

## SIMULATE SKILL MIX TO VALIDATE A RESOURCE PLANNING SYSTEM

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### ABSTRACT

Resource management, planning, and provisioning are first-order issues for service providers in today's IT service market. Project managers must pro-actively ensure they have sufficient resources to meet expected future skill demand while ensuring their existing resources are fully utilized. In this paper, we developed a simulation method that generates realistic demand and skill mixture scenarios to validate an optimization-based resource planning system.

### 1 INTRODUCTION

IBM Global Business Services (GBS) provides IT outsourcing to large corporate customers. The GBS account team assigned to a customer must meet the customer's varying IT needs by providing high-quality services at minimal cost. The management, planning, and provisioning of development resources to meet client skill demand is challenging. We developed a resource planning system that optimally assigns available resources with the right skills to customer demand. To validate this system for large-scale deployment, we collected real data from a representative GBS account, built a simulator that captures the relevant statistical characteristics exhibited in the data, utilize the simulator to generate representative scenarios, and fed the scenarios to the resource planning system to quantify its value.

Various approaches have been proposed to address workforce planning problems. Naveh et al. (2007) applied a constraint programming approach to plan workforces. Lu et al. (2006) used stochastic loss networks to model demand dynamics and uncertainty to derive a set of rules for optimal workforce management. Safaei et al. (2012) used a simulation-optimization approach to schedule staff to restore power after interruptions. However, none of these works addressed the skill-matching issue that is critical to real-world IT resource planning.

### 2 SIMULATE RESOURCE SKILL MIX

A resource may have more than one skill and multiple resources may possess the same skill. One difficulty arises when attempting to simulate resources is that existing data are too scarce to build a skill mix model. Let  $S$  denote the set of skills. A resource may have  $n = 1, 2, \dots, |S|$  skills. Let  $Q$  denote a probability distribution over positive integers. Define  $q_n = Q(n)$  as the probability that a resource has *exactly*  $n$  distinct skills. Given that a resource has  $n$  distinct skills, let  $P_n$  denote the probability distribution from which these  $n$  distinct skills are drawn.  $P_n$  is a probability distribution over  $S^n$ , the Cartesian product of  $n$  skill sets  $S$ . The skill distribution for any give resource can be written as a mixture of  $P_n$ :

$$q_1 P_1 + q_2 P_2 + \dots + q_{|S|} P_{|S|}.$$

To generate skills for a resource, we first draw the number of skills for the resource from distribution  $Q$ . Let  $n$  be the value selected. We then draw a vector of  $n$  distinct skills from set  $S^n$  according to distribution  $P_n$ .

We estimate the distributions for  $Q$  and  $P_n$  using actual data from our pilot account. We estimate  $Q$  by computing the percentage of resources in the data with  $n$  skills. Estimating  $P_n$  directly from the data for large  $n$  is difficult as there are very few users with many skills. Instead, we approximate  $P_n$  by using  $P_1$  and assuming that a resource's skills are independent. Specifically, we approximate  $P_n$  using  $P_n \approx P_1 \times P_1 \times \dots \times P_1$ . Our approximation for  $P_n$  repeatedly draws a single skill  $n$  times from  $P_1$ . It ignores the correlations between consecutive draws and may generate duplicate skills. Duplicate skills should not be a major issue when  $n$  is small relative to the number of skills. This significantly reduces the complexity of the estimation task.

Figure 1 shows the empirical distribution of  $P_1$  on the data from our pilot account (blue curve). We use a geometric distribution

$$P_1 = (1 - \theta)^{k-1} \theta$$

to fit the data and estimate the value of parameter  $\theta$  as  $\theta_R = 0.0671$ . The magenta curve in Figure 1 shows the probability computed based this estimated  $\theta$  value. The x-axis represents skill ids sorted by their popularity among resources, i.e., the smaller the id is, the more resources that have the skill.

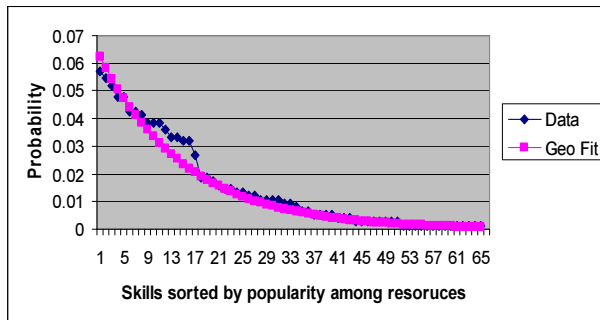


Figure 1. Skill distribution across resources.

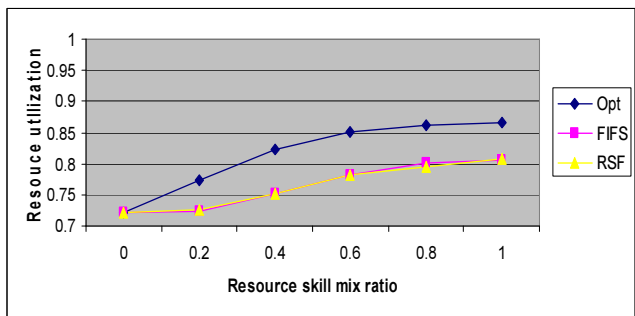


Figure 2. Resource utilization of 3 approaches

Each demand requires a single skill and thus is easy to simulate. Fed the simulated skill mixture and demand scenarios into our resource planning system, we were able to show that our system achieves 5%-8% efficiency gain over FIFO (first in first serve) and RSF (demand requiring rare skills served first) approaches, two heuristics popular among practitioners (see Figure 2).

## REFERENCES

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