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Service Level Differentiation in Multi-robots Control

Ying Xu, Tinglong Dai, Katia Sycara, *Fellow*, *IEEE,* Michael Lewis*, Member, IEEE*

Abstract— **In this paper we explore the effects of service level differentiation on a multi-robot control system. We examine the premise that although long interaction time between robots and operators hurts the efficiency of the system, as it generates longer waiting time for robots, it provides robots with longer neglect time and better performance benefiting the system. In the paper we address the problem of how to choose the optimal service level for an operator in a system through a service level differentiation model. Experimental results comparing system performance for different values of system parameters show that a mixed strategy is a general way to get optimal system performance for a large variety of system parameter settings and in all cases is no worse than a pure strategy.**

I. Introduction

A critical challenge to practice in robotics lies in moving beyond the current many operators per UV control found in the Predator and other deployed systems [10] to applications in which a single operator becomes able to control multiple UVs. In this new multirobot setting the operator must choose which robot to control sometimes trading off the performance of one for another.

Crandall et al. (2005) described an operator's interaction with a robot as a sequence of control episodes in which an operator interacts with the robot for period of time (IT) raising its performance above some upper threshold after which the robot is neglected for a period of time (NT) until its performance deteriorates below a lower threshold when the operator must again interact with it [5]. The duration of the IT/NT intervals depend on the task requirements which determine appropriate performance thresholds (at a minimum an underwater robot, for example, cannot be allowed to drift more than 180˚ off course and still reach its destination), the threshold values (lowering performance thresholds shortens IT and lengthens NT) and level of automation (increasing automation increases NT). This model is very general and can describe a range of human-robot system performance from very poor to the best obtainable. In practice thresholds are rarely found to be fixed [14]. For example in a complex task such as picking waypoints for a robot that must avoid underwater obstacles and mines while following routes designed to prevent detection, an operator pressed for time might assign a shorter path but at the cost of needing to return to controlling that robot sooner.

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Ying Xu, Tinglong Dai and Katia Sycara are with Carnegie Mellon University, Pittsburgh, PA, USA (email: {yingx1, tdai, katia}@cs.cmu.edu).

Michael Lewis is with University of Pittsburgh, Pittsburgh, PA, USA (ml@sis.pitt.edu)

Olsen's fan-out model [5, 12] fixes these thresholds to give an upper bound on the number of independent homogeneous UVs that a single human can manage. This upper bound is computed by identifying how long an individual robot can be neglected, and then determining how many other robots can receive interactions during this neglect interval.

Since the limiting resource in the system is the human attention, we can model the operator as a queue and the robots as clients that request service. This paper presents a queuing model addressing two issues: 1) individual differences in operator skills/capabilities, and 2) trade-off between human interaction and performance. In many cases, such as assigning waypoints for underwater robots mentioned above, we can see that the IT and NT are not independent but can be interrelated (the longer IT leading to the longer NT) This motivates introducing a model of service differentiation into the queuing HRI model. Specifically, allowing the operator to choose a mixed service strategy, in which with probability p, he/she offers the robot better and more complete service with a longer IT time, which should support a longer NT time and higher performance during the NT interval; on the other hand, with probability (1-p), the operator offers a comparatively lower level service interaction to the robot, which decreases the robot's interaction time IT and other robots' waiting time TQ (time in queue) , but supports a shorter neglect time NT and perhaps less satisfactory performance for the robot during the NT interval.

Our paper makes the following contributions: it introduces the conjecture that IT duration and quality are correlated with performance and length of the subsequent NT interval and explores the tradeoffs for multirobot systems. We also propose the first *closed system model* for human-robot teams that meets the assumptions of Crandall's (2005) informal neglect tolerance model. A closed system model is one where robots arrive, get served and return for service. Most of queuing models in the literature are open queue because they are easier to analyze. Close queue models are far more difficult to construct and analyze. They are even more challenging to develop and analyze when service differentiation is also modeled. However, close queue models with service differentiation are applicable to human control of multiple robots since typically the operator controls a known number of robots that may require repeated service during system operation, thus returning to the queue.

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One key finding we provide is that TQ depends on IT and NT, and also affects the system total performance.

II. Related Work

In a recent survey of human control of robot teams Goodrich and Schultz [10] argued for increased research into techniques and approaches for increasing the number of robots a single human can manage. The paper also summarized work on two measurements designed to assess human-multirobot performance: fan-out and team performance prediction.

Fan-out, introduced by Olsen [12], refers to the maximum number of homogeneous robots a single operator can control. Olsen also gives a direct and simple computation function for fan-out from NT and IT based on fitting additional ITs into the NT period. This expression was modified by Cummings in 2007 to take robot waiting time into account [7]. Because their definitions of fan-out are threshold based they can be presumed to predict additive improvements in performance, plateauing at the fan-out number.

Crandall in 2003 introduced the first method to predict the performance of human-robot teams [4] and extended it in 2007 proposing two key performance metrics for multi-robot control: interaction efficiency (IE), representing the effectiveness of the robot during human-robot interaction time, and neglect efficiency (NE) measuring robots' performance during neglect time [6]. Crandall's new metrics were defined with integral functions, more accurate and specific than the averages used in [4]. Crandall's newer model provides a basis for our service differentiation model, which predicts these metrics from human's service/ level choices through different human-robot interaction times [6].

Another important aspect in our model relates to applying queuing theory to multiple robot control. Cummings et al [7] introduced queueing theory into multirobot control using a simplified open system as an example. However, as [13] demonstrated, closed and open systems can act in dramatically different ways. A closed system is needed to fit the basic human-multiple robots control model we have described, yet is far more complicated to analyze.

As [8] discovered, wait time (TQ) plays a critical role in the prediction of a human controller's capacity for multiple robot supervisory control. The paper specifically decomposed TQ into three components: queue waiting time (WTQ), interaction waiting time (WTI) and waiting time caused by loss of situation awareness (WTSA), which turned out to be the most critical. While our paper does not attempt to fit human data it extends this approach by predicting WTQ from IT, NT, and other metrics of the model.

There is extensive literature related to service-level differentiation application. As space here is limited, we mainly refer to the working paper by Anand et al in 2009 [1], which studies the optimal "quality-speed tradeoff" in customer intensive services. They focus on an open queueing system with a single service level and investigate the strategic behavior of the service provider and the consumers [1].

III. Model and Algorithm

We study a system with a single operator who interacts with multiple robots. The tasks are homogeneous in the sense that their service requirements follow the same stochastic distribution. The operator has freedom to choose between high/low-quality interactions, a mixed strategy, i.e. provide high-quality interaction with a certainty probability. The tradeoff here is that high-quality service requires longer service time and endogenously longer waiting time for the robot, but also promises longer neglect working time and better performance during the neglect times, while the fast but low-quality interaction does the reverse. Our objective is to identify the best mixed strategy for the operator to optimize system performance.

Under the same problem settings, we model the human-robot system as an open or a closed queue, respectively. The system can be viewed as an open queue when the correlation between the arrival process and service process can be ignored, which is certainly not realistic. Additionally, we model the system as a closed queue in which the robots' arrival process is dependent on the human operator's service process. We show that different modeling approach yields strikingly different optimal strategies.

A. Open Queue

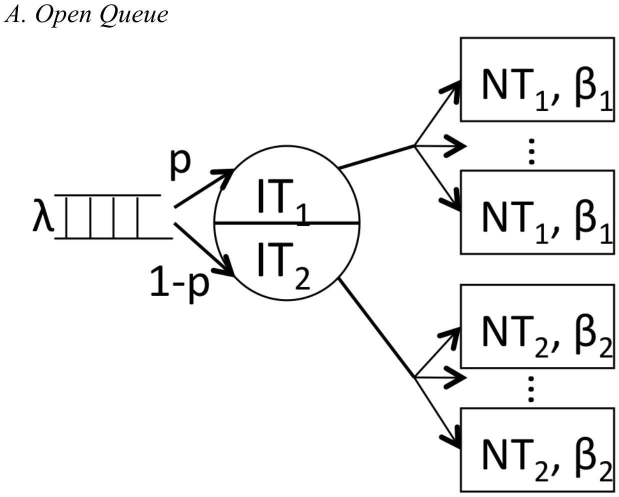

Fig. 1. Human Robot Interaction Modeled as an Open System

Arrival and Service Process. All the robot arrivals follow a Poisson process with the rate of λ. The operator uses a mixed strategy such that each robot receives high-quality service with probability p, and low-quality service with probability $1-p$. After the service, the robot continues its mission. The next time the same robot needs services from the human operator, it will be treated as a new robot. Fig. 1 illustrates the configuration of the queue model. The operator deals with the queueing robots on a First Come-First Serve (FCFS) discipline and offers two types of service: 1) high-quality service with an interaction time exponentially distributed with the mean of IT_1 and 2) low-quality-short-time with the interaction time exponentially distributed with the mean IT_2. If the robot receives high quality service, then it has a neglect time of NT_1 and neglect efficiency β_1 during the neglect times; otherwise, the robot has a neglect time of NT_2 and neglect efficiency of β_2. The probability p could be interpreted as the fraction of robots receiving high-quality service during the whole planning horizon. Here we assume without loss of generality that $IT_1>IT_2$, $NT_1>NT_2$ and $\beta_1>\beta_2$. Furthermore, the utilization of the operator is strictly less than 1 so as to enable system stability, i.e.,

$$\lambda\left(p \cdot IT_1 + (1-p)\cdot IT_2\right) < 1 \text{, or } \quad p < \frac{1-\lambda IT_2}{\lambda(IT_1 - IT_2)},$$

Performance Metrics. We have defined β_1 and β_2 as the robots' efficiency after they have been provided with high- and low-quality services, respectively. We treat the performance during the *IT* and *TQ* time as a penalty (denoted by **(-α)** to the whole system's performance since during those times the robot does not do useful work for the system). The system utility, denoted by U, is defined as

$$U = -\alpha(E[TQ] + E[IT]) + (E[\beta NT])$$

Maximizing the system utility is essentially the tradeoff between service quality and service speed: On the one hand, with a higher p, more robots receive high-quality service from the human operator, and the average performance during autonomous working state would be higher; on the other hand, as p increases, the system suffers from longer service and waiting times.

Performance Optimization. We first note from the service process that

$$E[IT] = p\cdot IT_1 + (1-p)\cdot IT_2$$

$$E[\beta NT] = p\beta_1 NT_1 + (1-p)\beta_2 NT_2$$

The mean waiting time can then be obtained through standard results of M/G/1 queue model,

$$E[TQ] = \frac{\lambda}{2(1-\lambda E[IT])}\left(p\cdot IT_1^2 + (1-p)\cdot IT_2^2\right)$$

To solve the constrained optimization problem, we first study the second-order derivative of U to p. We prove that under system stability condition, the inequality $\partial^2 U / \partial p^2 < 0$ always holds, which means that U is concave in p. The optimal solution p^* is defined by the following equation:

$$\left.\frac{\partial U}{\partial p}\right|_{p=p^*} = -\alpha\left(\left.\frac{\partial E[TQ]}{\partial p}\right|_{p=p^*} + \left.\frac{\partial E[IT]}{\partial p}\right|_{p=p^*}\right) + \beta \left.\frac{\partial E[NT]}{\partial p}\right|_{p=p^*} = 0$$

Solving the above first-order condition yields the following optimal solution:

$$p^* = \frac{1-\lambda\cdot IT_2}{\lambda(IT_1 - IT_2)} - \sqrt{\frac{\alpha\lambda(IT_1 + IT_2 - \lambda\cdot IT_1\cdot IT_2)}{2(IT_1 - IT_2)[\beta_1\cdot NT_1 - \beta_2\cdot NT_2 - \alpha(IT_1 - IT_2)]}}$$

We see from the above function that p^* is decreasing in α, and increasing in β_1, β_2, NT_1 and, NT_2. How p^* changes with λ varies and we shall see this through simulations later on.

B. Closed system

1) Model introduction

Most of the time, an operator is in charge of a group of robots and one robot makes repeated interaction with one operator for commands or services etc. We claim that closed system is more realistic than open system model related to multi-robots control. As shown in Fig. 2, all the robots coming to the operator (as the subsystem 1) are not from outside of the system, but from the subsystems 2 and 3. In addition, the total number of robots in the system is constant and defined as N. Thus the arrival process of the robots to the operator is not following Poisson or any other common distributions; instead, it is affected by the neglect time and neglect efficiency of all the robots.

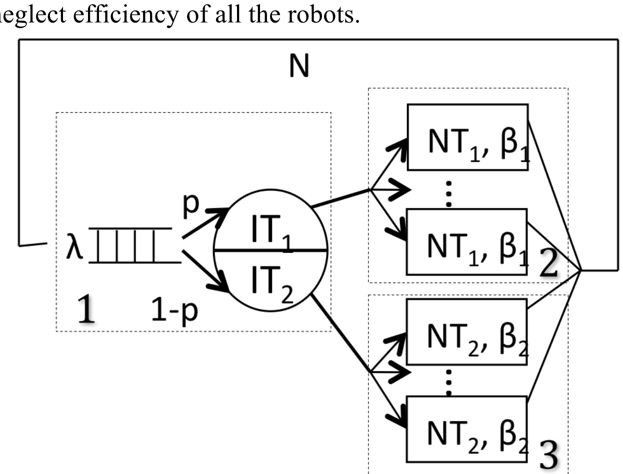

Fig. 2. Human Robot Interaction Modeled as a Closed System. In the analysis, we divide the system into three subsystems as the dash box bounded

To analyze the average performance of the system, we keep all the assumptions that also hold in the open system. The only difference is here the N replaces the arrival rate λ and the main problem comes from how to characterize the average waiting time *E[TQ]* in a closed system.

2) Algorithm

In this part, we determine the optimal service level p through two steps: first we decide the mean of waiting time and secondly we solve the performance maximization problem.

Above all, we need to derive the queue waiting time in the closed HRI system. Here we also assume that all the time variables are random variables following exponential distributions with the corresponding mean IT_1, IT_2, NT_1, NT_2. Thus in the system we have a server with non-exponentially distributed service time and robots whose inter-arrival times do not follow Poisson process. Based on [9] our model can be expressed in product form as:

$$P(n_1, n_2, n_3) = \frac{1}{G(N)} F_1(n_1) F_2(n_2) F_3(n_3)$$

where $G(N)$ is a normalizing constant

and $n_1 + n_2 + n_3 = N$

As shown in Fig.2, we divide the whole system into three subsystems, the human operation center, the part of the system with robots that receive high level of service with corresponding neglect time and neglect efficiency and finally the part of the system with robots that receive low level of service with corresponding neglect time and neglect efficiency. In the above product form, $P(n_1, n_2, n_3)$ presents the probability that there are n_i number of robots in the ith subsystems. $F_i(n_i)$, as a probability function for the ith subsystem, is defined as follows:

$$F_1(n_1) = (\overline{IT})^{n_1} = (p \cdot IT_1 + (1-p) \cdot IT_2)^{n_1}$$

$$F_2(n_2) = \frac{(NT_1 \cdot p)^{n_2}}{n_2!}$$

$$F_3(n_3) = \frac{(NT_2 \cdot (1-p))^{n_3}}{n_3!}$$

With the product form function, a traditional convolution method is adopted to compute the normalizing constant $G(N)$ following [3]. Accordingly, we could compute $P(n_1, n_2, n_3)$ as well as $P_i(n_i)$, the probability that there are n_i number of robots in the ith subsystem. We derive the average waiting time as: $E[TQ] = \frac{E[N_1]}{X}$, where the average number of robots in the human operation center $E[N_1]$ and system throughput X can both be determined by the system state probability:

$$E[N_1] = \sum_{n_1=0}^{N} n_1 P_1(n_1) \text{ and } X = \frac{1 - P_1(0)}{p \cdot IT_1 + (1-p) \cdot IT_2}$$

The latter function is based on the rule that throughput equals to the mean service rate times the utilization.

In the open system case, we have introduced that the system performance measurement is defined as:

$$U = -\alpha(E[TQ] + pIT_1 + (1-p)IT_2) + p\beta_1 NT_1 + (1-p)\beta_2 NT_2$$

For performance maximization, we take the first derivative of U function to the service differentiation level p and the optimal p^* satisfies either $\frac{\partial U}{\partial p^*} = 0$ or if not feasible, p^* is chosen as a boundary point 0 or 1. Unlike the study in an open case, the closed form representation of the waiting time *E[TQ]* could not be derived, in other word, we cannot analytically determine the exact solution for the optimal p^*. Therefore, a searching methodology is adopted and the whole algorithm is presented in Fig. 3.

Input: system parameters IT_1, IT_2, NT_1, NT_2, β_1, β_2
Output: optimal p^* maximizing U
For each p between 0 and 1 do
  Compute $G(N)=g(N,3)$
    // Initialization
    $g(0,k) = 1$ for $k = 1,2,3$; $g(i,1) = F_1(i)$
    // convolution method
    For each k = 2,3 do
      For each n from 1 to N do
        $g(n,k) = \sum_{m=0}^{n} F_k(n) g(n-m, k-1)$
    Until $g(N,3)$ computed
  Compute $P(n_1, n_2, n_3)$

Fig. 3 optimal p^* searching algorithm for closed system

Note that in a closed system, the trade-off between service quality and service time becomes more complicated as longer service time generates longer neglect time, but also lower arrival rate to the operator, which alleviates the queue congestion created by longer interaction time. Furthermore, the detailed optimal strategy is illustrated in the simulation.

IV. Simulation and Numerical Study

In this section, we firstly study the sensitivity of optimal p^* with other parameters in both open and closed system. Secondly, we obtain the effects of mixed-strategy on the system performance comparing with pure service strategy in both open and closed system. We mainly adopt two types of service data: high average IT_1, NT_1 and low average IT_2, NT_2. The data set of IT and NT is obtained from the results of a human multirobots interaction experiment, in which human control multiple simulated robots to search for victims in a damaged building [14].

A. Open system

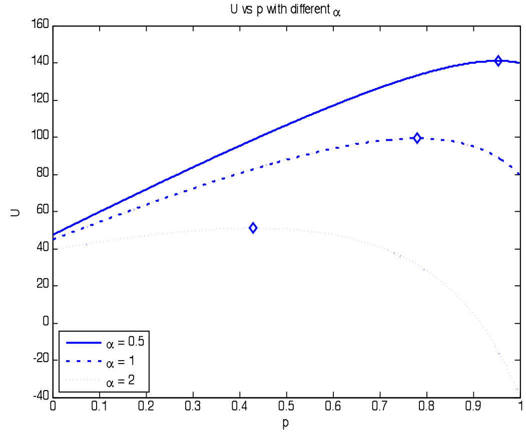

Fig. 4 System performance changes with *p* under different *α* parameters. *U* is concave in *p* and the optimal *p* decreases as *α* increases.

As we mentioned in the model section, the system utility function *U* is concave in *p* as Fig. 4 shows. The diamond labels on the dotted graphs show the optimal p^* generating the highest system performance under different values of *α*.

Fig. 5 shows the trend of how the optimal p^* changes with *λ*. The left hand side axis of the figure denotes values of *p*, whereas the right hand axis denotes value of *U*. The solid line in Fig. 5 shows that p^* decreases discretely as *λ* increases, which follows the fact that large *λ* generates more congested system which can be counterbalanced by shorter IT with shorter waiting time. Moreover, there is a special bound of *λ* (from 0.05 to 0.2 in the figure), below which, only high-quality service is needed and above which, *p* is zero and fast service is needed. How the optimal *U* change with *λ* is also presented in the dashed (green) line. Specifically, comparing the optimal system utility with the utility generated without service differentiation (see Fig. 6) we see that service differentiation improves the whole system performance.

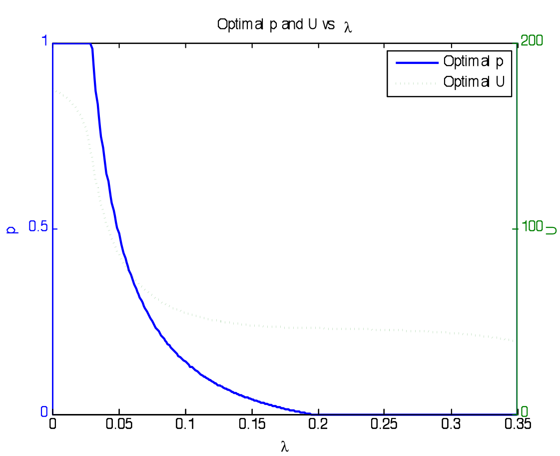

Fig. 5. Optimal solution p^* and system performance *U* decreases as arrival rate *λ* increases in an open system. A bound of *λ* (around 0.2) exists for service differentiation

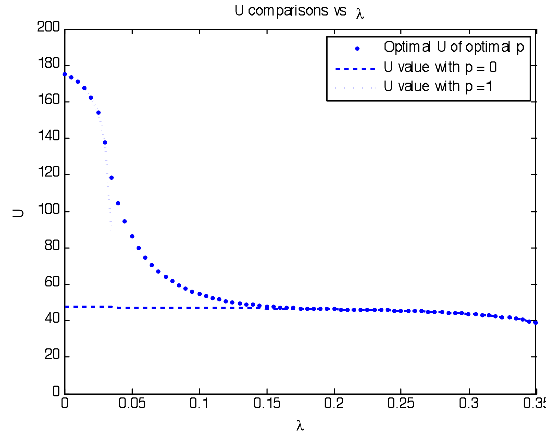

Fig. 6. Optimal system performance *U* compared with benchmark values generated by single service type (dashed line with *p=0* and dotted line with *p=1*) in open system. We see that a mixed strategy greatly improves the system performance

B. Closed system

1) Waiting time

We present a plot (Fig. 7) comparing the waiting time provided by the model and solution procedure and the simulated value to check the accuracy of the algorithm. In Fig. 7 the scattered dots stand for results of the simulation, while the smooth line shows the model results. Three different groups of line and dots represent different number of robots in the system, namely *N* equals to 8, 10 and 12. From Fig. 7, we see that though the simulation results have random distribution, the computed smooth curve provides best fit to those data in all the three cases.

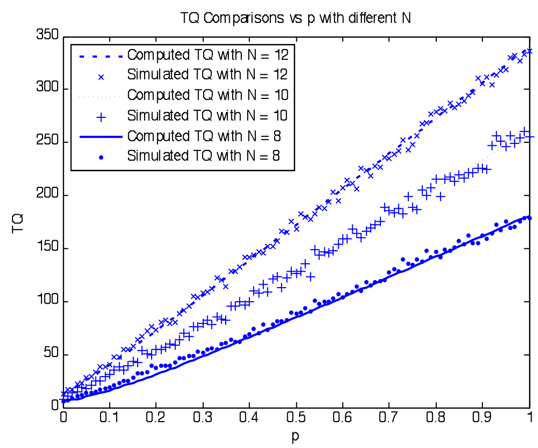

Fig. 7. Computed *E[TQ]* compared with simulation *E[TQ]* under different number of robots N

2) Performance maximization

We are still interested in the sensitivity of optimal p^* with other parameters, especially the number *N* of robots in the closed system.

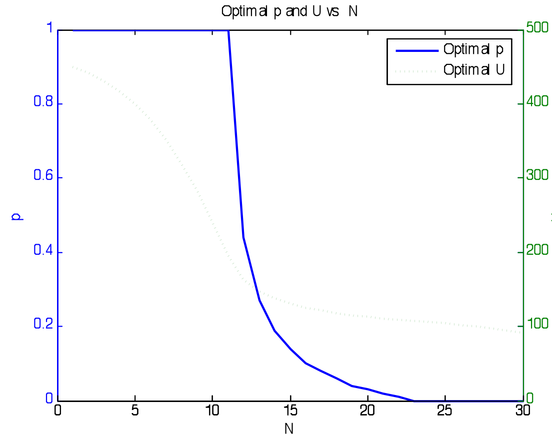

Fig. 8. Optimal solution p^* and system performance U as the number N of robots increases in a closed system. A bound of N exists for service differentiation

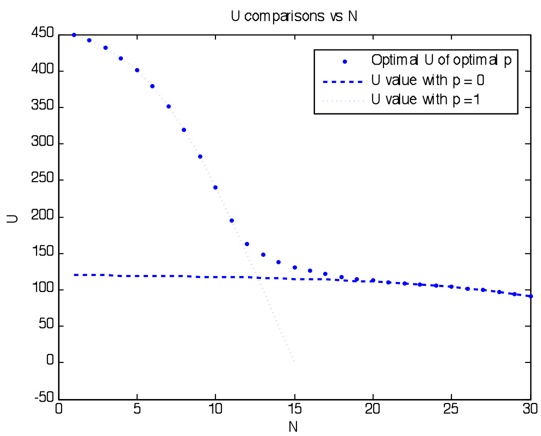

Fig. 9. Optimal system performance U compared with benchmark values generated by single service type (dashed line with $p=0$ and dotted line with $p=1$) in closed system. A cut-off N' exists that separates the optimal service strategy.

From Fig. 8, we still see that there is a bound for N for choosing mixed strategy as the optimal. Comparisons of the optimal system performance U with the pure strategy in Fig. 9 show that in closed system a mixed strategy is not as efficient as in the open system. However, we find that a special cut-off N' exists in the system (around 13 on the x-axis in Fig. 9), which alters the optimal interaction strategy from high level to low level.. It shows that based on the number of robots and the system conditions, an appropriate pure strategy could work well for the system, either high level or low level based on the number of robots in the system. On the other hand, a pure strategy with deterministic *IT* is not applicable to all ranges of number of robots. A pure service type sometimes may not work even when only one additional robot has been added into the system. For example in Fig. 9 when robots number increases from 12 to13 with a pure strategy ($p=1$), the system utility drops from 150, above another pure strategy ($p=0$) to 100, below it.

V. Conclusion

The presented model identifies the optimal service strategy to maximize system performance in multi-robot control through a service level differentiation method based on two types of service: high-quality-long-time and low-quality-short-time. Modeling different levels of service is motivated by real human performance data which shows a wide variety of ITs related to variations in demands on the operator. While the earlier neglect tolerance model assumed a fixed efficiency threshold for each robot our model relates IT and NT to optimal system performance allowing the individual thresholds to vary. This increased flexibility not only improves team performance but agrees with human data [14, 11] showing performance per robot to decrease smoothly with increasing team size rather than dropping abruptly upon reaching the fan-out threshold.

Our first model for an open queue system allowed us to find exact analytic solutions. While an open system model has been used by other researchers in this area [7] and may provide an approximation of systems with long NTs it cannot accommodate the basic assumption of repeated interactions made by the neglect tolerance model and fan-out estimators. Our second closed system model is much more realistic since it models the inter-dependency between the service process and arrival process. This model is very challenging and we were only able to find solutions algorithmically. Experimental results comparing system performance for different values of system parameters show that a mixed strategy is a general way to get optimal system performance for a large variety of system parameter settings (e.g.; values of λ, number of robots) and in all cases is no worse than a pure strategy.

References

[1] K.S.Anand, M.Pac, and S. Veeraraghavan, "Quality-speed conundrum: tradeoffs in customer-Intensive Services", *Wharton School working paper,* 2009.

[2] F. Baskett , K. M. Chandy , Richard R. Muntz , F. G. Palacios, "Open, Closed, and Mixed Networks of Queues with Different Classes of Customers", *Journal of the ACM (JACM)*, v.22 n.2, p.248-260, April 1975

[3] J. P. Buzen, "Computational algorithms for closed queueing networks with exponential servers", *Communications of the ACM*, v.16 n.9, p.527-531, Sept. 1973

[4] J. W. Crandall, C. N. Nielsen, and M. A. Goodrich. "Towards predicting robot team performance", In *Proc. of IEEE Int'l Conf. on Systems, Man, and Cybernetics*, pages 906--911, 2003.

[5] J. W. Crandall, M. A. Goodrich, D. R. O. Jr., and C. W. Nielsen. "Validating human-robot interaction schemes in multi-tasking environments." *IEEE Trans. on Systems, Man, and CyberneticsPart A: Systems and Humans*, 35(4), 2005.

[6] J. W. Crandall , M. L. Cummings, "Developing performance metrics for the supervisory control of multiple robots", *Proceedings of the ACM/IEEE international conference on Human-robot interaction*, March 10-12, 2007, Arlington, Virginia, USA

[7] M. L. Cummings, C.E. Nehme, and J. Crandall. 2007b. "Predicting operator capacity for supervisory control of multiple UAVs", *Studies in Computational Intelligence* (SCI) 70,11-37 (2007)

[8] M. L. Cummings and P. J. Mitchell, "Predicting controller capacity in supervisory control of multiple UAVs", *IEEE Transactions on Systems, Man, and Cybernetics—Part A: Systems and Humans*, vol. 38, no. 2, pp. 451–460, 2008.

[9] P. J. Denning , J. P. Buzen, "The Operational Analysis of Queueing Network Models", *ACM Computing Surveys (CSUR)*, v.10 n.3, p.225-261, Sept. 1978

[10] M. A. Goodrich , A. C. Schultz, "Human-robot interaction: a survey", *Foundations and Trends in Human-Computer Interaction*, v.1 n.3, p.203-275, February 2007
[11] C. Humphrey, and J. Adams, "Assessing the scalability of a multiple robot interface", *Human Robot Interaction Conference*, ACM, 239-246, 2007.
[12] D.R. Olsen Jr., and S.B. Wood, "Fan-out: Measuring Human Control of Multiple Robots", In *Human Factors in Computing Systems* (CHI' 04), Vienna, Austria: ACM Press, 2004.
[13] B.Schroeder, A.Wierman, and M. Harchol-Balter, "Closed versus Open System Models: a Cautionary Tale", *Proceedings of Networked Systems Design and Implementation (NSDI 2006)* . San Jose, CA, May 2006, pp. 239-252
[14] H. Wang, M. Lewis, P. Velagapudi, P. Scerri, and K. Sycara, "How search and its subtasks scale in N robots", *Human Robot Interaction Conference*, ACM, 141-148, 2009.
[15] R. Work, "Naval transformation and the Littoral Combat Ship", Washington, DC: Center for Strategic and Budgetary Assessments, 2004.