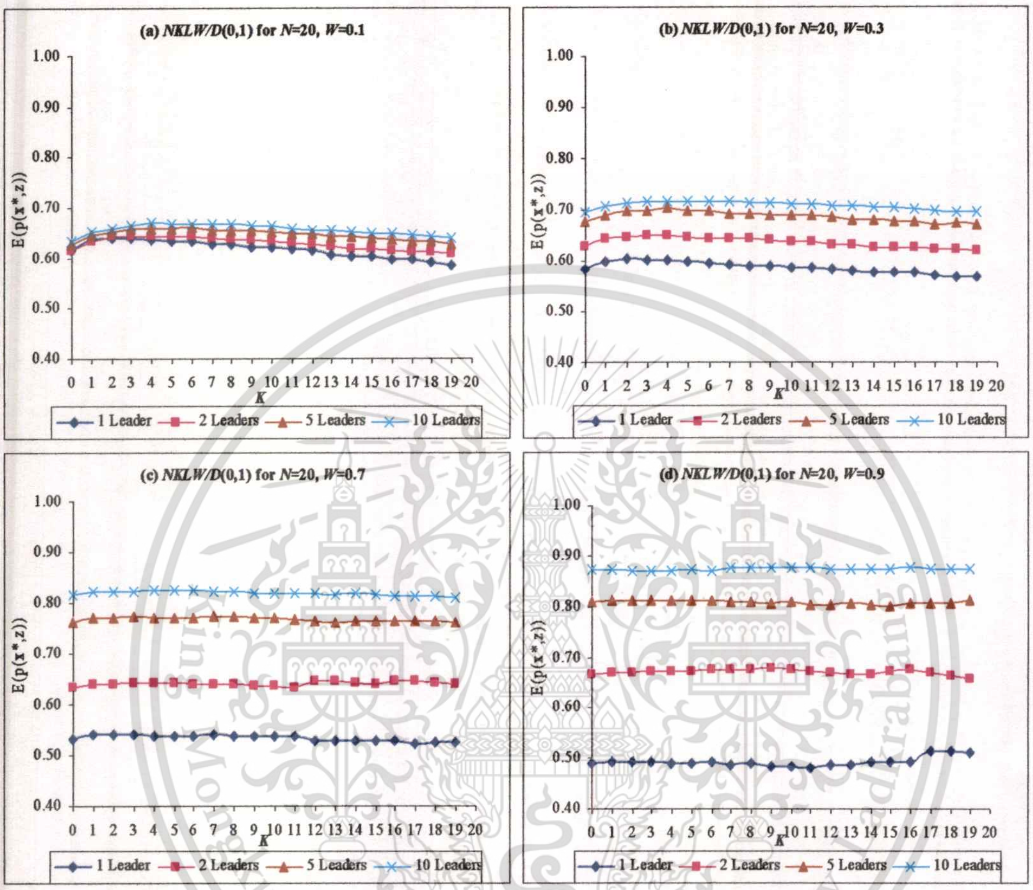


Figure 4.7: Expected Performance of a Local Maximum Team in the Weighted Direct Model as a Function of K with a Choice of 1, 2, 5, and 10 Leaders When N = 20, μ= 0, and W = 0.1, 0.3, 0.7, and 0.9, Respectively.

Aside from the interaction catastrophe issue, another observation drawn from Figure 4.7 is that, except for the case when there is only one candidate for the leader position, the higher the weight to put onto the leader, the higher the expected team performance grows, as evidenced by the upward trends of the top three curves going from a lower W to a higher W. For the 1-leader case, the more the weight of the leader is, the lower the team performance becomes.

Similar conclusions and observations can also be drawn from Figure 4.8 when the leader is more skillful, or more precisely μ = 2, as opposed to the random leader case when μ = 0 in Figure 4.7, all else being unchanged. Again, the skill level of the leader is proved to be an important factor for improvement in team performance as evidenced by the upward move of all the corresponding curves from Figure 4.7 to Figure 4.8.

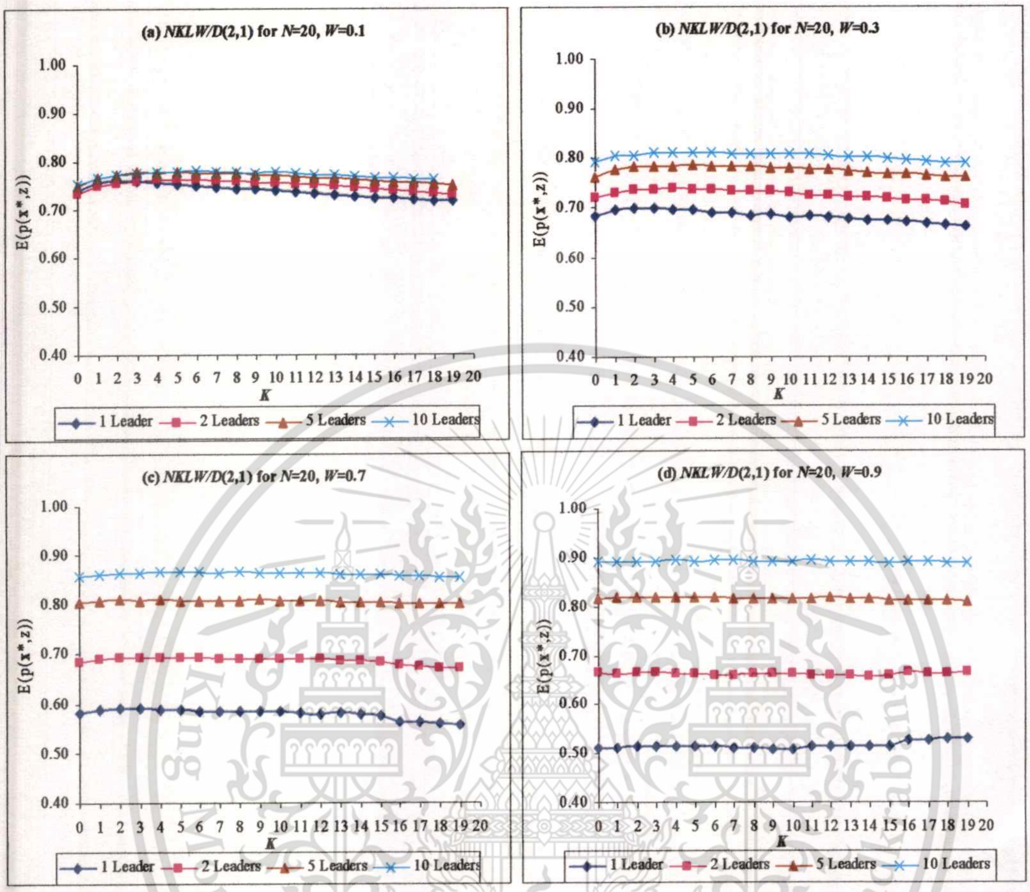


Figure 4.8: Expected Performance of a Local Maximum Team in the Weighted Direct Model as a Function of K with a Choice of 1, 2, 5, and 10 Leaders When $N = 20$, $\mu = 2$, and $W = 0.1, 0.3, 0.7$, and 0.9, Respectively.

In this section, computer simulation results has been reported for studying and comparing the effects of having a choice of multiple leaders, the skill of the leader, and the weight of the leader's direct contribution on team performance in the indirect and direct models.

In the following chapter, computational models for studying permanent and rotating leadership will be proposed. A comparison of the simulation results demonstrate that effects of permanent and rotating leadership on team performance when teams have full interaction among team members will be also concerned.

CHAPTER 5

PERMANENT AND ROTATING LEADERSHIP MODELS

A number of mathematical models both with and without the leadership concept have been proposed in chapter 2. One particular leadership model, namely, the *NKL* model, reveals one significant finding that having multiple candidates for the leader position in a team with interaction among team members is more beneficial to team performance than having just one fixed leader, given that all the candidates for the leader position have no particular skills.

This result is an inspiration for new computational models to be proposed in this chapter in order to test the importance of leadership types or modes on the overall team performance. More precisely, the leadership modes to be examined here are classified into two categories, namely, *permanent* and *rotating*. The definition and assumptions of each leadership mode will later be given.

In the next section, the development of the proposed computational models for studying permanent and rotating leadership modes in teams along with their assumptions and limitations are explained in details. Computer simulation results obtained from the corresponding proposed models are discussed. Conclusions and suggestions of this research work are presented in the final section.

5.1 Permanent and Rotating Leadership Models

In this section, new computational models that integrate permanent and rotating leadership are proposed, one at a time. According to *the amount of time* a team leader stays active in the position, leadership can be classified into two mutually exclusive groups referred to here as *modes*. The first mode, namely, *permanent leadership*, is referred to the situation where the initial team leader has never changed as long as the team stays intact. In contrast, the second mode, namely, *rotating leadership*, is referred to the situation where the team leaders keep changing from one person to another for an equal period of time. It is noted that all of the team leaders considered here are chosen only from within their own teams. Also, the team leaders are assumed to contribute both directly and indirectly to team performance.

In comparison with the *NK* model, each team here has an equal number of team members, that is, *N*, and every member interacts with every other member in the team, that is, $K=N-1$. Apart from that, in terms of difficulties and complexities, the tasks assigned for all teams, either with permanent or rotating leadership, are assumed evenly comparable. More notably, a new important factor is introduced into this type of models for the first time and it is "time". The proposed models will identify which leadership mode is better over time. Starting with modeling permanent leadership in teams, it is then followed by rotating leadership.

5.1.1 The Permanent Leadership Model

In this model, it is assumed that a team consists of N people and they have to work together for a certain period of time. Every member is expected to interact with every other member on the team. It should be noted that there are no replacements on the team members. Also, one of the members will be randomly chosen as the team leader after a first time period and that member will stay in the leader position until the mission of the team is accomplished and thus the leader is called *permanent*. All notations and parameters to be used in this permanent leadership model are as follows:

- T = the number of time periods
- t = the index of the time period
  $t = 0$ means the beginning of time period 1
  $t = i$ means the end of time period i, $i = 1, 2,\dots,T$
- $p^t(\mathbf{x})$ = the overall performance of team **x** at the end of time period t
- $\Phi(m, s)$ = the cumulative distribution function (*cdf*) of a normal distribution with mean m and standard deviation s
- μ_t = the learning ability of the chosen leader at time period t
- $SN(\mu,\sigma)$ = the shifted normal distribution where μ represents the skill level of the chosen leader and σ represents its variability

When a person tries to learn something new, it usually takes some time to adapt him/herself in the beginning; therefore, the learning ability tends to increase slowly at first. After the adjusting period is over, the person will learn faster until his/her learning ability approaches its maximum level. Thereafter, due to this limitation, it will be difficult to learn more. This pattern of a person's learning ability can be represented by a *cdf* curve of a normal distribution, $\Phi(m,s)$. As illustrated in Figure 5.1, varied from person to person, the learning ability forms an *S-shape*. For the x-axis to be viewed as time, the *cdf* curves will be shifted to the right so that at period 1, a person will have some learning ability as shown in Figure 5.2.

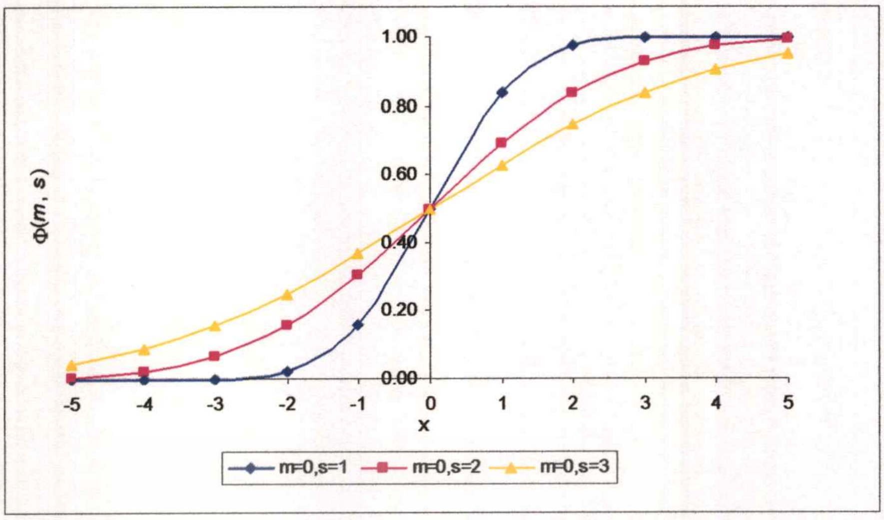


Figure 5.1: The Cumulative Distribution Function (*Cdf*) for Normal Distributions (*M*,*S*).

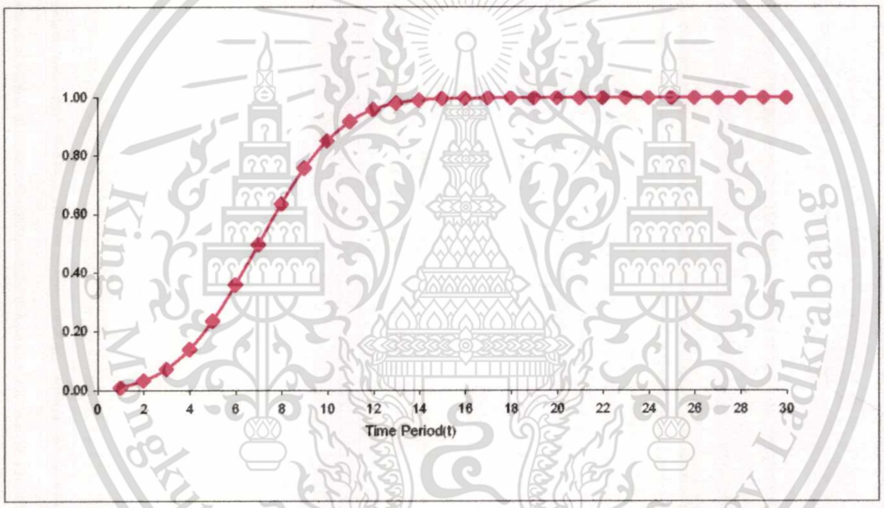


Figure 5.2: The Shifted *Cdf* Curve of a Normal Distribution (M=0, S=2) or A Person's Learning Ability Curve.

After the first time period where team members are supposed to get preliminarily acquainted, a leader is designated and stay in the position permanently until the team is dissembled. His learning ability level at time *t*, μ_t, obtained from a shifted *cdf* of a normal distribution will be used to find the team performance at each time period by the following steps.

Step 1: Initialization. Since the team begins with no leader, it is natural to estimate the initial team performance at the end of period 1 as a uniform random number between 0 and 1, that is, $p^1(\mathbf{x}) \sim U[0,1]$. Equivalently, $p^1(\mathbf{x}) \sim SN(0,1)$ which could mean that the team already has a no-skill team leader because $\mu = 0$.

Step 2: Leader Selection. Select a team leader by randomly generating his/her associated learning ability curve. Set $t = 2$.

Step 3: Performance Computation. Read the leader's learning ability at time t or μ_t and use μ_t to compute the team performance at time period t from a shifted normal distribution, that is,

$$p^t(\mathbf{x}) \sim SN(\mu,\sigma) = SN(c\mu_\tau,1)$$

where μ represents the skill level of the chosen leader and σ represents its variability which is, without loss of generality, set at 0 and c is a constant or real number between 1 and 3.

Step 4: Evolution. Set $t = t + 1$ and repeat *Step 3* until the $t = T$.

In this permanent leadership model, due to the way $SN(\mu,\sigma)$ is constructed as well as μ_t being an ascending number from 0 to 1 taken from the learning ability S-shaped curve, the leader's skill, μ, is then set to equal $c\mu_t$ in order to increase the possibility of team performance approaching 1, as the leader becomes more skillful over time. The value of the constant c runs from 1 to 3. When it is close to 1, the leader's skill is lower and also increases more slowly over time; while when c is close 3, the leader's skill increases more quickly and thus helps improve the chance the team performance reaches its maximum value of 1 faster.

Simulation results of the proposed permanent leadership model and its discussions will be presented after another computational model for the other leadership mode is proposed below.

5.1.2 Rotating Leadership Model

An important assumption of the following rotating leadership model that differentiates it from the previous model is that each team member now takes a turn, thus *rotates*, in leading the team for an equal amount of time. Each member as a leader also has his/her own learning ability curve. For comparison purposes with the permanent leadership model, there is no team leader in the first time period. After the end of period 1, an arbitrary team member is appointed for the leader position for one period and then rotates to another member for another period until each and every member has once become a leader. For this reason, it is further assumed that the number of time periods the team has a leader is equal to the number of team members, that is, $T = N - 1$. An additional notation for use in this model is

- $U(a_t, b_t)$ = a uniform distribution between a lower bound a_t and an upper bound b_t at time period t, where a_t and b_t are real numbers between 0 and 1 and $a_t < b_t$.

The steps for finding the team performance at each time period proceed as followed.

Step 1: Initialization. Similar to the permanent leadership model, the team begins with no leader. Thus, the initial team performance at the end of period 1 is generated from a uniform distribution between 0 and 1, that is, $p^1(\mathbf{x}) \sim U[0,1]$.

Step 2: Leader Selection. Select a team leader by randomly generating his/her associated learning ability curve. Set $t = 2$.

Step 3: Performance Computation. Compute the lower bound a_t as a function of the previous leader's learning ability, μ_{t-1}, and the previous period's team performance, $p^{t-1}(\mathbf{x})$, as follows

$$a_t = (\mu_{t-1})(p^{t-1}(\mathbf{x}))$$

and set b_t at its maximum value, that is, $b_t = 1$.Then, generate the performance of the team with the leader at time t from the uniform distribution between a_t and b_t, that is, $p^t(\mathbf{x}) \sim U(a_t, b_t)$.

Step 4: Rotation. If $t = T$, stop. Otherwise, set $t = t + 1$ and rotate the leader position to another member by randomly selecting a member who has not been a leader yet along with generating his/her new corresponding learning ability curve. Then, go back to *Step 3*.

In this rotating leadership model, team performance is generated from a uniform distribution. However, its lower bound a_t depending on the team performance and the leader's learning ability from the last period tends to move up and away from 0. This means that the next leader dependent on his learning ability at the corresponding time has somehow learnt from the previous leader. As time goes by, the learning skill of any person tends to move up even though each person has a different learning curve. According to the formula for computing a_t in Step 3, the closer μ_{t-1} approaches 1, the closer a_t is to $p^{t-1}(\mathbf{x})$ implying that the current period's team performance may only be slightly worse than the last period's because $p^t(\mathbf{x}) \sim U(a_t,1)$. Consequently, comparable to the permanent leadership model, the method for computing team performance here increases the possibility of team performance in reaching 1 over time.

5.2 Computer Simulation Results and Discussions

In this section, computer simulation results of the proposed two leadership models are reported. The simulations are implemented on MathLab. For each of the two models, 500 identical and independent problems are randomly generated. Each problem has the number of time periods $T = 30$ and the number of team members $N = 29$ so that every member can get a chance to become a leader in the rotating leadership model.

At the end of each time period, the expected team performance of each model is calculated. In the permanent leadership model, the leader's learning ability curve in each random problem has parameters $m = 0$ and $s \sim U[1,3]$ while the constant c in $SN(c\mu_t,0)$ is set at 3. Similarly, in each of the rotating leadership problems, each rotating leader has a learning ability curve with parameters $m = 0$ and $s \sim U[1,3]$.

Simulation results presented in Figure 5.3 show that the expected team performances in both models are roughly comparable in the beginning up to a certain period of time. Then, the teams with permanent leaders seem to outperform the teams with rotating leaders. However, as time grows longer, both curves are again as good and eventually reach the maximum performance of 1.

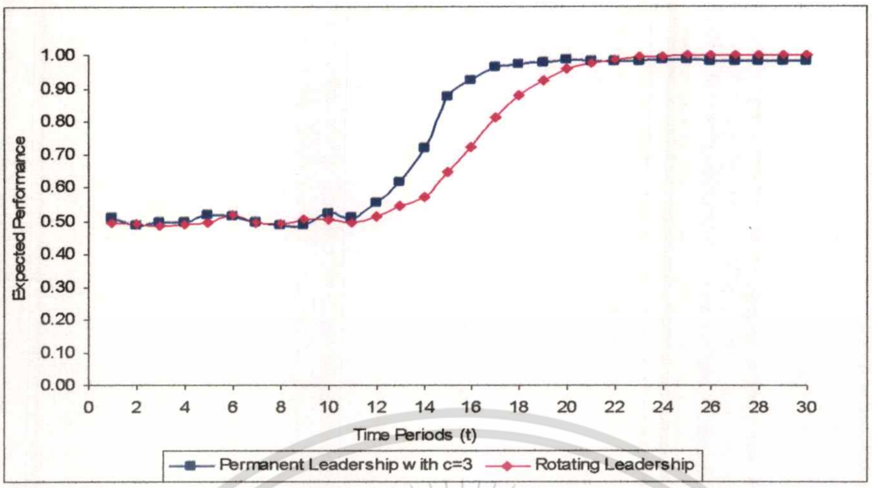


Figure 5.3: Expected Team Performances in the Permanent and Rotating Leadership Models as a Function of the Time Periods.

In another experiment, to test the effects of the constant *c* in the permanent leadership model, problems similar to the previous experiment are randomly generated with *c* = 2, 3, and 4, respectively. For comparison purposes, all the permanent leadership curves along with the previous rotating leadership curve are plotted together in Figure 5.4.

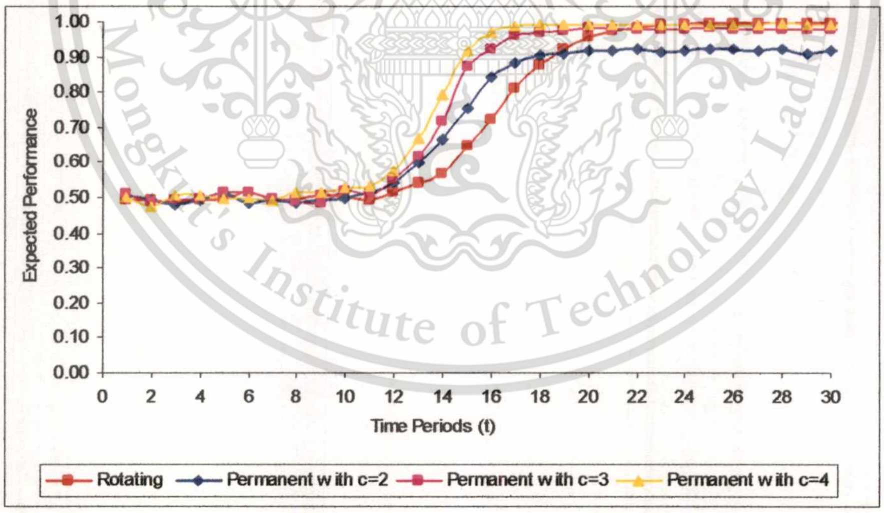


Figure 5.4: Expected Team Performances in the Permanent Leadership Models When Constant *C* = 2, 3, and 4 Together With Expected Team Performance of the Rotating Leadership Model as a Function of the Time Periods.

When comparing each permanent curve with the rotating curve separately, similar observations drawn from Figure 5.3 can also be concluded here. Nevertheless, for a smaller constant *c* such as when *c* = 2, towards the end of the time periods, the permanent curve cannot catch up with the rotating curve resulting in lower expected performance. This effect of permanent leadership being outperformed in the long run lessens as c increases.

Furthermore, when considering all of the three permanent curves together, their patterns are similar except that the team performance in the smaller c curves increases more slowly. One important finding obtained here is that teams with permanent leadership perform better than teams with rotating leadership when the time the teams stay assembled is not long. In contrast, when the teams have more time to work together, rotating the leader position seems to be a recommended idea as each rotating leader has more time to learn and adjust from the previous leaders. This is one of the reasons for most long-running organizations to have their leaders in several levels rotated after certain periods of time.

In this section, computer simulation results have been reported for studying the effects of permanent and rotating leadership on performance. In the following chapter, a summary of the work done thus far along with proposed future work will be presented.

CHAPTER 6

Empirical Research for Permanent and Rotating Leadership

Despite the importance of the leaders on the team performance, not much empirical research has been dedicated to examining this relationship. Particularly, the impact of leadership types or *modes* on team performance has not yet been thoroughly investigated. Consequently, this is an inspiration for empirical to be proposed in this chapter in order to verify the significance of leadership modes on team performance. There are several modes of team leadership commonly known; for instance, emerging, permanent, rotating, and designated leadership.

In this chapter, team leadership modes are classified into two groups according to the time constraint, namely, *permanent* and *rotating* whose define in the previous chapter. Empirical research using questionnaire survey for team projects in undergraduate management classes is proposed. More precisely, the effects of leadership modes on team performances measured by the scales from the questionnaires and the grades the teams receive for their team assignments are investigated.

6.1 An Empirical Survey at the University of Technology Sydney (UTS)

In this section, the methodology of the proposed study is first explained. It is followed by the measures and the analysis of the empirical results.

Methodology

Description and Hypotheses

An empirical survey for studying the relationship between leadership modes and team performance is simultaneously carried out in six sections of the Managing People class at the School of Business, University of Technology Sydney (UTS) in Australia for the duration of one semester. In each section of the class, the students are approximately divided into eight teams, each of which basically consists of six members. As for the leadership modes to assign for each team, the total numbers of teams are split in half for the permanent and rotating modes. Once the teams have been formed, they are assigned equivalent and identical team projects for the whole semester.

In this research, the definition of the two leadership modes for investigation is given as follows. The first of the two modes, namely, permanent leadership, refers to appointing only one person to be as the team leader throughout the entire assignment time period. The appointed leader is chosen right after the first time period spent on the team members for getting acquainted with each other. Rotating leadership refers, in contrast, to the situation when each and every team member alternately assumes the leader position for an equal period of time.

Each time period in this survey comprises two weeks. The entire semester covers fourteen weeks in total. Therefore, the first time period or the first two weeks is used by the teams for getting familiar with each other. Then, the leader chosen after the first two weeks stays on in the leader position for the next twelve weeks for the permanent leadership case; whereas for the rotating case, each of the six members served as a leader for just two weeks until everyone has once become a leader.

In total, 288 questionnaires are distributed in class after the semester is over and the project is finished. 220 completed questionnaires were returned to their teacher, creating an overall response rate of 76.39 percent. The hypotheses of this research are stated in the following:

H_0: the effects of permanent and rotating leadership on team performance are not different.

H_1: the effects of permanent and rotating leadership on team performance are different.

Sample

Respondents in this study are 220 students from various classes which are taught by different teachers. An outstanding characteristic of this sample is that the men are a majority of the students. Secondly, the feature of this sample is related to the country where the student comes from. Almost all students are from Asia and some of them are from Australia and New Zealand, Western Europe, Middle East, America and Eastern Europe and Russia. Age group of students is a third feature of this sample. For instance, 87.7 percent are 20-29 years old, 10.9 percent are 30-39, 0.9 percent are under 20, and the rest are above 40. The forth feature is the different educational background such as Science and Engineering, Marketing, Accounting, Finance, Economics, Health studies, Social Science, and others. The final feature of this sample is that almost all students had work experiences (37.3 percent in Science and Engineering, 10.5 percent in Marketing, 10 percent in Finance, 9.1 percent in Accounting, and the rest in other areas).

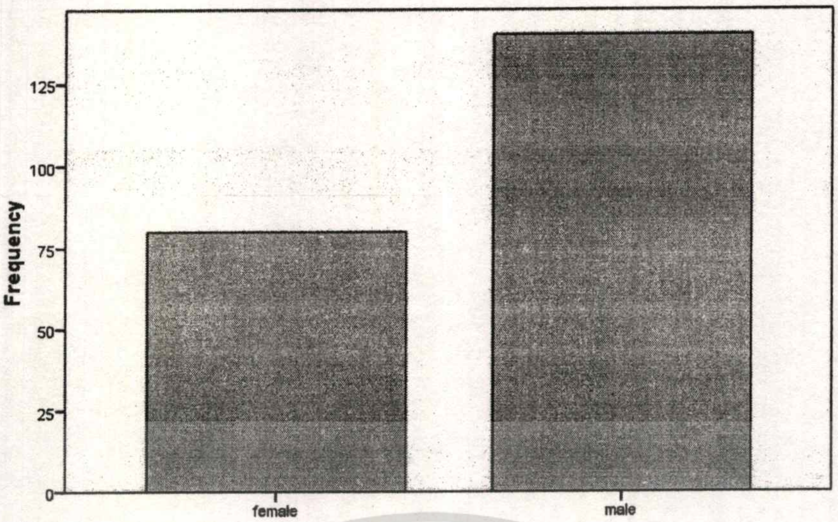


Figure 6.1: Genders of the Respondents

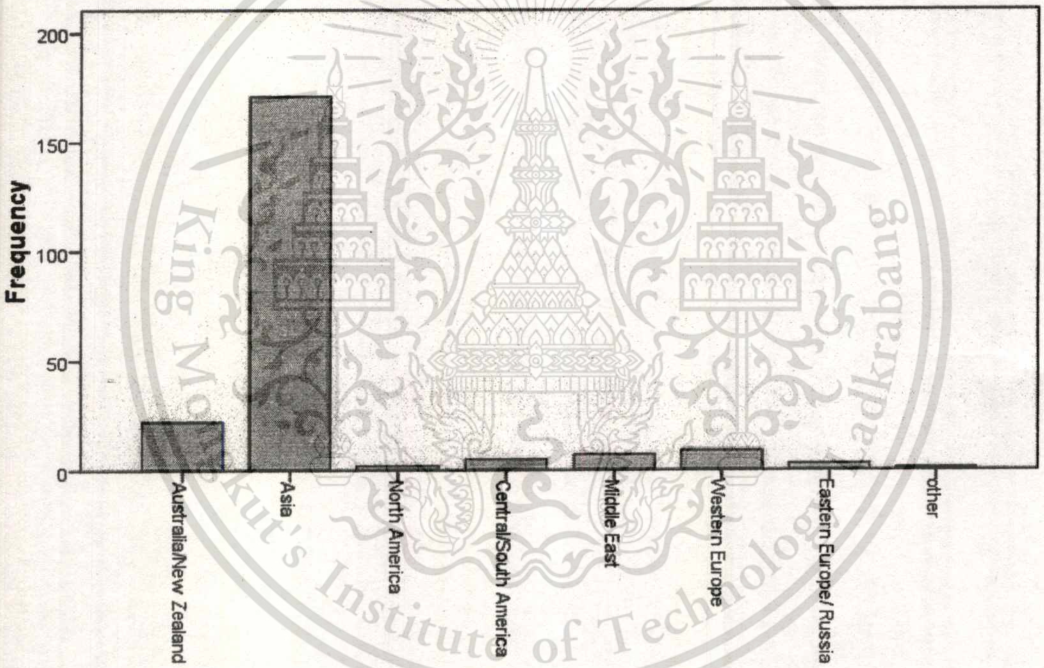


Figure 6.2: Countries Where the Respondents Are From

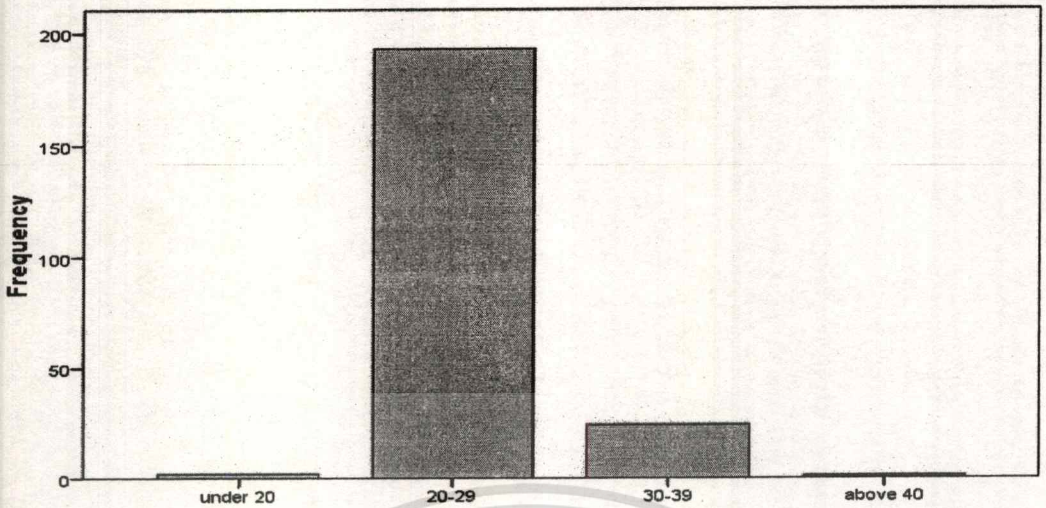


Figure 6.3: Ages of the Respondents

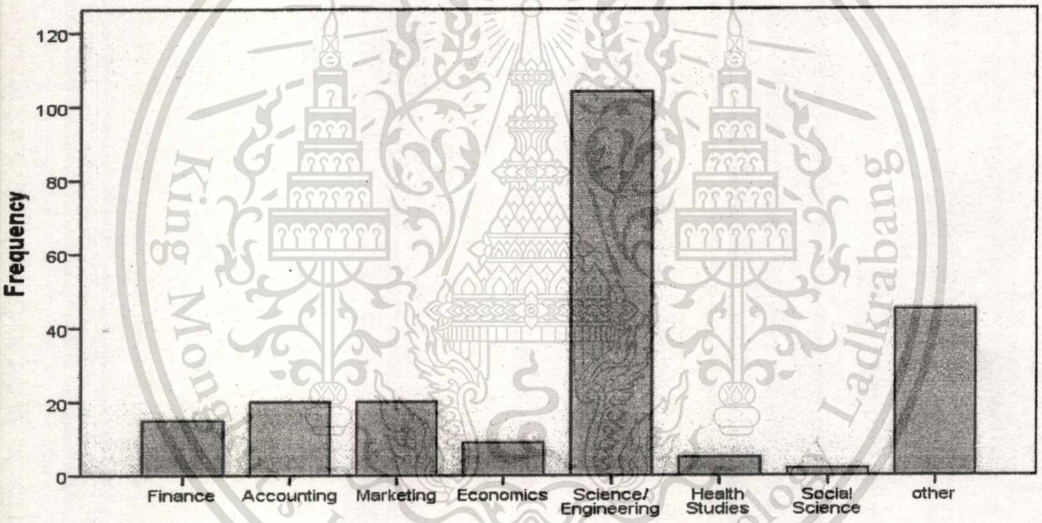


Figure 6.4: Educational Backgrounds of the Respondents

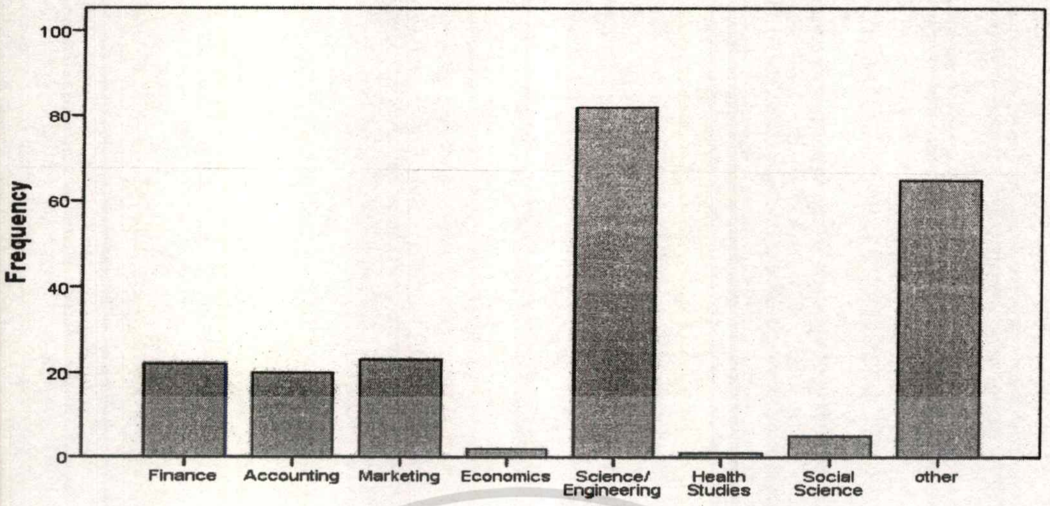


Figure 6.5: Work Experiences of the Respondents

6.2 Measures and Analysis

The performance of each team is contributed by both the scores on the questionnaire and the final evaluation by the teacher on the team project with the ratio of 30:70. The questionnaire basically contains questions regarding how well the team performs as a whole. The same questionnaire is used in both permanent and rotating leadership cases. However, for the permanent case, the team performance is based on that one chosen leader only; while for the rotating case, the performance is based on an average of all rotating leaders.

Additionally, it may be difficult for team members to assess the performance of team using a single measure. Therefore, the team performance in the questionnaire is evaluated by a seven-point Likert scale with responses ranged from "strongly disagree" (1) to "strongly agree" (7). The Cronbach's alpha used in estimating the reliability of multi-item scales is reported for this questionnaire at 0.89 which is an acceptable value.

The teachers' evaluation on the team final work at the end of the semester comes from the quality of their presentation and the cooperation among the team members. To avoid the bias that could occur from giving points to the questionnaire by the team members, the teachers' grades are weighted higher at 70 %.

Analyses are carried out in two stages with the Statistical Package for the Social Sciences (SPSS) Version 16. First, descriptive statistics are used to analyze the demographic information of the respondents which has been reported in the previous section. The second stage is the reliability analysis and the T-test for two independent samples.

6.3 Results and Discussion

The major objective of this chapter is to examine the relationship between leadership modes and team performance as evident by the questionnaire scores and the grades the team receives from the teacher. In order to test the hypotheses stating that the impacts of permanent and rotating leadership on team performance are not different, the T-test for two independent samples is used. The results of the T-test shown in Table 6.1 indicate that the null hypothesis is rejected. Therefore, the effects of the two leadership modes on team performance are significantly different.

To take a closer look into the difference between these two leadership cases, in Table 6.2, the mean of the team performance for the permanent leadership case (79.78 out of 100) is better than that for the rotating leadership case (72.87 out of 100). This result seems to contrast with some people's common instincts. Due to the fourteen-week time limitation for this study, the permanent leaders have more time than each of the rotating leaders who has only two weeks in learning and adjusting themselves to fit into the team. Hence, this can be one of the contributing factors for the permanent-leader teams outperforming the rotating-leader teams in this study.

However, for the longer time period when rotating leaders are allowed more time in each turn on the leader position, the rotating-leader teams may perform better than the permanent-leader teams because the rotating leaders can realize the mistakes of the previous rotating leaders and find a way to fix them.

	T	**df**	**Sig. (2-tailed)**
Team Performance	-6.054	218	.000

Table 6.1. Results of the Two Independent Samples T-Test

	Group	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**
Team Performance	*Rotating Leadership*	112	72.87	2.16335	.18483
	Permanent Leadership	108	79.78	2.88322	.31647

Table 6.2. Group Statistics

In this chapter, the results of the empirical research for studying the effects of permanent and rotating leadership on team performance have been reported. In the following chapter, a summary of the work done thus far along with possible future work will be provided.

CHAPTER 7

SUMMARY AND FUTURE WORK

7.1 Summary

In this thesis, complex systems with interacting components are the main focus of the study. Efforts have been made on making the mathematical models more realistic and more applicable to the team-replacement problem.

More specifically, in chapter 3, a new method for choosing the interacting positions that affect the individual contribution to team performance in the multiple complex systems with an effort of making the model more realistic is presented. The RANDOM method used in the paper arbitrarily select the internal and the external interacting positions based on the values of K and C, respectively. This proposed method is applied to the *NKC* model using various algorithms in the process of replacing team members to achieve a more effective team. In addition, due to the random nature of this proposed method, the numbers of positions affected by a position of interest are unequal.

More appropriately, therefore, proposed modifications on some replacement algorithms, especially the ones with interaction effects, namely, SK/average and SKC/average have been presented. Computer simulation is used in implementing the proposed ideas. The simulation results on the effectiveness and efficiency aspects of the local maximum team obtained have been reported. This is a proof that the *NKC* model for studying multiple complex systems is robust.

On another significant note, in chapter 4, indirect and direct contributions of a leader to overall team performance have been incorporated into existing mathematical models for studying team replacement with motivational leadership. A leader indirectly contributes to overall team performance through regular leading roles. Most likely, in some situations, the leader may have to participate in the team's tasks as an ordinary team member and thus contributes directly to team performance. A modification from the indirect $NKL(\mu,\sigma)$ model to capture also the direct contribution results in the direct $NKL/D(\mu,\sigma)$ model. The weight of the leader's contribution is another factor added into the $NKL/D(\mu,\sigma)$ model in order to increase flexibility in differentiating the leader's direct contribution level that could happen in reality. This more general direct model designed for the situation when everyone on the team except the leader has an equal weight becomes the weighted direct $NKLW/D(\mu,\sigma)$ model.

All of the existing indirect and proposed direct leadership models are then experimented by computer simulation to see the impact of various parameters of the models. In the case when there is no interaction among team members, having a choice of multiple random leaders, or leaders who do not have any particular motivating skill, does improve the expected performance of the team in general. As for when interaction is observed, having a choice of multiple random leaders improves the expected team performance regardless of the amount of interaction both in the indirect and direct models. Especially, in the direct model, a choice of multiple leaders can also attenuate the interaction catastrophe associated with high level of interaction.

The skill level of the leader in both the indirect and direct models is also another instrument for enhancing the expected team performance. Besides, in the direct $NKL/D(\mu,\sigma)$ model, together with the skill level, having a choice of multiple leaders reduces the interaction catastrophe. As for the last model proposed in this paper, simulation results on the weighted direct $NKLW/D(\mu,\sigma)$ model show that, in general, the more the weight to put on the leader's direct contribution is, the higher the expected team performance grows.

Particularly, in chapter 5, new computational models for studying teams with permanent leadership and rotating leadership have been proposed. A team with a permanent leader is defined here as a team with a random leader who once chosen will remain the leader as long as the lifespan of the team while a team with rotating leaders points to a team for which every member rotates as a leader for one equal time period.

Based on these definitions, results from computer simulations indicate that in the beginning stage of the team lifespan, either leadership mode affects the expected team performance in a similar way, that is, as the team and its leader take time to learn about each other, the team performance stays leveling; only little improvement is observed over time.

Later in the second stage, both leadership modes significantly improve their relevant expected team performances but permanent leaders even with modest learning ability potentially outperform rotating leaders.

However, for longer time, in the final stage, it gets more difficult for any person who is leading the team to increase its performance. As a result, the team performances stay almost stationary in both types of leadership. Also, in the long run, a team with rotating leaders may perform better than a team with a permanent leader who has low learning ability.

Last but not least, in chapter 6, to test the robustness of permanent and rotating leadership models, an empirical research for examining the effects of the leadership modes on team performance has been presented. The empirical experiment takes place in post-graduate management classes at the University of Technology Sydney, Australia. The performance of a team is measured by both the questionnaire rating and the grading judged by the teacher on the performance of the team's submitted project. The results of the empirical research based on the fourteen-week time limitation indicate that the permanent-leader teams are more effective than the rotating-leader teams.

7.2 Proposed Future Work

The two methods of choosing the interacting positions used in chapter 3 has only one-way effect, i.e., they affect the performance contribution of the considered position but not the other way around. Hence, it is natural to assume such two-way effect for future research work.

Moreover, the idea of direct contribution leadership used in chapter 4 may be applied to mathematical models that incorporate other roles of leadership such as cooperation. Empirical studies relevant to the assumptions of the models are also suggested to be carried out so that their results can be compared and contrasted with the simulation findings. For that matter, these mathematical models will be more useful, practical, and applicable to the real-world problems.

In addition, possible future research ideas to follow chapter 5 are those that remove one or several assumptions underlying the models in order to make the models more realistic. The following provides some practical examples.

- In this research, the permanent leader is selected randomly. There are no particular requirements for the leader position. As in reality, the person who serves as the permanent team leader should be very competent in leading the team. He/she may has to undertake some specific training courses before assuming the leader position. How to incorporate these aspects of reality into the computational models are quite challenging.
- In the rotating leadership model, every team member gets a chance to become a leader. What if this assumption is relaxed? That is, not everyone can be a leader. In other words, the leader can be selected only from a group of some certain team members, how would this affect the model?
- Also in the rotating leadership model, it is further assumed that whoever in the leader position can only be there for just one time period. Although in this research, it does not exactly specify how long one time period is, it should be wise for the model to be able to allow the leader to resume the position whether for more than one consecutive period or for some other periods in the future.

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APPENDIX

List of Publications

[1] Leenawong, C., and Wattanasiripong N., " Choices of Interacting Positions on Multiple Team Assembly." **Lecture Notes in Artificial Intelligence 4682,** 2007, pp. 282-291.

[2] Wattanasiripong N., and Leenawong, C., "Mathematical Models for Studying Indirect and Direct Contribution Leadership." **Far East Journal of Mathematical Education,** vol. 2, 2008, pp. 121-141.

[3] Wattanasiripong N., and Leenawong, C., "The Effects of Permanent and Rotating Leadership on Team Performance." **The 3rd International Colloquium on Business and Management,** 2010.

[4] Wattanasiripong N., and Leenawong, C., "Computational models for studying leadership modes." **Far East Journal of Mathematical Sciences,** vol. 38(1), 2010, pp. 121-136.

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