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RESOURCE PLANNING FOR LOGISTICS PROFESSIONAL SERVICES ORGANIZATIONS

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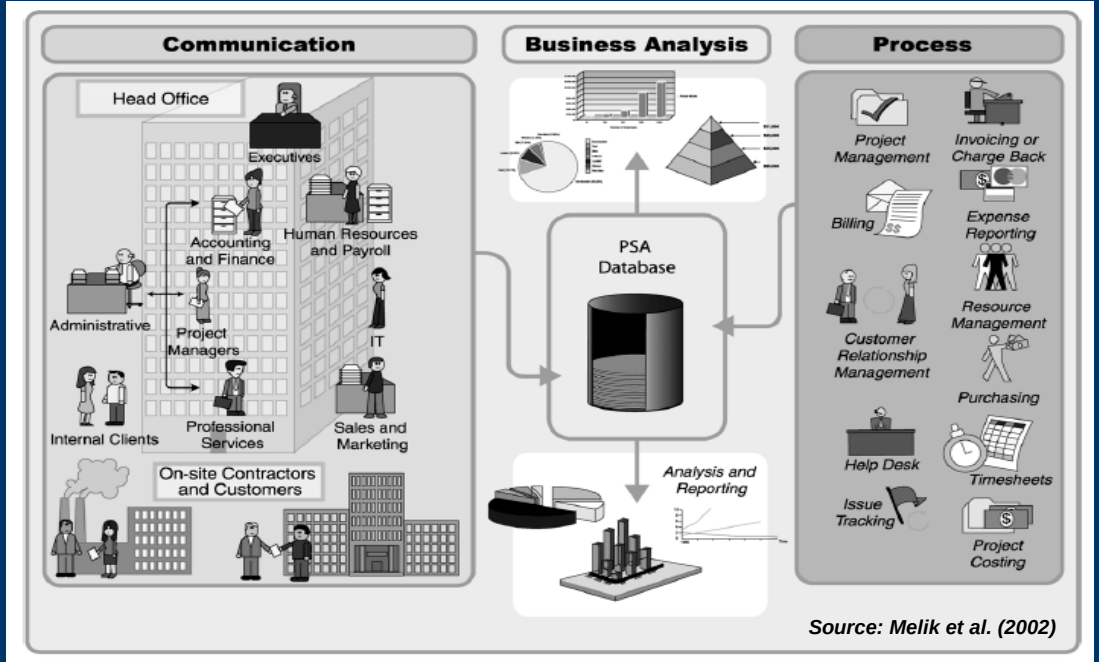

Source: Melik et al. (2002)

A Collaboration Between

Resource Planning for
Logistics Professional Services Organizations

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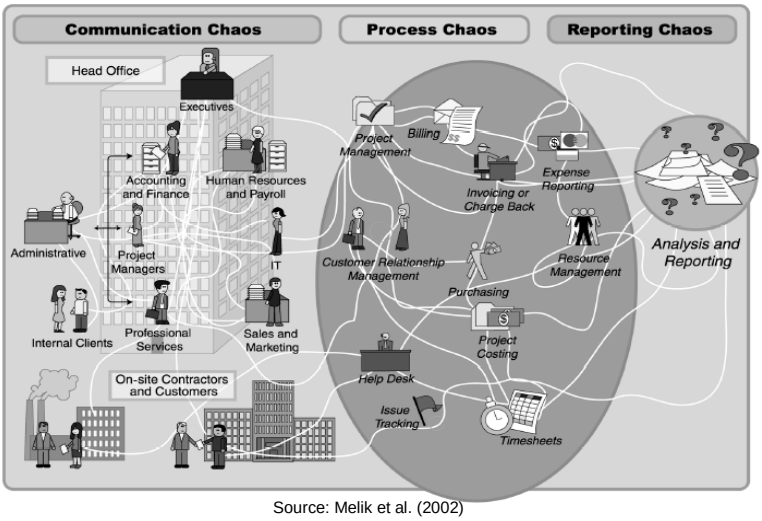
Resource Planning for Logistics Professional Services Organizations

Executive Summary

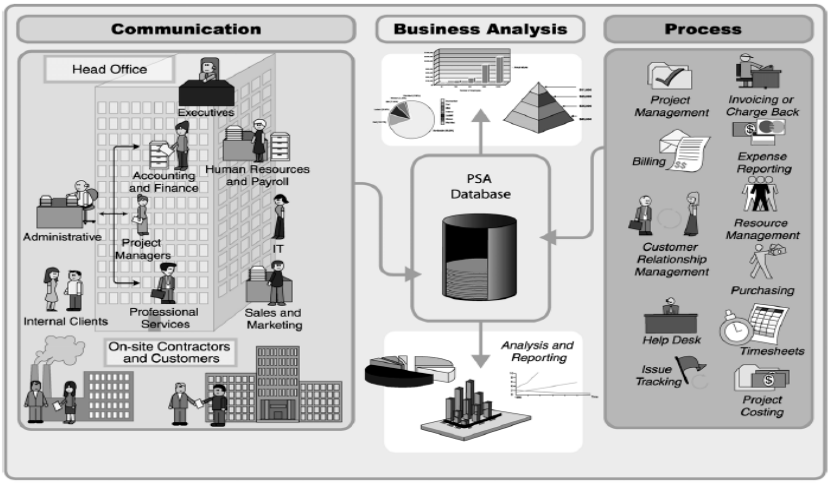
Logistics professional services organizations enable professionals to complement one another to offer a broad range of services, achieve scale and scope economies, and jointly develop a shared reputation that leverage their collective efforts. Unlike other businesses, they have unique ways of working with unique challenges and opportunities. They operate through projects, that is, through discrete engagements for external and internal clients, delivered according to an agreed-upon scope, schedule, fee, and a set of deliverables. Their projects, contracts and engagements often follow a familiar course, from one job to the next, with standard phases and tasks. Examples of logistics professional services firms include IT services businesses in logistics domain, management consulting firms with logistics focus, and research organizations that provide logistics solutions. Professional services in general are studied in Aranda (2003), Dawson (2000), DeLong and Nanda (2003), Deltek (2004), Hofferberth and Goodreau (2003), Melik et al. (2002) and Schiele and McCue (2006). In this study, we focus on logistics professional services, even though the proposed ideas are applicable in the more general context. Improving the performance of logistics professional services suppliers is critical to a company's business performance. In a logistics professional services organization, people and time are important resources. Just as the effective management of the goods supply chain transformed vast sector of the manufacturing and retail industries, effective management of the logistics professional services will transform the logistics professional services corporations. The rapid growth of logistics professional services and consulting firms brings about new challenges and a new reality to the industry. To meet these challenges, we need to understand real views of costs and capabilities, and then develop proper technology to track and manage the services business. Given the lumpy demand of the business, logistics professional services organizations are ridden with inefficient processes and behavior (Figure 1). Resources are not utilized at their optimal capacities, collaboration is less than ideal, billing cycles are lengthy, project status is based on outdated information, and project costs are not managed or known with certainty, all of which lead to a less-than-productive organization and decreased profitability. Logistics professional services automation (LPSA) solutions address these inefficiencies in much the same way that ERP solutions address the business processes for more traditional industries (Deltek (2004) and Melik et al.(2002)). By automating the business processes involved in logistics professional services firms, its processes would be much more streamlined (Figure 2). The benefits reaped from LPSA solutions have significant impact on the bottom line of these organizations. From increased staff utilization and employee productivity to reduced personnel turnover and higher customer satisfaction, LPSA solutions show a positive return on investment for services organizations. Already, SAP reports 22% internal rate of return (IRR) for some of its clients' of mySAP CRM. To thrive in the global market, these organizations have to optimize their resources to deliver on customer commitments, increase utilization and minimize costs. A global service delivery model that utilizes a

consistent methodology no matter where the customer or the consultants are located is critical to the company's success. One needs to better manage the pipeline to determine which efforts will yield the greatest commercial benefit to prove business value over low-cost competitors. At present, in the context of logistics professional services organizations, there is as yet no proven system or methodology for optimally using a firm's global resources for service delivery. This research proposes a system and a methodology for identifying staffing patterns between the projects of a logistics professional services organization and for optimally planning the resources.



Source: Melik et al. (2002)

Figure 1: Scenario Before Process Automation and Optimization



Source: Melik et al. (2002)

Figure 2: Scenario After Process Automation and Optimization

Logistics Professional Services Management

Services supply chain activities, in general, can be classified into two broad categories, namely, services activities with consumer and non-consumer focus (Figure 3). The characteristics of consumer focused research are high customer contact and involve intensive marketing. Retail, wholesaling, front office and self-service activities of a services supply chain are some examples that fall into this category. Services activities which are non-consumer focused are internal services that add value and have the characteristics of low customer contact. Information technology services, and business consulting services, are some examples of this kind of services.

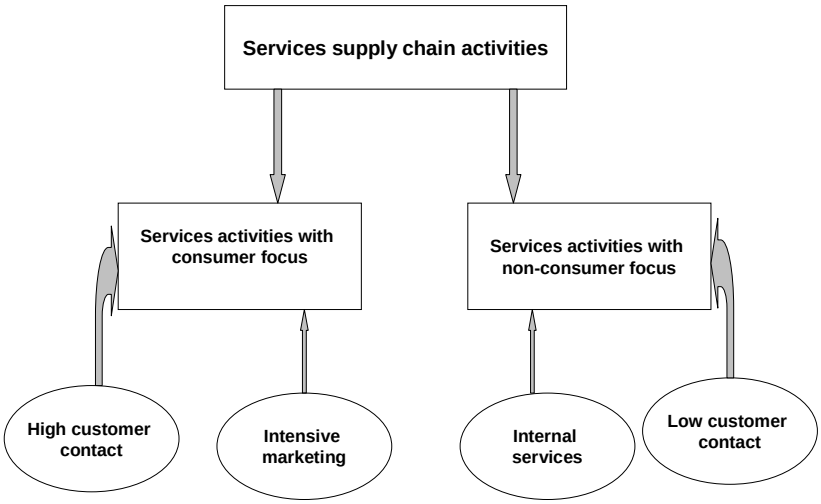


Figure 3: Classification of Services Supply Chain Activities

Taxonomy of services between varying degree of consumerism and marketing is shown in Figure 4. Our focus is looking at logistics professional services which have the characteristics of low consumerism and low customer contact (circled in red). Primarily the consulting practices of logistics professional services organizations would be for the organizations which fall in the category of high marketing and low consumerism in the developed taxonomy (circled in blue).

Logistics professional services offer consulting practices for logistics and supply chain organizations. The consulting solutions offered would fall into any of the following business consulting areas, namely, (i) operations strategies, (ii) business strategies, (iii) conceptual frameworks for services, (iv) supply and demand management, (v) quality management, (vi) outsourcing and procurement management, (vii) inventory management, (viii) revenue management, (ix) risk management, (x) information technology management, (xi) marketing management, (xii) customer relationship management, and (xiii) resource management. The relationship between these consulting practices can be understood by interpreting Figure 5 as follows. Each of these consulting topics can be studied independently or by deriving insights from others or as a subtopic of others. As conceptual

frameworks for services business is constituted by business strategies and operational strategies they can be studied as a subtopic of these. Insights on business strategies and operations strategies can also be obtained from the conceptual frameworks of various services businesses. Similarly other topics, like supply and demand management, quality management, and so forth, can be studied by deriving insights from conceptual frameworks or as a subtopic of business or operations strategies.

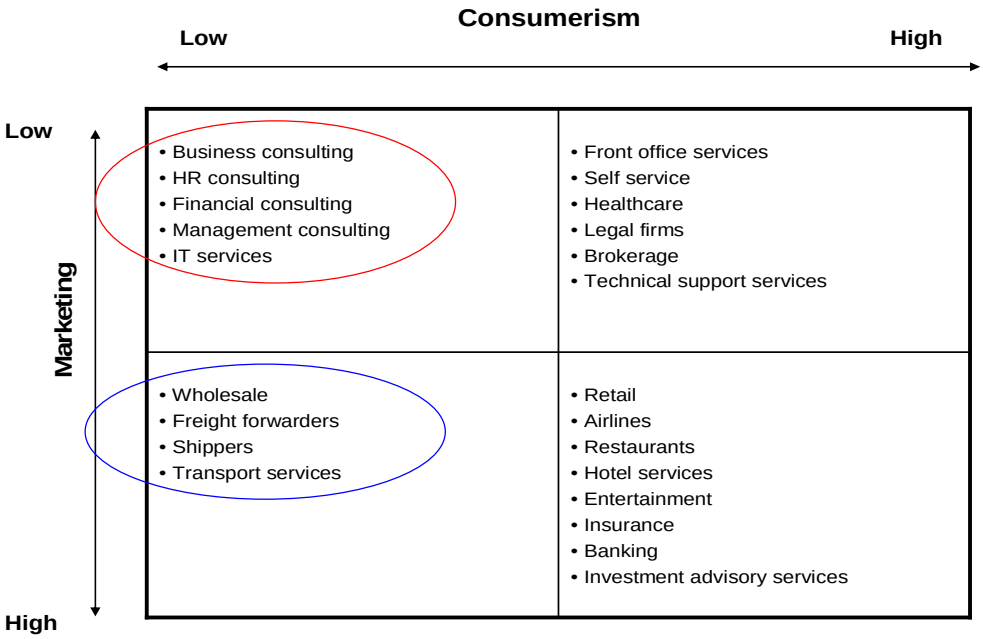


Figure 4: Taxonomy of Services

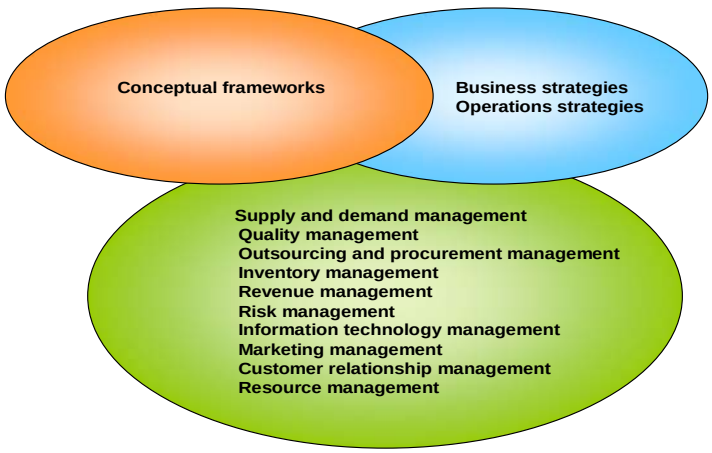


Figure 5: Business Consulting Framework

Resource Planning

Resource planning and management in the context of logistics professional services is an important business consulting practice to look at, as most of the organizations are ridden with inefficient processes. The primary focus of resource management in the context of logistics professional services organizations is to devise efficient strategies for developing and managing human resources. Depending on the demand requirements, human skills either need to be hired for a services project or the available skills need to be trained to execute the project successfully. In this study we develop system and methodology for optimally managing the talent (various skills) in logistics professional services organizations. For effectively delivering various projects in the pipeline by efficiently utilizing the talent of the organization (Figure 6), the system develops optimal plan.

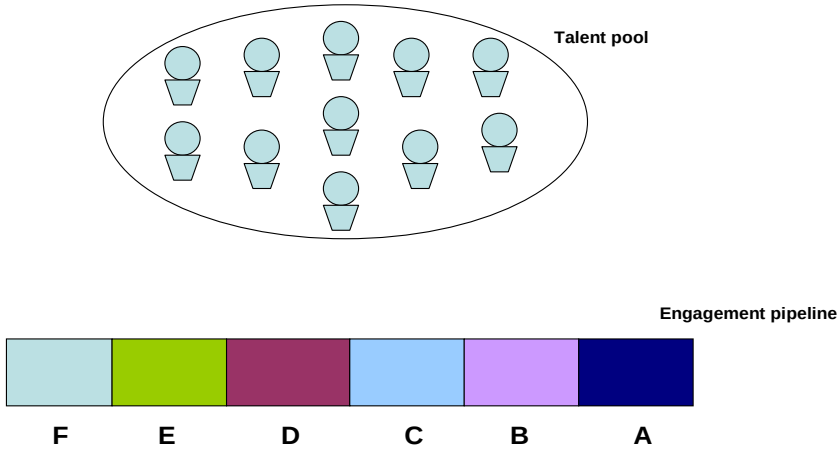


Figure 6: Resource Management

System Overview

The decision support system allows the decision manager to create staffing templates for the future projects based on the projects that were executed over the past. The system identifies patterns among the projects in the database (history). For identifying commonalities and extract patterns among the projects the system uses the methodologies from the methodology suite. The architecture of the proposed system is shown in Figure7. The workflow of the system is as follows. The decision manager chooses a project in the pipeline and evaluates the skills requirement for the project. To evaluate the skills requirement the manager identifies the cluster to which the project belongs. The clusters are obtained by the system apriori by identifying commonalities between the projects in the database.

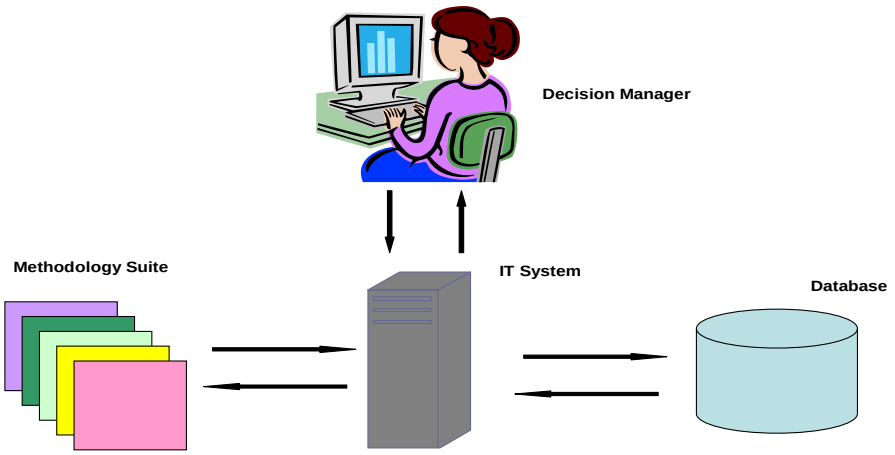


Figure 7: Architecture of the System

Methodology Overview

The closed engagements are grouped using clustering, semi-supervised clustering or other machine learning approaches. Staffing plans are obtained for the various groups based on the similarity of the projects that forms the group.

Cluster analysis, also called data segmentation, has a variety of goals. All relate to grouping or segmenting a collection of objects (also called observations, individuals, cases, or data rows) into subsets or "clusters", such that those within each cluster are more closely related to one another than objects assigned to different clusters. Central to all of the goals of cluster analysis is the notion of degree of similarity (or dissimilarity) between the individual objects being clustered. There are two major methods of clustering -- hierarchical clustering and k-means clustering. These methods could be further classified as shown in Figure 8.

Hierarchical clustering is further subdivided into *agglomerative* methods, which proceed by series of fusions of the n objects into groups, and *divisive* methods, which separate n objects successively into finer groupings.

Agglomerative clustering is further classified into single linkage, complete linkage, average linkage, average group linkage, and Ward's method.

(i) Single Linkage Clustering (Minimum or Nearest-Neighbor Method): The dissimilarity between two clusters is the *minimum dissimilarity* between the members of the two clusters. This method produces long chains which form loose, straggly clusters. This method has been widely used in numerical taxonomy.

(ii) Complete Linkage Clustering (Maximum or Furthest-Neighbor Method): The dissimilarity between two groups is equal to the *greatest dissimilarity* between a member of cluster *i* and a member of cluster *j*. This method tends to produce very tight clusters of similar cases.

(iii) Average Linkage Clustering: The dissimilarity between clusters is calculated using cluster *average* values and then fused.

(iv) Within Groups Clustering: Clusters are fused so that within cluster variance is minimized.

(v) Ward's Method: Cluster membership is assessed by calculating the total sum of squared deviations from the mean of a cluster. The criterion for fusion is that it should produce the smallest possible increase in the error sum of squares.

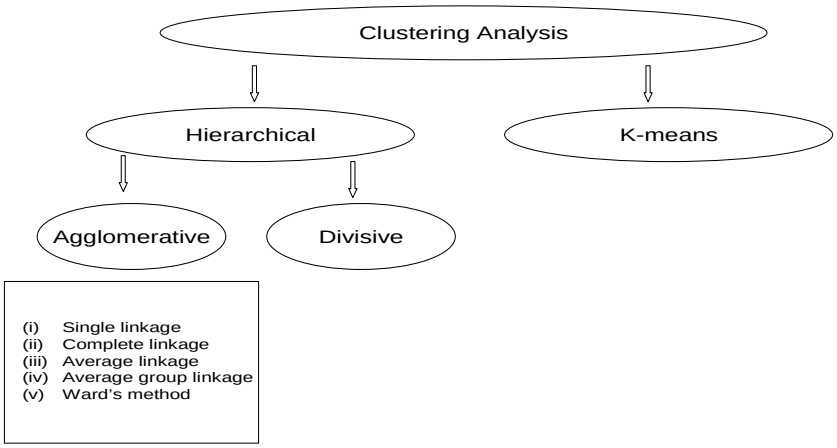


Figure 8: Taxonomy of Clustering Methods

System Behavior

We demonstrate the behavior of the system on a simple use case scenario. Let A, B, C, D, be the closed service engagements of a firm. Let them be of similar type, say, SAP CRM engagements. The bill of resources of A, B, C, D, are shown in the system input of Figure9. Using the bill of resources information of A, B, C, D, staffing plan for a SAP CRM engagement in the service engagement pipeline of the organization can be computed. The computed staffing plan for any SAP CRM engagement is as shown in the system output of Figure 9.

The behavior of the system was also analyzed for the service engagements of IBM Corporation. The analysis suggested that the output obtained were practicable. Some of the resource planning templates obtained in the IBM case study is presented in Figure10.

System Input

Engagement	*Skill I*	*Skill II*	*Skill III*	*Skill IV*
A	*80*	*10*	*5*	*5*
B	*60*	*20*	*10*	*10*
C	*70*	*20*	*5*	*5*
D	*75*	*10*	*10*	*5*

System Output

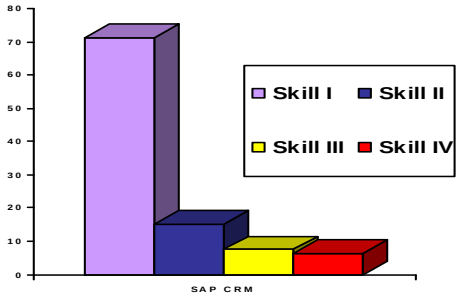


Figure 9: Demonstration on a Use Case Scenario

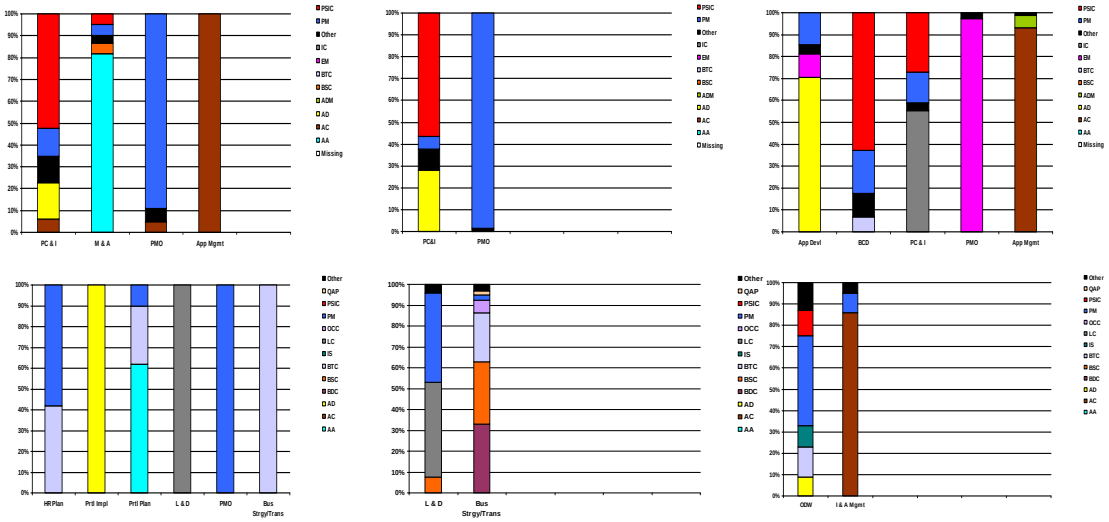


Figure 10: Resource Planning Templates in a Case Study

Conclusion and Future Study

In this study we proposed an analytics and optimization system for generating staffing plans for the pipeline projects of a logistics professional services organization. The methodology that was considered for the study is based on k-means clustering approach. The k-means approach is a supervised learning approach. In the future, we plan to study semi-supervised learning methodologies for developing staffing templates.

Clustering without supervision is termed as unsupervised clustering. Unsupervised clustering approach can be significantly improved using supervision. Clustering under partial supervision is termed as semi-supervised clustering. Semi-supervised clustering and semi-supervised learning are widely studied in the machine learning literature over the recent years (Ando and Zhang (2005), Basu (2005), Basu et al. (2006), Brefeld and Scheffer (2006), Bilenko et al. (2004), Cohn et al. (2003)). In the future study, we propose to develop a system for staffing analysis based on semi-supervised clustering. In the first phase the system assigns cluster labels to the projects. In the second phase, the system gets input from the supervisor and reassigns cluster labels, if needed. The second phase could be an iterative phase. Semi-supervised clustering can be either constraint-based, i.e., changes are made to the clustering objective to satisfy user-specified labels/constraints, or metric-based, i.e., the clustering distortion measure is trained to satisfy the given labels/constraints. The study would address constraint based semi-supervised clustering. However, in the first phase the system could assign cluster labels based on other vector based clustering approaches like hierarchical clustering or k-means.

Other challenges, include:

- Developing analytics and optimization system for forecasting resources based on the pipeline demand.

- Developing system for other areas of business consulting in the context of logistics professional services management.

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