TOWARD SYSTEMATIC DESIGN OF KNOWLEDGE-INTENSIVE SERVICE DELIVERY NETWORKS

by

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A dissertation submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in
Information Technology

Charlotte

2011

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ABSTRACT

SU DONG. Toward systematic design of knowledge-intensive service delivery networks (Under direction of DR. RAM KUMAR and DR. MONICA JOHAR)

Effective management of IT-enabled services is becoming increasingly important. These services are often delivered by networks of knowledge workers who constitute Knowledge Intensive Service Delivery Networks (KISDN). This dissertation contributes to the effective design and management of KISDN by presenting two mixed integer programming models which integrate disparate streams of research. The first model facilitates analysis and managerial benchmarking of KISDN. We focus on how the performance of such networks depends on the interaction between workflow decisions, information flow networks (IFNs) structure and knowledge management decisions. We propose that knowledge about IFNs and worker competencies can be effectively used to make workflow decisions. Our results, based on the study of different IFN archetypes, illustrate practices for effective management of KISDN. Recognizing existing IFNs, increasing randomness in IFNs, nurturing weak or performative ties depending on the archetype, assigning tasks based on effective worker competence, and selectively delaying assignment of tasks to workers can enhance business value. The second model focuses on the design of IFNs. Organizations are increasingly creating and using IFNs to transfer knowledge. However, there is limited understanding of the design of IFNs to maximize knowledge sharing. Our results demonstrate the impact of worker competency heterogeneity, number of skills supported by the firm, and time (cost) associated with knowledge sharing on the design of efficient IFNs.

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CHAPTER 1: INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

Organizations increasingly use knowledge-intensive IT services delivered from multiple locations. For example, US Internetworking (www.USi.com) claims that over 70% of its employees have at least one certification (such as a CISCO networking) and of these, 90% have multiple certifications and are located in the US and India. These employees may interact with each other, and constitute knowledge intensive service delivery networks (KISDN). Management of such KISDN is an important, yet under-researched area.

This research recognizes the complex nature of the KISDN by integrating concepts from prior research on task assignment (Sahni and Gonzalez, 1976), modeling knowledge exchange in organizations (Levine and Prietula, 2006), knowledge diffusion in networks (Cowan and Jonard, 2004), assessing the value of knowledge creation (Chen and Edgington, 2005), and mining and using organizational social relationships (Guy et al., 2008). A review of the previous literature sheds light on the factors impacting the performance of the KISDN. However, the KISDN, as a complex system, has not received adequate attention. The dynamics between the factors affecting KISDN performance require further investigation. Hence, through a series of essay, this research systematically studies these factors to facilitate the design of the KISDN.

The first essay presents an analytical model to manage the performance of a knowledge-intensive service organization whose performance depends on a combination of task-assignment and knowledge management decisions. We illustrate how information flow networks can be effectively used to make task to worker assignments and underscore the importance of paying careful attention to the location of 'experts' in different parts of an organizational network. Specifically, we focus on the following research question: *how do task assignment, knowledge management strategies (knowledge acquisition from co-workers) and information flow networks impact the financial and operational performance of organizations under different service environments*? We prove that the problem is NP-hard and propose a heuristic in order to analyze the impacts of the factors on firm performance. Additionally, we show that organizations could benefit from waiting to make assignments, and should dynamically assign service tasks in batches using an assignment heuristic. Ways in which firms can strategically manage the impacts of information flow network structures are also discussed.

The second essay focus on the design of the information flow network of KISDN identified in essay one. A mathematical model is proposed to study important factors associated with the design of such networks. There is a growing interest in managing organizational social relationships to facilitate knowledge sharing (Abrams et al., 2003). IBM (2006) research center has promoted the use of Social Network Analysis (SNA), "a set of tools for mapping important knowledge relationships between people or departments", in order to understand organizational social relationships which could facilitate or impede knowledge sharing. However, prior research mainly focuses on ad-hoc use of existing organizational social relationships to share knowledge. There is limited research that helps managers systematically understand the design and use of the information flow networks in KISDN to facilitate knowledge sharing. Hence, we formally pose the following research question in the second essay: *how should organizations design and use their information flow networks in order to maximize employees' knowledge gain through sharing under different organizational environments*?

This dissertation is organized as follows: Chapter 1 provides an overview of the literature on Knowledge Intensive Service Delivery Networks (KISDN). Since the study of KISDN involves various streams of research, we have defined the scope of the investigation in Chapter 1. Chapters 2 and 3 discuss the two essays. Chapter 2 starts with a brief review of relevant literature to motivate the research questions, which is followed by the discussion of the analytical model. After that, we propose a heuristic to solve the problem. Simulation experiment design and results are then discussed, followed by the model extension, discussion and contributions. Chapter 3 also starts with relevant literature, and presents an analytical model afterwards. Similarly, a solution heuristic is proposed, which is followed by experiment design and results. Chapter 4 summarizes the contributions of the two studies and offers a conclusion to the dissertation.

1.2 Literature Review

The following sections discuss the relevant literature on KISDN and information flow networks that facilitates knowledge sharing within KISDN. More comprehensive literature will be reviewed in subsequent chapters for each essay.

1.2.1 Knowledge-Intensive Service Delivery Networks

This KISDN research is related to the call for development of a "service science" discipline which integrates perspectives from multiple traditional disciplines such as information science, management science, social sciences and MIS (Bardhan et al., 2008; Chesbrough and Spohrer, 2006; IfM and IBM, 2008). The significant role of services in today's economy is realized by many organizations. Services stand for jobs and growth. But the evolution of the knowledge-intensive service industries also results in a new level of management difficulty and coordination complexity. For example, the delivery of IT-based services has engaged multiple business units and different geographies, creating new challenges for organizations to evaluate, implement and manage (Bardhan et al., 2008). The lack of a strong conceptual foundation for such "service science" attracts attentions from scholars and managers alike (Chesbrough and Spohrer, 2006).

Prior research has recognized the importance of knowledge management in service delivery (Chesbrough and Spohrer, 2006; Maula, 2007), and the need to conceptualize service delivery as a process with "a focus on dynamic resources such as knowledge and skills" (Lusch et al., 2008). Maula (2007) argues that emerging "service science" should focus on knowledge-intensive services, knowledge and information management, and the dynamic complexity of the system. She justifies that knowledge in knowledge-intensive services should include employees' expertise and experience, process or system of services, and competence and capability to innovate, learn and renew. Knowledge and information management should emphasize on "the acquisition, availability, creation and sharing of knowledge, competence and intellectual capital" (Maula, 2007). Such a conceptualization with a focus on knowledge and skills of the workers is lacking in the prior research on call centers (Gans et al., 2003) and IT services (Buco et al., 2003).

Our research studies KISDN that have knowledge-intensive service tasks with service level agreements (SLAs). SLA contracts for IT service delivery such as e-business often specifies the delivery of service functions, service quality measurement criteria, and penalties of failing to deliver quality service on time (Buco et al., 2003; Sen et al., 2009). Penalties for SLA violations can be refund to customers specified relative to the service cost (Buco et al., 2003). Considerable variability in customer preferences and service impacts the effective pricing and resource allocation mechanisms which are needed to deliver services at the promised quality level. Hence, effectively managing SLAs creates new challenges to IT services delivery. For example, firms need to dynamically allocating limited resources to minimize financial penalties due to SLA violations. Sen et al. (2009) propose a mechanism for SLA formulation that features a dynamic priority based price-penalty scheme targeted to individual customers. They prove that their proposed scheme is more effective than a fixed-price approach. Buco et al. (2003) study the design rationale of an integrated set of business oriented service level management (SLM) technologies developed by IBM. They find that a dynamic priority pricing approach can yield socially superior results. In addition, they demonstrate that demand heterogeneity can be addressed effectively in SLAs through dynamic resource allocation mechanism such as a price-penalty scheme that they proposed.

In KISDN, employees often have multiple skills which allow them to provide heterogeneous services supported by the organization. However, their competence level for these skills may vary significantly (Kim et al., 2008). This competence heterogeneity creates space for knowledge sharing among employees within organizations. Prior research also demonstrates that employees get information and acquire knowledge primarily by consulting their colleagues or friends when performing tasks (Cross et al., 2001). In addition, organizations allow workers to take training sessions to acquire knowledge (Chen and Edgington, 2005). Both training and knowledge sharing can increase the productivity of existing workforce by improving the overall employees' competence level. Our research recognizes the dynamic nature of knowledge and skills of workers by allowing them to vary over time during service delivery. We focus on organizations that provide knowledge-intensive services with SLAs, support multiple skills, have varying levels of worker competence, and often require knowledge acquisition. Such organizations are increasingly important given the trend in IT towards delivering software as a service (Mackie, 2007).

1.2.2 Information Flow Networks Facilitating Knowledge Sharing

The ability to create and share knowledge effectively and efficiently could be the basis for retaining competitive advantage in this ever changing economy (Abrams et al., 2003; Center for Knowledge Governance, 2004; Goh 2002). In order to facilitate knowledge sharing, many firms have invested heavily on knowledge management projects that emphasize the use of technologies which seldom bring in the expected (Abrams et al., 2003). Interestingly, many projects focusing on the use of technology failed in the past (Carroll, 2008). On the other hand, organizations are finding that employees are much more likely to consult their peers and colleagues (using organizational social relationships) for information and knowledge rather than use electronic knowledge bases and other technologies that firms adopted (Cross et al., 2001). In addition, the structure of such information flow networks could significantly impacts knowledge sharing in KISDN (Abrams et al., 2003).

Prior research suggests that there is significant value of facilitating knowledge sharing among employees. Zhang et al. (2005) identifies four types of benefits of employees sharing knowledge in knowledge-intensive organizations: (a) it can increase and enrich the intellectual capital of an organization; (b) it ensures organizational advantage, lessen organization's dependency on individuals, and reduce potential loss of job-hopping; (c) it allows individuals to get more concentrated knowledge from the organization, and therefore increase personal competitive ability; and (d) it reduces the cost of accumulating knowledge within the organization. It is important to note that organizations can effectively create social relationships by providing physical environment (face to face communication platform), adopting motivation mechanisms, and using team/project assignment (Ardichvili et al., 2003, Bartol and Srivastava, 2002, Zhang et al., 2005). However, employee having excessive social relationships may create issues for IFNs (IBM, 2006). Cross et al. (2001) find that too many social connections produce significant stress and information overload for employees, which decreases the efficiency of the groups that they belong to. Hansen (2002) argues that establishing direct connections in a knowledge network provides immediate access to related knowledge, but requires significant time and effort to create/maintain. Moreover, replying on employees with large number of social connections to transfer knowledge creates potential risks to an organization such that if these employees leave the organization, the information flow network that facilitates knowledge sharing could break down.

CHAPTER 2: SYSTEMATIC DESIGN AND ANALYSIS OF KNOWLEDGE INTENSIVE SERVICE DELIEVERY NETWORKS

2.1 Introduction

We study KISDN whose objective is to maximize financial performance over a finite planning horizon. We focus on the following research question: *how do task assignment, knowledge management strategies (knowledge acquisition from co-workers) and organizational networks impact the financial and operational performance of organizations under different service environments*? In our opinion, this is an important, yet under-researched question.

Assignment of different types of service tasks over time to a pool of agents is a complex problem. We formulate a Mixed Integer Programming (MIP) model, discuss its complexity, and present a heuristic that combines optimization and simulation in order to facilitate systematic analysis of the above research question. The proposed heuristic integrates ideas from prior research on task assignment, knowledge management, and social network analysis. Quality of the solutions produced by the heuristic compares favorably with optimal solutions. Our results provide several interesting insights into the dynamics of the service environment.

First, this research contributes to the emerging stream of research on social networks in IS by proposing and illustrating the value of using social network information for service task assignment in knowledge sharing environments. Use of social networks to access the knowledge of co-workers addresses a call in prior research

(Lusch et al., 2008) to use dynamic resources such as knowledge and skills in service delivery. We demonstrate the significant additional value that can be generated by such sharing. Second, prior research on call centers (Gans et al., 2003) and IT support (Kim et al., 2008) typically assume that service requests are picked from a queue and assigned randomly to available workers. This research, on the other hand, illustrates that organizations could benefit from waiting to make assignments, and assign service tasks in batches using an assignment heuristic. The significance of the value of waiting, anchored in the theory of real options (Trigeorgis, 1996) is discussed. Third, we demonstrate the effect of network topology, network density and worker's willingness to help on performance of the organization through knowledge sharing. A network topology where experts are distributed throughout the organization as opposed to being concentrated or clustered consistently outperforms other network structures. We discuss ways to reduce this performance difference between network topologies by intentionally increasing network density and/or providing incentives to enhance worker's willingness to help. In addition, we also illustrate how an organization can strategically use worker training as a means to mitigate the effects of network structure. Fourth, computational results illustrate how worker specialization occurs in a multi-skill environment and how the degree of specialization is a function of the network topology and density. Research and managerial implications of these results are discussed.

2.2 Literature Review

As discussed in Chapter 1, the study of KISDN integrates different streams of research including task assignment (Sahni and Gonzalez, 1976), modeling knowledge exchange in organizations (Levine and Prietula, 2006), knowledge diffusion in networks (Cowan and Jonard, 2004), assessing the value of knowledge creation (Chen and

Edgington, 2005), and mining and using organizational social relationships (Guy et al., 2008).

The assignment of a group of tasks to a number of agents in a manner that only each agent is assigned one task and each task is assigned to one agent is a classic problem in operations research. Efficient solution procedures such as the Hungarian method are available for this problem (Ahuja et al., 1993). Several extensions of the basic assignment problem have been studied (Sahni and Gonzalez, 1976). The Generalized Assignment Problem (GAP) is one such extension which has been proven to be NP-hard (Sahni and Gonzalez, 1976). GAP assigns a number of agents to a number of tasks. Any agent can be assigned to perform any task, incurring some cost and profit that may vary depending on the agent-task assignment. In addition, each agent has a budget. The sum of the costs of task assigned to it cannot exceed this budget. The objective of the GAP is to maximize the total profits of the assignment while meeting all the budget constraints. In the KISDN optimization problem, studied in this dissertation, there is stochastic demand for tasks. These tasks are assigned to an agent or a limited number of agents at a time. Agents are prohibited from carrying out more than one task at a time (but could perform multiple tasks over time) and firms incur costs when they perform these tasks. Costs are also incurred when there is either a surplus demand for service (similar to wait time penalties) or surplus supply of workers (similar to cost of “workers sitting on the bench”). The firm’s performance is optimized over a planning horizon. The GAP can be polynomially transformed to an arbitrary instance of the KISDN optimization problem, as discussed.

This research integrates ideas from different streams of knowledge management research that consider the effectiveness of help-seeking behavior. Levine and Prietula (2006) use agent-based simulation to study the impact of different types of ties (strong, weak and performative) between workers in the context of knowledge sharing behavior in social networks. Similar to our research, they study the scenario where employees have a set of skills which are used to perform relevant tasks. Knowledge could be obtained through self-learning or exchange with other employees. They illustrate that having some performative ties in an organization improved average task completion times. However, they do not optimize task assignment or consider different types of network topologies. This research is also related to Cowan and Jonard (2004) who use simulation to study the impact of different types of network topologies in the context of knowledge diffusion across organizations. They find that the average knowledge is maximal in Small World Networks when diffusion reaches the steady state. Nevertheless, their problem is different from the one studied in this research and did not include optimization of task assignment, or different types of connections (ties) between nodes in the network. This research optimizes task assignment to workers, who can improve competence by seeking help from co-workers using ties. It compares the impact of different network topologies, network densities and worker's willingness to help on knowledge sharing and service delivery.

In our model extension, we also consider the value of organized knowledge transfer (training). Chen and Edgington (2005) use simulation to study the effect of different training strategies on organizational value. They conclude that allowing workers to decide on when to go for training does not maximize organizational returns. However, they do not consider knowledge sharing among co-workers or optimize the task assignment.

This dissertation is also related to emerging research on social networking. IS researchers are increasingly interested in social networking (Agarwal et al., 2008). Organizations are recognizing the value of understanding social networks and influencing the formation of networks (www.orgnet.com; Guy et al., 2008; Sahoo et al., 2008). There is a growing body of research on mining social networks from different types of organizational data including email, wikis and blogs (Aron et al., 2004; Van Der Aalst et al., 2005), and using social networks in organizations (Kilduff and Tsai, 2003). Leading IT service providers such as IBM are building tools to mine social networks from internal organizational data as well as external data and make these social networks available to other applications through Application Program Interfaces (APIs) (Guy et al.., 2008). Shen et al. (2003) study task assignment in workflow settings and use social network information to assign tasks to groups. However, they focus on using social network information to help manage group dynamics and mechanisms. They do not consider knowledge sharing among group members when assigning tasks, and did not study the impact of social network structures on assembling workgroups.

The model presented in the following sections integrates ideas from these streams of research and proposes the use of organizational social network information in improving operational and financial performance of KISDN.

2.3 Model Development

This section develops a mathematical model of KISDN, which are knowledge-intensive service systems with distributed resources. Such organizations can be found in a wide range of service sectors like management consultancy, design services, computer and IT-related services (Evanschitzky et al., 2007; Windrum and Tomlonson, 1999).

This model helps to develop a better understanding of how people, technology, organization, and shared information engage in dynamic value co-creation. Such an understanding facilitates managerial benchmarking of KISDN. Figure 1 describes the process of value co-creation in such a service system. The arrows in the figure illustrate the value co-creation process, starting from the bottom left.

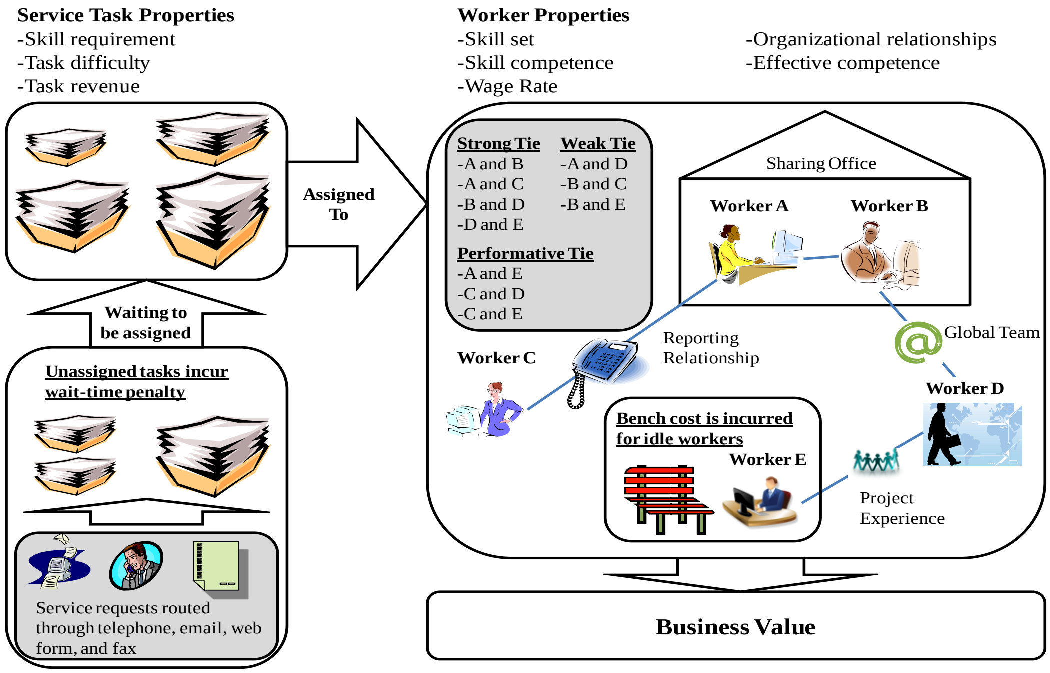


FIGURE 1: An organizational (Virtual Network) with ties between workers

In such a system, service requests need not be limited to telephone requests and may be routed through other communication channels such as faxes or emails or filling out web forms (Levine and Kurzban, 2006). In cases where service requests are routed through multiple levels, our focus is on the higher, more knowledge-intensive, levels of support. The bottom left portion of Figure 1 illustrates that it is not necessary for service tasks to be handled immediately by knowledge workers, though there often is a cost of delay due to factors such as service level agreement penalties (Buco et al., 2003). These knowledge-intensive service tasks vary in terms of task difficulty, required skills and associated revenue. For example, service tasks related to management consultancy concerning mergers and post-merger integration, require distinct skills such as law, finance and so on (Evanschitzky et al., 2007; Windrum and Tomlonson, 1999), and service tasks related to computer and IT often require skills such as database management and C/C++.

As shown in Figure 1, in order to generate business value, these service tasks need to be effectively assigned to workers. The revenue resulting from task completion is based on the skills required, the market revenue for tasks requiring those skills, and how difficult the task is. Workers in KISDN vary in terms of competences in these skills and organizational networks that they belong to. The time a worker takes to complete a task (requiring particular skills) could vary due to differences in worker competences (Chen and Edgington, 2005; Davenport and Prusak, 1998). The complexity of these service-tasks often requires knowledge-workers to share their distinctive capabilities in order to provide unique services (Davenport and Prusak, 1998). Therefore, it is possible that when workers are assigned to tasks, workers consult other co-workers to complete tasks efficiently (Levine and Prietula, 2006; Szulanski, 1996). Such competence exchange is an important characteristic of service systems (Maglio and Spohrer, 2008) and is a function of worker properties and the types of ties between workers. This represents an important step in value co-creation. Figure 1 illustrates that reporting relationships, membership in global teams and project experience facilitate ties. As described later, technology can play an important role in facilitating competence exchange.

As shown in Figure 1, some workers in such organizations may remain idle ("sit on the bench") during any point in time. Organizations may continue to pay out wages to idle workers, thus negatively impacting business value co-creation.

2.3.1 Model Formulation

Mathematical modeling is a useful tool to understand key variables that describe a problem and their relationships. The model variables described in Table 1 represent the different elements of KISDN. In addition, mathematical modeling helps understand the relationships between different variables, and produces a solution that can serve as a benchmark. This approach is appropriate in the context of service systems such as KISDN, when the goal is a better understanding of different factors in the value co-creation process. We model the problem of co-creating value in KISDN using mixed integer programming. This approach is appropriate in scenarios where some variables, such as assigning a worker to a task, are binary and others, such as worker competence, are continuous in value.

We formulate a Mixed Integer Programming (MIP) model where service tasks requiring skilled workers are assigned to competent personnel, if available. The firm's objective is to maximize the firm's expected payoff over a planning horizon (P). We consider the planning horizon (time) to be divided into a set of discrete assignment periods $t \in \{1,..,T\}$ where t represents the assignment period number. At the start of every assignment period t, the organization makes task to worker assignments based on the number of unassigned tasks in the system, and the availability and competence of workers. Note that the length or duration of an assignment period (Δ) represents a context–specific unit of time (minutes, five minutes, fifteen minutes, etc) within which any newly arriving tasks are queued but no assignment decisions are made. The notation is outlined in Table 1. Since the skills required by different service requests (tasks) could vary, we assume that there are total of S skills supported by the firm and a total of M task types in terms of their skill(s) requirement. Particularly, $q_s^m = 1$ when task of type $m \in \{1,...,M\}$ requires skill $s \in \{1,..,S\}$, 0 otherwise. Note that $\sum_{s=1}^{S} q_s^m \geq 1$, for each m. In addition, in line with prior research on managing IT service tasks (Buco et al., 2003; Sen et al., 2009), we assume that the arrival rate of tasks of type m follows a Poisson distribution with mean λ_m, and the tasks arriving in each time period are independent of each other. The organization has K workers, and during each assignment a worker may be assigned to a service task, or kept idle (kept on bench). As discussed earlier, the firm may continue paying out wages to workers even when they are sitting on the bench. In addition, for each un-assigned task, the firm incurs a wait-time penalty per unit time. Hence, the firm's objective consists of the following terms: *net payoff (revenue – cost) from completing tasks*, *the cost of workers sitting idle* and, *the wait-time penalty from un-assigned tasks*. Next, we briefly discuss how each of these terms is calculated. Additionally, we also outline how the uncertainty associated with some of the problem parameters is handled.

TABLE 1: Major model parameters and decision variables

Symbol	**Definition**	**Type**
Decision Variables		
A_{kjt}	= 1, if worker k is assigned to task j in period t ; = 0, otherwise, with $t \in \{1,2,\ldots,T\}$	Decision Variables
H_{klst_i}	= 1, if worker l provides help in skill s to worker k using tie i in period t ; = 0, otherwise, with i = 0, 1, or 2, indicates a strong, weak, or a performative tie	
System Environment		
Ph	Planning Horizon	Exogenous Variables
Δ	The length or duration of each period	
T	Total number of time periods, with $T = Ph / \Delta$	
K	Total number of workers in the organization	
S	Total number of skills supported by the organization	
Pc	Coefficient of task wait-time penalty per period, with $Pc \in [0,1]$	

TABLE 1 (Continued)

Task Related		
M	Total number of *type* of tasks	Exogenous Variables
N_{Max}	Maximum number of tasks that have arrived over Ph	
B_s	Billing rate per period for skill s	
Q_s^m	= 1, if task type m requires skill s ; = 0, otherwise, with $m \in \{1,2,\ldots,M\}$	
Ta_{jt}	= 1, if task j arrives in period t ; = 0, otherwise	
Tr_{js}	= 1, if task j requires skill s ; = 0, otherwise	
N_t	Total number of tasks that have arrived up to and including period t , with $N_t = \sum_{u=1}^{t} \sum_{j=1}^{N_{Max}} Ta_{ju}$	
Bm_{js}	Time for a benchmark worker to complete component in task j that requires skill s	
R_j	Revenue from completing task j , with $R_j = \sum_{s=1}^{S} B_s Bm_{js} Tr_{js}$	
λ_m	Arrival rate per period of task type m	
Tt_s	The average time required to complete skill s component in tasks by a benchmark worker	
Worker Related		
Ww_k	Wage rate per period for worker k	Exogenous Variables
Bc	Bench-cost coefficient, with $Bc \in [0,1]$	
Wr_s	Wage rate per period for skill s for a worker of competence = 1	
ρ_{kl_i}	= 1, if there is a tie of type i exists between workers k and l ; = 0, otherwise, with i = 0, 1, or 2, indicates a strong, weak, or performative tie respectively	
Wc_{kst}	Worker k's competence in skill s in period t , $Wc_{kst} \in (0,4]$. $Wc_{kst} \approx 0$ indicates an expert and $Wc_{kst} = 4$ indicates a novice worker. For our purposes a value = 1 indicates a benchmark worker. Workers could take any values in this range of 0 to 4 (Wc_{ks1} are exogenous variables, and $Wc_{kst}\ \forall t \in \{2,\ldots,T\}$ are derived variables)	Derived Variables
Wt_{kjt}	= 1 if worker k completes task j by period t, = 0, otherwise	
Ec_{kst}	Worker k's effective competence in skill s in period t after consultation, with $Ec_{kst} \in (0,4]$	
Wb_{kt}	= 1 if worker k is busy in period t, = 0, otherwise	
Knowledge Acquisition		
κ	Knowledge retention coefficient, with $\kappa \in [0,1]$	Exogenous Variables
Hc_i	Overhead coefficient associated with worker providing consultation over tie of type i, with i = 0, 1, or 2, indicates a strong, weak, or performative tie respectively	
Wh_{k_i}	Worker k's willingness to help over tie of type i, with i = 0, 1, or 2, indicates a strong, weak, or performative tie respectively ($Wh_{k\_0} \geq Wh_{k\_1} \geq Wh_{k\_2}$)	
Ga_{klst_i}	Represents worker k's gain in skill s from worker l using tie i in period t, with i = 0, 1, or 2, indicates a strong, weak, or performative tie respectively	Derived Variables
Ga_{kst}	Represents worker k's gain in skill s in period t, after consultation	
Network Related		
Rp	Rewiring probability	Exogenous Variables
Nd	Network density	

2.3.1.1 Net Payoff from Completing Tasks

The assignment of worker k to task j in period t depends on (a) task revenue (R_j), and (b) costs associated with completing tasks.

2.3.2.1.1 Task Revenue

Rather than directly choosing the revenue for a task, we arrive at this expression by first developing the expression at the skill level. We assume that the revenue for a task is a function of the skills required to complete the task and time that a benchmark worker (of competence 1) in the organization would take to complete the task. Hence, if β_s represents the billing rate per unit time for skill s, the revenue from task j is given by, $R_j = \sum_{s=1}^{S} \beta_s \vartheta_{js} \phi_{js}$. Here, ϑ_{js} is equal to one if task j requires skill s, zero otherwise and ϕ_{js} represents time required by a benchmark worker (of competence 1) to fulfill the requirement in skill s for task j. This billing scheme is consistent with an industry practice of charging a standardized rate for a task based on task complexity (USi 2009).

2.3.1.1.2 Costs Associated with Completing Tasks

The total cost associated with completing a task is a product of the time to complete the task and the worker's wage rate (h_k). The total time worker k takes to complete a task consists of two components, (a) time required to complete the task based on worker k's competence, (b) overhead incurred by worker k as a result of providing help to co-workers. These components are discussed below.

Time Required to Complete a Task

Worker k's competence (expertise) in skill type s, in assignment period t is given by $W_{kst} \in (0,4]$, such that the time taken by worker k to complete task j is given by

$\sum_{s=1}^{S} \vartheta_{js} W_{kst} \phi_{js}$. Thus, small values of W_{kst} indicate an expert worker, while larger values indicate a novice. In assignment period *t*, a worker, once assigned to a task, can acquire additional knowledge by consulting co-workers. We model the extent of knowledge gained by worker *k*, as a result of consulting co-worker *l*, as depending on: (a) the difference in their competence levels at that point in time $(W_{kst} - W_{lst})$, (b) worker *l*'s willingness to help (α_l^i). A worker's willingness to help is a function of the *worker* and the *type of tie* (strong, weak or performative) shared by co-workers *k* and *l*. Prior organizational research (Baum and Berta, 1999; Hansen and Løvås, 2004; Levine and Kurzban, 2006) has reported that individuals in organizations prefer using strong ties first (because they are more willing to help), followed by weak ties and performative ties. We model this by assuming $\alpha_l^0 \geq \alpha_l^1 \geq \alpha_l^2$, where 0, 1, and 2 represent strong, weak and performative ties respectively. Therefore, $G_{kst} = \sum_{l=1}^{K} \sum_{i=0}^{2} G_{klst}^i \Lambda_{klst}^i$ represents worker *k*'s gain in skill *s* in period *t* after consultation. Here, $G_{klst}^i = (W_{kst} - W_{lst}) \alpha_l^i$ is the extent of help acquired by worker *k* from worker *l* (sharing a tie of type *i*), and $\Lambda_{klst}^i = 1$ (*decision variable*) if worker *l* provides help using tie *i* to worker *k* (0 otherwise), in skill *s* in period *t*. Note that we allow worker *k* to gain help at most from one worker in period *t* in skill *s* (i.e., $\sum_{l=1, l \neq k}^{K} \sum_{i=0}^{2} \Lambda_{klst}^i \leq 1$). Finally, worker *k*'s effective competence in skill *s* in period *t* is given by $C_{kst} = W_{kst} - G_{kst}$. Therefore, the actual time a worker takes to complete a task, after knowledge acquisition, is given by, $\sum_{s=1}^{S} \vartheta_{js} C_{kst} \phi_{js}$.

We propose that organizations could *push* a help source by combining social network information with competence information. Tools such as IBM SOcial Network ARchitecture (SONAR) (Guy et al., 2008) provide social network information that can be combined with competence information from other available tools such as Microsoft's Skills Planning und (and) Development (SPUD) (Davenport and Prusak, 1998), Knowledge Interchange Network (KIN) and Tacit Systems EKG (Cross et al., 2001).

It is important to note that a worker's competence in the current period W_{kst} is a function of knowledge acquired in prior periods. We assume that every time a worker completes a task there is an improvement in the workers competence (i.e., W_{kst} decreases) due to consultation. This assumption is consistent with human capital theory (Becker 1962) and prior research on knowledge management (Chen and Edgington 2005). W_{ks1} represents the worker's initial competence level (at the beginning of the planning horizon). Here, $X_{kjt} = 1$ (*decision variable*) when worker *k* has been assigned to task *j* in assignment period *t*, 0 otherwise and $F_{kjt} = 1$ if task *j* is completed by period *t* (0 otherwise). Hence, the competence gained from tasks completed by assignment period *t* is $\sum_{m=1}^{t-1}\sum_{j=1}^{N_{t-1}} X_{kjm}\vartheta_{js}\omega G_{ksm}F_{kjt}$. Here, we introduce a retention coefficient, $\omega \in [0,1]$, to capture the reusable proportion of knowledge gained from consulting co-workers. For example, $\omega < 1$ implies that the worker retains only a fraction of the learning for tasks in future periods. Therefore, worker *k*'s competence in period *t* is modeled as, $W_{kst} = W_{ks1} - \sum_{m=1}^{t-1}\sum_{j=1}^{N_{t-1}} X_{kjm}\vartheta_{js}\omega G_{ksm}F_{kjt}$.

Overhead Associated with Providing Help

While consultation may benefit the worker receiving help, it is possible that a competent worker may be burdened by having to help multiple workers in a given period. Therefore, the organization must take the cost of proving help into account when choosing a help source. We model this cost by increasing the time taken by worker *k* to complete his/her assigned task, when helping co-workers. Particularly, this additional time (overhead) in period *t* is modeled as, $\sum_{s=1}^{S}\sum_{l=1,l\neq k}^{K}\sum_{i=0}^{2}\varpi^{i} Z_{kt} \Lambda^{i}_{lkst}$. Here, ϖ^{i} is the overhead coefficient associated with worker *k* providing help over a tie of type *i*, such that $\varpi^{i} = 0$ when there is no overhead from providing help. Such an overhead is relevant only when worker *k* is busy ($Z_{kt} = 1$), and increasing in the total numbers of workers being helped $(\sum_{\substack{l=1\\l\neq k}}^{K}\sum_{i=0}^{2}\Lambda^{i}_{lkst})$.

Finally, *total task time* for worker *k* is the sum of,

(a) time required to complete task *j* based on worker *k*'s competence, $\sum_{s=1}^{S} X_{kjt}\vartheta_{js}\phi_{js}C_{kst}$.

(b) overhead incurred by worker *k* as a result of providing help to co-workers, $\sum_{s=1}^{S}\sum_{l=1,l\neq k}^{K}\sum_{i=0}^{2}\varpi^{i}\Lambda^{i}_{lkst}Z_{kt}$.

Therefore, the total cost of completing tasks over the planning horizon is given by, $\sum_{t=1}^{T}\sum_{k=1}^{K} h_k \sum_{s=1}^{S}(\sum_{j=1}^{N_t} X_{kjt}\vartheta_{js}\phi_{js}C_{kst} + \sum_{l=1,l\neq k}^{K}\sum_{i=0}^{2}\varpi^{i}\Lambda^{i}_{lkst}Z_{kt})$.

In summary, our model incorporates four factors that have been recognized in prior research (Cross et al., 2001) as being important for effective knowledge sharing. These factors are: (a) "knowing what another person knows" which we model as worker competence W_{kst}, (b) "willingness to engage in problem solving" which we model as α_k^i, (c) "being able to gain access" which we model by incurring a cost of providing help when a worker is busy, and (d) "degree of safety in the relationship" which we model using different values for α_k^i, based on the type of tie.

2.3.1.2 Cost Associated With Workers Sitting on Bench

When a worker is not competent enough to perform any task or there are no tasks available for him to perform, the worker might just have to sit idle for that assignment period. However, the firm incurs a cost for workers sitting on the bench, since it may continue to pay out wages to these workers. In our model, Z_{kt} equal to zero indicates that the worker is available in period *t*, and is not busy with any task assigned to him in a previous period. Therefore, the cost associated with the workers that are kept idle in period *t* is given by, $\sum_{k=1}^{K}((1-Z_{kt})-\sum_{j=1}^{N_t}X_{kjt})h_k\theta_b$. Here $\theta_b \in [0,1]$ is the proportion of the wage paid when a worker is kept idle. This allows organizations to distinguish between a worker's wage rate when assigned a task versus sitting on bench. It is often equal to one in practice.

2.3.1.3 The Wait-Time Penalty from Unassigned Tasks

As discussed earlier, many IT service requests are time critical and delays in responding to these requests can often result in significant penalties for the firm. To capture this we introduce a task level wait-time penalty per period $\theta_a \in [0,1]$. Here, θ_a represents the reduction in the task revenue (billing rate) for every time period that the task is kept waiting in the system. Hence, if N_t represents the total number of tasks that have arrived till period *t*, the total wait-time penalty incurred in period *t* is given by,

$$\sum_{j=1}^{N_t}((1-\sum_{m=1}^{t}\sum_{k=1}^{K}X_{kjm})\sum_{s=1}^{S}\vartheta_{js}\beta_s)\theta_a \ .$$

Thus, the KISDN optimization problem can be formulated as:

Objective Function[1]

$$Max\sum_{t=1}^{T}\left(\begin{array}{l}\sum_{k=1}^{K}(\sum_{j=1}^{N_t}X_{kjt}R_j-h_k\sum_{s=1}^{S}(\sum_{j=1}^{N_t}X_{kjt}\vartheta_{js}\phi_{js}C_{kst}+\sum_{l=1,l\neq k}^{K}\sum_{i=0}^{2}\varpi^i\Lambda_{lkst}^iZ_{kt}))\\ -\sum_{k=1}^{K}(1-Z_{kt}-\sum_{j=1}^{N_t}X_{kjt})h_k\theta_b-\sum_{j=1}^{N_t}((1-\sum_{m=1}^{t}\sum_{k=1}^{K}X_{kjm})\sum_{s=1}^{S}\vartheta_{js}\beta_s)\theta_a\end{array}\right)$$

Total Task Revenue – Total Costs Associated with Completing Tasks (including the overhead of providing help) – Total Bench Cost – Total Wait Time Penalty

Assignment Constraints

$$\sum_{j=1}^{N_t}X_{kjt}+Z_{kt}\leq 1 \quad \forall k\in\{1,..,K\},t\in\{1,..,T\} \ ,$$

Worker *k* can be assigned in the current period *iff* worker *k* is not busy with any tasks.

$$\sum_{t=1}^{T}\sum_{j=1}^{N_t}(X_{kjt}\sum_{s=1}^{S}\vartheta_{js}\phi_{js}C_{kst})+\sum_{t=1}^{T}(1-Z_{kt}-\sum_{j=1}^{N_t}X_{kjt})+\sum_{t=1}^{T}\sum_{l=1,l\neq k}^{K}\sum_{i=0}^{2}\sum_{s=1}^{S}\varpi^i\Lambda_{lkst}^iZ_{kt}\leq T \quad \forall k\in\{1,..,K\},$$

Total time spent by a worker on tasks and on the bench cannot exceed *T*.

$$\sum_{k=1}^{K}\sum_{t=1}^{T}X_{kjt}\leq 1 \quad \forall j\in\{1,..,N_{Max}\}$$

$$\sum_{j=N_t+1}^{N_{Max}}X_{kjt}=0 \quad \forall k\in\{1,..,K\},t\in\{1,..,T\},$$

A task can only be assigned once and after it arrives in the system.

$$F_{kjt}(\sum_{m=1}^{t-1}(t-m-\sum_{s=1}^{S}(C_{ksm}\vartheta_{sj}\phi_{sj}+\sum_{q=m}^{t-1}\sum_{l=1,l\neq k}^{K}\sum_{i=0}^{2}\varpi^i\Lambda_{lksq}^i))X_{kjm}/T+F_{kj(t-1)})\geq 0$$

---

[1] The linearized version of the above constraints is provided in Appendix A.

$$2F_{kjt} \geq (\sum_{m=1}^{t-1}(t-m-\sum_{s=1}^{S}(C_{ksm}\vartheta_{sj}\phi_{sj}+\sum_{q=m}^{t-1}\sum_{l=1,l\neq k}^{K}\sum_{i=0}^{2}\varpi^{i}\Lambda_{lksq}^{i}))X_{kjm}/T+F_{kj(t-1)}$$

$$\sum_{m=1}^{t-1}X_{kjm}-F_{kjt} \geq 0 \qquad \forall\, k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, t \in \{2,..,T\},$$

F_{kjt} = 1 if worker *k* completes task *j* by time period *t*, 0 otherwise.

Λ_{klst}^{i} =1 if worker *k* gets help in skill *s* from worker *l* using tie *i* in time period *t*, 0 otherwise.

$$Z_{kt} = \sum_{m=0}^{t-1}\sum_{j=1}^{N_{t-1}}(1-F_{kjt-1})X_{kjm} \qquad \forall k \in \{1,..,K\}, t \in \{2,..,T\}\ ,$$

Z_{kt} = 0 if worker *k* is available in period *t* (i.e., not busy), 1 otherwise.

Knowledge Acquisition Constraints:

$$G_{klst}^{i} = (W_{kst}-W_{lst})\alpha_{l}^{i} \qquad \forall k,l \in \{1,,K\}, l \neq k, s \in \{1,,S\}, t \in \{1,,T\}, i \in \{0,1,2\}, \rho_{kl}^{i}=1$$

G_{klst}^{i} represents worker *k*'s gain in skill *s* from worker *l* using tie *i* in time period *t*.

$$\sum_{l=1,l\neq k}^{K}\sum_{i=0}^{2}\Lambda_{klst}^{i} \leq 1 \qquad \forall k \in \{1,..,K\}, \rho_{kl}^{i}=1, s \in \{1,..,S\}, t \in \{1,..,T\}$$

Worker *k* can get help from only one worker *l* using one type of tie in skill *s* in period *t*.

$$G_{kst} = \sum_{l=1,l\neq k}^{K}\sum_{i=0}^{2}G_{klst}^{i}\Lambda_{klst}^{i}\ \forall k \in \{1,..,K\}, s \in \{1,..,S\}, t \in \{1,..,T\}$$

$$C_{kst} = W_{kst} - G_{kst} \quad \forall k \in \{1,..,K\}, s \in \{1,..,S\}, t \in \{1,..,T\}$$

G_{kst} represents worker *k*'s gain in skill *s* in time period *t*, after consultation.

C_{kst} is worker *k*'s effective competence of skill *s* in time period *t* after consultation.

$$W_{kst} = W_{ks1} - \sum_{m=1}^{t-1}\sum_{j=1}^{N_{t-1}}X_{kjm}\vartheta_{js}\omega\ G_{ksm}F_{kjt} \qquad \forall k \in \{1,..,K\}, s \in \{1,..,S\}, t \in \{2,..,T\}$$

Updating worker *k*'s current competence (W_{kst}) based on knowledge acquired in prior periods

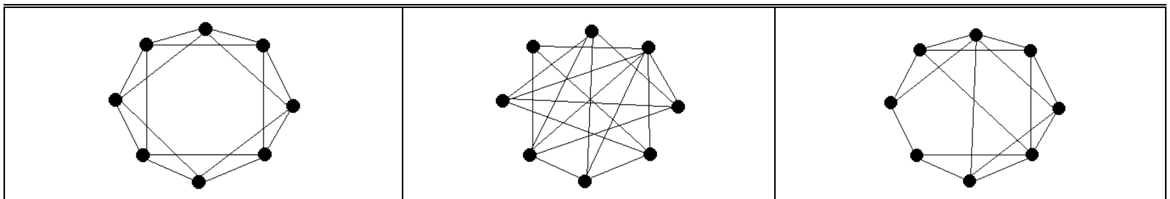
■

2.3.1.4 Handling Uncertainty in problem parameters

Recall that the firm's objective is to study how task assignment, knowledge management strategies and organizational networks interact in order to impact its financial and operational performance. In that context, using expectations to estimate the type of tasks (ϕ_{js}), arrival of tasks (λ_s), initial competence of the workforce (W_{ks1}), and knowledge acquisition parameters ($\alpha^i_{idle}, \alpha^i_{busy}, \omega$) removes the notion of uncertainty. However, we believe this is a relevant aspect of the firm's knowledge management problem. Therefore, in order to handle uncertainty more appropriately, the firm can draw different vectors of values for each of these parameters i.e., the firm conceptualizes the value as a random draw from an appropriate distribution. The firm considers random draws from the estimated distributions of the unknown values, solves independent problems for each instance, and takes the expected value across multiple instances. *Note that the MIP formulated in the previous section can be interpreted as the knowledge management problem faced by the firm for <u>one such instance</u>*. Given that the estimated distribution is continuous in nature, it is impractical to estimate the outcomes for all possible situations. However, if the number of instances (draws) selected is large enough, they would provide a reasonable approximation. The firm can basically estimate the value of its knowledge management strategies based on all the instances and the probabilities of each of the instances. This helps lend greater generalization to the model results.

2.3.2 Network Structures

We consider three types of organizational network structures: Clustered Networks (CN), Random Networks (RN), and Small-world Networks (SN) (see Figure 2). These three network configurations are generated by "rewiring" the *same* total number of connections (Watts and Strogatz, 1998). In CN, all interactions are spatially local and a worker is directly connected to the *same* small number of his nearest neighbors, i.e., a large number of cliques with few or no connections between them. This implies that in CN there tends to be large overlap between strong and weak ties, i.e., a friend are also a friend of a friend. On the other hand, RN have few or no cliques between workers. Hence, unlike CN, in these networks there is very little overlap between strong and weak ties of a worker. Lastly, SN lie somewhere in between CN and RN by having some cliques with limited connections between cliques.



(a) Clustered Networks (CN)	(b) Random Networks (RN)	(c) Small-World Networks (SN)

FIGURE 2: Different organizational network structures

2.4 Solution Procedure

2.4.1 Problem Complexity

The KISDN optimization problem discussed in the previous section can be solved. However, a practical issue is whether realistic problems can be solved in a reasonable amount of time. Hence, we next discuss the complexity of our problem.

Theorem 1: *The KISDN optimization problem over some planning horizon is NP-hard*.

The main idea behind the proof is that the generalized assignment problem (Sahni and Gonzalez, 1976) can be polynomially transformed to an arbitrary instance of the KISDN optimization problem over some planning horizon *T*. In this construction, an item and a bin in the generalized assignment problem correspond, respectively, to a task and a worker. Assigning tasks to a worker corresponds to the notion of packing items in a bin. Appropriate choices for the service environment, worker, task and knowledge acquisition parameters complete the construction of an instance of the KISDN optimization problem. For any positive integer $J^{'}$, the decision question "does there exist a valid task-to-worker assignment such that the firm's profit over the planning horizon T is greater than or equal to $J^{'}$?" posed on the constructed instance is equivalent to solving the decision version of the generalized assignment problem.

Consider the decision problem Q_{KOP} corresponding to the KISDN optimization problem over some planning horizon.

Decision Problem (Q_{KOP}): *Given the number of workers K, and the number of tasks N_{Max}, set values W_{ks1}, h_k, for each worker k, values ρ_{kl}^{i} for each worker pair (k, l), values ϑ_{js}, ϕ_{js}, R_j, η_{jt} for each task j, and values T, S, ω, θ_a, θ_b, α_k^i, ϖ^i and a specified number J, does there exist a task-to-worker assignment such that the firm's profit over the planning horizon T is greater than or equal to J ?*

We now show that the decision version of generalized assignment problem can be polynomially transformed to Q_{KOP}.

Generalized Assignment Problem (GAP): *Given a finite set of bins $B = \{b_1, b_2, .., b_m\}$ with capacity c_i for each bin b_i, and a finite set of items $S = \{x_1, x_2, .., x_n\}$, set weight w_{ij} and profit p_{ij} for each pair of item x_j and bin b_i, and a specified number $J^{'}$, does there exist a feasible packing, such that the total profit $\sum_{i=1}^{m}\sum_{j=1}^{n} p_{ij}x_{ij} \geq J^{'}$?*

A constraint in the GAP is that each item can only be packed into any one of the bins, $\sum_{i=1}^{m} x_{ij} \leq 1 \quad \forall j \in \{1,..,n\} \quad (A.1)$. A bin, however, can take multiple items, but should not exceed its capacity c_i, $\sum_{j=1}^{n} w_{ij}x_{ij} \leq c_j \quad \forall i \in \{1,..,m\} \quad (A.2)$.

Given the generalized assignment problem, we now map it to an arbitrary instance of Q_{KOP} as follows. Each worker and task correspond to a bin b_i and an item x_j respectively in the generalized assignment problem. We construct an arbitrary instance of Q_{KOP} by setting $\eta_{j1}=1$ and $\eta_{jt}=0$, $\forall t>1$, $\forall j \in \{1,..,N_{Max}\}$, such that $N_t = N_{Max} \forall t$. This implies that all tasks arrive in the system at period 1. Also, $\theta_a = 0$, and $\theta_b = 0$ so that, there will be no penalty of keeping tasks waiting or keeping workers idle. In addition, we set $\alpha_k^i = 0$, and $\varpi^i = 0$ such that there will be no knowledge sharing among workers. One task can only be assigned to one worker, but a worker can perform multiple tasks over the planning horizon *T*. Therefore, this arbitrary instance of Q_{KOP} is given as follows:

$$\text{Maximize} \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{j=1}^{N_{Max}} X_{kjt}\left(R_j - h_k \sum_{s=1}^{S} \vartheta_{js}\phi_{js}W_{ks1}\right)$$

$$\sum_{j=1}^{N_{Max}} X_{kjt} + Z_{kt} \le 1 \qquad \forall k \in \{1,.,K\}, t \in \{1,.,T\} \tag{A.3}$$

$$\sum_{k=1}^{K}\sum_{t=1}^{T} X_{kjt} \le 1 \qquad \forall j \in \{1,.,N_{Max}\} \tag{A.4}$$

$$\sum_{t=1}^{T}\sum_{j=1}^{N_{Max}}(X_{kjt}\sum_{s=1}^{S} W_{ks1}\vartheta_{sj}\phi_{sj}) + \sum_{t=1}^{T}(1 - Z_{kt} - \sum_{j=1}^{N_{Max}} X_{kjt}) \le T \qquad \forall k \in \{1,.,K\} \tag{A.5}$$

$$F_{kjt}(\sum_{m=1}^{t-1}((t-m) - \sum_{s=1}^{S} W_{ks1}\vartheta_{sj}\phi_{sj})X_{kjm} / T + F_{kj(t-1)}) \ge 0 \quad \forall k \in \{1,.,K\}, j \in \{1,.,N_{Max}\}, t \in \{2,.,T\} \tag{A.6}$$

$$2F_{kjt} \ge \sum_{m=1}^{t-1}((t-m) - \sum_{s=1}^{S} W_{ks1}\vartheta_{sj}\phi_{sj})X_{kjm} / T + F_{kj(t-1)} \quad \forall k \in \{1,.,K\}, j \in \{1,.,N_{Max}\}, t \in \{2,.,T\} \tag{A.7}$$

$$\sum_{m=1}^{t-1} X_{kjm} - F_{kjt} \ge 0 \qquad \forall k \in \{1,.,K\}, j \in \{1,.,N_{Max}\}, t \in \{2,.,T\} \tag{A.8}$$

$$Z_{kt} = \sum_{m=1}^{t-1}\sum_{j=1}^{N_{Max}}(1 - F_{kjt-1})X_{kjm} \qquad \forall k \in \{1,.,K\}, t \in \{2,.,T\} \tag{A.9}$$

The capacity constraint (A.5) in the Q_{KOP} means that the sum of the time taken to complete the assigned tasks and the time that the worker may be kept idle, cannot exceed the length of the planning horizon *T*. This corresponds to constraint (A.2) in the generalized assignment problem. Thus, it is easy to see that for $J = J'$ the solution of this instance of Q_{KOP} provides a solution to the generalized assignment problem. Moreover, the generalized assignment problem is known to be NP-hard (Sahni and Gonzalez, 1976). Hence Q_{KOP} is NP hard.

■

2.4.2 Dynamic Assignment Heuristic (DAH)

If the planning horizon (*P*) was equal to the length or duration of a single period (i.e., $P = \Delta$ implying $T = 1$), then the maximization problem would be similar to an assignment problem with inclusion and exclusion constraints. However, when the planning horizon is divided into multiple periods ($T > 1$), then this problem can be solved for each period successively. In other words, we first determine the optimal assignment and the optimal payoff in the first period. Next, we set up the problem for the second period. To achieve this we use the assignment information from the first period, and take into account of all the new tasks that have arrived and the workers that have become available between period one and two. In addition, we update the worker's competences based on the task assignment in the first period. The optimal assignment and payoff for the second period can be obtained by using this information. Similarly, the assignment for the second period then sets up the problem for the third period, and so on. This would essentially be a *greedy* algorithm (with no look-ahead), wherein the emphasis, is on maximizing the payoff for only that period. In contrast, the proposed DAH improves over the greedy approach in two ways, (a) allows for dynamic assignment using a *One-Period Look Ahead* (OPLA) policy and (b) using suitable approximations, incorporates the *value of learning* viz., how the worker's knowledge acquisition in the current period impacts performance in future tasks.

2.4.2.1 One-Period Look Ahead Policy (OPLA)

DAH uses a *One-Period Look Ahead* (OPLA) policy to decide whether to make assignments now or to wait until the next period. For each period *t*, the OPLA policy compares the objective functions of the following two scenarios: (a) making assignments in periods *t* and *t*+1successively (i.e., objective function value = π_a), (b) wait and make assignments only in period *t*+1 (objective function value = π_b). In both scenarios, we approximate the task arrivals for period *t*+1. We assume that *on average*, for each task of type *m*, λ_m tasks with task times equal to $\sum_{s=1}^{S} q_s^m \varsigma_s$ arrive into the system between period *t* and *t*+1. In the first scenario, π_a is the *sum* of objective function values in assignment period *t* and the successive period *t*+1. Note that in the second scenario, since no assignments are made in period *t*, the firm incurs additional costs in terms of wait-time penalty (for unassigned tasks) and bench cost (for idle workers). Thus, π_b is the objective function value from assignments at period *t*+1 *less* the additional costs stated above. Of course, these additional costs could be offset by making improved assignments in period *t*+1 (since a larger pool of tasks and workers is available). Hence, if $\pi_a < \pi_b$, OPLA policy will choose to wait for one period. Otherwise, the assignments are made in period *t*. This approach (OPLA) is applied repeatedly at every assignment period *t*. Hence, it is possible for the heuristic to wait for more than one period before making an assignment.

2.4.2.2 Estimating the Future Value of Learning

The *value of learning* depends on (a) number of additional tasks of type *m* completed as a result of learning $(\delta_{kmjt}^1 - \delta_{kmjt}^2)$, and (b) the revenue from each of these tasks $\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s$. Here δ_{kmjt}^1 and δ_{kmjt}^2 are the expected number of tasks of type *m* performed by worker *k* using skill s, over the remainder of the session with and without learning, respectively. In order to approximate the values of δ_{kmjt}^1 and δ_{kmjt}^2, we need to consider – (a) the amount of time remaining in the planning horizon after the task assigned in period *t* is completed $(T-(t+\sum_{q=1}^{S} \vartheta_{jq}\phi_{jq}C_{kqt}))$, (b) the likelihood of the worker getting assigned to a task of type *m* in the future, after completing task *j* in period *t* (χ_{kmjt}), (c) the workers effective competence, in skill *s*, with and without learning, $(W_{kst}-\omega G_{kst})$ and W_{kst}, respectively, and (d) the arrival rate of tasks of type *m* (λ_m).

Note that, $\lambda_m(T-(t+\sum_{s=1}^{S} \vartheta_{js}\phi_{js}C_{kst}))$ represents the expected number of tasks of type *m* that will arrive in the remainder of the planning horizon. We propose that, since workers compete for tasks, the proportion of these tasks that can get assigned to worker *k* will depend upon *his competence in task type m relative to his co-workers.* Thus, the likelihood of assigning a task of type *m* to worker *k* is given by $\chi_{kmjt}^{1\_a} = \sum_{s=1}^{S} q_s^m (4-(W_{kst}-\vartheta_{js}\omega G_{kst})) / \sum_{l=1}^{K}\sum_{s=1}^{S} q_s^m (4-(W_{lst}-\vartheta_{js}\omega G_{kst}))$, after learning (while doing task *j*), and $\chi_{kmt}^{2\_a} = \sum_{s=1}^{S} q_s^m (4-W_{kst}) / \sum_{l=1}^{K}\sum_{s=1}^{S} q_s^m (4-W_{lst})$ without it.

On the other hand, even if there was no competition from co-workers, the maximum number of tasks of type *m* that worker *k* can complete in the remainder of the planning horizon can be estimated as the ratio of the time remaining in the planning horizon to the average time taken by worker *k* to complete a task of type *m*. Mathematically, this ratio is $(T-(t+\sum_{s=1}^{S}\vartheta_{js}\phi_{js}C_{kst}))/\sum_{s=1}^{S}q_s^m(W_{kst}-\vartheta_{js}\omega G_{kst})\varsigma_s$ and $(T-(t+\sum_{s=1}^{S}\vartheta_{js}\phi_{js}C_{kst}))/\sum_{s=1}^{S}q_s^m W_{kst}\varsigma_s$, with and without learning respectively. In this case, we propose that the proportion of these tasks that can get assigned to worker *k* will depend upon *his competence in task type m relative to his competence in other types of tasks.* Thus, the likelihood of assigning a task of type *m* to worker *k* is $\chi_{kmjt}^{1\_b}=\sum_{s=1}^{S}q_s^m(4-(W_{kst}-\vartheta_{js}\omega G_{kst}))/\sum_{u=1}^{M}\sum_{s=1}^{S}q_s^u(4-(W_{kst}-\vartheta_{js}\omega G_{kst}))$, after learning (while performing task *j*), and $\chi_{kmt}^{2\_b}=\sum_{s=1}^{S}q_s^m(4-W_{kst})/\sum_{u=1}^{M}\sum_{s=1}^{S}q_s^u(4-W_{kst})$ without it.

Therefore, we estimate δ_{kmjt} based on which of the two scenarios mentioned above places a *tighter constraint* on the number of tasks of type *m* that can be assigned to worker *k*. That is,

$$\delta_{kmjt}^{1}=Min\{\lambda_m(T-(t+\sum_{s=1}^{S}\vartheta_{js}\phi_{js}C_{kst}))\,\chi_{kmjt}^{1\_a},\frac{(T-(t+\sum_{s=1}^{S}\vartheta_{js}\phi_{js}C_{kst}))\chi_{kmjt}^{1\_b}}{\sum_{s=1}^{S}q_s^m(W_{kst}-\vartheta_{js}\omega G_{kst})\varsigma_s}\}\quad\text{and}$$

$$\delta_{kmjt}^{2}=Min\{\lambda_m(T-(t+\sum_{s=1}^{S}\vartheta_{js}\phi_{js}C_{kst}))\chi_{kmt}^{2\_a},\frac{(T-(t+\sum_{s=1}^{S}\vartheta_{js}\phi_{js}C_{kst}))\chi_{kmt}^{2\_b}}{\sum_{s=1}^{S}q_s^m W_{kst}\varsigma_s}\}.$$

2.4.2.3 MIP formulation for each Period *t*

Similar to Section 2.3 (MIP), in each period *t*, the firm's objective consists of the following terms: *net payoff from completing tasks, the cost of workers sitting idle*, and *the wait-time penalty from un-assigned tasks*. In addition the DAH objective consists of the *approximation for the value of learning* in the current period on future periods. As discussed earlier, this depends on the number of additional tasks of type *m* completed as a result of learning $(\delta^1_{kmjt} - \delta^2_{kmjt})$, and the revenue from each of these tasks $\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s$. Mathematically, this is given by, $\sum_{k\in \hat{k}_t}\sum_{j\in \hat{n}_t}\sum_{m=1}^{M}\sum_{s=1}^{S} X_{kjt} q_s^m \beta_s \varsigma_s (\delta^1_{kmjt} - \delta^2_{kmjt})$. Here, $\hat{n}_t$ is the *set* of un-assigned tasks and $\hat{k}_t$ is the *set* of available workers at the beginning of period *t*. Using the same notation as in Section 2.3 (Table 1), in period t , the firm's maximization problem using DAH, can be we written as,

$$Max \sum_{k\in \hat{k}_t}\left(\sum_{j\in \hat{n}_t} X_{kjt} R_j - \sum_{s=1}^{S}(\sum_{j\in \hat{n}_t} h_k X_{kjt} \vartheta_{js}\phi_{js} C_{kst} + \sum_{l\notin \hat{k}_t}\sum_{i=0}^{2} h_l X_{kjt} \varpi^i \Lambda^i_{klst}) + \sum_{j\in \hat{n}_t}\sum_{m=1}^{M}\sum_{s=1}^{S} X_{kjt} q_s^m \beta_s \varsigma_s (\delta^1_{kmjt} - \delta^2_{kmjt}) \right)$$
$$- \sum_{k\in \hat{k}_t}(1 - \sum_{j\in \hat{n}_t} X_{kjt}) h_k \theta_b - \sum_{j\in \hat{n}_t}((1 - \sum_{k\in \hat{k}_t} X_{kjt}) \sum_{s=1}^{S} \vartheta_{js}\beta_s)\theta_a$$

Subject to,

$$\sum_{j\in \hat{n}_t} X_{kjt} \le 1 \quad \forall k \in \hat{k}_t \ ,$$

$$\sum_{k\in \hat{k}_t} X_{kjt} \le 1 \quad \forall j \in \hat{n}_t \ ,$$

$$X_{kjt} \in \{0,1\} \quad \forall j \in \hat{n}_t,\, k \in \hat{k}_t, s \in \{1,..,S\} \qquad \blacksquare$$

The assignment constraints are similar to Section 2.3, where we ensure that each task can only be assigned to one worker. Also, a worker can be assigned to a task, or kept idle in period *t*. The extent of knowledge acquired from a co-worker (G_{kst}) and hence the effective competence (C_{kst}), can be calculated in a fashion similar to the one described in Section 2.3.1.

2.4.2.4 Implementation of the Hungarian Method

To solve the maximization problem, in order to estimate the values for π_a and

π_b , we use the Hungarian method (Cormen et al., 2001). The Hungarian method models the assignment problem as a *p*-by-*q* profit matrix, where each element $a_{k,j}$ represents the profit of assigning the *k*-th worker to the *j*-th task. Recall that in our assignment problem, there is a payoff associated with assigning worker *k* to task *j*, or to the bench. In addition, we also model a waiting-time penalty for each unassigned task in the system. Even so, we show that our assignment problem can be solved using the Hungarian method by generating an adjusted profit matrix.

In the adjusted profit matrix, the payoff associated with assigning each task $j \in \hat{n}_t$ to each worker $k \in \hat{k}_t$ (which is $a_{k,j}$) is sum of the payoff $(R_j - \sum_{s=1}^{S}(\vartheta_{js}\phi_{js}h_k C_{kst} + \sum_{l \notin \hat{k}_t}\sum_{i=0}^{2}\vartheta_{js}\varpi^i h_l \Lambda^i_{klst}) + \sum_{m=1}^{M}\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s(\delta^1_{kmjt} - \delta^2_{kmjt}))$ and the wait-time penalty ($\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a$) associated with task *j* (Block A in Figure 3). Note that, as in the MIP, we only allow one worker to provide help to worker *k* in skill *s* in period *t*.

Therefore, for each task *j*, worker *l* provides help to worker *k* $(\Lambda^i_{klst} = 1)$, *iff*

$$(W_{kst} - W_{lst})\alpha^i_l\phi_{js}\vartheta_{js}h_k - \varpi^i h_l \geq \underset{g,f,r}{Max}\{(W_{kst} - W_{gst})\alpha^r_g\phi_{js}\vartheta_{js}h_k - \varpi^r h_g \ , (W_{kst} - W_{fst})\alpha^r_f\phi_{js}\vartheta_{js}h_k \ , 0\}$$
$$\forall g \notin \hat{k}_t, f \in \hat{k}_t, l \neq g, f, r \in \{0,1,2\}$$

The payoff associated with keeping a worker *k* on bench is period *t* is given as, $-h_k\theta_b$ (Block B in Figure 3). The number of rows in our adjusted profit matrix is determined by the number of available workers at the beginning of period *t* ($|\hat{k}_t|$) , i.e., $p = |\hat{k}_t|$. And, the number of columns is the sum of the number of available tasks in period *t* ($|\hat{n}_t|$), and an additional option of keeping the worker idle (i.e., $q = |\hat{n}_t| + 1$).

$$
\begin{array}{rcc}
 & \text{Block A} & \text{Block B} \\
\left|\hat{k}_t\right| \text{ workers} \left\{ \vphantom{\begin{matrix} a \\ a \\ a \\ a \end{matrix}} \right. &
\underbrace{\boxed{\begin{matrix} a_{1,1} & a_{1,2} & \cdots & a_{1,|\hat{n}_t|} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,|\hat{n}_t|} \\ \vdots & \vdots & & \vdots \\ a_{|\hat{k}_t|,1} & a_{|\hat{k}_t|,2} & \cdots & a_{|\hat{k}_t|,|\hat{n}_t|} \end{matrix}}}_{\left|\hat{n}_t\right| \text{Tasks}} &
\underbrace{\boxed{\begin{matrix} a_{1,|\hat{n}_t|+1} \\ a_{2,|\hat{n}_t|+1} \\ \vdots \\ a_{|\hat{k}_t|,|\hat{n}_t|+1} \end{matrix}}}_{\text{Bench}}
\end{array}
$$

FIGURE 3: Profit matrix for the Hungarian method used in DAH

In this section, we present the formal proof for using the adjusted task profit ($R_j - \sum_{s=1}^{S}(\vartheta_{js}\phi_{js}h_k C_{kst} + \sum_{l\notin\hat{k}_t}\sum_{i=0}^{2}\vartheta_{js}\varpi^i h_l \Lambda^i_{klst}) + \sum_{m=1}^{M}\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s(\delta^1_{kmjt}-\delta^2_{kmjt}) + \sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a$) in the profit matrix. The task payoff and the wait-time penalty in period t is given by

$$
\sum_{k\in\hat{k}_t}\sum_{j\in\hat{n}_t} X_{kjt}\left(R_j - \sum_{s=1}^{S}(\vartheta_{js}\phi_{js}h_k C_{kst} + \sum_{l\notin\hat{k}_t}\sum_{i=0}^{2}\vartheta_{js}\varpi^i h_l \Lambda^i_{klst}) + \sum_{m=1}^{M}\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s(\delta^1_{kmjt}-\delta^2_{kmjt})\right)
$$
$$
-\sum_{j\in\hat{n}_t}(1-\sum_{k\in\hat{k}_t}X_{kjt})\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a
$$

This could be written as follows:

$$
\sum_{k\in\hat{k}_t}\sum_{j\in\hat{n}_t} X_{kjt}\left(R_j - \sum_{s=1}^{S}(\vartheta_{js}\phi_{js}h_k C_{kst} + \sum_{l\notin\hat{k}_t}\sum_{i=0}^{2}\vartheta_{js}\varpi^i h_l \Lambda^i_{klst}) + \sum_{m=1}^{M}\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s(\delta^1_{kmjt}-\delta^2_{kmjt})\right)
$$
$$
-\sum_{j\in\hat{n}_t}\left(\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a - \sum_{k\in\hat{k}_t}X_{kjt}\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a\right)
$$
$$
=\sum_{k\in\hat{k}_t}\sum_{j\in\hat{n}_t} X_{kjt}\left(R_j - \sum_{s=1}^{S}(\vartheta_{js}\phi_{js}h_k C_{kst} + \sum_{l\notin\hat{k}_t}\sum_{i=0}^{2}\vartheta_{js}\varpi^i h_l \Lambda^i_{klst}) + \sum_{m=1}^{M}\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s(\delta^1_{kmjt}-\delta^2_{kmjt})\right)
$$
$$
-\left(\sum_{j\in\hat{n}_t}\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a - \sum_{j\in\hat{n}_t}\sum_{k\in\hat{k}_t}X_{kjt}\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a)\right)
$$

$$
=\sum_{k\in\hat{k}_t}\sum_{j\in\hat{n}_t} X_{kjt}\left(R_j - \sum_{s=1}^{S}(\vartheta_{js}\phi_{js}h_k C_{kst} + \sum_{l\notin\hat{k}_t}\sum_{i=0}^{2}\vartheta_{js}\varpi^i h_l \Lambda^i_{klst}) + \sum_{m=1}^{M}\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s(\delta^1_{kmjt}-\delta^2_{kmjt})\right)
$$
$$
+\sum_{k\in\hat{k}_t}\sum_{j\in\hat{n}_t}X_{kjt}\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a - \sum_{j\in\hat{n}_t}\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a
$$

$$= \sum_{k\in\hat{k}_t}\sum_{j\in\hat{n}_t} X_{kjt}\left(R_j - \sum_{s=1}^{S}(\vartheta_{js}\phi_{js}h_k C_{kst} + \sum_{l\notin\hat{k}_t}\sum_{i=0}^{2}\vartheta_{js}\varpi^i h_l \Lambda^i_{klst}) + \sum_{m=1}^{M}\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s (\delta^1_{kmjt} - \delta^2_{kmjt}) + \sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a \right)$$
$$- \sum_{j\in\hat{n}_t}\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a$$

Since $\sum_{j\in\hat{n}_t}\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a$ is a constant for time period *t*, our objective function could be solved using $R_j - \sum_{s=1}^{S}(\vartheta_{js}\phi_{js}h_k C_{kst} + \sum_{l\notin\hat{k}_t}\sum_{i=0}^{2}\vartheta_{js}\varpi^i h_l \Lambda^i_{klst}) + \sum_{m=1}^{M}\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s (\delta^1_{kmjt} - \delta^2_{kmjt}) + \sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a$ as the adjusted task profit.

Updating the Overhead Associated with Providing Help

One subtle aspect of DAH is that the cost of providing help is estimated only for busy workers $(k \notin \hat{k}_t)$, prior to making assignments. However, it is possible that post-assignment (using the Hungarian method) some of the previously idle workers may also become busy. In that case, we need to check, for every such worker *l*, whether the cost of providing help incurred by *l* is offset by the benefit to every worker *k* being helped, and update the competence levels accordingly.

Therefore, after making assignments using Hungarian method, we check whether $\sum_{s=1}^{S}\sum_{i=0}^{2}\varpi^i h_l \Lambda^i_{klst} - \sum_{j\in\hat{n}_t}\sum_{s=1}^{S} X_{kjt}(W_{kst} - W_{lst})\alpha^i_l \phi_{js}\vartheta_{js}h_k \le 0$, where $l, k \in \hat{k}_t$ and worker *k*, *l* are assigned to tasks in period *t*.

(a) if $\sum_{s=1}^{S}\sum_{i=0}^{2}\varpi^i h_l \Lambda^i_{klst} - \sum_{j\in\hat{n}_t}\sum_{s=1}^{S} X_{kjt}(W_{kst} - W_{lst})\alpha^i_l \phi_{js}\vartheta_{js}h_k \le 0$, we allow worker *l* to help worker *k*. However, as discussed in Section 2.3.1.1, worker *l* incurs overhead $(\varpi^i h_l)$ from providing help to worker *k*.

(b) if $\sum_{s=1}^{S}\sum_{i=0}^{2}\varpi^{i} h_l \Lambda^{i}_{klst} - \sum_{j\in\hat{n}_t}\sum_{s=1}^{S} X_{kjt}(W_{kst}-W_{lst})\alpha_l^{i}\phi_{js}\vartheta_{js}h_k > 0$, we stop worker l from helping worker k in period t, and update worker k's time to complete task j as, $\sum_{s=1}^{S}\vartheta_{js}\phi_{js}W_{kst}$. ■

Finally, Figure 4 summarizes the DAH.

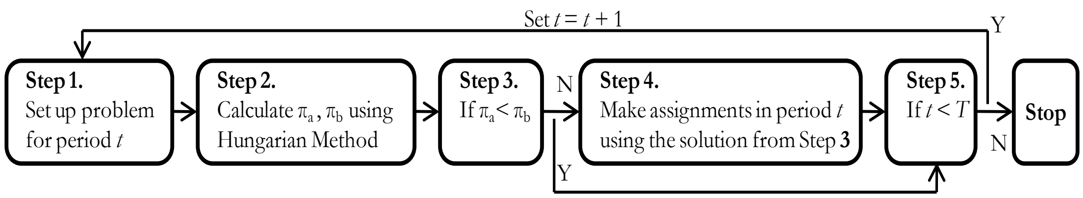


FIGURE 4: Dynamic Assignment Heuristic (DAH)

2.5 Simulation Design

The complexity of the problem precludes analytical solution and requires us to use simulation. Other studies in IS have used simulation with synthetic data in order to provide stylized insights into relationships between key variables when the underlying phenomenon is complex and real world data is difficult to obtain. Such studies include the value of knowledge management (Chen and Edgington, 2005), electronic markets (Jones et al., 2006), the performance of IS teams (Rao et al., 1995), and security portfolios (Kumar et al., 2008). The value of our model is primarily to provide generalized insights into the operation of KISDN. This section describes the design of simulation experiments including, key parameters and their estimation. Fifty replications of each sample path were used, and average values of system performance measures were calculated. Such an approach using average performance analysis is consistent with prior MIS research (Chen and Edgington, 2005; Jones et al., 2006; Kumar et al., 2008; Rao et al., 1995; Sen et al., 2009). Simulations were extremely

TABLE 2: Parameter values used in computational experiment

Type	Parameter	Value	Comments
System Environment	T	1,200 time periods	Assuming that each time interval is 10 minutes.
	K	100 workers	
	S	4 skills	Comparable to Cowan and Jonard (2004), and Prabhakar et al. (2005).
	θ_a	0.1, 0.3, 0.5	The penalty coefficients of 0.1 and 0.3 are in the range of actual SLAs (Buco et al., 2003; Send et al., 2009).
Worker Related	h_s	$h_1 = 4, h_2 = 6, h_3 = 8, h_4 = 10$	Wage rate per period for skill s for a worker of competence = 1. This range is comparable to values reported at payscale.com and Sen et al. (2009).
	θ_b	1	
	W_{ks1}	$N(1.4,0.4), N(1.4,0.45), N(1.4,0.5)$ $\forall k \in \{1,..,K\}, s \in \{1,2,3,4\}$	Microsoft's SPUD project recognized 4 skill levels (Davenport and Prusak, 1998). Hence we used a range of 0-4 for worker competence A normal distribution of worker competence is consistent with prior research (Sayın and Karabatı 2007).
	h_k	$h_k = \sum_{s=1}^{S} h_s(\frac{4-W_{ks1}}{3S})$, $\forall k \in \{1,..,K\}$	Derived from $W_{ks1} \in (0,4]$, $W_{ks1} = 1$ is a benchmark worker.
Task Related	β_s	$\beta_1 = 6, \beta_2 = 9, \beta_3 = 12, \beta_4 = 15$	A 50% gross profit margin was added to h_s. This is comparable to Sen et al. (2009).
	M	6	$\sum_{s=1}^{S} q_s^m = 2,\ \forall m \in \{1,..,M\}$ Sen et al. (2009) reports 3 types of services based on real data. We use a greater range of services.
	ϕ_{js}	$N(\varsigma_s, \sigma_s), \forall s \in \{1,2,3,4\}$ $\varsigma_1 = 5, \varsigma_2 = 10, \varsigma_3 = 15, \varsigma_4 = 20$ $\sigma_1 = 2, \sigma_2 = 4, \sigma_3 = 6, \sigma_4 = 8$	Sen et al. (2009) reports mean and maximum values for task times in the range of 30 minutes to 8 hours. HP (2007) reports problem resolution times of 4 hours to 10 days. The values used in our simulations are comparable.
	λ_m	$\lambda_m = 1, \forall m \in \{1,..,M\}$	Task arrival follows a Poisson distribution comparable to prior research (Buco et al. 2003; Sen et al. (2009). Arrival rates used are comparable to Sen et al. (2009).
Knowledge Acquisition	ω	0.1, 0.2, 0.3	We experimented with multiple values of knowledge retention. The results are not qualitatively different for higher values.
	ϖ^i	$\varpi^0 = 0.1\sim0.6, \varpi^1 = 0.3\sim1.8, \varpi^1 = 0.5\sim3$	We experiment with a range of values to study the sensitivity of our results.
	α_k^i	$\alpha_k^0 = N(0.45,0.03), \alpha_k^1 = N(0.25,0.02),$ $\alpha_k^2 = N(0.05,0.01) \forall k \in \{1,..,K\}$	Cowan and Jonard (2004) uses values in the range 0.5-1 for strong ties and recognize that high values close to 1 are unrealistic. Baum et al. (1999), Hansen and Løvås (2004), Levine and Kurzban (2006) discuss the fact that values depend on the type of tie.
Network Related	γ	0, 0.9, 1	Rewiring Probability
	κ	10%, 12%, 14%, 16%, 18%, 20%	Network Density

computation-intensive. Hence, they were run on a cluster of 160 Intel Xeon CPUs on Dell blade servers with Red Hat Enterprise Linux operating system. The average time for running each replication of a sample path was 2.4 hours.

Table 2 describes the numerical values, and justification for parameters used in our simulation experiments. Where possible, we have attempted to base these values on ranges that could be encountered in practice and/or prior research. These parameters can be divided into five categories: service environment, workers, tasks, knowledge acquisition, and network. Each of these is described below. In our opinion, service environment, worker, and task parameters can be estimated relatively easily. Knowledge acquisition parameters included in our model could be estimated approximately and help sensitize the organization to KISDN management issues that involve these parameters.

2.5.1 Service Environment Parameters

The service environment was simulated for a planning horizon P of 1200 time periods. As discussed earlier, it is important to realize that the actual value of each time period could be context sensitive. We assume 100 workers (K) and 4 skills (S) for our simulations. This represents a relatively small service organization. Larger values would significantly enhance computational complexity. Prior research on knowledge transfer (Cowan and Jonard, 2004) and technical support (Prabhakar et al., 2005) has used 5 and 3 skills respectively. As outlined before, we use wait time penalties to model the impact of customer waiting and use different values of penalty coefficients (θ_a) in our simulation experiments. As mentioned in Table 2, the choice of values is comparable to actual service level agreements (SLAs) (Buco et al., 2003, Sen et al., 2009).

2.5.2 Worker Parameters

We use two worker related parameters: hourly wage rate for a benchmark worker (of competence 1) for skill *s* (h_s), and initial competence of worker *k* in skill *s* (W_{ks1}). The hourly rate for worker *k* (h_k) is calculated from these as shown in Table 2. These values were chosen to be comparable to the range of values encountered in practice (www.payscale.com and Sen et al., 2009). In addition, we assume the bench cost coefficient (θ_b) is one. Consistent with prior research on worker cross training (Sayın and Karabatı, 2007) a normal distribution of worker competence was assumed. Empirical research on the operation of IT service environments has illustrated the presence of considerable worker heterogeneity in service task completion (Kim et al., 2008). We chose a range of four for worker competence, based on the Microsoft SPUD project (Davenport and Prusak, 1998) which recognizes four levels of worker competence in each skill. A mean of 1.4 was chosen to allow for a normal distribution of worker competence in the range 0-4. While it is easy to measure worker's wage rate (h_k), it is more difficult to measure worker's competence (W_{kst}). However, there is a growing trend of using technology to assess workers, competence and store them in a skill database. Tools such as Microsoft's SPUD (Davenport and Prusak, 1998) and KIN and Tacit Systems EKG (Cross et al., 2001) have been adopted by service organizations in order to measure and store worker competence for use in decision making.

2.5.3 Task Related Parameters

We assumed that the time taken by a benchmark worker to complete the requirement in skill *s* for task *j*, is given by $\phi_{js} = N(\varsigma_s, \sigma_s)$ with values (in minutes) for each type of skill given in Table 2. We assume six types of tasks in terms of their skill requirement, each task requires two skills, and an equal arrival rate (λ_m) for each task type *m*. Task arrival rates and task times are in the range that could be encountered in practice[2] (HP, 2007; Sen et al., 2009). Sen et al., (2009) reports mean and maximum values for task times in the range of 30 minutes to 8 hours, and HP (2007) reports problem resolution times of 4 hours to 10 days. In our simulation, for example, a task requiring skills 1 and 2 would have a mean task time of 15x10 =150 minutes, and a maximum time of 330 minutes. The billing rate for each skill (β_s) is calculated based on the hourly rate for workers, assuming a profit margin of 50%, which is comparable to prior research (Sen et al., 2009). Setting a standardized billing rate (β_s) for a task based on the skill required is consistent with industry practice (USi, 2008).

2.5.4 Knowledge Acquisition Parameters

The willingness to help (α_k^i), the overhead coefficient (ϖ^i) and the knowledge retention coefficient (ω), are parameters designed to capture the characteristics of the knowledge acquisition environment. Willingness to help has been extensively researched (Cabrera and Cabrera, 2002). This parameter is a function of the type of tie (Baum and Berta, 1999; Hansen and Løvås, 2004; Levine and Kurzban, 2006). Cowan and Jonard, (2004) uses values in the range 0.5-1 for strong ties and recognizes that high values close to 1 are unrealistic. The values chosen by us are in this range. Cabrera and Cabrera (2002) provide an extensive discussion of techniques to enhance willingness to help. The overhead coefficient captures an individual's cost of providing help and depends on the type of tie (Marsden and Campbell, 1984). In our simulations

[2] A mean processing time per incident of 360 minutes was reported in discussions with a senior corporate systems support manager of a leading systems software vendor in 2009-2010.

we assume that the time spent on *each* help transaction is small, relative to task times[3]. For *each* help transaction, the values for the overhead coefficient chosen in Table 2 translate to a maximum of 2.5%, 7.2%, and 12% for strong, weak and performative ties, respectively, for an average task time of 25 periods. It should be noted that when a worker helps multiple co-workers, the overhead incurred would be significantly large. Exact parameter estimation could be difficult. However, the intent is not to be able to estimate these parameters accurately, but to force organizations to think about whether these parameters are low or high and to consider ways to enhance their value. Such an approach is consistent with prior simulation based knowledge management research (Chen and Edgington, 2005). Knowledge retention coefficient forces organizations to think about synergies between tasks performed and is similar to the concept of reuse which has been used in other contexts such as software engineering (Schilling et al., 2003). Learning while completing tasks has greater value in scenarios where the knowledge retention ratio is high. We experiment with a range of values for these parameters.

2.5.5 Network Parameters

A clustered network with 100 nodes (workers) was created by connecting each node with κ of its nearest neighbors. SN and RN were created by disconnecting the link and reconnecting it with probabilities of 0.09 and 1 respectively using the Watts and Strogatz algorithm (Watts and Strogatz, 1998). It is important to note that the Watts and Strogatz algorithm maintains the same average number of neighbors even though

---

[3] This is consistent with practice, based on discussions with a senior support manager of a leading systems software vendor, and observations at a service organization specializing in the financial services industry.

the network topology changes. The values of κ used are described in Table 2. We generate 50 different samples (with different connectivity) for each type of network. We simulate the performance of each of these 50 networks, and report the average performance.

Organizations have been increasingly adopting tools to capture information flow networks. Commercial software such as InFlow (www.netorg.com) and IBM SONAR (Guy et al., 2008) allow organizations to extract organizational network information from emails, blogs, and other sources.

2.6. Simulation Results

This section presents important results from our experiments. These results illustrate the stylized behavior of KISDN in terms of measures of operational performance (Average total task time), financial performance (Objective function value), knowledge diffusion (Number and type of ties used per worker, average competence level of the workers in the organization, worker specialization), and assignment dynamics[4]. The impact of some of our parameters such as willingness to help is well researched (Cabrera and Cabrera, 2002). We merely note that increased willingness to help improves financial and operational performance and helps knowledge diffusion of KISDN, as expected. Our focus is on the impact of network structure (network topology and network density) on KISDN performance, since this is a relatively under-researched area.

2.6.1 Impact of Network Structure

---

[4] $T = 1200$; $K = 100$; $M = 6$; $S = 4$; $\beta_s = 6, 9, 12, 15$; $\lambda_m = 1$; $\theta_a = 0.1$, $\theta_b = 1$; $\kappa = 10\%$; $h_s = 4, 6, 8, 10$, $\forall s \in \{1,2,3,4\}$; $\omega = 0.2$; $\alpha_k^0 = N(0.45, 0.03)$, $\alpha_k^1 = N(0.25, 0.02)$, $\alpha_k^2 = N(0.05, 0.01)$; $\varpi^0 = 0.1$, $\varpi^1 = 0.3$, $\varpi^2 = 0.5$
Differences between network structures were tested for statistical significance using multiple paired t-tests, $p<0.05$

In order to compare the three networks structures (RN, CN and SN) we observed their financial performance, operational performance, and knowledge diffusion characteristics for different values of the willingness to help parameter.

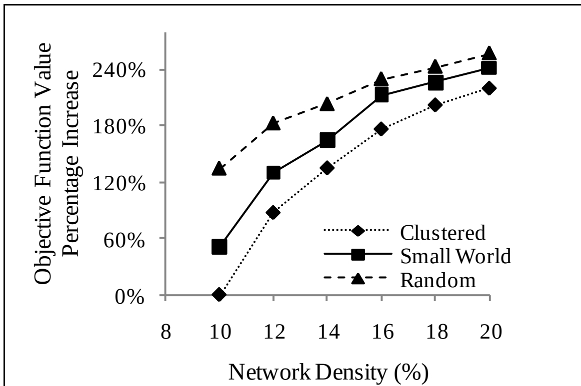


FIGURE 5: Objective function value for different values of network density

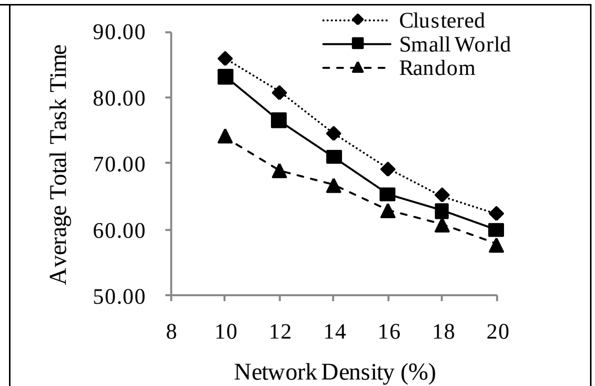


FIGURE 6: Average total task time for different values of network density

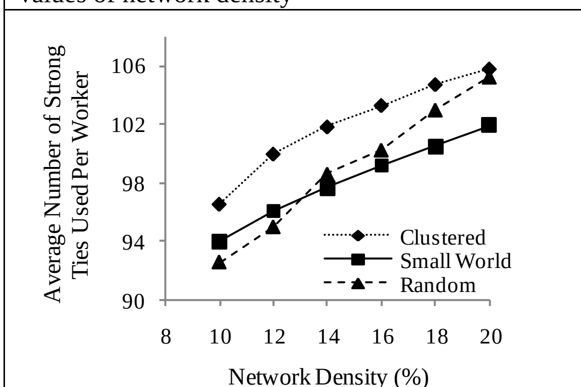


FIGURE 7: Strong ties used per worker for different values of network density

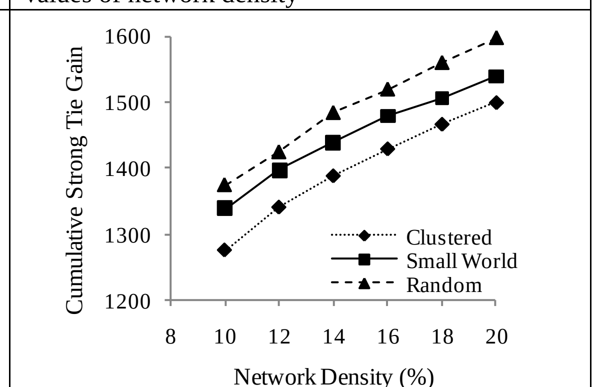


FIGURE 8: Cumulative strong tie gain for different values of network density

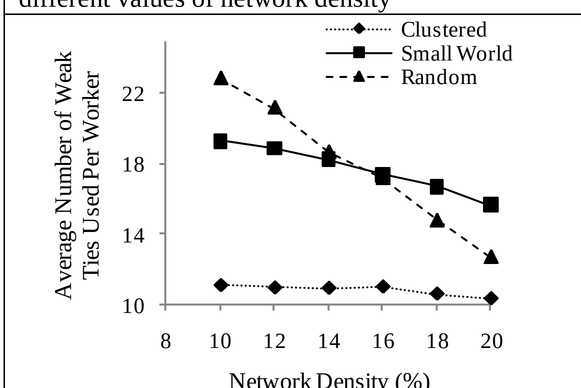


FIGURE 9: Weak ties used per worker for different values of network density

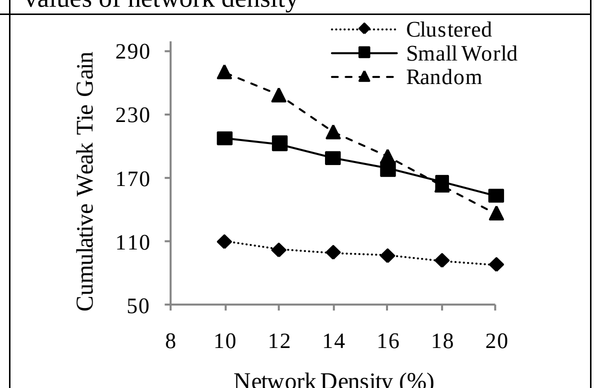


FIGURE 10: Cumulative weak tie gain for different values of network density

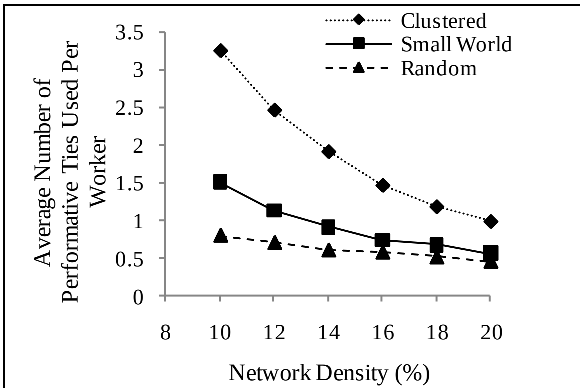


FIGURE 11: Performative ties used per worker for different values of network density

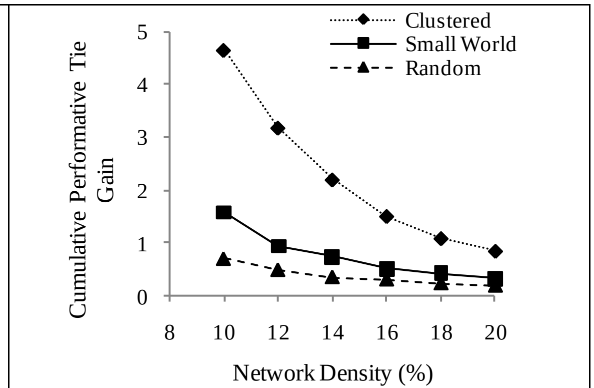


FIGURE 12: Cumulative performative tie gain for different values of network density

We observe that the financial performance (Figure 5) and operational performance (Figure 6) increase as networks become denser. Additionally, we notice that RN outperform the other network topologies[5]. However, the difference between RN, and the other two network topologies, decreases as network density increases. These results are driven by knowledge sharing behavior, which in turn, depends on network topology and network density. Next, we analyze knowledge sharing behavior in detail.

Recall that, in our model the total time a worker spends on a task is a function of his effective competence, which in turn depends on extent of knowledge acquired from co-workers. And the extent of knowledge exchange between two co-workers depends on the *type of tie shared* and the *competence difference* between them. Typically, strong ties are the preferred method of consultation, since they have a higher willingness to help and the least overhead coefficient (Baum and Berta, 1999; Hansen and Løvås, 2004; Levine and Kurzban, 2006). However, the number of strong ties that each worker has is limited. Weak ties have a lower willingness to help, but are greater in number as compared to strong ties. Finally, performative ties allow a worker to connect to any

[5] Based on average performance over 50 replications

worker in the system, and although they are the most in number, they are the least efficient in terms of both willingness to help and the overhead of providing help. The average number of strong ties per node increases as network density increases. Since strong ties are the most effective means of acquiring knowledge, this accounts for improved financial and operational performance with increase in network density (Figures 5, 6). Also, as network density increases to relatively high values, the three network topologies tend to become similar, reducing performance differences between them.

While the number of strong ties is the same across the three network structures, the type of knowledge sharing behavior invoked by each network structure is very different. This is largely driven by the fact that as workers acquire knowledge from each other to perform tasks; cliques tend to become similar over time (in terms of knowledge vectors of workers). Therefore, the amount of knowledge gained by using strong and weak ties within cliques becomes limited as compared to using same ties from outside the clique, if they exist. In addition, within cliques there is a high overlap between the strong and weak ties, making weak ties redundant. As discussed earlier, CN have no or very few strong and weak ties outside cliques. In contrast, RN have very few cliques and many strong and weak ties distributed across the network. SN are somewhere in the middle with a small number of cliques having connections across them.

For reasons discussed earlier, workers in all three network topologies, prefer to use strong ties, therefore the number of strong ties used per worker (Figure 7) is much higher than weak tie (Figure 9) and performative tie use (Figure 11). Note that, the number of strong ties used is about the same for all three network topologies (Figure 7).

However, RN, and SN use a much larger number of weak ties (Figure 9), compared to CN, which uses a much larger number of performative ties (Figure 11). Figures 8, 10, and 12 indicate that RN benefits most from strong and weak tie use, in terms of knowledge gained and CN benefits the least, since workers in cliques tend to be similar. In essence, we find that the RN invokes the most efficient knowledge sharing behavior between workers and this explains why it outperforms SN and CN.

TABLE 3: Min/Max/Average performance differences across network structures

Objective Function Value Difference (% Improvement)						
Network Density (%)	SN over CN			RN over CN		
	Avg.	Min	Max	Avg.	Min	Max
10	51.4	10.2	232.3	134.6	25.5	459.0
12	22.7	1.5	393.3	50.7	13.6	1132.9
14	12.6	-5.7	280.9	28.9	6.2	531.9
16	13.1	-0.2	73.2	19.2	-3.4	151.4
18	7.9	-0.5	77.3	13.4	-5.8	100.3
20	6.8	-3.1	21.2	11.5	-3.8	71.5

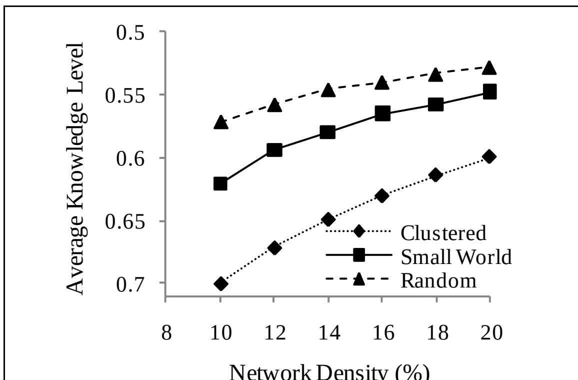


FIGURE 13: Average knowledge level for different values of network density

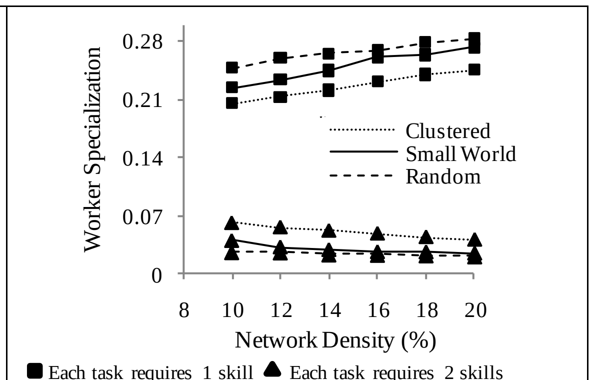


FIGURE 14: Worker specialization for different values of network denstity

In addition to the average analysis, we also studied minimum and maximum performance differences across the three network structure (Table 3). We observed that *when network density is high*, it is possible for some sample paths (less than 2.5% of all instances) that CN *slightly* outperforms (by less than 0.5-6%) RN or SN. This suggests that, on occasion, when network density is high, the experts may be nicely distributed amongst CN cliques, such that it is able to slightly outperform the other networks. However, for the most part (viz., *on average* across all instances), for the reasons already provided, CN performs poorly compared to SN and RN, in that order.

These effects are further illustrated in Figures 13 and 14, where we plot the average knowledge level of workers and average worker specialization (coefficient of variation of competence across skills for all workers). In every time period t, the standard deviation of competence across S skills of worker k is given by σ_{kt}. Hence, the average coefficient of variation of competence across skills over all workers is, $(1/K)\sum_{k=1}^{K}(\sigma_{kt}S/\sum_{s=1}^{S}W_{kst})$. Each clique in a CN may contain a subset of experts and this limits both the amount and range of knowledge that can be gained by individuals in that clique. In RN and SN, which have no or very few cliques, workers have access to a greater number of experts. Hence, there is greater knowledge diffusion in RN and SN, resulting in a higher knowledge level (Figure 13) compared to CN. It is important to note that knowledge diffusion (due to consultation) when a task requires multiple skills is different compared to knowledge diffusion in a scenario where a task requires only one skill. In the former scenario, each worker is able to improve his expertise in multiple skills, when performing tasks. In the latter case, since workers are assigned to tasks that require only one skill, learning during task assignment results in improved competency in that skill. In this case, repeated assignments, which use the skill that the worker is most proficient in lead to further specialization and higher knowledge variance (Figure 14). Therefore, when a task requires one (two) skill, each consultation increases (decreases), knowledge variability across skills. Given that RN better facilitate help seeking behavior, RN results in higher (lower) worker specialization when a task requires one (two) skill(s), compared to CN.

Note that increasing network density has the most impact in the case of CN and least in the case of RN (Figures 5, 6, 13, 14). The marginal value of additional neighbors is highest in the case of CN. CN are dependent on strong ties for knowledge transfer and benefit much more from access to new expertise, compared to RN and SN, which can access a broader range of help sources (outside cliques).

2.6.2 Impact of Cost of Providing Help on Relative Network Performance

In order to extend the robustness of the model trends seen thus far, we study the relative performance of the different network structures as we increase the cost of providing help. Note that, in these experiments the cost of providing help is increased in such a way that the relative cost of providing help via strong, weak or performative ties is maintained. As the overhead from providing help increases it is beneficial to acquire knowledge from only those co-workers where the knowledge gain can offset the cost. In other words, for a worker to be able to use his closest ties (strong and weak) it is critical that there be enough heterogeneity in skills across workers in his closest network (i.e, more potential for knowledge gain). The lack of enough heterogeneity in closest ties results in a reduction in the use of closest ties, increased use of performative ties, and reduced financial performance (Figure 15). In addition, we find that as the cost of providing help decreases the difference between network structures decreases. Since RN invokes the most efficient help sharing behavior, for reasons discussed in Section 2.6.1, RN continues to outperform SN and CN, in that order[6].

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[6] It is trivial to see that, if the overhead of providing help is high enough to preclude access to co-

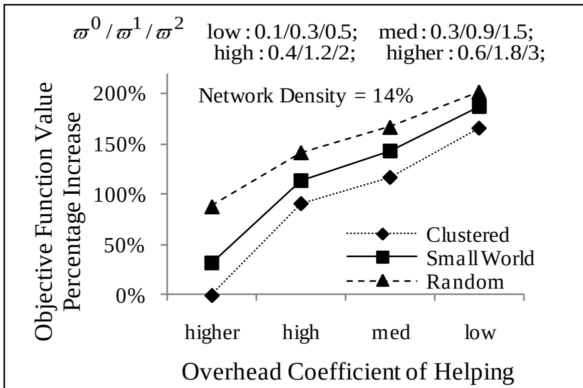

FIGURE 15: Impact of different overhead coefficient of helping on objective function value

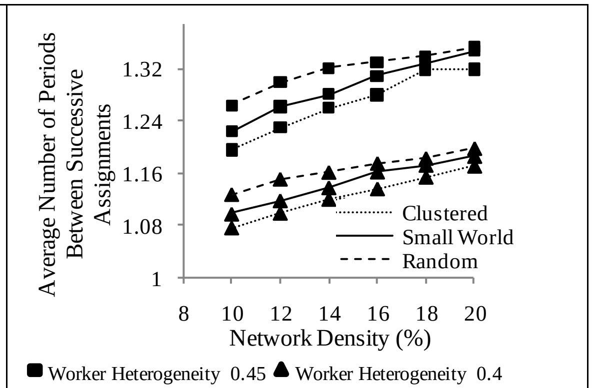

FIGURE 16: Periods between successive assignments for different network density

2.6.3 Impact of Various Parameters on Assignment Decision Dynamics

Recall that the DAH uses OPLA to make a decision whether to wait for one period or make an assignment during that time period. We refer to this as the assignment decision. Hence, the time between successive assignments is dynamic and could be multiple time periods. The assignment decision is related to the costs and benefits of keeping tasks waiting or workers idle in the system. As discussed earlier, we assign a wait-time penalty for each time period that a task is waiting in the system. Also, the firm continues to pay out wages to all workers that are kept on bench. The benefit comes from the fact that, in each assignment period, the firm can now choose from a larger pool of un-assigned tasks and workers, with varying competences, resulting in improved assignments of tasks to workers. Thus, the net benefit from waiting to make an assignment depends on the number of tasks waiting to be assigned and the magnitude of the wait-time penalty. Hence, we study how the assignment decision depends on various factors such as, worker heterogeneity and network density.

Worker heterogeneity refers to the variation in skill levels across workers, for a given number of workers. Recall that the intuition behind delaying assignment is that

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workers, there would be no difference between network structures.

the firm can choose from a larger pool of un-assigned tasks and workers with varying competences. Therefore, when there is significant worker heterogeneity, waiting results in better task to worker assignments (in terms of revenue from task completion and future value of learning). This is because there is a greater degree of mismatch between workers' competence level and the requirement of the arriving tasks. Conversely, for homogenous workers it is trivial to see that there would be no value of waiting. This is illustrated in Figure 16 where the average number of time periods between assignments for a low value of worker heterogeneity (0.40) is less than that for higher values of worker heterogeneity (0.45). This intuition can also be interpreted in terms of real options theory (Trigeorgis, 1996) and is discussed in Section 2.10.

Figure 16, also plots the average number of time periods between assignments as a function of network density. Increasing network density increases the pool of available workers through strong ties and results in higher knowledge levels (Figure 13) and lower worker heterogeneity (not shown here). Hence, increasing network density reduces the value of waiting and results in more frequent assignments. Another important factor that affects the frequency of assignments is the wait-time penalty associated with un-assigned tasks. Since CN have the lowest average knowledge levels (Figure 13) and highest task completion times (Figure 6), they tend to have a larger number of tasks waiting in the system (hence largest wait-time penalty). This explains why the number of periods between assignments is the smallest for CN.

2.7 Performance Evaluation of DAH

2.7.1 Comparison with MIP Solution (using CPLEX)

To evaluate the performance of our heuristic, we solve the MIP formulation using CPLEX for *small problem instances* and compare it against the solution using

DAH. This methodology is consistent with prior research (Dawande et al., 2008; Kumar et al., 2007). Particularly, we compare the CPEX gap (% difference between CPLEX solution and CPLEX upper bound) to the DAH gap (% difference between DAH solution and CPLEX upper bound (or optimal solution, where applicable)).

All experiments were run using CPLEX (Version 12.1) on Core 2 Duo E4500 computers (2.2GHz, 3GB RAM) with Windows XP as the operating system. We allowed each instance to run for 10 hours to get a reasonable solution (in terms of CPLEX Gap). We also used the DAH (coded in NetLogo and Java) to solve the same instances.

The problem size is restricted due to the long compute times involved in CPLEX. Still, we design our experiments such that several model parameters that can affect the heuristic performance are varied, while staying within limits of reasonable problem size/complexity for CPLEX. These parameters include the wait-time penalty, the heterogeneity of workforce competence, planning horizon, task per period and average task time. We chose multiple (2 or 3) levels for each of these parameters giving us a total of 48 ($3*2^4$) problem classes. Within each of the 48 classes, ten problem instances were generated (by taking draws from the relevant distributions for uncertain parameters as outlined in Section 2.3.1.4). The results of the solution comparison between MIP and DAH are reported in Table 4. For completeness, we provide the minimum and maximum performance GAP of DAH, in addition to the average over all sample paths. In each case, for the sample path that results in minimum and maximum performance of DAH, we also record the corresponding CPLEX GAP. This helps us approach the worst case performance of DAH when compared with CPLEX.

TABLE 4: Percentage gap of DAH results from CPLEX solution*

ID	Penalty Coefficient	Worker Heterogeneity	Planning Horizon	Task Per Period	Average Task Time	DAH Gap (%)			CPLEX Gap (%)		
						Avg	Min	Max	Avg	Min	Max
1	0.1	N(1,0.35)	10	6	3	4.6	2.7	6.8	16.9	12.1	18.3
2				6	6	7.0	5.6	8.9	**N/A**	**N/A**	**N/A**
3				3	3	4.0	2.8	4.9	14.4	12.8	16.4
4				3	6	4.1	3.3	5.2	15.2	14.4	16.5
5			6	6	3	3.6	1.7	4.8	9.9	8.4	7.0
6				6	6	5.0	3.6	7.1	6.9	7.7	9.3
7				3	3	2.1	1.2	3.1	7.9	7.0	5.3
8				3	6	3.5	0.5	5.7	4.0	0.7	5.7
9		N(1,0.45)	10	6	3	3.1	0.2	4.6	15.6	11.0	19.6
10				6	6	6.8	6.0	7.3	**N/A**	**N/A**	**N/A**
11				3	3	3.1	2.0	4.3	9.7	8.3	10.6
12				3	6	4.0	3.4	4.7	13.8	13.3	14.7
13			6	6	3	2.9	1.1	4.5	9.1	8.4	7.0
14				6	6	3.9	3.2	4.2	9.8	7.7	12.6
15				3	3	2.3	0.5	3.9	8.6	7.0	5.3
16				3	6	3.3	2.0	5.0	6.8	2.0	10.4
17	0.3	N(1,0.35)	10	6	3	3.5	1.7	5.5	12.6	7.9	15.8
18				6	6	6.6	2.9	10.0	**N/A**	**N/A**	**N/A**
19				3	3	3.1	1.6	4.6	10.1	8.8	11.9
20				3	6	3.1	2.0	5.1	13.1	10.7	15.5
21			6	6	3	1.0	0.1	1.9	7.9	6.1	10.0
22				6	6	3.8	1.4	5.2	6.2	**0.0****	10.8
23				3	3	0.7	0.3	1.4	7.0	5.8	8.5
24				3	6	1.5	0.3	3.0	2.4	**0.0****	8.0
25		N(1,0.45)	10	6	3	2.7	0.1	3.6	12.9	9.1	16.8
26				6	6	6.4	4.1	7.5	**N/A**	**N/A**	**N/A**
27				3	3	1.8	0.9	2.3	9.3	8.4	11.8
28				3	6	2.9	1.8	5.0	12.1	9.9	15.6
29			6	6	3	1.5	0.1	3.0	7.5	5.7	9.1
30				6	6	3.9	3.0	5.4	6.6	2.1	9.9
31				3	3	0.4	0.0	1.1	6.3	5.3	7.4
32				3	6	1.4	0.5	2.6	3.1	**0.0****	7.9
33	0.5	N(1,0.35)	10	6	3	2.9	1.5	3.9	11.0	7.7	15.9
34				6	6	5.7	3.2	7.0	15.9	14.2	17.6
35				3	3	1.8	1.4	2.3	8.8	8.3	10.0
36				3	6	2.6	2.2	3.1	12.7	11.1	14.0
37			6	6	3	1.7	0.9	3.0	7.8	6.1	9.0
38				6	6	3.7	1.5	5.6	5.1	**0.0****	9.0
39				3	3	0.8	0.6	1.1	6.2	5.4	7.7
40				3	6	1.6	0.2	3.1	1.6	**0.0****	6.3
41		N(1,0.45)	10	6	3	1.7	0.2	2.7	10.3	7.9	12.0
42				6	6	5.2	3.4	6.5	**N/A**	**N/A**	**N/A**
43				3	3	1.5	0.7	2.1	6.7	5.4	7.4
44				3	6	2.4	1.4	3.6	10.3	9.0	13.6
45			6	6	3	1.7	0.4	2.5	6.1	5.5	7.6
46				6	6	3.9	2.9	5.0	**N/A**	**N/A**	**N/A**
47				3	3	0.6	0.1	1.3	5.1	4.5	6.3
48				3	6	1.2	0.1	2.3	0.1	**0.0****	0.3

* Number of Workers = 15, CPLEX Gap = (CPLEX Upper Bound – CPLEX Solution)/CPLEX Upper Bound; DAH Gap = (CPLEX Upper Bound – DAH Solution)/CPLEX Upper Bound

** Optimal Solution for CPLEX, therefore, DAH Gap = (CPLEX Optimal Solution – DAH Solution) / CPLEX Optimal Solution, N/A – CPLEX solution was not obtained

First, for the problem instances that CPLEX solves to optimality, the DAH solution is also *near-optimal* (≤1.4% DAH GAP). For all other problems, where CPLEX cannot be solved to optimality, we compare against the CPLEX upper bound. In these cases, it can be seen that our DAH provides significantly better lower bounds than CPLEX solution (on average < 5% DAH GAP), across the wide variety of problem classes. Even when we compare the minimum and maximum DAH GAP, over all sample paths and across all problem classes, the performance of DAH is very robust. Finally, in terms of compute time, the DAH solution is obtained in a few seconds compared to 10 hours for CPLEX. Next we discuss how some of the model parameters affect the DAH performance.

The DAH solution gets closer to the upper bound when worker heterogeneity increases. This is because, when worker heterogeneity is high, there is more benefit from waiting to make assignments and value of learning from co-workers. Both these effects are captured by DAH. Similarly, as wait-time penalty increases or the planning horizon decreases, the DAH assumption of looking *only* one-period ahead before making assignment decisions becomes more realistic. Hence, for the most part, we find that as wait time penalty increases or planning horizon decreases, DAH gap also decreases. On the other hand, as the average task time increases, workers take longer to become available. Hence, the OPLA scheme becomes less optimal, since we would like to look further down the planning horizon (more than one period) before making assignment decisions. This explains why the DAH gap, for most part, increases with average task time. In such scenarios, DAH performance can be improved by adjusting the length of the assignment period (Δ) in proportion with the task times. Finally, as the number of tasks per period increases, the need for finding the optimal worker-to-task assignment increases, in order to compensate for wait time penalty. In this situation, the OPLA scheme again becomes less optimal, resulting in a higher DAH gap.

2.7.2 Comparison with Greedy Heuristic

We also compared the performance of DAH with a Greedy heuristic. The main distinction of the greedy approach is that (a) at every period, the greedy heuristic makes the best available worker-to-task assignment *without pre-fetching any benefits from learning* in the current period on future performance and, (b) it does *not* use OPLA. In Figure 17, we plot the performance difference between DAH and greedy approach versus network density. The problem parameters are identical to those in Section 2.5. It is evident from the data that the DAH significantly outperforms the greedy approach (Table 5). Note that the performance benefit of DAH over greedy reduces as network density increases. This is because an increase in network density facilitates better knowledge diffusion, i.e., reduces knowledge heterogeneity across workers and increases average knowledge level. This in turn, reduces the value of dynamic assignments and learning from consultation, resulting in a lower performance difference versus the greedy heuristic.

TABLE 5: Percentage improvement of DAH over Greedy approach

DAH over Greedy (% Improvement)									
# of neighbors	CN			SN			RN		
	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max
10	240.0	37.5	763.5	151.5	24.4	1557.5	80.7	14.5	2198.4
12	102.7	26.3	2158.8	80.3	22.0	449.5	55.7	15.5	202.5
14	72.8	19.5	940.2	63.5	16.6	234.5	47.9	13.8	149.6
16	53.2	16.3	251.0	41.9	17.0	128.4	38.0	12.2	119.5
18	43.8	14.9	198.4	38.0	12.6	134.0	33.7	11.4	89.1
20	38.4	12.3	126.9	33.0	10.5	97.8	29.1	9.5	81.7

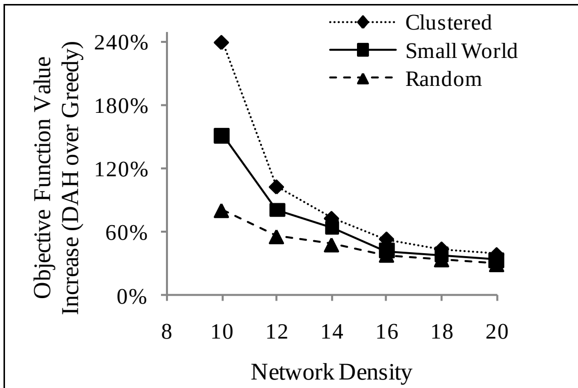


FIGURE 17: Comparison between DAH and Greedy approach for different values of network density

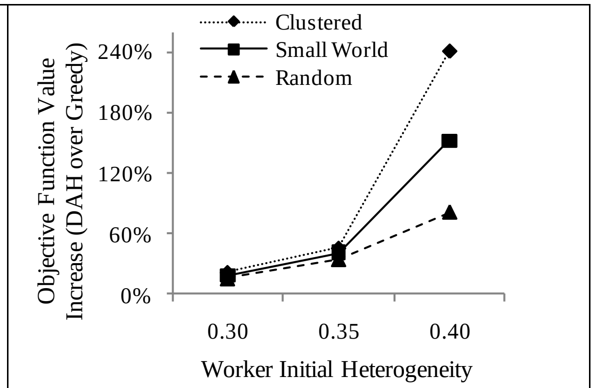


FIGURE 18: Impact of worker initial heterogeneity on DAH performance over Greedy approach. Network density = 10%

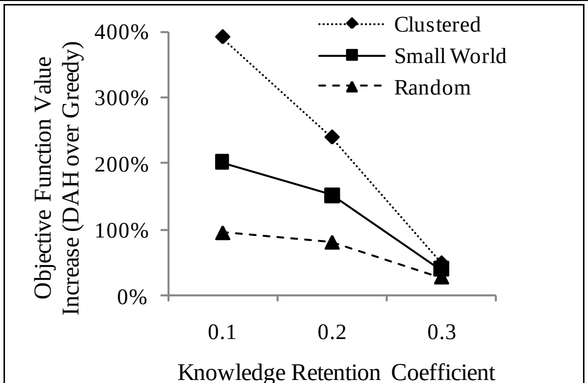


FIGURE 19: Impact of different knowledge retention coefficient on DAH performance over Greedy approach. Network density = 10%

For similar reasons, it is easy to see that the performance advantage of the DAH heuristic would reduce as worker heterogeneity reduces (Figure 18). A similar trend is expected when the knowledge retention rate is high, since it facilitates rapid diffusion of knowledge. This reduces the value of learning from co-workers as well as benefit of waiting to make an assignment (Figure 19).

2.7.3 Comparison with Periodic Assignment Heuristic

Finally, we also compare the performance of DAH with a Periodic Assignment Heuristic. The main distinction is that in the Periodic Assignment Heuristic, we choose a *fixed* number of periods between successive assignments for the *entire planning horizon*. Particularly, we calculate marginal revenue and marginal cost for different values of number of periods between assignments (i.e., 1, 2, 3, etc) and select the value at which marginal revenue is equal to marginal cost. In contrast, recall that in DAH the periods between assignments are *dynamic* and controlled by the OPLA scheme. It is important to note that in the Periodic Assignment Heuristic, similar to DAH, we pre-fetch the value of learning in the current period on future periods. In Figure 20, it can be seen that the DAH significantly outperforms the Periodic Assignment Heuristic (Table 6). However, for the same reasons discussed in Section 2.7.2, the relative benefit of DAH over the Periodic Assignment Heuristic decreases as network density increases. It is important to note that the performance advantage of DAH also reduces for high values of wait time penalty (Figure 21). In this case, assignments are more likely to be made every period, making the distinctive feature of the DAH viz., dynamic assignment via OPLA, less critical.

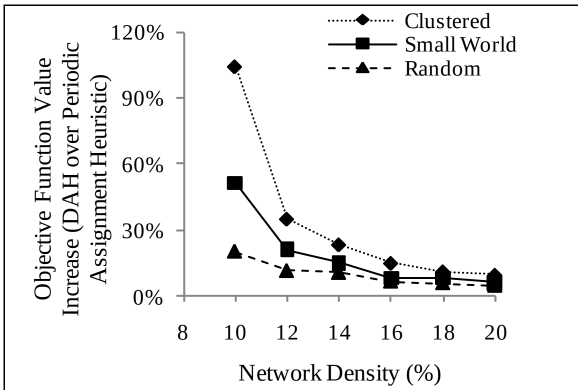


FIGURE 20: Comparison between DAH and Periodic Assignment Heuristic for different network density

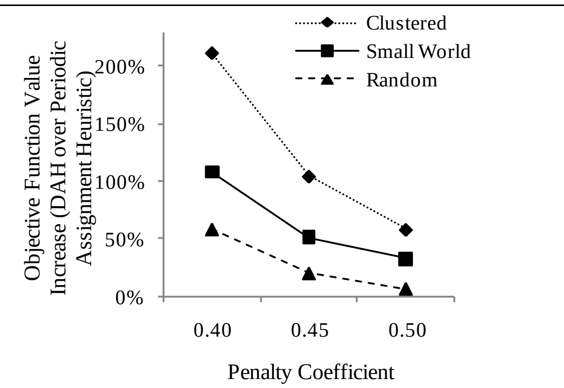


FIGURE 21: Comparison between DAH and Periodic Assignment Heuristic for different wait time penalty coefficient

TABLE 6: Percentage improvement of DAH over periodic assignment policy

DAH over Periodic Assignment Policy (% Improvement)									
# of neighbors	CN			SN			RN		
	Avg	Min	Max	Avg	Min	Max	Avg	Min	Max
10	104.3	9.4	402.6	51.3	5.5	599.3	19.9	2.1	732.0
12	34.9	5.1	817.6	21.1	4.7	124.0	11.2	1.2	51.7
14	23.3	1.2	298.2	15.0	3.0	61.5	10.4	2.1	38.0
16	14.8	1.1	61.5	8.1	2.2	22.4	6.5	1.8	20.5
18	11.0	1.3	39.6	7.9	2.3	33.6	5.8	2.2	17.6
20	9.4	1.5	30.4	6.0	1.2	21.7	4.6	2.4	14.1

2.8 Model Extension

2.8.1 Using Training to Reduce Differences Between Networks

As discussed earlier, the extent of knowledge exchange (and hence knowledge diffusion) between co-workers depends on the type of network structure. However, it may not be possible to easily alter the organizational network structure of a firm, in order to improve knowledge diffusion. Therefore, we propose an extension to the basic model (outlined in Section 2.3) where a firm can use *training* as a means to effectively improve the knowledge diffusion process. The firm can provide an opportunity for workers to undertake training and improve competence in one or more skills, in addition to consulting other co-workers. By allowing workers to take training, the firm can mitigate some of the drawbacks associated with SN and CN. Specifically, training can be used to strategically ensure that specialized knowledge does not get limited to cliques and that access to knowledge across all workers becomes homogenous.

The use of training is prevalent in knowledge management literature. Chen and Edgington (2005) discuss two factors affecting knowledge acquisition through training. One factor is the sophistication of the knowledge provided in the training, which determines the maximum gain in competence (for a skill) that a worker could obtain after undergoing training. The other factor is the trainee's learning rate which is affected by unique, individual mental models (Anderson, 1995). Hence, the same training could result in different competence gains for different workers. In our model, τ_{st} represents the maximum competence level offered by a training session, in skill *s* in assignment period *t*. We assume that not all training sessions are equally efficient. In addition, $\varphi_k^s \in (0,1)$ represents the learning rate associated with worker *k* for a training session in skill *s*.

In this extension, we allow workers to be engaged in training, in addition to be assigned to service tasks at any point in time. The revenue (from task completion), bench-cost (from idle workers), and wait time penalties (from tasks waiting in the system), are calculated similar to Section 2.3. There are two types of costs associated with training. First is a direct cost, related to the wages paid out to workers when in training. We model this as a product of the worker's wage rate (h_k) and the time required to complete the training (ψ_{st}). The second cost is indirect, and is related to the fact that assigning a worker to training makes him unavailable for any other task. As a result, the firm might incur additional wait-time penalties on tasks waiting in the system while the worker is in training. This is modeled by adding an additional assignment constraint to the MIP in Section 2.3. The benefit associated with training comes from the improvement in the worker competence after training. Similar to learning from co-workers (as modeled in Section 2.3), this improved competence allows the worker to complete future tasks more efficiently. Here, $(W_{kst} - \tau_{st})\varphi_k^s$ is the potential improvement in the worker's competence after undergoing training. $Y_{kst} = 1$ (*decision variable*) indicates that worker *k* has been assigned to a training session in skill *s* in period *t* (and 0 otherwise), and $L_{smt} = 1$ if a training in skill *s* that started in period *m* is completed by period *t* (and 0 otherwise). Consequently, worker *k*'s competence in period *t* is,

$$W_{kst} = W_{ks1} - \sum_{m=1}^{t-1} \sum_{j=1}^{N_{t-1}} X_{kjm} \vartheta_{js} \, \omega \, G_{ksm} F_{kjt} - \sum_{m=1}^{t-1} L_{smt} Y_{ksm} (W_{ksm} - \tau_{sm}) \varphi_k^s$$

In Figure 22, we study how the competence offered by training affects the firm's performance. We find that, adding training as a means of knowledge acquisition benefits the organization, irrespective of the network structure. It is important to note that CN benefit the most from offering training (highest percentage increase compared to SN and RN) as well as from increasing the level of competence offered by training (highest slope compared to SN and RN). This is because training enhances the knowledge diffusion and acquisition process by ensuring that knowledge does not get *stuck* in cliques in CN and SN. Although RN continue to outperform (not shown), they are least sensitive to the competence offered by training.

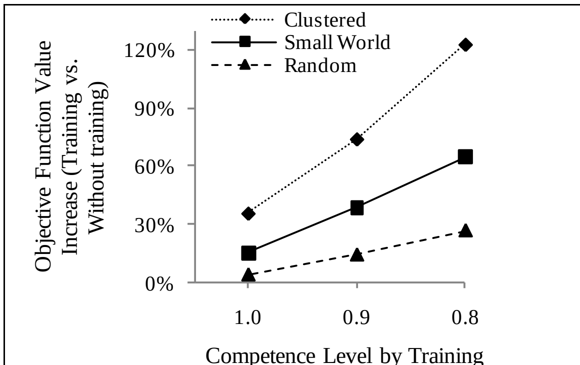


FIGURE 22: Impact of training competence level on objective function value

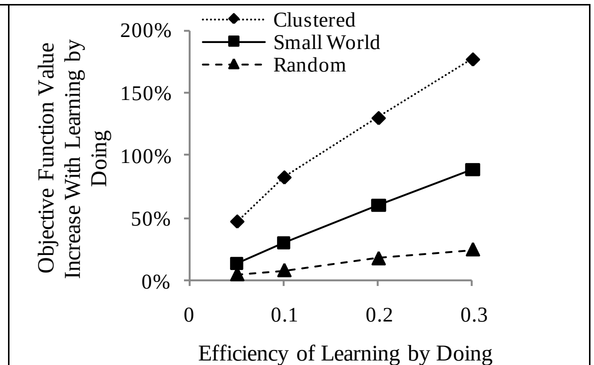


FIGURE 23: Impact of learning by doing on objective function value

2.8.2 Incorporating Learning By Doing

As discussed earlier, we allow workers to improve competence in one or more skills based on consultation with other co-workers. However, it may be possible that due to cost overhead, worker availability, etc., a worker may have to complete a task without any help from co-workers. In such a case, the worker may be able to improve his competence, simply by virtue of completing tasks (even if there was no consultation involved). This can be interpreted as "*learning-by-doing*". Therefore, we propose an extension to the basic model (outlined in Section 2.3) where a worker's competence can improve through "*learning-by-doing*", in addition to "*learning from others*". We propose the extent of learning-by-doing in skill s depends on three components: (a) proportion of time spent in skill s when completing task j (*i.e.*, $\phi_{js} / \sum_{s=1}^{S} \phi_{js}$), (b) worker k's current competence (W_{ksm}), since we expect that the potential for learning-by-doing is greatest when the worker is less competent, and (c) individual worker's learning efficiency (ξ_k^s) (Anderson, 1995; Chen and Edgington, 2005). Therefore, worker k's competence in period t is given by,

$$W_{kst} = W_{ks1} - \sum_{m=1}^{t-1} \sum_{j=1}^{N_{t-1}} X_{kjm} \vartheta_{js} \ \omega \, F_{kjt} \left(G_{ksm} (\sum_{l=1}^{k} \sum_{i=0}^{2} \Lambda^{i}_{klsm}) + (\phi_{js} / \sum_{s=1}^{S} \phi_{js}) W_{ksm} (1 - \sum_{l=1}^{k} \sum_{i=0}^{2} \Lambda^{i}_{klsm}) \xi_k^s \right)$$

Here, $\sum_{l=1}^{k} \sum_{i=0}^{2} \Lambda^{i}_{klsm}$ =1 indicates *learning from others* and $\sum_{l=1}^{k} \sum_{i=0}^{2} \Lambda^{i}_{klsm}$ =0 indicates *learning-by-doing*.

In Figure 23, as expected, we find that the all the three network structures benefit from learning by doing, and this benefit increases as the learning efficiency increases. In addition, similar to training, we find that CN benefit the most from learning by doing, and RN benefit the least. Hence firms could encourage learning-by-doing to improve the performance of existing CN and SN.

2.9 Limitations and Future Research

Worker competence, in this research, was initially generated randomly and then allowed to evolve based on task performance, knowledge sharing, learning-by-doing, and training using one training policy. Alternative training policies such as deliberate cross-training in conjunction with recruitment decisions could be evaluated. Our research has used one model of learning by doing. Future research could explore other models. The results presented in this dissertation assume knowledge depreciation is negligible. Future research could study KISDN performance under high knowledge depreciation conditions. While we have assumed a fixed compensation structure, the model could be extended to compare different compensation structures. This dissertation assumed that the arrival of tasks are independent based on a wide variety of service research (Buco et al., 2003; Sen et al., 2009). Future research could examine interdependent task arrivals, for example by extending the unit of analysis in this dissertation (a single KISDN) to multiple interrelated KISDNs. This extension would be analogous studying queuing networks (Bolch, 2006) and is likely to be more complex and computation-intensive. This research has assumed a fixed capacity (workers). Future research could examine interrelated capacity planning and task assignment decisions. We concentrate on individual-oriented service tasks. However, one could consider a team-oriented service scenario. Modeling such a scenario is similar to modeling a project and would depend on the structure of the project and the team. Our focus has been on task assignment. However, organizations might be interested in other objectives such as maximizing knowledge sharing, for future use. Alternative model formulations to study this are interesting areas of future research.

2.10 Discussion and Conclusion

Trends in networking, globalization and evolution of software as a service are increasing the importance of studying KISDN. In our opinion, managing KISDN is an important aspect of the emerging discipline of service science, which is of increasing interest to MIS researchers. To the best of our knowledge the MIP model presented in this dissertation and the DAH represent the first attempt to systematically analyze an important and complex research question in the context of delivering IT as a service. Since the KISDN optimization problem is NP hard, the DAH represents a reasonable approach to solving this problem for realistic problem sizes. The value of such analytical modeling lies in the identification and integration of parameters and relationships into a framework that help to structure the debate on how to manage KISDN (Lusch et al., 2008).

Our analysis has indicated that organizations can benefit from not assigning service tasks immediately (by using dynamic assignment). In other words, waiting to make an assignment is valuable since it results in higher revenue due to better task to worker assignment. Each assignment decision can be conceptualized as making an investment (incurring costs) in return for revenue. At any point in time, an organization has the option to make such an investment or to defer the investment. Exercising the option (making an assignment), in turn results in the option to make another investment (assignment) in the next period. As seen in our results, the value of such an option increases with increased uncertainty of the underlying asset (worker heterogeneity). Such a scenario can also be thought of as a compound or nested exchange option which can be valued analytically only in some special cases (Trigeorgis, 1996).

To the best of our knowledge, this research is the first to propose how the information flow network can be combined with worker competence information to improve operational and financial performance of KISDN. Specifically, we integrate literature and tools for mining information flow networks (Guy et al., 2008; Van Der Aalst et al., 2005) with literature and tools for measuring knowledge competencies (Cross et al., 2001; Davenport and Prusak, 1998) and propose combining these two types of tools to provide information that can be used for task assignment. Our results also underscore importance of weak ties in improving organizational performance. Recognizing the importance of weak ties and nurturing them, in our opinion, is an important managerial implication from our results.

Organizations may currently resemble CN or SN and not RN. Our results indicate that organizations could improve knowledge transfer by creating RNs. Ways of doing this include job rotation, and facilitating communication between key individuals (Davenport et al., 1998). Complete reorganization to RN may be expensive or infeasible. Our results indicate that improving network density, particularly in the case of CN could significantly improve knowledge transfer and consequently organizational performance. Creating SN by means of links between cliques is also desirable, particularly at higher network densities. Also, in cases where it is non-trivial for organizations to change the organizational network structure, managers should focus on strategically training workers or providing incentives to improve worker's willingness to help, in order to maximize performance. Encouraging learning by doing may also complement other knowledge management strategies. It is hoped that this research will serve as useful framework for IS researchers as well as practitioners interested in knowledge management, service science and social networks.

CHAPTER 3: UNDERSTANDING KEY ISSUES IN DESIGNING AND USING INFORMATION FLOW NETWORKS IN THE CONTEXT OF KNOWLEDGE-INTENSIVE SERVICE DELIVERY

3.1 Introduction

There is a growing recognition that employees' knowledge is an organization's most valuable asset, particularly in knowledge-intensive environments such as consulting, research, and IT service delivery (Dong et al., 2011; Davenport et al., 1997; Dyer and Nabeoaka, 2000). Prior IS research has also recognized that "making personal knowledge available to others is the central activity of the knowledge-creating company. It takes place continuously and at all levels of the organization" (Nonaka et al., 2000). Hence, firms are increasingly investing in Knowledge Management (KM) projects expecting to improve employees' knowledge levels (Goh, 2002). For example, McKinsey has long had an objective of spending 10% of its revenues on developing and managing intellectual capital (Davenport et al., 1997). Buckman Laboratories estimated that the firm would spend 7% of its revenues on knowledge management (Davenport et al., 1997). The global KM market had been projected to reach 8.8 billion dollars during 2005 (Malhotra, 2005). Most KM research has thus far focused on information technologies (Cross et al., 2001; Davenport and Prusak, 1998), with relatively little discussion on how knowledge can be shared effectively among employees using organizational social relationships (Levine and Prietula, 2006). In practice, however, organizations are finding that employees often prefer to consult their peers and colleagues (organizational social relationships) in order to acquire knowledge, rather than access electronic knowledge bases (Cross et al., 2001). Hence, this research focuses on better understanding how organizations can maximize knowledge transfer among interconnected employees.

Recognizing the importance of using organizational social relationships to transfer knowledge, an increasing number of Chief Knowledge Officers (CKOs) are moving from a technological KM strategy to a socialization-based strategy. Such a strategy uses IT-facilitated information flow networks (IFNs) to facilitate knowledge sharing (Nicolas, 2004). These IFNs use ties (or information flow connections) between individuals in order to transfer knowledge. As discussed in the chapter 2, organizations can effectively capture existing IFNs. Furthermore, in the chapter 2, we show that the structure of the information flow networks and associated knowledge sharing behavior significantly impact organizational performance and employees' knowledge level.

Prior research suggests that organizations can create organizational relationships through actions such as co-location, project and work group assignments, facilitating communication through technology tools, and incentives (Kotlarsky and Oshri, 2005; Lengnick-Hall and Lengnick-Hall, 2003, Nonaka et al., 2000). These relationships, in turn, facilitate information flow. Hence, we focus on how organizations should design and use their information flow network such that knowledge sharing is maximized. We seek to better understand which organizational factors should be considered when designing and using such networks. Such an understanding facilitates effective design and use of effective information flow networks in KISDN, and is an important, yet under-researched area (IBM, 2006; Leung and Glissmann, 2010).

Consistent with chapter two, we study organizations in knowledge-intensive service delivery environment, where organizations support multiple skills, have varying levels of worker competence, and require knowledge sharing among co-workers. However, we focus on the objective of maximizing employees' knowledge gain through sharing in this Chapter. More specifically, we have focused on the following research question: *how should organizations design and use their information flow networks in order to maximize employees' knowledge gain (over a planning horizon) through sharing under different organizational environments*? We formulate a Mixed Integer Programming Model (MIP), and present a heuristic in order to facilitate systematic analysis and understanding of the above research question. In trying to answer this question, we examine organizations with different distributions of expertise and examine the optimal information flow networks.

The rest of this chapter is organized as follows. Section 3.2 provides a review of related literature. This is followed by the model development in section 3.3. A heuristic is proposed in section 3.4 to solve the problem. Selected numerical results are presented in section 3.5. Limitations and conclusions are provided in section 3.6 and 3.7.

3.2 Literature Review

Our research integrates concepts from prior research on knowledge view of the organization (Alavi and Leidner, 2001; Grant, 1996; Nonaka et al., 2000), creating and using social relationships to facilitate knowledge sharing (Davenport et al., 1997; Sahoo et al., 2008), efficiency and tradeoffs associated with knowledge sharing (Borgatti and Cross, 2003; Hansen, 2002), and modeling knowledge exchange in organizations (Cowan and Jonard, 2004; Levine and Prietula, 2006).

3.2.1 Knowledge View of the Organization

The knowledge-based view of the organization (Grant, 1996) argues that knowledge resides within individual workers, and the primary role of the organization is knowledge application. In addition, this view of the organization also recognizes that knowledge transfer is a critical determinant of sustainable competitive advantage (Grant, 1996).

Nonaka et al. (2000) also argue that “knowledge and the capability to create and utilize such knowledge are the most important sources of a firm’s sustainable competitive advantage”. They propose that researchers look inside the firm, and focus on the activity, strategy, structure, and culture of the firm, to see how it produces knowledge. They also identify several important factors that impact knowledge creation. Such factors include knowledge vision, organizational forms, incentive systems, corporate culture and organizational routines, and leadership. Knowledge vision determines what types of knowledge are created, and “the value system that evaluates, justifies and determines the quality of knowledge” (Nonaka et al., 2000). Organizational forms represent the way that the organization is configured and structured. Incentives such as monetary compensation, peer recognition, and the sense of belonging can effectively motivate knowledge sharing. Organizational culture and organizational routines, and leadership could either promote or hinder organizational knowledge creation.

Alavi and Leidner (2001) highlight that “it is less the knowledge existing at any given time per se than the firm’s ability to effectively apply the existing knowledge to create new knowledge and to take action that forms the basis for achieving competitive advantage from knowledge-based assets.” Furthermore, they claim that information technologies may play an important role in effectuating the knowledge-based view of the firm. Knowledge management within organizations can be facilitated by advanced information technologies.

3.2.2 Creating and Using Organizational Social Relationships to Share Knowledge

Prior research suggests that organization relationships can be created using a variety of activities. For example, Hansen (1999) examine knowledge sharing across organizational subunits and find that establishing long-term collaboration relationships between different subunits can be used to facilitate knowledge transfer. However, people in a subunit are required to spend time cultivating such relationships through frequent visits to and meetings with people in another subunit. Kotlarsky and Oshri (2005) present two case studies carried out at SAP and LeCroy to illustrate the importance of establishing social ties and sharing of knowledge among distributed IS development teams. Their cases suggest that facilitating face-to-face interactions is an effective mechanism for creating social relationships. In particular, a short visit to a remote location prior to a formal introduction of the team, and non-hierarchical communication with high quality messages through open community channels after face-to-face activities, is important for establishing social relationships between team members. Lengnick-Hall and Lengnick-Hall (2003) study the problem of adopting a human resource management approach to build relationships that turn social capital into competitive advantage. They argue that through building and nurturing relationships, organizations can locate and share knowledge rapidly and respond to market changes. They propose the use of work teams and project teams to establish relationships among workers. Work teams often remain intact for long periods and have time to develop trust. But project teams need to develop and adjust relationships quickly to be effective.

However, great care needs to be exercised when creating and using organizational IFNs for knowledge management. For example, lack of knowledge sharing caused by inefficient IFNs in Chrysler Corporation results in significant decrease in performance (Lengnick-Hall and Lengnick-Hall, 2003). In summary, organizations can effectively create social relationships and facilitate knowledge transfer using such relationships. Yet, we underscore the importance of paying careful attention to the design of such information flow networks.

3.2.3 Efficiency and Trade-offs Associated with Knowledge Sharing

This research is also related to the efficiency of knowledge sharing. Prior research demonstrates that the strength of the social relationship significantly affects the efficiency of knowledge sharing (Borgatti and Cross, 2003; Cross et al., 2001). Granovetter (1973) categorizes the strength of social relationships into three group (strong, weak, and absent) based on a combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services. In this research, we focus on two types of relationships: direct relationship (strong), and indirect relationship (weak), which involve different efficiencies and costs when being used to facilitate knowledge transfer.

Direct ties involve significant interactions between two workers, and are often associated with commitments of sharing knowledge (Hansen, 1999). Hence, direct ties are effective in terms of transferring knowledge. Indirect ties, on the other hand, allow workers to access larger number of colleagues than strong ties, but often suffer low quality help (Hansen, 1999; Constant et al., 1996). In order to develop strong ties between workers, considerable amount of time and interactions are required, while indirect ties could exist between acquaintances who share common contacts (Hansen, 1999; Constant et al., 1996). While direct ties allow workers to share knowledge more effectively, they can be harmful when knowledge transferred is less complicated, because of the time and efforts are required to establish and maintain these social connections (Hansen 2002). As a result, having excessive number of direct ties could decrease knowledge sharing efficiency. IBM (2006) also recommend firms to carefully coordinate knowledge sharing because workers who are engaged in successive sharing activities could reduce the productivity and efficiency of the groups that they belong to.

3.2.4 Modeling knowledge sharing within organizations

In summary, prior research recognizes that knowledge sharing is desirable and can be facilitated though mechanisms such as incentives. However, the problem of what characterizes a desirable information flow network is poorly understood. It is important for organizations to better understand the characteristics of effective information flow networks in order to design such networks.

This research develops a model to facilitate understanding of what constitutes an effective (optimal) information flow network. It integrates and further develops ideas from prior research that has modeled knowledge sharing. Cowan and Jonard (2004) use simulation to study the impact of different types of network topologies in the context of knowledge diffusion across organizations. The social network where knowledge diffuses is pre-defined and static. Each agent has a vector of multiple knowledge types with varying levels of competences. Knowledge transfer takes place through a myopic barter exchange only if there is a direct connection between two workers and trading benefits both parties. Their problem is different from the one studied in this research in that it did not consider creation of new social relationships to improve knowledge sharing, or different types of connections (indirect relationships) between nodes in the network. Levine and Prietula (2006) use agent-based simulation to study the impact of different types of ties (strong, weak and performative) between workers in the context of knowledge sharing behavior in social networks. Their agents are embedded in local groups of direct ties, such as project teams, which again do not change. Each agent has a set of skills with varying competence levels. Tasks are randomly assigned to agents who may or may not have enough competence to complete. Knowledge, if needed, is attained either through self-learning, acquisition through exchange with another agent, or both. However, their social networks were static, and did not consider the cost of multiple social connections.

This research studies the problems of maximizing knowledge sharing by creating and using social relationships. It examines the impact of worker heterogeneity, number of skills, time (cost) of transferring knowledge, on the design of the effective organizational information flow networks.

3.3 Model Development

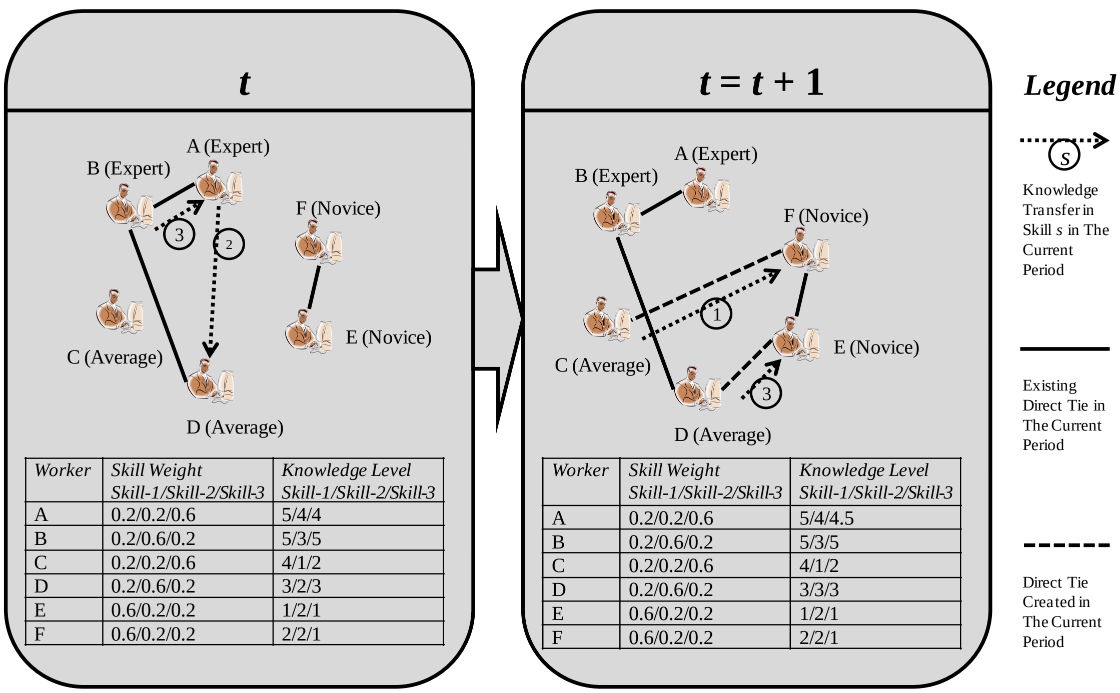
3.3.1 Model Preliminary

We model the problem of designing information flow networks inside a firm for effective knowledge management. The firm's objective is to maximize the total knowledge level of the organization over a planning horizon by creating and using direct and indirect organizational social relationships between co-workers. The use of information flow networks for effective knowledge management is illustrated in Figure 24. We consider an organization with a heterogeneous workforce that supports multiple skills. Workers vary in terms of competences in these skills and the organizational networks that they belong to. Workers also vary in terms of the importance (weight) they have for each skill based on the types of tasks performed by each worker. For example, in a software consulting firm, functional consultants are required to have a deeper functional knowledge of the system and the customer processes as compared to the technical aspects of the system. On the other hand, technical consultants need to focus on the technical aspects of the software system, such as database design and system security. Figure 24 illustrates that each worker has a knowledge level and a relative weight for each skill.

Workers within the firm are connected through organizational information flow networks. In such an environment, workers competence level is directly associated with organizational value, and there is a constant need to acquire knowledge (Hansen 1999). Direct relationships occur between workers who can seek knowledge from each other *directly* through organizational or social relationships (Guy et al., 2008; Sahoo et al., 2008). Examples of such direct relationships include office mates, close friends, team members, etc. In Figure 24, in period *t*, worker A and B, B and C, and E and F, have direct relationship with each other. Workers connected by indirect relationships do not know each other directly, but have direct relationships with one or more (common) workers. Common workers play a bridging role that allows the two workers to get acquainted and to share knowledge with each other. In Figure 24, in period *t*, worker A and C have indirect relationship with each other. Note that we treat knowledge transfer over direct and indirect relationships as *directional*. For example, if employee B transfers knowledge to employee A, it does not suggest any reverse knowledge flow from A to B. The idea of knowledge transfer through organizational relationships is consistent with prior research (Sahoo et al., 2008, Davenport et al., 1997).

Organizations can effectively create direct relationships using strategies such as project team, work group, long-term interactions, face-to-face activities (Hansen, 1999;

Kotlarsky and Oshri, 2005; Lengnick-Hall and Lengnick-Hall, 2003). Time (effort) is required to establish these direct ties. Indirect relationships can be seen as by-products of creating such direct ties. We study an organizational problem of assigning workers to transfer knowledge using both direct and indirect ties, over the planning horizon. We discretize the planning horizon into time periods. It is important to note that the length of each period is context-specific and could be one day, one week, one month, etc. During any period, a worker may or may not be assigned to participate in the knowledge transfer activities. Moreover, workers may provide as well as acquire knowledge in the same period. In Figure 24, in period t+1, direct relationships between worker pair C and F, and D and E are created to facilitate knowledge transfer.



Worker	*Skill Weight Skill-1/Skill-2/Skill-3*	*Knowledge Level Skill-1/Skill-2/Skill-3*
A	0.2/0.2/0.6	5/4/4
B	0.2/0.6/0.2	5/3/5
C	0.2/0.2/0.6	4/1/2
D	0.2/0.6/0.2	3/2/3
E	0.6/0.2/0.2	1/2/1
F	0.6/0.2/0.2	2/2/1

Worker	*Skill Weight Skill-1/Skill-2/Skill-3*	*Knowledge Level Skill-1/Skill-2/Skill-3*
A	0.2/0.2/0.6	5/4/4.5
B	0.2/0.6/0.2	5/3/5
C	0.2/0.2/0.6	4/1/2
D	0.2/0.6/0.2	3/3/3
E	0.6/0.2/0.2	1/2/1
F	0.6/0.2/0.2	2/2/1

FIGURE 24: Creating and using information flow networks to transfer knowledge

We model the efficiency of knowledge transfer process as a function of the type and strength of the relationship. Direct relationships are more efficient than indirect relationships (Levine and Prietula, 2006). Also, we use the age of a relationship as a measure of its strength. Knowledge transfer efficiency is also affected by the status of the worker. That is, we consider reduced knowledge acquisition efficiency (overhead) for workers who acquire and provide knowledge at the same time.

3.3.2 Model Formulation

Mathematical modeling is a useful tool to understand key variables that describe a problem and their relationships. The model variables described in Table 7 represent the different elements of the problem of designing information flow networks. In addition, mathematical modeling helps understand the relationships between different variables, and produces a solution that can serve as a benchmark. Understanding the relationship between the current state of an organization and the managerial benchmark produced by the model facilitates organizational change (Liberatore et al., 2000). This approach is appropriate in the context of a knowledge management problem where the goal is to design optimal information flow networks that maximize the overall knowledge level of the organization. We model the problem of designing information flow networks using mixed integer programming (MIP).

We consider the planning horizon is divided into a set of discrete periods $t \in \{1,..,T\}$. The length of each period represents a context specific unit of time after which the organization re-assesses the knowledge levels of its workers. Prior research on knowledge management suggests that knowledge level of workers can be captured and documented effectively using tools such as Microsoft SPUD (Davenport and Prusak, 1998), KIN and Tacit Systems EKG (Cross et al., 2001). In each period, the organization may create new direct ties or use existing direct and indirect ties, for effective knowledge management.

TABLE 7: Major model variables and decision variable

Symbol	Definition	Type
$X^t_{kls\_i}$	= 1 if worker *k* transfers knowledge in skill *s* to worker *l* using tie *i* during period *t*; = 0 otherwise. $k,l \in \{1,2,..,K\}$. Note that $X^t_{kls\_i}$ and $X^t_{lks\_i}$ are two different variables.	Decision Variable
K	Total number of workers	Exogenous Variables
T	Planning Horizon	
S	Total number of skills supported by the organization	
β_{ks}	Relative importance (value) of worker *k*'s knowledge in skill *s* to the organization, with $\beta_{ks} \in (0,1), \sum_{s=1}^{S} \beta_{ks} = 1$	
α_{k_i}	Efficiency of acquiring knowledge using relationship *i* (*i* = 0,1 represent direct, indirect relationship respectively)	
ϖ_i	Time coefficient of each worker providing knowledge using relationship *i* (*i* = 0,1 represent direct, indirect relationship respectively)	
θ	Time coefficient of creating direct ties	
W^t_{ks}	Worker *k*'s competence level in skill *s* at the beginning of period *t*, with $W^t_{ks} \in [W_{sMin}, W_{sMax}], W_{sRange} = W_{sMin} - W_{sMax}$.(W^1_{ks} are exogenous variables, and $W^1_{ks}\ \forall t \in \{2,\ldots,T\}$ are derived variables)	Derived Variables
D^t_{kl}	=1 if there is a direct tie between worker *k* and *l* in period *t* (could be existing tie, or new tie created during period *t*), = 0 otherwise.	
V^t_{kl}	=1 if there is an indirect tie between worker *k* and *l* (worker *k* and *l* share at least one common co-worker connected by direct tie) in period *t*; = 0 otherwise.	
M^t_{kls}	=1 if worker *k*'s knowledge in skill *s* is better than worker *l*'s at the beginning of period *t*; = 0 otherwise.	
G^t_{kls}	The amount of knowledge can be transferred from worker *k* to worker *l* in skill *s* during period *t*.	
$H^t_{kl\_i}$	The time incurred by worker *k* in providing knowledge to worker *l* in period *t* using relationship of type *i*. Worker *k* incurs a fixed time θ when creating and using a direct relationship to transfer knowledge for the first time.	
Z^t_k	=1 if worker *k* is busy with transferring knowledge to other workers (as a result of assignments in previous periods) in period *t*, = 0 otherwise.	
$F^{t\_m}_{kl}$	=1 if *till* the beginning of period *t*, worker *k* has finished transferring knowledge to worker *l* as a result of assignment made in period *m*, = 0 otherwise.	
$J^{t\_m}_{kl}$	=1 if *during* period *t*-1, worker *k* finishes transferring knowledge to worker *l* (as a result of assignment made in period *m*) and becomes available to provide knowledge to other workers in period *t*, = 0 otherwise.	

We assume an organization that supports *S* skills and has *K* workers. We assume a heterogeneous workforce where workers could have varying levels of competence in each skill. This skill set (competence values) for a worker is defined as the knowledge vector of a worker. In our model, $W_{ks}^{t} \in [W_{sMin}, W_{sMax}]$, represents worker k's competence in skill s at the beginning of period t. Larger (smaller) values indicate an expert (novice) worker. Here, $W_{sMin} (W_{sMax})$ represents the minimum (maximum) competence level in skill s. In addition, as mentioned earlier, we assume that workers vary in term of the importance (weight) they have for each skill, based on the types of tasks required of them. We use $\beta_{k}^{s} (\in [0,1], \sum_{s=1}^{S} \beta_{k}^{s} = 1)$ to capture the relative importance of skill s for worker k. Therefore, the total competence of worker k, in period t, weighted by the importance of different skills is given by, $\sum_{s=1}^{S} W_{ks}^{t} \beta_{k}^{s}$. During each assignment a worker may or may not be assigned to knowledge sharing activities.

The firm's objective is to maximize the cumulative *weighted* competence level of all workers, across all skills supported by the organization, over the planning horizon. This is given by, $Max \sum_{t=1}^{T} \sum_{k=1}^{K} \sum_{s=1}^{S} \beta_{ks} W_{ks}^{t}$

Next, we discuss additional details.

3.3.2.1 Time required to transfer knowledge

We assume that the total time to taken by worker k to transfer knowledge to worker l depends on: (a) knowledge difference between workers k and l, (b) type of tie between the workers k and l and, (c) work load of the work providing help.

The amount of knowledge that worker k can transfer to worker l at the beginning of period t is given by, $G_{kls}^{t} \in [0, W_{sMax}]$. If ϖ_{i} is the time taken to transfer a unit of knowledge over a tie of type i, the time taken by worker k to transfer knowledge to worker *l*, in skill *s*, in period *t*, is given by $\sum_{s=1}^{S} G_{kls}^{t} X_{kls\_i}^{t} \varpi_i$. Here $X_{kls\_i}^{t}$ (*decision variable*) is equal to one if worker *l* is assigned to acquire knowledge from worker *k*, in period *t*, in skill *s*, over a tie of type *i*. It is important to note that knowledge transfer is directional, i.e., worker *k* transferring knowledge to worker *l* does not imply any knowledge flow *l* to *k* ($X_{kls\_i}^{t} \neq X_{lks\_i}^{t}$). Since direct ties are more efficient than indirect ties (Levine and Prietula, 2006), we assume $\varpi_1 \geq \varpi_0$, where 0 and 1 represent direct and indirect ties, respectively.

In each period *t*, workers can share knowledge using existing direct or indirect relationships, or create new direct relationships. $D_{kl}^{t} \; \forall t \in \{1,..,T\}$ (derived variable) is equal to one if there is a direct tie between worker *k* and *l* during period *t*, and zero otherwise. Therefore, $(D_{kl}^{t} - D_{kl}^{(t-1)} = 1)$ indicates the absence of pre-existing direct ties between workers *l* and *k*, in period *t*. In the absence of pre-existing direct ties between workers, organizations need to facilitate direct ties between workers, in order to effectively transfer knowledge. Since the creation of new direct ties requires time (effort), we introduce a set up coefficient (θ) to capture the time required to facilitate a direct relationship between a pair of workers. Note that, the relationships between worker *k* and *l* are bidirectional i.e., $D_{kl}^{t} = D_{lk}^{t}$. Similarly, $V_{kl}^{t} \; \forall t \in \{1,..,T\}$ (derived variable) is equal to one if there is an indirect tie between worker *k* and *l* during period *t*, and zero otherwise. Note that workers do not incur a setup cost when using indirect ties since these are by-products of creating direct ties. Thus, the *knowledge transfer time* from worker *k* to worker *l* using direct ties, in period *t*, is given by,

$\theta(D_{kl}^{t}-D_{kl}^{(t-1)})+\sum_{s=1}^{S}G_{kls}^{t}X_{kls\_0}^{t}\varpi_{0}$. Along the same lines, the *knowledge transfer time* using indirect relationships is given by, $\sum_{s=1}^{S}G_{kls}^{t}X_{kls\_1}^{t}\varpi_{1}$.

Note that multiple workers may be assigned to the same worker for knowledge acquisition, at the same time. However, we assume that the acquisition requests are queued and the knowledge transfer process is sequential, based on the order in which the requests are made. In our model, Z_{k}^{t} (derived variable) is equal to one if in period *t*, worker *k* is *not* busy with knowledge provision assignments made in previous periods, and zero otherwise. In our model, F_{kl}^{t-m} (derived variable) is equal to one if, by period *t*, worker *l* has finished receiving knowledge from worker *k* as a result of knowledge acquisition assignments made in period *m* (zero otherwise).

Therefore, the total time to transfer knowledge is the sum of *knowledge transfer time* and *waiting time* (time in the queue before knowledge sharing starts). For details refer to other knowledge sharing constraints in the model formulation.

3.3.2.2 Knowledge diffusion using direct ties

We model the extent of knowledge gained by worker *k*, as a result of consulting co-worker *l*, as depending on: (a) knowledge difference between worker *k* and worker *l* at the beginning of the knowledge transfer process (G_{kls}^{t}), (b) the knowledge provision load of worker *l* (number of other workers assigned to acquire knowledge from worker *l*), and (c) the strength of the direct relationship between worker *k* and worker *l*.

In this model, workers are allowed to provide and acquire knowledge in the same period. However, when a worker is providing and acquiring knowledge at the same time, it affects his knowledge acquisition efficiency. We model this overhead as reduced knowledge acquisition efficiency in periods where the worker is simultaneously providing and acquiring knowledge i.e., $\alpha_{l\_i\_busy} < \alpha_{l\_i\_idle}$, where i is equal to zero (one) for direct(indirect) ties. It is important to note that, it can take multiple periods for worker l to acquire knowledge. Therefore, the average knowledge acquisition efficiency for worker l between periods m and q, over a tie of type i, is given by, $(\sum_{r=m}^{q-1}(\alpha_{l\_0\_busy} Z_l^r + \alpha_{l\_0\_idle}(1-Z_l^r))/(q-m))$.

We assume that the strength of direct ties can vary based on age of the relationship between two workers. In our model, $\sum_{u=1}^{m} D_{kl}^u$ indicates the age of the direct relationship between workers k and l, in period m. Thus, $\sum_{u=1}^{m} D_{kl}^u / T$ represents efficiency of knowledge transfer between workers k and l, in period m.

W_{ls}^1 represents the worker's initial competence level (at the beginning of the planning horizon). Therefore, in period t, worker k's updated competence, in skill s, as a result of knowledge acquisition from co-workers, using direct and indirect ties, is given by,

$$\begin{aligned} W_{ls}^t = W_{ls}^1 &+ \sum_{q=1}^{t-1}\sum_{m=1}^{q-1}\sum_{k=1;k\neq l}^{K}(\sum_{u=1}^{m-1} D_{kl}^u / T) J_{kl}^{q-m} X_{kls\_0}^m G_{kls}^m \sum_{r=m}^{q-1}(\alpha_{l\_0\_busy} Z_l^r + \alpha_{l\_0\_idle}(1-Z_l^r))/(q-m) \\ &+ \sum_{q=1}^{t-1}\sum_{m=1}^{q-1}\sum_{k=1;k\neq l}^{K} J_{kl}^{q-m} X_{kls\_1}^m G_{kls}^m \sum_{r=m}^{q-1}(\alpha_{l\_1\_busy} Z_l^r + \alpha_{l\_1\_idle}(1-Z_l^r))/(q-m) \\ &\forall l \in \{1,2,..,K\}, \forall s \in \{1,2,..,S\}, \forall t \in \{2,..,T\} \end{aligned}$$

Finally, the Information Flow Network (IFN) optimization problem can be formulated as,

Objective function:

$$Max \sum_{t=1}^{T}\sum_{k=1}^{K}\sum_{s=1}^{S} \beta_{ks} W_{ks}^t$$

Knowledge Sharing Relationship Constraints:

$$D_{kl}^{t} \le D_{kl}^{(t-1)} + \sum_{s=1}^{S}(X_{kls\_0}^{t} + X_{lks\_0}^{t}) \qquad \forall k,l \in \{1,2,..,K\}, k \ne l, \forall t \in \{2,..,T\}$$

$$D_{kl}^{t} \ge 0.5 D_{kl}^{(t-1)} + \sum_{s=1}^{S}(X_{kls\_0}^{t} + X_{lks\_0}^{t})/(2S) \qquad \forall k,l \in \{1,2,..,K\}, k \ne l, \forall t \in \{2,..,T\}$$

$$D_{kl}^{t} = D_{lk}^{t} \qquad \forall k,l \in \{1,2,..,K\}, k \ne l, \forall t \in \{2,..,T\}$$

D_{kl}^{t} =1 if there is a direct tie between worker *k* and *l* in period *t* (could be tie facilitated in previous periods, or new tie created during period *t*), = 0 otherwise.

$$V_{kl}^{t} \le \sum_{\substack{u=1\\u\ne k,l}}^{K} D_{ku}^{t} D_{lu}^{t} \qquad \forall k,l \in \{1,2,..,K\}, k \ne l, \forall t \in \{1,..,T\}$$

$$V_{kl}^{t} \ge (\sum_{\substack{u=1\\u\ne k,l}}^{K} D_{ku}^{t} D_{lu}^{t})/(K-2) \qquad \forall k,l \in \{1,2,..,K\}, k \ne l, \forall t \in \{1,..,T\}$$

V_{kl}^{t} = 1 if there is an indirect tie between worker *k* and *l* (worker *k* and *l* share at least one common co-worker connected by direct tie) in period *t*; = 0 otherwise.

$$X_{kls\_1}^{t} \le V_{kl}^{(t-1)} \qquad \forall k,l \in \{1,2,..,K\}, k \ne l, \forall s \in \{1,2,..,S\}, \forall t \in \{2,..,T\}$$

$$X_{kls\_1}^{t} \le 1 - D_{kl}^{t} \qquad \forall k,l \in \{1,2,..,K\}, k \ne l, \forall s \in \{1,2,..,S\}, \forall t \in \{2,..,T\}$$

Worker *l* acquires knowledge from *k* in skill *s* in period *t* using indirect tie *iff* 1) there is an existing indirect tie in period *t*–1, and 2) there is no direct tie between *k* and *l*.

Knowledge Sharing Assignment Constraints:

$$\sum_{i=0}^{1}\sum_{k=1;k\ne l}^{K}\sum_{s=1}^{S} X_{kls\_i}^{t} + \sum_{m=1}^{t-1}\sum_{k=1}^{K} F_{kl}^{t-m} \le 1 \qquad \forall l \in \{1,2,..,K\}, \forall t \in \{1,2,..,T\}$$

Worker *l* can acquire knowledge from at most one worker in one skill across *S* skills in period *t*, *iff* worker *l* has finished receiving knowledge from all workers assigned.

$$\sum_{i=0}^{1}\sum_{l=1;k\ne l}^{K}\sum_{s=1}^{S} X_{kls\_i}^{t} \le 1 \qquad \forall k \in \{1,2,..,K\}, \forall t \in \{1,2,..,T\}$$

Worker *k* can provide knowledge to at most one worker in one skill in period *t*.

$$T - \sum_{t=1}^{T}\sum_{l=1;l\ne k}^{K}\sum_{i=0}^{1} H_{kl\_i}^{t} - \sum_{t=1}^{T}(1 - Z_{k}^{t}) \ge 0 \qquad \forall k \in \{1,..,K\}$$

Total time spent by worker *k* providing knowledge and being idle cannot exceed the planning horizon *T*.

Other Knowledge Sharing Constraints:

$$M_{kls}^{t} \geq (W_{ks}^{t} - W_{ls}^{t})/W_{sRange} \qquad \forall k,l \in \{1,2,..,K\}, k \neq l, \forall s \in \{1,2,..,S\}, \forall t \in \{1,2,..,T\}$$
$$M_{kls}^{t} < (W_{ks}^{t} - W_{ls}^{t})/W_{sRange} + 1 \qquad \forall k,l \in \{1,2,..,K\}, k \neq l, \forall s \in \{1,2,..,S\}, \forall t \in \{1,2,..,T\}$$

M_{kls}^{t} = 1 if worker *k*'s knowledge in skill *s* is better than worker *l*'s at the beginning of period *t*; = 0 otherwise.

$$G_{kls}^{t} = M_{kls}^{t}(W_{ks}^{t} - W_{ls}^{t}) \qquad \forall k,l \in \{1,2,..,K\}, k \neq l, \forall s \in \{1,2,..,S\}, \forall t \in \{1,2,..,T\}$$

G_{kls}^{t} is the amount of knowledge can be transferred from worker *k* to worker *l* in skill *s* during period *t*.

$$H_{kl\_0}^{t} = \theta(D_{kl}^{t} - D_{kl}^{t-1}) + \sum_{s=1}^{S} G_{kls}^{t} X_{kls\_0}^{t} \varpi_0$$
$$H_{kl\_1}^{t} = \sum_{s=1}^{S} G_{kls}^{t} X_{kls\_1}^{t} \varpi_1 \qquad \forall k,l \in \{1,2,..,K\}, k \neq l, \forall t \in \{1,..,T\}$$

$H_{kl\_i}^{t}$ is the time incurred by worker *k* in providing knowledge to worker *l* in period *t* using relationship of type *i*. Worker *k* incurs a fixed time θ when creating and using a direct relationship to transfer knowledge for the first time.

$$Z_{k}^{t}(t - \sum_{m=1}^{t-1} \sum_{l=1;l\neq k}^{K} \sum_{i=0}^{1} H_{kl\_i}^{m} - \sum_{m=1}^{t-1}(1 - Z_{k}^{m})) \geq 0 \qquad \forall k \in \{1,2,..,K\}, \forall t \in \{1,..,T\}$$
$$Z_{k}^{t} \geq (t - \sum_{m=1}^{t-1} \sum_{l=1;l\neq k}^{K} \sum_{i=0}^{1} H_{kl\_i}^{m} - \sum_{m=1}^{t-1}(1 - Z_{k}^{m}))/T \qquad \forall k \in \{1,2,..,K\}, \forall t \in \{1,..,T\}$$

Z_{k}^{t} = 1 if worker *k* is busy with transferring knowledge to other workers (as a result of assignments in previous periods) in period *t*, = 0 otherwise.

$$F_{kl}^{t-m}(t - \sum_{q=1}^{m-1} \sum_{r=1;r\neq k}^{K} \sum_{i=0}^{1} H_{kr\_i}^{q} - \sum_{i=0}^{1} H_{kl\_i}^{m} - \sum_{q=1}^{m-1}(1 - Z_{k}^{q})) \geq 0$$
$$F_{kl}^{t-m} \geq (t - \sum_{q=1}^{m-1} \sum_{r=1;r\neq k}^{K} \sum_{i=0}^{1} H_{kr\_i}^{q} - \sum_{i=0}^{1} H_{kl\_i}^{m} - \sum_{q=1}^{m-1}(1 - Z_{k}^{q}))/T$$
$$\forall k,l \in \{1,2,..,K\}, k \neq l, \forall t,m \in \{1,..,T\}, m < t$$

F_{kl}^{t-m} = 1 if *till* the beginning of period *t*, worker *k* has finished transferring knowledge to worker *l* as a result of assignment made in period *m*, = 0 otherwise.

$$J_{kl}^{t-m} = F_{kl}^{t-m} - F_{kl}^{(t-1)-m} \qquad \forall t \in \{2,..,T\}, \forall m \in \{1,..,T\}, m < t$$

J_{kl}^{t-m} = 1 if *during* period t-1, worker k finishes transferring knowledge to worker l (as a result of assignment made in period m) and becomes available to provide knowledge to other workers in period t, = 0 otherwise.

$$W_{ls}^{t} = W_{ls}^{1} + \sum_{q=1}^{t-1}\sum_{m=1}^{q-1}\sum_{k=1;k\neq l}^{K}(\sum_{u=1}^{m-1} D_{kl}^{u}/T) J_{kl}^{q-m} X_{kls\_0}^{m} G_{kls}^{m} \sum_{r=m}^{q-1}(\alpha_{l\_0\_busy} Z_{l}^{r} + \alpha_{l\_0\_idle}(1-Z_{l}^{r}))/(q-m)$$
$$+ \sum_{q=1}^{t-1}\sum_{m=1}^{q-1}\sum_{k=1;k\neq l}^{K} J_{kl}^{q-m} X_{kls\_1}^{m} G_{kls}^{m} \sum_{r=m}^{q-1}(\alpha_{l\_1\_busy} Z_{l}^{r} + \alpha_{l\_1\_idle}(1-Z_{l}^{r}))/(q-m)$$
$$\forall l \in \{1,2,..,K\}, \forall s \in \{1,2,..,S\}, \forall t \in \{2,..,T\}$$

W_{ls}^{t} is worker l's knowledge in skill s at the beginning of period t. ■

3.4 Solution Procedure

The IFN optimization problem discussed in the previous section is difficult to solve as the number of workers increases. Hence, we propose a heuristic that uses connection based assignments at discrete points in time in order to solve the problem.

3.4.1 Connection Based Heuristic (CBH)

The IFN optimization problem can be solved for each period successively. In other words, we first determine the knowledge sharing assignments and the optimal knowledge gain in the first period. Next, we set up the problem for the second period. To achieve this, we use knowledge transfer information from the first period and take into account workers' knowledge provision load and workers' availability to acquire knowledge at the beginning of the second period. In addition, we update their knowledge level based on knowledge sharing activities in the first period. The optimal worker-to-worker knowledge transfer activities for the second period can be obtained by using the above information. Similarly, the knowledge transfer activities for the second period then sets up the problem for the third period, and so on. This would essentially be a greedy algorithm, wherein the emphasis is to find the optimal assignment for each period.

Instead, CBH considers the impact of knowledge sharing activities in the current period on future periods. First, we consider the potential benefits to other workers connected to the worker acquiring knowledge. Particularly, we consider the extent of knowledge that can, overtime, diffuse to other workers connected to the worker acquiring knowledge. Second, we consider the opportunity cost for the worker providing knowledge. That is, we consider the fact that once a worker is assigned to provide knowledge he becomes temporarily unavailable to other workers.

Similar to section 3.3, in each period *t*, firm's objective is to maximize the cumulative *weighted* competence level of all workers, across all skills supported by the organization. In addition, CBH objective includes, an approximation for the potential future benefits of knowledge sharing activities in the current period, and the opportunity costs associated with workers providing help. Let $\hat{k}_t$ be the *set* of workers available to acquire knowledge at the beginning of period *t*. As mentioned earlier, the time to transfer knowledge can include a *waiting time*. In CBH, p_{klst_i} represents the period when worker *l* starts acquiring knowledge from worker *k.* Note that, $p_{klst\_i} \geq t$. And, q_{klst_i} be the time period when *k* finishes transferring knowledge to worker *l,* in skill *s*, over a tie of type *i* (either by creating new tie or using existing tie).

The value of assigning worker *l* to acquire knowledge from worker *k*, in period *t*, is consists of three terms: (a) the cumulative value of worker *l*'s knowledge gain, (b) the future value of worker *l*'s knowledge gain, and (c) the opportunity cost of assigning worker *k* to acquire knowledge from worker *l*.

Cumulative Value of Worker l's Knowledge Gain

Worker *l*'s knowledge gain from worker *k*, using direct tie, can be written as, $\phi^{gain}_{klst\_0} = \beta_{ls}(\sum_{u=1}^{t-1} D^{u}_{kl} / T)G^{t}_{kls} \sum_{r=p_{klst\_0}}^{q_{klst\_0}}(\alpha_{l\_0\_busy}Z^{r}_{l} + \alpha_{l\_0\_idle}(1-Z^{r}_{l}))/(q_{klst\_0} - p_{klst\_0})$.

Similarly, the knowledge gain over, indirect tie, can be written as, $\phi^{gain}_{klst\_1} = \beta_{ls}G^{t}_{kls} \sum_{r=p_{klst\_1}}^{q_{klst\_1}}(\alpha_{l\_1\_busy}Z^{r}_{l} + \alpha_{l\_1\_idle}(1-Z^{r}_{l}))/(q_{klst\_1} - p_{klst\_1})$, .

Future Value of Worker l's Knowledge Gain

In order to estimate the future value of knowledge acquisition in period *t*, we need estimate how much of the acquired knowledge in period *t* can diffuse to other workers connected to *l* in future periods. We measure this by calculating the average additional knowledge gain ($\varphi^{future}_{klst\_i}$) for all workers connected to *l*. Where,

$$\varphi^{future}_{klst\_i} = \sum_{j=1, j\neq l,k}^{K}(D^{t}_{lj}\alpha_{j\_0\_busy}(\sum_{u=1}^{q_{klst\_i}} D^{u}_{lj}/T) + (1-D^{t}_{lj})V^{t}_{lj}\alpha_{j\_1\_busy})\beta_{js}(G^{t}_{ljs} + G^{t}_{kls}) / \sum_{j=1, j\neq l,k}^{K}((1-D^{t}_{lj})V^{t}_{lj} + D^{t}_{lj})M^{t}_{ljs}.$$

Opportunity Cost of Assigning Worker l to Acquire Knowledge from Worker k

Assigning worker *l* to acquire knowledge from worker *k* makes *k* unavailable to provide knowledge to other workers from period p_{klst_i} to period q_{klst_i}. This delays knowledge provision to any other worker who can potentially acquire knowledge from *k*. We measure the opportunity cost (φ^{opp}_{klst}) by using the average knowledge that worker *k* could transfer to other workers connected to him.

$$\varphi^{opp}_{klst} = \sum_{j=1, j\neq k,l}^{K}(D^{t}_{kj}\alpha_{j\_0\_idle}(\sum_{u=1}^{t-1} D^{u}_{kj}/T) + (1-D^{t}_{kj})V^{t}_{kj}\alpha_{j\_1\_idle})\beta_{js}G^{t}_{kjs} / \sum_{j=1, j\neq k,l}^{K}((1-D^{t}_{kj})V^{t}_{kj} + D^{t}_{kj})M^{t}_{kjs}.$$

Hence, in each period *t*, the INF optimization problem can be written as,

Objective function:

$$Max\sum_{l\in\hat{k}_t}\sum_{\substack{k=1\\k\neq l}}^{K}\sum_{s=1}^{S}\sum_{i=0}^{1}X_{kls\_i}^{t}\varphi_{klst\_i}^{gain}(T-q_{klst\_i})+\sum_{l\in\hat{k}_t}\sum_{\substack{k=1\\k\neq l}}^{K}\sum_{s=1}^{S}\sum_{i=0}^{1}X_{kls\_i}^{t}\varphi_{klst\_i}^{future}(T-q_{klst\_i})$$

$$-\sum_{l\in\hat{k}_t}\sum_{\substack{k=1\\k\neq l}}^{K}\sum_{s=1}^{S}\sum_{i=0}^{1}X_{kls\_i}^{t}\varphi_{klst}^{opp}(q_{klst\_i}-p_{klst\_i})$$

Knowledge Sharing Relationship Constraints:

$$\sum_{i=0}^{1}\sum_{\substack{k=1\\k\neq l}}^{K}\sum_{s=1}^{S}X_{kls\_i}^{t}\leq 1 \qquad \forall l\in\hat{k}_t,$$

Worker *l* can only acquire help from at most one worker across *S* skills in period *t*.

$$\sum_{i=0}^{1}\sum_{\substack{l=1\\l\neq k}}^{K}\sum_{s=1}^{S}X_{kls\_i}^{t}\leq 1 \qquad \forall k\in\{1,2,..,K\}$$

Worker k can only provide knowledge to at most one worker across S skills in period t.

$$T-X_{kls\_i}^{t}q_{klst\_i}\geq 0 \qquad \forall k\in\{1,..,K\},\forall l\in\hat{k}_t, k\neq l,\forall s\in\{1,...,S\},\forall i\in\{0,1\}$$

Knowledge transfer cannot exceed the planning horizon T.

Using Hungarian Method to solve the problem for each period t

Next, we show how to solve the problem for each period *t* using Hungarian methods. We calculate the profit matrix of all possible worker-to-worker knowledge transfer activities, where each element $a_{l,k,s,i}$ represents the expected value of assigning worker *l* to acquire knowledge from worker *k* in skill *s* using tie *i*. As discussed above, there expected value of assigning worker *l* to acquire knowledge from worker *k* can be calculated as $a_{l,k,s,i}=\varphi_{klst\_i}^{gain}(T-q_{klst\_i})+\varphi_{klst\_i}^{future}(T-q_{klst\_i})-\varphi_{klst}^{opp}(q_{klst\_i}-p_{klst\_i})$ (Block A in Figure 25). In addition, we allow workers to not acquire knowledge in period *t* (Block B in Figure 25), where the profit equals zero ($a_{l,K+1}=0$).

We then test the feasibility of each knowledge transfer activity. First, worker *l* cannot transfer knowledge to himself. Thus, the profit of assigning worker *l* to acquire knowledge from *l* is set to $-\infty$ to prevent this assignment

($a_{l,l,s,i} = -\infty \;\; \forall l \in \hat{k}_t, s \in \{1,2,..,S\}, i \in \{0,1\}$). Second, each knowledge transfer activity cannot exceed the planning horizon *T*. Hence, we check the value of $T - q_{klst\_i}$ for each possible worker-to-worker assignment ($a_{l,k,s,i}$). If $T - q_{klst\_i} < 0$, we set the value of $a_{l,k,s,i}$ to $-\infty$ such that it will not be selected.

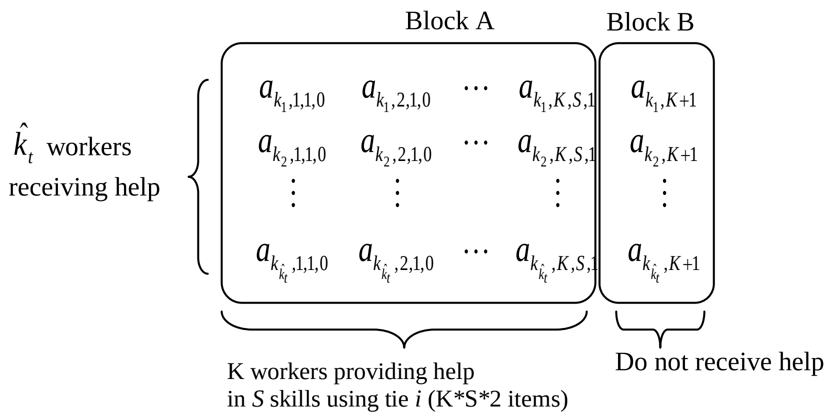


FIGURE 25: Profit Matrix for the Hungarian Method used in CBH

Finally, Figure 26 summarizes the Connection Based Heuristic.

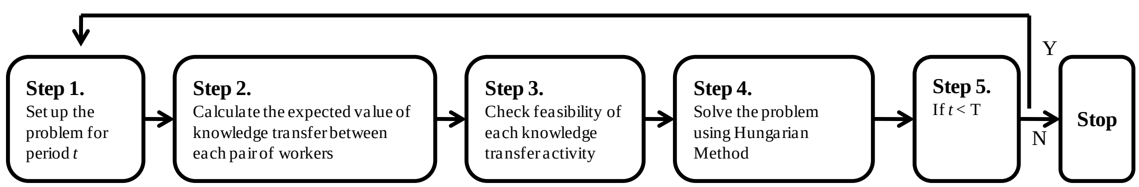


FIGURE 26: Connection Based Heuristic (CBH)

3.4.2 Performance of Connection Based Heuristic (CBH)

To evaluate the performance of our heuristic, we solve the MIP formulation using CPLEX for small problem instances and compare it against the solution using CBH. This methodology is consistent with prior research (Dawande et al., 2008; Kumar et al., 2007). In terms of compute time, the CBH solution is obtained in a few seconds compared to 10 hours for CPLEX. We observe that maximum gap between the CPLEX solution and the CBH solution (CBH Gap) is about 7% for the problems solved using

CPLEX (Table 8). The performance of our CBH is comparable with existing researching adopting this methodology (Dawande et al., 2008; Kumar et al., 2007).

TABLE 8: Percentage Gap of CBH results from CPLEX solution

Problem Class	Worker Heterogeneity	Number of Workers	MIP Problem Size: Rows × Columns (Non-zeros)	CPLEX Gap (%)	CBH Gap (%)	CPU time for CBH (sec)
1	Low	10	26,530×19,785(104,175)	6.59	3.71	0.71
2		12	49,407×32,745(189,895)	7.42	3.92	0.81
3		14	87,323×56,175(391,635)	7.98	5.13	0.72
4		16	159,275×98,565(771,115)	8.14	7.12	1.01
5	Med	10	26,530×19,785(104,175)	5.71	3.70	0.78
6		12	49,407×32,745(189,895)	7.51	3.60	0.68
7		14	87,323×56,175(391,635)	7.56	4.92	0.97
8		16	159,275×98,565(771,115)	7.73	7.09	0.77
9	High	10	26,530×19,785(104,175)	5.91	3.17	0.89
10		12	49,407×32,745(189,895)	7.71	3.59	0.78
11		14	87,323×56,175(391,635)	8.16	4.87	0.97
12		16	159,275×98,565(771,115)	8.13	6.96	0.86

* Number of Skills = 2, Time to create direct tie = 2, Planning horizon = 10, $\varpi_0 / \varpi_1 : 1/2$,

** Low Worker Heterogeneity ~*N*(2.5, 0.8), Medium Worker Heterogeneity ~*N*(2.5, 1), High Worker Heterogeneity ~*N*(2.5, 1.2).

3.5 Experiment Design

The complexity of the problem precludes analytical solution and requires us to use simulation. Simulation with synthetic data allows us to obtain insights into relationships between key variables impacting the design of the information flow networks. This approach is appropriate when the underlying phenomenon is complex and real world data is difficult to obtain, and is used in studying knowledge management (Buco et al., 2003).

This section describes the design of simulation experiments including, key parameters and their estimation. Fifty replications of each sample path were used, and average values of system performance measures were calculated. Same as in section 2.4.1, simulations were extremely computation-intensive. Experiments were run on a cluster of 160 Intel Xeon CPUs on Dell blade servers with Red Hat Enterprise Linux operating system. The average time for running each replication of a sample path was 1 hour.

TABLE 9: Experiment parameter values

Type	Parameter	Values	Justification
System Environment	K	100	
	S	2/3/4/5	In Cowan and Jonard (2005) "Each agent has a 5-category knowledge vector" and Prabhakar et al. (2005) refers to: "Programming Skills, Operating System Skills, Database, ERP, and e-Commerce Server Skills."
	T	100	
Worker Related	β_k^s	Each worker is randomly specialized in one skill	In Backes-Gellner and Mure (2008) "in industries, such as precision mechanics, insurances, etc., skills requirements are less homogenous, so the variance in the skill weights distribution is assumed to be larger." Our parameter values are consistent with Backes-Gellner and Mure (2008).
	W_{ks}^1	Follows Normal Distribution: $N(2.5, 0.8)$ /$N(2.5, 1.0)$ /$N(2.5, 1.2)$	Lester (2005) proposed five categories to assess employee's skill level. A normal distribution of worker competence is consistent with prior research (Sayın and Karabatı, 2007).
Knowledge Transfer	α_i	0.15~0.4	We experiment with a range of values in order to study the sensitivity of our results.
	ϖ_i	ϖ_0 : 6/10/14/18, ϖ_1 : 10/15/20/25	In Hansen (2002), "relying on established direct relations may ease the difficulties of transferring noncodified knowledge, …, reducing the time it takes to explain the knowledge and understand one another".
	θ	5/10/15/20	We experiment with a range of values in order to study the sensitivity of our results.

Table 9 describes the numerical values, and justification for parameters used in our simulation experiments. Where possible, we have attempted to base these values on ranges that could be encountered in practice and/or prior research. Since parameters related with knowledge sharing in our model are difficult to obtain, we experiment with multiple values to sensitize the organization to information flow network design issues that involve these parameters.

We consider a population of 100 workers, with an average of two direct ties per worker. Each worker has multiple skills. Workers' knowledge level in each skill at the beginning of the planning horizon (W_{ks}^1) is initialized by selecting from a normal distribution. After that, workers are categorized into three groups – expert, average, and novice – based on their average initial knowledge level across skills. Based on prior research, workers with an average knowledge level ($\sum_{s=1}^{S} W_{ks}^1 / S$) between 0 and 2 are defined as Novices, between 2 and 3 as average worker, and between 3 and 5 as experts (Lester, 2005). Note that the each worker's total weight of all skills remains 100% regardless of the number of skills supported by the organization ($\sum_{s=1}^{S} \beta_k^s = 100\%$). On the other hand, each worker is set to be specialized in a random skill $\hat{s}$, by increasing the value of $\beta_k^{\hat{s}}$ such that $\beta_k^{\hat{s}} = 3\beta_k^s \quad \forall s \in \{1,..,S\}, s \neq \hat{s}$. At the beginning of the planning horizon, each worker randomly decides whether to transfer knowledge or not, representing the organization's initial status. If he decides to transfer knowledge, he randomly selects one of his colleagues (through direct or indirect tie) and picks a randomly skill. In summary, each worker randomly shares knowledge at the beginning of the planning horizon, which represents the current state of no management of information flow networks. Organizations then systematically decide which direct ties to create, and which ties to use, in order to effective share knowledge through information flow networks over the planning horizon.

Our objective was to better understand the process by which knowledge is shared, and as well as the structure of information flow networks, for different types of worker populations. Also we varied worker expertise distribution, time coefficient of providing knowledge over direct and indirect ties, and number of skills supported by the organization.

3.6 Results and Discussion

We present selected results from our experiments to illustrate the properties of effective information flow networks in terms of measures of knowledge gain, and sharing behavior between and within different groups[7]. We present the following sets of results: (a) the structure of effective information flow networks (as described by the number and types of ties between and within a different types of worker groups), (b) the impact of worker heterogeneity on knowledge gain and sharing, (c) the impact of time (cost) of creating and using knowledge sharing relationships, and (d) the impacts of number of skills supported by the organization on knowledge gain and sharing.

3.6.1 The Structure of Effective Information Flow Networks

As discussed earlier, we have three different groups of workers (experts, average and novice workers) in the organization. We seek to understand the similarities and differences between these groups of workers in terms of knowledge sharing behavior. Specifically, we are interested in similarities and differences between these groups in terms of the use of direct and indirect ties to facilitate knowledge transfer. We expect firms to facilitate novice workers to create ties with expert and average workers in order to improve knowledge sharing. However, the relative importance and roles of different types of workers is not always clear. Our results indicate that it is not optimal for a firm to just facilitate knowledge sharing between expert workers and novice workers. Average workers have a crucial intermediary role to play in facilitating knowledge flow. Table 10 indicates that the highest number of direct/indirect ties occur between

[7] Base parameter value used in the experiment: K=100, S= 5, T=100, $\varpi_0 = 10$; $\varpi_1 = 20$; $\theta = 10$; $\alpha_{0\_idle} / \alpha_{0\_busy} / \alpha_{1\_idle} / \alpha_{1\_busy}$ = 0.4/0.3/0.2/0.1; W_{ks}^{s} ~N(2.5,1)

TABLE 10: Number of ties used per worker within groups and between groups

Problem Class	**Worker Heterogeneity**	**Number of skills**	**Ties Used Per Worker Within Groups**						**Ties Used Per Worker Between Groups**					
			Expert (Direct/Indirect)		Average (Direct/Indirect)		Novice (Direct/Indirect)		Expert-Average (Direct/Indirect)		Expert-Novice (Direct/Indirect)		Average-Novice (Direct/Indirect)	
			D	**I**	**D**	**I**	**D**	**I**	**D**	**I**	**D**	**I**	**D**	**I**
1	Low	2	0.43	0.41	0.79	0.77	0.19	0.12	0.43	0.84	0.21	0.43	0.31	0.50
2	Med	2	0.52	0.47	0.68	0.61	0.27	0.18	0.47	0.95	0.27	0.56	0.37	0.63
3	High	2	0.57	0.49	0.59	0.51	0.32	0.21	0.50	1.01	0.31	0.69	0.40	0.69
4	Low	3	0.29	0.27	0.86	0.82	0.15	0.09	0.34	0.60	0.14	0.27	0.26	0.39
5	Med	3	0.39	0.33	0.77	0.69	0.20	0.13	0.41	0.76	0.20	0.41	0.33	0.53
6	High	3	0.46	0.34	0.69	0.58	0.26	0.17	0.46	0.87	0.24	0.50	0.37	0.63
7	Low	4	0.22	0.15	0.91	0.87	0.11	0.05	0.27	0.44	0.09	0.20	0.20	0.29
8	Med	4	0.30	0.23	0.82	0.73	0.16	0.11	0.34	0.59	0.17	0.32	0.29	0.43
9	High	4	0.34	0.28	0.74	0.65	0.21	0.15	0.41	0.72	0.22	0.41	0.34	0.55
10	Low	5	0.14	0.15	0.97	0.91	0.08	0.05	0.20	0.32	0.08	0.13	0.15	0.22
11	Med	5	0.22	0.21	0.86	0.78	0.13	0.10	0.31	0.50	0.13	0.24	0.24	0.35
12	High	5	0.29	0.24	0.80	0.70	0.18	0.12	0.37	0.63	0.18	0.31	0.29	0.45

experts and average workers, followed by the ties between average workers and novices, and then between experts and novices. Table 10 suggests that the number of direct and indirect ties within the average worker groups is higher than the number of ties within the novice and expert groups. In addition, we note that indirect ties between experts and novices have a crucial role to play in facilitating knowledge sharing, since they are much larger in number than direct ties between experts and novices (Table 10).

Effective knowledge transfer tends to take place in short bursts (knowledge transfers of short duration) between workers who do not have very high knowledge differences. Such knowledge transfer allows the worker providing knowledge and the worker gaining knowledge, to become available relatively quickly for additional knowledge provision and /or knowledge acquisition. In addition, such a knowledge transfer pattern allows direct ties created between workers to become available to other workers for indirect tie formation, relatively quickly. The following sections explain the underlying dynamics of the knowledge diffusion process in greater detail.

This result has important managerial implications. Organizations need to recognize the valuable bridging role that average workers can play in facilitating knowledge transfer. Our results indicate that ties between average and expert workers can have large network effects and facilitate effective knowledge transfer. This result is contrary to the common practice of facilitating knowledge transfer between experts and novices.

3.6.2 The Impact of Knowledge Transfer Efficiency and Worker Heterogeneity on Creation and Use of Ties

This section facilitates a deeper understanding of the dynamics of knowledge sharing and diffusion by studying the impact of knowledge transfer efficiency and worker heterogeneity on tie creation and use. The term knowledge sharing refers to knowledge exchange between pairs of workers. Knowledge diffusion, on the other hand, refers to the change in the cumulative knowledge level of the workforce over time.

We observe (Figure 27) that high knowledge acquisition efficiency result in better knowledge diffusion, (as measured by total cumulative weighted knowledge gain over the planning horizon), as expected. Interestingly, we also notice that knowledge diffusion over the planning horizon decreases as the worker heterogeneity increases. This merits additional explanation.

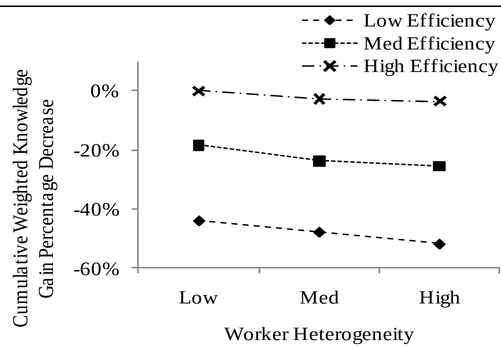


FIGURE 27: Cumulative weighted knowledge gain percentage decrease for different values of worker heterogeneity[8]

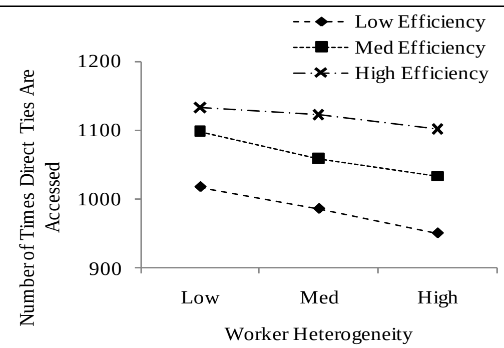


FIGURE 28: Number of times direct ties are accessed for different values of worker heterogeneity

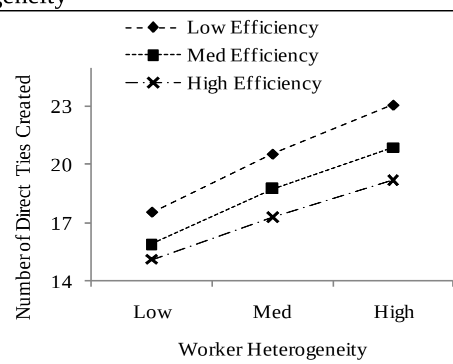


FIGURE 29: Number of direct ties created for different values of worker heterogeneity

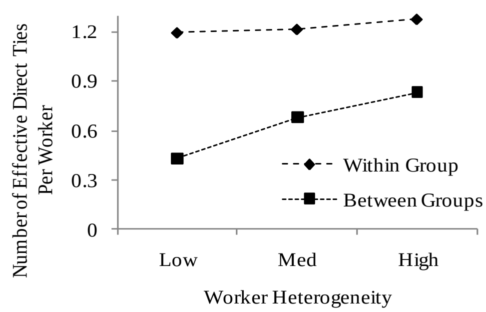


FIGURE 30: Number of effective direct ties per worker for different values of worker heterogeneity

[8] Low worker heterogeneity – $N(2.5, 0.8)$; Medium worker heterogeneity – $N(2.5, 1.0)$; High worker heterogeneity – $N(2.5, 1.2)$; Low efficiency – 0.4/0.3/0.2/0.1; Medium efficiency – 0.6/0.45/0.3/0.15; High Efficiency – 0.8/0.6/0.4/0.2.

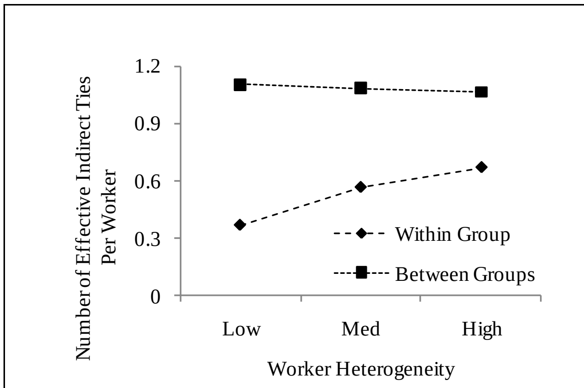


FIGURE 31: Effective indirect ties used per worker for different values of worker heterogeneity

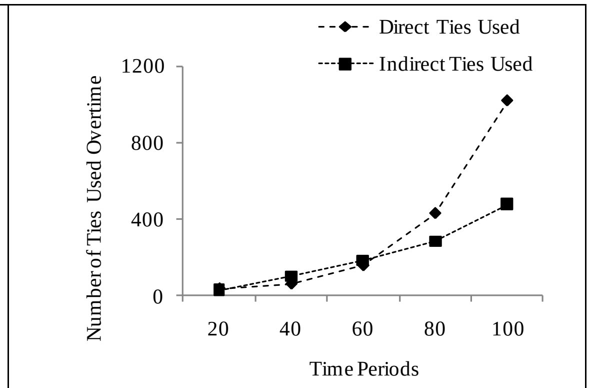


FIGURE 32: Number of ties use over time for low worker heterogeneity

Recall that, in our model, workers have three methods of acquiring knowledge: using an existing direct tie, creating a direct tie, and using an indirect tie. The amount of knowledge acquired is a function of type of tie (direct or indirect ties), knowledge difference between two workers, and efficiency of knowledge sharing. Worker's competence is updated after knowledge acquisition is complete, which may last for multiple time periods. Using existing direct ties to acquire knowledge is the most efficient method as discussed above. However, existing direct ties may not provide access to competent workers. Thus, relatively abundant but inefficient indirect ties may to be used. Alternatively, additional direct ties could be created to access competent workers while incurring the setup cost. It is important to note that irrespective of the type of ties used/created, workers who are engaged in providing knowledge during a time period, are less efficient in acquiring knowledge. Knowledge transfer occurs in short bursts in environments characterized by low worker knowledge heterogeneity as discussed in Section 3.3.2.1. Thus, in low worker heterogeneity environment, larger pool of workers is available for consultation as compared to workers in high worker heterogeneity environment. Over time, this results in greater knowledge diffusion (Figure 27).

When worker knowledge heterogeneity is high, on average, each knowledge transfer results in larger amount of knowledge acquired, but also takes longer, as compared to a scenario where worker heterogeneity is low. This explains why the total number of times that direct and indirect (not shown) ties used decreases as worker knowledge heterogeneity increases (Figure 28).

Interestingly, we observe that the number of direct ties created over the planning horizon increases as worker heterogeneity increases (Figure 29). This can be attributed to longer knowledge transfer times associated with increased worker heterogeneity, as discussed above. Longer knowledge transfer times reduce the opportunity to make a competent worker available to multiple workers over the planning horizon. Hence, new direct ties, providing access to available competent workers, need to be created in order to facilitate knowledge diffusion. We also observe that number of direct ties created decreases as knowledge acquisition efficiency increases (Figure 29). Note that high efficiency allows workers to acquire knowledge faster, which increases the pool of available competent workers for consultation and provides opportunities for reuse of existing ties over time. Thus, reducing the number of direct ties created over the planning horizon.

It is important to note that there are more direct ties within groups than between groups, while more indirect ties are used between groups than within groups (Figures 30 and 31). This is because knowledge difference within a group is lower compared to knowledge difference between groups. As discussed earlier, small knowledge difference allows worker quickly share knowledge with each other, resulting in faster knowledge diffusion. Direct ties are the preferred method of knowledge transfer because of better efficiency and less time to transfer knowledge. Hence, more direct ties are used within group than between groups (Figure 30).

Next we focus on the pattern in which different types of ties are used, over the planning horizon. In the beginning of the planning horizon, there are relatively fewer direct ties and it takes time to establish new direct ties. This limits access to competent workers via direct ties in the beginning of the planning horizon. On the other hand, indirect ties are relatively abundant and provide better access to competent workers, although they are less efficient than direct ties. This explains why in the beginning of the planning horizon, indirect tie usage is slightly larger than direct tie usage (Figure 32). Over time, direct ties are systematically created to transfer knowledge and facilitate knowledge diffusion. Note that, the strength of existing and newly created direct ties increases with time, increasing the difference in knowledge sharing efficiency between direct and indirect ties. In addition, knowledge diffusion results in improved access to competent workers via direct ties. Hence, we observe in Figure 32 that the use of direct ties significantly exceeds the use of indirect ties over time (time period greater than 60).

3.6.3 Impacts of Various Time (Cost) Coefficients

In order to examine the robustness of the model trend seen thus far, we study the impact of various time coefficients on the number of direct ties created during the planning horizon. Three types of time coefficients are examined: time to create direct ties, time to transfer knowledge using direct ties, and time to transfer knowledge using indirect ties. Note that, in these experiments the time to transfer one unit of knowledge using direct ties is always smaller than the time required using indirect ties. It is not surprising that as the time to create direct tie increases, the cumulative weighted knowledge gain decreases (Figure 35). Similar trends are observed when time to transfer using direct/indirect ties increases (Not shown). Note that creating new direct ties to transfer knowledge is less attractive as time to create direct tie increases. Thus, the number of direct ties created decreases as the time to create direct tie increases (Figure 33).

Interestingly, as the time to transfer knowledge using direct ties increases, we observe that more direct ties are created regardless of the heterogeneity of the workforce (Figure 34). As time to transfer knowledge using direct/indirect ties increases, the time that workers are engaged in each knowledge transfer is longer, making them unavailable to other workers for consultation. Thus increasing the need to create new direct ties to acquire knowledge.

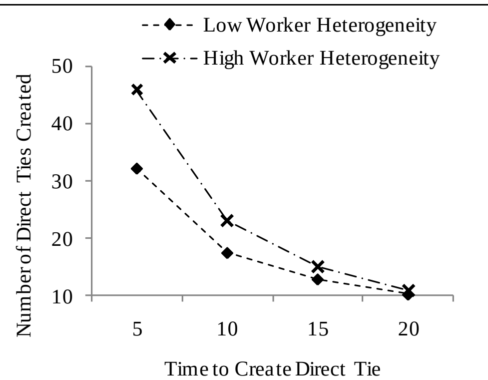


FIGURE 33: Number of direct ties created for different values of time to create direct ties

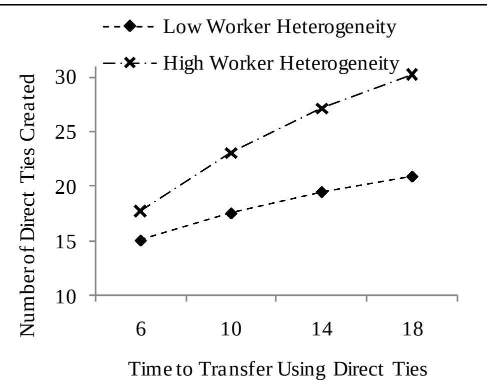


FIGURE 34: Number of direct ties created for different values of time to transfer knowledge using direct ties

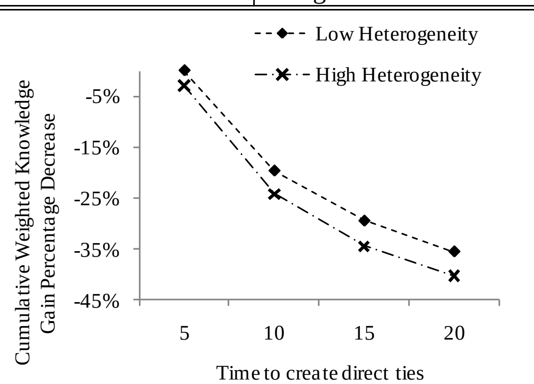


FIGURE 35: Cumulative weighted knowledge gain percentage decrease for different values of time to create direct ties

3.6.4 Impacts of Number of Skills Supported by The Organization

The number of skills supported by an organization has interesting impacts on knowledge diffusion dynamics. Note that for each worker, the total weight of all skills sums up to one regardless of the number of skills supported by the organization. Hence, as the number of skills increases, the weight for each skill reduces. Each worker may need to improve knowledge in multiple skills depending on the weight of each skill and the existing knowledge level in a skill. Recall that the objective of an organization is to maximize the total weighted knowledge of all workers over a fixed planning horizon. As a result, the amount of time each worker spends on acquiring knowledge in each skill decreases, reducing the cumulative weighted knowledge gain (Figure 36).

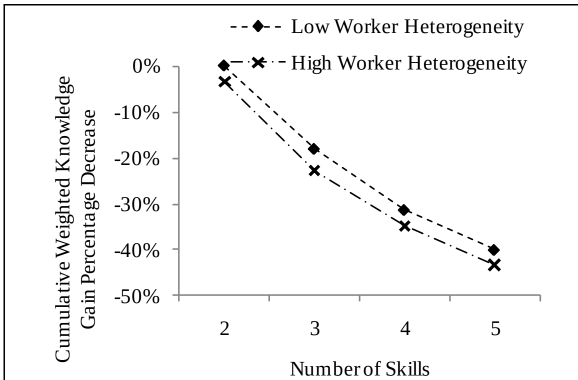


FIGURE 36: Cumulative weighted knowledge gain percentage decrease for different values of number of skills

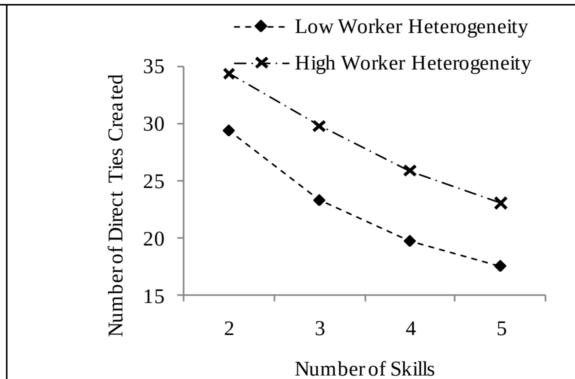


FIGURE 37: Number of direct ties created for different values of number of skills

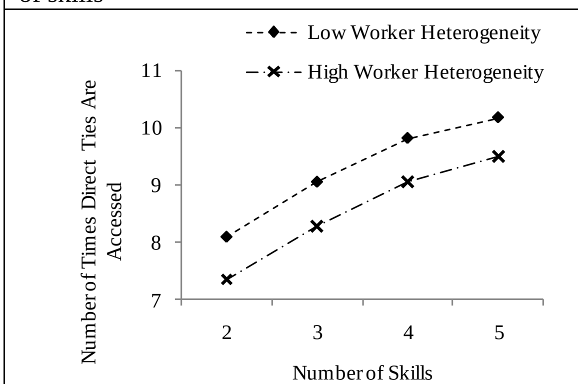


FIGURE 38: Number of times direct ties are accessed for different values of number of skills

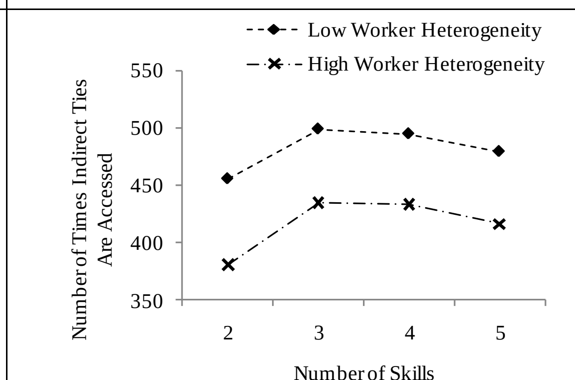


FIGURE 39: Number of times indirect ties are accessed for different values of number of skills

We observe that in Figure 37, the total number of direct ties created decreases as the number of skills increases. As discussed earlier, whether to use existing ties or create new ties to transfer knowledge depends on the availability of the knowledge provider and the amount of knowledge that can be transferred. As the number of skills increases, the likelihood of acquiring knowledge using existing direct/indirect ties also increases since many workers need to acquire knowledge in multiple skills. There is less need to create direct ties to acquire knowledge, and can re-use existing ties to transfer knowledge for multiple skills. Hence, as the number of skills supported by the organization increases, the total number of times direct ties are used increases (Figure 38).

Organizations that support multiple skills allow workers to re-use both direct and indirect ties to transfer knowledge. However, number of times that indirect ties are used does not always increase as the number of skills increases. Recall that existing direct ties are the preferred method of acquiring knowledge, but are limited in numbers. On the other hand, indirect ties are less efficient, but have access to wider range of workers. As the number of skills supported by an organization increases from 2 to 3, existing direct and indirect ties used increase as a result of tie re-use (Figure 39). But as the number of skills supported increases from 3 to 5, re-using existing direct ties become dominant that there is less need to use indirect ties to transfer knowledge. Thus, reducing the number of times indirect ties are used (Figure 39).

3.7 Limitations and Future Research

In this research, we assume that workers stay with the company across the planning horizon. As the model in this research was designed to study knowledge acquisition and provision over the planning horizon for a limited planning horizon, this is not a limiting assumption. However, it is possible that employees change their jobs and leave the company. Additionally, the company could hire workers to fill job openings. Workers leaving and joining the company (labor turnover) could affect the performance of the IFNs. Labor turnover may be harmful to the company if skilled workers are often leaving, taking away their social ties inside the firm at the same time. While companies could hire employees to fill the vacancy, time is required for new hires to establish social ties to share knowledge inside the company. Future research could study the impact of labor turnover on the design and performance of IFNs. In this research, knowledge depreciation is assumed to be negligible. Additional research opportunities involve the design of IFNs under high knowledge depreciation scenarios. This research assumes that the knowledge sharing activities are organized in a fashion such that knowledge transferred from only one worker to another worker at a time. One may argue that knowledge transfer could involve more than two workers at a time. For example, knowledge can be transferred through seminars provided by co-workers to share their expertise with other team members, group discussions between multiple members in the same office, and other group related techniques. Future research could study IFNs that allow knowledge to be transferred among a group of employees. This extension would involve further exploration about group knowledge sharing dynamics, and is likely to be more complex. In this research, we focus on the design of using direct and indirect ties to facilitate knowledge sharing. Future research could examine different types of direct/indirect ties (team members, office mates, and reporting relationships) and associated efficiency and costs to further help organizations establish the IFNs to transfer knowledge.

3.8 Conclusions

"Knowledge intensive service providers are highly dependent on human workers who possess specialized knowledge and skills." (Leung and Glissmann, 2010) Such companies are increasingly interested in "the optimal design" that meets the organizational needs such as employee skill development (Leung and Glissmann, 2010). The MIP presented in this research aims to understand the design of effective IFNs to maximize knowledge sharing. The value of the model lies in understanding important factors to consider when designing and using IFNs. The model and solution procedure proposed in this chapter can be used either as a starting point for organizational design or as a means of benchmarking existing organizations.

Our results underscore the important bridging role that average workers can play in facilitating knowledge transfer. We observe that most knowledge sharing happens between average workers and experts, followed by knowledge sharing between average workers and novices. Our results also provide insights into the use of the effective IFNs. We find that organizations seem to benefit from knowledge transfer between workers who do not have very high knowledge differences. Such knowledge transfer allows workers who are sharing knowledge to become available relatively quickly for additional knowledge provision and/or knowledge acquisition. This finding is contrary to the common practice of transferring large amount of knowledge between experts and novices.

Both direct ties and indirect ties are valuable to the company and may complement each other. Direct ties are used more within groups than between groups, while more indirect ties are used between groups than within groups. In organizations where large number of skills are supported, there is less need to create additional direct ties to transfer knowledge since workers can re-use their existing ties. However, organizations benefit less from knowledge sharing during the same planning horizon when the number of skills supported by the company increases.

CHAPTER 4: CONCLUDING REMARKS

Organizations increasingly use knowledge-intensive IT and IT-enabled services delivered from multiple locations. Employees in such organizations may interact with each other in order to deliver high quality service and constitute knowledge-intensive service delivery networks (KISDN). KISDN are not limited to IT service, and include other knowledge-intensive services that are facilitated by sophisticated IT such as some types of management, financial services and engineering consulting services. The dissertation aims to understand the management and design of such KISDN - an important, yet under-researched area with significant potential for IS as well as interdisciplinary research.

The dissertation first presents a mixed integer programming model which integrates perspectives from multiple traditional disciplines such as information science, management science, social sciences and IS. Specifically, KISDN in this dissertation represent service systems with a significant emphasis on knowledge management in a distributed resource environment. The proposed model considers worker competence, organizational information networks, worker availability and task characteristics. We propose the use of IT to perform integrated business analytics which combines the above mentioned factors in support of the service workflow process. The results suggest the significant additional value that can be generated by facilitating knowledge sharing using organizational IFNs, in conjunction with information regarding worker competence, worker availability, and service tasks. Additionally, a network topology where communication between random workers in the organization is encouraged (random networks) is preferred over other network structures in terms of KISDN performance. We also discuss ways to reduce the performance difference between network topologies by intentionally increasing network density, and strategically using worker training when altering the network structure might be difficult.

Another mixed integer programming model was proposed to further study the design of the IFNs in different organizational environments. Given the fact that employees could be much more likely to turn to their peers and colleagues for knowledge rather than access electronic knowledge bases that firms build, organizations are increasingly interesting in facilitating knowledge sharing among employees through IFNs. To the best of our knowledge, there is limited research on the design of such IFNs. The model proposed in chapter 3 aims at maximizing knowledge sharing by creating and using social relationships under different organizational factors such as the heterogeneity of the workforce, efficiency and costs associated with knowledge sharing, and number of skills. The results suggest that a more heterogeneous workforce benefits less from knowledge sharing using IFNs, requires more direct relationships to be created than a less heterogeneous workforce. Our results indicate that the process of knowledge sharing does not necessarily occur just between the expert workers and novice workers. Average workers play a crucial intermediary role in facilitating knowledge flow. As the number of skills supported by the organizations increases, less direct relationships are facilitated as a result of re-using the same tie for multiple skills. However, organizations benefit less from knowledge sharing since each worker spends less time on each skill. Our results indicate that the cost of creating new direct ties is crucial in improving knowledge sharing benefits. Organizations should explore technology-facilitated means of creating new direct ties.

In summary, this dissertation contributes to the emerging field of service science, by advancing our understanding of service systems in knowledge-intensive distributed resource environments. The first model proposed can serve as a managerial benchmarking framework for KISDN management, which allows organizations to examine dynamics between different factors impacting KISDN performance. The second model enables organizations to understand the design and the use of IFNs to maximize knowledge sharing. This, in turn, facilitates systematic design of KISDN.

REFERENCES

Abrams, L., Cross, R., Lesser, E., and Levin, D.Z. Nurturing interpersonal trust in knowledge sharing networks. *Academy of Management Executive*, 17, 4 (2003), 64-77.

Agarwal, R. Gupta, A.K. and Kraut, R. (ed.) Special Issue: The interplay between digital and social networks. *Information Systems Research*, 19, 4 (2008)

Ahuja, R.K. Magnanti, T.L. and Orlin, J.B. *Network Flows: Theory, Algorithms, and Applications.* New Jersey: Prentice Hall, 1993.

Alavi, M., and Leidner, D.E. Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. *MIS Quarterly*, 25, 1 (2001), 107-136.

Anderson, J.R. *Cognitive psychology and its implications (8th Edition)*. Worth Publishers, 1995.

Ardichvili, A., Page, V., and Wentling, T. Motivation and barriers to participation in virtual knowledge-sharing communities of practice. *Journal of Knowledge Management*, 7, 1 (2003), 64-77.

Aron, A., McLaughlin-Volpe, T., Mashek, D., Lewandowski, G., Wright, S.C., and Aron, E.N. Including others in the self. *European review of social psychology,* 15, (2004), 101-132.

Backes-Gellner, U., Mure, J. The Skill-Weights Approach on Firm Specific Human Capital: Empirical Results for Germany. Leading House Working Paper. Zurich. 2008

Bardhan, I. Demirkan, H. Kannan, P.K. and Kauffman, R.J. (ed.) Call For Papers. *JMIS.* 2008. Available: http://www.jmis-web.org/cfp/cfp_jmis2008_ijec2008_special_issues_0310.pdf

Bartol, K.M., and Srivastava, A. Encouraging Knowledge Sharing - The Role of Organizational Reward Systems. *Journal of Leadership and Organization Studies,* 9, 1 (2002), 64-76.

Baum, J.A.C., and Berta, W.B. Sources, dynamics and speed: Population-level learning by organizations in a longitudinal behavioral simulation. In Miner, A.S. and Anderson, P. (ed.) *Population-Level Learning and Industry Change* (Advances in Strategic Management), 16, 155-184. Stamford CT: JAI Press, 1999.

Becker, G.S. Investment in human capital. *Journal of Political Economy,* 70, 5 (1962), 9-49.

Bolch, G., Greiner, S., de Meer, H., and Trivedi, K.S., *Queueing Networks and Markov Chains: Modeling and Performance Evaluation with Computer Science Applications*. Wiley-Interscience, 2006.

Borgatti, S.P., and Cross, R. A Relational View of Information Seeking and Learning in Social Networks. *Management Science*, 49, 4 (2003), 432-445.

Buco, M.,Chang, R.,Luan, L.,Ward, C., Wolf, J., and Yu, P. Managing eBusiness on demand SLA contracts in business terms using the cross-SLA execution manager SAM. *Proceedings of IEEE International Symposium on Autonomous Decentralized Systems*. 2003.

Cabrera, A., and Cabrera, E. Knowledge sharing Dilemmas. *Organization Studies*, 23, 5 (2002), 687-710.

Carroll, T.N. Harnessing Knowledge Dynamics-Principled Organizational Knowing & Learning. *Computational and Mathematical Organization Theory*, 14, (2008), 52-55.

Center for Knowledge Governance, Mission, Content, Projects, Organization, 2004. Available: http://www.cbs.dk/content/download/23853/329921/file/Mission.pdf

Chen, N.K., and Edgington, T. Assessing value in organizational knowledge creation: considerations for knowledge workers. *MIS Quarterly*, 29, 2 (2005), 279-309.

Chesbrough, H., and Spohrer, J. A research manifesto for services science. *Communications of the ACM*, 49, 7 (2006), 35-40.

Constant, D., Sproull, L., and Kiesler, S. The kindness of strangers: The usefulness of electronic weak ties for technical advice. *Organization Science*, 7, 2 (1996), 119-135.

Cormen, T.H., Leiserson, C.E., Rivest, R.L., and Stein, C. *Introduction to Algorithms*, The MIT Press, September 1, 2001.

Cowan, R., and Jonard, N. Network structure and the diffusion of knowledge. *Journal of Economic Dynamics and Control*, 28, (2004), 1557-1575.

Cross, R., Parker, A., Prusak, L., and Borgatti, S.P. Knowing what we know: supporting knowledge creation and sharing in social networks. *Organizational Dynamics*, 30, 2 (2001), 100-120.

Davenport, T.H., DeLong, D.W., and Beers, M.C. Building Successful Knowledge Management Projects. Center for Business Innovation Working Paper, 1997.

Davenport, T.H. and Prusak, L. *Working Knowledge*. Boston: Harvard Business School Press, 1998.

Dawande, M., Johar, M., Kumar, S., and Mookerjee, V.S. A Comparison of Pair Versus Solo Programming Under Different Objectives: An Analytical Approach Source. *Information Systems Research*, 19, 1 (2008), 71-92.

Dong, S., Johar, M., and Kumar, R., A Benchmarking Model for Knowledge Intensive Service Delivery Network Management. *Journal of Management Information Systems*, 2011, forthcoming.

Dyer, J.H., and Nobeoka, K. Creating and Managing a High-Performance Knowledge-Sharing Network: The Toyota Case. Strategic Management Journal, 21, (2000), 345-367.

Evanschitzky, H., Ahlert, D., Blaich, G., and Kenning, P. Knowledge Management in Knowledge Intensive Service Networks: A Strategic Management Approach. *Management Decision, 45,* 2 (2007), 265-283.

Gans, N., Koole, G., and Mandelbaum, A. Telephone call centers: tutorial, review, and research prospects. *Manufacturing & Service Operations Management*, 5, 2 (2003), 79-141.

Goh, S.C. Managing effective knowledge transfer: an integrative framework and some practice implications. *Journal of Knowledge Management*, 6, 1 (2002), 23-30.

Granovetter, M.S. The strength of weak ties. *American Journal of Sociology*, 78, (1973), 1360-1380.

Grant, R.M. Toward A Knowledge-Based Theory of The Firm. *Strategic Management Journal*, 17, Winter (1996), 109-122.

Guy, I., Jacovi, M., Shahar, E., Meshulam, N., Soroka, V., and Farrell, S. Harvesting with SONAR - The value of aggregating social network information. In M. Burnett, M. Costabile, T. Catarci, B. Ruyter, D. Tan, M. Czerwinski, and A. Lund (eds.), *Online Social Networks*. *Proceeding of the twenty-sixth annual SIGCHI conference on Human factors in computing systems*. New York: ACM Press, 2008, pp. 1017-1026.

Hansen, M.T. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative Science Quarterly*, 44, 1 (1999), 82-111.

Hansen, M.T. Knowledge Networks: Explaining Effective Knowledge Sharing in Multiunit Companies. *Organization Science*, 13, 3 (2002), 232-248.

Hansen, M.T., and Løvås, B. How do multinational companies leverage technological competencies? Moving from single to interdependent explanations. *Strategic Management Journal*, 25, 8 (2004), 801-822.

HP, HP Software-as-a-Service (SaaS) operations overview, customer handbook. 2007.

Available: http://h20230.www2.hp.com/pdf/SaaS_Customer_Handbook.pdf

IBM, Improving workplace collaboration: Social network analysis. 2006. Available: http://domino.watson.ibm.com/odis/odis.nsf/pages/solution.13.html

IfM and IBM. Succeeding through service innovation: A service perspective for education, research, business and government. Cambridge, United Kingdom, 2008.

Jones, J.L., Easley, R.F., and Koehler, G.J. Market segmentation within consolidated e-markets: A generalized combinatorial auction approach. *Journal of Management Information Systems*, 23, 1 (2006), 161-182.

Kilduff, M. and Tsai, W. *Social Networks and Organizations*. London: Sage Publications Ltd, 2003.

Kim, Y., Krishnan, R., and Argote, L. The Learning Curve of IT Knowledge Workers in a Computing Call Center. Working paper, Carnegie Mellon University, Pittsburgh, PA. 2008.

Kotlarsky, J., and Oshri, I. Social Ties, Knowledge Sharing and Successful Collaboration in Globally Distributed System Development Projects. *European Journal of Information Systems*, 14, 1 (2005), 37-48.

Kumar, S., Dawande, M., and Mookerjee, V.S. Optimal Scheduling and Placement of Internet Banner Advertisements. *IEEE Transactions on Knowledge and Data Engineering* 19, 11 (2007), 1571-1584.

Kumar, R.L., Park, S. and Subramaniam, C. Understanding the Value of Countermeasure Portfolios in Information Systems Security. *Journal of Management Information Systems*, 25, 2 (2008), 241-280.

Lengnick-Hall, M.L., and Lengnick-Hall, C.A. HR's Role in Building Relationship Networks. *Academy of Management Executive*, 17, 4 (2003), 53-63.

Lester, S. Novice to Expert: the Dreyfus model of skill acquisition. 2005. Available: http://www.sld.demon.co.uk/dreyfus.pdf

Leung, Y.T., and Glissmann, S.M. A clustering approach to the design of knowledge-intensive service providers. December 2011. Available: http://domino.research.ibm.com/library/cyberdig.nsf/papers/58C6B1D509E8DCA68525780000603960

Levine, S.S., and Kurzban, R. Explaining clustering in social networks: towards an evolutionary theory of cascading benefits. *Managerial and Decision Economics*, 27, 2-3 (2006), 173-187.

Levine, S.S., and Prietula, M. "Towards a Contingency Theory of Knowledge Exchange in Organizations," in Academy of Management Best Paper Proceedings, Atlanta, GA, 2006.

Liberatore, M., Hatchuel, A., Weil, B., and Stylianou, A. An organizational change perspective on modeling. *European Journal of Operational Research*, 125, (2000), 184-194.

Lusch, R.F., Vargo, S.L., and Wessels, G. Toward a conceptual foundation for service science: Contributions from service-dominant logic. *IBM Systems Journal*, 47, 1 (2008), 5-14.

Mackie, K. SaaS to grow and go global, analyst says. 2007. Available: http://www.adtmag.com/article.aspx?id=20369

Maglio, P.P., and Spohrer, J. Fundamentals of service science. *Journal of the Academy of Marketing Science*, *36*, 1 (2008), 18-20.

Malhotra, Y. Integrating knowledge management technologies in organizational business processes: getting real time enterprises to deliver real business performance. *Journal of Knowledge Management*, 9, 1 (2005), 7-28.

Marsden, P.V., and Campbell, K.E. Measuring Tie Strength. *Social Forces*, 63, 2 (1984), 482-501.

Maula, M. Managerial and research perspective on knowledge intensive services. Paper presented at The European Conference on Knowledge Management ECKM, Italy, 2007.

Nicolas, R. Knowledge management impacts on the decision-making process. *Journal of Knowledge Management*, *8*, 1 (2004), 20-31.

Nonaka, I., Toyama, R., and Nagata, A. A firm as a knowledge-creating entity: a new perspective on the theory of the firm. Industrial and Corporate Change, 9, 1 (2000), 1-20.

Prabhakar, B., Litecky, C.R., and Arnett, K. IT skills in a tough job market, *Communications of the ACM*, 48, 10 (2005), 91-94.

Rao, H.R., Chaudhury, A., and Chakka, M. Modeling team processes: Issues and a specific example. *Information Systems Research* 6, 3 (1995), 255-285.

Sahni, S., and Gonzalez, T. P-complete approximation problems. *Journal of the Association for Computing Machinery*, 23, (1976), 555-565.

Sahoo, N., Krishnan, R., and Callan, J. Formation of citation and reply ties over intra-organizational blog network. *CIST Proceedings Washington D.C.*, 2008

Sayın, S., and Karabatı, S. Assigning cross-trained workers to departments: A two-stage optimization model to maximize utility and skill improvement. *European Journal of Operational Research*, 176, 3 (2007), 1643-1658.

Schilling, M.A., Vidal, P., Ployhart, R.E., and Marangoni, A. Learning by doing something else: variation, relatedness, and the learning curve. *Management Science*, 49, 1 (2003), 39-56.

Sen, S., Raghu, T.S., and Vinze, A. Demand heterogeneity in IT infrastructure services: modeling and evaluation of a dynamic approach to defining service levels. *Information Systems Research*, 20, 2 (2009), 258-276.

Shen, M., Tzeng, G., Liu, G. Multi-criteria task assignment in workflow management systems. Proceedings of the 36th Hawaii International Conference on System Sciences, 2003.

Szulanski, G. Exploring internal stickiness: impediments to the transfer of best practice within the firm. *Strategic Management Journal*, 17, (Winter Special Issue 1996), 27-43.

Trigeorgis, L. Real Options: Managerial Flexibility and Strategy in Resource Allocation. Cambridge: The MIT Press, 1996.

USinternetworking Inc. (USi) USi FlexAdvantage™: The right level of support when you need it, at the right price. 2008. Available: http://www.usi.com/service-based-pricing.aspx

Van Der Aalst, W.M.P., Reijers, H.A., and Song, M. Discovering social networks from event logs. *Computer Supported Cooperative Work*, 14, 6 (2005), 549-593.

Watts, D.J., and Strogatz, S.H. Collective dynamics of small-world networks. *Nature*, 393, (1998), 440-442.

Windrum, P., and Tomlonson, M. Knowledge-intensive services and international competitiveness: a four country comparison. *Technology Analysis and Strategic Management*, *11,* 3 (1999), 391-405.

Zhang, L., Li, J., and Shi, Y. Study on improving efficiency of knowledge sharing in knowledge intensive organization. X. Deng and Y. Ye (Eds.): WINE 2005, LNCS 3828, 816-825.

APPENDIX A: LINEARIZED VERSION OF KISDE OPTIMIZATION PROBLEM

Here we provide the linearized version of the KISDN optimization problem discussed in Section 2.3. We use this for solving our problem instances in CPLEX.

Objective Function:

$$Max \sum_{t=1}^{T} \left(\begin{array}{l} \sum_{k=1}^{K} \left(\sum_{j=1}^{N_t} X_{kjt} R_j - h_k \sum_{s=1}^{S} \left(\sum_{j=1}^{N_t} \vartheta_{js} \phi_{js} A_{kjst} - \sum_{\substack{l=1 \\ l \neq k}}^{K} \sum_{i=0}^{2} \varpi^i Q_{lkst}^i \right) \right) \\ - \sum_{j=1}^{N_t} \left(\left(1 - \sum_{m=1}^{t} \sum_{k=1}^{K} X_{kjm}\right) \sum_{s=1}^{S} \vartheta_{js} \beta_s \theta_a \right) - \sum_{k=1}^{K} \left(1 - Z_{kt} - \sum_{j=1}^{N_t} X_{kjt}\right) h_k \theta_b \end{array} \right)$$

Where,

$$A_{kjst} \geq C_{kst} + 4X_{kjt} - 4 \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, s \in \{1,..,S\}, t \in \{1,..,T\}$$

$$A_{kjst} \leq 4X_{kjt} \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, s \in \{1,..,S\}, t \in \{1,..,T\}$$

$$A_{kjst} \geq 0 \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, s \in \{1,..,S\}, t \in \{1,..,T\}$$

$$A_{kjst} \leq C_{kst} \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, s \in \{1,..,S\}, t \in \{1,..,T\}$$

A_{kjst} captures $X_{kjt} C_{kst}$ where $C_{kst} \in (0,4)$ and $A_{kjst} \in (0,4)$.

$$Q_{klst}^i \geq Z_{kt} + \Lambda_{lkst}^i - 1 \qquad \forall k,l \in \{1,..,K\}, k \neq l, s \in \{1,..,S\}, i \in \{0,1,2\}, t \in \{2,..,T\}$$

$$Q_{klst}^i \leq 0.5(Z_{kt} + \Lambda_{lkst}^i) \qquad \forall k,l \in \{1,..,K\}, k \neq l, s \in \{1,..,S\}, i \in \{0,1,2\}, t \in \{2,..,T\}$$

$Q_{klst}^i \in \{0,1\}$ captures $Z_{kt} \Lambda_{lkst}^i$ where $Z_{kt} \in \{0,1\}$ and $\Lambda_{lkst}^i \in \{0,1\}$.

Assignment Constraints

$$\sum_{j=1}^{N_t} X_{kjt} + Z_{kt} \leq 1 \qquad \forall k \in \{1,..,K\}, t \in \{1,..,T\}$$

$$\sum_{j=N_t+1}^{N_{Max}} X_{kjt} = 0 \qquad \forall k \in \{1,..,K\}, t \in \{1,..,T\}$$

$$\sum_{k=1}^{K} \sum_{t=1}^{T} X_{kjt} \leq 1 \qquad \forall j \in \{1,..,N_{Max}\}$$

$$\sum_{t=1}^{T} \sum_{j=1}^{N_t} \sum_{s=1}^{S} \vartheta_{js} \phi_{js} A_{kjst} + \sum_{t=1}^{T} \left(1 - Z_{kt} - \sum_{j=1}^{N_t} X_{kjt}\right) + \sum_{t=1}^{T} \sum_{s=1}^{S} \sum_{\substack{l=1 \\ l \neq k}}^{K} \sum_{i=0}^{2} \varpi^i Q_{lkst}^i \leq T \quad \forall k \in \{1,..,K\}$$

$$B_{kjmt} \geq X_{kjm} + F_{kjt} - 1 \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, m \in \{1,..,t-1\}, t \in \{2,..,T\}$$

$$B_{kjmt} \leq 0.5(X_{kjm} + F_{kjt}) \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, m \in \{1,..,t-1\}, t \in \{2,..,T\}$$

$B_{kjmt} \in \{0,1\}$ captures $X_{kjm}F_{kjt}$ where $F_{kjt}, B_{kjmt} \in \{0,1\}$.

$$U_{kjt} \geq F_{kjt} + F_{kj(t-1)} - 1 \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, m \in \{1,..,t-1\}, t \in \{2,..,T\}$$
$$U_{kjt} \leq 0.5(F_{kjt} + F_{kj(t-1)}) \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, m \in \{1,..,t-1\}, t \in \{2,..,T\}$$

$U_{kjt} \in \{0,1\}$ captures $F_{kjt}F_{kj(t-1)}$ where $F_{kjt} \in \{0,1\}$.

$$H_{kjmst} \geq C_{ksm} + 4B_{kjmt} - 4 \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, m \in \{1,..,t-1\}, s \in \{1,..,S\}, t \in \{2,..,T\}$$
$$H_{kjmst} \leq 4B_{kjmt} \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, m \in \{1,..,t-1\}, s \in \{1,..,S\}, t \in \{2,..,T\}$$
$$H_{kjmst} \geq 0 \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, m \in \{1,..,t-1\}, s \in \{1,..,S\}, t \in \{2,..,T\}$$
$$H_{kjmst} \leq C_{ksm} \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, m \in \{1,..,t-1\}, s \in \{1,..,S\}, t \in \{2,..,T\}$$

H_{kjmst} captures $C_{ksm}B_{kjmt}$ where $B_{kjmt} \in \{0,1\}$ and $H_{kjmst} \in (0,4)$.

$$R^{i}_{lkjsmqt} \geq B_{kjmt} + \Lambda^{i}_{lksq} - 1 \quad \forall k,l \in \{1,..,K\}, k \neq l, s \in \{1,..,S\}, i \in \{0,1,2\}, m,q,t \in \{2,..,T\}, j \in \{1,..,N_{Max}\}$$
$$R^{i}_{lkjsmqt} \leq 0.5(B_{kjmt} + \Lambda^{i}_{lksq}) \; \forall k,l \in \{1,..,K\}, k \neq l, s \in \{1,..,S\}, i \in \{0,1,2\}, m,q,t \in \{2,..,T\}, j \in \{1,..,N_{Max}\}$$

$R^{i}_{lkjsmqt} \in \{0,1\}$ captures $B_{kjmt}\Lambda^{i}_{lksq}$ where $B_{kjmt}, \Lambda^{i}_{lksq} \in \{0,1\}$.

$$V^{i}_{lkjsqt} \geq X_{kjt} + \Lambda^{i}_{lksq} - 1 \qquad \forall k,l \in \{1,..,K\}, k \neq l, s \in \{1,..,S\}, i \in \{0,1,2\}, q,t \in \{2,..,T\}, j \in \{1,..,N_{Max}\}$$
$$V^{i}_{lkjsqt} \leq 0.5(X_{kjt} + \Lambda^{i}_{lksq}) \quad \forall k,l \in \{1,..,K\}, k \neq l, s \in \{1,..,S\}, i \in \{0,1,2\}, q,t \in \{2,..,T\}, j \in \{1,..,N_{Max}\}$$

$V^{i}_{lkjsqt} \in \{0,1\}$ captures $X_{kjt}\Lambda^{i}_{lksq}$ where $X_{kjt}, \Lambda^{i}_{lksq} \in \{0,1\}$.

$$\sum_{m=1}^{t-1}(B_{kjmt}(t-m) - \sum_{s=1}^{S}(\vartheta_{js}\phi_{js}H_{kjmst} + \sum_{q=m}^{t-1}\sum_{\substack{l=1 \\ l\neq k}}^{k}\sum_{i=0}^{2}R^{i}_{lkjsmqt}))/T + U_{kjt} \geq 0$$

$$2F_{kjt} \geq \sum_{m=1}^{t-1}(X_{kjm}(t-m) - \sum_{s=1}^{S}(\vartheta_{js}\phi_{js}A_{kjsm} + \sum_{q=m}^{t-1}\sum_{\substack{l=1 \\ l\neq k}}^{k}\sum_{i=0}^{2}V^{i}_{lkjsqm}))/T + F_{kj(t-1)}$$

$$\sum_{m=1}^{t-1}X_{kjm} - F_{kjt} \geq 0 \qquad \forall k \in \{1,..,K\}, j \in \{1,..,N_{Max}\}, t \in \{2,..,T\}$$

$$Z_{kt} = \sum_{m=1}^{t-1}\sum_{j=1}^{N_{t-1}}(X_{kjm} - B_{kjm(t-1)}) \qquad \forall k \in \{1,..,K\}, t \in \{2,..,T\}$$

Knowledge Acquisition Constraints:

$$G^{i}_{klst} = \alpha^{i}_{l}(W_{kst} - W_{lst}) \qquad \forall k,l \in \{1,..,K\}, l \neq k,, s \in \{1,..,S\}, t \in \{1,..,T\}, i \in \{0,1,2\}, \rho^{i}_{kl} = 1$$

G^{i}_{klst} represents worker k's gain in skill s from worker l using tie i in time period t.

$$\sum_{\substack{l=1 \\ l\neq k}}^{K}\sum_{i=0}^{2}\Lambda_{klst}^{i} \leq 1 \quad \forall k \in \{1,..,K\}, s \in \{1,..,S\}, t \in \{1,..,T\}, \rho_{kl}^{i} = 1$$

The above constraint ensures that worker k gets help only from a single worker l, through all ties, in time period t.

$$D_{klst}^{i} \geq G_{klst}^{i} + 4\Lambda_{klst}^{i} - 4 \qquad \forall k,l \in \{1,..,K\}, l \neq k, s \in \{1,..,S\}, t \in \{1,..,T\}, i \in \{0,1,2\}, \rho_{kl}^{i} = 1$$
$$D_{klst}^{i} \leq 4\Lambda_{klst}^{i} \qquad \forall k,l \in \{1,..,K\}, l \neq k, s \in \{1,..,S\}, t \in \{1,..,T\}, i \in \{0,1,2\}, \rho_{kl}^{i} = 1$$
$$D_{klst}^{i} \geq 0 \qquad \forall k,l \in \{1,..,K\}, l \neq k, s \in \{1,..,S\}, t \in \{1,..,T\}, i \in \{0,1,2\}, \rho_{kl}^{i} = 1$$
$$D_{klst}^{i} \leq G_{klst}^{i} - 4\Lambda_{klst}^{i} + 4 \qquad \forall k,l \in \{1,..,K\}, l \neq k, s \in \{1,..,S\}, t \in \{1,..,T\}, i \in \{0,1,2\}, \rho_{kl}^{i} = 1$$

D_{klst}^{i} captures $G_{klst}^{i}\Lambda_{klst}^{i}$ where $\Lambda_{klst}^{i} \in \{0,1\}$ and $D_{klst}^{i} \in (0,4)$.

$$G_{kst} = \sum_{\substack{l=1 \\ l\neq k}}^{K}\sum_{i=0}^{2} D_{klst}^{i} \quad \forall k \in \{1,..,K\}, s \in \{1,..S\}, t \in \{1,..,T\}, \rho_{kl}^{i} = 1$$

G_{kst} is the maximum gain worker k can get in skill s through all ties, where $G_{kst} \in (0,4)$.

$$C_{kst} = W_{kst} - G_{kst} \qquad \forall k \in \{1,..,K\}, s \in \{1,..,S\}, t \in \{1,..,T\}$$

C_{kst} is worker k's effective competence after searching for help, in period t and skill s.

$$P_{kjsmt} \geq G_{ksm} + 4B_{kjmt} - 4 \qquad \forall k \in \{1,..,K\}, \forall j \in \{1,..,N_{Max}\}, \forall s \in \{1,..,S\}, \forall m \in \{1,..,t-1\}, \forall t \in \{2,..,T\}$$
$$P_{kjsmt} \leq 4B_{kjmt} \qquad \forall k \in \{1,..,K\}, \forall j \in \{1,..,N_{Max}\}, \forall s \in \{1,..,S\}, \forall m \in \{1,..,t-1\}, \forall t \in \{2,..,T\}$$
$$P_{kjsmt} \geq 0 \qquad \forall k \in \{1,..,K\}, \forall j \in \{1,..,N_{Max}\}, \forall s \in \{1,..,S\}, \forall m \in \{1,..,t-1\}, \forall t \in \{2,..,T\}$$
$$P_{kjsmt} \leq G_{ksm} \qquad \forall k \in \{1,..,K\}, \forall j \in \{1,..,N_{Max}\}, \forall s \in \{1,..,S\}, \forall m \in \{1,..,t-1\}, \forall t \in \{2,..,T\}$$

P_{kjsmt} captures $G_{ksm}B_{kjmt}$ where $B_{kjmt} \in \{0,1\}$ and $G_{ksm} \in (0,4)$.

$$W_{kst} = W_{ks1} - \sum_{m=1}^{t-1}\sum_{j=1}^{N_{t-1}} \omega P_{kjsmt} \vartheta_{js} \qquad \forall k \in \{1,..,K\}, s \in \{1,..,S\}, t \in \{2,..,T\}$$

Worker k's updated competence in period t.

■

APPENDIX B: MODEL EXTENSION DETAILS

B-1 Formulation for KISDE Optimization Problem with Training

Here we present the model for the KISDN optimization problem with training. We only provide new and modified constraints which are different from the Model discussed in section 2.3. Other constraints can be found in section 2.3.

Objective Function

$$Max\sum_{t=1}^{T}\left(\begin{array}{l}\sum_{k=1}^{K}(\sum_{j=1}^{N_t}X_{kjt}R_j-h_k(\sum_{s=1}^{S}(\sum_{j=1}^{N_t}X_{kjt}\vartheta_{js}\phi_{js}C_{kst}+\sum_{\substack{l=1\\l\neq k}}^{K}\sum_{i=0}^{2}\varpi^i\Lambda_{lkst}^iZ_{kt})))-\sum_{k=1}^{K}\sum_{s=1}^{S}Y_{kst}h_k\psi_{st}\\-\sum_{j=1}^{N_t}((1-\sum_{m=1}^{t}\sum_{k=1}^{K}X_{kjm})\sum_{s=1}^{S}\vartheta_{js}\beta_s)\theta_a-\sum_{k=1}^{K}(1-Z_{kt}-\sum_{s=1}^{S}Y_{kst}-\sum_{j=1}^{N_t}X_{kjt})h_k\theta_b\end{array}\right)$$

Assignment Constraints

$$\sum_{j=1}^{N_t}X_{kjt}+\sum_{s=1}^{S}Y_{kst}+Z_{kt}\leq 1\quad \forall k\in\{1,..,K\},t\in\{1,..,T\}\ ,$$

Worker k can be assigned in the current period *iff* worker k is not busy with any tasks/training.

$$\sum_{t=1}^{T}\sum_{j=1}^{N_t}(X_{kjt}\sum_{s=1}^{S}\vartheta_{js}\phi_{js}C_{kst})+\sum_{t=1}^{T}\sum_{s=1}^{S}Y_{kst}\psi_{st}+\sum_{t=1}^{T}(1-Z_{kt}-\sum_{s=1}^{S}Y_{kst}-\sum_{j=1}^{N_t}X_{kjt})+\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{\substack{l=1\\l\neq k}}^{K}\sum_{i=0}^{2}\varpi^i\Lambda_{lkst}^iZ_{kt}\leq T$$
$$\forall k\in\{1,..,K\},$$

Total time spent by a worker on tasks, training, and on the bench cannot exceed T.

$$L_{smt}\geq((t-m)-\psi_{sm}+1)/T\qquad \forall s\in\{1,..,S\},t\in\{1,..,T\},$$
$$L_{smt}((t-m)-\psi_{sm})\geq 0\qquad \forall s\in\{1,..,S\},t\in\{1,..,T\},$$

$L_{smt}=1$ if a training in skill s that started in period m is completed by time period t , 0 otherwise.

$$Z_{kt}=\sum_{m=0}^{t-1}\sum_{j=1}^{N_{t-1}}(1-F_{kjt-1})X_{kjm}+\sum_{m=0}^{t-1}\sum_{r=0}^{t-1}\sum_{s=1}^{S}(1-L_{srt})Y_{ksm}\qquad \forall k\in\{1,..,K\},t\in\{2,..,T\}\ ,$$

Z_{kt} = 0 if worker k is available in period t (i.e., not busy), 1 otherwise.

Knowledge Acquisition Constraints:

$$W_{kst} = W_{ks1} - \sum_{m=1}^{t-1}\sum_{j=1}^{N_{t-1}} X_{kjm}\,\omega\,\vartheta_{js} G_{ksm} F_{kjt} - \sum_{m=1}^{t-1} L_{smt} Y_{ksm} (W_{ksm} - \tau_{sm})\varphi_k^s \;\; \forall k \in \{1,..,K\}, s \in \{1,..,S\}, t \in \{2,..,T\}$$

■

B-2 Heuristics for Solving KISDE Optimization Problem with Training

Similar to Appendix A.2.2, the value of training depends on (a) number of additional tasks of type m completed as a result of training in skill s $(\delta_{kmst}^3 - \delta_{kmst}^4)$, (b) the revenue from each of these tasks $(\sum_{r=1}^{S} q_r^m \beta_r \varsigma_r)$, and (c) the cost of sending workers to training. Similar to δ_{kmjt}^1 and δ_{kmjt}^2 used to calculate the value of learning, δ_{kmst}^3 and δ_{kmst}^4 are given as follows,

$$\delta_{kmst}^3 = Min\{\lambda_m (T - (t + \psi_{st}))\,\chi_{kmst}^{3\_a} \;,\; (T - (t + \psi_{st}))\chi_{kmst}^{3\_b} / (\sum_{r=1}^{S} q_r^m W_{krt} \varsigma_r - q_s^m \varphi_k^s \varsigma_s (W_{kst} - \tau_{st}))\}$$

$$\delta_{kmt}^4 = Min\{\lambda_m (T - t)\chi_{kmt}^{4\_a} \;,\; (T - t)\chi_{kmt}^{4\_b} / \sum_{r=1}^{S} q_r^m W_{krt} \varsigma_r\}$$

$$\chi_{kmst}^{3\_a} = (\sum_{r=1}^{S} q_r^m (4 - W_{krt}) - q_s^m \varphi_k^s (W_{kst} - \tau_{st})) / (\sum_{l=1}^{K}\sum_{r=1}^{S} q_r^m (4 - W_{lrt}) - q_s^m \varphi_k^s (W_{kst} - \tau_{st}))$$

$$\chi_{kmst}^{3\_b} = (\sum_{r=1}^{S} q_r^m (4 - W_{krt}) - q_s^m \varphi_k^s (W_{krt} - \tau_{st})) / \sum_{u=1}^{M} (\sum_{r=1}^{S} q_r^u (4 - W_{krt}) - q_s^m \varphi_k^s (W_{krt} - \tau_{st}))$$

$$\chi_{kmt}^{4\_a} = \sum_{r=1}^{S} q_r^m (4 - W_{krt}) / \sum_{l=1}^{K}\sum_{r=1}^{S} q_r^m (4 - W_{lrt})$$

$$\chi_{kmt}^{4\_b} = \sum_{r=1}^{S} q_r^m (4 - W_{krt}) / \sum_{u=1}^{M}\sum_{r=1}^{S} q_r^u (4 - W_{krt})$$

Recall from Section 2.8.1 that by sending workers to training the organization can incur costs in terms of additional wait time penalties. This cost of keeping tasks waiting has two components: (a) keeping existing tasks waiting, $\sum_{m=1}^{M}\theta_a \hat{n}_{mt}(\sum_{r=1}^{S} q_r^m \beta_r)\psi_{st}/K$ where $\hat{n}_{mt}$ is the number of available type m tasks at time period t, and (b) keeping new tasks waiting (that arrive during ψ_{st}), $\sum_{m=1}^{M}(\theta_a \lambda_m (\sum_{r=1}^{S} q_r^m \beta_r)\psi_{st}(\psi_{st}+1)/2K)$.

Hence, the payoff from assigning workers to training depends on, (a) the number of additional tasks completed as a result of taking training in skill s $(\delta_{kmst}^3 - \delta_{kmst}^4)$, (b) the revenue from each of these tasks $(\sum_{r=1}^{S} q_r^m \beta_r \varsigma_r)$, and (c) the cost of keeping tasks waiting $(\sum_{m=1}^{M}\hat{n}_{mt}(\sum_{r=1}^{S} q_r^m \beta_r)\psi_{st}/K + \sum_{m=1}^{M}(\theta_a \lambda_m (\sum_{r=1}^{S} q_r^m \beta_r)\psi_{st}(\psi_{st}+1)/2K))$.

Let $\hat{n}_t$ be the *set* of un-assigned tasks and $\hat{k}_t$ be the *set* of available workers at the beginning of period t. Using the same notation as in Section 2.3 (Table 1), in period t , the firm's maximization problem using DAH, can be we written as follows,

Objective Function

$$\sum_{k\in\hat{k}_t}\sum_{j\in\hat{n}_t} X_{kjt}\left(R_j - \sum_{s=1}^{S}(h_k \vartheta_{js}\phi_{js}C_{kst} + \sum_{l\notin\hat{k}}\sum_{i=0}^{2}\vartheta_{js}\varpi^i h_l \Lambda_{klst}^i) + \sum_{m=1}^{M}\sum_{s=1}^{S} q_s^m \beta_s \varsigma_s (\delta_{kmjt}^1 - \delta_{kmjt}^2)\right)$$
$$+\sum_{k\in\hat{k}_t}\sum_{s=1}^{S} Y_{kst}\left(\sum_{m=1}^{M}(\sum_{r=1}^{S} q_r^m \beta_r \varsigma_r (\delta_{kmst}^3 - \delta_{kmst}^4)) - \sum_{m=1}^{M}\theta_a \hat{n}_{mt}(\sum_{r=1}^{S} q_r^m \beta_r)\psi_{st}/K - \sum_{m=1}^{M}(\theta_a \lambda_m (\sum_{r=1}^{S} q_r^m \beta_r)\psi_{st}(\psi_{st}+1)/2K)\right)$$
$$-\sum_{j\in\hat{n}_t}(1-\sum_{k\in\hat{k}_t} X_{kjt})\sum_{s=1}^{S}\vartheta_{js}\beta_s\theta_a - \sum_{k\in\hat{k}_t}(1-\sum_{s=1}^{S} Y_{kst} - \sum_{j\in\hat{n}_t} X_{kjt})h_k\theta_b$$

Subject to,

$$\sum_{j\in\hat{n}_t} X_{kjt} + \sum_{s=1}^{S} Y_{kst} \le 1 \quad \forall k\in\hat{k}_t, \quad \text{and} \quad \sum_{k\in\hat{k}_t} X_{kjt} \le 1 \qquad \forall j\in\hat{n}_t ,$$

$$X_{kjt}\in\{0,1\} \text{ and } Y_{kst}\in\{0,1\} \quad \forall j\in\hat{n}_t,\, k\in\hat{k}_t,\, s\in\{1,..,S\}$$ ■

APPENDIX C: NETLOGO INTERFACE