E-lancing : A Tool for Yield Management in the IT Service Industry

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ABSTRACT

This paper investigates *e-lancing,* the emerging online marketplace for IS outsourcing. *E-lancing* is a new kind of market mechanism comprised of electronically connected freelancers (either individuals or organizations) joined into networks to provide IT services. As the Internet's capacity continues to grow exponentially every year, e-lancers proliferate, enabled by IT and subsequent market liquidity. Moreover, this decentralized, individual-oriented electronic market mechanism will be more common as traditional, large companies find difficulties in hiring and firing employees due to initial sunk costs and legal issues.

We propose the strategic use of online spot market, a typical e-lancing tool to assign jobs to workers, for yield management from the IT service provider's perspective. Given the fixed capacity of a firm's IT workforce, the nature of IT projects, demand uncertainty, and growing competition among IT vendors, IT service firms cannot avoid occasionally holding some excess workforce. By utilizing its excess workforce by means of e-lancing, a firm can prevent price competition in the conventional channel, reach customers in the online channel, and hence increase profits. We reduce our problem to the stochastic knapsack problem and employ Markov decision theory in order to obtain the global optimal admission control solution for our stochastic knapsack problem over the set of all policies. The model considers an IT service firm which receives projects through two channels: a conventional procurement channel and an online spot market such as *Elance Online* (www.elance.com). The proposed model determines optimal admission policies to maximize the expected total discounted profit over infinite horizon. We illustrate numerical examples to characterize the structure of optimal policy.

Our model captures the most important characteristic of IT projects where if a project is admitted, it seizes a random number of workers simultaneously, then it releases all the workers at the same time after occupying for the project duration. In addition, implementing two job classes requiring different service rates with different sizes of bulk arrivals into the standard Markov decision model is a distinctive contribution, providing a benchmark model which will be useful to investigate various demand control problems of IT service providers. The key contribution of this study is to examine a new revenue model, verify its feasibility and effectiveness, and provide a optimal strategy to successfully implement this revenue model. Given growing competition in the IT service industry, the optimal admission control policy presented in this paper will provide managerial insights on the agile and flexible project management applicable to offshore and US-based IT service firms.

1. Introduction and Motivation

The IT service industry has been continuously growing at more than 10 percent per year (Gartner Research 2002) since IT outsourcing was acknowledged, decades ago, as a useful strategy for lowering costs, earning economies of scale and accessing specialized resources. Furthermore, offshore IT outsourcing has exploded, spurred by its exclusive advantages of cost savings and large labor pools. But at the same time, customers are squeezing IT vendors for price cuts. As a result of these changes in the business environment, substantial competition among offshore and US-based vendors is expected. Giant, global IT-service firms such as *Accenture* and *EDS* are opening their own software development centers in India to compete with local companies such as *Infosys* and *Wipro* (Kumar and Sinha 2003). The challenge now to IT service providers is how to manage their resource in order to survive the competition.

Since *people* are the most important resource in a service company unlike in a product company, adequate staffing has been a crucial task for an IT service provider (Gartner Research 2001). Given the fixed capacity of a firm's workforce, the nature of IT projects, and demand uncertainty in the market, IT service firms cannot avoid occasionally holding the excess workforce. Many IT service firms want to maintain their workforce capacity at a sufficient level in order to respond quickly to high market demand or a large project order. Consequently, a firm may hold idle workers when it faces low demand or the termination of a large project. Maintaining idle workers, however, incurs double costs to the firm without generating any revenue; the wages of the idle employees and the training costs. Myopic remedies to deal with this challenge, ad-hoc staffing-up and layoff, involve high initial sunk costs of staffing-up and potential legal disputes followed by layoff, disabling the firm's agility. Furthermore, when IT service providers have a large number of idle employees, the situation lends itself to price competition among vendors (Kim, Shi and Srinivasan 2004), which would lower their revenues in a long run.

Drawing primarily on Markov decision theory, we develop a model for an IT service provider to control excess workforce in the context of yield management. The staffing problem of an IT service provider has the characteristics shared in hotel and airline industries where yield management has been successfully employed. IT service firms have strict capacity constraints and the costs of making any adjustment – hiring, training, or firing new IT professionals - are high just like hotels and airlines (Kim et al, 2004). Moreover, the inventory of IT professionals can bee seen perishable just like hotel rooms and airplane seats in that the excess idle workforce incurs operational cost including employees' salary without generating any revenue and the availability will disappear unless used now. Observing these similarities between IT service industry and hotel/airline industries, we develop an Markov decision model for an IT service provider to achieve yield management by effectively reduce excess workers through *e-lancing*, the secondary channel, when the market demand of conventional channel is low.

The motivation of this research stems from the view in which the advances in information technology are affecting firm and market structures, shifting toward more use of decentralized markets rather than hierarchies to coordinate economic activity (Malone, Yates and Benjamin, 1987). According to their definition, *markets* coordinate the flow of materials or services through supply and demand forces and external transactions between different individuals and firms while *hierarchies* coordinate the flow of materials by controlling and directing it according to a predetermined managerial decision. IT has significantly reduced coordination costs of electronic markets which were relatively higher than in the hierarchical organizational form. Moreover, the *electronic brokerage effect* increases the number of alternatives, increase the quality of the alternative selected and hence decreasing the production cost significantly in the electronic market structure (Malone et at 1987). Motivated by these factors favoring decentralized markets over hierarchies in the Internet age, this research aims at developing an intelligent tool to help IT service providers make agile and flexible staffing decisions taking advantage of the electronic sales channel.

E-lancing is a new market mechanism comprised of electronically connected freelancers (either individuals or organizations) joined into networks to provide IT services (Malone and Laubacher 1998). The most common type of market mechanism for e-lancing, considered as the secondary channel in our model, is the online reverse auction, where the buyers post projects such as software development and website design as a form of RFP (Request for Proposal), and then IT service firms bid for them. Online auctions enable firms to efficiently outsource small projects that, mostly, involve less than six person-months of effort (Snir and Hitt 2003). Examples of currently operated Web-based IT service markets include *Elance Online* (www.elance.com), *Prosavvy* (www.prosavvy.com), *RentACoder* (www.rentacoder.com) and *Guru* (www.guru.com). *Elance Online* is the leading Web-based project marketplace that connects small- and medium-sized businesses with a global pool of IT service providers. More information about several e-lancing Web sites is given in Table 1.

TABLE 1. Major e-lancing Web sites

	Elance Online (www.elance.com)	***Guru*** (www.guru.com)	***Rent A Coder*** (www.rentacoder.com)
Description	The largest global online freelancer site. It targets the small and medium businesses throughout various industries.	The site claims to have the largest membership with over 451,000 professionals throughout various industries.	One of the largest coding freelance sites for software buyers and coders.
Client payment method	Clients can divide the project into stages and pay based on each stage.	Clients pay the entire amount of the project fees into an escrow account.	Clients pay the entire amount of the project fees into an escrow account.
Fees for clients	Free	Free	Free
Fees for providers	Providers must pay a monthly fee to retain membership. The membership fees range from \$30 to \$245 monthly.	Basic membership includes a free membership but requires a 10% project transaction fee.	Free membership with a 15% project transaction fee.

The online spot market used as the secondary channel in our model also includes reverse auctions embedded in e-sourcing solutions. Various e-sourcing solutions available in the market typically have similar functions to those of Web-based marketplaces such as an RFP generator, a potential supplier database, a support for various reverse auction types and an interactive bid solicitation mechanism (Forrester Research 2004). Major e-sourcing solution vendors in the current market are described in Table 2. In addition, the secondary channel in our model may include e-procurement suites provided by vendors such as *Elance*, *PeopleSoft*, *IQNavigator* and *Ariba* since they typically include an e-sourcing solution.

TABLE 2. Major vendors of e-sourcing solutions[1]

Type	Description	Vendors
Managed, hosted e-sourcing service	Provides consulting and hosted application	*FreeMarkets, ATKPS, ICG Commerce, Ariba, Ketera, Global eProcure, Perfect Commerce, SnyerDeal, Iasta*
Self-service hosted e-sourcing	Provides hosted application	*FreeMarkets, ATKPS, Procuri, Ariba, Ketera, Frictionless, Emptoris, B2eMarkets, SAP, Oracle*, and various e-markets
Licensed software	Provides licensed product operated behind corporate fire wall	*Ariba, SAP, Oracle, PeopleSoft, i2, Portum, ATKTPS, Frictionless, B2eMarkets*, others

In this paper, we investigate how IT service providers can improve productivity by integrating the e-lancing channel into their business model. Specifically, we propose strategic use of online service marketplace, e-lancing, to manage excess capacity of an IT vendor's labor pool. We argue that if an IT service firm dynamically decides to participate in online reverse auctions, a typical e-lancing tool, to receive projects that occupy idle employees, it may not only gain additional profits by reaching customers in the online channel, but also avoid price competition in the conventional channel.

2 Literature Review

The goal of yield management is to maximize revenue per unit capacity by employing price-discrimination. Many researchers have studied the use of online auction as a secondary channel for yield management to dispose of a firm's excess inventory while the firm sells its products through the primary conventional channel at list price (Pinker et al. 2003; Vulcano, van Ryzin, & Maglaras 2002). Gallego and van Ryzin (1994) solve the optimal pricing policy as a function of the stock level and the length of the horizon. This price-discrimination approach is preferred when a perishable inventory has to be sold before a deadline, which is typical in retail

[1] Source: Forrester Research, Inc. Jan 5, 2004

industry. Our model enables us to investigate how much discount is allowed in the secondary, e-lancing channel.

However, while we consider the IT workforce of service providers as perishable inventory as discussed in the previous section, the typical IT projects usually require a group of IT professionals simultaneously. Consequently, the price of contracts can be high. The literature suggests that when they are large contracts, not just individual customers' orders, offers should be accepted or rejected. Therefore the decision variables in our model include the binary variable for admission control as well as the bidding price in the secondary channel. There have been extensive efforts on such admission controls combining queueing theory with inventory management (Brumelle and Walczak 2003; Carr and Duenyas, 2000). In Caldentey and Wein (2005), the authors model a single-product manufacturing system for a firm using two selling channels: long-term contracts and a spot market of electronic orders. The manufacturer simultaneously decides on a busy/idle policy for the machine in addition to an accept/reject policy for e-orders. Unlike most prior research on revenue management, the difficulty of modeling our problem lies on the fact that an IT service firm produces services, not physical goods. Our model captures the more complex characteristics of service firm: the IT workers (servers) are rented for a random amount of time and they remain available again in the firm (system) to serve the next project (job) after serving the current job.

Our problem can be reduced to the stochastic knapsack problem (Ross 1995). A stochastic knapsack consists of c identical servers and K job classes arriving. Each class is characterized by its size, b_k, arrival rate, λ_k and mean holding time, $1/\mu_k$. If an arriving class-k job is admitted into the knapsack, it holds b_k servers for a service time which is exponentially distributed with mean $1/\mu_k$ and releases b_k servers simultaneously after the service time generating a reward, r_k. The objective of the problem is to control admission of jobs into the knapsack in order to maximize total reward. Admission controls in a stochastic knapsack problem have been studied by many researchers with various setups (Ross 1995; Ormeci and Burnetas 2004; Papastavrou, Rajagopalan and Kleywegt 1996). Any of these prior models does not capture all the requirements of our problem. In order to obtain the global optimal admission control solution for the stochastic knapsack problem, we employ Markov decision processes to optimize over the set of all policies (Ross 1995; Ross and Tsang 1989).

3 Model Development and Assumptions

Our model considers an IT service firm that receives IT projects through two channels: a conventional procurement channel and an online auction spot market. The firm first fulfills the orders from the conventional channel and then decides whether to participate in the online auction depending on the current workforce. The assumptions made in our model are as follows:

(1) There is neither staff augmentation nor loss during the period considered in the analysis. That is, the total number of IT workers in the firm remains constant.

(2) The contract price (i.e., the project value) is an increasing function with respect to team size and project duration.

(3) The pool of IT workers is composed of homogeneous developers/programmers both in terms of their skills and performance. Although each project team in the real world typically consists of a different number of developers with varying skills and experience, we restrict our focus to homogeneous workers at this preliminary stage of analysis. However, the model can be extended to allow heterogeneous workers.

(4) The effects of employee training and experience on a worker's quality improvement are ignored. However, we may consider introducing the aspect of employee's quality improvement due to training into the model later.

(5) The market is segmented according to project sizes. Specifically, the conventional channel consists of those projects with larger sizes and slower arrival rates, and projects with smaller size and more frequent arrival rates comprise the online channel.

(6) The projects of each class arrives according to Poisson distribution with rate λ_i.

(7) The project duration of each class follows exponential distribution with mean $1/\mu_i$.

The workforce management problem in the IT service firm is modeled as a dynamic admission control problem in a two-class Markovian loss service system with multi-servers receiving random batches. The schematic diagram of the two-class channel system is depicted in Figure 1. The summary of notations for a general multi-class channel system is given in Table 3.

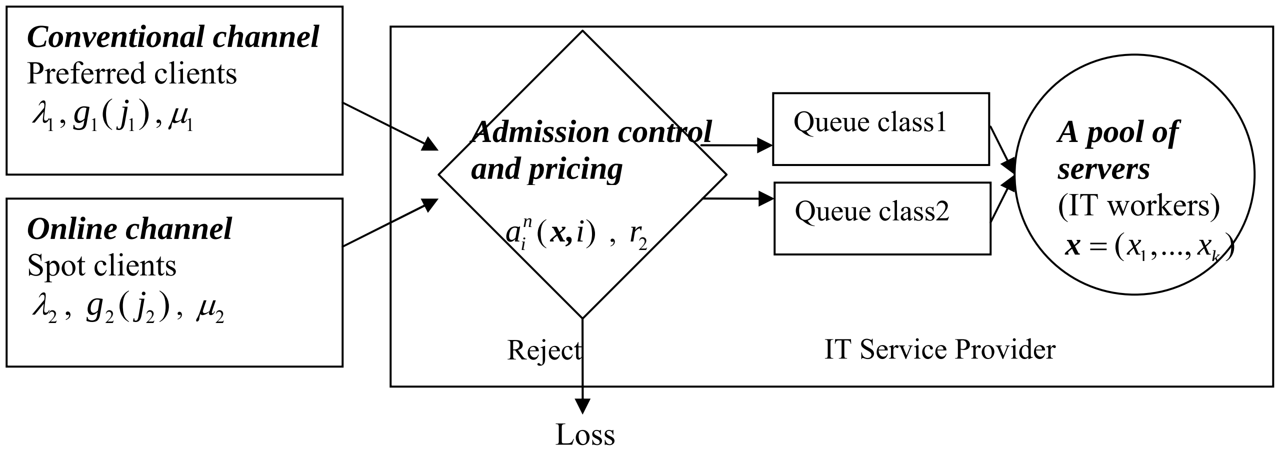


FIGURE 1. A schematic model of the system for the e-lancing revenue management

The IT staff pool in the IT vendor is represented as a pool of multi-servers. The incoming projects are modeled as two customer classes. The first class of projects requires an immediate and high-priority service since there is a significant penalty such as $\mu_1 < \mu_2$ if the demand in the conventional channel is not satisfied with priority. The second class of projects is served in a low-priority fashion, where the IT service firm is allowed to control the arrival of the orders by means of auction participation control. The arrival of each project requires a number of IT workers, j_i, simultaneously with probability $g_i(j_i)$, which implies a bulk arrival. If the project is admitted, j_i workers are released at the same time after a project duration with mean $1/\mu_i$.

TABLE 3. Summary of Notations

c	Total number of workers (IT Professionals) in the IT service firm.
K	Total number of channels. (K=2)
λ_i	Expected class-*i* project arrival rate, $\lambda_i = \lambda_1 g_1(j_1) + \lambda_2 g_2(j_2) = \lambda_i \sum_{i=1}^{K} g_i(j_i)$
$1/\mu_i$	Expected class-*i* project duration
j_i	Team size (project load): The number of workers required within one project of class-*i*.
$g_i(j_i)$	Probability distribution function of team size. $g_i(j_i)$=P[team size= j_i]
$a^n(\boldsymbol{x}, i)$	Action parameter for class-*i* projects when the state is $(\boldsymbol{x}, \boldsymbol{j})$ at the *n*th

	decision epochs. 1 for admission and 0 for rejection.
x_i	Number of busy workers working on class-*i* projects
$\boldsymbol{x} = (x_1, ..., x_K)$	Vector of number of busy workers
$(\boldsymbol{x}, i)$ $= (x_1, ..., x_K,\ i)$	State parameter which indicates that x_i class-*i* jobs are observed in the system when a class i has arrived.
$V_n\ (\boldsymbol{x}, i)$	The maximal total expected reward for the system starting in state $(\boldsymbol{x}, \boldsymbol{j})$ over *n* decision epochs in the horizon.
δ	Discount factor
r_i	Class-*i* project price per man month
$P(r_2, q)$	Probability of winning the auction given the IT service provider's quality q and bidding price r_2.

We define state $(\boldsymbol{x}, i) = (x_1, ..., x_K,\ i)$, which indicates that x_i workers working on class-*i* projects are observed in the system when a project of class i has arrived. The state space is:

$$S = \{(x_1, ..., x_K, i) \mid x_1, ..., x_k = 0, 1, ..., c\ ;\ \sum_{i=1}^{K} x_i \le c\ ;\ i = 0, 1, .., K\}.$$

The system is in state $(\boldsymbol{x}, 0)$ if there are $\boldsymbol{x} = (x_1, ..., x_k)$ busy workers in the system and no arrivals of project. In state $(\boldsymbol{x}, 0)$, the only action is to leave the system alone and hence action a=0 is the only feasible decision. In state $(\boldsymbol{x}, i \ne 0)$ observed only at arrival epochs, the decision maker may admit or reject the incoming project, so that $a(x_1, ..., x_K, i \ne 0) \in \{0, 1\}$, where action 0 corresponds to rejecting and 1 to admitting the arriving project. Moreover, state $(\boldsymbol{x}, i \ne 0)$ refers to the instantaneous states at the arrival epochs. As soon as the admission and rejection decisions are made upon an arrival, the system moves immediately to another state $(x_1, ..., x_i + a\ j_i, .., x_K\ , 0)$ according to the decision made.

Note that the original problem is a continuous-time Markov decision process where the times between decision epochs are exponentially distributed with a state-dependent rate. We use the well-known uniformization technique which allows us to obtain the equivalent process with uniform sojourn time distribution in every state (see Lippman 1975). In the uniformized system, the system state is observed at random times which are exponentially distributed with the stateindependent, constant transition rate, which is called the uniformization constant. Therefore we can use the algorithms for discrete-time Markov decision process after uniformization. For uniformization, we consider the service completion epochs as fictitious decision epochs in addition to the real decision epochs which are the arrival epochs of projects. Note that uniformization adds more decision points at service completion and fictitious service completion points while the actual meaningful decision needs to be made only at the arrival points. Although it increases the number of states and hence the number of additions and multiplications, it leads to sparser transition matrices and thus accelerated algorithms (Ross and Tsang 1989; Tijms 1986 pp 213-214, Puterman 1994 Chapter 11). Therefore it is recommended applying uniformization when analyzing continuous-time Markov decision processes.

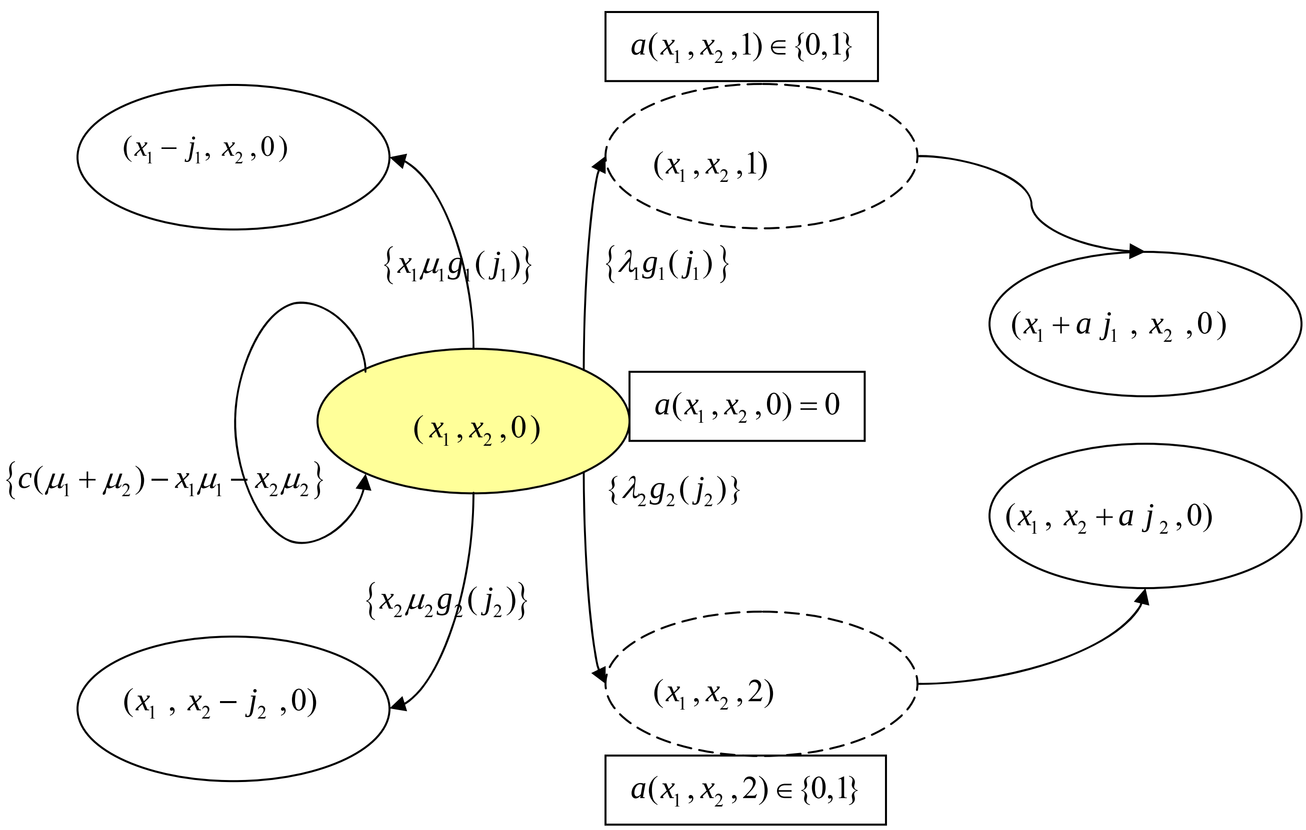


FIGURE 2. Symbolic representation of the state transition structure: The numbers in brackets represent the transition probability after uniformization and normalization. The dotted circles represent instantaneous states. Each ending node recursively continues its transition as in state $(x_1, x_2, 0)$ in the center.

For our specific problem, we consider a 2-channel system (K=2). We define the uniformization constant to be $\lambda_1+\lambda_2+c(\mu_1+\mu_2)$, the maximum possible rate out of any state. We normalize it by assuming $\lambda_1+\lambda_2+c(\mu_1+\mu_2)=1$. At each transition epoch, we have one of the following transitions with the corresponding probability: an arrival of projects with probability $\lambda_1\sum g_1(j_1)+\lambda_2\sum g_2(j_2)$, a service completion with probability $x_1\mu_1\sum g_1(j_1)$ + $x_2\mu_2\sum g_2(j_2)$, and a fictitious service completion due to uniformization with probability $c(\mu_1+\mu_2)-x_1\mu_1-x_2\mu_2$. Figure 2 illustrates the possible transitions and the transition probabilities.

Based on the Bellman equation, the maximal total expected reward for the system starting in state $(\boldsymbol{x},0)$ over n decision epochs in the horizon for a 2-class system (K=2) yields the following recursive relation:

$$
\begin{aligned}
V_n(\mathbf{x},0)=\{&\lambda_1\sum_{j_1=1}^{c-(x_1+x_2)} g_1(j_1)\max_{a_1^n}[V_{n-1}((x_1+a^n j_1,\ x_2,0)+a^n j_1 r_1\frac{1}{\mu_1}] \\
&+\lambda_2\sum_{j_2=1}^{c-(x_1+x_2)} g_2(j_2)\max_{a_2^n}[V_{n-1}(x_1,\ x_2+a^n j_2 P(r_2,q)\ ,0)+a^n j_2 r_2\frac{1}{\mu_2}P(r_2,q)] \\
&+x_1\mu_1\sum_{j_1=1}^{x_1} g_1(j_1)\,V_{n-1}(x_1-j_1,\ x_2,0)\ +\ x_2\mu_2\sum_{j_2=1}^{x_2} g_2(j_2)\,V_{n-1}(x_1,\ x_2-j_2,0) \\
&+(c(\mu_1+\mu_2)-x_1\mu_1-x_2\mu_2)\,V_{n-1}(x_1,\ x_2,0)\ \}\ /(\delta+1)
\end{aligned}
$$

$$
0\le\sum_{i=1}^{2}x_i+\sum_{i=1}^{2}a^n j_i\le c
$$

The IT service firm's problem is to decide whether to participate in an online auction and determine a bid price. The goal is to dynamically control the auction participation rate and hence the number of idle workers over an infinite horizon. The first two terms represent the admission controls for incoming class-*i* projects. The manager needs to decide whether to admit (a^n=1) or reject (a^n=0) the incoming project to maximize the profit. Then, the corresponding state becomes $(x_1+a\ j_1,\ x_2,0)$ for the incoming class-1 projects and $(x_1,\ x_2+a\,j_2,0)$ for the incoming class-2 projects regardless of the decision. When the incoming project is admitted, the reward $a_i^n j_i r_i/\mu_i$ is accumulated. The firm's profit from the online spot channel (class-2) depends on the probability of winning the auction. The probability is a function of the quality of the firm, the bid price, the number of bidders and other parameters (Snir and Hitt 2003). The third and fourth terms represent the service completions of class-*i* projects. The fifth term is due to the uniformization. Finally, $1/(\delta+1)$ is multiplied for δ-discounting effect (Tijms 1986; Puterman 1994). The optimal policy is obtained by using the value-iteration algorithm over infinite horizon (See Tijms 1986; Puterman 1994) and the results are illustrated in the next section.

4. Numerical Computation

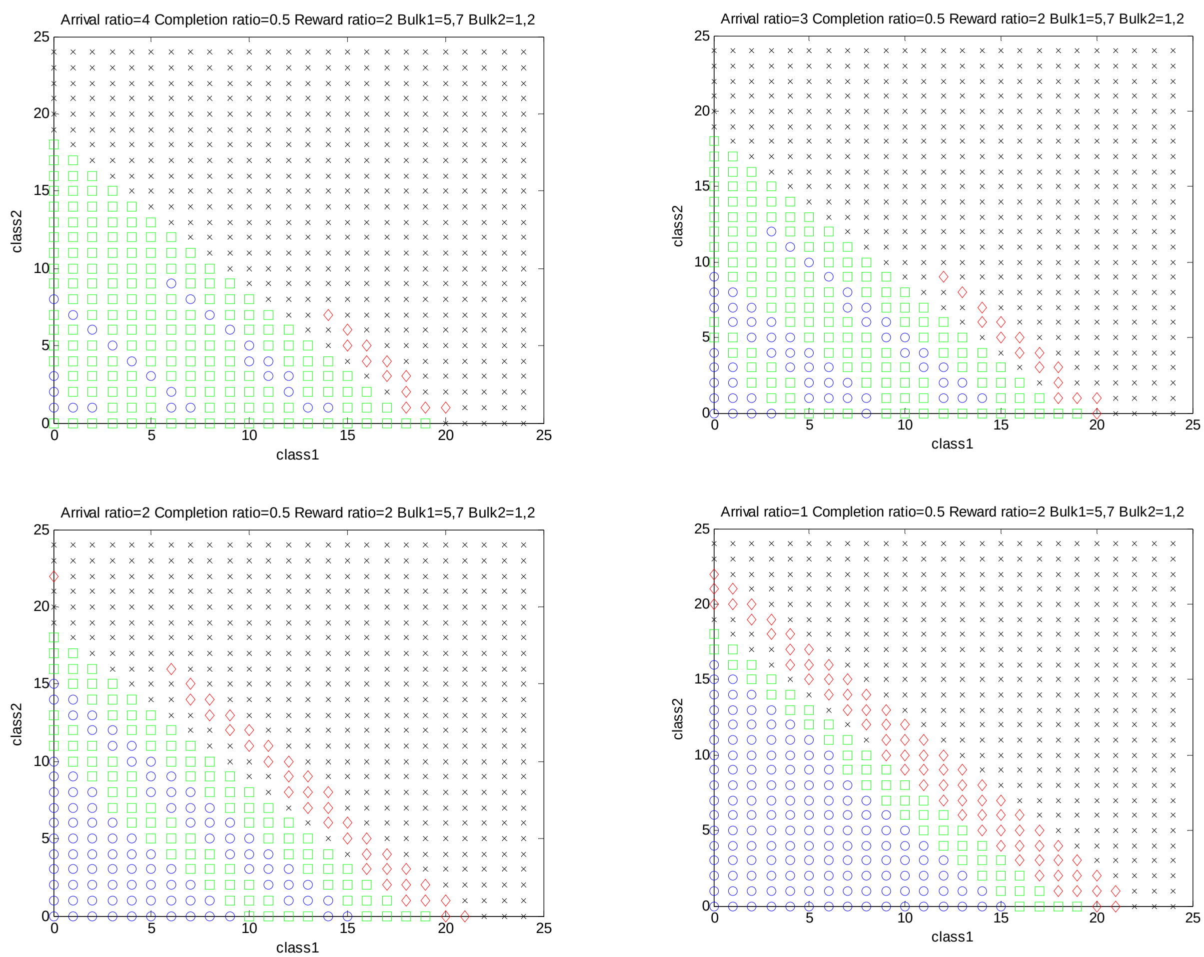
Several numerical examples have been solved by using value-iteration algorithm to investigate the structure of the optimal policy. The primary result is that the optimal policy is not of the threshold type, where the secondary market project (class 2) is admitted if and only if the number of idle workers in the firm is less than a fixed threshold. Rather, the optimal policy is of a more complex form as seen in Figure 3, 4, and 5. The complexity of the optimal policy implies that manual, ad-hoc decisions on IT professional staffing might cause excess idle workers and loss in revenue and therefore the presented model is useful as a decision support tool to provide the optimal policy.

The optimal policy appears to depend on the arrival rate ratio, the project duration ratio, the reward ratio, and the bulk sizes in two channels. Although our examples assume the uniform distribution of bulk sizes, other distributions could be used. For simplicity, we set $P(r_2, q)=1$ and leave the further examination of the effect of the online auction parameters as future research.

4.1. The effect of arrival rate

Keeping other parameters constant, the experiments were performed to examine the effect of arrival rate of projects. As the relative arrival rate of class 1 increases, the system rejects more projects of class 2. In Figure 3, when the ratio of the class-1 arrival rate to the class-2 rate is 4 (the upper left plot), the optimal policy shows square symbols in majority of states, indicating that the optimal policy accepts class 1 but rejecting class 2 in most of states with a few class-2 admissions. As the ratio decreases to 1 (the lower right plot), more circles and diamonds are observed, indicating that the optimal policy accepts both classes in many states and accepts class 2 but rejects class 1 in some states, respectively.

The effect of the relative arrival rates on the behavior of the optimal policy can be interpreted as the tradeoff between the risks of having idle workers and the expected future reward. When the demand in the primary channel is low (the arrival rate of class 1 is slow), there is higher risk of having excess idle workers in the future, and therefore the optimal policy admits more class 2 projects. For example, when the arrival ratio is 2, the optimal policy blocks class 2 in state (10, 10) in order to ensure enough number of workers for a future arriving class-1 project because the system is willing to wait for the high-profit margin project at the cost of taking risk of having future idle workers. On the other hand, when the ratio is 1, the optimal policy admits class 2 in the same state (10,10) to mitigate the risk of having idle workers in the future after realizing the low demand of class 1.



○-Accept both , □ - Accept class1 and reject class 2

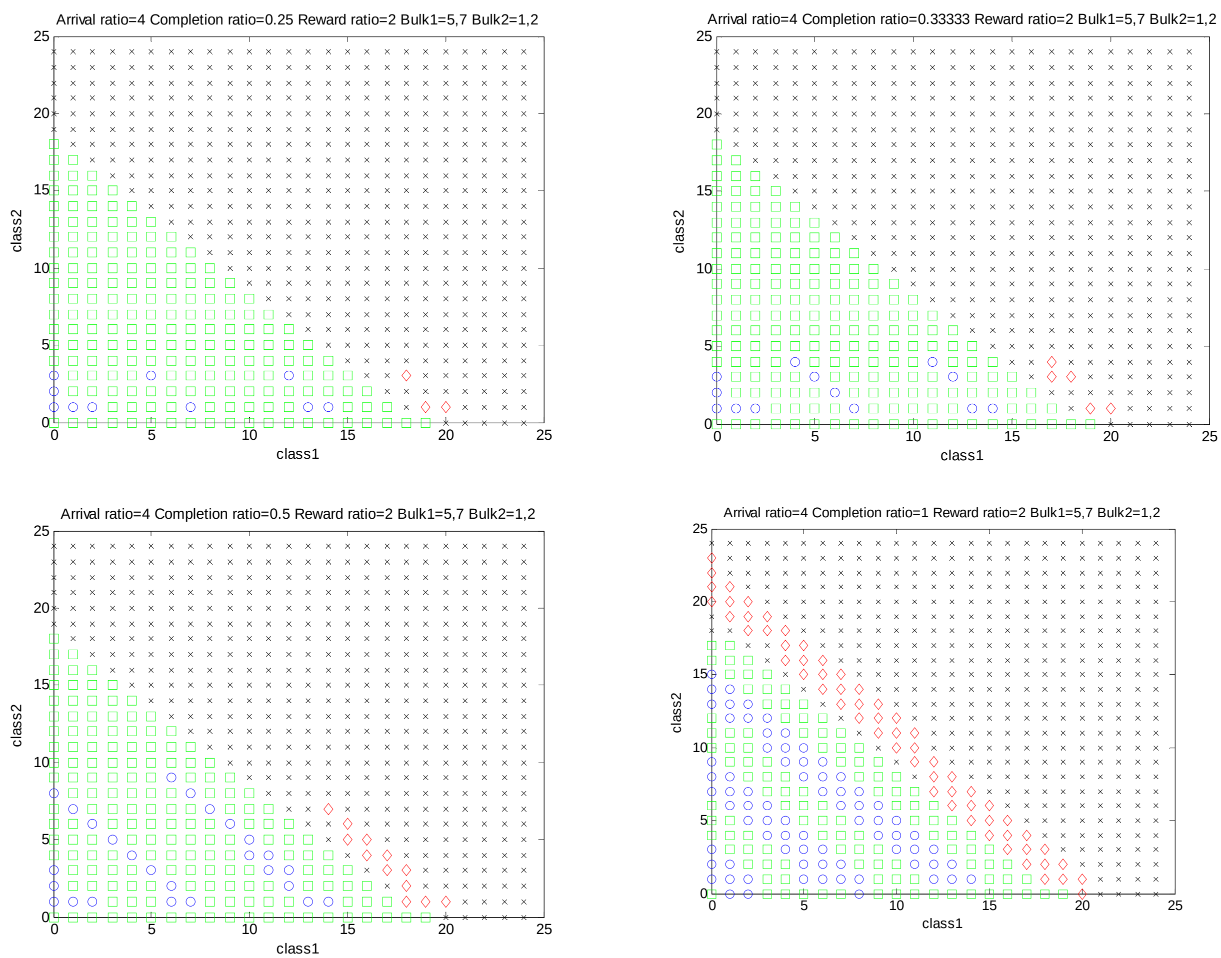
◊ - Reject class1 and accept class 2, × – Reject both

c=24, $\lambda_2 = 1, \mu_1 = 0.1, \mu_2 = 0.2, r_1 = 10, r_2 = 5, j_1 \sim U(5,7), j_2 \sim U(1,2)$

FIGURE 3. The effect of arrival rates

4.2. The effect of project duration

The effect of project duration ($1/\mu_i$) is illustrated in Figure 4. Note that the project duration is related to the magnitude of the reward as well as the rate of busy workers being released free in the next epoch. As the relative project duration of class 1 is longer (the upper left plot in Figure 4), the optimal policy blocks incoming class-2 projects in more states. It is because the longer project duration of class-1 project makes the class-1 projects more attractive by generating greater revenue.



○-Accept both , □ - Accept class 1 and reject class 2

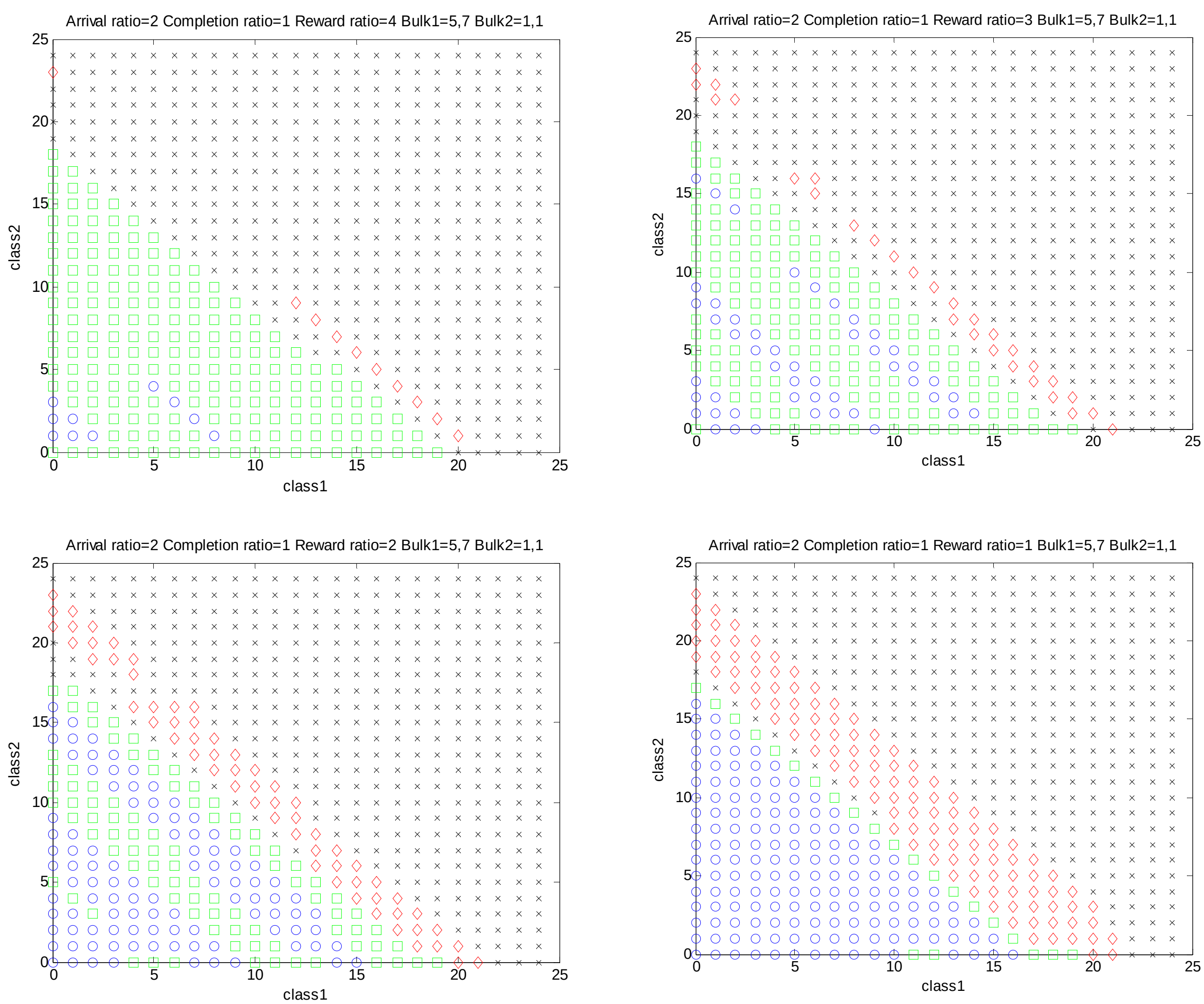
◊ - Reject class 1 and accept class 2, × – Reject both

c=24, $\lambda_1 = 4, \lambda_2 = 1, \mu_1 = 0.1,\ r_1 = 10, r_2 = 5,\ j_1 \sim U(5,7),\ j_2 \sim U(1,2)$

FIGURE 4. The effect of project duration

4.3. The effect of reward

The magnitude of reward of each class is directly related to the attractiveness of the class. It is evident in Figure 5 that as the relative reward of class 2 increases, the optimal policy rejects class-2 projects in more states. In Figure 5, the upper left plot is when the relative reward of class 2 is the highest and the lower right plot is the lowest relative reward of class 2. An interesting point of this analysis is that the decision maker can obtain information about how deep discount to offer to clients in online channel compared to the primary channel in order to maximize the utilization of its workers depending on various other parameters in two channels.



○-Accept both , □ - Accept class1 and reject class 2

◊ - Reject class1 and accept class 2 , × – Reject both

FIGURE 5. The effect of rewards

$$c=24,\ \lambda_1 = 2, \lambda_2 = 1, \mu_1 = 0.1,\ \mu_2 = 0.1,\ r_2 = 5,\ j_1 \sim U(5,7),\ j_2 \sim U(1,1)$$

4.4 The effect of team size

The experiments to study the effect of team sizes in each class have been conducted. The interpretation of the results is currently in progress. Keeping other parameters constant, the comparison of revenues with different team sizes in both classes will be conducted.

5. Concluding Remarks and Contribution

Historically, the way people do business has been affected by the coordination technology available. Improved network technology, i.e., coordination technology, has introduced new commercial opportunities to e-lancers by providing increased efficiency through reduced transaction costs. This decentralized, individual-oriented electronic market mechanism will be essential for a strategic sourcing to design agile organizations by deploying resources quickly and efficiently in response to diverse market changes. The key contribution of this study is to examine a new revenue model, verify its feasibility and effectiveness, and provide a dynamic strategy to successfully implement this revenue model.

One theoretical contribution is to expand the knowledge of yield management literature, concentrated mainly on physical goods, into the IT service industry. From a methodological perspective, our model captures the most important characteristic of IT projects where if a project is admitted, it seizes a random number of workers simultaneously, then it releases all the workers at the same time after occupying for the project duration. In addition, implementing two job classes requiring different service rates with random batch arrivals into the standard Markov decision model is a distinctive contribution, providing a benchmark model which will be useful to investigate various demand control problems of IT service providers. On a practical level, given growing competition in the IT service industry, the analysis of the optimal auction participation control policy will provide managerial insights applicable to the management of excess manpower for offshore and US-based IT service firms such as *IBM*, *Accenture*, and *EDS*.

Certain assumptions, of course, would need to be relaxed to accommodate real world conditions more precisely. Nevertheless, we believe that the model captures the essential factors to analyze the value of the emerging e-lancing market. It would be interesting to incorporate the notion of risk into the model. The model can take the project management risk such as scopecreeping and scheduling overrun into account. This paper considers only one side of e-lancing application where the IT service provider serves as an e-lancer in order to disposes of its available capacity when the market demand is low. Another interesting research topic that we wish to investigate in future is the flexible staffing model with which an IT service provider contracts with individual e-lancers in e-lancing markets for flexible staffing management when market demand is high.

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